B.E. PROJECT ON

USING MACHINE LEARNING ALGORITHMS FOR PROGNOSIS OF INTERNET GAMING DISORDER AND SMARTPHONE ADDICTION

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CERTIFICATE OF ORIGINALITY

We, Mehak Malhotra, 2018UIC3016, Mudit Mahajan, 2018UIC3018, Raghav Kaushal, 2018UIC3020, Shloka Gupta, 2018UIC3150 hereby declare that the Project-Thesis titled 'Using Machine Learning Algorithms for Prognosis of Internet Gaming Disorder and Smartphone Addiction' which has been submitted to the Department of Instrumentation and Control Engineering, Netaji Subhas Institute of Technology, Delhi (University of Delhi) in partial fulfillment of the requirement for the award of the degree of Bachelor of Engineering is original and not copied from the source without proper citation. The manuscript has been subjected to plagiarism checks by Turnitin software. This work has not previously formed the basis for the award of any Degree.

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CERTIFICATE OF DECLARATION

This is to certify that the Project-Thesis titled 'Using Machine Learning Algorithms for Prognosis of Internet Gaming Disorder and Smartphone Addiction' which is being submitted by Mehak Malhotra (2018UIC3016) Mudit Mahajan (2018UIC3018) Raghav Kaushal, 2018UIC3020, Shloka Gupta, 2018UIC3150 to the Department of Computer Engineering, Netaji Subhas Institute of Technology (University of Delhi) in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology, is a record of the thesis work carried out by the students under my supervision and guidance. The content of this thesis, in full or in parts, has not been submitted for any other degree or diploma.

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Abstract

Smartphones have become an integral part of our daily lives, combining media players, digital cameras, navigation, and high-speed internet access in a single device. Misuse of this privilege has been shown in previous research to have a negative impact on people, as they tend to overlook their personal well-being and fail to care for their environment. Excessive smartphone use is linked to poor academic performance, irregular sleeping patterns, lower life satisfaction, anxiety, stress, and general mental health. In this study, we created an Android application (Activity Tracker) to track the various events of each user relating to smartphone usage, such as the number of calls, text messages sent and received each day, and daily usage of various types of applications, which were then grouped into buckets, i.e. Social, Entertainment, Utility, Gaming and Shopping, and Food and Drinks as features, and their correlation to smartphone addiction was computed. With 73.3 percent accuracy, we were able to determine whether the participants were addicted to smartphones or not.

MOBAs (Multiplayer Online Battle Arenas) have quickly become one of the most popular types of online video games. Excessive gaming participation has been linked to Internet Gaming Disorder in previous studies (IGD). Internet Gaming Disorder has been linked to psychological issues such as impulsivity, anxiety, and ADHD (Attention Deficit Hyperactivity Disorder) (ADHD). In this work, we develop a method for predicting if a PlayerUnknown's Battlegrounds (BGMI, a MOBA game) player suffers from IGD and psychological disorders such as ADHD and Generalized Anxiety Disorder using game and player statistics as well as a self-esteem measure (GAD). We collect game and player statistics from BGMI players in Asian nations, and then use supervised machine learning models to predict the occurrence of IGD, ADHD, and GAD. Initial tests and findings reveal that we can accurately predict IGD, ADHD, and GAD with 89 percent, 78 percent, and 78 percent accuracy, respectively. The game statistics of BGMI gamers indicate a substantial positive correlation with IGD, ADHD, and GAD, implying that MOBA games are harmful.

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

IGD: Internet Gaming Addiction

ADHD: Attention Deficit Hyperactivity Disorder

GAD: Generalized Anxiety Disorder

IA: Internet Addiction

OCD: Obsessive-Compulsive Disorder

YDQ: Young's Diagnostic Questionnaire

MMOGs: Massively Multiplayer Online Games

MMORPGs: Massively Multiplayer Online Role-Playing Games

MOBA: Multiplayer Online Battle Arena

BGMI: BATTLEGROUNDS MOBILE INDIA

IGDS9-SF: Internet Gaming Disorder Scale–Short-Form

ASRS: ADHD Self-Report Scale

PIU: Problematic Internet Use

Chapter 1

INTRODUCTION

1.1 Introduction

Internet and smartphone use are ingrained in contemporary society and have changed the way we live our lives more than any other technological medium yet. Despite this, relatively little is known about the effects of internet addiction on psychological functioning, mental health, and general well-being. Everyday use of the internet provides advancements in public and private activities, but the virtual environment also provides settings for new types of risk behaviors of individuals. These addictions have negative repercussions, such as the development of numerous psychiatric diseases that impede the users' growth and mental well-being. Our study looks into the cause-and-effect relationship between technology and psychological problems. In this section, we go through three significant addictions that have arisen as a result of excessive use of technology.

1.1.1 Internet Addiction

Internet addiction is a type of behavioural addiction in which a person gets reliant on the usage of the Internet or other online technologies to cope with life's difficulties. In doing that an individual feels the need to spend a great deal of time on the Internet, to the point where other areas of life such as relationships, work or health are allowed to suffer. Although it hasn't been recognised as an addiction yet this study is aimed at proving that it should be recognised as a severe addiction.

One of the first hints of internet addiction was given by Dr KS Young in 1996. The study provided a description of adolescent internet addiction and examined significant differences in terms of gender, type of school and online behaviors.

Further, the relationship of adolescent internet addiction to spiritual intelligence, psychological wellbeing and social desirability was explored. His research led to the creation of the Young's Diagnostic Questionnaire (YDQ), a 20-item questionnaire that can be used to assess the degree of internet addiction in adults[1].

Internet Addiction (IA) causes impulsive behaviors in its users[2] and is often associated with other major psychological disorders. According to a study by YI-Lung Chen et al, there is a bidirectional association between insomnia and internet addiction. It suggests that internet addicts had lower nocturnal sleep duration and poorer sleep quality. It also causes sleep snoring, sleep apnea, bruxism, and nightmares by disrupting the circadian cycle[3].

Excessive or poorly regulated preoccupations, cravings, or behavior related to computer use and internet access that cause impairment or suffering are all examples of problematic internet use[4]. Machine Learning classification models such as Logistic Regression and Naive Bayes have also been applied to predict internet addiction using variables associated with compulsivity and impulsivity [5].

Internet addiction and substance abuse often go hand in hand with each other. Most of the time, those who abuse alcohol or drugs are those with the predisposition to get addicted to the Internet as it serves as a means of escape from reality. A study from The Recovery Village and various Universities shows that when Internet addicts go offline or stop using the computer, they experience withdrawal symptoms similar to those experienced by drug addicts[6].

1.1.2 Internet Gaming Disorder

Video gaming is a hobby enjoyed by young and old across the globe. In 2021, there were almost 1.48 billion gamers across Asia, making it the largest market for video gaming worldwide, with Europe coming in second place with a gaming audience of 715 million. In total, there were an estimated 3.24 billion gamers across the globe. There are two major types of video games and therefore two major types of video game addictions[8]. Standard video games are generally designed to be played by a single player and involve a clear goal or mission, such as rescuing a princess. The addiction to these games is often related to completing that mission or beating a high score or preset standard. The other type of video game addiction is associated with online multiplayer games. These games are played online with other people and are especially addictive because they generally have no end. Gamers with this type of addiction enjoy creating and temporarily becoming online characters. They often build relationships with other online players as an escape from reality[9]. For some, this community may be the place where they feel they're the most accepted.

MMOGs (Massively Multiplayer Online Games) allow multiple users to play together, making competitiveness a significant part of the genre. These games need a high level of concentration and response time, as well as strategizing and skill refining. Players establish teams, practice their talents, and compete to increase their game rank and status. A vast number of participants play the game at the same time, using different avatars [9]. These games are hugely popular because they appeal to players of all ages and genders, as well as their tastes and hobbies.

BGMI, League of Legends, and DOTA2 are examples of multiplayer online battle arena (MOBA) games in which two teams of numerous people compete against one other. The goal of the game is usually to demolish the enemy team's base or to defeat each of the opposing team's characters. Individual character development and collaborative team spirit are key to MOBA games.

The negative consequences of gaming were first noted in 1983 [10], describing how video games might be harmful to youngsters. The next study was based on self-reports of young male players as published by Shotton [11]. Although at that time there were no proper psychometric instruments for backing these studies, surprisingly, it was later found out that self-reports agree with standardized measures. At the onset of the 21st century, online gaming became very popular and several studies of Internet gaming addiction took place [12], [13].

Internet gaming addiction is a behavioral addiction that can be defined in a variety of ways using various criteria. As per Griffiths [14], there are several biopsychosocial processes that lead to the development of addictions, including the following components. First, the behavior is salient (the individual is preoccupied with gaming). Second, the individual uses the behavior in order to modify their mood (i.e, gaming is used to escape reality or create the feeling of euphoria). Third, tolerance develops (the individual needs increasingly more time to feel the same effect). Fourth, withdrawal symptoms occur upon discontinuation of the behavior (the individual feels anxious, depressed, and irritable if they are prevented from playing). Fifth, interpersonal and intrapersonal conflict develops as a consequence of the behavior (the individual has problems with their relationship, job, and hobbies, and lack of success in abstinence). Finally, upon discontinuation of the behavior, the individual experiences relapse (they re-initiate gaming). These studies gave birth to a clinically accepted disorder, Internet Gaming Disorder (IGD), which has gained significant attention from researchers all over the globe since its inclusion in Section 3 of the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) [15].

1.1.3 Smartphone Addiction

Given the portability, convenient Internet access, and functions that allow for multitasking, smartphones could promote dependence to a greater degree than regular mobile telephones or Internet access from a computer. They serve as a replacement for computers, laptops, tablets and other similar devices. Increased smartphone dependency is a putative risk factor for industrial injuries or automobile accidents (via disrupted concentration), muscular pain, and anxiety. Increased use of smartphones also relates to mental health problems, such as increasing depression and anxiety.

