Abstract   Many nations have imposed lockdowns due to the COVID-19 pandemic as a measure to prevent the spread of disease among its population. These lock-downs have confined people at their homes which is leading them to use digital technologies such as Internet, social media, smartphones, more than ever before. The problematic use of these digital technologies may impact their mental and emotional health. This chapter discusses the role of machine learning to assess addiction to various digital technologies and its impact on mental and emotional health and on sleep quality during the COVID-19 pandemic. Three case studies are provided to demonstrate how machine learning can be used to assess these addictions and related disorders during the pandemic. Gaussian mixture clustering is implemented to group people with similar Twitter usage patterns to identify addictive Twitter usage during the pandemic. The results convey that 11.71% of users show addictive Twitter usage patterns and 4.05% of users show highly addictive Twitter usage patterns while 2.70% of users show dangerously addictive usage patterns. “Sadness” and “anger” are the dominating emotions among these users in contrast to “happiness” which is the dominating emotion among non-addictive users. A similar approach is used to cluster students with similar smartphone usage patterns and nomophobia scores to identify nomophobic behavior during the pandemic. The results show that 4.5% of students are at extremely high risk whereas 73% of students are at high risk. A review of studies identifies the emergence of machine learning for assessment of mental and emotional health during the COVID-19 pandemic. A case study on sleep quality assessment using data from wearable sensors convey that sleep quality of students...
has been reduced significantly during the pandemic with a maximum decrease of 90.90%.

Keywords Digital technologies • Behavioral addiction • Machine learning • Mental health

1 Introduction

Addiction to digital technologies is a type of non-substance addictions which is a subset of behavioral addictions. The term technological addiction encompasses wide range of addictions such as Internet addiction [1], social media addiction [2, 3], smartphone addiction [4], online gaming addiction, and online gambling addiction. When people spend significant amounts of time using these digital technologies, and Internet-related activities developing dependency on these technologies for social interaction, entertainment and information retrieval, it leads to negative outcomes including problematic and addictive behaviors. Furthermore, technological addiction to an extent causes mental impairments [5–8], emotional instability [5, 9] and sleep disorders [10–12].

The coronavirus disease 2019 (COVID-19) epidemic has spread across the world. Countries are imposing nationwide lockdowns to control the spread of the disease. The lockdowns are affecting the daily lives of people around the world leading them to use digital technologies, including the Internet, social media, and smartphones more than ever before. According to Statista [13], worldwide 40% of Internet users were using their laptops more than ever before during the pandemic whilst 32% and 22% of worldwide Internet users increased their usage of desktops and tablets, respectively. Smart TV and media streaming service usage was also surged with around 30% of worldwide Internet users using these services more than ever. An average of 14% of Internet users worldwide were utilizing game consoles more than ever before as a direct result of the COVID-19 outbreak and its associated lockdowns. Global survey reports of increased use of in-home media consumption by the Internet users revealed, on an average 51% of worldwide respondents were watching films and shows on streaming services such as Netflix more. More than 45% of worldwide Internet users spent longer on social media and messaging services. A large proportion (35%) of worldwide Internet users agreed on spending more time on computer and video games and listening to more streaming services such as Apple music and Spotify. However, a small proportion of worldwide Internet users professed to have read more magazines and newspapers (16% and 14% respectively). Interestingly, at least 50% of respondents in most countries said that they were watching more news coverage. Also, 14% of respondents agreed to have created and uploaded more videos on YouTube and TikTok.

The emergence Artificial Intelligence (AI) and Machine Learning (ML) based methods in various applications in the context of COVID-19 has been reported [14–
A review of publications emphasizing on the use of AI in the COVID-19 research domains was conducted by Hossain et al. [15]. It identified various research domains including epidemiological characteristics, diagnostics, prevention and control, psychological conditions leveraging the techniques of AI during this pandemic.

The pervasiveness of interactive functions such as chat rooms and forums on the Internet make it more addictive in nature compared to the less interactive functions and cause significant impairment to their family, social, financial, and professional lives and health.[1]. Signs of tolerance, withdrawal, and craving existed among the addictive Internet users [17] and the negative consequences of excessive use of digital technologies included preoccupation with the Internet, feeling of excitement or euphoric when online, going online to escape other problems, obsessive-like characteristics, socializing online more than in person, staying online longer than planned and losing track of time [18, 10]. Moreover, the most vulnerable group to addictive usage of digital technologies is students due to the accessibility of the Internet and the flexibility of their schedules [19] which also affects their academic performance [20]. Moreover, Social networking is widespread and convenient method to stay in touch with family and friends amidst social distancing directives during the COVID-19 pandemic, nevertheless timeless use of these technologies is further impacting the mental health of people causing anxiety, depression, sleep problems and others. Several instruments have been devised to assess the addiction to digital technologies. For instance, Media and Technology Usage and Attitudes Scale (MTUAS) [21] is a long, 66-item scale for assessment of extent of media and technology usage. However, it cannot assess different types of technological addictions such as Internet Addiction, social media addiction and smartphone addiction. Therefore, the research problem is to assess addiction to different types of digital technologies during the COVID-19 pandemic and its impact on mental health employing various machine learning techniques for reliable and accurate results.

