The COVID-19 pandemic seriously affected research work and universities across the globe. My research work began in January 2021, when most of the countries, including the UK, were still experiencing lockdowns amidst the pandemic. Due to safety restrictions and lockdowns, it was not possible for me to attend the university personally for roughly six to seven months. This complicated the initial part of the research. I was unable to meet with my supervisors face to face, utilize the facilities at the university such as libraries, laboratory facilities, or office space, or participate in events and workshops on campus. These initial months are generally critical to determining the course of the research, establishing methods, and developing support structures.Missing out on this slowed down the project's progression and necessitated numerous modifications. To maintain the research's continuation, I kept coordinating with my supervisors through online meetings. I also adjusted the schedule and emphasized the work to be undertaken at home, such as reading literature, planning, and writing. These measures allowed the continuation of the work despite the situation, but the overall speed of the research suffered. The following note is provided to describe the impact the pandemic had on the initial phases of the research and to offer context for the difficulties encountered and the ways they were overcome.

Investigating the Generalisability of Machine Learning Algorithms for Classifying Mental Illnesses in Low- and Middle-Income Countries Using Multimodal Data from Smartphones and Social Media

Ranjith Venkatachala

A thesis submitted in partial fulfilment of the requirements of the University of Kent for the Degree of Doctor of Philosophy

June 2025

DECLARATION

I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy being studied at the Universities of Kent. I also declare that this work is the result of my own investigations, except where the thesis identifies work undertaken jointly with others. In these cases I have made clear exactly what was accomplished by others and what I have contributed myself, and have not plagiarised the work of others.

Ranjith Venkatachala   Dr Chee Siang Ang

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Abstract:

Mental health disorder is a major health concern globally, with high prevalence rates in low to middle-income countries like India. Access to mental health care is often limited in these countries due to several factors such as poor health infrastructure, lack of skilled mental health workers, and the social stigma. Thus, many patients fail to receive timely intervention, which can lead to the worsening of their conditions and increased challenges in managing their mental health over time. The widespread use of smartphones and social media presents an opportunity to address these challenges. These digital platforms (social media and smartphones) produce vast amounts of data regarding people's daily activity, social interaction, and online behaviour, which could yield useful information on their state of mental illness. The purpose of this study is to investigate "how such digital information can be harnessed to understand and classify the mental illness", especially in regions where traditional healthcare services are either scarce or difficult to access.

This PhD study investigates methodologies to classify broad range of mental and neurodevelopmental disorders using both social media and smartphone sensor data. The first study uses machine learning algorithms like CNN and Word2Vec to classify different mental illness disorders such as anxiety, autism, schizophrenia, depression, bipolar, and borderline personality disorder based on information gathered from various social media platforms such as Twitter and Reddit. We collected large datasets from Reddit and Twitter, which were analysed to develop models capable of effectively identifying patterns associated with these mental health disorders. The results showed that the models were consistent across platforms with positive evaluation scores like precision, recall, and F1-score to validate the effectiveness of the classification methods.

The second study addresses the shortcomings of lab-based research for classifying neurodevelopmental disorders like attention-deficit/hyperactivity disorder (ADHD) by utilizing smartphone sensor data for a more objective classification approach. Accelerometer, location tracking, application usage, and interactions with the smartphone interface (e.g., keyboard and touch gestures) were collected from a sample size of 43 participants, 21 with ADHD and 22 without ADHD. The analysis revealed significant differences in attention-related activity patterns between the two groups, with variations in attentiveness and interaction patterns serving as strong indicators of ADHD. These findings suggest that smartphone sensor data can be used to classify ADHD-related behaviours and also provides insightful information with regards to attentiveness-related activity patterns.

The third study targets the classification of eating disorders based on smartphone sensor information. It involved accelerometer and location information, together with application use, keyboard interaction, and touch movements. A sample size of 45 subjects were involved: those with no eating disorders, those with moderate eating disorders, and those with severe eating disorders. Statistical analysis revealed

unique patterns of behaviour most particularly in meal sessions like longer periods of screen inactivity and abnormal touch movements among people with severe eating disorders. Machine learning models could detect such patterns with accurate classification of eating disorders based on their severity. In addition, this research aimed to examine practical and methodological concerns in smartphone-based mental health research among low- and middle-income countries (LMICs). These included issues such as participant recruitment with limited smartphone availability, management of device variability of performance and connectivity, and accommodation of cultural and geographic differences in digital behavior and expression of mental health. Strategies to overcome these problems, including adaptive data collection methods and culturally sensitive study designs, were also debated to enhance the reliability, accessibility, and effect of smartphone-based mental health research in scarcity environments.

This PhD study shows how digital data from social media and smartphones can help classify neurodevelopmental and mental disorders. Such methodologies involve non-invasive, affordable, and scalable means for detecting health-related patterns for mental disorders. The findings suggest that digital data could play a key role in improving early identification and supporting intervention efforts, particularly in resource-poor settings where access to mental health professionals and clinical resources is limited.

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Economic and Regional Classifications

- **LMIC**: Low- to Middle-Income Countries
- **HIC**: High-Income Countries
- **LIC**: Low-Income Countries
- **UMIC**: Upper-Middle-Income Countries
- **GDP**: Gross Domestic Product
- **PPP**: Purchasing Power Parity
- **GNI**: Gross National Income
- **OECD**: Organisation for Economic Co-operation and Development
- **WHO**: World Health Organization
- **UNDP**: United Nations Development Programme

Mental Health and Healthcare

- **DMHI**: Digital Mental Health Intervention
- **MH**: Mental Health
- **ADHD**: Attention-Deficit/Hyperactivity Disorder
- **BPD**: Borderline Personality Disorder
- **MDD**: Major Depressive Disorder
- **PTSD**: Post-Traumatic Stress Disorder
- **SCZ**: Schizophrenia
- **ED**: Eating Disorders
- **CBT**: Cognitive Behavioral Therapy
- **RCT**: Randomized Controlled Trial
- **DSM-5**: Diagnostic and Statistical Manual of Mental Disorders, 5th Edition

Digital and Computational Methods

- **ML**: Machine Learning
- **AI**: Artificial Intelligence
- **NLP**: Natural Language Processing
- **LIWC**: Linguistic Inquiry and Word Count
- **CNN**: Convolutional Neural Network
- **LSTM**: Long Short-Term Memory (Neural Network)
- **SVM**: Support Vector Machine
- **RF**: Random Forest

- **TF-IDF**: Term Frequency-Inverse Document Frequency
- **API**: Application Programming Interface
- **F1**: F1 Score (evaluation metric in machine learning)
- **AUC**: Area Under the Curve (evaluation metric)
- **ROC**: Receiver Operating Characteristic

Social Media and Smartphone Data

- **SNS**: Social Networking Sites
- **SM**: Social Media
- **IoT**: Internet of Things
- **GPS**: Global Positioning System
- **EDA**: Electrodermal Activity
- **HRV**: Heart Rate Variability
- **ACC**: Accelerometer
- **GYRO**: Gyroscope
- **APP**: Application
- **OS**: Operating System (e.g., Android, iOS)

Study/Methodological Terminology

- **RCT**: Randomized Controlled Trial

CHAPTER 1

INTRODUCTION

1.1 Background and Significance

Mental health disorders disturb mood, thoughts, behaviours, and interpersonal relationships to an extent that they significantly interfere with daily life (World Health Organisation, 2021). In the United Kingdom, mental health disorders are estimated to cost the economy around GBP 105 billion annually, with 70 million lost workdays per year (Centre for Mental Health, 2010; Fayyad et al., 2016). Mental health disorders present a significant public health challenge worldwide and in low- and middle-income countries (LMIC), where limited resources and infrastructure further increase the burden. It is estimated that 76–85% of people with mental health disorders in low- and middle-income countries (LMIC) do not receive treatment (WHO, 2021; Koenen et al., 2017). The mental health disorders cost the world economy $5 trillion in 2030, of which LMIC carries a disproportionate burden (UN, 2020). Attention deficit hyperactivity disorder (ADHD) and other neurodevelopmental disorders are becoming an increasing concern for LMIC, with prevalence rates of approximately 5–8% (often higher in high-income countries) (Fayyad et al., 2017). Although eating disorders are commonly viewed as disorders in high-income countries, recent findings suggest that they are becoming more common in low- and middle-income countries (LMIC), especially among adolescent girls and young women. Eating disorders are no longer the condition of privilege that they once were, with LMIC reporting rates as high as 13.4% due to cultural changes, urbanisation and media influence (Beat Eating Disorders, 2019). People perceive mental health conditions through a filter of stigma, spiritual beliefs and misconceptions, making access to care even more challenging (Patel & Thornicroft, 2009). The lack of availability of mental health services in these areas is compounded by systemic barriers, financial constraints and geographical remoteness, which limit access to care. (WHO, 2021; Valsecchi et al., 2018).

Barriers to Mental Health Care in LMIC:

a) Stigma and Cultural Barriers: In the context of LMIC, people suffering from mental health disorders face negligence and discrimination due to the stigmas attached to such illnesses, as well as cultural practices and beliefs that view this illness as a spiritual or moral issue rather than a health-related cause. This leads to discrimination against people who wish to access mental health services, where people's concern is that an individual may be separated from society (Patel and Thornicroft, 2009; Greene et al., 2021; Vaishnav, 2023). When we consider the treatment gap, the stigma of mental health disallows many from seeking assistance, thus leading to worsening of their situation (World Health Organisation, 2021; Dickson, 2024).
b) Limited Availability of Mental Health Professionals: In the context of LMIC, there is a shortage of mental health professionals, with as few as 0.1 to 0.5 mental health workers per 100,000 population (World Health Organisation, 2021; Eissazade, 2024). Thus, millions of

other people, mostly in rural areas, have no or very little access to mental health services due to the limited trained personnel (Nguyen et al., 2019). Furthermore, similar challenges exist regarding the number of psychiatric beds available. There are an average of five psychiatric beds to one hundred thousand people in most low-income settings, resulting in long waiting periods and congestion where few facilities are available (World Health Organisation, 2021; Masoomi et al., 2023).

c) Financial Barriers: Financial barriers remain one factor in accessing mental health care services within LMIC. Most of the population cannot afford the drug prices and the costs of active treatment at the clinics. As a result, mental health care is mostly not included in the national health policy (Patel and Thornicroft, 2009). This debt disproportionately affects those in rural and lower-income countries and regions where the cost of healthcare can be extremely high (World Health Organisation, 2021).

d) Geographical Barriers: Geographical barriers are often regarded as one of the strongest barriers, especially in the LMIC; this normally applies to those in rural or metropolitan areas. More than 50 % of people living in developing countries do so from the countryside, because of this, the part of the population has limited or no access to the care and treatment provided (Patel and Thornicroft, 2009). Lacking the transportation facility and lacking the means and ways of movement in most places results in many people going without care or treatment.

Early intervention plays a vital role in preventing the advancement of mental disorders and enhanced long-term outcomes. In LMIC, there is a lack of mental health education, a lack of resources and services, which causes delayed diagnosis and interventions that result in worse mental outcome (World Health Organisation, 2021). There should be investment in mental health care, and early intervention programmes in these countries to decrease the mental disorder burden in the future (Patel and Thornicroft, 2009).

Digital technology facilitates the use of mobile health (mHealth) apps for data analysis, data storage, and data acquisition to enable people to manage their mental illness despite their financial, social, and geographical limitations (Naslund et al., 2017). In low- and middle-income nations (LMIC), where traditional healthcare infrastructure may be limited, smartphones have also become a tool in enhancing the accessibility of mental healthcare (Bardus et al., 2019). Smartphones offer the much-needed privacy, affordability, and real-time solutions for LMIC. Compared to digital technologies and specialties in mental healthcare, specialists in mental healthcare are not easily accessible, which serves to eliminate barriers, including stigma as well as geographic distance. Although digital technologies have high potential, the challenge of digital literacy as well as the need for apps that are relevant to the local population must still be overcome to fully harness smartphones for improving the treatment of mental illness in these locations (Patel et al., 2018). Examples include the use of smartphone apps to monitor sleep and physical activity to manage attention deficit hyperactivity disorder (ADHD) symptoms and eating disorders by monitoring eating habits and the delivery of cognitive behavioural therapy (Bardus et al., 2019).

1.2 Literature Gap

Limitations in the current literature on mental health and technology include a lack of cross-cultural studies, a focus on common disorders (depression, anxiety), and significant challenges in translating findings into the real-world. The list goes on with significant challenges in translating findings into real-world, scalable solutions. Addressing these gaps will be important for developing more inclusive and evidence-based interventions (Epstein et al. 2016).

a) Most research on mental health and the use of technology is heavily biased towards the Western perspective. This bias ultimately causes limitations in our knowledge of how variations in culture may affect social media use, perceptions of mental health, and technology access in other regions emphasises: "There is a pressing need for more cross-cultural studies which investigate how different cultures interact with technology and perceive mental health. This involves researching the impact of social media on various populations' mental health and how such a resource is or is not available within a culture of mental health (Mayes et al., 2015). To bridge this knowledge gap, this PhD study includes a study from a low- to middle-income country (LMIC), India, presenting a distinctly different sociocultural and infrastructural context from that in high-income Western societies. It also informs understanding how differences in digital availability and cultural perspectives on mental health disorders influence the efficacy and availability of digital mental health interventions (DMHI) (Mayes et al., 2015).
b) While most of the research is focused on common mental health disorders, such as depression and anxiety, relatively less attention is given to other disorders, like ADHD and eating disorders, due to this gap, the needs and challenges concerning conditions that were lesser researched may go unnoticed, and interventions may not fit for these less known disorders (Karaca et al., 2016). This PhD thesis explores the application of different methods for mental health disorders such as ADHD and eating disorders, particularly in LMIC.
c) Most research on ADHD and eating disorders using sensor data from smartphones focused mainly on isolated data sources, such as screen interactions or application usage, without integrating multimodal data. This limitation restricts our understanding of how combining diverse sensor inputs might enhance classification accuracy (Mantel et al., 2022). In our PhD study, we have used a combination of data from multiple sensors of smartphones, such as

accelerometers, gyroscopes, application usage, touch and screen interaction to provide a more comprehensive view of user behaviour. This allows for more continuous collection of data, capturing complex patterns that may not be seen in single sensor studies, while improving the classification models of mental health conditions (Bardus et al., 2019).

d) Most existing research is carried out in well-equipped clinical or laboratory environments, which might not accurately represent the healthcare challenges faced in many regions worldwide, especially countries with limited resources (Ware et al., 2022). By using smartphones to monitor mental health disorders, we overcome one of the most important limitations of lab-based studies, which lack ecological validity. Smartphones offer the ability to continuously monitor mental health symptoms in natural environments in which where people live and interact, providing a more accurate reflection of daily experiences and current mental health status (Naslund et al., 2017).

1.3 Aim and Objectives of the Study

1.3.1 Aim

To leverage digital data from various sources (social media, smartphone usage) to improve the identification of mental health conditions and neurodevelopmental disorders, mainly focusing on individuals from low to middle-income backgrounds.

1.3.2 Research Questions:

a) To develop a model able to classify variation in social media usage among online communities that represent various mental health disorders, and to identify the most significant linguistic and behavioural features that characterize these variations.
b) To develop and evaluate a model able to distinguish between individuals with and without Attention-Deficit/Hyperactivity Disorder (ADHD) using smartphone-based behaviour and sensor data, and to explain the most predictive features underlying this distinction.
c) To develop and evaluate a model able to distinguish between individuals with and without eating disorder using smartphone-based behaviour and sensor data, and to explain the most predictive features underlying this distinction.
d)To study and record practical and methodological concerns regarding the implementation of technology-based mental health research in a low- and middle-income country (LMIC) context, including challenges, limitations, and strategies to effective data collection and participant recruitment.
e) How can multimodal smartphone data, including sensor, usage, and behavioural patterns, be utilised to enhance the classification of mental health conditions such as ADHD and eating disorders?

1.4 Research Scope

1.4.1 "In the Wild" Studies

We aim to capture how people naturally behave and feel about mental health in everyday life, rather than in a controlled lab environment. In comparison to lab-based studies, our studies emphasise ecological validity rather than trying to limit the outcome of change to the specific variables under test (known as internal validity). Ecological validity refers to the findings as more applicable in the real-world and demonstrating how people act outside a lab. Although useful insights are given into mental health in everyday life by these studies, they can control the outside influences on a lesser degree (cutting back on internal validity), but they provide more practical and useful insights regarding creating real-world mental health interventions (Baker & Wheelock, 2020).

1.4.2 Passive Sensing

Passive sensing involves ongoing data capture by wearable or mobile devices without user involvement or input. This method relies on a range of sensors within devices like wearables or smartphones, e.g., accelerometers, Global Positioning System (GPS), gyroscopes, and microphones. The data gathered through passive sensing captures activities, behaviours, and contexts that depict the user's everyday life in real-time (Stylios et al., 2021). In the view of Klasnja & Pratt (2012) (Veiga et al., 2023), the primary source of data comes generally from sensors built into smartphones and wearables (Lin et al., 2020; Huang et al., 2016). For instance, accelerometers are used to monitor the amount and coordination of physical activities; GPS sensors monitor location and travel patterns; microphones monitor the sounds within the environment that might indicate social interactions or current conditions (Veiga et al., 2023). These sensors might constantly be on but work in the background, capturing data without the need for the active co-operation of the participant (Stylios et al., 2021). One advantage of passive sensing is that it produces little user burden. As data capture occurs automatically and without user encroachment on a person's activities, there is little or no need for direct user engagement in the device to capture data, keeping interruptions of natural acts to a bare minimum (McCallum et al., 2018). This type of ongoing background data capture will provide a comprehensive and detailed sketch of users' experience and engagements than the conventional self-report assessments (Veiga et al., 2023). This level also enables monitoring of acts and contexts that spread across a long duration, which is applicable in the study of patterns and trends in mental well-being and illness (Stylios et al., 2021). Overall, passive sensing is a significant advancement in data collection. It is utilised to understand user behaviour and mental health, offering numerous valuable insights with minimal interference to daily life (Hickey et al., 2021).

1.5 Structure of the Thesis

This thesis is organised to find how digital data, mostly from social media and smartphone sensors, can be used for health monitoring, focusing on mental health.

Chapter 1: Introduction provides the background and motivation for the research. It identifies gaps in the existing studies and outlines the main research questions and objectives. The scope of the study is defined, focusing on real-world studies and passive sensing.

Chapter 2: Presents the literature survey, a critical review of existing research. It covers the concept of digital footprints and how they are used in business, finance, and healthcare. It looks at how digital footprints, particularly from social media and smartphones, are used in healthcare to monitor both physical and mental health. This chapter also covers the basics of machine learning and its use in healthcare, along with relevant case studies.

Chapter 3: Study 1: This chapter (Chapter 3) focuses on classifying mental illness from social media data. It describes how data collection, text analysis, and machine learning were performed in the study, stating the results and discussing them.

Chapter 4: Study 2: Classifying neurodevelopmental disorders using smartphone sensor data. The chapter (chapter 4) describes the collection, preprocessing, and analysis of data to classify neurodevelopmental disorders like ADHD and presents the validation of the models.

Chapter 5: Study 3: Classification of eating disorders using smartphone sensor data. The chapter (chapter 5) describes the collection, preprocessing, and analysis of data to classify eating disorder and presents the validation of the models.

Chapter 6: Summarises several key research findings from contributions, followed by a discussion regarding how these inform healthcare; discusses obstacles that either burden or create opportunities for digital health technologies in a set of low-income through middle-income nations. In the same chapter, some kind of recommendations while doing future research have been quoted; a few challenges in the implementation level of digital health technology at different levels.

CHAPTER 2

LITERATURE REVIEW

2.1 Digital Footprint

2.1.1 Overview of Digital Footprint

The term "digital footprint" refers to the massive amount of digital data people leave behind after online activities, including social network posts, website visits, and online transactions (IBM, 2023a). A digital footprint includes all information from personal data, such as full name, address, telephone number, email address, to other behavioural data, identifying social media activities, search queries, and websites that have been visited (Regan & Jesse, 2019). Data sources include data gathered from web browsing to record the sites visited and link clicks, social media activity (including Facebook, Twitter, LinkedIn, and Instagram). Email, messaging, communications sent and received, data collected by smartphone or tablet applications, usage of cloud storage, streaming, and other online digital tools (BBC, 2023; IBM., 2023). Online transactions create records that include the list of things purchased, payment methods used, and transaction histories. Cookies and tracking pixels allow websites to monitor user behaviour for targeted advertising, while online forms and surveys capture personal information (Regan and Jesse, 2019). We may learn about human behaviour and decision-making processes by evaluating digital footprints and decision-making based on the vast amount of data (BBC, 2023; IBM., 2023).

We can further categorise digital footprint as active and passive, including various data forms. (1) Active data, in which the user is required to execute a task or act to collect it, such as filling out a survey, or active data is usually connected with some participant burden, which raises the difficulty of keeping participants interested over longer intervals. (Spinazze, P., et. al,2019). (2) Passive data traces associated with an individual, either left by someone else or obtained through activities retrieved from the user, such as smartphone data. The absence of context in passive data renders it more difficult to understand the underlying causes of specific behaviours or patterns due to the absence of direct input. The PhD thesis focuses on both activities, such as surveys and passive data sources from mobile digital devices and electronic activities (including device activity, social media, etc.) (Sano, A. et al.,2018).

Understanding consumer behaviour is critical for driving business success, influencing successful public policies, and ensuring individual well-being. Investigating individuals' digital footprints can significantly improve decision-making processes and outcomes in various industries, including marketing, finance, law enforcement, education, human resources, e-commerce, social research, insurance, and public health. (Spinazze, P et al., 2019).

2.1.2 Digital Footprint in LMIC

In LMICs, digital footprints comprise several types of data trails made by multiple online actions performed by individuals, for example, social media usage, mobile payments, e-commerce and other government transactions. For instance, in Kenya the M-Pesa system enables individuals to send money to and receive money from each other through their mobile phones and records financial transactions, and in India the Adhar card identifies individuals for several digital purposes and reveals a plenty of information about access and delivery of social services (Divi et al., 2024). These digital footprints are triggered through the increasing penetration of cheap smartphones and internet access, especially in the urban context (Dudu et al., 2024). Passive data would encompass GPS tracking of mobility or application use in general and would also capture automatically (Scandola, 2023). For instance, GPS data of ride-hailing platforms such as Ola or Bolt generates information about urban mobility or navigating patterns through the analysis of Flipkart or Jumia consumption patterns through their browsing histories (Tiony, 2024). These datasets greatly influence socio-economic behaviours and trends and hence can act as a basis for monitoring public health, market analysis, and the development of policies in general (World Bank, 2023; Mehta et al., 2022).

The digital divide between rural and urban areas in terms of data inclusion is a problem, as rural areas in most cases have poor digital infrastructure and low smartphone penetration. For example, while urban Indian users are heavy users of digital payment platforms such as Paytm, their rural counterparts may be dependent on cash transactions, which may leave their economic activity under-represented in the digital data sets. Cultural and gender differences also affect participation: for example, women in certain parts of the world are limited in their use of mobile devices, which creates a gender gap in digital footprints. Moreover, the general weakness of data protection frameworks, with the absence of regulation in some parts of sub-Saharan Africa, for example, potentially raises concerns about protection against data abuse. Despite these challenges, digital footprints have transformative potential in ways such as tracking disease outbreaks using mobility data in a public health crisis or assessing financial resilience through mobile money trends. Obstacles can be overcome by inclusive policies and ethical practices, which will make them a powerful instrument for equitable development and decision-making (World Bank, 2023; Mehta et al., 2022).

2.2 Application of Digital Footprints

Digital footprints are crucial in various fields, including marketing, finance, law enforcement, education, human resources, e-commerce, social research, insurance, and public health.

2.2.1 Analysis of Digital Footprints in Business and Commerce

Understanding digital footprints is crucial in business and commerce as they influence marketing strategies, e-commerce, and overall business operations. This analysis will explore the study and application of digital footprints across various domains, such as marketing and e-commerce.

2.2.1.1 Analysis of digital footprint in marketing

Digital data from consumer online behaviour (social media posts, browsing history, and purchasing behaviour) is essential to marketers, as it helps them to better understand their customers (Mohammad, 2022). This information allows for a more precise marketing effort, resulting in highly targeted advertising campaigns that effectively reach the target population (BenMessaoud et al., 2019). Analysing digital footprints allows marketers to segment customers according to their online behaviour, leading to more personalised messages and products (Gadhavi, J et al.,2019). For example, a sportswear company can use consumer social media engagement, browsing patterns and purchasing decisions to develop personalised marketing strategies, target advertising, work with influencers and create audience-friendly content (Micheli et al., 2018). Analysis of digital footprints can provide valuable data for marketers and increase product engagement and sales (Liang, S.Z. Remembrance: 2024; Grewal et al., 2006; Pavlou & Fyviston, 2006).

2.2.1.2 Analysis of Digital Footprints in E-commerce

Digital footprints are essential in e-commerce since they reveal critical user behavioural trends, including customer support interactions, browsing patterns, purchase histories, feedback, reviews, and wish-lists (Luhung, 2023). Users' digital footprints on an e-commerce site are simply the tracked products that users have looked at, items added to carts, and purchases. E-commerce retailers use this information to personalise recommendations and enhance marketing campaigns to increase user engagement for an enhanced shopping experience at the customer level (Masrianto et al., 2022). Digital traces are very important to researchers, particularly to social researchers, because the digital marks indicate spikes in the attitudes, patterns, and activities of people. A good example is the use of social media entries to harvest data through the duration of an electoral campaign to enable scholars to comprehend the preferences of the voters, the political mood, and the public opinion (Golder, S.A. et al., 2014; Joensuu-Salo, 2021; Suratman et al., 2023).

2.2.2 Digital Footprint Analysis in Finance and Legal

The importance of digital footprints goes beyond business and commerce, reaching into the finance and legal sectors. Analysing digital footprints is crucial for financial monitoring, as it helps detect fraud and assists law enforcement investigations. This section explores the processes involved in analysing and using digital footprints in these areas (finance and law enforcement).

2.2.2.1 Digital Footprint Analysis in Finance

Digital footprint analysis becomes increasingly vital in the finance sector as it helps to inform investment decisions. It assists in creating more accurate predictions, risk assessment, and trend analysis through the understanding of clients in-depth and results in more informed investment decisions (Gupta et al., 2008; Mohammad et al., 2022). Financial institutions can discover new risks, market inefficiencies, as well as potential investment opportunities using digital footprints (Gupta et al., 2008). Financial institutions are in positions to get insight into client conduct and creditworthiness using data from multiple sources that include web-based transactions, social media use, and browser histories (BenMessaoud et al., 2019). LenddoEFL is an example of this, as it employs digital footprints to evaluate credit risk in developing markets, and this process helps individuals with restricted financial histories to acquire credit. This approach of using digital data has demonstrated its effectiveness in enhancing the precision of risk assessment and decreasing the frequency of nonpayment, thereby promoting financial inclusivity (LenddoEFL., 2021).

2.2.2.2 Analysis of Digital Footprints in Law Enforcement

Digital footprints play a vital role in the fight against cyber threats, as individuals and businesses are at a higher risk of online fraud and identity theft. Digital footprints are employed by law enforcement agencies to establish connections among suspects, victims, and related parties and to reconstruct timelines. The efficiency and accuracy of law enforcement activities are also enhanced through digital footprints that enhance the use of conventional investigation techniques (Boyd and Crawford 2012; Gupta et al. 2008). For example, in the case of the 2015 cyber-attack against Ubiquity Network Inc., hackers sent emails to the employees directing them to make wire transfers of money, which resulted in unauthorised wire transfers amounting to $46.7 million. The investigators analysed the digital footprints, examined email headers, metadata, and server records sent to the employees, and worked with financial institutions to identify fund transfers. They were able to freeze assets, thereby tracing the money trail. The attackers were identified, and the scope of the attack was understood through the combination of digital evidence and traditional investigative techniques (Ravi Sen, 2022).