India had 1.2 billion mobile subscribers in 2021, of which about 844 million are smartphone users[16][17]. It is expected to reach 1 billion by 2024, according to a report by Deloitte. The need for smartphones is predicted to rise as more people use the internet; this demand will be fueled by the need to adopt fintech, e-health, and e-learning. Billieux [18] has argued that there is insufficient evidence for behavioral and neurobiological similarities between excessive smartphone use and other types of addictive behaviors. Panova and Carbonell [19] also argued that there is insufficient evidence to support the diagnosis of smartphone addiction and finally Montag et al. [20] have argued that excessive smartphone use is a form of Internet Use Disorder. Eilish Duke et al. [21] performed a study to establish a link between smartphone use and loss of productivity which can be attributed to the interruptions it causes in daily work life.

To analyze smartphone addiction, Min Kwon et al. revised the smartphone addiction scale to realize a shorter smartphone addiction scale (short version) consisting of a 10 item questionnaire with a cut-off score of 31 for males and 33 for females. Due to problems associated with the self-assessment of the SAS-SV Shin C et al. devised a mechanism to automatically detect problematic use of smartphones by means of an application, collecting information like event initiated sessions (on/off), total apps used per day, call to SMS ratio and other parameters[22].

In our study, we take the research a step further by using a self-developed Android application to collect features such as total call duration, the number of calls and texts per day, and so on, as well as the novelty of analyzing each application used by participants and categorizing them into five buckets: social, entertainment, utility, gaming and shopping, and food and beverages. These buckets were created using tags linked with each app on the Google Play Store. We use these traits as input to our supervised learning models to predict smartphone addiction, as well as analyze them to see if there is a link between them and smartphone addiction.

1.2 Problem Motivation

The use of smart devices has risen exponentially. The number of smartphone users in the world was about 6.2 billion in 2021 [9]. India is likely to have a billion users by 2024. Excessive smartphone use has a negative impact on people's daily lives since they tend to overlook not only their personal well-being but also their environment. Smartphones are key perpetrators of Internet Addiction [23], [24], as well as many psychological and physical disorders, because they are so intimately linked to the Internet.

Poor academic performance, abnormal sleeping habits, lower life satisfaction, anxiety, tension, and overall mental well-being are some of the negative consequences of excessive smartphone use[25]. The rapid growth of smartphone addiction, which is classified as a disorder similar to substance abuse in DSM – 5, as well as its prevalence among people of all ages, has prompted the authors to investigate how to predict whether someone is addicted to their phone by correlating phone usage factors[26].

1.3 Problem Statement

1.3.1 Classification of android applications into different buckets to predict smartphone addiction

This study aims at predicting smartphone addiction by studying participants' screen time patterns through a self-developed application(Activity Tracker). We then try to categorize the application into different categories with the help of the tags associated with each application on the Google Play Store. We then study the screen time patterns of addict and non-addict participants, analyze gender-wise variation and compare the usage levels of these applications to get an insight into the general trend.

1.3.2 Prognosis of psychological disorders in BGMI Players

This work aims to construct a prediction model that predicts the likelihood of a player suffering from Internet Gaming Disorder (IGD), Attention Deficit Hyperactivity Disorder (ADHD), and Generalized Anxiety Disorder (GAD) using supervised machine learning. The approach uses BGMI players' gaming statistics and a self-reported self-esteem metric to make accurate predictions. Using the acquired data, some meaningful inferences about game statistics, psychological diseases, and personal details of participants were also made.

1.4 Overview of thesis

Smartphones have become an integral part of our daily lives, combining the functions of music players, digital cameras, web browsers, games, navigation, and high-speed internet access in a single device. They've become so ingrained in our culture that excessive use is now considered an addiction. Smartphone addiction has been shown to share many characteristics with drug and substance abuse [36]. The increasing usage of smartphones, or rather, their overuse and misuse, is thus an important study topic that must be thoroughly investigated.

In Chapter 1, We create an Android application (Activity Tracker) to keep track of our participants' everyday activities, such as screen time, the number of texts and calls, and duration. We categorize the apps into five categories: social, entertainment, utility, gaming and commerce, and food and beverages. Using the aforementioned features, we apply cutting-edge machine learning algorithms to forecast the possibility of a person being hooked to smartphones, as well as derive connections between addiction levels and smartphone usage habits. We also show a link between these features and smartphone addiction, and parallels between addicted and non-addicted users.

The relationship between technical progress and psychiatric disorders is examined in this thesis. The authors were prompted to conduct in-depth research on the BGMI game and its implications due to its recent popularity and controversial banning news in India. BGMI is part of the Multiplayer Online Battle Arena (MOBA) game genre, which is now the most popular since it engages users by forcing them to compete against one another in a battle setting. These games, such as League of Legends, promote Internet gaming addiction, which leads to a slew of psychiatric problems. The authors picked three primary disorders that were most common among addicted gamers, that are Internet Gaming Disorder (IGD), Attention Deficit Hyperactivity Disorder (ADHD) and Generalized Anxiety Disorder (GAD).

A survey was circulated on several platforms, BGMI forums and threads, groups on social networking websites like Facebook, Twitter, and Reddit, and among students participating in BGMI tournaments at college fests, containing the players' BGMI-IDs, demographic details, the platform they play on, the country they reside in, and questionnaires to assess disorders. This information was pre-processed and evaluated for several studies, as described in detail in Chapters 2 and 3.

In Chapter 2, we develop a prediction model that predicts the likelihood of a player suffering from Internet Gaming Disorder (IGD), Attention Deficit Hyperactivity Disorder (ADHD) and Generalized Anxiety Disorder (GAD) using supervised machine learning algorithms. The model takes gaming statistics of BGMI players along with their self reported self-esteem measure to make predictions with considerable accuracy of around 80%. Several meaningful inferences about gaming statistics, psychological disorders and personal details of players were also derived using the collected data.

In chapter 3, we give the conclusions and inferences that were made by various studies that were conducted in this thesis.

Chapter 2

CLASSIFICATION OF ANDROID APPLICATIONS INTO DIFFERENT BUCKETS TO PREDICT SMARTPHONE ADDICTION

2.1 Introduction

Smartphones have become an integral part of our daily lives, combining the functions of music players, digital cameras, web browsers, games, navigation, and high-speed internet access in a single device. They have become a potential substitute for laptops, personal computers, and a variety of other devices, in addition to cell phones. According to a study, **the number of smartphone users globally is expected to be 7 billion by 2024**[9][10]**.** India is likely to have 1.1 billion users by 2024. The considerable increase can be credited to user-friendly applications accessible on platforms such as Android and IOS, which are constantly updated.

With approximately 560 million internet users, India is the world's second-largest online market. By 2023, it is expected that the country would have over 650 million internet users. Despite the enormous number of internet users, the country's internet penetration rate was approximately 50% in 2020. In that year, over half of India's 1.37 billion people had an internet connection. Compared to just five years ago, when the internet penetration rate was around 27%, there has been a steady increase in online accessibility. Increased availability of low-cost data plans, as well as various government initiatives under the Digital India campaign, combined to make mobile the country's primary internet access. 4G networks were the most popular in both urban and rural India.

The misuse of this privilege is a major source of worry. An average Indian consumes approximately 1GB of data per day, compared to 4GB per month previously, a 650 per cent increase in data usage, with 50% of the time spent on chat, surfing, video-streaming, social networking, and image apps[27]. Smartphones have a negative impact on people because they cause them to overlook their personal well-being and their environment. According to a study, using a smartphone while driving impairs driving efficiency and thereby increases the likelihood of an accident. Smartphones are key perpetrators of Internet Addiction, as well as many psychological and physical disorders, because they are so intimately linked to the Internet[28]. Excessive smartphone use is linked to poor academic performance, irregular sleeping patterns, lower life satisfaction, anxiety, stress, and general mental health[29].

Smartphone addiction has been shown to share many characteristics with drug and substance abuse[30]. The increasing usage of smartphones, or rather, their overuse and misuse, is thus an important study topic that must be thoroughly investigated.

In this study, we create an Android application (Activity Tracker) to track the daily activities of our participants, such as screen time, the number of texts and calls received, and duration; we also propose a novel division of the various applications used by the participant into five buckets: Social, Entertainment, Utility, Gaming and Shopping, and Food and Drinks.

Using the above-mentioned features, we apply cutting-edge machine learning algorithms to forecast the possibility of a person being hooked to smartphones and to derive connections between addiction levels and smartphone usage habits.

2.2 Review of Literature

The growing use of smartphones has led to an increased amount of problematic usage leading to Smartphone addiction. This has a negative impact on an individual's social life as well as generating health issues. In this section, we'll go over some previous research on smartphone usage habits and how they relate to addiction and problematic use.

Bianchi and Phillips used extraversion, self-esteem, neuroticism, gender, and age as potential predictors of mobile usage. They discovered a link between mobile phone use and the psychological characteristics mentioned previously [31]. The MPPUS (Mobile Problem Usage Scale) was used to identify problematic smartphone usage. The questionnaire focuses on current trends in behavior and technological addiction, as well as information regarding people's relationships with their smartphones.

Global smartphone adoption has resulted in previously unheard-of addicted behavior. Lin's research provided diagnostic criteria and the development of a smartphone application (App) to detect smartphone addiction. The trend in smartphone use over a month was determined using a unique empirical mode decomposition (EMD). Smartphone addiction is linked to the daily use count and trend of this frequency. The association between tolerance symptoms and the median duration of a use epoch, as well as the relationship between the tolerance symptoms and the trend for the median duration of a use epoch, were used to quantify excessive usage. The assisted self-reporting use time of psychiatrists is much lower, and the overall smartphone use time documented via the App and the degree of underestimation were both positively connected with actual smartphone use. The study claimed that smartphone addiction might be detected with a diagnostic interview and EMD analysis of app-generated parameters[32][33].

Mads Bødker et al. employed Theory of Computational Value (TCV) to assess smartphone user experience and discovered how the device's conditional, functional, social, emotional, and epistemic value changes over time with each user. Lee et al. developed SmartLogger Software to log a variety of application events such as power on/off, touch inputs, phone events (call/SMS) and such and concluded that risk groups exhibit highly skewed usage patterns and are more addicted to Mobile Instant Messaging(MIM) applications, followed by voice calls, SMS, and emails[34]. Because the study focused on smartphone addiction, Xiang Ding et al. used a correlation analysis to find that compulsive open times and usage time are good indicators of app addiction [35].