This chapter discusses about the applications of ML for prediction of addictive use of digital technologies and its impact on mental and emotional health during the COVID-19 pandemic. Section 2 discusses about Internet addiction with excessive use of Internet during the pandemic. It discusses about the existing approaches to assess Internet addiction. Section 3 discusses about excessive use of social media during the pandemic and existing approaches to evaluate social media addiction followed by a case study to assess addictive Twitter usage during the COVID-19 pandemic using machine learning. Section 4 discusses about the assessment of smartphone addiction and its associated psychological disorders. It presents a case study to evaluate excessive usage of smartphone during the pandemic using machine learning. Section 5 discusses about how addiction to digital technologies affect mental health of people and reviews studies employing machine learning for assessment of mental and emotional health during the COVID-19 pandemic followed by a case study to assess sleep quality of undergraduate students. Finally, Sect. 6 concludes the chapter.
2 Internet Addiction

There exist multiple terms used to refer Internet addiction namely, Problematic Internet Use (PIU), Excessive Internet Use, Compulsive Internet Use, Pathological Internet Use, and Internet Addiction Disorder (IAD) describing the negative effects of excessive use of Internet on personal lives of Internet users. However, everyone using the Internet is not necessarily a victim of problematic use. Griffiths [22] has argued that many of the users who are excessively using the Internet may be using it as a medium to fuel other addictions and cannot be referred to as Internet addicts. He put forward a need to distinguish between addictions to the Internet and addictions on the Internet. Wąsiński and Tomczyk [23] provided a clear definition of Internet addiction stating, “it may become problematic only for those who are unable to control their online activities”. Addicted individuals abandon their everyday activities and devote their time to the activities that they discover on the Internet. In simple terms, Problematic Internet Use refers to the use of the Internet that creates interference in one’s personal daily life in the form of psychological disruptions, social withdrawal, sleep deprivation, reduced school or work performance in a person’s life [10, 20, 24, 25].

According to American Psychiatric Association’s Diagnostic and Statistical Manual of Mental Disorders-Fourth Edition (DSM-IV) [17], Internet addiction is a blanket term covering an extensive variety of behaviors and impulse control problems. These behaviors are categorised into five specific subtypes as follows:

- **Cyber relationship addiction**: It includes excessive involvement in online relationships and addiction to social networking platforms to the point where one prefers virtual relationships over real-life friends.
- **Information overload**: It is associated with compulsive web surfing eventually leading to lower work productivity
- **Net compulsions**: It is associated with obsessive online gambling, shopping or online trading often resulting in financial crisis.
- **Computer addiction**: It is associated with obsessive computer game-playing.
- **Addiction to inappropriate material**: It is associated with the compulsive use of websites with adult content.

2.1 Excessive Internet Usage During COVID-19 Pandemic

As per the reports of OpenVault’s Broadband Insights [26], the average broadband consumption has increased to 402.5 GB for the first quarter of 2020 as compared to 273.5 GB during the same time last year which sums up to 47% increase. It also results in 17% rise over the fourth quarter of 2019. Overall Internet usage surged by 47% in first quarter of 2020 largely due to the COVID-19 pandemic. There are
various applications and services responsible for this growth. It has been reported by Infineon [27] that 50,000 years’ worth of media streaming was observed in just one day, on April 4. This is due to the increased reliance of people on streaming services. Netflix, a media streaming service has seen a 22% growth in subscribers. Peloton, a collaborative workout company’s user membership growth rose by 66%. The use of social media has increased considerably leading to a 27% increase in daily Facebook traffic flow and a 26% growth in quarterly sessions on LinkedIn. Also, 25% rise in monthly downloads has been seen by TikTok. Moreover, messaging applications such as WhatsApp have been retrieving twice as many video and voice calls. Social video applications have also seen a flow in acceptance, with Bunch receiving 1 million downloads in just seven days and House party, a social video and gaming application seeing a 70% increase in monthly signups. Nintendo, a video gaming company has seen 41% surge in monthly profit.