2.2.3 Analysis of Digital Footprints in Human Resources

A digital footprint is analogous to a professional fingerprint in the case of human resources and captures a person's activities on the internet, interactions, and contributions. These include digital CVs constructed on platforms like LinkedIn that enable job seekers to provide their employment background, skills, and recommendations and present a snapshot of their professional journey. Also, you could engage in communications with your peers and industry group participants or simply participate in industry-relevant groups to establish your presence on the web. In this way, the potential employer will have a good idea about your networking ability and contacts acquired within the industry. Sharing information through blog posting, insight posting, or participation in webinars is a means to uncover your level of expertise and thinking. For instance, the effective human resource manager might gather useful knowledge about the candidate's personality, the ability to communicate effectively, and working preferences by checking a LinkedIn profile, tweets, and blog entries. A positive good-looking presence on the web may provide you with more job opportunities; adverse information may create doubts about you. (Batchelor, M. 2021; Holman, D. 2022).

2.3 Analysis of Digital Footprints in Healthcare

Digital footprints in healthcare provide valuable insights into behaviours and health-related activities, covering both the public and individual health domains. The digital traces, such as social media posts, website visits, search histories, and data from mobile health applications, offer a wealth of data that can be used to improve various aspects of healthcare.

2.3.1 Digital Data Sources in Healthcare

Several data sources that may serve public health have digital footprints (Lokmic-Tomkins et al., 2022). Examples of digital indicators and their potential use in surveillance and prevention in the field of health are presented in Table 2.1. Social media use, web use, and mobile healthcare apps are among the digital measures that play a significant role in healthcare in the modern era. Social media aids tracking of disease patterns, capture of the patient's journey, and enhancement of public health communication. Web browsing and search history indicate areas of concern of users, inform the development of educational content, and guide targeted public health interventions. Mobile health apps provide personalised care, facilitate remote monitoring by professionals, and contribute useful data to research on trends in population health.

Table 2.1: Digital Indicators and Applications in Health Surveillance and Intervention

Digital Indicator	Application Areas	Description.
Social Media Posts	Disease Surveillance and Trend Analysis	Social media platforms can be useful for analysing user-generated content related to health, including disease prevalence, treatment effectiveness, and public attitudes (King et al., 2019).
	Patient Insights and Experiences	People often share their health experiences, symptoms, and treatment outcomes on social media (Rahmatizadeh et al., 2024).
	Public health communication	Social media can be a valuable tool for public health agencies to disseminate health information, promote preventive measures, and address misconceptions while engaging with the public and encouraging healthy behaviours (King et al., 2019).
Website Visits and Search History	Targeted Interventions	Analysing website visits and search history provides valuable insights into health concerns and interests (Kvardová et al., 2020).
	Educational Materials Development	Understanding online search trends makes creating relevant educational materials possible. Websites can offer accurate health information, debunk myths, and raise awareness (Pot et al., 2020).
	Public Health Campaigns	Data on popular health-related searches informs campaign strategies. Public health agencies can optimise messaging and reach the right audience (Lussier et al., 2020).
Mobile Health Applications (Apps)	Personalised Healthcare	Mobile health apps collect data on physical activity, sleep, heart rate, nutrition, and more, enabling personalised health recommendations and interventions (Silverman et al., 2023).
	Remote Monitoring	Healthcare providers can remotely monitor patients' progress using health metric-tracking apps, adjust treatments, and prevent complications (Mahdizadeh et al., 2018).
	Research and Insights	Aggregating application data provides valuable insights into population health trends, allowing researchers to study lifestyle patterns, adherence to health goals, and risk factors (Kammerer et al., 2020).

2.3.2 Analysis of Digital Footprints in Physical Healthcare

The growing application of digital technologies in healthcare has changed the way we monitor, manage, and respond to public health. Healthcare providers can use social media platforms, mobile health apps, and web search data to monitor disease outbreaks more effectively, personalise patient care, create effective public health campaigns, and provide remote monitoring of patients. These applications of digital health tools lead to initiative-taking and precise healthcare interventions that enhance outcomes and public health. Examples of the use of digital health data in public health and personalised care are presented in Table 2.2.

Table 2.2: Applications of Digital Health Data in Public Health and Personalised Care

Application	Description.	Example
Disease Surveillance and Trend Analysis	Tracking disease outbreaks and monitoring public health trends using digital footprints.	Researchers used social media data during the COVID-19 pandemic to track the spread of the virus and identify hotspots (Salathé et al., 2012)
Personalised Interventions	Designing targeted health interventions and personalised healthcare recommendations based on data from mobile health apps and search histories.	A diabetes management app provides tailored diet and exercise recommendations based on the user's activity (Quinn et al., 2011).
Campaign Strategies	Data from online searches and website visits informs public health campaigns, optimising messaging and targeting the right audience.	Analysis of search trends for smoking cessation can help design effective anti-smoking campaigns (Ayers et al., 2014).
Remote Monitoring and Diagnosis	Using data from mobile health apps to monitor patients remotely, adjust treatments, and prevent complications.	Cardiac patients use a wearable device to track their heart rate and send data to their doctor for real-time monitoring (Chan et al., 2012)

2.3.3 Analysis of Digital Footprints in Mental Healthcare

Incorporating digital technologies into mental health care has created novel opportunities for enhancing patient outcomes. By combining data from diverse sources such as social media, mobile health apps, and search engines, healthcare practitioners can improve disease surveillance, personalise interventions, optimise awareness campaigns, and enable remote monitoring. Table 2.3 shows some examples of digital applications in mental health monitoring, intervention, and awareness.

Table 2.3: Digital Applications in Mental Health Monitoring, Intervention, and Awareness

Application	Description	Example
Disease Surveillance and Trend Analysis	Tracking mental health trends and identifying risk factors using digital footprints.	During the COVID-19 epidemic, researchers examined posts on platforms such as Twitter and Facebook to find increases in phrases associated with depression and anxiety. By monitoring these trends, they were able to identify areas with rising mental health difficulties and better distribute resources to those areas. (NHS, 2024).
Personalised Interventions	Designing targeted mental health interventions and personalised therapy recommendations based on data from mobile health apps and search histories.	Consider utilising a mental health app that prompts you to track your mood and everyday activities. Based on this information, the app may recommend specific mindfulness exercises, such as breathing techniques or guided meditations, to help you manage stress or anxiety. It may also recommend treatment sessions or self-help materials appropriate for your present mental condition and lifestyle (NHS, 2019)
Campaign Strategies	Data from online searches and website visits informs mental health awareness campaigns, optimising messaging and targeting the right audience.	Public health organisations may analyse search engine data to ascertain the information individuals seek regarding mental health support. For example, if the number of enquiries for "how to deal with depression" increases, this information can be used to develop targeted campaigns that aim to address common concerns and misconceptions about depression, thereby reducing stigma and encouraging individuals to seek assistance (Duncan, F et al., 2021).
Remote Monitoring and Diagnosis	Using data from mobile health apps to monitor patients' mental health remotely, adjust treatments, and prevent crises.	Patients diagnosed with bipolar disorder may be required to wear a device that monitors their mood fluctuations, sleep patterns, and physical activity. This information is transmitted to their therapist, who can track their condition in real-time. The therapist can intervene early to prevent a crisis by adjusting treatment plans or providing immediate support if the device detects indicators of a potential mood swing. (NHS, 2019)

2.4 Social Media Analysis

Social media websites are used to communicate with people, provide personal experiences, voice opinions, and access information. Social media has made its way into life and has found application on platforms such as Facebook, Twitter, Instagram, and TikTok for diverse purposes (Xu et al. 2023). Social media enables users to reach out to friends and relatives and provides access to information and entertainment (Zeraatkar & Ahmadi, 2018). Social media sites are used for the exchange of knowledge, debate participation, and self-expression. The enormous amount of data generated by social media users serves as a valuable source for the study of human behaviour (Kroetz et al., 2021). Social media data contains a vast amount of information about individuals' beliefs, life, and activities that may be used to interpret social trends (Ghahramani et al., 2022). Monitoring and analysing enormous amounts of user activities have made social media analysis applicable in the areas of marketing, public health, and social sciences (Li et al., 2023). With a rise in the users of social media websites, the amount of data produced also increases. Experts may use social media data to acquire insights on new trends, establish the movements towards public opinions, and even foretell future behaviours through tracking data patterns (Pradyumn, 2018).

2.4.1 Types of Social Media

Social networking sites, content community sites, and location-based social media are the three types of social media applications. More specifically:

2.4.1.1 Social Networking Sites

Social networking sites (SNS), often known as "social media platforms," are the most common sort of social media, and their popularity is growing globally. Facebook, Google+, Twitter, Instagram, LinkedIn, and Xing are common instances of SNS. In the United Kingdom, more than half of all people use a social networking site at least once every week (Ofcom 2013). Social networks enable opportunistic interactions of users over internet-based channels and allow them to selectively present both broad and limited audiences, either asynchronously or in real-time (Carr & Hayes, 2015). According to the latest survey reports, more than half of the population uses social media, and time spent on social media accounts for two-thirds of total internet usage. (Kemp S. Digital 2020), (Obar & Wildman, 2015). This highlights the importance of obtaining representative data to determine how social networking site use is linked to a wide range of health indicators (all of which were examined in the same sample), as well as whether there is a link between negative health indicators and people who are considered to have a higher risk of problematic use. As a result, not only is it necessary to investigate the usage of social media in connection to health in-depth, but it is also necessary to employ nationally representative data that includes a variety of individual factors and health indicators (Torous, J. et al,2018).

2.4.1.2 Content community sites

Content communities are browser programs that allow users to exchange media content, including movies, images, presentations, audio, and internet links. For example, YouTube, Flickr, and Dailymotion; YouTube appears to be the most successful of all content communities, with over one billion visitors to the site every month. In 2014, over six billion hours of video were watched monthly, with 100 hours being added per minute (YouTube 2014). Flickr has ninety-two million members who post one million photographs every day, despite being less popular, but still amazing in terms of size (Flickr 2010). According to Jin et al. (2010), publishing and viewing a picture or video in a content community constitutes an "implicit vote" in favour of or against the themes depicted. As a result of collecting data on such "votes," the wisdom of the social media crowd is exposed, allowing prediction and forecasting in fields such as politics, economics, and marketing (Goh & Lee, 2014).

2.4.1.3 Location-based social media

Location-based social media (LBSM) are online or mobile programmes that allow users to create a list of other users with whom they share their physical location at a certain moment (referred to as "check-in"), which is generally related to a specific venue or area. Location-based social media is a type of location-based service, which are software programmes that give information based on the user's and device's location. This concept encompasses a variety of applications, including navigation, location-based advertising, mobile personal guides, and more. Examples of LBSM include Facebook Places and Gowalla, the latter of which was shut down in 2012 after being acquired by Facebook. Facebook Places ceased to operate as a standalone programme in August 2011, and its check-in functionality was integrated into the main Facebook platform. In 2011, 4% of all US adults used their smartphones to check-in to locations using location-based digital platforms, and this percentage rose to 12% among individual mobile phone users. Moreover, the development and use of LBSM raise significant considerations regarding user privacy and data collection, emphasising the importance of understanding the implications of these technologies (Zhang & Lu, 2014; Cain, 2014; Hamari & Selos, 2017).

2.4.2 Linguistic Analysis

Linguistic analysis examines how language is used in social media posts to find markers linked to mental health conditions. Word choices, sentence structures, and patterns in users' online communications are used to identify signs of emotional distress, cognitive biases, and psychological states. For instance, tools such as Linguistic Inquiry and Word Count (LIWC) organise words into emotive and cognitive clusters. These digital biomarkers can improve early detection and intervention efforts to understand the relationship between language and psychological well-being (Yang et al., 2024; Coppersmith et al., 2014). In summary, linguistic analysis has become a powerful tool for extracting valuable insights from the vast amount of user-generated content on social media platforms. Huerta, D. et al., (22021) have uncovered trends, patterns, and correlations that significantly affect public health monitoring, intervention strategies, and understanding the complex relationship between language and well-being (Huerta, D. et al., 2021). (Huerta, D. et al., 2021) have achieved this by using sentiment analysis, topic modelling, and identifying linguistic indicators. However, addressing the challenges posed by the informal nature of online communication remains a critical task to ensure the accuracy and reliability of these analysis (Huerta, D. et al., 2021).

2.4.3 Sentiment Analysis

Sentiment analysis is a method that is used to determine the emotional tone of written content, particularly on platforms such as social media, forums, and reviews. Sentiment analysis is a method which is used to assess the emotional overtones in user-generated material. Sentiment analysis provides important information about whether the conveyed attitude in the text is positive, such as optimistic, joyful, affectionate, or grateful; negative, such as angry, sad, fearful, or critical; neutral, such as informative or objective; or more mixed sentiment, such as bittersweet, resigned, or supportive. For example, Coppersmith et al. (2015) studied the emotional tone of tweets to detect depression on Twitter using sentiment analysis. To classify tweets and to detect which users are depressed, one can use a combination of sentiment scores with linguistic features (Coppersmith G. et al., 2015). A study by Johns Hopkins University researchers used sentiment analysis to assess public sentiment towards COVID-19 vaccines on social media platforms such as Reddit, Facebook, and Twitter. Abualigah, L et al. (2020) studied the determinants of vaccine hesitancy and public acceptance by tracking tweets that conveyed positive, negative, or neutral sentiments. (Abualigah, L et al., 2020).

Sentiment analysis with the LIWC tool involves text involves analyzing text along psychologically, emotionally, and socially relevant dimensions. The LIWC tool uses a dictionary that categorises words into over 90 categories, including "Positive Emotion" and "Negative Emotion," through which it can quantify emotional tone and give insight into the psychological states represented in the text. LIWC can detect sentiment and uncover the deeper patterns in cognitive processing, social interaction, and affective states just by looking for the presence of specific words related to such emotional states as happiness, anger, sadness, or anxiety (Pennebaker et al., 2001).

2.4.3.1 Key Approaches to Sentiment Analysis

There are two types of approaches to sentiment analysis: lexicon-based and machine learning-based.

a) Dictionary-based approach: This method uses predetermined lists of words with specified emotions. For example, positive words like "happy" or "joyful" are labelled as positive, but negative words like "angry" or "frustrated" are labelled as negative. Sentiment is controlled by the text's frequency and kind of words (Liu 2021).

b) Machine learning-based approach: Machine learning models are trained on labelled data, allowing the system to learn from textual patterns and categorise sentiment more accurately (Liu, 2021).

2.4.3.2 Applications of Sentiment Analysis

Sentiment analysis has applications in business and marketing, social media monitoring, political sentiment analysis, and customer support.

a) Business and Marketing: Companies employ sentiment analysis to evaluate public opinion on products or services, monitor brand reputation, and understand consumer feedback (Go et al., 2009).
b) Social Media Monitoring: Sentiment analysis is widely used to monitor public responses to news, events, or public figures on platforms such as Twitter or Facebook (Bail et al., 2018).
c) Political Sentiment: Political analysts employ sentiment analysis to analyse voter sentiment, reactions to political campaigns, and public sentiment regarding policies (Bail et al., 2018).

2.4.4 Application in Physical Healthcare

Social media data can be used in healthcare surveillance, providing real-time surveillance and intervention opportunities. Among the most prominent social media platforms is Twitter, which has provided several benefits to the surveillance of physical health. It is done in real-time since it allows for easy and fast diffusion of health information and may be used to trace disease outbreaks. For instance, it allows for real-time monitoring of disease outbreaks and health-related behaviours using geotagged tweets mentioning symptoms, which can give instantaneous insights into the spread of diseases (Salathé et al., 2012). Research conducted by Paul & Dredze (2011) indicates that Twitter surveillance is useful in monitoring influenza using symptomatic tweets. By examining tweets, Paul and Dredze (2011) showed that Twitter may be useful for public health surveillance. This was especially clear during the 2009 H1N1 influenza pandemic, when real-time monitoring of the disease's spread was done by gathering and analysing tweets reporting flu symptoms. With its huge user base and community features, Facebook contributes to general healthcare by promoting patient engagement and creating support groups for individuals with chronic conditions. Research done by Paul and Dredze (2011) reveals that Facebook provides emotional support and health education, thus significantly affecting patients' well-being. According to research by Paul and Dredze (2011), Facebook groups—especially those for people with chronic diseases like diabetes or cancer—help spread important health information and offer emotional support. Through peer-to-peer support, resource sharing, and connections with others going through similar struggles, these networks help patients' psychological health and overall health outcomes. Users can share their fitness routines, dietary habits, and health journeys, motivating others to promote healthier lifestyles (Alalwan et al., 2017). Alalwan et al. (2017) explored how Instagram's focus on photos and videos enables users to monitor their health and encourage others to follow better habits. Because the platform is community-driven, users are encouraged to share their success, which may greatly influence behaviour modification by offering social recognition and support.

Healthcare-related discussions on social media platforms such as Facebook and Twitter provide valuable insights into public health trends. Healthcare providers can use these platforms to assess patient experiences and emerging issues, which can be helpful for health planning and policy making. It also provides an opportunity to understand public behaviours regarding health care through analysis of social media data, which can be used to develop targeted interventions or campaigns. This relationship between social media activities and health trends has been established with platforms providing rich data sources for understanding healthy behaviours in real-time that aid in speeding up public health responses (Salathé et al., 2013). The usefulness of social media in addressing major public health issues is demonstrated by notable success stories, such as its utilisation during the H1N1 pandemic to communicate information about disease prevention and management of the public's concerns (Salathé et al., 2013).

2.4.5 Application in Mental Healthcare

Social media content, including posts, comments, and messages, provides insight into a person's psychological condition, social relationships, and emotional displays. Moreover, general health-related information, such as postings on diet, exercise, medicine, health concerns, etc., is also available on such sites. Social media data can reflect a user's mental health awareness, attitude, and action towards it, as well as an approach to the larger aspect of health care. The social media data presents innovative ways to measure a person's mood and state of mind. Twitter, Facebook, and Instagram provide valuable information that can be used to identify issues such as depression and anxiety (De Choudhury et al., 2013).

During the Bell LetsTalk campaign, Twitter users often share personal stories, provide mental health advice, and raise awareness of mental health services. The hashtag has become a popular forum for people to discuss issues such as depression, anxiety, and mental health in general. A person writes, "I'm struggling with anxiety but visiting my therapist today. It's OK to seek assistance. "BellLetsTalk ♡." This tweet acknowledges mental health challenges, demonstrates proactive behaviour—seeking therapy—and helps break down the stigma associated with mental health concerns (Brailovskaia, J., & Schillack, H. 2020). Facebook groups for mental health, such as "mental health support" or "Anxiety and Depression support," enable members to discuss their mental health experiences and coping skills and seek help from others. A Facebook user posts in a group, "I've been feeling overwhelmed recently and wanted to seek help", Have you tried mindfulness or breathing techniques for anxiety?. This post represents a person seeking help, demonstrating an understanding of mental health techniques (such as mindfulness), and taking an active approach to anxiety management (Naslund, J. A. et al.,2016). Instagram users frequently post personal mental health experiences and support self-care techniques. Influencers and organisations utilise the platform to promote awareness about topics such as eating disorders, body image, depression, and anxiety. A person shares a photo of themself with the remark, "Embracing my journey with mental health." Therapy has transformed my life, and I'm now learning to love myself again. If you want assistance, please do not hesitate to contact us at: "MentalHealthMatters", "EndTheStigma". This post demonstrates a good shift in attitudes towards mental health treatment and self-acceptance, with a focus on breaking down the stigma associated with therapy and mental health (Fardouly, J et al.,2015). Social media will remain an important avenue used to increase awareness among people regarding mental health, hence reducing stigmatisation. Social media's public opinion campaigns can change the general attitude towards mental illness by creating an understanding of what it is and demanding action in seeking support (Naslund et al., 2016).

2.5 Smartphone Sensors Analysis

Mobile devices, such as smartphones and tablets, have become essential accessories, with more devices on the globe than humans. Given the amount of time individuals spend on their smartphones, information on their behaviour and health state is informative and easily accessible (Spinazze, P., et.al, 2019; Levenson et al., 2016)). Smartphone technology has evolved rapidly, significantly changing technological advancements and their impact on society. Originally designed as simple communication tools, smartphones have evolved into complicated gadgets with capabilities like internet access, advanced cameras, and various applications that expedite daily chores. This change has impacted how people communicate and use technology daily. People use smartphones extensively in fields like education, healthcare, and entertainment, creating new opportunities for societal engagement. As smartphones became more widely used, the interaction between technology and consumers grew stronger, resulting in an omnipresent and flexible usage culture.

The smartphone data collection capabilities enable researchers to gain insights into user behaviour. Smartphone devices enable researchers to identify patterns and collect valuable data about how users interact with their environment. Smartphones provide critical insights for designing strategies to increase individual and social well-being by allowing data collection and analysis on user behaviour (Spinazze, P., et. al,2019; Levenson et al., 2016).

2.5.1 Smartphones

2.5.1.1 Overview of Smartphone Sensors and Applications

Modern smartphones include sensors and software features that allow for a wide range of capabilities, from basic user interactions to advanced applications in gaming, navigation, and health monitoring. The smartphone sensors gather real-time information and adapt to human behaviour and environmental conditions to simplify the experience. Table 2.4 show types of smartphone sensors and their functional applications.

Table 2.4: Smartphone sensors and their functional applications

Sensor	Function	Uses
Accelerometer	Measures acceleration forces in three dimensions (x, y, z axes). It is essential for fitness monitoring and gaming applications to detect device orientation, motion, and vibration.	Detects phone orientation, counts steps, and motion-based controls in apps and games (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Gyroscope	Measures the rate of rotation around the phone's three axes	Enhances motion sensing, used in VR applications, gaming for tilt-based controls (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Location (GPS)	Determines the phone's precise location using satellite signals	Navigation apps, location-based services, and geotagging photos (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Keyboard	A keyboard sensor detects key inputs and converts them into signals a computer can understand.	Text input, shortcuts, and gesture typing (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Screen (Ambient Light Sensor)	Measures the ambient light level around the phone, protecting battery life and improving the user experience.	Automatically adjusts screen brightness to improve visibility and save battery life (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Touch (Touchscreen Sensors)	Detects touch inputs on the screen, which enables users to interact directly with the display.	User interface navigation, multi-touch gestures, and drawing apps (Kulkarni P et al., 2021; Laport-López, F et al., 2020)
Application Notification	Notifications are utilised to inform users about significant events and application updates.	Alerts users to new messages, updates, and other notifications (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)
Application Foreground Usage	Foreground utilisation in applications is the term for the state of an application that is currently in use and visible to the user.	Usage analytics, battery management, and app switching (Kulkarni, P et al., 2021; Laport-López, F et al., 2020)

2.5.1.2 Location Tracking

Smartphones also incorporate recently developed technologies such as GPS (Global Positioning System) and Bluetooth, which are essential for accurate location tracking. GPS allows mobile phones to communicate with satellites to find out where they are. Bluetooth is used for transferring data and connecting devices wirelessly over short distances. These technologies are needed for various applications, such as navigation, location and use of ride-sharing apps and food delivery services, which have improved user experience (World Health Organisation, 2020). deductible. Developed by Niantic, Inc., Pokemon GO is a good example of how GPS and augmented reality can be used correctly and efficiently to develop location-based games that combine the virtual and real-world. This game captures virtual Pokémon and integrates them with various features worldwide using GPS. Thus, the players must familiarise themselves with their surroundings to capture and interact with Pokémon. PokéStops and Gyms are the core features of this app, linked with real-life locations, keeping users moving and engaged at a more prolific level. Users can share their progress and how much they have achieved with others on their social media pages and arrange community events; thereby, a robust social online community is created, ensuring there is always player interaction. Pokémon GO has encouraged more physical activity and outdoor exploration, fostering economic activity with local businesses. (Niantic, 2016). Zombies, Run is a fitness app created by Six to Start that makes running an interactive game. Players assume the character of "Runners" in a post-apocalyptic world overrun by zombies, with real-world mobility influencing gameplay. The software uses GPS to track users' whereabouts and speeds, incorporating their jogging or walking into mission goals such as avoiding zombie hordes or gathering supplies. As players walk, they receive audio updates that feature immersive tale components and reminders to outrun nearby zombies. This gamified approach combines fitness and storytelling, enticing users to remain active while completing objectives. In short, using location data has improved our lifestyle. Besides navigation, location monitoring is used in many potential data applications (Hamari, et al.,2016).

2.5.1.3 Application usage trends

Mobile applications have become part of modern life in this digital world, causing a massive shift in individual behaviour and overall societal setup. The ability to connect the consumer with worldwide networks, communicate in real-time, and easily access data has completely redefined how individuals and communities operate through these mobile applications. Mobile apps make people's lives easier and are very influential in changing, "how communities worldwide communicate and interact"? revolutionising the way communication used to be with their features of instant sharing and talking. TikTok, which ByteDance established, has become a global phenomenon predominantly due to its sophisticated recommendation algorithm (Amaral et al., 2023). The app can generate a highly personalised "For You" feed by monitoring user behaviour, including the duration of video viewing, the number of likes, the number of shares, and the number of repetitions. TikTok's emphasis on brief, entertaining, and highly shareable content has resulted in unprecedented levels of engagement (Amaral et al., 2023). The app's data-driven approach to content recommendation has fuelled sustained user growth and engagement, as evidenced by its surpassing of 1 billion monthly active users by 2021. Amazon leverages real-time data from its mobile app to deliver personalised advertising, enhancing user engagement and driving conversions. Amazon's algorithms instantly provide tailored product recommendations and ads by tracking in-app activities such as browsing history, search queries, purchase patterns, and geolocation. For example, suppose a user looks at a certain product on Amazon. In that case, the advertisement—even the recommendation on the homepage and notifications—will switch to complementary products or as an alternative (Seah & Koh, 2020; Flaherty et al., 2017). Powered by artificial intelligence (AI) and machine learning, such a dynamic approach is helping Amazon improve relevance, enhance the shopping experience, and drive sales through more targeted, real-time advertising (Shiyab, 2024).

2.5.1.4 Privacy and Data Security Concerns

One of the big issues that smartphone apps facilitate is privacy, particularly about data. These risks come with unauthorised data collection and data sharing, creating ethical questions as it is something that it cannot be told to the users how the data will be used. Most applications have most of the mandate to access data by the user, which is being used by third parties that might abuse the data: location data, contact numbers, messages, etc (Amaral et al., 2023). That is, users should feel confident with their applications, and if they understand that their data is not secure, confidence in mobile apps disappears. For example, service-oriented businesses are most affected by the breach because such businesses depend on trust and the interaction process with consumers. Privacy breaches have very serious implications, including identity theft and money loss. Some proposed solutions include having more data protection features installed by the app developers and the platform owners, more sensitive encryption, and more explicit user agreements that are plain and clear. These include new product innovations, for example, end-to-end encryption, plain and clear user agreements, regular security and updates testing. Therefore, the above strategies will see developers make users more confident and compliant with international regulatory standards in the digital space. A very good example is the case of the data privacy scandal between Facebook and Cambridge Analytica, which shows how smartphone apps can help prevent privacy breaches, notably regarding unauthorised data collection and sharing. It was reported in 2018 that the political consulting firm Cambridge Analytica had misused personal information on millions of Facebook users without their consent (Seah & Koh, 2020). Through the seemingly harmless app "This is Your Digital Life," information from 87 million users was collected for political usage, even though only 270,000 users had ever downloaded the app. This has huge implications for ethics since people whose data was breached had no clue how third parties used and disseminated that data. This created a loss of trust, especially in service-based companies such as Facebook, whose functioning is based on user trust for its proper working. The company thus received a $5 billion fine from the Federal Trade Commission, along with changing its privacy policies to comply with strict laws on data protection such as GDPR and CCPA (Isaak & Hanna, 2018). This case indicates the need for transparency, stronger encryption of data, and clear agreement on the user's part to protect users' data and ensure trust in the digital platform (Flaherty et al., 2017).