2.3 Methodology

In this study, we created an Android application (Activity Tracker) to track the various events of each user pertaining to smartphone usage, such as the number of calls/texts sent/received each day, user-initiated events (power on/off), and daily usage of various types of applications, which were later grouped into buckets (Social, Entertainment, Utility, Gaming, and Shopping/food and drinks) based on their tags mentioned on Google Play Store, details of which are provided below in table 2.1.

The app also included a questionnaire to collect socio-demographic information and responses to the Smartphone Addiction Scale (Appendix B). Our study included 51.04 percent female Android smartphone users and 48.95 percent male Android smartphone users, with an average age of 24.04 years.

The Android application (Activity Tracker) was used to collect data from all of the individuals recruited for the study. The participants were given seven days to install the application. During these seven days, all of their activities relating to the use of various smartphone applications, the number of messages sent/received, and the amount of time spent on calls and on the smartphone as a whole were tracked.

The application requires three permissions in order to function properly: access to usage statistics from multiple smartphone applications, reading call records, and receiving and sending messages. Following the successful installation of the application, the participant was required to complete a survey, which consisted of a Smartphone Addiction Scale – Short Version (SAS – SV) questionnaire, in order to determine the ground truth of each participant before categorizing them as addicted – 1 or non-addicted – 0. Following that, participants completed a single-item questionnaire in which they self-analyzed and rated their self-esteem on a scale of 1 ('extremely low') to 7 ('very high')[36].

2.3.1 Android Application

Android application modules- Each participant's data is collected on a daily basis by the application. The information gathered by the app is as follows:

Screen Time: Every participant's daily screen-on time (in milliseconds) was recorded. This was accomplished through the use of a never-ending service that runs in the background and is invoked whenever it is destroyed. When the participant turned on or off the smartphone's screen, a broadcast receiver was used to trigger an intent. The entire screen duration of each day was calculated using the interval between each on and off action, and the sum of screen duration for all days yielded the overall smartphone usage feature

App Usage: The daily screen-on time (in milliseconds) of each participant was recorded. This was done by using a never-ending service that runs in the background and is called whenever it is destroyed. A broadcast receiver was utilized to activate an intent when the participant turned on or off the smartphone's screen. The period between each on and off action was used to calculate the total screen duration for each day, and the sum of screen duration for all days yielded the overall smartphone usage feature.

Call Logs: The Call Log provider keeps track of all calls made and received. CONTENT URI is used by this provider to access call log entries. For a week, the call history is retrieved daily.

Messages: In the SMS app, the telephony content provider stores all sent and received text messages. To access SMS/text messages, this provider employs content URI. For a week, the frequency of messages sent and received is retrieved on a daily basis.

Every 24 hours, the data collected from each individual's smartphone is uploaded to the server using an AsyncTask, which allows us to do long-running tasks/background operations and display the results on the UI (User Interface) thread without disrupting the main thread. It was critical to saving the data on a secure server after it was collected. This is the application's back-end, which is supported by Google Cloud Firestore.

Google Cloud Firestore: Cloud Firestore is a flexible, scalable database for mobile, web, and server development from Firebase and Google Cloud. It keeps data in-sync across client apps through real-time listeners and offers offline support for mobile and web so you can build responsive apps that work regardless of network latency or Internet connectivity.

The data is transmitted from the application as a JSON Object and then stored as a JSON Array in the cloud. This phase generates an a.json file, which is then transformed into CSV format. This CSV file is used as an input for the data cleaning phase, which involves preprocessing and cleaning the data.

2.3.2 Measures Smartphone Addiction Scale - Short Version (SAS-SV)

Smartphone Addiction Scale (SAS)

The smartphone addiction scale (SAS) was improved by Min Kwon et al. and a 10-item version was established. Each response might range from 'Strongly Agree' to 'Strongly Disagree,' with a score of 1 to 6 assigned to each response. The ultimate score was calculated by summing the scores for each question. Our participants' scores vary from 10 to 53. For boys, a cut-off value of 31 is recommended, whereas, for girls, a cut-off value of 33 is recommended.

Single Item-Self Esteem

It is a single-item self-esteem scale that allows participants to self-analyze and score their own self-esteem on a Likert scale of 1 ('extremely low') to 7 ('very high')[36].

2.4 Experiments

2.4.1 Features

The application collects the data on daily basis from each participant. The data collected through the application is as follows:

1. **Age**: The age of participants was collected in years.
2. **Gender**: If the participant was a male or female.
3. **Screen-on Duration**: The total amount of time that has been spent on the smartphone each day with the screen turned on.
4. **Number of Messages**: The total number of text messages that have been sent/received by the participant each day.

5. **Number of Calls**: The total number of calls that were made/received by the participant each day.
6. **Duration of Calls**: The total duration of calls that were made/received by the participant each day.
7. **List of Applications**: Day-wise list of applications that were used by the participant.
8. **Usage Duration of Application**: Day-wise usage duration of each application used by the participant.
9. **Esteem Score**: The self-esteem of a participant on a Likert scale of 1-7.[36]
10. **Smartphone Addiction Questionnaire Score**: The resultant score was computed through Smartphone Addiction Scale – Short Version (SAS – SV).[37]

Each participant's set of features was further processed, given labels for ease of calculation, and utilized as input features for the machine learning model. To begin, the participants' Android applications (activity tracker) were categorized into five buckets, as indicated in table 2.1. These buckets were created using tags from Android apps on Google Play, which were then grouped together into a larger category.

S.No	Bucket	Tags	Example	Label
1.	Social	Social/Communication	WhatsApp/Facebook/Instagram	Soc
2.	Entertainment	Entertainment/Music/Video Player	Netflix/Wynk/Saayn/Amazon Prime	Ent
3.	Utility	Maps/Navigation/Photography/Education/News	Google Docs/Google Maps/Inshorts/DuoLingo	Uti
4.	Gaming	Gaming/Adventure/Sports/Strategy/Adventure	PokemonGo/PUBG/Clash Royal	Game
5.	Shopping/food and drinks	Shopping/food and drinks	Zomato/Myntra/Swiggy/Amazon	SFD

Table 2.1: Description of buckets for each Android Application

All the features **(Screen-on Duration, Number of Messages, Number of Calls, Duration of Calls and Bucket-Wise Application Usage)** was added for each participant over the course of 7 days of study to compute the cumulative sum as shown in table 2.2.

S.No	Input Features	Description (cumulative sum)	Label
1.	Total Screen-on Duration	Sum of Screen-on Duration	SOD
2.	Total Number of Messages	Sum of number of messages sent/received	NOM
3.	Total Number of Calls	Sum of number of calls dialed/received	NOC
4.	Total Duration of Calls	Sum of duration of calls dialed/received	DOC
5.	Social	Sum of usage duration of all applications in 'Soc' bucket	Soc
6.	Entertainment	Sum of usage duration of all applications in 'Ent' bucket	Ent
7.	Utility	Sum of usage duration of all applications in 'Uti' bucket	Uti
8.	Gaming	Sum of usage duration of all applications in 'Game' bucket	Game
9.	Shopping/food and drinks	Sum of usage duration of all applications in 'SFD' bucket	SFD
10.	Esteem Score	Single integer ranging from 1 to 7 to indicate self-esteem of each participant	esteem_score

Table 2.2: In put Features to Smartphone Addiction Prediction ML Model

The smartphone addiction model output labels as shown in table 2.3. The output feature to depict smartphone addiction is computed by using the Smartphone Addiction Questionnaire Score and Gender as follows:

- For **males**, the threshold value of score was **31**, above which they were classified as addicted.
- For **females**, the threshold value of score was **33**, above which they were classified as addicted.

S.No	Result	Label
1.	Addicted	1
2.	Non-Addicted	0

Table 2.3: Smartphone Addiction Model Output Labels

2.5 Results and Discussion

Table 2.4 summarizes the efficacy of various categorization models used to predict Smartphone Addiction. We divide the dataset into two parts: 85 percent training and 15% test, and find that Decision Tree produces the best results, with a maximum accuracy of 73.3 percent on the test data set and 90.0 percent on the training data set.

2.5.1 Accuracy on various classifiers

S.No	Model	Accuracy (test)	Accuracy (Train)
1.	Decision Tree	73.3%	90.0%
2.	Decision Tree with Adaboost	60%	100%
3.	Logistic Regression	67%	69.1%
4.	K-Nearest Neighbors	53.3%	80.2%
5.	Naïve Bayes	53.3%	72.8%

Table 2.4: Training and testing accuracy of various classification models used

2.5.2 Pearson Correlation

S.No	Feature	Smartphone Addiction
1.	Total Screen-on Duration	0.119
2.	Total Number of Messages	0.111
3.	Total Number of Calls	-0.040
4.	Total Duration of Calls	-0.106
5.	Social	0.208
6.	Entertainment	0.012
7.	Utility	-0.19
8.	Gaming	0.18
9.	Shopping/food and drinks	0.201
10.	Esteem Score	0.169

Table 2.5: Pearson Correlation between input features and Smart Phone Addiction

The Pearson Correlation coefficient can range from -1 to +1. The Pearson product-moment correlation coefficient (PPMCC) or bivariate correlation, sometimes known as Pearson's r, is a measure of the linear correlation between two variables X and Y. A positive correlation shows that as one parameter's value rises, the value of the associated parameter rises as well. A negative correlation shows that while one parameter's value rises, the value of the corresponding parameter falls. There is no correlation between the parameters when the correlation coefficient is zero.

The Pearson Correlation coefficient can range from -1 to +1. The Pearson product-moment correlation coefficient (PPMCC) or bivariate correlation, sometimes known as Pearson's r, is a measure of the linear correlation between two variables X and Y. A positive correlation shows that as one parameter's value rises, the value of the associated parameter rises as well. A negative correlation shows that while one parameter's value rises, the value of the corresponding parameter falls. There is no correlation between the parameters when the correlation coefficient is zero. The total number of calls and applications present in the ‘Entertainment’ bucket shows a negligible correlation to the addiction levels.