2.2 Assessment of Internet Addiction: Conventional Approach

The earliest pragmatic research conducted on addictive Internet use was by Young in 1996 [1]. Young [1] developed an 8-item questionnaire to assess the traces of addiction among Internet users. The questionnaire was based on DSM-IV [17] criteria for pathological gambling. Later, in 2008, Young [5] developed a 20-item scale assessing frequency of Internet use, frequency of interaction on Internet, its various negative impacts on one’s personal life and its impact on mental and emotional health (anxiety, depression, mood, nervousness). The assessment is predominantly known as Internet Addiction Test (IAT). In 1997, Brenner [28] devised a 32-item instrument called the Internet-Related Addictive Behavior Inventory (IRABI) with all the items as dichotomous. In 1999, Pratarelli et al. [18] formulated a set of analytical criteria to examine possible constructs underlying Internet addiction. A of 93-item questionnaire was formulated, with items related to categorical demographic and Internet use and dichotomous items. Another attempt in formulating a reliable Internet addiction scale was made by Beard and Wolf [24] in 2001. They tried to modify the Young’s questionnaire, based on concerns with the objectivity and reliance on self-report by removing vague terms and clarifying some terminologies. Furthermore, Rotunda et al. [10] devised a tool names as the Internet Use Survey (IUS) which analyses three components comprising demographic data and Internet usage; negative consequences and experience associated with Internet use; personal history and psychological characteristics of participants. The authors focussed on the need to consider contextual and dispositional factors associated with frequent Internet use rather than inaccurately assuming it as excessive, pathological, or addictive. Later, in 2003, Shapira et al. [29] anticipated that problematic Internet use be conceptualized as a form of impulse control disorder. They modified their diagnostic criteria for problematic Internet use
containing broader aspects. A bigger study was conducted by Greenfield [30] called the Virtual Addiction Survey (VAS). The VAS focussed on descriptive information items including frequency and duration of Internet use, specific purpose of Internet usage, and clinical items such as disinhibition, loss of time, and behavior online. Lately, Chen et al. [31] developed a Chinese Internet addiction scale in 2003 which is commonly known as Chen Internet Addiction Scale (CIAS). The scale is based on a questionnaire exploring weekly on-line hours, habitual domains, and experience of Internet usage. Later, the scale was revised, and CIAS-R was developed with modification of item wording and addition and elimination of some items. More recently, Demetrovics et al. [32] devised an 18-item scale and named it as Problematic Internet Use Questionnaire (PIUQ) which contains three subscales: obsession, neglect, and control disorder.

2.3 Assessment of Internet Addiction: Machine Learning Based Approach

In the last decade, automation has been introduced for detection of Internet addiction and problematic Internet use by several researchers utilizing various data mining and machine learning techniques. Di et al. [33] utilized Support Vector Machines for automated detection of Internet addiction disorder among Chinese college students using data from CIAS and multiple personality questionnaires. Their model achieved a high performance with accuracy of 96.32% in detecting Internet addiction Nandhini et al. [34] implemented multiple machine learning classification algorithms including Naive Bayes, JRip, ZeroR, J48, RepTree using data from a survey to evaluate Internet addiction disorder among Indian students. Ji et al. [35] proposed a model for detection of Internet addiction utilizing a rule-based model, extended classifier which combines Reinforcement Learning and Evolutionary Computation. They used responses to CIAS as their dataset. Ioannidis et al. [36] employed machine learning techniques such as Logistic Regression, Random Forests and Naïve Bayes for detection of problematic Internet use utilizing the IAT data.

3 Social Media Addiction

Social Networking Sites are virtual platforms providing wide-ranging services to its users such as interaction with real-life friends, and other people with similar interests to maintain online relationships. Instant messaging applications refer to communication platforms which deliver more engaging, one-to-one interactions in contrast to social networking platforms which promote one-to-many conversations.
But since both provide virtual interaction among users, both can be considered as social media platforms. Over the last decade, social media use has become increasingly prevalent in daily activities and hence, various researchers are studying the prevalence and effects of social media addiction. Social media addiction belongs to the category of cyber relationship addiction among various Internet addiction categories as described in Sect. 2.

Social Network Mental Disorder (SNMD) is a disorder among social media users associated with undue use of social media applications accompanied with a loss of the sense of time and withdrawal including feelings of anxiety, depression, anger, or tension on inaccessibility of the social networking applications [37]. SNMDs are social-oriented and tend to happen to users who are dependent on social networking platforms for interacting with others. These people generally lack offline interactions and hence, seek cyber-relationships for compensation.

3.1 Excessive Use of Social Media During Covid-19 Pandemic

The impact of COVID-19 outbreak and its associated lockdowns has been seen as increased global in-home media consumption including the social media by the Internet users worldwide. According to Statista [13], around 45% of worldwide Internet users spent longer on messaging services such as WhatsApp and Facebook messenger whilst 44% of worldwide users agreed on spending longer on social media including Facebook, Instagram and Twitter during the pandemic.

Participants from Philippines, Italy, China and Brazil were most likely to be spending more time on social networking platforms. Participants from Spain, Italy, China and Philippines were most likely to be spending more time on social networking platforms. Several cities in the United States have instructed their residents to stay at home during the pandemic. A survey was conducted in U.S. in March 2020 to ask users whether they believe that they will use selected social media more if restricted at home due to the pandemic. YouTube, Facebook and Instagram were popular social media platforms that users were estimating to increase their usage during being at home.

According to Statista [13], various social media platforms have been used during the pandemic, with Facebook being the most used with 78.1% of U.S. adults using the platform. The second-most used platform was Instagram, with 49.5% of U.S. adults using it.

India went into a country-wide lockdown on March 25, 2020, which was extended until May 17, 2020. A survey was conducted to explore the impact of lockdown on media usage across India and it was observed that there was a spike in usage of social networking applications in the first phase of the lockdown. The usage stabilized in the further phases of lockdown. Respondents reported to have been using social networking applications for as high as five hours. In contrast,
users spent just over three hours using social media platforms in the weeks before the coronavirus lockdown.