2.5.2 Smartphone Sensors in Physical Healthcare

Smartphones are great for tracking health activity due to their availability, mobility, widespread use, and superior technological capabilities. Smartphone advanced technological features and wide usage have brought immense health monitoring, tracking, management, and sensing changes. Smartphone devices can support continuous health monitoring by exploiting integrated sensors, such as accelerometers, gyroscopes, or optical sensors, to derive the spatiotemporal context. For example, the Apple heart study demonstrates how effectively smartphones detect irregular heart rhythms. The research used the Apple Watch's heart rate sensor to identify potential irregular heartbeats among the participants, enabling early medical intervention and reducing the risk of stroke (Apple Inc., 2019). As for health tracking, smartphones support a detailed management system regarding physical activity, sleep, and dietary habits. For example, the Fitbit app allows one to track the number of steps taken in a day, the types of exercises performed, and the duration of the exercises. In this regard, a good example is the MHealth Trial, which investigated the level of effectiveness that health applications on mobile phones have in managing diabetes. For example, those participants who used a mobile application to monitor their blood glucose levels, medication compliance, and physical activity showed improved glycemic control compared to traditional methods (Holmen et al., 2014). Holmen et al., (2014)'s study has shown how smartphone applications could help with self-management and chronic disease management (Holmen et al., 2014).

Smartphones have been useful in telemedicine delivery; they are one of the major enablers for the remote delivery of health. In a pandemic setting, companies such as Teladoc Health and Doctor on Demand have proven to be useful platforms for virtual consultation, allowing for minimal contact without compromising the continuity of care (Shah & Badawy, 2021). Moreover, the adoption of smartphones in the Mobile Alliance for Maternal Action (MAMA) programme in sub-Saharan Africa reduced cases, resulting in maternal and neonatal deaths (MAMA, 2017; Cao et al., 2023). Finally, the effects of smartphone sensing on health management are worth addressing, given the availability of real-time data that allows for early diagnosis of problems and personalised treatment coordination (Sun et al., 2018). For example, continuous glucose monitors connected to smartphones for diabetes patients continually monitor sugar levels in the blood and, in real-time, offer them far more information than before for decision-making, time to make required modifications in treatment programmes (Wagner et al., 2022). Overall, smartphones are revolutionising healthcare by combining monitoring, tracking, administration, and sensing into a single coherent system that ensures better health outcomes and promotes proactive health management. Through apps and integrated sensors, smartphones transform health management and monitoring and improve physical health monitoring by using embedded sensors like accelerometers, gyroscopes, application usage, GPS, Touch screen, etc. (MAMA, 2017; Estai et al., 2016).

Smartphone sensors play an important role in monitoring and enhancing physical health. Accelerometers, a required smartphone sensor, help monitor a user's physical activity level and movement pattern. These sensors measure acceleration forces to determine when a person is undergoing dynamic movements (such as walking or running) or when a person maintains static postures (such as sitting or standing). This data allows for the measurement of step count, estimation of calories burned, and an analysis of the type, intensity, and duration of exercise. Further, accelerometer data is key in walking and balance measurements, timing walks, capturing reaction times, and giving cognitive tests, all of which give a comprehensive measurement of an individual's physical capability and state of health (Godfrey & Conway, 2021; Trost & Zheng, 2020). For instance, in a study about fall detection in the elderly patient population, accelerometers, combined with gyroscopes, reached a sensitivity of 91% and specificity of 95%, greatly increasing patient safety (Hosseini et al., 2021).

Essential to any smartphone, accelerometers are used to monitor activity levels and movement patterns. These data thus lend themselves to measures of step counts, approximate energy expenditure, and the analysis of type/duration of intensity in exercise with other measurements. Additionally, accelerometer data are applied to assess footstep timing, balance measures, reaction time capture, and the administration of cognitive tests across the spectrum of physical function impairment and health status (Godfrey & Conway, 2021; Trost & Zheng, 2020). One case demonstrated how the detection of falls in elderly patients improved by adding a gyroscope to an accelerometer while achieving 91% specificity at 95%, improving safety for elderly people (Hosseini et al., 2021). Hosseini et al., (2021) claimed an accuracy of 87% when predicting disease using accelerometers to perform gait analysis on Parkinson's patients (Hua et al., 2020). Heart rate variability can be measured using embedded heart rate monitors in smartphones. These indicators indicate the cardiovascular health status during physical activities. In a related way, an accelerometer and GPS study reported that 120 postsurgical patients monitored showed 20% faster recovery from mobility-monitoring devices. This made it possible to tailor rehabilitation programmes to the special needs of the patients. For example, sleep sound pattern analysis with microphones can help monitor breathing patterns to identify conditions like sleep apnoea (Kwon et al., 2021).

Touch screens and screen sensors play a key role in physical health applications because of user–system interactions involving visual feedback. For example, touch interfaces aid real-time workout adjustment through interactive exercise routines (Lee et al., 2022). Furthermore, the light sensors also serve to follow up on environmental conditions that are needed for various illuminations and help in following up on activity levels (Wang et al., 2021). In health-related apps, keyboard inputs facilitate user behaviour tracking, enabling further information to be gathered to support personalised health interventions (Banaei et al., 2021). The light sensors also monitor light exposure, helping manage light-dependent conditions that may manifest, such as circadian rhythm disorders (Zhao et al., 2022). Smartphone sensors provide heterogeneous data to be used in healthcare that has been personalised. In this respect, a personalised diabetes management programme using glucose monitoring applications and physical activity sensors improved glycaemic control, with an HbA1c reduction of 1.5% (Wu J et al., 2022). On the other hand, personalised feedback on blood pressure monitoring and activity data helped reduce systolic blood pressure by an average of 10 mmHg to manage hypertension effectively (Smith et al., 2020). In this way, smartphone sensors have opened a wide array of data pertinent to personal health management and have become irreplaceable in modern healthcare. Health surveillance systems further extend this premise by integrating individual sensor capabilities into more comprehensive, multidimensional monitoring methodologies.

Health surveillance is comprehensive in that it integrates several smartphone sensors into healthcare. This happens due to the existence of accelerometers, GPS, heart rate monitors, and gyroscopes that enhance the effectiveness and reliability of the monitoring system with a multidimensional perspective on health. For example, based on accelerometer data, GPS data, and heart rate sensor data, one study with 500 participants achieved a 25% gain in health anomaly detection over the single sensor method (Ding et al., 2021). This has made it possible to manage chronic diseases, for example, chronic obstructive pulmonary disease, more closely using integrated accelerometers, GPS, and environmental sensors, with a 15% reduction in rehospitalisations post-monitoring (Patterson et al., 2020). In another study with 300 people, including those tested for sleep quality through accelerometers and microphones, there was a 90% success rate in detecting sleep disorders (Liu et al., 2021). The usefulness of the apps to health is based on the ease with which people can use them to engage with the tools for managing health through the touch screens and screen sensors for inputting data (Lee et al., 2022).

2.5.3 Smartphone Sensors in Mental Healthcare

The ease of use of smartphones, their mobility, and technological advancement have made smartphones a perfect tool for monitoring mental disorders. Smartphones' advanced technological capabilities and extensive use have yielded tremendous monitoring, tracking, management, and sensing change in the field of healthcare. Smartphones can monitor mental disorders continuously using onboard sensors that include accelerometers, gyroscopes, GPS, and usage data of applications to sense changes in mood or mental illness triggers to detect early decline in mental condition. For instance, the "Mindstrong Health study" proved how smartphones can effectively detect early signs of a decline in mental condition. Keyboard typing data and usage patterns of smartphones have been used to predict the early symptoms of depression and anxiety that went undetected earlier to provide timely interventions and minimise the risk of serious mental illness. Smartphones also make possible very detailed management systems that can track one's mental health by monitoring key indicators, such as sleep patterns, physical activity, and social interaction. Other apps include Moodpath and Headspace, which allow users to keep track of their feelings and stress levels and even carry out exercises in mindfulness. An example of this includes the 'Blue Ice' app trial to prove the efficiency of smartphone interventions to support mental well-being (Yang et al., 2022). The app helps adolescents to self-manage self-injury by reducing distress through activities and the identification of other ways of coping. In one study, this app proved useful in the reduction of self-harm behaviours and in enhancing emotional regulation among adolescent's outcomes (Edbrooke-Childs et al., 2018).

Through remote consultations and intervention, smartphones have also played a vital role in telepsychiatry. Virtual mental health care platforms became critical during the COVID-19 pandemic, such as "Talkspace and BetterHelp", which have continuously provided therapy and counselling services without physical contact. Smartphones suggest significant potential for similar benefits in the care of people with mental health issues in low-resource settings (Anissa, 2024). In Zimbabwe, the 'Friendship Bench' is an initiative approach used in mobile technology to link community health workers with individuals suffering from depression and anxiety for better mental health outcomes (Chibanda et al., 2016). Smartphone sensing real-time data has been revolutionary in altering how treatment for mental health disorders can occur based on a personalised approach, which is then taken to change how care coordination can be handled. For instance, smartphone applications are integrated with wearable devices that monitor sleep quality. The ability to intervene quite easily is achieved as these applications even pinpoint the irregular occurrences of sleep patterns and then prompt the person accordingly to make changes in the treatment plan as appropriate (Beard et al., 2019). Apps and built-in smartphone sensors assist in the early detection, monitoring, and coordination of treatments for mental health disorders (Chibanda et al., 2016).

Smartphone sensors, including accelerometers, gyroscopes, GPS tracking, and light sensors, provide data that may be used to observe trends or changes in an individual's behaviour. For example, data gathered through an accelerometer and a gyroscope may monitor physical activity and patterns of motion that may be associated with changes in mental status. In a group of 500 individuals, decreased use of social apps and gaming was strongly linked to a greater chance of having depressive episodes and highlights the value of tracking activities for monitoring mental disorders (Faurholt-Jepsen et al., 2019). Using GPS data, one can identify social behavioural patterns and levels of activities correlated with mental illnesses (Miller et al., 2020). For example, predicting anxiety levels for a monitoring study involving 250 participants achieved an accuracy rate as high as 82% by analysing changes in mobility profiles along with mobile phone use patterns on its basis; this was done through utilising GPS and accelerometer data (Zhao et al., 2021). Furthermore, voice modulation methods may be employed if necessary for detecting psychological problems that are related to depression or anxiety, hence showing how microphones work as part of their analysis system (AlHanai et al., 2021). According to a recent survey among two hundred students who have already been studied, they revealed that by applying smartphone sensors, they found less communication among students, accompanied by an increase in signs of depression because such students do not speak out often (Faurholt-Jepsen et al., 2020). Additionally, the data collected by GPS sensors provides valuable insights into social interaction and movement patterns (Gawrilow & Guderley, 2020). Like the location data can reveal patterns in individuals with eating disorders, such as frequent visits to food-related venues or isolated locations, which can provide insight into their social behaviours and psychological states (Rundle & Rehkopf, 2021; Vancampfort, D., & Stubbs, B., 2018). In addition to mental health monitoring, the data collected from smartphone sensors can also incorporate broader behavioural patterns, including ADHD and eating disorders.

The use of applications can further help us learn more about the behaviour, while the application data tells us how people interact with their smartphones and shows us the patterns related to ADHD symptoms (Kim et al., 2019). With this, it is attention problems and impulsive behaviour in which people with ADHD switch between tasks often and use applications inconsistently. According to Ware et al. (2022), it has been established that people who shift from one application to another and engage with more than one application are showing symptoms that relate to ADHD (Ware et al., 2022). The analysis of the frequency and the duration by which a person uses the screen will provide insight into the individual's mental health and behavioural aspects. This, especially if it is done for long hours at a stretch on certain activities, could be indicative of conditions like ADHD (Alageel et al., 2021). Studies have even established that this long-term use of social media applications and entertainment software could have a positive correlation with symptoms of ADHD, which include hyperactivity and inattention (Brown & Williams, 2023). In addition, screen interaction patterns like tapping and scrolling can extract meaningful knowledge of how an individual interacts and self-regulates. These interactions can also confirm if someone is acting quickly without thinking or is not able to limit their movements, which depicts that they have an issue related to ADHD. Researchers identified a correlation between specific touch patterns and ADHD symptoms, which may be utilised for early detection of ADHD (Gawrilow & Guderley, 2020). The fusion of social media analytics and smartphone sensor information may provide an in-depth look into the user's level of physical activity, sleep patterns, mobility patterns, and environmental effects. Data harnessed from built-in sensors and wearable devices by analysing a person's interactions on social media provides capacity for continuous tracking of a wide range of health metrics, including but not limited to heart rate, steps, sleep duration and quality, exposure to environmental factors, and air quality. The richness of these data from smartphones and social media allows not only the detection of subtle changes in an individual's health status but also offers an opportunity for personalised health recommendations and timely interventions for everybody according to their specific and unique needs (Aydin, 2023). Smartphone sensor data provides insight into the user's physical activity, sleep patterns, mobility behaviours, and environmental exposures. Therefore, integrating smartphone sensors in healthcare is a huge step forward. The sensors would provide in-depth, real-time monitoring and personalised care, ensuring better patient physical, mental, and general health outcomes. Their nature ensures that the feedback given is timely and personal concerning care, likely to enhance the user's health and well-being. In addition to their application in the identification of behavioural patterns associated with conditions such as ADHD, smartphone sensors are also being employed to monitor and comprehend eating disorders.

Eating disorders are mental health problems that have the potential to cause physical and emotional damage. Through technology, researchers have been on the front line in discovering new and improved ways of identifying, preventing, and treating eating disorders. Schneidergruber, T et al. (2023) argue that food cravings play a key role in leading to unhealthy eating habits; therefore, food cravings can be a prime target for intervention and prevention. Schneidergruber T. et al.'s (2023) study aims to determine if it is possible to detect and forecast episodes of food cravings based on passive data from a smartphone. Schneidergruber T. et al. (2023), in their study, worked with 56 participants who recorded their food craving six times a day for 14 days. It used momentary food craving ratings as the dependent variable and other predictor variables, as well as environmental factors like noise, light, device movement, screen activity, notifications, and time of the day, which were recorded within 150 to 30 minutes before these food craving ratings. Finally, research by Schneidergruber, T et al. (2023) showed that it is possible to predict state craving using external and internal factors that could be sensed through smartphone sensors or the usage patterns of most participants. Meegahapola, L et al.'s (2020) study provides reasoning for inferring college students' food consumption levels by using smartphone sensing and self-reports. The authors employed a mobile sensing application that integrates self-reports with passive sensing on the smartphone. This method helped them acquire a novel dataset of 84 college students in Mexico, recording location, activity, social interactions, and self-reported food intake. Meegahapola, L et al. (2020) published that factors like sociability and activity types/levels are correlated to food consumption levels. For instance, those students who were more sociable and spent more time with others had more intake than the lesser sociables. The students who were more active and thus spent more time on high-intensity activities had more intake than the lesser actives. Meegahapola et al., (2020) have several critical public health and education uses. For one, it showed that food consumption data can be captured much more accurately and reliably via smartphone sensing and self-reports compared with the conventional method of collecting food consumption data: dietary surveys. Second, the study has identified various factors associated with the food consumption of college students: sociability and types and levels of activities. This information can be used in developing targeted interventions to help college students make healthier food choices (Meegahapola, L et al., 2020). A study by Bangamuarachchi, W. et al. (2022) proposes a novel framework for eating event detection using smartphone sensors, application usage, location, and accelerometer. The main difference between the proposed framework and food diaries uses smartphones instead of wearables like wristbands or necklaces. Of these, 12,016 self-reports by 58 college students consisted of 1,837 eating events and 10,179 non-eating events. Research presented herein indicates that features such as time of the day, screen usage, accelerometer data, and location contain information about eating/not-eating events.

2.6 Overview of Machine Learning: Types, Techniques, and Applications

2.6.1 Definition

Machine learning (ML) is a subfield of artificial intelligence (AI) that focuses on creating algorithms that enable computers to learn from data and make decisions based on that data. It involves applying statistical techniques to allow computers to improve their performance on a certain task over time without being explicitly programmed (Jain, A. 2023).

2.6.2 Types of Machine Learning

Machine learning can be broadly classified into four types (Jain, A. 2023).

a) In this supervised learning approach, one trains the model on a labelled dataset, where the output of each example used to train the model is known. The idea is to learn a mapping from inputs to outputs that allows one to make predictions on the labels of new unseen data. Some common algorithms used in supervised learning are linear regression, logistic regression, support vector machines, decision trees, random forests, and neural networks. Illustrative example: Suppose we need to create an image classifier to differentiate between cats and dogs. We'll train our machine learning algorithm by using a bunch of labelled images of both cats and dogs. Then, when given new pictures, the algorithm can determine their category- cat or dog. This is the essence of supervised learning, particularly in image classification, a part of the loop into the brain in the paper (Jain, A. 2023).

b) Unsupervised Learning: Unsupervised learning is the way a model learns to be fitted to the input data unlabelled, which is different from the concept of unsupervised learning. A large proportion of analysis on unsupervised learning is used to find the structure in a set of data items. K-means clustering, hierarchical clustering, principal component analysis, and independent component analysis are some of the most used algorithms. Example: Consider a data set that includes details of customers who have purchased at the store. By clustering, the algorithm can be used to determine consumer groups with similar purchasing behaviour and, therefore, detect potential consumers without clearly defined labels. Such data can be helpful for organisations in finding their target clients and identifying anomalies (Jain, A. 2023).

c) Semi-supervised learning: This type of learning is midway between supervised and unsupervised learning, which uses labelled and unlabelled data. It is particularly useful when acquiring labelled data, which is expensive, time-consuming, or resource-demanding. This approach proves successful when the dataset is expensive and time-consuming. We apply semi-supervised learning when labelled data needs resources and abilities for training and learning. We use such strategies when dealing with partly labelled but largely unlabelled data. We can use unsupervised algorithms to predict labels input we use supervised techniques. This is more applicable for datasets of images where most of the images are not labelled. For instance, when developing a language translation model, labelling translations for each sentence pair could be resource-intensive. The technique allows the models to learn labelled and unlabelled sentence relationships, increasing accuracy (Jain, A. 2023).

d) Reinforcement learning: This is a type of machine learning where an agent learns to make decisions by taking actions in an environment with the goal, in the end, to maximise a concept of cumulative reward. The most important concepts within reinforcement learning are Markov Decision Processes (MDPs), Q-learning, and Deep Q-networks (DQN). Example: Google's self-driving car, AlphaGo, in which a bot competes against humans and even itself to improve its performance in the Go game. Each time we feed in data, they learn and incorporate it into their understanding, known as training data. The more it learns, the better it becomes trained and thus experienced to give solutions (Jain, A., 2023).

2.6.3 Applications of Machine Learning

Machine learning is emerging as a powerful tool for improving decision-making, enhancing operational efficiency, and creating innovative solutions across multiple sectors. In the following section, we will examine application of machine learning, such as the financial sector, marketing, manufacturing, and healthcare, where machine learning substantially impacts.

2.6.3.1 Applications in Finance

Machine learning is important in financial fraud detection. These models can spot odd activity in real-time by examining transaction data, therefore helping to stop fraud from getting out of hand (Bolton and Hand, 2002). For example, J.P. Morgan Chase has added machine learning to enable investors and traders to make informed decisions using an edge in share market prediction. Stock market prediction has proved to be challenging due to a variety of factors, including geopolitical factors and economic information. Often, traditional methods overlook all these factors. The bank utilizes machine and deep forms of learning to analyse past market trends and financial news. With the addition of machine learning, the accuracy of the stock market predictions by J.P. Morgan Chase has enhanced to enable the trader to identify lucrative opportunities and to effectively manage risks (Fisher et al., 2019).

2.6.3.2 Applications in Marketing

Marketing is being transformed by machine learning (ML), which offers sophisticated tools for consumer segmentation, targeting, and personalised engagement. Companies can use machine learning to deliver highly personalised marketing efforts by analysing extensive consumer data, including purchase history, online behaviour, and demographics. Machine learning helps unfold the meaning of data about consumers that include data about their purchase history and their online behaviours. It helps companies create marketing strategies that are more closely matched to their target audience and are highly customised (Choudhury et al., 2020). Coca-Cola has a practice that highly relies on machine learning to make its marketing more precise and efficient. Machine learning of the kind used by Coca-Cola enables the identification of emerging trends and tastes through the analysis of real-time trends on social media as well as feedback that the customers provide. It enables the offering to be personalised for different segments of the customers. Personalised marketing has enhanced brand loyalty, higher conversion rates, and increased engagement. Coca-Cola has observed enhanced returns on its marketing investments due to these targeted campaigns. (Ryan, 2018).

2.6.3.3 Applications in Manufacturing

Predictive maintenance in manufacturing is largely driven by machine learning. By examining real-time sensor data about machines, corporations can determine in advance that equipment will fail and subsequently reduce downtime and increase the lifespan of machinery (Lee et al., 2015). Siemens has implemented machine learning in its operations to foretell when maintenance on manufacturing machinery will need to occur to avoid expensive outages. In manufacturing, unplanned equipment failure would lead to huge losses and production downtime. Siemens uses sensors in its equipment to gather information that machine learning algorithms later use to determine patterns that indicate a potential problem. The system detects that a machine needs to be maintained even before its complete failure. Siemens has minimised outages in its equipment by 15% using predictive maintenance and through that enhanced productivity and lower maintenance expenditures (Siemens AG, 2019).

2.6.3.4 Applications in Healthcare

Using machine learning models allows for projections regarding the outcomes of patient treatments, including the probability of contracting certain diseases. These Machine learning models use electronic health information and images taken during different medical tests running algorithms such as decision trees and neural networks that facilitate early detection and personalised treatment plans. One example is IBM Watson for Oncology, an outstanding example of how this concept has been applied to healthcare by using machine learning. Developed jointly by IBM and Memorial Sloan Kettering Cancer Centre, Watson for Oncology employs machine learning algorithms which help oncologists determine how patients with cancer should be treated. Various patient medical records, clinical trial results, and other relevant academic resources go into Watson for Oncology's massive database. The unstructured data from clinical notes are processed using natural language processing (NLP), while structured information from electronic health records is evaluated through specific algorithms. It then adopts machine learning methods that identify patterns and estimate probabilities of cancers (Ferrucci, 2012).

2.7 Case Studies and Research on Health Classification using social media and smartphone sensor data

Machine learning (ML) significantly impacts health classification through the analysis of social media and smartphone data. ML models can process large amounts of unstructured data from these platforms to identify patterns and gain insights into an individual's physical and mental health. Integrating machine learning improves these systems' accuracy and scalability, enabling real-time health monitoring.

2.7.1 Case Studies and Research on Health Classification Using Social Media Data

In recent years, social media platforms such as Twitter, Facebook, and Instagram have become valuable data sources for understanding human behaviour, emotions, and health conditions. User-generated content on these platforms allows researchers to gather extensive data on physical and mental health, including expressions of well-being, stress, depression, and other psychological states. This data has paved the way for machine learning (ML) techniques to analyse patterns, identify trends, and predict health outcomes (Lane et al. 2023). Social media data has unique characteristics that make it valuable for health research. It offers real-time information, large-scale datasets, and often unfiltered insights into individual and community health perceptions (Tufts et al. 2018). Compared to traditional health data collection methods like surveys or interviews, social media data continuously monitors health-related discussions and behaviours. For example, individuals might tweet about their health concerns, share fitness progress on Instagram, or join support groups for chronic illnesses on Facebook. This data allows researchers to conduct detailed health classification studies that capture various aspects of physical health, such as diet or exercise habits, and mental health, such as stress levels, anxiety, and depression (Zhang et al. 2021).

2.7.1.1 Physical Health Classification

Social media data has been acknowledged as a source of understanding physical health conditions. For example, Bian et al. (2016) tracked physical activity levels based on aggregating textual and visual data from social media. Bian et al. (2016) designed a model that aggregates the textual information extracted from the posts and images, which are indicative of exercise activities, and tracks the overall exercise patterns of users. For textual data, Bian et al. (2016) aggregated natural language processing (NLP) techniques, such as latent Dirichlet allocation (LDA), for topic modelling and word embeddings, such as word2vec, to feature extraction. Bian et al. (2016) used convolutional neural networks to recognise and categorise images of exercise activities. These techniques when combined enhanced the capacity of their model to track and classify user patterns of activities (Amaral et al., 2023). Chung et al. (2017) employed machine learning to predict the pattern of obesity through the analysis of Facebook data, user engagement, sentiments expressed through Facebook, and the posts posted. Chung et al. (2017) developed models to predict community-level obesity trends by analysing the content and frequency of posts. This approach provided insights into lifestyle and dietary patterns contributing to obesity at a population level (Chung et al., 2017); (Seah & Koh, 2020). De Choudhury et al. (2013) focused on how Twitter could be used to monitor the mental state of users, with particular emphasis on depression. De Choudhury et al. (2013) work studied the changes in the patterns of tweeting behaviour that may mirror various mental states and hence could serve as an indicator of potential depression symptoms.

Content analysis, posting rate, as well as social metrics of the tweets were some of the approaches that identified behavioural signals that indicate depression. Support vector machines have been used by De Choudhury et al. (2013) to classify users on the likelihood of having depression. The model for this tool is `Trained' on labelled datasets in which the mental health professionals had annotated user tweets as showing signs of depression or not (De Choudhury et al.,2013). For example, Sadilek et al. (2021) predicted the risk of diabetes based on user lifestyle patterns in social media. The developments associated with hypotheses derived from social media posts that reflect diets, physical activities, and health behaviours led to inferences about the risk of developing diabetes. Sadilek et al.

(2021) extracted information on food consumption, exercise routines and sedentary behaviour using natural language processing and image recognition techniques directly from posts and images. Using the content of text and images, Sadilek et al. (2021) look for lifestyle factors that would factor into the risk of diabetes. Sadilek et al. (2021) tried to develop predictive models using random forests and logistic regression through training on the datasets labelled by way of knowing the health status of the users. Sinnenberg et al. (2016) studied social media data for the risk factors of cardiovascular diseases. Sinnenberg et al. (2016) tried to estimate the level of CVD risk through constant monitoring of user behaviour associated with an unhealthy lifestyle, such as smoking (Perry et al., 2017), lack of exercise, and eating badly. Sinnenberg et al. (2016) utilised NLP for extracting keywords in social media posting about risk factors for cardiovascular disease and image recognition for analysing pictures of unfavourable habits. Users were classified afterward using decision trees and neural networks after assessing the tendency towards cardiovascular disease. Models predict cardiovascular risk both individually and in population terms by analysing the frequency and type of postings praising risk factors (Sinnenberg et al.,2016; Guan et al., 2023).