2.5.3 Gender Variation

The ratio of male participants who are smartphone hooked is substantially higher than the female participants, as illustrated in figure 2.1. 74.5 per cent of guys are addicted to smartphones, while the remaining 25.6 per cent are not. Figure 2.2 shows that 53.1 per cent of females are addicted to their smartphones, while 46.9% are not. According to the findings, guys are more likely than females to be addicted to their smartphones.

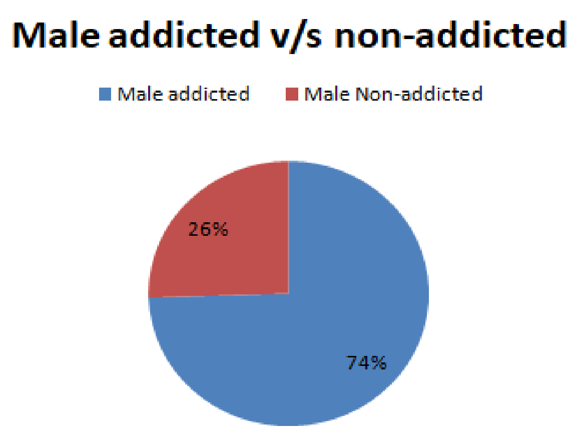


Figure 2.1: Addicted and Non addicted male participants

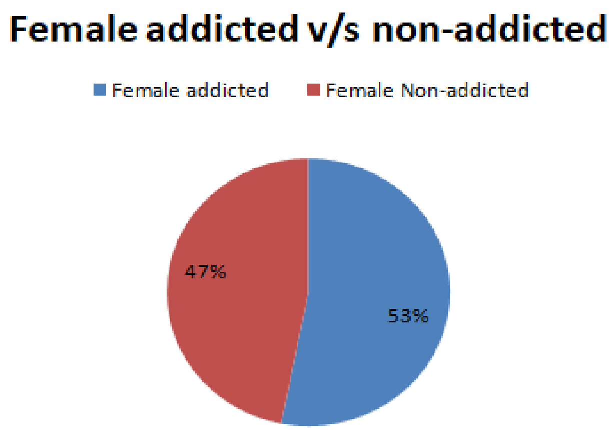


Figure 2.2: Addicted and Non addicted female participants

2.5.4 Normalized usage factor

A comparison of the numerous consumption characteristics between addicted and non-addicted people is undertaken, as illustrated in bar graph 4.3. The quantity of total engagement each participant has with the phone is higher among smartphone addicted participants, according to the screen on usage factor. The amount of text messages and phone calls had a less impact on predicting smartphone addiction among participants. The usage of social and entertainment apps raises the amount of addiction, whereas non-addictive participants use more utility apps than social, entertainment, or gaming apps, implying that using a smartphone for work is not an addiction.

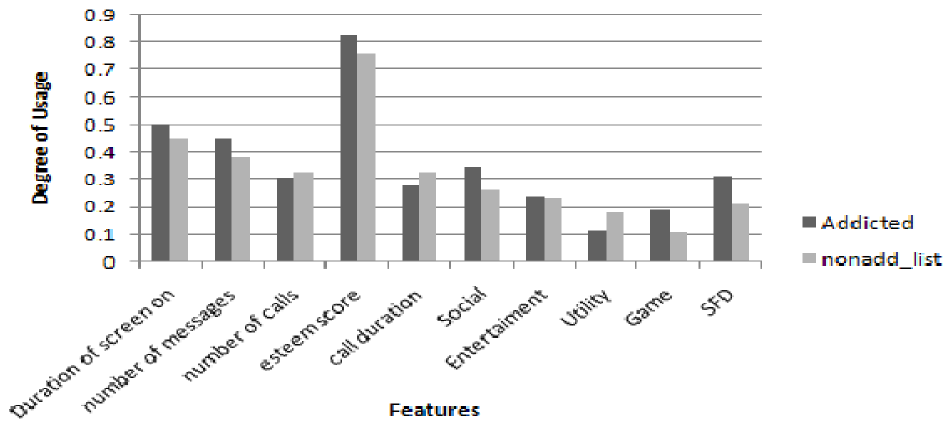


Figure 2.3: Comparison between Normalized Degree of Usage and types of applications

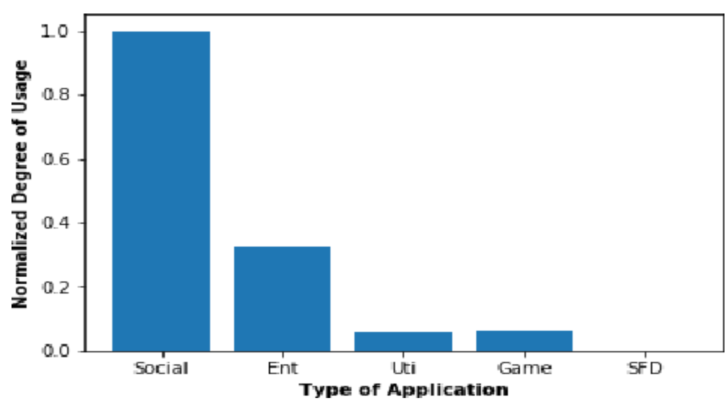


Figure 2.4: Comparison between various buckets on the basis of degree of usage

2.5.5 Comparison between usage of applications

To examine the application usage pattern, we compute the mean time spent by all participants on applications belonging to each bucket, normalize results, and present a bar graph as shown in figure 2.4. We discovered that users spent the most time on social apps, followed by entertainment and gaming apps, and the least amount of time on shopping and food and beverages apps.

2.5.6 Conclusions and Summary

In this study, we suggested a method for predicting if a participant suffers from smartphone addiction by combining numerous events related to smartphone use, such as the number of calls/texts received each day, the types and daily usage of programmes, and a self-esteem score. We employed supervised algorithms to extract 10 smartphone usage features from our participants using an android application. We also suggest a novel method for dividing the numerous applications utilized by the participant into five buckets, namely social, entertainment, utility, gaming, and shopping, as well as food and drinks, and computing their link with smartphone addiction. We were able to accurately detect whether the individuals were addicted to their smartphones using our method. Each application has been categorized into a small number of buckets. We can divide this classification into additional categories, yielding more input features for supervised models to learn.

Chapter 3

PROGNOSIS OF PSYCHOLOGICAL DISORDERS IN BGMI PLAYERS

3.1 Introduction

Internet gaming has become one of the most popular leisure activities among internet users globally since the introduction of multiplayer online games. Excessive video gaming has been linked to harmful repercussions in several studies and has been linked to a variety of issues. Internet Gaming Disorder (IGD)[38] is a persistent, habitual, and excessive engagement in gaming that has gotten a lot of attention from researchers all over the world since it was included in Section 3 of the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013). The debate and concerns surrounding the diagnosis of IGD and the validity of the DSM-5 IGD evaluation criteria [39], [40] have continued, and more study into the diagnosis of IGD and the validity of the measures evaluating the proposed criteria is needed.

According to previous studies, people with IGD are more prone to have other mental and psychiatric illnesses. They are more prone to clinically severe psychiatric problems such as Obsessive-Compulsive Disorder (OCD), Attention Deficit Hy- peractivity Disorder (ADHD), and anxiety. IGD and ADHD have been linked in young adults, with participants diagnosed with ADHD exhibiting increased IGD severity, impulsivity, and anger [41]. Students diagnosed with ADHD perform poorly in college, have weaker social skills, and have low self-esteem. As a result, IGD's consequences can obstruct people's personal and professional development, making it a major problem.

An online gamer can access a vast library of games from a variety of genres over the Internet. Multiplayer Online Battle Arena (MOBA) games (BGMI, League of Legends, DOTA2) are currently the most popular type of games played on the internet. MOBA games are a type of online game in which players/teams compete against one another. The goal of the game is usually to demolish the enemy team's base or to defeat each of the opposing team's characters.

MOBA games are still relatively new, despite their popularity, and only a few studies have looked into the effects and consequences of excessive game playing in this genre. To establish linkages between excessive MOBA game involvement and impulsivity constructs, [42] used self-reported impulsivity tests as well as an assessment of problematic video game use. However, no attempt has been made to evaluate the game and player statistics of a MOBA game (BGMI) in order to determine whether the gamer has IGD and is at risk of developing psychological problems like ADHD and anxiety.

In the present study, we aim to analyze and use the **game and player statistics** of online gamers playing **BATTLEGROUNDS MOBILE INDIA** (BGMI - a MOBA game) in addition to self-measure of self-esteem of the gamers from Asian countries to predict whether they are suffering from **IGD** and if they are likely to develop psychological disorders such as **Generalized Anxiety Disorder (GAD) and ADHD** using **machine learning classification algorithms**.

3.2 Review of Literature

3.2.1 Supervised Learning

Supervised Learning is a type of machine learning in which we teach the machine using well-labeled data. We have input variables and output variables, and we learn the mapping function from the input to the output using an algorithm. The goal is to develop an accurate mapping such that we can correctly predict the output for any new input data. Supervised Machine Learning problems can be categorized as a regression or classification problem.

- Classification: A classification problem is when the output variable is a category, such as *Red* or *blue* or *disease* and *no disease.*
- Regression: A regression problem is when the output variable is a real value, such as *dollars* or *weight*.

3.2.2 Classification

Classification is a strategy for dividing our data into a desirable and unique number of classes, each with its own label. A classification model is used to anticipate discrete responses and attempts to derive certain conclusions from observed data. When given a dataset of houses, for example, a classification algorithm can attempt to predict if the prices of the houses will sell for more or less than the recommended retail price. The houses will be classified here according to whether their prices are above or below the stated price. There are two types of classifiers

- Binary Classifier: A classification problem in which there are just two distinct classes or outcomes. For example Male and female, spam email and non-spam email.
- Multi-Class Classifier: There are more than two distinct classes in this classification problem. For instance, categorization of soil kinds and classification of crop types.

There are different types of classification algorithms:

3.2.2.1 Naive-Bayes Classifier

The Bayes theorem inspired Naive Bayes, a probabilistic classifier. The qualities are conditionally independent under a simple assumption. With the above assumption applied to Bayes theory, the classification is done by obtaining the maximum posterior, which is the largest P(Ci|X). By merely counting the class distribution, this assumption drastically minimises the computational cost. Naive Bayes is a very simple algorithm to develop, and it has produced good results in the majority of applications.