### 3.2 Assessment of Social Media Addiction: Conventional Approach

A set of Berner’s addiction scales were developed in the past decade to evaluate addiction to various social networking sites. To evaluate addiction to Facebook, Bergen Facebook Addiction Scale (BFAS) [2] was constructed consisting of 18 items. The scale comprised six items, each one based on individual core aspect of addiction namely, salience, mood modification, tolerance, withdrawal, conflict, and relapse. Later, Bergen Social Media Addiction Scale (BSMAS) [3] was constructed to cover the addictive usage of all social network sites which is alternatively known as Bergen Social Networking Addiction Scale (BSNAS). BSMAS and BFAS compose same addiction evaluation criteria and structure of items though BSMAS using the word “social media” instead of “Facebook” where social media refers to commonly used platforms such as Facebook, Twitter, Instagram, etc. Bergen’s addiction scales have been related to addiction’s negative outcomes (e.g., poor sleep quality, anxiety, depression). In 2015, Idubor [38] investigated Social Media Usage and Addiction Levels among university students of Nigeria. He developed an instrument named as Social Media Utilisation and Addiction Questionnaire (SMUAQ) which comprised respondents’ personal information and two major sections evaluating social media utilization and level of addiction. More recently, Liu et al. [39] developed a Chinese social media addiction scale comprising seven conventional dimensions of behavioral addiction, i.e. compulsive use, withdrawal, negative consequence, mood alteration, salience, tolerance, and relapse, and two additional dimensions which are preference for online social interaction and continued use (continuous use of social media despite being aware of its negative consequences). Addiction evaluation instruments to evaluate addiction to specific social media platforms also exist in literature. Twitter Addiction Scale (TAS) was developed as a customized version of Internet Addiction Test by replacing the word “Internet” with “Twitter” [40]. The Instagram Addiction Scale (TIAS) [41] was devised to measure addiction behavior on Instagram. TIAS consists of two sub-scales which are Instagram Feed Addiction and Instagram Stories Addiction.

### 3.3 Assessment of Social Media Addiction: Machine Learning Based Approach

Recent studies show the evidences of employing machine learning techniques for prediction and assessment of social media addiction. Leong et al. [42] proposed a
neural network-based model for prediction of social media addiction and validated their model on data of 615 Facebook users. Shuai et al. [43] attempted to predict Social Network Mental Disorder Detection (SNMDD) by exploiting features extracted from social network data using machine learning techniques. In their work they detected three types of SNMD namely, Cyber Relationship Addiction, Net compulsion, and Information Overload using semi supervised learning techniques. They further extend their study [37] by introducing SNMD-based Tensor Model (STM) to improve the accuracy.

3.4 Case Study I: Machine Learning for Analysis of Addictive Use of Twitter During COVID-19 Lockdown in India

This case study aims to determine the effects of the pandemic and the lockdown on the behavioral health of people based on their tweets during the first two phases of lockdown in India. This case study analyses usage patterns of twitter users focusing on addictive usage.

Tweets have been collected during the first two phases of lockdowns (25 March 2020–14 April 2020 and 15 April 2020–3 May 2020) in India. The tweets have been collected based on two categories as follows:

- **Emotion-based tweets** to get the information of users who frequently express their feelings and emotions on social media platforms such as Twitter. Four basic emotions: happiness, sadness, anger/disgust, and surprise/fear have been considered in this work. Scraping of emotion-based tweets has been done using the hashtags of emotion words for each emotion. The emotion words are collected from existing literature [44, 45]. Lexical variants of these emotion words have also been considered.

- **Situation-based tweets** for analysing the active twitter users expressing their views on current situation. Scraping of these tweets has been done based on hashtags related to the current situation in India. Further, subjectivities of situation-based tweets are assessed and tweets with subjectivity equal to 0 have been discarded for the further process. This is done to exclude informative user profiles such as news portal profiles and e-commerce profiles for optimal analysis of addictive usage on Twitter.

After removing the duplicate tweets, total data comprises 7664 tweets. The user profiles with more than 3 tweets among the collected tweets by same username during 40 days of lockdown period are selected for analysis of their usage patterns. 222 such users have been identified. To get the information on daily usage patterns of the selected user profiles all the tweets during the 40 days of lockdown
period from each user profile have been scrapped. Also, emotion of a user has been labelled based on the most used emotion word (including hashtags) among all the tweets posted by a user during this period.

A non-supervised machine learning based technique named as Gaussian Mixture Model Clustering has been used to cluster users based on similar usage pattern. 15 features of users’ tweeting patterns have been sent as input to the clustering algorithm. These features include number of tweets posted in each of the least active 7 days, number of tweets posted in each of the most active 7 days and total number of tweets posted during the 40 days study period.

The result of clustering is depicted in Fig. 1, which gives the distribution of clusters. Optimal number of clusters is chosen based on Bayesian Information Criterion (BIC) and gradient of BIC scores. The optimal number of clusters is chosen to be five. BIC score corresponding to five clusters is 1825.