2.7.1.2 Mental Health Classification

Social media data has been acknowledged as a source of understanding mental health conditions. For example, Reece A. et al. (2017) conducted an experiment in which they used NLP and sentiment analysis on the tweets to find potential users at risk of depression to classify users into mental health categories. For example, Reece, A. G. et al. (2017) analysed sentiment scores and tweet language patterns to classify users' mental health states. Meanwhile, the study conducted by Reece, A. G. et al. (2017) used a combination of natural language processing and sentiment analysis through machine learning methods such as support vector machines and logistic regression to analyse Twitter data. Reeece, A. G. et al. (2017) utilised algorithms that classified the tweets based on the sentiment ratings and discovered some linguistic patterns associated with depression. The model was, therefore, trained on labelled data to recognise the depressed language, and hence, it could find out users' mental health statuses with high levels of accuracy. Extending this strategy, Bakhshi et al. (2019) identified anxiety symptoms by analysing Instagram posts. A whole picture of users' mental health is gathered by merging text analysis with image recognition. Bakhshi S. et al. (2019) integrated convolutional neural networks (CNNs) for image data to identify images and find visual signals related to anxiety symptoms. Their multi-modal approach allowed deep investigation of user mental health conditions by integrating textual and visual information. (Bakhshi S. et al., 2019).

Social media platforms, especially discussion sites like Reddit, have been employed in the prediction of mental health risks such as suicide. Coppersmith et al. (2018) identified users at risk of suicide based on their language in posts to the social media site Reddit. Coppersmith et al. (2018) aimed to apply NLP techniques featuring linguistic cues such as the frequency of first-person pronouns, negative sentiment, and future-oriented language. Different machine learning algorithms like Support Vector Machine, Random Forest, etc., were applied in putting a model on labelled datasets to recognise posts by users with suicidal ideation. Thus, the research findings can be detected by machine learning models with high suicide risk identifications. This could depict how social media data can act like early warning systems in which mental health professionals may intervene before crises escalate (Coppersmith et al., 2018). Nguyen et al. (2014) detected signs of PTSD in a model which analysed the posts posted on Facebook by the users. Nguyen et al. (2014) work was designed to ascertain whether the emotional tone and the use of language were indicative of symptoms of PTSD amongst social media users. Nguyen et al. (2014) used NLP to screen for psychological markers in avoidance of language and expressions of distress, something quite common with people who have PTSD. Nguyen et al. (2014) implemented logistic regression and decision trees to develop a predictive model that classified the users based on their mental health status. It was deducted that subtle signs of PTSD could be uncovered from data on social media, hence providing a non-invasive tool for mentally unstable conditions (Nguyen et al. 2014). Shen et al. (2020) explored the feasibility of Instagram in tracking anxiety and depression from both a visual and textual standpoint. Shen et al. (2020) employed CNNs for image recognition and NLP for text analysis through users' images and captions. As one might expect, some of these visual features included darker colours in each image, along with less social interaction. These further arose from negative sentiments expressed in captions. Such a multimodal approach, mixing image content analysis and text analysis, allowed the researchers to more easily detect mental health symptoms based on users' Instagram habits (Shen et al. 2020).

2.7.2 Case Studies and Research on Health Classification Using Smartphone Sensor Data

In recent years, the fusion of smartphone technology and machine learning has unlocked new possibilities in health monitoring, covering both physical and mental health. Smartphones, equipped with various sensors like accelerometers, gyroscopes, and GPS, produce large volumes of data that can be used for ongoing, non-intrusive monitoring of users. When paired with sophisticated machine learning algorithms, this data allows for identifying and categorising health-related patterns.

2.7.2.1 Physical Health Classification

Smartphone sensors are important in physical health monitoring because they provide real-time data for different categories of health. The sensors, including accelerometers, gyroscopes, and heart rate monitors, capture detailed information on physical and physiological measures, greatly assisting in assessing and keeping health conditions in check. Accelerometers measure acceleration and, therefore, allow one to classify physical activities, including walking, running, or sitting. For instance, Ravi et al. (2005) classified using accelerometric data to recognise activities with ML algorithms such as decision trees, K-Nearest Neighbours (KNN), and SVMs to classify different kinds of physical activities, for example, walking, running, sitting, etc. In the research of Ravi et al. (2005), they proved how sensor data can be used for monitoring and assessing the level of physical fitness of the body. Similarly, Wang et al. (2016) developed a health monitoring system that made use of sensors embedded within smartphones for the monitoring of various body measurements, including heart rate and physical activity, and employed ML algorithms—random forests and neural networks—for analysing the data from these sensors to detect abnormal patterns. This is an example of how smartphones can be used for complete health monitoring. Real-world examples include practical uses for smartphone sensors in health grouping, with Yao et al. (2015) paying special attention to fall detection by smartphone accelerometer data, developing an ML model based on a Support Vector Machine for spotting patterns that suggest falls, and providing a rapid alert system for those at risk of falling. The study by Yao et al. (2015) used smartphone accelerometer data to detect falls by building a machine learning-based Support Vector Machine model for spotting patterns that suggest a fall and propose a rapid alert system for those under threat. Banaee et al. (2013) investigated heart rate classification with smartphone sensors in their physical health parameter classification studies. Banaee et al. (2013) developed ML models (Artificial Neural Networks (ANNs) and decision trees) to analyse heart rate patterns and spot anomalies like arrhythmias (irregular heartbeats caused by abnormal electrical signals in the heart) (Banaee H. et al. 2013). Using smartphone accelerometer data, Kwapisz et al. (2011) accurately classified walking, running, and cycling activities. Kwapisz et al. (2011) carried out this analysis by employing algorithms based on random forests and support vector machines, thus achieving high levels of accuracy. Kwapisz et al. (2011) specifically brought out the richness of smartphones for tracking one's activity and fitness in a personalised way. In another study, Azmi and Rahman et al. (2024) developed a system for fall detection using a smartphone accelerometer and gyroscope data. It was possible to detect falls based on the dynamics of body movement, as a feature from decision trees and k-Nearest Neighbours. It gives timely alerts for prevention and rescue in case studies for elderly people (Azmi and Rahman et al.,2024).

2.7.2.2 Mental Health Classification

Smartphone sensors are very important in health monitoring because they provide real-time data for different categories of health. Researchers have also used smartphone sensors to keep an eye on mental health. For instance, Cai et al. (2017) used physiological data from smartphone sensors to detect stress levels. Cai et al. (2017) used ML models (support vector machines (SVMs) and random forests) to classify stress based on heart rate variability. This proved that smartphone data could help manage stress and monitor mental health (Cai, L. et al. 2017). Similarly, Tobias et al. (2020) merged sensor data and self-reported mood checks to track changes. This gave a comprehensive impression of mental well-being and highlighted the advantage of using multiple data streams to track depression. Gradient Boosting Machines (GBMs) and Long Short-Term Memory (LSTM) networks algorithms were used to conduct temporal pattern analysis on sensor data as well as mood change analysis and provide an overall overview of mental well-being status (Tobias et al., 2020). Logistic regression and support vector machines (SVMs), as used in the study by Saeb et al. (2015), identified depression using smartphone behavioural patterns in the form of call records, SMS frequency, app use and GPS data. Their machine models established that depression individuals exhibited lesser social engagement in the form of lesser calls and message sending and irregular patterns in their everyday routines, including their sleep patterns. The algorithms effectively identified depression through these patterns of human behaviour. In a study by Grünerbl et al. (2017), bipolar disorder was identified using the use of random forests to determine the mood states using smartphone GPS data. In the study by Grünerbl et al. (2017), unique patterns in the movements in the manic and depression phases were observed—manic stages involved more movements and distances travelled and depressive stages involved lower mobility. With their capacity to deal effectively with complex, non-linear relationships in the data, the random forests easily differentiated these mood states. Sarker et al. (2018), besides using decision trees and hidden Markov models (HMMs), also identified anxiety and stress in smartphones through sensor data in the form of accelerometers, GPS and the microphone. Sarker et al. (2018) utilised machine models in determining major stress incidents based on physical movements, voice patterns and path of movement. The use of the HMMs in the study was particularly effective in the identification of temporal patterns and switches in the stress pattern. Schueller et al. (2017) examined the detection of depression using smartphone behavioural analysis. Schueller et al. (2017) considered smartphone usage patterns, including frequency of calls, volume of text messages, and use of apps. Logistic Regression and random forests were the machine learning models applied. It effectively identified behavioural changes related to depression, thus offering a novel way of health surveillance. In another work, Zhang et al. (2018) developed a system for real-time mood prediction by analysing smartphone sensor data with user-supplied mood surveys. Support Vector Machines (SVM) and Gradient Boosting Machines (GBM) provided valuable insights into mood fluctuations to enable timely mental health support and intervention.

2.7.2.3 ADHD Classification

Some studies suggest that sensor data from smartphones, could help to identify ADHD patients and potentially overcome the limitations of traditional clinical trials (Faraone et al., 2015). By analysing these sensor data, researchers can identify patterns and characteristics associated with ADHD, providing important insights for diagnosis and treatment. Accelerometer sensors have played a vital role in creating techniques to monitor ADHD in children (Faust et al., 2019). These sensors are also able to capture body part movement data and offer useful information on ADHD impact and the changes in the associated behaviour brought about by a specific treatment. For example, researchers strapped small accelerometer devices to the hips of children to assess the effect of fidget spinners on gross motor skills and attention in class (Faust et al., 2019). In ADHD classification, "touch data" refers to the data obtained from a smartphone's touchscreen. These touch interactions, including taps, swipes, and gestures, can provide valuable insights into an individual's attention levels and concentration. Analysing touch data allows researchers to identify distractibility, impulsivity, or hyperactivity patterns that indicate ADHD. Researchers can gain valuable insights into users' cognitive and behavioural patterns by carefully assessing touch interaction's frequency, duration, and intensity (Johnson, J.R., 2019). Collecting application use data entails exploring the apps frequently used by those with ADHD on their mobile phones. What the data reveals about their preferences, areas of interest, and typical routines can prove useful. With analysis of how long and how often the apps have been used, the patterns and trends related to distractibility, impulsivity, and hyperactivity can be determined. For example, regularly switching between different applications or spending prolonged periods on gaming or social media may suggest challenges in attention management and self-control (Johnson, J.R. 2019). Location data, which includes GPS coordinates or Wi-Fi signals, is used to determine the geographical position of the smartphone. This information offers useful insights to the mobility and geographical patterns of ADHD patients to enable researchers to detect the patterns of movements that include frequent changes in location, irregular travel trajectories or spending a considerable amount of time in specific locations. Such patterns may have the connotations of hyperactivity, impulsivity, poor time management, and organisation. It also provides researchers with useful insights into the mobility and geographical behaviour of ADHD individuals towards a complete study of their routine activities and schedules (Johnson, J.R. 2019).

Numerous studies have explored the viability of smartphone and wearable device data in the classification of neurodevelopmental and mental disorders, such as depression symptoms and the symptoms of ADHD. In a study to predict the symptoms of ADHD in university students using smartphone data in the form of SMS usage, Ware et al. (2022) utilised machine learning algorithms in a pilot study among five participants. With promising early results, the authors recognised that the study was limited by a small participant sample as well as the use of SMS data. In their work, ware et al.,(2020) assessed the performance of the models using several different metrics following the identification of features in smartphone sensor measurements, application usage patterns, and Wi-Fi network information. However, the study identified limitations in the form of reduced generalizability, privacy threats posed by passive data capture, and biases in the machine algorithms as potential weaknesses in the approach (Ware et al., 2020).

In a study by Şengül et al. (2021), daily user activities were forecasted using accelerometer and gyroscope data from a smartwatch connected to a mobile phone (Şengül et al. 2021). Şengül et al.

(2021) used a combined data fusion approach to demonstrate effectiveness in categorising activities such as running, walking, and driving. Nevertheless, the study was restricted to three activities and a small data sample of 20 participants, and there was uncertainty about how generalisable the study was to the broader population (Şengül et al. 2021). Moshe et al. (2020) also performed a study to determine the role of smartphone and wearable device data in the prediction of depression and anxiety symptoms. The study involved tracking 60 adults for two weeks and analysing parameters like location, smartphone use, activities, sleep patterns, and heart rate variability. Although the study found relationships between certain data and mental symptomatology, it also identified limitations in the form of a small and possibly biased population sample, the fact that the study was observational, and the inability to determine causes.

2.7.2.4 Eating disorder Classification

Eating disorders represent serious mental conditions that result in both physical and emotional distress. It is through technological advancements that researchers are discovering new and better techniques for detection, prevention, and treatment for eating disorders. A recently conducted study by Fardouly, J et al. (2022) focused on the relationship between smartphone use, Instagram use, body dissatisfaction, and eating disorders. The results indicated that increased smartphone use may be associated with symptoms of eating disorders and a higher degree of body dissatisfaction. Furthermore, the study found no significant disparities in Instagram usage between women with a history of eating disorders and those without eating disorders (Fardouly, J et al., 2022). Schneidergruber, T et al. (2023) argue that food cravings play a crucial role in unhealthy eating habits, and food cravings can be a prime. Schneidergruber, T et al. (2023) contend that food cravings are a key aspect of poor eating patterns, and food cravings are a potential candidate for prevention and intervention. The study by Schneidergruber T. et al. (2023) aims to establish whether future food cravings can be identified and predicted using passive smartphone sensor data without requiring repeated questionnaires. The study by Schneidergruber T. et al. (2023) involved 56 participants logging their food cravings six times a day for 14 days. The study utilised momentary food craving ratings as the dependent measure and a variety of predictor variables that include environmental variables such as noise, light, device motion, screen use, notifications, and the hour of the day reported within 150 to 30 minutes of these food craving ratings. target for intervention and prevention. Schneidergruber T. et al.'s (2023) study aims to determine if upcoming food cravings can be detected and predicted using passive smartphone sensor data, eliminating the need for repeated questionnaires. Schneidergruber T. et al.'s (2023) research involved 56 participants who recorded their food cravings six times a day over 14 days. The study used momentary food craving ratings as the dependent variable and several predictor variables, including environmental factors like noise, light, device movement, screen activity, notifications, and the time of day recorded within 150 to 30 minutes before these food craving ratings. In conclusion, Schneidergruber, T et al.'s (2023) study suggests that craving states can be forecasted based on external and internal factors, which can be measured through smartphone sensors or usage patterns in most participants (Schneidergruber, T et al., 2023).

Meegahapola, L et al. (2020) presents a novel approach to infer food consumption levels of college students using smartphone sensing and self-reports. The authors collected a dataset of 84 college students in Mexico using a mobile application that combines passive smartphone sensing and self-reports. The app collected data on the students' location, activity, social interactions, and self-reported food consumption. Meegahapola, L et al. (2020) found that several factors were associated with food consumption levels, including sociability and activity types and levels. For example, more sociable students (i.e., who spent more time with others) ate more than less sociable students. More active students (i.e., those who spent more time on high-intensity activities) ate more than less active students. Meegahapola, L et al.'s (2020) research has several important implications for public health and education. Firstly, it shows that smartphone sensing, and self-reports can collect data on food consumption levels that are more accurate and reliable than traditional methods, such as dietary surveys. Secondly, the research identifies several factors associated with college students' food consumption levels, such as sociability and activity types and levels. This information can be used to develop targeted interventions to help college students make healthier food choices (Meegahapola, L et al., 2020). Bangamuarachchi, W. et al. (2022) introduce a framework for detecting eating events using smartphone sensors (application usage, location, and accelerometer). This framework distinguishes itself from traditional food diaries using smartphones rather than wearables (wristbands, necklaces, etc.). The study collected data from 58 college students, resulting in 12,016 self-reports, including 1,837 eating events and 10,179 non-eating events. The research reveals that features like time of day, screen usage, accelerometer data, and location can indicate eating and non-eating events. Machine learning models achieved an AUROC of 0.65 for participant-independent prediction, which improved to 0.81 with personalised techniques. However, the study has limitations, including a small and non-representative sample, limited generalizability to college students, and potential cultural and ethical concerns. (Bangamuarachchi, W et al., 2022).

2.8 Challenges and Future Developments

Although smartphone sensors have made considerable progress in health monitoring, it's crucial to acknowledge their limitations.

a) Limitations in Current Applications: One of the biggest problems is the intrinsic limitations of smartphone sensors that are designed to enhance user experience and not precise health monitoring functions. This can lead to decreased accuracy and reliability of data yielded as opposed to specialised medical devices. Smartphone CMOS image sensors, for instance, can gauge heart rate and monitor skin diseases but may incur errors as opposed to specialised medical tools. Smartphone sensors have lower sensitivity than traditional health monitoring instruments, resulting in performance discrepancies in applications like sleep-tracking, gait analysis, and biometric authentication (Sumit Majumder et al.,2019).

b) Privacy and Data Security Concerns: Using smartphone sensors to collect and store sensitive health data raises privacy and security concerns. As gadgets gather personal data including location, physiological markers, and behavioural trends, deploying robust data security and privacy measures becomes important. Safeguarding the security and integrity of the information becomes important to build user trust and facilitate broader usage of the technologies in society (Sumit Majumder et al.,2019).

c) User Compliance Issues: User compliance and engagement are crucial to achieving the potential of smartphone-based monitoring systems for healthcare. Overcoming the hurdles of having cumbersome interfaces, the perception that there is an invasion of their privacy and the differential receptivity across different demographic segments are critical to achieving long-term compliance. Improving user experience through strategies, showing the value in frequent use and offering actionable insights derived through sensor data are vital in maintaining user compliance and realising the potential of these technologies (Sumit Majumder et al.,2019).

2.9 Conclusion and Future Scope

Despite all the progress made in digital mental health interventions (DMHI), some research gaps remain. First, the notable gap in the research is the overrepresentation of homogeneous, often Western populations in DMHI studies; many such studies focus exclusively on common mental health disorders, such as depression and anxiety, to the detriment of other important conditions also benefiting from digital interventions. Most of the research conducted addresses very common disorders such as depression and anxiety, while ADHD and eating disorders have been neglected. This, in turn, faces a narrow focus and directly overlooks the diverse socio-cultural, economic, and environmental factors that influence mental health within a global context. Therefore, it leads to results that quite often cannot be generalised on broader and more diverse populations, especially about LMIC or resource-poor settings. Furthermore, the absence of participants from these underrepresented groups means that little is known about how DMHI can be tailored to consider cultural norms of mental health stigma, varying levels of digital literacy, and how socio-economic barriers impinge upon access to these technologies. Without this inclusiveness, the potential utility of DMHI in diverse contexts can never be fully realised. This brings in the issue of cross-cultural inclusiveness, a gap in the current literature (Torous et al., 2021), (Onnela & Rauch, 2016). While most studies indicate that DMHI interventions can be effective under controlled conditions, there is a complete lack of research into the challenges associated with deploying such interventions at scale in real healthcare systems-particularly low-resource or public health environments (Onnela & Rauch, 2016).

Our work stands in line with calls for diversification in participant recruitment, which has been identified as a prerequisite for increasing the reliability and generalizability of studies. We focus on participants from LMIC to provide deeper insight into mental health experiences and conditions in settings where mental health interventions are often less accessible. This targeted approach helps to mitigate the biases typical of studies conducted in higher-resource environments and provides a more representative view of mental health in these regions. Further, by extending our research to include a larger variety of data sensors and behavioural inferences, we can capture an understanding of the underlying behaviour of various mental health conditions. This not only enhances our analytic depth but also provides deep insights into the behavioural and environmental factors influencing mental health in LMIC settings, where the landscape of mental health can be fundamentally different from that in developed countries. Real-world data collection via smartphones overcomes one major limitation of traditional lab-based studies: a lack of ecological validity (Iflaifel et al., 2023). Smartphones provide the real-time monitoring of mental health signs in the real-world, which can mirror people's real mental states as they occur in everyday life. In contrast to a controlled laboratory environment, smartphones provide real-time changes in mental health and provide a real representation of a person's mental health in the circumstances of everyday life that is critical in developing personalised and timely interventions. The findings also estimated the potential for using such a device to monitor day-to-day changes in levels of attention and activity in a smartphone sensor-based study of ADHD diagnosis. This example illustrates how real-time data gathered through smartphones have the potential to enhance our understanding of mental health and enable more precise assessment possible in everyday life, particularly in impoverished settings (Wright et al., 2022). Beyond this, our work also tries to address health issues of the LMIC, where limited resources and infrastructure have been substantial impediments to mental health interventions. As Patel et al. (2016) point out, such focus ensures that mental health interventions apply and accessible only to those who need these interventions.

In LMIC, we use classification techniques for conditions like eating disorders and ADHD to enhance the precision and accessibility of mental care in this setting. Finally, the fusion of information from various smartphone sensors like accelerometers, app use, touch, screen and location data generate a richer view of user actions (Wright et al., 2022)). Combining these different sensor inputs allows for a continuous, environmentally valid data collection that captures complex patterns of behaviour that might otherwise be overlooked in a single sensor study. This multi-sensor approach will improve classification models for predicting mental health conditions more accurately. Continual data collection ensures that patterns of behaviour are monitored over time and thus provide a reliable picture of how mental health conditions progress or improve with various interventions (Wright et al., 2022).

CHAPTER 3

GENERALISABILITY OF MACHINE LEARNING TO CATEGORISE VARIOUS MENTAL ILLNESSES USING SOCIAL MEDIA ACTIVITY PATTERNS

Chapter 1 provides a motivation and the importance of the use of digital footprint and passive sensing to monitor mental health, especially "in the wild". It highlights the gaps in the literature on real-world, scalable monitoring solutions and sets clear objectives for the classification of mental health conditions using a digital data pathway to deeper investigation in subsequent literature. Above mentioned objectives are elaborated in chapter 2, which describes a literature review on the role of digital footprints, social media, and smartphone data as an enabling tool for many sectors, including healthcare. Study 1 (chapter 3) utilises social media data to classify mental illnesses as proof that sentiment and linguistic analysis can be conducted in a naturalistic setting. The methodology, results, and discussion of study 1 elaborate on the challenges and opportunities that the data from social media bring about in the field of mental health classification and present further opportunities for investigation with other data sources.

3.1 Introduction

3.1.1 Background

Mental health disorders are the most concerning worldwide, affecting over 970 million people in the world. The most prevalent clinical conditions include major depression, anxiety, bipolar disorder, and schizophrenia. According to the World Health Organisation (2022), mental health, considered a person's well-being, has become an important issue due to poor access to effective mental health services, especially in low to middle-income countries. This, therefore, calls for the urgent need for innovative solutions that can bridge the gap in mental health care. Over the past few years, social media platforms have become important places for discussing issues related to mental health, including Twitter and Reddit forums. These allow people who experience them to share experiences, obtain support, and discuss their issues, which might reduce some of the isolation individuals can feel. Social media becomes a supplementary channel for many individuals to say what they want and feel without the barriers that exist in a conventional setting (Gonzalez et al., 2020). Social media data reflect real expressions of mental health. Such continuously updated information may provide insights into the emotional states of a population, coping mechanisms, and how societal factors influence mental health. With so much data to analyse, researchers have increasingly used linguistic tools like LIWC, or Linguistic Inquiry and Word Count. LIWC allows an analysis of social media posts' emotional tone and linguistic features, thus enabling insights relevant to mental health (Pennebaker et al., 2007).

3.1.2 Problem Statement

Social media itself has become a significant source of data to look at live public discourse, stigma, and personal experiences associated with individuals who are concerned with mental health.

However, applying ML technology in this opportunity comes with various significant challenges that must be dealt with for the application to succeed. Some of the best possible challenges are listed as follows:

a) A limited number of studies consider how mental health talk differs across various social media platforms. Each platform has unique features and attracts distinct types of users, and these aspects might play a huge role in shaping discussions and expressions related to mental health. For example, Twitter, with its character limit of 280 characters, needs to have messages concise and striking; this often has a consequence of oversimplification of expressions about complex mental health issues. On the contrary, Reddit allows longer messages with in-depth discussions, which may be impossible with more limited messages (Cohen & Tsur, 2020). These differences in discourse styles and user engagement across platforms create varied needs for data collection and analysis methods, making understanding these platform-specific dynamics more important.

b) While single platform discussions on mental health, which machine learning models would have analysed, are promising, generalisation within multiple platforms remains under-explored. It has been documented that model, which have been trained on one platform's data, for example, Twitter, perform terribly upon application to another, say, Reddit (Dahlhaus et al., 2020). The differences in user behaviour, language, and interaction patterns on these platforms impede model transferability and negatively affect accuracy in model performance concerning identifying and classifying mental health content. The approach will be toward developing a robust ML framework that can adapt to the distinctive nature of various social media settings.

c) One critical issue of the data used in mental health analysis concerning social media is class imbalance within the datasets. Many datasets contribute to a significant difference in representatives, and there are only a few disorders that have little attention given compared to the prevalent issues of anxiety and depression (Dahlhaus et al., 2020). This section displays an imbalance, which can be a problem for training machine learning algorithms due to the sensitivity of many of these algorithms to biased data. This will yield poor accuracy and performance in identifying fewer common disorders. For example, mental health problems that are not often reported or discussed may have a general deficiency in data for model training, making the creation of accurate and reliable classification systems difficult. Addressing class imbalance lays the most crucial foundation in enhancing the ultimate efficacy of ML applications in mental health analysis (Gonzalez et al., 2023).

3.1.3 Significance of the Study

The study 1 addresses the concerns raised by improving cross-platform understanding, which benefits all mental healthcare and research stakeholders.

a) Cross-Platform: Understanding structural differences in the varied social media platforms forms a strong basis for tailoring mental health resources and interventions. The differences in user demographics across the different platforms drive how topics related to mental health are discussed. For instance, younger users may prefer Twitter for brief content, while Reddit supports deeper, threaded conversations. Further, these differences in content format focus for each platform affect how mental health experiences are represented; Pinterest is a visual storytelling platform (Lee 2023) while Reddit allows for longer storytelling (White 2020). Community norms and moderation practices vary with consequences for the tone and safety of the discussion; At the same time, guidelines on some platforms promote a free flow of conversation, while the guidelines on others are more restrictive (Brown et al., 2022). Algorithms have become important in content visibility selection, influencing how users engage in mental health topics. Identifying such differences creates an avenue to develop focused mental health campaigns that could better appeal to platform users and increase engagement and support. In sum, a cross-platform examination highlights ways social media structures frame mental health discourse to inform intervention better design sensitive to context (Green & Black, 2024).

b) Generalizability of the Machine Learning Models: This research examined the generalizability of machine learning models in developing more robust analytical tools to identify mental health states across various online contexts. Adapting these models to various data sources is an important step toward increasing accuracy and reliability in mental health assessments for diverse and dynamic environments (Bär et al., 2020). Machine learning techniques help identify and classify specific mental states by analysing language usage, sentiments, and user behaviour across platforms (Kumar & Gupta, 2022). Such advancements may allow healthcare professionals and researchers to understand mental health issues in different settings better and thus develop better intervention strategies that best suit the peculiar characteristics of each platform. Beyond this, these tools hold great promise for offering further understanding into the prevalence and manifestation of mental health conditions across demographic and cultural contexts, with all its implications for more nuanced perspectives on digital-age mental health.

c) Balancing Data: This will go further into methods for balancing data to improve model performance on underrepresented mental health conditions, hence adding to fairness in analysis. Doing so will further assist the Machine learning models in identifying or classifying different mental health disorders more accurately. It has vital implications for stakeholders because this will be a channel for better informed researchers, healthcare providers, and policymakers who stand a better chance of designing improved mental health interventions.

3.1.4 Research Aim and Objectives

To address the identified issues, the study 1 proposes an aim and specific objectives that will guide its approach. These objectives focus on advancing ML approaches to analyses linguistic markers in mental health discussions across different platforms.