Since it requires linear time rather than the expensive iterative approximation employed by many other types of classifiers, it can quickly scale to larger datasets. The zero probability problem can be a problem with naive Bayes. When the conditional probability for a given property is zero, the prediction is invalid. A Laplacian estimator must be used to fix this explicitly.

$$\underbrace{P(c \mid x)}_{\text{Posterior Probability}} = \frac{\overbrace{P(x \mid c)}^{\text{Likelihood}}\,\overbrace{P(c)}^{\text{Class Prior Probability}}}{\underbrace{P(x)}_{\text{Predictor Prior Probability}}}$$

$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Figure 3.1 Naive-Bayes Classifier

3.2.2.2 Support Vector Machine (SVM)

The training data is represented as points in space split into categories by a clear gap as broad as possible in a support vector machine. New examples are then mapped into the same space and classified according to which side of the gap they fall on. SVMs work well in high-dimensional domains and employ only a portion of training points in the decision function, making them memory-efficient.

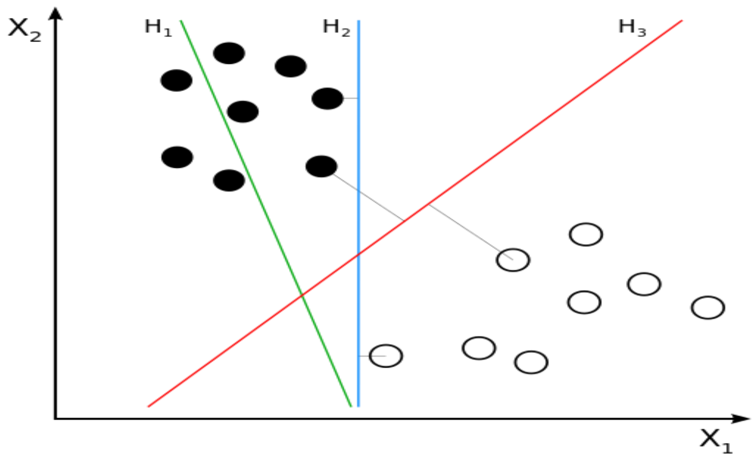


Figure 3.2: Support Vector Machine Classifier

As shown in figure 3.1 H1, H2, H3 are three hyper-planes. H1 is a bad example of a hyper-plane as it does not separate classes, H2 does separate classes but with only a small margin. H3 is a good hyper-plane as there is a considerable difference between classes.

3.2.2.3 k-Nearest Neighbor (KNN)

The KNN classifier classifies an item based on the majority vote of the object's neighbors in the input parameter space. The item is allocated to the class that has the most members among its k (integer) closest neighbors. The KNN algorithm isn't actually a learning algorithm. It simply sorts items according to how similar their features are.

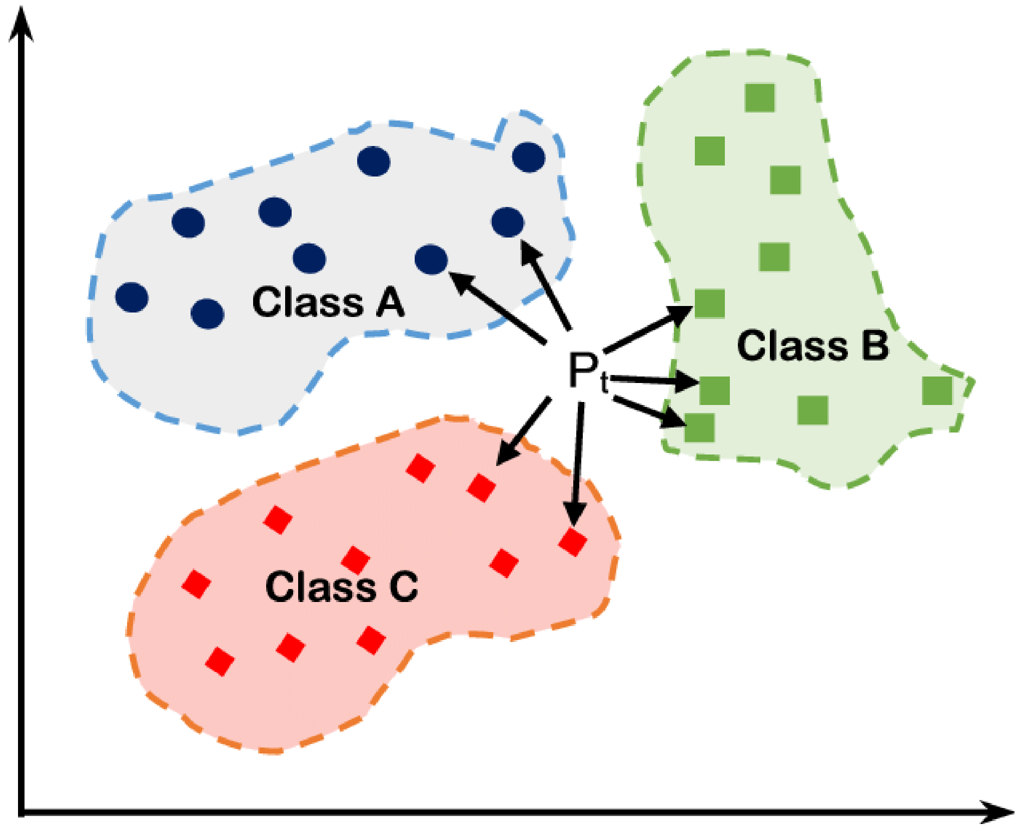


Figure 3.3 KNN-Classifier

3.2.2.4 Decision Tree Classifier

A Decision Tree Classifier uses a tree-like paradigm to make decisions. As shown in figure 3.2, it divides the sample into two or more homogeneous sets (leaves) depending on the most significant differentiators in the input variables. It repeats recursively until the data is successfully split in all leaves or the maximum depth is reached.

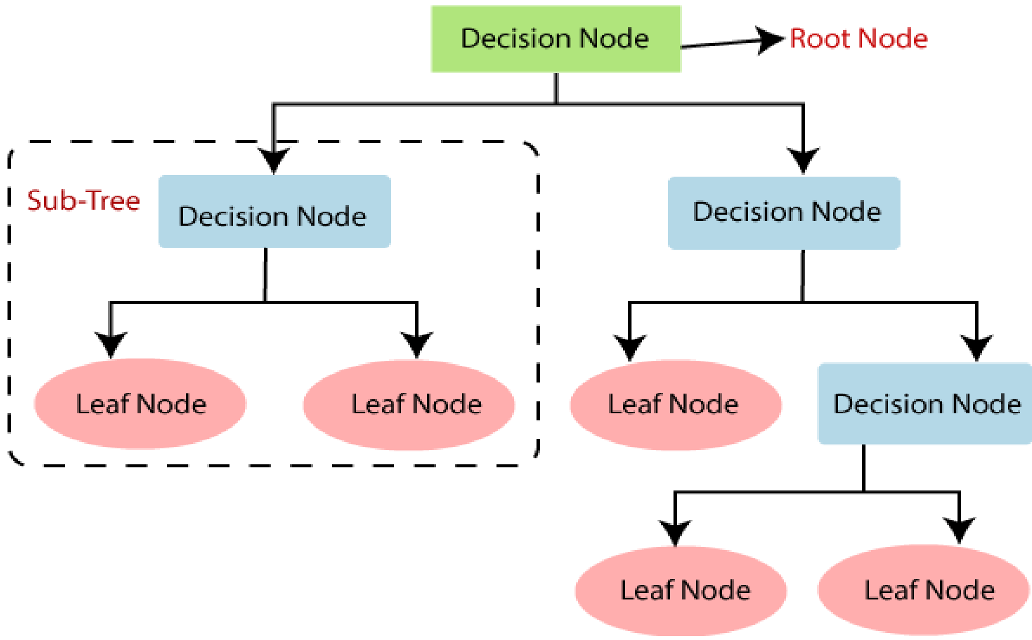


Figure 3.4: Decision Tree Classifier

3.2.2.5 Random Forest Classifier

The random forest classifier is an ensemble model that develops many trees and classifies objects based on their votes. The class with the most votes from all the trees is allocated to an object. In most circumstances, a random forest classifier reduces overfitting and is more accurate than decision trees.

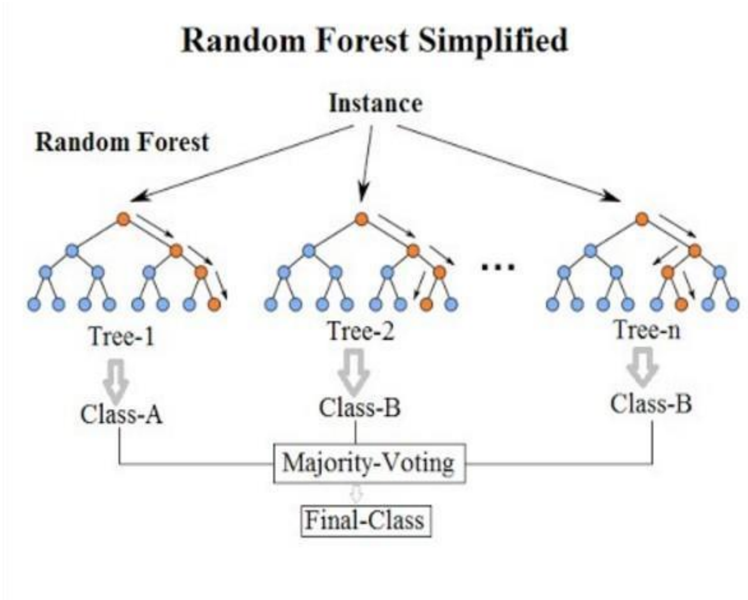


Figure 3.5: Random Forest Classifier

3.3 Methodology

3.3.1 Participants

The goal of this study was to find a group of online players who regularly played the game PlayersUnknown Battlegrounds (BGMI). The data was collected by sending out a link to an online survey. The survey included questions about a user's sociodemographic and gameplay information, as well as the study's main psychometric tools. Participants were sent to the survey after clicking the link, and electronic consent was obtained from all participants as a condition of participation in the study.