For each cluster, average number of tweets posted by users, and overall emotion of users during the study period have been analysed. The results of this analysis have been presented in Table 1. Based on this analysis, the usage of users in these clusters are identified as normal, frequent, addictive, highly addictive and dangerously addictive.

It can be observed that 11.71% of users show addictive usage patterns and 4.05% of users show highly addictive usage patterns with sadness as a dominating emotion among these users while 2.70% of users show dangerously addictive usage patterns with anger as a dominating emotion among these users.

![Clusters of Users Based on Usage Pattern](image)

**Fig. 1** Distribution of clusters based on twitter usage patterns
4 Smartphone Addiction

Smartphones usage has grown to the extent where the phones have become an integral part of everyone’s lives. Today, smartphones are used throughout the day for multiple reasons, including communication, productivity, utilities, and even entertainment, social networking, and gaming. Smartphone addiction is a shifting technological addiction as the mobile phones have evolved to smartphones encompassing varied Internet features and applications [46]. Smartphone addiction refers to overuse of smartphones with corresponding functional impairments. Several terminologies have been used in the literature to refer smartphone addiction such as Problematic Mobile Phone use (PMPU), Problematic Smartphone Usage (PSU) mobile phone dependency, mobile phone addiction, and smartphone use disorder. Studies have been reported assessing the effect of smartphone addiction on daily lives of people. Hawi et al. [46] present strong evidence on the adverse effect of smartphone addiction on academic performance of university students by studying link between smartphone multitasking and the decline in academic performance. Recent investigations have explored novel psychological variables in association with smartphone addiction. These variables are nomophobia and Fear of Missing Out (FOMO).

Nomophobia is a phobia of millennials which is abbreviation of No Mobile Phone Phobia. It is defined as a disorder of the modern world which describes the

| Clusters | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 |
|----------|-----------|-----------|-----------|-----------|-----------|
| Number of students | 142 (63.96%) | 39 (17.57%) | 26 (11.71%) | 9 (4.05%) | 6 (2.70%) |
| Mean of average number of tweets posted daily | 1.52 | 4.09 | 11.53 | 21.39 | 42.56 |
| Overall emotion of most of users | Happiness [Happiness (60%), Sadness (23%), Anger/Disgust (3%), Surprise/Fear (14%)] | Happiness [Happiness (51%), Sadness (36%), Anger/Disgust (3%), Surprise/Fear (10%)] | Sadness [Happiness (27%), Sadness (42%), Anger/Disgust (23%), Surprise/Fear (8%)] | Sadness [Happiness (11%), Sadness (56%), Anger/Disgust (33%), Surprise/Fear (0%)] | Anger [Happiness (0%), Sadness (33%), Anger/Disgust (67%), Surprise/Fear (0%)] |
| Type of usage | Normal | Frequent | Addictive | Highly addictive | Dangerously addictive |
discomfort in the form of nervousness, distress and/or anxiety caused by the non-availability of a smartphone which also includes fear of not being able to access information and communicate or losing connection with people [47–49]. Nomophobia occurs as a result of overuse and dependency on smartphones for social networking and information retrieval and arises from feeling of not being able to do calling, messaging, losing internet connectivity and access to social networking, and losing access to online information [50] leading to nomophobic people being anxious in such situations. Nomophobia has been studied to impact psychological, social, academic, and professional lives of smartphone users [24, 51]. Such people tend to keep their phone switched on 24 h a day and even take their phone to bed causing sleep disorders. Arora and Chakraborty [52] reviewed the studies on nomophobia to identify the techniques used to detect nomophobia. It was found in their review that most of the studies used self-reporting-based techniques to diagnose nomophobia with Nomophobia Questionnaire (NMP-Q) framed by Yildirim and Correia [50] being the most used instrument. The NMP-Q is a 20-item questionnaire devised for evaluation of nomophobia where higher scores correspond to higher nomophobia severity.

FOMO involves the fear of missing out on pleasing and enjoyable experiences of smartphone usage. It involves the apparent need to persistently stay connected with the social network [53]. FOMO has been associated with anxiety and depression severity [54–57] and with symptoms of smartphone addiction severity [55, 56, 58].

4.1 Excessive Smartphone Usage During COVID-19 Pandemic

According to Statista [13], media device usage has been increased worldwide among Internet users due to coronavirus outbreak. As a result of this, around 70% of Internet users worldwide were using their smartphones more, though this varied significantly by country. People were using their smartphones excessively during the COVID-19 pandemic. In China and the Philippines around 86% people were using their phones more.