Aim: To develop ML approaches for analysing the linguistic markers of mental health-related social media activity and evaluate model generalizability across Twitter and Reddit.

Objectives:

a) Identify key linguistic markers in mental health discussions on Twitter and Reddit.
b) Develop ML models to categorise social media activities into distinct mental illness groups.
c) Assess the cross-platform performance of models trained on one platform when applied to another, with attention to linguistic nuances.

3.2 Literature Survey

An increasing number of individuals are utilising social media sites such as Twitter, Facebook, Reddit, and Instagram to express themselves and communicate with others in real-time. As a result, vast amounts of social data are created, comprising important information about people's interests, emotions, and behaviours (Nasrullah, S. and Jalali, A., 2022). Social media is transforming how people self-identify as having a mental health condition and how they interact with others who have had similar experiences, frequently inquiring about treatment, and side effects and reducing feelings of stigma and loneliness. The study of prominent social media sites such as Reddit and Twitter may provide a glimpse into what patients are most concerned about (more so than their physicians) (Gkotsis, G et. al,2017). Furthermore, this form of large-scale user-generated content (social media) provides a unique chance to study mechanisms underlying mental health disorders. For example, research on children and adolescents has indicated that frequent daily usage of social networking sites is independently related to poor self-rating of mental health, greater levels of psychological distress, and suicidal thoughts (Coppersmith, G et. al,2015), (De Choudhury, M. & De, et. al,2014), (Sampasa-Kanyinga, H et. al,2015).

Beyond simple features such as frequency of usage, researchers have now employed more sophisticated methods, to extract in-depth usage pattern features such as linguistic style, affective content of the posts, the interaction pattern as characterised as a social graph to predict mental health condition associated with specific social media posts (De Choudhury, M., and De, S., 2014). The language used in Reddit forums dedicated to mental health has been studied to discover linguistic traits that might be useful in creating future applications to detect individuals who require immediate assistance (Gkotsis, G et. al,2016). Users' self-disclosure in Reddit mental illness forums has been studied to create language models that explain social support, which has been found to contain informational, emotional, instrumental, and prescriptive information. Even though Redditors (Reddit users) are not paid for their work, the feedback expressed in the comments is of remarkably high quality. It can be both emotional and useful as well as informative. This is a crucial difference to social media platforms like Twitter, where sharing health information is frequently broadcast or an emotional outburst and not always about seeking out accurate or detailed information about diagnosis and treatment (De Choudhury et al., 2013). (De Choudhury, M., and De, S., 2014).

Social media data has been identified as one of the resources for gaining knowledge about mental illness. For example, Twitter data has been utilised to develop classifiers that can identify individuals who are depressed (De Choudhury et al., 2013). Coppersmith et al. (2015a) used Twitter data to identify linguistic characteristics that may be used to classify Twitter users into those suffering from mental illness and those who are not suffering from mental illness (Coppersmith et al., 2015a). Dinu et.al, (2021) used Reddit data to classify various mental illness groups based on user's posts rather than individual users or groups of users supervised machine learning, which is used for categorisation or prediction modelling, offers the advantage of accounting for complicated interactions between variables that were previously unknown. As datasets become larger and variables become more complex, machine learning techniques may become a useful tool in psychiatry to correctly detangle variables linked with patient outcomes (Tate et. Al,2020), (Dwyer DB et. Al,2018). Several researchers have used the machine learning model on social media data and healthcare for classifying various mental illness groups. For example, G Gkotsis et.al, (2017) collected data from 11 different mental health subreddit and developed a multiclass classification model. If a user suffers from several mental health issues, such as anxiety and depression, the user can submit posts in multiple subreddits. If the model is trained on posts from users with multiple symptoms, the multiclass classification model may suffer from noisy data. Kim et. Al, (2020) collected data across six mental health related subreddit and developed six binary classification models for each mental illness (Anxiety, Autism, Bipolar, borderline personality disorder (BPD),

Depression, and schizophrenia) and utilised pre-trained word vectors rather than random initialisation which yields superior results, however, the classification model suffers from noisy data if the model is trained with the post of users with multiple symptoms.
Numerous studies show that language usage, social expressiveness, and interaction are important mental health indicators. Linguistic Inquiry Word Count (LIWC), a validated technique for the psychometric evaluation of language data (Pennebaker et al., 2007), has been used extensively to analyse linguistic features associated with various mental illnesses. For example, De Choudhury, M., et al gathered Twitter posts from individuals who had been diagnosed with depression and used the Linguistic Inquiry and Word Count (LIWC) to examine the linguistic and emotional characteristics of the tweets (De Choudhury, M., et al. 2013). Coppersmith, G et. al, (2015), also emphasised that associated language patterns, such as the use of first-person pronouns, negative emotions, and angry words, had a significant relationship with mental problems. There are several research that examines the relationship between language usage and mental health. According to Aaron Beck et.al (1967) cognitive theory of depression, depressed people tend to view themselves and their surroundings negatively. They frequently use negative terms and first-person pronouns while expressing themselves (I, or me). Rude et al. (2004) examined linguistic patterns of essays written by college students who are depressed, have been depressed in the past, and have never been depressed. His findings show that depressed students used fewer positive emotion words and more negative valence words.

Despite growing interest in the detection of mental illness, present efforts have mostly been limited to research on a single platform, with less emphasis given to generalisation across multiple social media platforms. The reason why it is important to check if the model can be generalised across different platforms.

a) First, even the most widely used social media platforms are not used by everyone, and most platforms only reach small segments of the population. As an illustration, 25% of US adults claim to use Twitter, (Smith & Anderson, 2018), while 18% of US adults claim to use Reddit (Auxier & Anderson, 2021). Social media users do not confine themselves to a single social media platform; instead, users efficiently navigate across multiple platforms to express themselves by exploiting variations among these platforms (Tandoc Jr, et. al,2019).

   Furthermore, social media data is skewed in terms of demographics. Twitter, for example, has a 55% overall adoption rate in the United States. However, approximately 38.5% of those aged 25 to 34 use Twitter, with the great majority using it multiple times per day. Furthermore, 57% of respondents claimed their primary motivation for accessing Twitter is to increase their understanding of current events. Reddit has a 39% overall adoption rate in the

United States. However, roughly 64% of those aged 18 to 29 use Reddit, with the great majority using it multiple times per day. 72% of respondents claimed their primary motivation for accessing Reddit is for entertainment (Davis, J.L. and Love, T.P., 2019). There are socio-demographic biases associated with social media, and these must be thoroughly investigated before drawing broad generalisations about the broader population. For example, although Reddit has a large user base with a wide range of socio-demographics, with an estimated 6% of internet users active on Reddit, there is a gender bias (8% of male internet users compared to 4% of female). With an estimated 18.7% of internet users active on Twitter, there is a bias towards male users (12.3% of male internet users compared to 6.4% of females) and a bias toward younger users, with a higher percentage of users aged 18-49 than those over 50 platforms (Duggan and Smith, 2013; Retka et al., 2019).

b) Different social media platforms may feature different usage patterns. For instance, Twitter may provide more frequent updates on an event, whereas Reddit may provide more critical analysis regarding the same events. Furthermore, Twitter may discuss political news and current events more rigorously than Reddit, but Reddit may be a better choice for news updates and entertainment discussions. Social media is mostly driven by normal users; therefore, a platform's suitability depends on how the corresponding users utilise it. For example, if a considerable number of people discuss an event, then the event is important. In an emergency, getting frequent updates is critical, so a platform with active users is better suited for this type of event. Thus, diverse characteristics of the contents published, user posting behaviour, and post spreading patterns across these platforms can prove to be useful for meeting certain requirements such as exploring notable events, live updates, or analysing news stories (Priya.s et. al,2021).

Therefore, in study 1, we investigate two popular social media sites, Reddit, and Twitter. Specifically, we are interested to examine how different/similar linguistic characteristics and patterns of activities are associated with different mental health groups in the two platforms. Following, we study how machine learning models trained on one platform are generalisable to another.

3.3 Methodology

3.3.1 Data Collection

We utilised Twitter's Streaming API (Application Programming Interface) to continuously collect Tweets with Depression, Anxiety, Bipolar, BPD (borderline personality disorder), schizophrenia, and autism between January 2017 to December 2018. The data on the category "subreddit r/Depression, r/Anxiety, r/Bipolar, r/BPD (borderline personality disorder), r/schizophrenia, and r/autism" on the Reddit dataset was obtained from the author (Kim, J., et. al,2020). Note that none of the user data contains any personally identifying information because it has all been anonymised; In all, 248,537 people contributed 606,208 posts across the six subreddits and 23,102,773 English tweets across six hashtags were extracted from Reddit and Twitter respectively (Kim, J., et. al,2020).

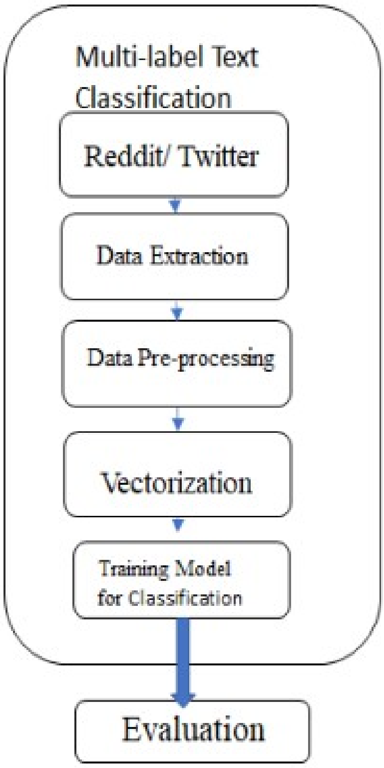


Figure 3.1: Methodology for Multi-label Text Classification Using Social Media Data (Abhishek Kaushik and Sudhanshu Naithani, 2015)

3.3.2 LIWC (linguistic Inquiry and Word Count)

"*LIWC is a transparent text analysis programme that counts words in psychologically meaningful categories*" (Tausczik, Y.R. and Pennebaker, J.W., 2010.) Pennebaker et al. (2015) describe approximately 90 variables that were analysed with LIWC. Table 3.1 provides a list of LIWC2022 dictionary language dimensions from the chosen set of LIWC categories.

Table 3.1 LIWC-22 Language Dimensions, (Boyd, R.L., et.al,2022)

LIWC Variables	Description	Examples	Entries in category
Clout	Relative social position, confidence, or leadership (Pennebaker et al.,2010)	--	--
Analytical thinking	Logical, formal, and hierarchical thinking processes (Pennebaker et al.,2010)	--	--
Authenticity	Perceived honesty, and genuineness (Pennebaker et al.,2015)	--	--
Emotional tone	Degree of positive/negative tone (Pennebaker et al.,2015)	--	--
Pronouns	Self-presentation and attention, ego, other people, and things, and involvement (Tay, D., 2020), (Boyd, R.L., et. al,2022).	I, them, itself	74/286
Verbs, Adverbs, and Adjectives	Content of communication (Coppersmith, G., et. al,2021), (Boyd, R.L., et.al,2022)	a, an, the, very, really, and, but, whereas	1560, 159/514, 1507
Death	Suicidal thoughts and related conversation (Park, A., and Conway, M., 2017), (Boyd, R.L.,et. al,2022)	death, dead, die, kill	109
Culture	Politics (political, legal), Ethnicity (racial, ethnic), Technology (scientific and technological) (Boyd, R.L., et. al,2022)	car, United States, govern, phone	772
Lifestyle	Leisure, work, religion, life, and money (Syah, T.A., et. al,2021), (Boyd, R.L., et. al,2022)	work, home, school, work	1437

3.3.3 Data pre-processing

The data sets input to these stages has various unwanted data and must be removed. Pre-processing steps involve removing the punctuation, Twitter-specific terms, special symbols, and numbers to obtain the data which is cleaned for analysis (Abhishek Kaushik and Sudhanshu Naithani, 2015). This stage usually handles dealing with noisy data. It is necessary to transform some data to make it suitable for analysis. This can be done with normalisation and attribute derivation methods (Abhishek Kaushik and Sudhanshu Naithani, 2015). The web is a huge source of data and the amount of data available from it is very huge and is referred to as big data. In this huge data, there is always some information that is not important and not required for the analysis purpose. The filtering of this data is huge and time-consuming. Attribute selection and numerous reduction techniques can be used to achieve data reduction. Some of the popular techniques used are stop word removal, stemming, tokenisation, etc (Abhishek Kaushik and Sudhanshu Naithani, 2015).

Data pre-processing was carried out before model training and evaluation. For each post/Tweet, we deleted unwanted punctuation and space. Then, we utilised Python's natural language toolkit (NLTK) to tokenise posts and filter commonly used terms (stop words) (Kim, J., et. al,2020), (Sinéad Dickson, 2019). Following that, all the words were transformed into lowercase, and stop words are removed. Porter Stemmer, a tool used to define a set of criteria for researching word meaning and source, was used on the tokenised words to convert a word to its root meaning and reduce the amount of word corpus (Kim, J., et. al,2020). Since we believe that posts with fewer than 25 characters may not include enough information to be classified, we eliminated such small posts/tweets from the mental group to reduce the quantity of the data. Following this process, information from 488,472 posts (Reddit) made by a total of 228,060 people and 15,932,364 posts from Twitter was used for the analysis. (Sarsam, S.M., et. al,2021), (Kim, J., et. al,2020).

3.3.4 Classification Models

The purpose of a classification algorithm is to select the appropriate categories from data, based on model parameters learned from training data, the classifier predicts categories for new data (Forouzani, S., 2016.). The classification step of the process determines the real mapping between the message and whether it belongs to a specific class (in the case of mental illness for example- (depression, anxiety, BPD, etc, or not)) (Korda. P et. al,2017).

We developed six binary classification models, each of which classifies the posts into one of the six keywords: depression, anxiety, bipolar, BPD, schizophrenia, and autism. We aimed to detect a potential mental health condition by constructing six different models for each mental disease, each of which incorporates data from users who have posted messages about specific mental problems. To construct a model for identifying depression, for example, we labelled tweets/posts with the depression hashtag/subreddit as depression class; the rest of the post is classified as a non-depression class. We divided our data into (i) training (80%) and testing (20%) (Reddit) (ii) training

(80%) and testing (20%) (Twitter) (iii) training (100% of Reddit data), testing (100% of Twitter data) (iv) training (100% of Twitter data), testing (100% of Reddit data). In the instance of the CNN classifier, we used the word2vec API of the Python package, Gensim, to incorporate words from pre-processed texts (Kim, J., et. al,2020).

Traditional machine learning algorithms primarily employ a bag of words or n-gram techniques to build feature vectors to train classifiers. Since there is a very limited number of words in short texts such as tweets, the traditional machine learning algorithms suffers from the curse of dimensionality and data sparsity issues. Nowadays, neural networks combined with word embeddings are used for text classification which has demonstrated a remarkable performance gain. (Parwez, M.A et.al,2019)

The architecture of a CNN model constitutes an input layer, a 1-Dimension pooling layer, a 1-Dimension convolutional layer, and an output layer. The first layer of the model is an embedding layer that represents the word embeddings of a 20-Dimensional pre-processed post, and its weight is set by the pre-trained word2vec. Second, a convolutional layer with word vector input consists of 128 filters. The next layer is a 128-layer max-pooling layer that takes the highest values from the CNN filters. The output of the max-pooling layer is routed via two densely linked layers, with the ultimate output being the probability of classification using the sigmoid activation function, which runs from 0 to 1. The batch size was set to 128, and the training epochs were set to 5. (Pei, S., Wang, L., Shen, T., and Ning, Z., 2019,), (Kim, J., et. al,2020).

The dataset was uploaded to Google Colab as a CSV (Comma-Separated Values) file using Google Drive. The model trained for about 220 hours for classification models which were trained on Twitter and performance was tested on Reddit,180 hours for classification models which were trained on Reddit and performance was tested on Twitter,240 hours for classification models which were trained and tested on Twitter and 60 hours for classification models which were trained and tested on Reddit.

3.4 Results

3.4.1 LIWC Statistical Results

Using the LIWC software, we retrieved linguistic characteristics from the posts/tweets. LIWC software is used to count the number of corresponding words and categorises them into 90 distinct feature variables using an existing list of words and categories (e.g., personal pronouns, positive/negative phrases). (Biggiogera, J., et.al,2021).

Table 3.2 displays the mean, and standard deviation of LIWC indicator ratings for the terms on Twitter and Reddit. The average word count for Twitter is 11.9 and for Reddit is 198.85. The analytic thinking indicator scores indicated that those on Twitter used more formal and logical terms, whereas those on Reddit used more informal and narrative expressions. The two LIWC indicator's ratings, clout, and authenticity, indicated that the post on Twitter conveyed their unfavourable sentiments less confidently and personally than people on Reddit. According to the emotional tone indicator ratings, posts on Reddit communicated with more negative expressions than posts on Twitter. However, both scores were less than 50, indicating that both Twitter and Reddit groups largely communicated using negative sentiments, which is expected given the nature of the discussion topics. The four LIWC indicators are rating pronoun, verb, adjective, and conjunctive indicate that interaction patterns are similar throughout various subreddits, and hashtags (Reddit and Twitter) are focused on content rather than people. (Yoo, M., Lee, S. and Ha, T., 2019), (Pennebaker, 2011). Computing mean and standard deviation across LIWC indicators, shows differences between Reddit and Twitter are statistically significant (p-value<0.005). The only exceptions, as observed, are the "male" categories and "negative emotions".

Table 3.2: Mean and standard deviation of LIWC indicator across various mental illness disorders

	Twitter		Reddit		T_Value
	Mean	Std	Mean	Std	
Word count	11.9025	6.34995	198.859	234.918	-2734.1000
Analytic	68.4048	29.0449	18.1242	19.2714	1199.2200
Authentic	44.9342	41.0435	84.7901	24.0225	-674.0100
Big Words	31.2922	18.7039	14.895	5.45739	611.6550
Dictionary	71.9869	21.3403	94.8394	4.28802	-747.8200
Tone	41.3287	40.5772	20.704	26.5385	352.1940
Death	0.51137	2.51326	0.36055	1.04442	23.9000
Pronoun	3.07715	6.08217	20.0709	4.9493	1927.0000
Verb	16.6657	13.8536	21.458	4.81217	-241.1700
Adverb	3.95159	6.68253	7.93442	3.45045	-414.3100
Adjective	9.93054	9.87667	6.28136	3.07183	257.7220
Male Reference	0.6800	2.9100	0.68834	1.68227	-0.8649
Female Reference	0.5500	2.6800	0.6868	1.71687	-35.9570
Negative emotion	2.6900	5.94	2.68354	2.61809	1.01508
Conjunction	0.7025	2.6481	7.6072	2.8480	810.3250
Clout	47.6	30.98	11.3	22.265	291.196

The post (Twitter and Reddit) consisted of encouragement words (positive sentiment) such as "friend", "love", "work", "today", "great", "time", "life", "think" and "right" whereas negative sentiment words related to "stress", "mental", and "anxiety" (Table 3.3). Our findings revealed that "time" was a popular topic of conversation, and it was related to "family", "friend", and "love."

Individuals may receive comfort and support from social media relationships with family and friends while keeping hopeful that they will soon spend time together. The words "home", and "work" connected with the word "life" were frequently brought up by those who were working from home or unemployed. These results show that most talks revolved around work-related problems. There was additional talk about "people," "worry," and "stress." suggesting talks were focused on how to overcome mental illness (Hung, M., et. al,2020).

Table 3.3 The most frequently used word stems from Twitter and Reddit user's post descriptions related to mental Illness

Twitter				Reddit			
Word	Frequency	Rows with Word	% of Rows with Word	Word	Frequency	Rows with Word	% of Rows with Word
Amp	940080	710242	9.2736	Time	371710	191927	41.1004
people	883407	772094	10.0812	Life	317105	163829	35.0833
Time	621330	573703	7.4908	People	285856	149326	31.9776
Day	556455	492958	6.4365	Year	278438	148516	31.8041
Life	498948	461547	6.0264	Day	267515	149157	31.9414
Love	425265	382664	4.9964	Friend	254676	123898	26.5323
Give	421597	402717	5.2582	Work	228378	122824	26.3023
Work	410108	376156	4.9114	Anxiety	204225	105729	22.6414
Year	396209	360660	4.7091	Start	199621	118414	25.3579
See	393048	369749	4.8278	Talk	182367	105836	22.6644
Talk	333709	306045	3.9960	See	172339	111272	23.8285
Great	327726	304222	3.9722	Thought	168401	106154	22.7325
Today	317043	301611	3.9381	Love	133905	76625	16.4089
mental	294956	275864	3.6019	Month	123387	84456	18.0859
school	288989	261007	3.4079	Job	119284	62546	13.394
stress	284533	259233	3.3848	Week	119033	80745	17.2912

3.4.2 Machine learning Model Evaluation

We employed the typical metrics for evaluating machine learning models: accuracy, recall, precision, and F1-score. The following are the definitions of these metrics:

$$Accuracy = TN + TN/(TP + FP + FN + TN)$$
$$Precision = TP/(TP + FP)$$
$$Recall = TP/(TP + FN)$$
$$F1 - score = 2 * (Recall * precsion)/(Recall + Precision)$$

Where TP is truly positive, FP is a false positive, TN is a true negative and FN is a false negative.

Table 3.4 highlights the performance of 6 binary classification models which were trained on Twitter and performance tested on Twitter. Among the six different posts, autism had the best accuracy (96.3 percent) on CNN. Other posts, r/anxiety, r/ schizophrenia, r/depression, and r/BPD also demonstrated high accuracy with CNN models, 84.5 percent, 85.8 percent, 84.3 percent, and 92.1 percent, respectively, and their F1-scores in identifying mental illnesses greater than the eighties (percent).

Table 3.4 Model evaluation of Convolutional Neural Network of 6 binary classification models which were trained and tested on Twitter.

Label		Precision	Recall	F1_score	Accuracy	Source
Autism	0	97	98	97.5	96.6	Twitter
	1	90.3	83.6	87.0		
Anxiety	0	86.2	87.5	86.9	84.5	
	1	84.7	84.8	84.8		
BPD	0	93.4	92.9	93.2	92.1	
	1	92.5	80.2	86.4		
Bipolar	0	97.3	98.5	97.9	95.9	
	1	96.5	96.2	96.4		
Schizophrenia	0	85.4	86.8	86.1	85.8	
	1	57.5	55.6	56.6		
Depression	0	83.9	86.5	85.2	84.3	
	1	84.4	88.7	86.6		

Table 3.5 highlights the performance of 6 binary classification models which were trained on Reddit and performance tested on Reddit. Among the six different posts, schizophrenia had the highest accuracy (96.6 percent) on CNN. Other posts, anxiety, autism, bipolar, depression, and BPD, also demonstrated high accuracy with CNN models, 91.9 percent, 91.3 percent,95.3 percent,87.2 percent, and 81.1 percent, respectively, and their F1 scores in identifying mental illnesses ranging above 50(percent).

Table 3.5 Model evaluation of Convolutional Neural Network of 6 binary classification models which were trained and tested on Reddit.

Label		Precision	Recall	F1_score	Accuracy	Source
Autism	0	94.7	95.3	95.0	91.3	Reddit
	1	59.4	55.7	57.6		
Anxiety	0	95.5	95.7	95.6	91.9	
	1	77.3	75.6	76.5		
BPD	0	86.2	87.9	87.1	81.1	
	1	83.4	84.7	84.1		
Bipolar	0	96.3	98.2	97.3	95.3	
	1	71.9	61.2	66.6		
Schizophrenia	0	98.7	96.4	97.6	95.9	
	1	64.3	49.6	57.0		
Depression	0	85.2	77.9	81.6	87.2	
	1	83.3	83.5	83.4		

Table 3.6 Model evaluation of Convolutional Neural Network of 6 binary classification models which were trained on Twitter and performance was tested on Reddit.

Label		Precision	Recall	F1_score	Accuracy	Source
Autism	0	87.5	98.4	93.0	88.4	Train-Twitter Test-Reddit
	1	94.6	19.8	57.2		
Anxiety	0	56.4	85.4	70.9	59.3	
	1	70.3	34.4	52.4		
BPD	0	95.3	95.8	95.6	86.9	
	1	32.3	26.9	29.6		
Bipolar	0	97.3	86.2	91.8	83.8	
	1	28.8	27.6	28.2		
Schizophrenia	0	90.3	96.5	93.4	94.5	
	1	81.6	24.4	53.0		
Depression	0	56.8	65.9	61.4	56.1	
	1	58.3	48.6	53.5		

Table 3.6 highlights the performance of six binary classification models which were trained on Twitter and performance tested on Reddit. Among the six different posts, schizophrenia had the best accuracy (94.5 percent) on CNN. Autism, bipolar, and BPD, also demonstrated high accuracy with

CNN models,88.4 percent, 83.8 percent, and 86.9 percent, respectively, and their F1 scores in identifying mental illnesses ranged from the 20's – 60's (percent), which were lower than those with class-balanced channels.

Table 3.7 Model evaluation of Convolutional Neural Network of six binary classification models which were trained on Reddit and performance was tested on Twitter.

Label		Precision	Recall	F1_score	Accuracy	Source
Autism	0	98.4	98.3	98.4	97.4	Train-Reddit Test-Twitter
	1	35.8	53.2	44.5		
Anxiety	0	84.4	81.8	83.1	72.3	
	1	44.3	46.7	45.5		
BPD	0	90.2	98.6	94.4	89.7	
	1	91.3	31.6	61.5		
Bipolar	0	92.6	77.5	85.1	73.1	
	1	58.2	48.9	53.6		
Schizophrenia	0	97.4	94.8	96.1	96.3	
	1	69.1	32.3	50.7		
Depression	0	51.3	61.6	56.5	52.2	
	1	52.8	42.5	47.7		

Table 3.7 highlights the performance of six binary classification models, which were trained on Reddit and performance tested on Twitter. Among the six different posts, schizophrenia had the best accuracy (97.4 %) on CNN. Schizophrenia, and BPD, also demonstrated high accuracy with CNN models,96.3%, and 89.7%, respectively, and their F1 scores in identifying mental illnesses ranged from the 30s – 60s (percent), which were lower than those with class-balanced channels.

As shown in Table 3.8, the classic CNN-based word2vec (Kim, J., et al.,2020) text classification approach has an average precision (Prec), recall rate, F1-score, and accuracy(acc) of 82.7,69.4,71.83, and 89.4 accordingly. The classification algorithms in the study 1 had an average precision, recall rate, F1-score, and accuracy of 82.5, 79.5, 80.5, and 91.5, respectively.

Table 3.8 Comparison of Model evaluation of Convolutional Neural Network, which was trained and tested on Reddit.