3.3.2 Measures

Participants were requested to provide sociodemographic data such as their age, gender, and country of origin. Each participant's gaming information, such as their BGMI username and gaming platform, was also collected. Participants that played on a mobile device were expected to submit screenshots of their game as well as player statistics. They were also required to fill out the following forms:

3.3.2.1 Internet Gaming Disorder Scale - Short Form (IGDS9-SF)

The IGDS9-SF [44] is a nine-item psychometric tool that measures the severity of Internet Gaming Disorder (IGD) as defined by DSM-5 (American Psychiatric Association, 2013). The following are some examples of questions: "Do you feel pre- occupied with your gaming behavior?","Do you feel more irritability, anxiety or even sadness when you try to either reduce or stop your gaming activity?","Do you feel the need to spend an increasing amount of time engaged gaming in order to achieve satisfaction or pleasure?". A five-point Likert scale was used to answer all nine questions: 1 ('Never'), 2 ('Rarely'), 3 ('Sometimes'), 4 ('Often'), and 5 ('Very often'). The overall score is calculated by summing the participants' responses to the nine questions. The IGDS9-SF scores range from 9 to 45.

3.3.2.2 Adult ADHD Self-Report Scale

The ASRS-v1.1 [45] is a six-item questionnaire that can be used to assess adults for ADHD. It is a subcategory of the 18-question WHO questionnaire's symptoms checklist and is based on the American Psychiatric Association's (DSM-IV-TR) . "How frequently do you have trouble tying up the final touches of a job once the challenging sections have been completed?" and "How often do you have issues remembering appointments or obligations?" are two examples of inquiries. The following alternatives were used to answer each of the six questions: 'Never’, ‘Rarely’, ‘Sometimes’, ‘Often’ and ‘Very Often’.

3.3.2.3 Generalized Anxiety Disorder (GAD-7)

The GAD-7 [46] is a seven-item anxiety scale that is used to screen for and measure the severity of Generalized Anxiety Disorder (GAD). "Do you feel worried, apprehensive, or on edge?" and "Are you unable to stop or control worrying?" are examples of questions to which participants responded. On a four-point Likert scale, 0 means "not at all," 1 means "a few days," 2 means "more than half the days," and 3 means "almost every day." By adding the answers to the questions, you can get the overall score. The GAD-7 scale runs from 0 to 21.

3.3.2.4 Single-Item Self-Esteem Value

The Single-Item Self-Esteem Scale[36] is a single-item self-esteem scale that can be used instead of the Rosenberg Self-Esteem Scale. Participants rate themselves on a seven-point Likert scale ranging from 1 to 7 ('Not very true of me').

3.3.3 Procedure

The gameplay data gathered through the poll was utilized to derive the participants' BGMI game and player statistics. BGMI's Developer API was used to extract gaming information from PC, Xbox, and PS4 gamers, whereas game and player statistics were acquired from mobile gamers utilizing screenshots of game statistics provided by participants. The survey data and statistics were filtered, pre-processed, and scores for each of the questionnaires used in the survey were produced. The scores and pre-processed data were used to train machine learning classifier models that may predict if an online gamer playing BGMI is likely to suffer from Internet Gaming Disorder (IGD) and psychiatric problems including ADHD and GAD.

3.4 Experiment and Analysis

3.4.1 Data Collection

PlayerUnknown's Battlegrounds (BGMI) is a multiplayer online battle royale game that can be played on a variety of platforms, including the Xbox One, PlayStation 4, PC, and mobile devices. As explained in section 3.3.2, an online survey hosted on Google Forms was used to collect socio demographic information about BGMI players as well as their responses to questionnaires assessing Internet Gaming Disorder (IGD) [41], ADHD [45], GAD [46], and Self Esteem [36], as summarized in Table 3.1.

The survey URL was shared on BGMI forums, as well as BGMI pages and groups on social media platforms including Facebook, Twitter, and Reddit. Due to the recent rise in popularity of BGMI mobile in India [23], BGMI tournaments are being held more frequently as part of gaming events and college fests, which have proven to be significant data providers. This study was done as a proof of concept to prove that BGMI causes psychiatric illnesses and hence support its ban in India. We did a pilot study and were able to successfully recruit 44 individuals as a consequence. The final sample had a mean age of 21.7 years, with 2 females and 42 males taking part. The data collecting took place from March 8th to March 30th.

S.no	Item	Description
1.	Demographic Details	This includes *Age*, *Gender* and *Country* of participants.
2.	PUBG Username	Unique *PUBG Username* of players is needed to extract their game statistics.
3.	Platform Played On	Participants were asked if they played on *XBOX*, *PS4*, *Mobile* or *PC*. Mobile users were further redirected to upload screenshots of their statistics.
4.	IGDS9-SF	Nine items questionnaire to assess Internet Gaming Disorder
5.	ASRS-v1.1	Attention Deficit HyperActivity Disorder (ADHD) is evaluated using this six item tool.
6.	GAD-7	An anxiety scale with 7 questions answered using 4 point Likert Scale.
7.	Self Esteem	One item measure of global self-esteem answered on a seven point Likert Scale

Table 3.1: Description of all items in the online survey

3.4.2 Feature Selection

To determine if a BGMI player had Internet Gaming Disorder (IGD), Attention Deficit Hyperactivity Disorder (ADHD), or Generalized Anxiety Disorder (GAD), we employed a set of 13 indicators shown in Table 3.2. (GAD). These characteristics can be classified into the following categories:

3.4.2.1 Gaming Related Features

Depending on the amount of partners, BGMI can be played in three different modes (Solo, Duo, and Squad). Player data were retrieved using Chicken Dinner, a Python BGMI JSON API wrapper that works for XBOX, PS4, and PC gamers, by collecting BGMI Usernames. Due to the API's lack of support for BGMI Mobile, players were asked to submit images of their player and game statistics in all three modes. The API returns 35 game statistics, and BGMI Mobile shows 19 of these in the app. Table 3.2 lists ten characteristics that are common between BGMI Mobile and those supplied through API. A total of 30 input game-related features were collected, ten for each of the three modes (solo, duo, and squad). Using two methodologies, distinct features from all three modes were combined into a single feature:-

Aggregate of features

Features expressed as whole or real numbers denoting statistics such as *number of rounds* and

kills were added from all three modes (Solo, Duo and Squad) to aggregate into a single feature.

e.g Kills = Solo kills + Duo kills + Squad kills

Features in this category include Headshots, Kills, Rounds played, Wins and Top10s.

Mean of features

Features that are expressed as ratios or percentages like *Top10%* and *Win Ratio*, the average value from all three modes (single, duo and squad) is considered as a single feature.

e.g Top10% = (Solo Top10% + Duo Top10% + Squad Top10%) / 3

Features in this category include Top10%, Win Ratio and Average Time Survived, Longest Time Survived and Round Most Kills.

This combination of features creates 10 final game related input features.

3.4.2.2 Demographic Features

Participants' age and gender are among the demographic characteristics. For convenience of calculation, both genders were given numerical labels: 1 for Male and 0 for Female.

3.4.2.3 Self Esteem Score

The self esteem score obtained from the one-item measure of global self-esteem [36] is also used as a feature. Participants answer on a seven-point Likert scale ranging from 1 (*'Not very true of me'*) to 7 (*'Very true of me'*).

Feature	Description
Demographic Details	This includes *Age* and *Gender* of Participants
Self Esteem	One item measure of global self-esteem answered on a seven point Likert scale.
Headshots	Number of enemy players killed with headshots.
Kills	Number of enemy players killed.
Longest Time Survived	Longest time survived in a match.
Rounds Played	Number of matches played.
Round Most Kills	Highest number of kills in a single match.
Top10's	Number of times this player made it to the top 10 in a match.
Wins	Number of matches won.
Average Time Survived	Average time survived in a match.
Top10's Percentage	Percentage of times this player made it to the top 10 in a match.
Win Ratio	Percentage of times this player has won a match.

Table 3.2: Summary of features input to the Classification Algorithms

3.4.3 Computing Scores of Questionnaire

In our study, participants were asked to complete questionnaires to determine whether they had Generalized Anxiety Disorder (GAD) [46], Internet Gaming Disorder (IGD) [44], or Attention Deficit Hyperactivity Disorder (ADHD) [45]. The questionnaires were part of an online survey that the participants completed. The following is how each questionnaire's score and result were calculated:

Internet Gaming Disorder

Participants completed the Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) [44], which consisted of nine questions on a 5-point Likert scale. After adding up the scores of all the questions, the total score ranged from 9 to 45, with each question's score ranging from 1 ('Never') to 5 ('Very Often'). A 36-point cutoff was proposed [44], with participants who scored more than 36 being diagnosed with Internet Gaming Disorder. The binary classification output labels were 1 ('Suffering from IGD') and 0 ('Not Suffering from IGD').

Attention Deficit Hyperactivity Disorder (ADHD)

The ASRS-v1.1 is a six-item questionnaire that can be used to test people for ADHD [45]. Every question, as shown in figure 3.6, has five possibilities from which to choose. If four or more ticks show in the dark region [45] of figure 3.6, a person is diagnosed with ADHD. For binary classification, the output labels were 1 ('Suffering from ADHD') and 0 ('Not Suffering from ADHD').

Please answer the questions below, rating yourself on each of the criteria shown using the scale on the right side of the page. As you answer each question, place an X in the box that best describes how you have felt and conducted yourself over the past 6 months. Please give this completed checklist to your healthcare professional to discuss during today's appointment.	Never	Rarely	Sometimes	Often	Very often
1. How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?					
2. How often do you have difficulty getting things in order when you have to do a task that requires organization?					
3. How often do you have problems remembering appointments or obligations?					
4. When you have a task that requires a lot of thought, how often do you avoid or delay getting started?					
5. How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?					
6. How often do you feel overly active and compelled to do things, like you were driven by a motor?					