4.2 Assessment of Smartphone Addiction: Conventional Approach

The first attempt to assess smartphone addiction was done by Bianchi and Phillips in 2005 [59]. They devised a 27-item scale named Mobile Phone Problem Use Scale (MPPUS) to evaluate problematic usage of mobile phones. Another attempt in devising a questionnaire for problematic usage of mobile phones was done in 2008 by Billieux et al. [60]. They named their instrument as Problematic Mobile
Phone Use Questionnaire (PMPUQ). The PMPUQ intends to assess actual as well as potential problematic usage of mobile phones by assessing 30 items developed to target dangerous use of mobile phone, financial problem because of mobile phone use, and dependence on mobile phone. Lately, Kwon et al. [4] in 2013 constructed the Smartphone Addiction Scale (SAS) which is a 33-item scale devised for smartphone addiction assessment which consisted of six factors including overuse, withdrawal, cyberspace orientated relationship, daily life disturbance, positive anticipation, and tolerance. Later, they developed a short version of SAS namely Smartphone Addiction Scale-Short Version (SAS-SV) which comprises 10 items which were selected using content validity [61]. In 2016, Csibi et al. [62] developed Smartphone Application-Based Addiction Scale (SABAS) is a 6-items. It is assessment of smartphones’ application-based addictions. In another recent study, Marty-Dugas et al. [63] Smartphone Use Questionnaires (SUQ-G&A) differentiates general smartphone usage from absent-minded smartphone usage. It uses scores of two 10-item scales named as, general (SUQ-G) and absent-minded (SUQ-A). SUQ-G emphases on specific uses of smartphone such as frequency of checking social media applications while SUQ-A deals with mindless usage such as frequency of checking mobile phone without realizing the purpose.

4.3 Assessment of Smartphone Addiction: Machine Learning Based Approach

Shin et al. [64] use a range of mobile phone usage data and identify several features in order to develop a machine learning based model for automated prediction of problematic use of smartphones. The algorithms used by them include Naïve Bayes, Support Vector Machines and AdaBoost and their model achieved and accuracy of 89.6% for detection of problematic smartphone use. Lawanont et al. [65] built a smartphone addiction recognition system based on smartphone usage data. Based on this data, they implemented a classification model utilizing Naïve Bayes, Decision Tree, K-Nearest Neighbor, and Support Vector Machines for recognition of likelihood of having smartphone addiction. In a recent study, Ellis et al. [66] utilized k-means clustering algorithm to cluster the users with similar smartphone usage behavior. They used the objective behavior data retrieved from Apple’s Screen Time application which automatically logs a series of behavioral metrics related to screen time over a period of seven days. In another more recent study, Elhai et al. [67] utilized supervised machine learning algorithms to detect PSU severity among Chinese undergraduate students. They also correlated FOMO, depression and anxiety symptoms with PSU severity using the data from responses to SAS-SV, Depression Anxiety Stress Scale-21, FOMO Scale, and Ruminative Responses Scale and concluded that FOMO had the largest relative contribution in modelling PSU severity. A more technically advanced research was conducted by Kim et al. [68]. They proposed a model based on Deep Belief Networks, K-Nearest
Neighbor, and Support Vector Machines for prediction of smartphone addiction levels in individuals. They use EEG signals of participants for emotion analysis of individuals and concluded that the risk group was more emotionally stable than the non-risk group especially in expression of emotion “Fear”.

### 4.4 Case Study II: Assessment of Nomophobia Among University Students During COVID-19 Pandemic Using Machine Learning

Due the COVID-19 pandemic, to maintain distancing Universities have been shifting from classroom-based teaching to online education. The online teaching approaches such as video lectures, sharing of study materials through distant learning services are leading students to use digital technologies including smartphones frequently and for long hours. As nomophobia occurs due to overuse and dependency on smartphones, this case study intends to identify the nomophobic behavior among undergraduate university students during the pandemic.

The materials used to collect data are NMP-Q [50] and an android mobile application which automatically collects usage data from the smartphones of the students. The attributes collected by the app are total phone usage in last 7 days (hours), total night-time usage in last 7 days (hours) and total number of times the phone has been unlocked in last 7 days. Using the app and the questionnaire data of 111 students was collected.

Gaussian Mixture clustering has been implemented to identify students at different levels of risk based on the similarity in their NMP-Q scores and smartphone usage pattern. The result of clustering is depicted in Fig. 2 which gives the

![Fig. 2 Distribution of clusters based smartphone usage patterns](image-url)
distribution of clusters. Optimal number of clusters is chosen based on Bayesian Information Criterion (BIC) and gradient of BIC scores. The optimal number of clusters is chosen to be four. BIC score corresponding to four clusters is 4362.

Students in each cluster have been analysed for average hours of daily smartphone usage and average hours of daily night-time smartphone usage. Based on the results, the levels of risk of students in the clusters are identified as Extremely High, High, Medium and Low. Table 2 gives the result of analysis of clusters.