Channel	Class	XGBoost (Kim, J., et al.,2020).		CNN (Kim, J., et al.,2020).				Proposed Methodology			
		F1-Score	Acc	Prec	Recall	F1-Score	Acc	Prec	Recall	F1 score	Acc
Depression	0	78.65	71.69	59	82	68.4	75	94.7	95.3	95	91.3
	1	58.02		89	71.8	79.5		59.4	55.7	57.6	
Anxiety	0	77.73	70.41	76	96.9	85.1	78	95.5	95.7	95.6	91.9
	1	55.92		88	41.4	56.3		77.3	75.6	76.5	
Bipolar	0	91.93	85.53	90	99.1	94.5	90	86.2	87.9	87.1	81.1
	1	53.39		87	38	53		83.4	84.7	84.1	
BPD	0	91.37	85.14	90	99.5	94.8	91	96.3	98.2	97.3	95.3
	1	46.43		92	32.7	48.2		71.9	61.2	66.6	
Schizophrenia	0	92.52	86.72	95	99.6	97	94	98.7	96.4	97.6	95.9
	1	40.97		81	24.9	38.1		64.3	49.6	57	
Autism	0	97.35	94.91	99	98.4	98.4	97	85.2	77.9	81.6	87.2
	1	38.31		48	49.4	48.7		83.3	83.5	83.4	

3.5 Discussion

a) Examine the Linguistic Characteristics and Patterns of Different Social Media Activities Associated with Different Mental Health Groups

The mental illness lexicon on a social media platform like Twitter and Reddit was analysed using LIWC, the similarities are (i) Both Twitter and Reddit groups communicated using negative sentiments, which is expected given the nature of the discussion topics. (Hung, M., et al.,2020), (Ríssola, E.A., et al.,2022), (Al-Mosaiwi and Johnstone et al.,2018). (ii) The talks (encouragement words (positive sentiment)) on both social media platforms (Twitter and Reddit) focuses on how people get support from family, friends and discuss problems regarding mental illness, which are a common topic of discussion among individuals suffering from mental illness (Hung.M et al.,2020). However, there are some differences i) Computing mean and standard deviation across LIWC indicators, shows differences between Reddit and Twitter are statistically significant by comparing a chosen set of LIWC categories [Clout, Analytical thinking, Authenticity, Tone, Pronoun, Death, Emotion]. They are different because of the following reasons i) This could be due to the restriction on words, or the depth of topics discussed on Twitter as compared to Reddit. ii) According to literature, length influences writing style, exhibiting specific linguistic aspects; for example, length limits disproportionately retain negative emotions, adverbs, articles, and conjunctions have the highest probability of being omitted. (Gligori et al., 2019)

b) To investigate whether a machine learning model can be developed to categorise a user's social media activity patterns into different mental illness groups.

In study 1, the machine learning model (CNN+word2vec) have been successfully able to classify various mental illness using social media platform (Twitter and Reddit).

We are comparing the proposed model which was trained and tested on Reddit with the (Kim, J., et al.,2020) model. Our proposed approach, in comparison has a greater classification effect, as well as a higher average recall rate, F1 score, and accuracy rate. Kim, J., et al.,2020, model achieved remarkable accuracy. However, our suggested model is simpler and has a lower level of complexity analysis, but it achieves a greater level of accuracy (2.11%). A critical step was taken to optimize the model by tuning the hyperparameter.

The Reddit model has the lowest F1-score on autism, bipolar, and schizophrenia which is due to the class imbalance problem (Kim, J., et al.,2020). The reason why the performance of Reddit is better compared to Twitter are (i)Reddit communities are monitored by individuals who volunteer to be moderators. Moderating privileges include the ability to delete posts, and comments from the community. A moderated Reddit post might become a safe space to discuss topics related to mental health. Reddit users may find it more comforting that a moderator may remove harsh or harmful messages or individuals from the subreddit (Reddit,2022), (Bushman, M., et al.,2021). (ii)The fact that there are more postings with promotional content on Twitter means that tweets on the symptoms of mental illness sometimes are diluted from other topics such as blogs about fitness or seminars about meditation. (Reddit,2022), (Bushman, M., et al.,2021), (De Choudhury, M., and De, S., 2014).

c) To understand if a machine learning model trained on a specific social media can generalise to other social media platforms.

We investigated machine learning classifiers (CNN+word2vec) to provide a generalised method for classifying mental illnesses using social media data (Twitter and Reddit). We train and test machine learning models using labelled Twitter datasets and then compare the performance of our trained models to other social media sources using non-Twitter datasets (Reddit). Despite the differences in linguistic characteristics between Reddit and Twitter, our machine learning models can generalise the model between social media platforms (Twitter and Reddit).

We compared the results of testing the Twitter and the Reddit model on Twitter to understand better how well each model generalises beyond the platform. The Reddit model seems to perform better than the Twitter model, indicating that the Reddit model can generalise better compared to another (Twitter) social media platform. The Reddit model tested on Twitter had F1 scores across various mental health conditions ranging from the twenties to sixties (percent) and had the lowest accuracy for depression and anxiety, and the Twitter model tested on Reddit had F1 scores across various mental illnesses ranging from 30s – 60s (percent) and had the lowest accuracy for depression, which is due to the class imbalance problem (Kim, J., et al.,2020).

The reason Reddit is better compared to Twitter are (i)We believe that the Reddit model is better at generalisation is due to the interaction structure of Reddit making it ideal for seeking expert opinions. Twitter may provide more frequent updates on an event, whereas Reddit may provide more critical analysis regarding the same events. Furthermore, Twitter users tend to discuss political news and current events more than Reddit. Still, Reddit may be a better choice for news updates and entertainment discussions (Priya.s et. al,2019). Twitter is suitable for getting frequent updates during an emergency or live event. Reddit's unrestricted post length plays a vital function in providing us with additional background information. The reason why Twitter may be better compared to Reddit are (i) In contrast to Reddit, imposing a post length constraint on Twitter helps to reduce biased and extreme viewpoints. Furthermore, an event on Twitter can be tracked for a longer period, which might be valuable for analysing its evolution (Priya.s et. al,2019). (ii) Twitter's high negative associativity suggests that information dispersion is heavily influenced by the user who created the tweet. When it is a user with many followers, it is more likely to spread quickly and widely. Reddit users do not have close communities, as seen by a low clustering coefficient, and a small number of related components, as a result, information spreads slowly on Reddit on average. (Prasha Shrestha, et.al,2020). Thus, there are significant differences between these two platforms (Twitter and Reddit) in terms of user behaviour as well as their conversation and posting patterns. However, given the abundance of these platforms available, each with its uniqueness in presentation, spreading patterns, and user interests, a comparative analysis of their efficacy would be beneficial (Priya.s et. al,2019).

We present a method for automatically identifying social media (Twitter and Reddit) posts related to mental health and then classifying them into theme-based groups (subreddit and hashtag) using a machine learning algorithm. Our research shows that users on the two different platforms have different themes of interest and different sentiments, indicating the need of examining cross-platform social media networks to offer a more comprehensive view of people's opinions. Rather than relying on a single platform, the integration of various Online Social Networks (OSNs) can assist stakeholders (politicians, and healthcare professionals) in gaining a more thorough understanding of community responses (Horawalavithana, S., et. al,2019).

Our long-term objective is to not only provide aid to clinical researchers, and policymakers in addressing communications on social media, but also to aid with individuals suffering from mental illness. To allocate resources more effectively and give help where it is most needed, the authority (policymakers, healthcare professionals, etc) must keep track of the population's mental health over time and across different geographic regions. Our findings might be beneficial for policymakers, academics, and healthcare professionals interested in understanding the occurrence of different mental health conditions and concerns over time and different locations. Hence better formulating policies, recommendations, and health promotion activities in response to address the issue. (Gkotsis, G et. al,2017).

CHAPTER 4

CLASSIFICATION OF ADHD USING SMARTPHONE SENSOR DATA

Study 2 (Chapter 4) classifies neurodevelopmental disorders, particularly ADHD, using sensor data from smartphones. This study (Study 2) will highlight the benefits of smartphone sensors in tracking patterns of neurodevelopmental disorders by reviewing the literature and methodology that inform its approach. Chapter 4 (Study 2) further explores the methodology, data extraction and model validation details, providing a more in-depth view of how neurodevelopmental disorders are classified, and highlights the complementary role of smartphone data in the digital extension of mental health solutions, as discussed in previous chapters.

4.1 Introduction

ADHD is one of the most common neurodevelopmental disorders from which people in the world presently suffer. Besides, it involves persistent patterns of inattention, hyperactivity, and impulsivity. Attention deficit hyperactivity disorder can affect both children and adults; an estimated prevalence is about 5% of children and 2.5% among adults (Cibrian et al., 2024; Welch et al., 2022). Assessment and treatment of ADHD conventionally have been done through direct, face-to-face contact with health professionals using behaviour assessments, parent-teacher reports, and pharmacological interventions (Cho & Talboys, 2024; Logan & McClung, 2018). However, most conventional methods often have limitations regarding accessibility, consistency, and generalisation to real-life. With the ever-increasing ubiquity of smartphones and wearable devices, clinicians and researchers can now monitor symptoms in real-time and naturalistic settings. This shift toward digital solutions offers, in fact, can complement traditional methods by allowing much more comprehensive and continuous symptom monitoring (Kuss et al., 2018; Denyer et al., 2023). Digital mental health interventions include mobile apps, online therapy portals, and smartphone sensors for passive data collection. These digital tools provide continuous and real-time data on individual behavioural trends for those with ADHD. Moreover, such digital tools also enable personalised and timely interventions that can significantly improve patient care quality (Murray et al., 2021; Panagiotidi & Overton, 2020). For instance, symptoms observed in real-time may inform healthcare providers of some behavioural change in a patient. This may allow this knowledge to lead to more customised treatment options. In this respect, digital tools have the potential to create significant difference in the lives not only of patients with ADHD but also of their healthcare workers and researchers in general. This influence impressively underlines the great power of the digital solution for mental health (Selaskowski et al., 2022; Kim et al., 2023).

4.1.1 Problem Statement

Despite the promising potential of digital mental health interventions (DMHI) to treat attention deficit hyperactivity disorder (ADHD), there exists a notable gap in the extant research focusing particularly on ADHD within the context of the interventions (Burrows & Rysdyk, 2022; Harris et al., 2022). Most of the literature to date has focused on disorders such as depression and anxiety disorders, and there is a lack of understanding regarding neurodevelopmental disorders like ADHD in respect to how they can best be treated using digital platforms (Baweja et al., 2021). Most diagnostic instruments for ADHD are barely objective; therefore, appropriate assessments are difficult to carry out, especially in resource-poor settings that have limited access to full mental health services. This is worse in LMIC, which may lack trained personnel and diagnostic tools (Asherson et al., 2022; Michaëlsson et al., 2022). Yet another aspect that requires serious attention is the cross-population generalizability of the machine learning algorithms being designed to diagnose and treat ADHD (Schoeman & Voges, 2022; French et al., 2023). Socio-economic factors are not taken into consideration for these models yet, which could vary considerably between population segments and, as in the case of the majority of fields of study, directly affect symptom management for ADHD (Reddy et al., 2019; Ter-Minassian et al., 2022). With these variables not considered, digital interventions may be no good since they will fail to attract diverse user populations or satisfy their needs. ADHD challenges call for robust and adaptive ML models that can address different contexts, especially for individuals in LMIC (Canals et al., 2020; Chen et al., 2020). Further, these should be designed incorporating socio-economic factors, cultural factors, and the characteristic features of ADHD to make better applicability and effectiveness in a wide range of cultures possible (Vaidyanathan et al., 2023; Grazioli et al., 2023). By filling the gaps that exist in research and model development, the potential for supporting individuals affected by ADHD through digital mental health interventions could be harnessed more effectively.

4.1.2 Significance of the Study

ADHD represents a significant broadening of the spectrum of mental health disorders that can be usefully addressed through digital mental health interventions. Recent studies have shown that machine learning models can classify ADHD using smartphone data, providing real-world behavioural insights. Such insights help customise treatment approaches to the individual and extend patient care beyond traditional healthcare settings. In LMIC, the value is added for people with ADHD because the availability of services for the mental health condition is poor in these regions (Patel et al. 2018). Digital solutions will bridge this gap by further easing access to care, enabling patients to self-manage their symptoms through evidence-based interventions (Firth et al. 2019). The findings from this study identify behavioural markers associated with ADHD and, therefore, are the most needed resources for researchers, policymakers, and healthcare providers. This study also seeks to promote inclusion and equity in mental health by developing scalable digital technologies that address the specific needs necessary for ADHD management in low-resource settings.

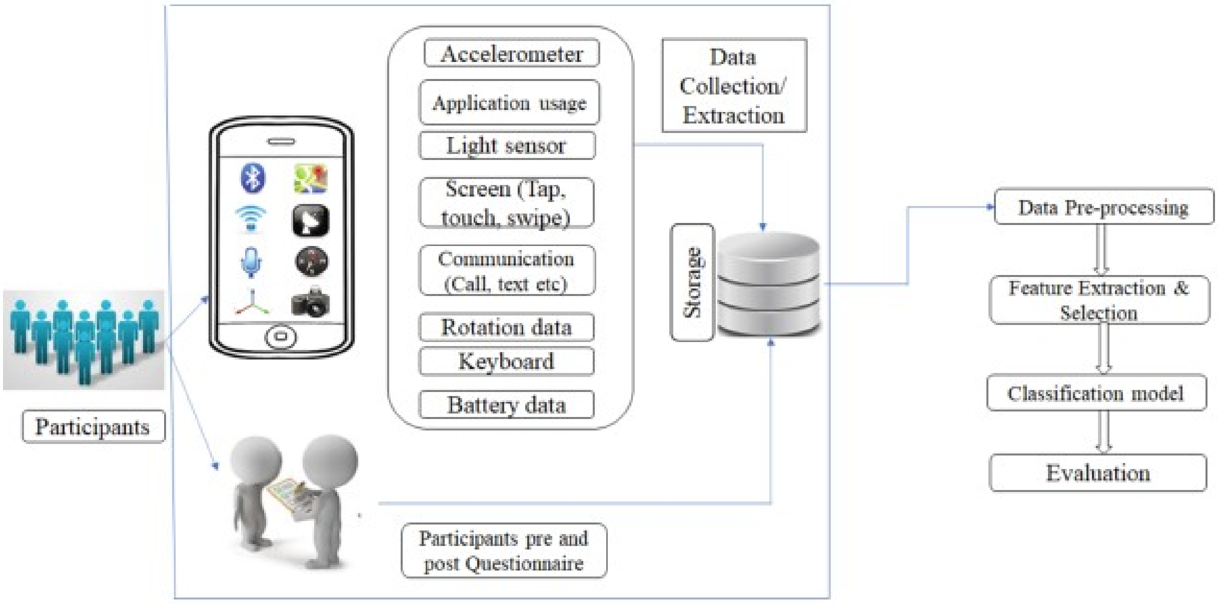


Figure 4.1: Methodology for ADHD Classification Using Smartphone Sensor Data

4.2 Methodology

4.2.1 Data Recruitment and Screening Process

The data of this study (study 2) was obtained from East West Institute of Technology, Bangalore, India, after getting ethics approval from East West University. We recruited 53 participants between the ages of 18-23 years, consisting of some individuals with prior ADHD and some without ADHD. Out of them, 23 had already been diagnosed with ADHD by healthcare professionals, while 30 had no prior ADHD diagnosis. The study was conducted by experienced clinicians to ensure accurate assessment, proper verification of diagnostic status, and adherence to ethical and professional standards. Evaluation was according to DSM-5 (American Psychiatric Association, 2013) criteria, which state that ADHD is a persistent pattern of inattention and/or hyperactivity-impulsivity that does impair. Clinicians measured and classified daily attention and inattentive behavior and were particularly concerned with the behaviors to ensure accurate diagnosis, valid classification, and adherence to DSM-5 criteria. Initially, 15 females and 38 males were recruited. Ten participants from control group were excluded from the study due to insufficient data or being identified as ADHD using the Adult ADHD Self-Report Scale (ASRS) or diagnosed with neurological conditions (including epilepsy), schizophrenia, or borderline personality disorder (BPD). one participant from ADHD group were excluded from the study due to diagnosed with neurological conditions (including epilepsy), schizophrenia, or borderline personality disorder (BPD). After exclusions, the final count for the study was 22 participants with ADHD and 21 without ADHD. The final dataset hence consisted of 43 participants (10 females and 34 males). We collected data from each participant for approximately one week. Prior to data collection, a psychiatrist was consulted to determine the most suitable smartphone sensors for the assessment of day-to-day attention-related behavior in an unobtrusive and ecologically valid manner. Based on these recommendations, the study made use of accelerometer, application usage, notification response time, screen time, app use, light data and location sensors' data. The modalities were identified as strongly relevant to the assessment of day-to-day changes in attention and behavioral patterns. Screen and application use metrics provided measures of focus time, task engagement, and switching activities, whereas accelerometer and gyroscope metrics provided data regarding restlessness and hyperactivity that are signatures of attention difficulties among individuals with ADHD. Location metrics were added to capture movement patterns and routine regularity, which can also be attributed to attention regulation. Our inclusion criteria for the study were two-fold: (1) participants must be Android user`s (Android version $\geq$ 5.0; iOS $\geq$ 8.0)., since iPhones do not allow us to monitor phone usage as required for our research, and (2) participants must be fluent in English, based on the study conducted by Intarasirisawat et al. (2020).

This study (study 2) aims to create a model that classifies individuals with ADHD from those without ADHD, using data collected from smartphone sensors that evaluate the person's activity (physical and digital) patterns. Figure 4.1 shows the four main phases of the activity identification framework: Data collection, Data preprocessing, Feature selection, and classification. Multiple sensors will be used to gather information about human usage and behaviour. After collecting the data, we preprocess it, which includes cleaning the raw data to make it suitable for analysis. Data preprocessing involves several steps, such as data cleansing (removing or cleaning missing, inconsistent data), data integration (merging data from multiple sources), data transformation (normalising, scaling, or transforming data), and data reduction (removing unwanted data) (Ang, C.S et al., 2023). We then extracted several features from the preprocessed data. We used a classification model based on Yang X et al.'s (2023) study to classify individuals with and without prior ADHD.

4.2.2 Data Collection

We used the "AWARE" Android phone application to track various data points such as location, light sensor data, keyboard typing behaviour, screen on/off timing, rotation sensor data, accelerometer sensor data and phone app usage for a week, based on the Sano et al. (2018) study. It is important to note that the app does not record the content of emails, calls or text messages. However, data such as timing of calls, text messages, typing behaviour and screen activity can provide valuable information on how often participants use their phones during the day and night. Additionally, the number of calls, text messages and contacts can help quantify their social interactions, as stated by the Yang et al. (2023) study.

Table 4.1a): Overview of software sensors used in the study and their usage (Van Berkel et al.,2022).

Sensor	Description
Application	Application usage and notifications on the device.
Installations	Application installations, removal, and updates.
Keyboard	Log keyboard input.
Screen	Monitors the screen status, such as turning it on and off and locking and unlocking it.
Touch	Tap, log clicks, and scroll up/down events.

As shown in Tables 4.1 a) and 4.1 b), hardware sensors (such as battery level, accelerometer, and GPS) and software sensors (such as application use and keyboard) can be used. How an individual uses different applications and how often they use them can provide valuable clues about their mental health and behaviour. Using the keyboard sensor makes it possible to record keystrokes and identify the specific application where they are being used (excluding password entries). Screen data can also determine a person's phone usage's timing, frequency, and duration. Like the keyboard sensor, screen touch dynamics may also indicate psychological states. For instance, an increased screen interaction rate could indicate a state of agitation or a manic episode.

Notification response time was approximated through integration of smartphone logs of application notifications, screen on/off, and app usage. For each delivered notification, the arrival time was recorded from the notification log. The initial follow-up event involving the device, e.g., screen unlock or opening of the corresponding application, was captured through screen on/off events and app usage logs. The response time for that alert was measured as the difference between the time of the initial interaction and the time of arrival of alert. This was done for all the alerts in the data collection period to provide a true measurement of user responsiveness to digital cues, a quantitative measure of attention and interaction with mobile phones in everyday situations.

Table 4.1 b): Overview of hardware sensors used in the study and their usage (Van Berkel et al.,2022)

Sensor	Description
Accelerometer	Acceleration is applied to the device.
Light	Level of ambient light.
Locations	Best location estimates of the users' current location.
Rotation	Orientation of the device.

By using the acceleration measurement, this sensor can detect both physical movements and periods of being still (Van Berkel et al., 2022). For physical activity identification such as sitting, walking, running, and standing, Google's Activity Recognition API was utilized. The API applies accelerometer data along with other smartphone sensors through sensor fusion to provide efficient and accurate recognition of the activities. Its integration facilitated the real-time recognition of walking, running, sitting, and standing at low computational overhead and battery-friendly performance over custom-built models. Light intensity exposure was acquired from the smartphone's ambient light sensor, which provided continuous feedback in lux. The mean light intensity per time window was calculated to estimate participants' exposure to light or dark conditions throughout the day. Unique location visits were detected with smartphone location data obtained from GPS and Wi-Fi positioning. Successive location points were clustered according to a spatial threshold to identify unique places visited by participants. Number of unique locations visited per day was then calculated, providing a measure of mobility and environmental interaction. The metric facilitated the identification of behavior patterns, like change in daily habits and potential correlation with attention and physical activity levels.

At the start of the study, each participant will fill out standardised pre-questionnaires on mental health.

Standardised pre-questionnaires on mental health include. (Sano, A., et.al,2018)

a) The Adult ADHD Self-Report Scale (ASRS)- The ASRS is a diagnostic tool designed by the WHO to screen for symptoms of ADHD in adults. It comprises eighteen questions that evaluate the severity and presence of ADHD symptoms in individuals (Kessler et al., 2005).
b) We will ask the participants to complete an Experience sampling method (ESM) questionnaire daily between noon and midnight for seven days.

4.2.3 Data Preprocessing and Feature Extraction

A. Data Preprocessing

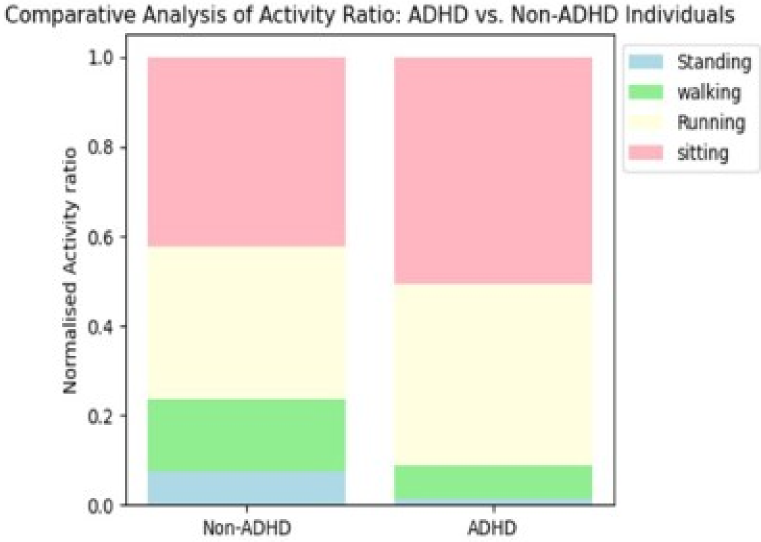
The input datasets we have at this stage contain unwanted data that needs to be removed, as mentioned by Abhishek et al. (2015). To convert the UNIX timestamps into a human-readable local date and time format, we will use the time zone data of each participant. Data collected from online diaries and phone data is often noisy, so the data preprocessing stage handles this noise. It's crucial to transform some of the data to make it suitable for analysis. This can be achieved through data cleaning techniques such as data quality evaluation, noise reduction, faulty data detection, and interpolating missing values (Abhishek et al., 2015; Sano et al., 2018).

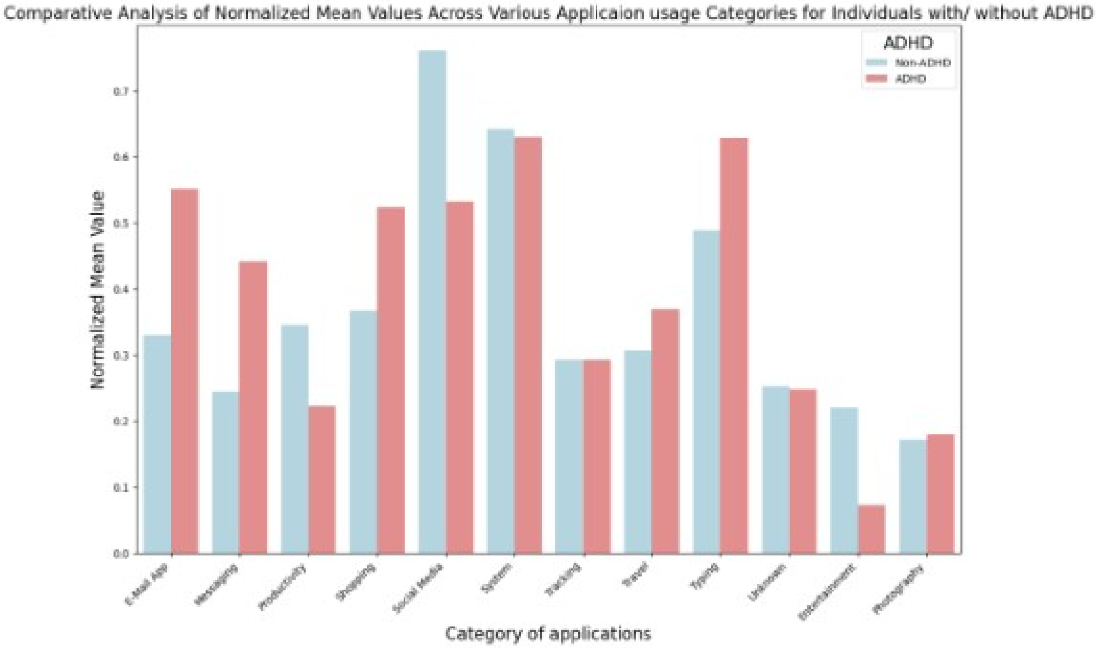
B. Feature Extraction

Table 4.2: Features extracted from smartphone data.

Sensor	Features extracted	Description
Location	Total distance, unique no of the location visited	Tracking the device's location provides insights into daily routines and mobility. (Moshe et al., 2021; Yang X et al.,2023; Intarasirisawat, J et al.,2020).
Light sensor	Light level readings	The light sensor captures ambient lighting conditions, which can impact attention and alertness levels (Moshe et al., 2021)
Keyboard sensor	Keystrokes (masked text), typing speed, typing accuracy	Analysing keyboard sensor data (keystrokes, typing speed) reflects cognitive processes and attention levels. Variations may indicate attention difficulties associated with ADHD. (Moshe et al., 2021; Intarasirisawat, J et al.,2020).
Screen on/off timing	Screen on/off duration, time of day of screen on/off	Recording screen on/off events helps identify usage patterns and screen time habits. Irregular patterns may indicate challenges with attention regulation and digital distraction in ADHD. (Moshe et al., 2021)
Accelerometer	Human Activity behaviour (running, walking, sitting, standing)	The accelerometer measures movement and acceleration, enabling the identification of hyperactivity, impulsivity, and restless behaviours observed in individuals with ADHD. (Moshe et al., 2021; Yang X et al.,2023; Intarasirisawat, J et al.,2020)
Phone app usage	The types of apps used, the duration and frequency of app usage, normalised entropy, Session duration, app count, app notification count, touch and scroll count, and nighttime phone usage are also recorded.	Monitoring app usage provides insights into digital behaviour, including excessive or impulsive app use and potential distractions. It helps assess focus and task-related difficulties in ADHD (Moshe et al., 2021; Yang X et al.,2023)

Extracting informative features from the raw data is essential to accurately classifying ADHD. Feature extraction aims to identify the most relevant features that can be used to train a classification model. Table 4.2 provides an overview of the various data types collected from mobile apps. It details the specific characteristics and measurements of each data type. (Moshe et al., 2021; Yang X et al.,2023; Intarasirisawat, J et al.,2020). All these features provide a wide range of data that can be effectively utilised to gain valuable insights into user behaviour, interaction patterns, and device usage characteristics during app usage on mobile devices.





b

Figure 4.2a) Activity Ratio of Different Behaviours in Individuals with and without ADHD Based on Accelerometer Sensor Data b) Comparison of Normalised Mean Values across various categories for Individuals with and without ADHD.