Figure 3.6: Adult ADHD Self-Report Scale (ASRS-v1.1)

Generalized Anxiety Disorder

The severity of Generalized Anxiety Disorder is measured using the GAD-7 [46], a seven-item anxiety scale with each item responded on a four-point Likert scale (GAD). GAD-7 scores vary from 0 to 21, with a score of 10 or higher representing a fair cut point for detecting cases with GAD. The overall score was calculated by adding the responses to all of the questions, with each question's score ranging from 0 ('Not at all') to 3 ('Almost every day'). For binary classification, the output labels were 1 ('Suffering from GAD') and 0 ('Not Suffering from GAD').

3.4.4 Classification Models

The detection of IGD, ADHD, and GAD is modeled as three discrete binary classification issues. Logistic Regression (LR), Naive Bayes (NB), Decision Tree (DT), Decision Tree with Adaboost, and K - Nearest Neighbors are five stand-alone supervised machine learning classifiers that we consider and apply.

3.5 Results and Discussion

Table 3.3 summarizes the results received when each classifier was used. Using the Logistic Regression (LR) classifier, we were able to predict Internet Gaming Disorder (IGD) and Generalized Anxiety Disorder (GAD) with a maximum accuracy of 89 percent and 78 percent, respectively. With an accuracy of 78 percent, the decision tree classifier was most effective in predicting Attention Deficit Hyperactivity Disorder (ADHD).

S.No	Model	IGD	ADHD	GAD
1.	Logistic Regression	89%	67%	78%
2.	Naive Bayes	88%	44.4%	77.8%
3.	Decision Tree	77.8%	78%	66.6%
4.	K - Nearest Neighbours	88%	66.6%	77.7%
5.	Decision Tree with Adaboost	88.8%	66.6%	66.6%

Table 3.3: Performance of different methods for binary classification

The Pearson Company Table 3.4 shows the relationship between the 13 input features and several diseases such as IGD, ADHD, and GAD. If the value is greater than zero, a direct positive correlation occurs, meaning that an increase in one variable causes an increase in the other. A value less than zero indicates a negative correlation, in which an increase in one variable causes a decrease in another, and vice versa. There is no link between the two if the Pearson's coefficient of the variables is zero**.**

It is clear that self-esteem has a negative relationship with IGD, ADHD, and GAD, implying that gamers with high self-esteem are less likely to suffer from these psychological diseases. This conclusion supports prior study, that found inverse relationships between self-esteem and anxiety, ADHD, and other mental illnesses.

As shown in Table 3.4, IGD is positively linked with 80% of the game and player data. Headshots, Kills, Longest Time Survived, Rounds Played, Rounds Most Kills, Top10s, Wins, and Win Ratio with higher values indicate Internet Gaming Disorder. With respect to IGD, Pearson's coefficient of Average Time Survived and Top10's percent is negative but goes to zero, indicating a very weak linear link. Similarly, 80 percent and 100 percent of characteristics are highly linked to ADHD and GAD, respectively. Thus, Pearson's large positive and small negative Pearson's coefficient values indicate that players with higher in-game statistics are more likely to have IGD, ADHD, or GAD. Players that spend a lot of time playing BGMI have higher values for all of these variables, such as the number of rounds played, victories, kills, or headshots, and are more likely to develop psychological illnesses.

Smaller Pearson's correlation values between Gender and IGD, ADHD, and GAD in Table 3.4 imply that gender has no bearing on the hazards connected with playing BGMI.

S.No	Feature	IGD	ADHD	GAD
1.	Age	0.18999	-0.09624	-0.15043
2.	Gender	0.0422	0.07800	0.04222
3.	Self Esteem	-0.10728	-0.06974	-0.10132
4.	HeadShots	0.27087	0.45662	0.25982
5.	Kills	0.34077	0.39817	0.30601
6.	Longest Time Survived	0.15571	0.34541	0.16738
7.	Rounds Played	0.30362	0.49618	0.11738
8.	Rounds Most Kills	0.30948	0.28266	0.27594
9.	Top10's	0.37222	0.21624	0.26175
10.	Wins	0.48817	0.116552	0.24547
11.	Average Time Survived	-0.00212	0.10940	0.19868
12.	Top10's%	-0.01044	-0.04794	0.15568
13.	Win Ratio	0.07603	-0.07329	0.14545

Table 3.4: Pearson Correlation between input features and various disorders

IGD is most favorably connected with the amount of wins, according to table 3.4. This indicates that internet gaming addicts have increased reward sensitivity, implying that the amount of wins acts as a motivator for BGMI players, motivating them to keep playing and exposing them to the risk of Internet Gaming Addiction.

The number of rounds played has the strongest link to Attention Deficit Hyperactivity Disorder (ADHD), suggesting that ADHD is linked to the amount of hours spent gaming. The number of rounds played by BGMI players solely reflects the amount of time spent and has no bearing on the players' skill level. This finding adds to prior research on the relationship between gaming and ADHD.

The age distribution of psychological problems is depicted in Figure 3.7 . It shows what percentage of people in each age group had IGD, ADHD, or GAD. All participants in online gaming who are between the ages of 24-27 suffer from Generalized Anxiety Disorder (GAD), which may indicate a reduction in interpersonal relationships. Internet Gaming Disorder does not affect adolescents, indicating a lack of exposure and parental oversight.

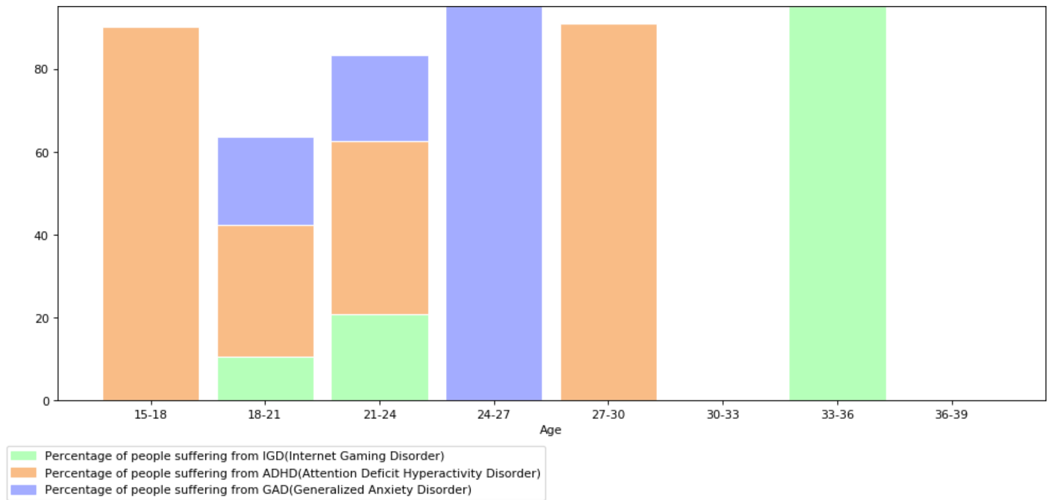


Figure 3.7: Percentage of participants suffering from various disorders for different age groups

Participants play BGMI on PC, Xbox One, PlayStation 4, and mobile devices. The BGMI game costs roughly $30 on XBOX, PC, and PS4, however it is free on mobile. This pricing disparity, combined with the additional expense of purchasing an XBOX or PS4, could be a big deciding factor in platform selection. Because this study was conducted in Asia's underdeveloped countries, the majority of users, as indicated in Figure 3.7, play BGMI Mobile for economic reasons.

All of these conclusions support the notion that BGMI game statistics are influenced by psychiatric problems.

3.6 Summary and Conclusion

In this study, we suggested a method for predicting if BGMI players from Asian nations suffer from Internet Gaming Disorder (IGD), Generalized Anxiety Disorder (GAD), or Attention Deficit Hyperactivity Disorder (ADHD) using game and player characteristics, as well as a self-esteem score (ADHD). We employed supervised algorithms to extract 13 features from our participants' game and player data. We were able to determine if the participants had IGD, ADHD, or GAD with high accuracy using our method. This was a pilot study, and future work could include confirming the technique with a much bigger group of people. Second, we only employed a small number of game statistics as input features to our models; future work could concentrate on training supervised models with a larger number of characteristics.

Chapter 4

CONCLUSIONS

4.1 Results

We proposed a method for tracking various events related to smartphone use, such as total screen time, number of calls, number of messages, and duration of application usage on a daily basis, as well as a self-esteem score and a smartphone addiction scale score, to determine whether a participant is addicted to their smartphone. We developed an android application to extract the smartphone usage features of our participants and used supervised algorithms to extract 10 attributes. We developed a novel method of categorizing the numerous applications utilized by the participants into five buckets, namely Social, Entertainment, Utility, Gaming and Shopping, and Food and Drinks, and computing their link with smartphone addiction. This method was quite effective in determining whether or not the participants were addicted to their smartphones. There is a comparison of the various consumption parameters between addicted and non-addicted people. The number of messages and calls has a slightly lower impact in predicting smartphone addiction among participants, and the use of social and entertainment apps increases the level of addiction, whereas non addicted participants use more utility apps, implying that they use smartphones for work and cannot be treated as an addiction. Another surprising finding was that males have a higher rate of smartphone addiction than females. The participants spend their maximum amount of time on ‘Social’ applications, followed by applications related to ‘Entertainment’ and ‘Gaming’ and least amount of time in ‘Shopping/Food n Drinks’.

We also used supervised machine learning methods to analyze and forecast Internet Gaming Addiction (IGD) and Smartphone Addiction (SA) in the current study. The authors also tried to link IGD and SA to a variety of psychological problems, including Internet Gaming Disorder (IGD), Attention Deficit Hyperactivity Disorder (ADHD), and Generalized Anxiety Disorder (GAD) (GAD).

We used PlayerUnknown's Battlegrounds (BGMI) game statistics to determine if a player has Internet Gaming Disorder (IGD), Generalized Anxiety Disorder (GAD), or Attention Deficit Hyperactivity Disorder (ADHD) (ADHD). We employed supervised algorithms to extract 13 features from our participants' game and player data. We were able to determine if the participants had IGD, ADHD, or GAD with high accuracy using our method. We also discovered that self-esteem had a negative relationship with IGD, ADHD, and GAD, implying that gamers with high self-esteem are less prone to these conditions. It was also discovered that IGD is favorably connected with 80% of game and player data. The number of rounds played has the strongest correlation with Attention Deficit Hyperactivity Disorder (ADHD), indicating a favorable relationship between ADHD and gaming hours.