It can be observed that 4.5% of students are at extremely high risk whereas 73% of students are at high risk.

| Clusters | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|----------|-----------|-----------|-----------|-----------|
| Number of students | 81 (73%) | 22 (19.8%) | 5 (4.5%) | 3 (2.7%) |
| Mean of average daily smartphone usage (hours) | 8.22 | 7.98 | 9.47 | 5.95 |
| Mean of average daily night-time usage (hours) | 4.62 | 5.01 | 8.03 | 6.89 |
| Level of risk | High | Medium | Extremely high | Low |

5 Impact on Mental and Emotional Health and Sleep

There exist empirical studies relating Internet addiction, social media addiction and smartphone addiction to mental health impairments such as anxiety [5, 8, 11, 12], depression [6, 8, 11, 69], stress [6, 7, 12, 70], aggressive behaviors [71], emotional instability [5, 9, 72] and sleep disorders [10–12, 70]. In fact, mental instability, emotional instability and sleep disruption are among the four key factors associated with excessive Internet/technology use as studied by several researchers [2, 3, 5, 10, 18]. These key factors are as follows:

- **Absorption**: it deals with over engrossment with the Internet to an extent often leading to staying on the Internet longer than planned due to the loss of track of time while using the Internet. It also deals with the tendency to socialise more on the internet than in person and emotional instability while using the Internet.
- **Negative Consequences**: It deals with the effects of excessive use of the Internet on one’s personal life. This happens when one prefers to be on the Internet than spending time with loved ones often leading to loss of loved ones, missing appointments, loneliness, eventually leading to anxiety and mental instability.
- **Sleep**: It deals with sleep pattern disruption due to excessive use of the Internet to an extent that one schedules his sleep around Internet use. It involves tendencies such as sleeping during the day and being online at night and having less than five hours of sleep because of Internet use.
• **Deception:** It deals with the tendency of lying to others online about one’s identity or amount of time spent online.

Several studies relate mental health problems such as anxiety and depression to problematic internet use [73–75], social media exposure [76], problematic online gaming [77, 78], excessive smartphone usage [79] during the COVID-19 outbreak. The problematic and timeless use of digital technologies during the pandemic are impacting the mental health of people causing anxiety, depression, sleep problems and multiple psychological commotions. The next section reviews studies employing machine learning techniques for assessment and analysis of mental and emotional disruptions during the pandemic.

### 5.1 Mental and Emotional Health

According to the study of Hossain et al. [15], a cluster of articles highlight a growing use of AI in COVID-19-related psychological research. In another research [80], the authors study the prevalence, need and applications of Artificial Intelligence technologies for mental health research during the COVID-19 pandemic. Venigalla et al. [81] developed a web portal for analysing the emotions of Twitter users of India during the COVID-19 pandemic. They considered six basic emotions (Anger, Disgust, Happiness, Surprise, Fear and Sadness). They believe that Machine Learning techniques could be used to improve the classification and plan to utilize these techniques in their future studies.

Table 3 lists the details of studies assessing and analysing mental and emotional health variables via machine learning techniques during the COVID-19 pandemic around the world. The articles have been retrieved from MEDLINE database and Google Scholar. The articles have been retrieved using the keywords (mental health OR emotional health) AND (machine learning) AND (COVID-19 OR coronavirus). The articles assessing mental or emotional health using other techniques, but machine learning have not been selected for the review. The studies have been reviewed to determine the following.

- Various machine learning techniques used for evaluation of mental and emotional health.
- Types of datasets used by researchers to assess mental and emotional health.
- Variables predicted for assessment of mental and emotional health.

### 5.2 Sleep

The adverse effects of overuse of digital technologies due to excessive screen time on sleep has also been reported in literature [89]. Vernon et al. [90] study the disruptions in daily activities and sleep activities caused by use of mobile phones in
adolescent and consider this as a big challenge. In this study conducted on high school students, it was found that poor sleep quality associated with late-night texting or calling was linked to a decline in mental health, including depression and low self-esteem. It was concluded that students who used their cell phones frequently in the evenings were at greater risk for depression the following year. It is also reported that excessive use of smartphones during the day, increase the likelihood of a sleeping disorder, stress, anxiety [12] leading to feeling of less physically active after experiencing these symptoms. It has been reported that Adults with Internet Addiction disorder have frequent difficulty initiating and maintaining sleep, non-restorative sleep, daytime functional impairment [91]. The addiction to digital technologies disrupts sleep quality by delayed bedtimes and reduced total sleep duration. The underlying mechanisms of these adverse associations between excessive screen time and sleep quality include time displacement (i.e., time spent on screens replaces time spent sleeping and other activities), psychological stimulation based on media content, and the effects of light emitted from devices on circadian timing, sleep physiology, and alertness.

| Table 3 | Studies utilizing machine learning for mental and emotional health assessment during the pandemic |
|---|---|
| S. No. | Reference | Data | Machine learning techniques | Psychological prediction |
| 1. | Lauren et al. [82] | Social media (twitter tweets) | Not mentioned | Psychological stress |
| 2. | Zhou et al. [83] | Social media (twitter tweets) | Logistic, regression, linear discriminant analysis, Gaussian Naïve Bayes | Depression |
| 3. | Guntuku et al. [84] | Social media (twitter tweets) | Not mentioned | Mental health based on sentiment, anxiety, stress and loneliness |
| 4. | Ćosić et al. [85] | Multimodal sensor-based data | Spiking neural networks, support vector machine, random forest, | Mental health disorders |
| 5. | Khattar et al. [86] | Questionnaire | Association rule mining | Overall mental and emotional health |
| 6. | Tummers et al. [87] | The CORD-19 dataset | K-means clustering | Intellectual disability |
| 7. | Li et al. [88] | Social media (Weibo posts) | Online ecological recognition | Scores of emotional indicators (anxiety, depression, indignation, and Oxford happiness) |
Case Study III: Sleep Quality Assessment During COVID-19 Pandemic

Rajkumar [92] reviewed the existing literature on the COVID-19 outbreak pertinent to mental health and concluded that symptoms of anxiety and depression and self-reported stress were common psychological reactions to the COVID-19 pandemic which might be associated with disturbed sleep. People are using digital technologies more than ever before which is leading to sleep deprivation in the form of late in-bed time, less duration of sleep, and increased sleep onset latency.