Figure 4.2 a) presents the activity ratio of different behaviours among individuals with and without ADHD, based on accelerometer sensor data, providing insights into the activity patterns of both groups. The study shows that both groups exhibit similar activity patterns, with sitting, standing, and walking being the most common activities. Furthermore, both the ADHD and non-ADHD groups engage in similar sedentary behaviour (sitting) and light physical activity (standing and walking).Overall, this graph highlights that while there are similarities in activity patterns between ADHD and non-ADHD individuals, no significant differences are observed based on accelerometer data.The data presented in Figure 4.2 b compares normalised mean values across various categories extracted from application foreground data for individuals with and without ADHD. Most categories (except social media and entertainment) show that the mean value of ADHD is greater than that of non-ADHD, indicating higher normalised mean values. The typing category has the highest normalised mean value for ADHD, while for non-ADHD individuals, it is social media.

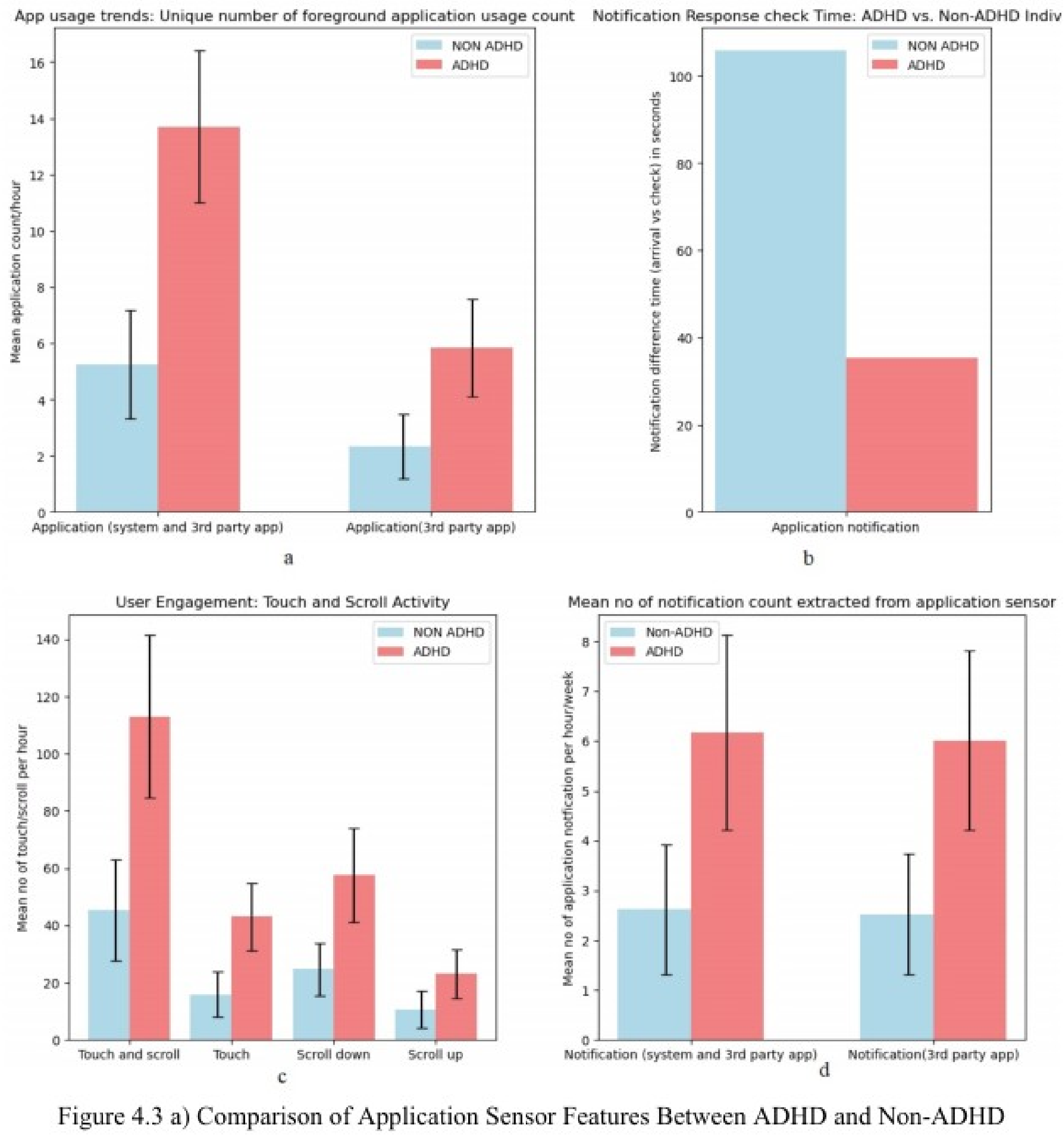


Figure 4.3 a) Comparison of Application Sensor Features Between ADHD and Non-ADHD Individuals b) Comparison of Notification Response Time in ADHD and Non-ADHD Individuals c) Comparison of Touch Sensor Feature Extraction Between Individuals with and without ADHD. d) Comparison of Application notification count Between ADHD and Non-ADHD Individuals

In Figure 4.3a), a comparison is made between the features of application sensors in individuals with and without ADHD. The "application count" feature refers to the number of unique foreground applications per hour. The results indicate that individuals with ADHD tend to use foreground applications more frequently, as their mean application usage is significantly higher than that of individuals without ADHD. The other three features (mean application installed, mean application notification, and mean application notification device) also exhibit significantly higher means for individuals with ADHD. Figure 4.3 b) compares notification response time between individuals with and without ADHD. The results show that participants with ADHD have a much shorter response time to notifications or alerts, approximately 40 seconds. In contrast, participants without ADHD demonstrate a significantly longer response time, with values close to 100 seconds. In Figure 4.3 c), a comparison is made between touch sensor feature extraction in individuals with and without ADHD. The results reveal that individuals with ADHD tend to engage more frequently with touchscreens through combined touch and scroll gestures, demonstrating a notably higher mean number of touch scroll actions. Additionally, they exhibit a slightly higher mean number of touch/actions per hour than the non-ADHD group. Both groups engage in touch interactions, but the disparity is more pronounced for individuals with ADHD. Furthermore, those with ADHD display a moderately higher mean number of scroll actions, indicating a heightened frequency of scrolling on touchscreens compared to their non-ADHD counterparts.

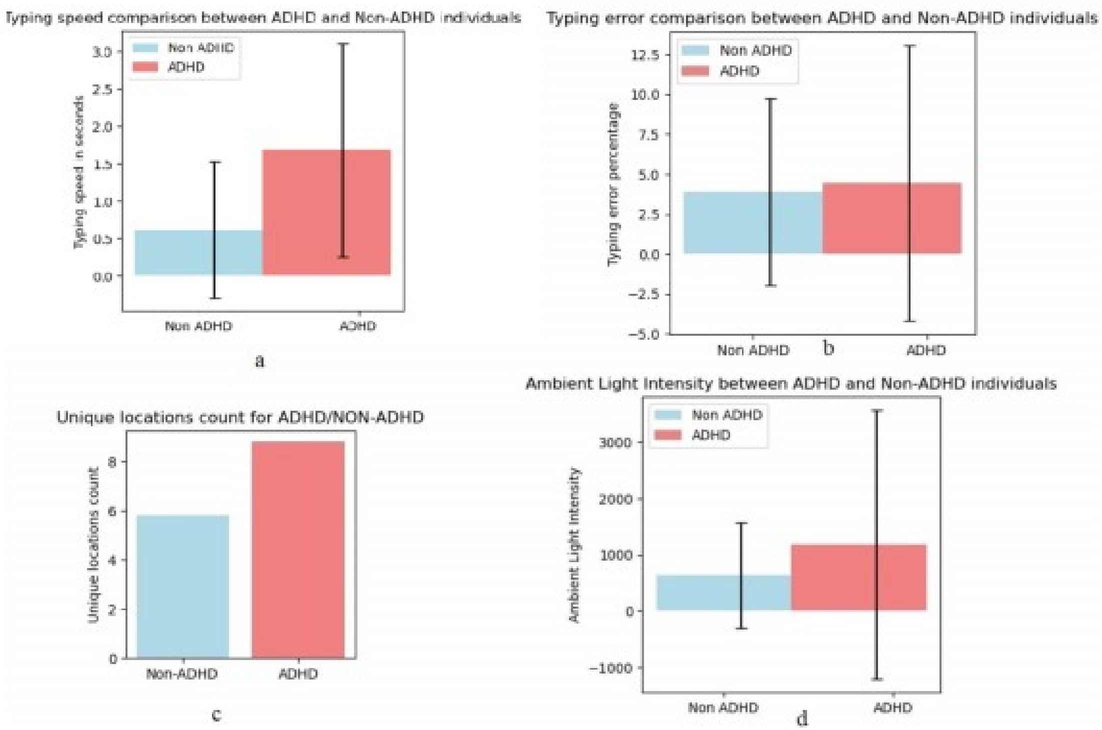
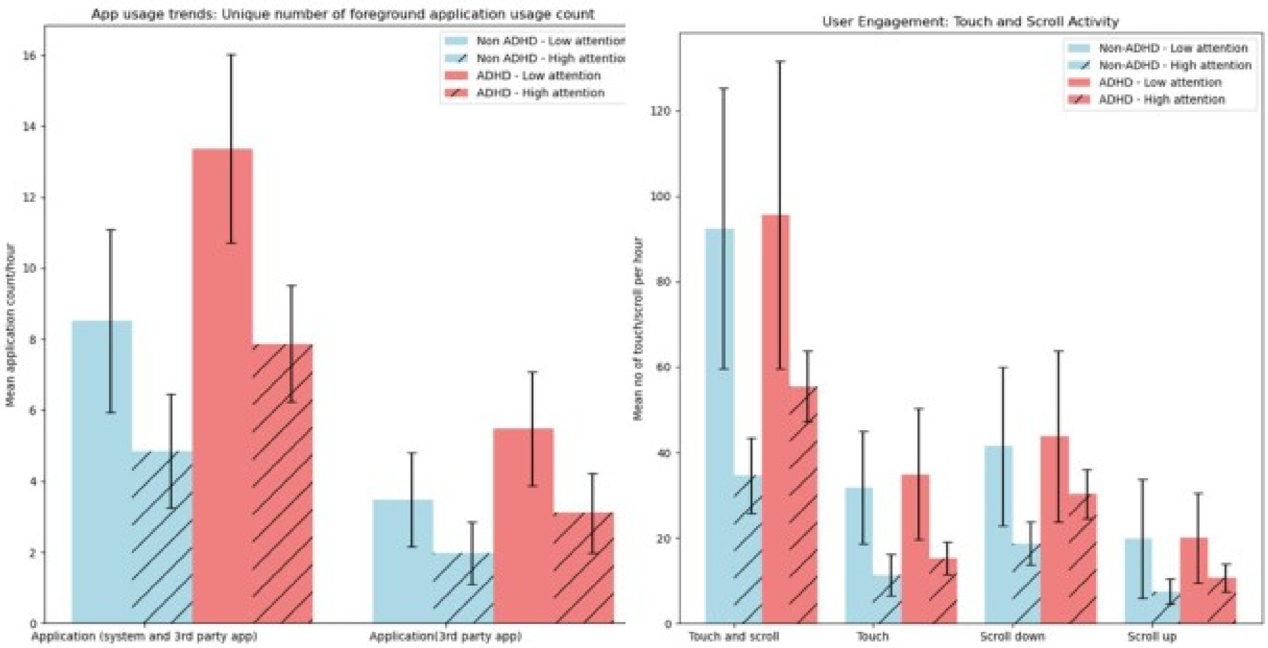


Figure 4.4 a) Typing Speed Comparison between Individuals with and without ADHD b) Typing Error Percentage in individuals with and without ADHD based on Keyboard data c) Comparison of Mean Unique Locations Count between individuals with and without ADHD d) Ambient light Intensity between ADHD and non-ADHD individuals.

In Figure 4.4 a), we compare the mean typing speed of individuals with and without ADHD. The results show that individuals with ADHD have a higher mean typing speed than those without. Figure 4.4 b) depicts the typing error percentage for the two groups, labelled "ADHD" and "Non-ADHD". Both groups exhibit similar error percentages, with individuals with ADHD having slightly higher errors. Figure 4.4 c) compares the mean unique locations per hour between individuals with and without ADHD. The results indicate that individuals with ADHD have higher mean unique locations count per hour than those without. Finally, Figure 4.4 d) shows the ambient light intensity for individuals with and without ADHD. Interestingly, individuals with ADHD exhibit higher ambient light intensity compared to their non-ADHD counterparts.



a b

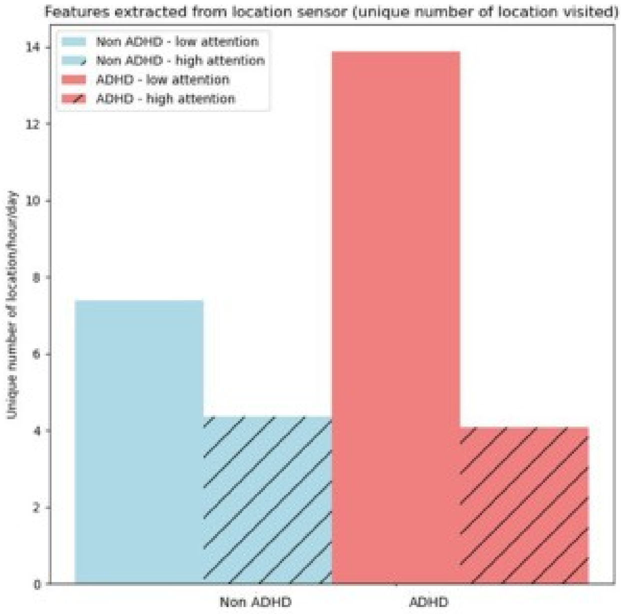
Figure 4.5 a) Comparison of Application Foreground Sensor Features based on ADHD and Attention Levels b) Comparison of Features Extracted from Touch Sensor for Individuals with Different Levels of ADHD and Attention

The graph presented in Figure 4.5 a) compares the attention levels of individuals with and without ADHD, based on data from the foreground sensors of their applications. The left-hand side of the graph represents "application count," while the right-hand side shows "application count (3rd party app)." For both categories, individuals with low attention, regardless of ADHD status, have the highest mean applications per hour/day. Error bars above each bar indicate the variability within each group. In summary, the graph suggests that individuals without ADHD but with high attention tend to use applications more frequently. In Figure 4.5 b), a graph compares touch sensor data for individuals with and without ADHD. The graph shows that individuals with ADHD and low attention levels exhibit the highest value for touch and scroll behaviour. Non-ADHD individuals with low attention levels also engage in touch and scroll activities. The highest touch behaviour is observed in individuals with ADHD but with higher attention levels, while the lowest touch behaviour is seen in individuals without ADHD and higher attention levels. Touch behaviour is highest in individuals with ADHD and low attention levels. Both individuals without ADHD and those with ADHD exhibit more touch interaction. The highest values are observed in individuals with low attention levels and ADHD, while the lowest values are observed in individuals with higher attention levels, regardless of ADHD status. Scrolling-up behaviour is low in all four categories, with minor differences. Overall, scrolling-up interactions are consistent across the groups.

Figure 4.6 a) displays a graph showing the variation in the number of locations participants visit. This variation is based on their attention levels and ADHD status. The graph highlights that the higher the attention levels, the more places the participants visit. Among participants without ADHD, those with high attention visited approximately 13 locations, while those with low attention visited around 8. Similarly, participants with ADHD and high attention visited around 14 locations, while those with low attention visited only around 7 locations. In Figure 7b, the graph compares the typing error percentages between individuals with ADHD and those without ADHD.

Figure 4.6 b) shows that non-ADHD individuals have lower typing error percentages at low and high attention levels. The light blue section corresponds to non-ADHD individuals with low attention, while the blue with stripes represents high attention. The average typing error percentage of non-ADHD participants is approximately 3.75%. On the other hand, individuals with ADHD have higher typing error percentages. The light red section corresponds to ADHD individuals with low attention, and the red section with stripes represents high attention. Their average typing error percentage is approximately 4.2%.

Figure 4.6 c) highlights that individuals with ADHD tend to make more typing errors, especially when their attention levels are low. Non-ADHD individuals consistently perform better in terms of accuracy during typing tasks. In Figure 6c, the graph shows the ambient light intensity between individuals with ADHD and those without ADHD. The graph highlights that during periods of high attention, individuals with ADHD experience higher ambient light intensity compared to their counterparts without ADHD. Conversely, non-ADHD individuals experience lower ambient light intensity during high attention.



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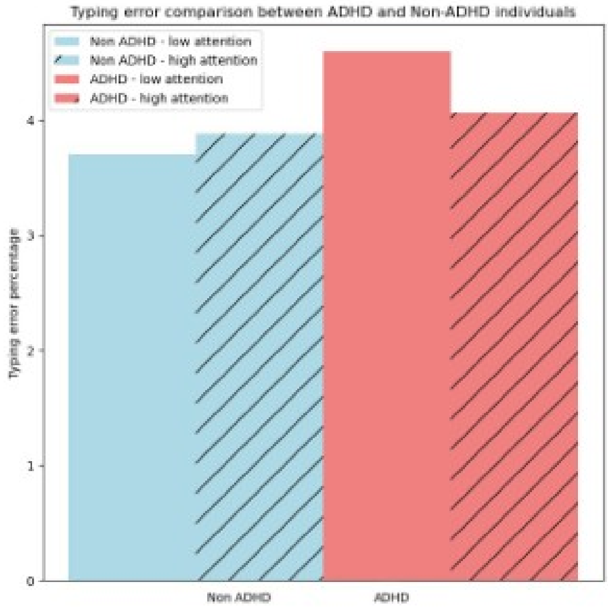

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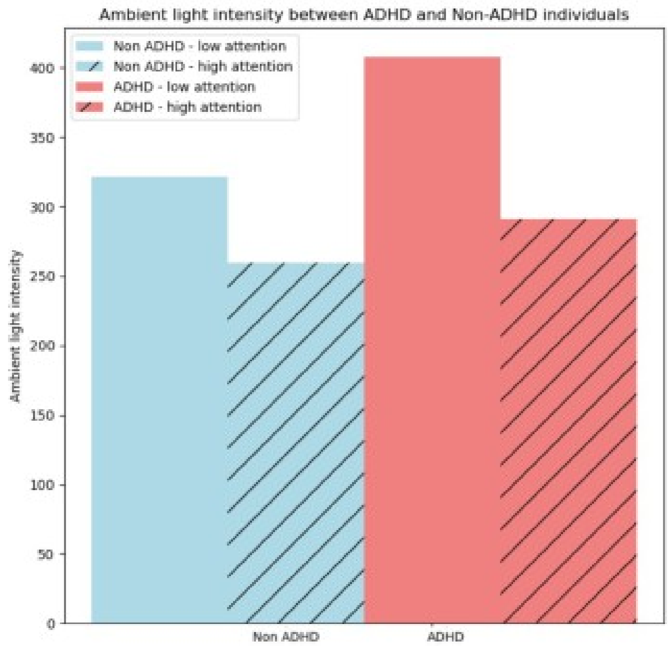

c

Figure 4.6 a) Unique no of locations visited per hour/day between individuals with and without ADHD b) Typing error percentage between individuals with and without ADHD c) Ambient light Intensity between individuals with and without ADHD.

Table 4.3 a): Behavioural and Sensor Features in ADHD Classification

Feature	Distinction	Reason	Approach
Location	ADHD individuals visit more unique locations (e.g., ~14 vs. ~7 per hour/day).	Reflects impulsivity and a preference for varied or less structured routines.	Track variability in movement to identify ADHD-specific routines and behavioural flexibility (Smith et al., 2021).
Light Sensor	Higher ambient light intensity in ADHD individuals, especially during high attention.	Suggests environmental sensitivity or preferences for brighter settings.	Use ambient light data to explore sensory or situational triggers affecting attention in ADHD (Nguyen et al., 2020).
Keyboard Sensor	ADHD individuals type faster and have higher error rates (4.2% vs. 3.75%).	Typing speed reflects impulsivity, while error rates highlight attention lapses.	Develop metrics for assessing attention and impulsivity through typing behaviour (Johnson & Patel, 2022).
Screen On/Off Timing	ADHD individuals exhibit more frequent screen on/off activity during nighttime.	Indicates disrupted sleep patterns or heightened nighttime engagement.	Monitor nighttime device usage as a marker for ADHD-related sleep disturbances (White & Lee, 2023).
Accelerometer	No significant difference in sitting, standing, or walking activities.	General activity levels do not vary significantly between ADHD and non-ADHD individuals.	Focus on other behavioural metrics such as movement variability or context-specific behaviours. (Singh et al., 2021).
Phone App Usage	- Higher app count and app notification response (40s for ADHD vs. 100s for non-ADHD). - Increased touch and scroll interactions in ADHD individuals, especially at low attention levels.	Reflects impulsivity and distractibility through heightened app engagement and touch behaviours.	Analyse app usage patterns and touch behaviours to assess impulsivity and real-time attention shifts (Kumar et al., 2020).

Table 4.3 a) details some of the distinguishing features of ADHD individuals vs. non-ADHD individuals, along with the rationale and methods to track these behaviours across a variety of sensors and data sources.

Table 4.3 b) discusses how several behaviours and sensors might be employed in the measurement of attention levels in individuals, pointing out distinctions based on both attention-related and ADHD-related factors. It lists the most important features, as well as the reasoning for each difference between attention levels and ADHD, together with the methodology for applying sensor data in the measurement of these variables.

Table 4.3 b): Behavioural and Sensor Features in assessing attention level.

Feature	Distinction (ADHD, Attention Level)	Reason	Approach
Application Count	Individuals with low attention (regardless of ADHD) have the highest mean applications per hour/day. High attention individuals without ADHD use applications more frequently.	Suggests that attention levels, more than ADHD status, drive the frequency of application usage.	Monitor application usage patterns to identify behaviour changes related to attention levels and ADHD status (Smith et al., 2022).
Touch Sensor (Tap & Scroll)	ADHD individuals with low attention exhibit the highest touch and scroll behaviour. Individuals without ADHD with low attention also engage in similar behaviours.	ADHD and low attention lead to more touch interactions. High attention correlates with lower touch behaviour.	Track touch interactions to assess attention-related behaviour and the impact of ADHD status on touch activities (Jones & Patel, 2021).
Locations Visited	High attention individuals (both ADHD and non-ADHD) visit more locations. ADHD individuals with low attention visit fewer locations.	Higher attention leads to more movement, possibly indicating greater engagement with the environment.	Analyse location data to assess the relationship between attention levels, ADHD status, and exploration behaviour (Lee et al., 2023).
Typing Error Percentage	ADHD individuals (especially with low attention) tend to make more typing errors compared to non-ADHD individuals, who perform better.	ADHD may impact typing accuracy, with low attention exacerbating the errors.	Measure typing error rates to evaluate cognitive performance and the effect of attention and ADHD on accuracy (Martinez et al., 2020).
Ambient Light Intensity	Individuals with ADHD experience higher ambient light intensity during high attention periods, compared to non-ADHD individuals.	Environmental factors like light intensity might influence or correlate with attention levels.	Monitor light intensity data to explore its connection with attention levels and ADHD status in different settings (Nguyen et al., 2021).

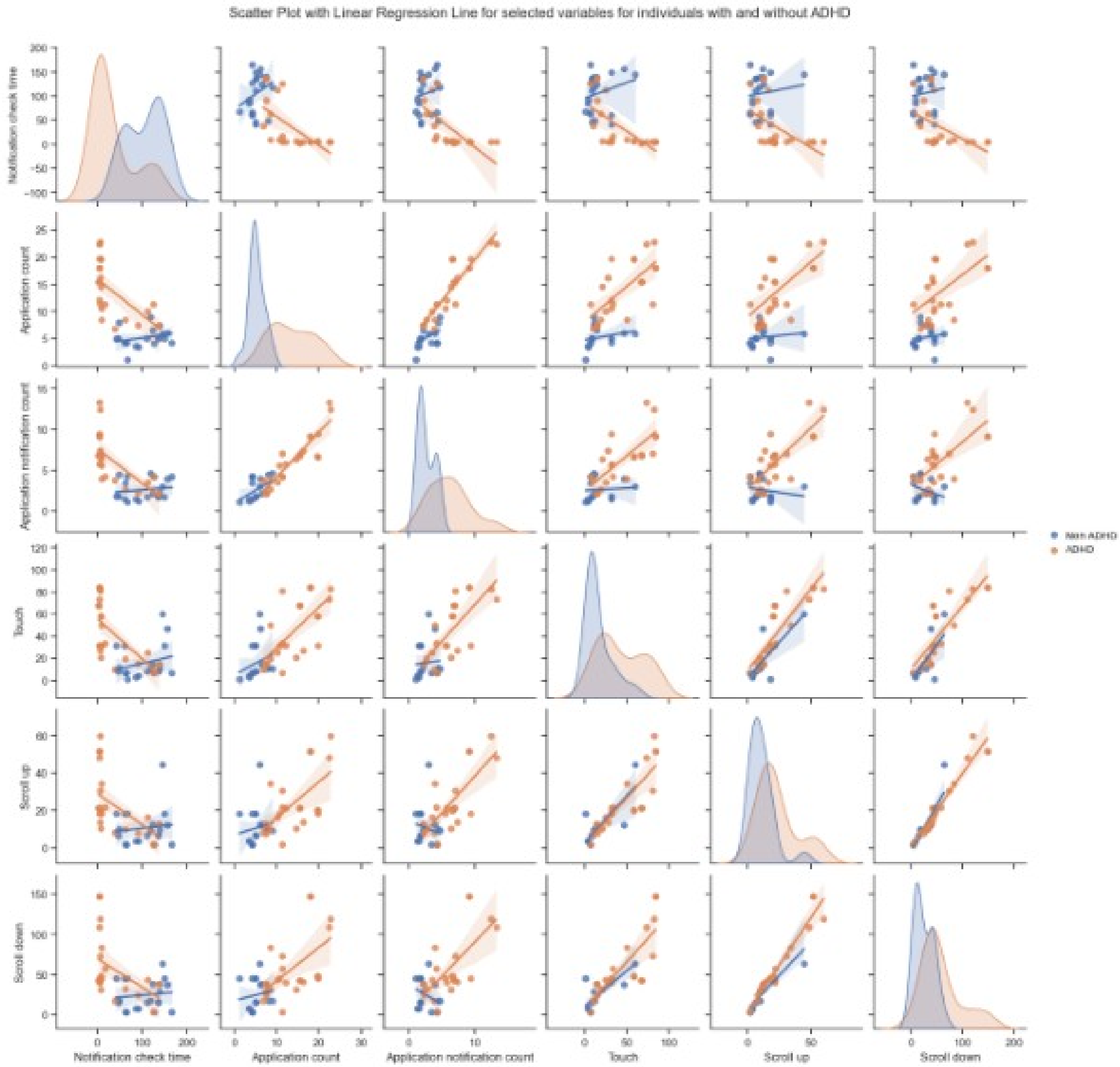

Figure 4.7: Correlation Matrix with Scatter Plots and Histograms (ADHD and Non-ADHD)

The scatterplot matrix depicted in Figure 4.7 examines the relationships among different variables for individuals with and without ADHD. The data points show scattering, and the regression line is almost horizontal. The scatter plot suggests a slight positive correlation between the time difference and mean application usage, indicating that the mean application usage tends to be higher as the time difference increases. Individuals who take longer to check notifications tend to receive more per hour. There is a negative correlation between the time difference and mean application notifications. Touch interactions exhibit a positive correlation with scroll down actions, meaning that as touch interactions increase, scroll down actions tend to increase as well. More touch interactions are associated with higher mean application usage, and this positive relationship also extends to mean application notifications. Additionally, more scroll down actions is associated with higher mean application usage. Similarly, a positive correlation exists between scroll actions and mean application notifications. To sum up, the scatterplot matrix provides insights into the behavioural patterns related to ADHD and various application interactions.