4.2 Further Improvements

Each app was placed into one of a few buckets in the study to predict smartphone addiction. As a result, this categorization can be reduced down into more buckets, giving our models additional input features, and future work can focus on training supervised models with a larger number of features.

Since the number of participants in the study to predict IGD, ADHD, and GAD was small, the study can be expanded to include a larger number of people who can be compared to a variety of different traits.

AppendixA

CIRCULATED ONLINE SURVEY

The circulated online survey collected the demographic information of participants and required them to fill certain measures. The survey was composed of the following items:

A.1 Demographic Details

1. Age
2. Gender
3. BGMI Username
4. Gaming Platform for BGMI

A.2 Questionnaire 1 (Internet Gaming Disorder Scale–Short-Form)

1. Do you feel preoccupied with your gaming behavior?
2. Do you feel more irritability, anxiety or even sadness when you try to either reduce or stop your gaming activity?
3. Do you feel the need to spend an increasing amount of time engaged in gaming in order to achieve satisfaction or pleasure?
4. Do you systematically fail when trying to control or cease your gaming activity?
5. Have you lost interest in previous hobbies and other entertainment activities as a result of your engagement with the game?

6. Have you continued your gaming activity despite knowing it was causing problems be- tween you and other people?
7. Have you deceived any of your family members, therapists or others because the amount of your gaming activity?
8. Do you play in order to temporarily escape or relieve a negative mood (e.g., helplessness, guilt, anxiety)?
9. Have you jeopardized or lost an important relationship, job or an educational or career opportunity because of your gaming activity?

A.3 Questionnaire 2 (Adult ADHD Self-Report Scale)

1. How often do you have trouble wrapping up the final details of a project, once the chal- lenging parts have been done?
2. How often do you have difficulty getting things in order when you have to do a task that requires organization?
3. How often do you have problems remembering appointments or obligations?
4. When you have a task that requires a lot of thought, how often do you avoid or delay getting started?
5. How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?
6. How often do you feel overly active and compelled to do things, like you were driven by a motor?

A.4 Questionnaire 3 (Generalized Anxiety Disorder)

1. Do you feel nervous, anxious or on edge?
2. Are you not able to stop or control worrying?
3. Do you worry too much about different things?
4. Do you have trouble relaxing?
5. Do you ever feel so restless that it is hard to sit still?
6. Do you become easily annoyed or irritable?
7. Do you feel afraid as if something awful might happen?

A.5 Questionnaire 4 (Single-Item Self-Esteem Scale)

1. Do you have high self-esteem?

Appendix B

SMARTPHONE ADDICTION SURVEY IN ANDROID APPLICATION

The survey was a part of the android application circulated amongst the participants and col- lected the demographic information of each participant and required them to fill certain mea- sures. The survey was composed of the following items:

B.1 Demographic Details

1. Age
2. Gender
3. Name

B.2 Questionnaire 1 (Smartphone Addiction Scale–Short Version)

1. Missing planned work due to smartphone use?
2. Having a hard time concentrating in class, while doing assignments, or while working due to smartphone use?
3. Feeling pain in the wrists or at the back of the neck while using a smartphone?
4. Won't be able to stand not having a smartphone?
5. Feeling impatient and fretful when I am not holding my smartphone?
6. Having my smartphone in my mind even when I am not using it?
7. I will never give up using my smartphone even when my daily life is already greatly affected by it?

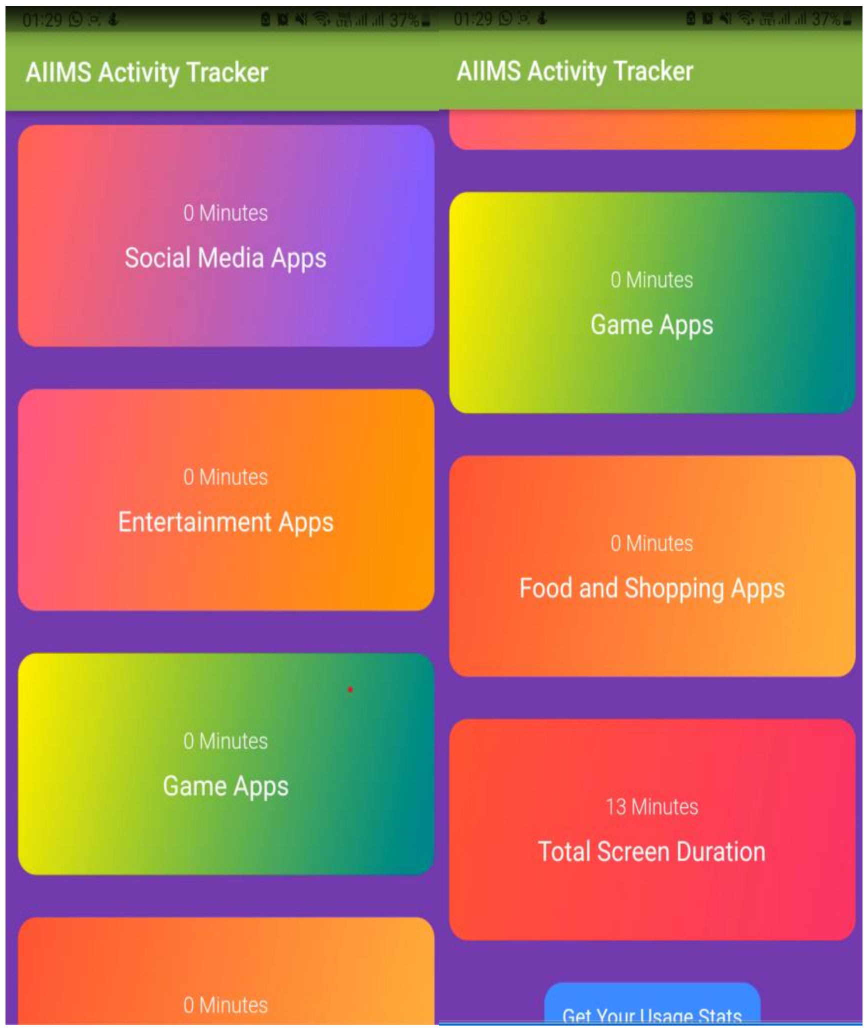
8. Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook?
9. Using my smartphone longer than I had intended?
10. The people around me tell me that I use my smartphone too much?

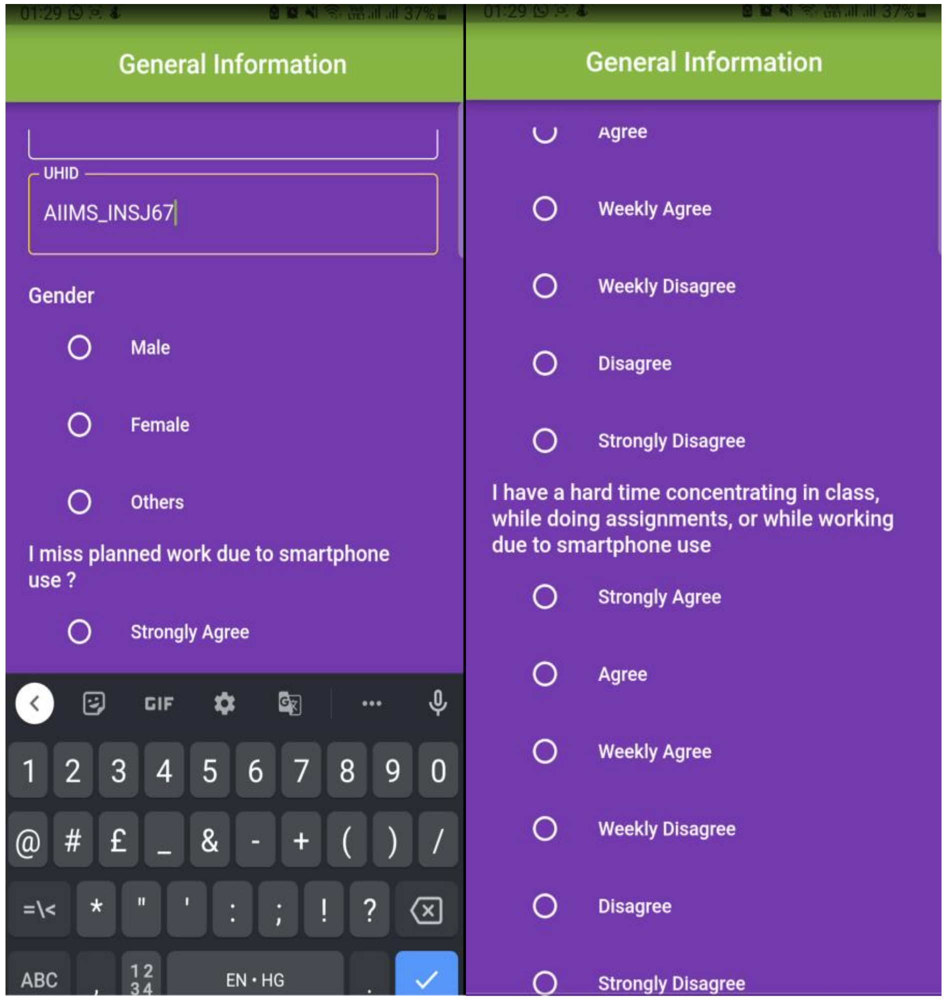
B.3 Questionnaire 2 (Single-Item Self-Esteem Scale)

1. Do you have high self-esteem?

Appendix C

SCREENSHOTS OF SMARTPHONE DATA COLLECTION ANDROID APPLICATION (ACTIVITY TRACKER)




General Information
UHID
AIIMS_INSJ67
Gender
Male
Female
Others
I miss planned work due to smartphone use ?
Strongly Agree
General Information
Agree
Weekly Agree
Weekly Disagree
Disagree
Strongly Disagree
I have a hard time concentrating in class, while doing assignments, or while working due to smartphone use
Strongly Agree
Agree
Weekly Agree
Weekly Disagree
Disagree
Strongly Disagree

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