Many wearables have been proposed and developed in the recent past to assess sleep with inbuilt sensors and the intervention of machine learning and deep learning algorithms with wearable technology for sleep quality assessment is evident to give impressive results [93]. This case study aims to assess daily sleep quality of Indian undergraduate students using data from smartwatches during the COVID-19 pandemic. Data of twelve undergraduate students has been collected for seven consecutive days before and after the imposition of lockdown in India and their daily sleep quality is assessed using the methodology proposed by Arora et al. [93]. Samsung Galaxy smartwatch and Xiomi MI smartband have been used for the collection of data.

The results obtained convey that daily sleep quality has been significantly decreased for maximum number of students with different values. The maximum decrease is observed to be 90.90% and the lowest decrease is observed to be 11.11%.

6 Research Model

This chapter studies the applicability of machine learning for assessment addiction to digital technologies and its impact on mental and emotional health and sleep. The research design includes study of addiction to various types of digital technologies, its assessment using conventional methods and machine learning techniques, its associated psychological disorders, and its impact on mental and emotional health further leading to various mental and emotional disorders and impacting sleep. Applicability of machine learning in assessment of these disorders has also been studied. Figure 3 presents the research model.

The model is justified with case studies analysing twitter addiction and nomophobia during the COVID-19 pandemic using unsupervised machine learning contributing to the existing literature in the domain of application of machine learning in mental and behavioral health.

The materials used for performing case studies are presented in Table 4.
7 Discussion and Conclusion

Addiction to digital technologies encompasses a wide range of behavioral addictions such as Internet addiction, social media addiction, smartphone addiction, online gaming addiction, etc. The use of digital technologies has increased with a high rate during the COVID-19 pandemic as people are confined at homes due to lockdowns imposed to prevent the spread of disease. This increases their dependency on these technologies for media streaming, information retrieval, social communications and...
so on. The high dependency on these digital technologies may lead to timeless, problematic and addictive usage and development of associated psychological disorders such as social network mental disorder, nomophobia, and fear of missing out. This chapter discusses the role of machine learning to assess addiction to various digital technologies during the COVID-19 pandemic. The chapter discusses about the existing approaches (conventional and machine learning based) of assessment of Internet addiction, social media addiction and smartphone addiction and their associated psychological disorders. Three case studies are provided to demonstrate how machine learning can be used to assess these addictions and related disorders during the COVID-19 pandemic. Gaussian mixture clustering is implemented to group people with similar Twitter usage patterns to identify addictive Twitter usage during the pandemic. The results show that 11.71% of users show addictive Twitter usage patterns and 4.05% of users show highly addictive Twitter usage patterns while 2.70% of users show dangerously addictive usage patterns. “Sadness” and “anger” are the dominating emotions among these users in contrast to “happiness” which is the dominating emotion among non-addictive users. A similar approach is used to cluster students with similar smartphone usage patterns and nomophobia scores to identify nomophobic behavior during the pandemic. The results show that 4.5% of students are at extremely high risk whereas 73% of students are at high risk. The results convey that a moderate proportion of users are addicted to digital technologies during the pandemic and emotions play a role in this addictive usage. The chapter also discusses how these behavioral addictions impact mental health of users leading to stress, anxiety, depression, emotional instability and sleep deprivation. A review of studies identifies the emergence of machine learning for assessment of mental and emotional health during the COVID-19 pandemic. A case study on sleep quality assessment using data from wearable sensors convey that sleep quality of students has been reduced significantly during the lockdown with a maximum decrease of 90.90%.

Prior studies indicate that addictive behaviors towards digital technologies are affected by gender and cultural differences [94–96] and Internet addiction relate to more serious issues such as cyberbullying [97], hence motivating researchers to study the problem and provide solutions to it. Researchers suggest users’ social media posts may affect human psychology and behavior during the COVID-19 pandemic [98]. A study analysing social media posts during the pandemic found that there exist high frequency of words like “death”, “test”, “spread”, and “lockdown” which suggests that people fear of being infected and death [99]. This research contributes to the existing literature of study of human behavior during the pandemic analysing their social media usage patterns, smartphone usage patterns and sleep patterns.

The chapter discusses the applicability of machine learning methods for accurate assessment of addiction to digital technologies and its impact on mental and emotional health and sleep. This chapter opens avenues for prediction of mental health disorders using supervised machine learning techniques. Also, overall behavioral health of people using data from questionnaires, social media, smartphones, and smartwatches can also be studied in future. Deep learning techniques for these predictions should also be explored.
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