4.2.4 Model Validation

We used typical metrics for evaluating machine learning models, such as accuracy (1), precision (2), recall (3), and F1-score (4). The following are the definitions of these metrics:

$\text{Accuracy} = \text{TP} + \text{TN}/(\text{TP} + \text{FP} + \text{FN} + \text{TN})$ (1)

$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$ (2)

$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$ (3)

$\text{F1} - \text{score} = 2 * (\text{Recall} * \text{precision})/(\text{Recall} + \text{Precision})$ (4)

Where TP is truly positive, FP is a false positive, TN is a true negative, and FN is a false negative.

Table 4.4: Model evaluation matrices (ADHD and Non-ADHD) (Validation)

Classifier	Accuracy	F1 Score	Precision	Recall
DT Classifier	0.8056	0.7222	0.6667	0.8333
GNB Classifier	0.8750	0.7778	0.8333	0.7500
AdaBoost Classifier	0.7500	0.6111	0.5833	0.6667

Table 4.5: Model evaluation matrices for participants with ADHD and without ADHD (low attention and high attention) (Validation)

Classifier	Accuracy	F1 Score	Precision	Recall
RF Classifier	0.8053	0.8019	0.8838	0.7778
GB Classifier	0.8003	0.7929	0.8857	0.7667
Logistic Regression	0.8422	0.8669	0.8407	0.9111
SVC	0.7937	0.8133	0.8278	0.8222
KNN Classifier	0.806	0.8218	0.8491	0.8222
DT Classifier	0.8362	0.8503	0.8738	0.8444
GNB Classifier	0.8422	0.8534	0.8796	0.8444
MLP Classifier	0.7884	0.7821	0.8474	0.7778
AdaBoost Classifier	0.7815	0.7804	0.8447	0.7556

Table 4.6: Model evaluation matrices for participants with ADHD (low attention and high attention) (Validation)

Classifier	Accuracy	F1 Score	Precision	Recall
GB Classifier	0.5714	0.7273	0.5714	0.9800
Logistic Regression	0.8095	0.8095	0.9000	0.7917
SVC	0.7857	0.7820	0.8778	0.7917
KNN Classifier	0.7857	0.8255	0.8139	0.875
DT Classifier	0.7619	0.7894	0.8444	0.7917
GNB	0.8333	0.8499	0.8917	0.8333
MLP Classifier	0.8571	0.8730	0.9000	0.8750
AdaBoost Classifier	0.7857	0.7947	0.8778	0.7917

Table 4.4, 4.5, 4.6 and 4.7 shows comparison of the F1-scores of different models for ADHD classification across various datasets, several key patterns in their performance can be observed. Table 15 shows model evaluation metrices to classify between participants with ADHD and without ADHD: The Gaussian Naive Bayes Classifier has the highest F1-score of 0.7778, indicating a good balance between precision and recall. The Decision Tree Classifier was a close follower with an F1 score of 0.7222 while the AdaBoost Classifier had an F1 score of 0.6111. GNB had a better identification of ADHD cases correctly with less false positives. Table 16 shows model evaluation metrices to classify between participants with ADHD and without ADHD with low and high attention level. Logistic Regression scores the best F1 in Table 16 for ADHD with different attention levels: low and high, with an F1 of 0.8669. Other notable performing classifiers are DT Classifier (F1=0.8503) and GNB Classifier with a score of 0.8534. Support Vector Classifier, also known as SVC, did well in these scenarios as well and posted 0.8133 along with KNN (0.8218), while the last spot has been held by AdaBoost Classifier, performing poorest for this task as stated with an F1 of 0.7804. Table 17 (ADHD participants with low and high attention), the MLP Classifier is leading among others, with an F1-score of 0.873, closely tagged by GNB Classifier of F1 = 0.8499, showing that this algorithm also does well in identifying the case for ADHD. The next goes to the performance of the Logistic Regression-based models with an F1 = 0.8095 and a performance of KNN-based models with an F1 = 0.8255. The Gradient Boosting Classifier has a relatively lower F1-score at 0.7273, though its high recall of 0.98 indicates that it is very good in picking out cases of ADHD, even if it is poor in precision. In Table 18, non-ADHD participants with low and high attention, high F1 values for distinguishing between the mental states manifest in RF Classifier - 0.7138 and for AdaBoost Classifier 0.6936, whereas there is a general sense of outperformance in overall precision or recall for RF Classifier (F1= 0.7005), and GNB Classifier being the weak one, whose F1 value is lowest- 0.572. While the performance of the best models is contributed by MLP Classifier and GNB Classifier on all

ADHD-focused datasets, the Logistic Regression also works effectively on most data, especially on ADHD cases and fluctuating attention levels. AdaBoost and GB proved more inconsistent, wherein AdaBoost generally performed a bit worse for ADHD-related tasks, whereas GB performed worst for the non-ADHD case. The performance of the RF Classifier was reasonable in several non-ADHD cases but didn't manage to outperform other models on ADHD classification.

Table 4.7: Model evaluation matrices for participants without ADHD (low attention and high attention) (Validation)

Classifier	Accuracy	F1 Score	Precision	Recall
RF Classifier	0.8229	0.7138	0.6119	0.8750
GB Classifier	0.8333	0.6416	0.7452	0.6667
Logistic Regression	0.8021	0.7005	0.5757	0.9167
SVC	0.7708	0.6591	0.5352	0.8750
DT Classifier	0.8229	0.6370	0.7333	0.6667
GNB Classifier	0.8021	0.5720	0.5008	0.7083
MLP Classifier	0.7500	0.6220	0.5282	0.7917
AdaBoost Classifier	0.8333	0.6936	0.7333	0.7500

4.2.5 Feature Importance

We start by getting data from a structured file format and handle any missing values using mean imputation. We then create a dictionary to store different results. This includes statistical test outcomes, means, standard deviations for ADHD and non-ADHD groups, and feature importance scores. We perform a two-sample t-test for each numeric column to compare the ADHD and non-ADHD groups. Additionally, we train a Random Forest classifier on the imputed data to determine feature importance. We add the resulting feature importance scores to the results dictionary. Finally, we analyse the relationships between numeric features and ADHD status. This provides valuable insights through statistical tests and machine learning feature importance analysis.

Table 4.8 presents a detailed comparison of key features extracted from individuals with ADHD and those without it, based on their application usage, touch interactions, and keyboard usage. Statistical analysis, including the Mann-Whitney U test, indicates significant differences between the two groups. Individuals with ADHD tend to exhibit unique behaviours, such as quicker notification check times, higher application counts, and more frequent touch and scroll interactions compared to their non-ADHD counterparts. Additionally, individuals with ADHD demonstrate faster typing speeds, suggesting potential differences in cognitive processing and motor skills. However, typing error percentages do not significantly differ between the two groups. These findings emphasise the usefulness of digital behavioural data in distinguishing between individuals with ADHD and those without ADHD.

Table 4.8: Top features from Application, Touch, keyboard sensor across classes ADHD and NON-ADHD: U- Whitney test, p-value (if p**<0.00001, if p*<0.02),

Features	Type	Feature Importance	W-Statistic	Mean feature value		Std Feature Value	
				ADHD	Non-ADHD	ADHD	Non-ADHD
Notification check time**	App Data	0.0541	64	35.3140	105.7036	48.5423	40.7997
Application count**	App Data	0.2087	470	13.6937	5.2438	5.1115	1.7704
Application notification count**	App Data	0.0223	418	6.1759	2.6236	3.0764	1.2227
Touch and scroll count**	Touch	0.0318	399	113.068	45.3747	60.3078	35.7558
Touch count*	Touch	0.0649	402	43.0128	15.8596	26.9739	15.5521
Long touch	Touch	0.0184	314	1.722	1.5452	0.8709	0.8570
Scroll down count*	Touch	0.0274	381	57.5561	24.7282	38.6999	18.0678
Scroll up count*	Touch	0.0395	389	23.132	10.6535	15.726	9.6558
Typing speed*	Keyboard	0.6658	64	0.2358	1.6091	0.1405	6.9665
Typing error percentage	Keyboard	0.3342	470	4.4284	3.8892	2.6468	2.2668

Table 4.9 displays the main features extracted from the accelerometer and location sensor data for ADHD and non-ADHD classes. It includes the feature importance, statistics, mean feature values, and standard deviations. The results from U-Whitney tests are also presented with reported p-values, indicating significance levels (if p<0.02, if p<0.00001). Activity features such as sitting, standing,

walking, running, and total activity were analysed for accelerometer data. They showed varying levels of importance between ADHD and non-ADHD classes. Notably, running activity was found to have higher importance for ADHD, while walking activity was more critical for non-ADHD. Ratios of walking, running, and sitting-to-standing activities were also examined, showing significant differences between the two classes. For location data, the unique location count from GPS data was found to be highly important for both classes. ADHD participants had slightly lower unique location counts than non-ADHD participants.

Table 4.9: Top features from Accelerometer and location sensor across classes ADHD and NON-ADHD: U- Whitney test, p-value (if p**<0.00001, if p*<0.02)

Features	Type	Feature Importance	Statistic	Mean feature value		Std Feature Value	
				ADHD	Non-ADHD	ADHD	Non-ADHD
Activity (Sitting)	Accelerometer	0.0881	182	179827.9	976258.6	299109.5	2072903.4750
Activity (Standing)	Accelerometer	0.1000	170	166252	236518.2	259954	404194.8699
Activity (Walking)	Accelerometer	0.0766	192	257627.5	96142.67	728679.8	140958.4778
Activity (Running)	Accelerometer	0.1282	208	187755.1	50713.89	461416.7	126000.2400
Activity (Total)	Accelerometer	0.0914	178	791462.5	1359633	1411504	2585638.8650
Activity (walking ratio)*	Accelerometer	0.1294	240	0.2351	0.1636	0.1587	0.1044
Activity (running ratio)*	Accelerometer	0.0780	214	0.1957	0.1715	0.1428	0.1405
Activity (Sitting standing ratio)*	Accelerometer	0.1043	172	1.812	2.2428	1.5136	2.0073
Unique Location Count*	Location (GPS)	0.8454	240	5.9343	8.2899	3.3434	5.3434

Table 4.10: Top features from Application, Touch, keyboard sensor across participants with low and high attention levels for participants with and without ADHD: U- Whitney test, p-value if (p**<0.00001, if p*<0.02)

Features	Type	Feature Importance	W-Statistic	Mean Feature value		Standard feature value	
				Attention level (low)	Attention level (high)	Attention level (low)	Attention level (high)
Application count**	App Data	0.0565	1664	5.948	12.1368	2.7084	4.8076
Mean application notification count**	App Data	0.0272	2252	2.1854	5.1046	1.2154	2.5882
Touch and Scroll count**	Touch	0.0174	2695	42.1923	94.7332	31.626	45.0884
Touch Count*	Touch	0.0143	2344	12.755	34.1142	12.5949	21.6478
Scroll down. Count*	Touch	0.0116	3198	22.928	43.2802	19.6371	17.2596
Scroll up count*	Touch	0.0183	2866	8.6513	19.9795	7.5965	12.5760
Typing speed*	Keyboard	0.6658	16472	0.2358	1.6091	0.1405	6.9665
Typing error percentage	Keyboard	0.3342	1664	4.4284	3.8892	2.6468	2.2668

Table 4.11: Top features from Application, Touch, keyboard sensor across participants with low and high attention levels for participants without ADHD: U- Whitney test, p-value (if p**<0.00001, if p*<0.02).

Features	Type	Feature Importance	U-Statistic	Mean feature value		Std feature value	
				Attention level (low)	Attention level (high)	Attention level(low)	Attention level (high)
Application count**	App Data	0.0471	683	7.876	13.3678	3.4255	4.4992
Application count night**	App Data	0.0188	678	7.7976	13.4097	3.3116	4.7716
Application count (system app)**	App Data	0.0412	758	4.866	7.9191	1.9914	2.625
Application notification count**	App Data	0.0471	767	2.7875	5.7057	1.7441	2.526
Application notification night**	App Data	0.0093	650	2.6738	5.6924	1.6527	2.6943
Touch and scroll count**	Touch	0.0184	839.5	55.5099	95.536	25.1687	36.371
Touch count*	Touch	0.0265	700	15.2383	34.8819	7.8399	17.7385
Scroll down count*	Touch	0.01	1117.5	30.2228	43.9001	13.9621	17.0045
Scroll up count*	Touch	0.0181	862	10.7096	20.0185	5.6869	9.8638

Table 4.12: Top features from Application, Touch, keyboard sensor across participants with low and high attention levels for participants with ADHD: U- Whitney test, p-value (if p**<0.00001, if p*<0.02),

Features	Type	Feature Importance	U-Statistic	Mean feature value		Std feature value	
				Attention level	Non-attention level	Attention level	Non-attention level
Application count**	App Data	0.0772	230	4.8537	8.5122	1.2700	3.7791
Application count night**	App Data	0.0276	637	4.6829	7.5420	1.3184	4.2794
Application count (system app) *	App Data	0.0394	254	3.1630	5.2420	0.7039	2.4787
Application notification count*	App Data	0.0240	454	1.8437	3.3346	0.5400	1.8782
Application notification night*	App Data	0.0141	800	1.7528	2.6616	0.5585	1.4914
Touch and scroll count	Touch	0.0234	395	34.6336	92.3693	32.5565	64.9130
Touch count*	Touch	0.0137	356	11.3456	31.8539	14.4851	30.6088
Scroll down count*	Touch	0.0116	417	18.7876	41.455	21.2131	18.1118
Scroll up count*	Touch	0.0307	428	7.4831	19.8646	8.3019	18.5807

The comparison of Table 4.11, 4.12 and 4.13 gives us a better understanding of digital interaction behaviours across individuals with varying levels of attention and ADHD status. We can see that certain features consistently emerge as significant metrics for understanding digital behaviours across all tables (11, 12, and 13). These features include metrics related to application usage, touch interaction, and typing behaviour. However, we can see differences in mean feature values and importance levels when we examine the variations across attention levels. For instance, individuals with high attention levels tend to exhibit higher mean values and importance levels for metrics like application count and notification count, indicating potentially more frequent digital interactions among this group. Conversely, features such as typing speed may vary significantly, suggesting differences in digital engagement efficiency between low and high attention groups.

4.4 Summary

The classification results demonstrate that smartphone sensor data can distinguish between ADHD and non-ADHD individuals. With the use of smartphone sensor data, clinicians can have real-time information about the activities and movements of individuals to have more objective and ongoing monitoring of symptoms in ADHD. This not only streamlines the diagnostic process but also facilitates the development of personalised treatment plans tailored to individual needs and behaviours. Furthermore, feature importance analysis yields valuable insights into the digital behaviours and physiological markers associated with ADHD. Significant disparities were observed in metrics such as application usage, touch interactions, and typing behaviour between individuals with ADHD and those without. ADHD participants exhibited faster notification check times, higher application counts, and more frequent touch interactions, suggesting the presence of ADHD-like behavioural patterns.

CHAPTER 5

CLASSIFICATION OF EATING DISORDERS USING SMARTPHONE SENSOR DATA

5.1 Introduction

Eating disorders are serious mental disorders with abnormal eating behaviour, concern about weight and form, and in many cases a serious interest in food, diet and appearance (Treasure & Schmidt, 2013; Kearns & Taddeo, 2019). Eating disorders are a complex set of disorders with features of anorexia nervosa, bulimia nervosa and binge eating disorder, with serious physical, psychological and social consequences (Smink et al., 2012; Grilo et al., 2013). Most patients with eating disorders have also been diagnosed with depression, anxiety or obsessive-compulsive disorder, which makes it even more difficult to classify and treat them (Stice et al., 2013; Kenny et al., 2021). Classification of eating disorders has traditionally relied on self-reported data, which are time-consuming and prone to bias. In addition, stigma - and the expectation of stigma - often leads to a lack of reporting, which delays diagnosis and treatment (Agbu and Ebele, 2014; Bloom et al., 2013). Smartphones offer a promising solution to these problems, as they allow continuous, passive, objective data collection (Kearns & Taddeo, 2019).

Indeed, modern smartphones have sensors such as accelerometers, gyroscopes, GPS, touch sensors, and more. This will provide scope to analyse a complete picture of the participant's pattern of behaviour. Sensors can be used to capture physical activity, sleep, trajectories of movements, and environmental factors that provide much more insight into behaviours related to a variety of mental health disorders (Woolley & Peterson, 2016; Daziel & Gill, 2021). Accelerometer signals can provide information about activity levels and patterns, and these can be informative in the classification of eating disorders (Hübel et al., 2020). To provide some examples, abnormal activity, which has been linked to anorexia nervosa, can be detected with ease using accelerometer-based monitoring (Lowe et al., 2019). GPS (location) data can be used to track the participant's mobility—for instance, avoidance of specific locations such as social settings or public spaces—can be a symptom of social judgmental fear or social anxiety (Numata et al., 2020). On the contrary, frequent visits to a specific location, such as gyms or fast-food places, could be a symptom of compulsive and rigid behaviours common in eating disorders (Gucciardi et al., 2004). The smartphone's sensors can also provide information about the user's level and rate of engagement with his or her smartphone. To provide some examples, compulsive or repetitive tapping, scrolling, or checking of specific eating-related apps can be a symptom of anxiety or emotional distress (Sowles et al., 2018). This can be linked to unhealthy activity such as abnormal calorie counting, frequent checking of fitness apps, or use of social media for body comparison (Masheb & Grilo, 2000).

High screen time with food or exercise applications, or longer hours spent in surfing social media, could be a sign of body obsession and weight regulation common in disorders like anorexia and bulimia (Hagan et al., 2003; Mathes et al., 2009). Frequent use of calorie tracking applications, exercise monitoring, or body image social media may be a sign of eating disorder behaviours (Kearns & Taddeo, 2019). In contrast, a preference to use specific apps during specific hours or in specific contexts—e.g., use of exercise apps during late nights—could be a sign of binge eating episodes or bulimia nervosa (Daziel & Gill, 2021). However, there are limitations in using smartphone sensor information in mental health classification. To begin with, there could be biases in terms of representativeness and accuracy in information. Smartphone possession and smartphone use habits vary extensively across different population segments (Bruneau et al., 2017). This could result in biased information or even the absence of a particular population in a dataset. Moreover, variations in sensor quality could lead to inaccuracy in information collection across devices (Miniati et al., 2021). It would thus be necessary to have strict preprocessing and model calibration to ensure algorithms work effectively across populations and environments (Lewis-Smith et al., 2020). It is thus imperative to correct these biases to ensure effectiveness and equity in smartphone-based solutions in the future.

5.2 Methodology

The data of this study (study 3) were obtained from East West Institute of Technology, Bangalore, India, after getting ethics approval from East West University. We recruited 55 participants between the ages of 18-23 years and collected data from each participant for approximately one week. Initially, 16 females and 39 males were recruited. Six participants from control group were excluded from the study due to insufficient data or diagnosed with neurological conditions (including epilepsy, schizophrenia, or borderline personality disorder (BPD)). The study will use questionnaires, such as the binge eating scale (BES), to classify whether participants have eating disorders or not. The methodology will involve recruiting participants based on their BES scores and categorising the severity of binge eating (None, moderate, and severe). The participants were classified into three categories depending on their BES scores: 16 participants with no eating disorder, 15 participants with a medium eating disorder, and 18 participants with a high eating disorder.; the main objective of this study is to gain insight into binge eating behaviours and their impact on individual's overall well-being. The final data set hence consisted of 49 participants (13 females and 36 males). Before the data collection, a nutrition expert (nutritionist) was consulted to obtain the best methods for capturing day-to-day eating patterns and nutrient consumption in naturalistic and non-intrusive manners. A manual food diary was included in the study to record the times of participants' meals, what food was consumed, and basic nutritional information. Eating timing supplied information about irregular eating habits, rate of meals, and potential instances of meal avoidance, while nutritional information allowed for patterns like restrictive eating or binge-eating behavior to be identified. Our inclusion criteria are as follows: (1) Participants must be Android users (Android version ≥ 5.0; iOS ≥ 8.0)

because iPhones do not allow us to monitor phone usage as required for our study, and (2) Participants must be 18 years, or older (3) Participants must be fluent in English.

At the start of the study, each participant filled out standardised pre-questionnaires. We asked the participants to complete a BES at the beginning of the study. The binge eating scale (BES) is a questionnaire consisting of 16 items. Eight of these 16 items describe observable actions related to binge eating, while the remaining eight focus on associated emotions and thoughts. Each item has four statements representing varying levels of severity. Participants choose the statement that best reflects their perceptions and feelings about their eating habits. The BES is scored by summing the values assigned to each of the 16 items, resulting in a score range from 0 to 46 (Timmerman, 1999). Based on BES scores, uncontrolled eating behaviour is categorised into three levels of severity:

a) Individuals scoring 17 or below are classified as non-binge eaters.
b) Those scoring between 18 and 26 are considered moderate binge eaters.
c) Individuals scoring 27 and above are identified as severe binge eaters.

During the study, a mobile food diary was used to capture details of their food intake, and end-of-the-day surveys were conducted to gather additional information on their activity, sleep, and mood. Participants were asked to provide data on their latest food intake, including when the eating episode occurred, food categories (meat, fish, bread, etc.), social context of eating (alone, with a date, with a group of friends, etc.), semantic eating location (home, university, restaurant, etc.), concurrent activities (reading, socialising, watching TV, etc.), and their mood and stress levels at the time of eating (on a 5-point scale).

This study (study 3) aims to develop a model for classifying participants with eating disorders and those without eating disorders using data obtained from smartphone sensors to evaluate a person's physical activity patterns. Figure 4.1 illustrates the four phases of a typical activity identification framework: (1) Data collection, (2) Data pre-processing, (3) Feature selection, and (4) Classification. Several sensors will be used to gather information about human behaviour. After data collection, we performed data pre-processing, which involves cleaning raw data to make it suitable for analysis. Data pre-processing includes several phases, such as data cleansing (removing or cleaning missing, inconsistent data), data integration (merging data from multiple sources), data transformation (normalising, scaling, or transforming data), and data reduction (removing unwanted data) Yang X et al., (2023).

We extracted several features from the pre-processed data. Based on the study by Yang X et al. (2023), we used a classification model to classify participants with and without prior eating disorders. Participants in the study will be asked to download a smartphone application called "AWARE." This application has been specifically designed to collect data regarding phone usage patterns. The data collected includes location data, battery sensor data (charging and discharging), light sensor data, keyboard data (typing behaviour), screen on/off timing, rotation sensor data (orientation of the phone), accelerometer sensor data (acceleration applied to the device), and phone app usage (e.g., social media, movies, music, games). Location data, obtained from GPS-enabled smartphones, can provide insights into the eating habits of individuals with eating disorders. This data can help researchers monitor individuals' movements and identify potential environmental factors that may trigger disordered eating behaviours. For example, Researchers can use location data to monitor how frequently individuals with eating disorders visit restaurants or grocery stores (Adams, 2018). Smartphone accelerometer data is another valuable resource for studying eating disorders. These accelerometers measure the phone's movement and can be used to track individuals' activity levels. Researchers can leverage accelerometer data to identify individuals who may be excessively restricting their food intake or engaging in excessive exercise due to their eating disorders (Brown, 2020). Screen data, which includes information on the duration and frequency of app usage and the types of content accessed on smartphones, is also valuable for identifying patterns related to disordered eating behaviours, such as excessive engagement with meal planning or weight loss apps (Jones, 2017). Touch data, which involves touchscreen interactions like swipe gestures and touch pressure, can be used to detect patterns related to engagement with gaming or self-monitoring apps. These patterns can potentially indicate the presence of disordered eating behaviours (Blake, 2018).

5.2.1 Data Analysis and Feature Selection/Extraction

Exploratory Data Analysis (EDA): In the initial stages of data analysis, it is crucial to clean and preprocess the smartphone data. This involves handling missing data, addressing outliers, and ensuring data quality. Exploratory data analysis (EDA) helps in understanding the distribution of data, relationships between variables, and usage patterns of smartphones. The input data sets may contain unwanted data that needs to be removed before analysis (Ang, C.S. et al., 2023). We will use the time zone data of each participant to convert the UNIX timestamps into a human-readable local date and time format. Data collected from online diaries and phone data can be noisy, and the data preprocessing stage handles noisy data. It is essential to transform some data to make it suitable for analysis. This can be done using data cleaning techniques such as data quality evaluation, noise reduction, detecting faulty data, and interpolating missing values (Ang, C.S. et al., 2023), (Sano, A. et al., 2018).

It is necessary to extract informative features from raw data to classify eating disorders effectively. Feature extraction involves identifying the most informative features that can be used to build a classification model. It can be possible to analyse screen time in a day, app use frequencies, variations in a user's day-to-day routines, and different metrics that can be a symptom of eating disorders. It is necessary to use feature engineering to enhance the informativeness of the data for classification. (Ang, C.S. et., 2023).

Table 5.1: Features extracted from smartphone data (Breit M et al.,2023), (Wang L et al.,2022), (Zhu F et al., 2014), (Bangamuarachchi W et al., 2022).

Data Source	Feature Name	Description
Mobile App Data	Food Types	Categorise the types of food individuals are tracking in apps.
	Food Quantities	Quantify portion sizes recorded by individuals.
	Meal Timing	Extract timestamps of meal entries for eating pattern analysis.
Location Data	Location Visits	Calculate the frequency of visits to specific places (e.g., restaurants, grocery stores).
	Distance Travelled	Quantify the distance travelled by individuals, potentially related to eating habits.
Smartphone Accelerometer	Activity Levels	Analyse accelerometer data to assess physical activity and sedentary behaviours.
	Activity Patterns	Identify patterns of excessive exercise or overly restricted food intake.
Gyroscope Data	Bodily Movements	Extract features related to bodily movements during eating episodes (e.g., speed, duration).
Screen Data	App Usage Patterns	Calculate the duration and frequency of app usage.
	Content Access	Categorise the types of content accessed on smartphones and quantify time spent on specific categories.
Touch Data	Touchscreen Interactions	Analyse swipe gestures and touch pressure to detect patterns related to engagement with specific apps.

Table 5.1 indicates a collection of characteristics derived from various data sources of smartphones that are relevant to insights on eating and patterns of behavior (Breit M et al., 2023; Wang L et al., 2022; Zhu F et al., 2014; Bangamuarachchi W et al., 2022). Data from mobile applications have information regarding food types, portion sizes, and when they are consumed, which can be utilized to categorize eating habits and research eating habits over long periods. Location data offer data on the visits to a particular location such as a restaurant or grocery store and the total distance traveled, which can be representative of food behavior mobility patterns. Accelerometer smartphone data are used to inform assessment of physical activity levels and identification of patterns of overexercise or restrictive food intake, while gyroscope data track body movement during meal occasions, such as the speed and amplitude of movement. Screen data focus on usage patterns and types of content viewed, informing digital exposure. Finally, touch data analyze touchscreen behavior, including swipe gestures and touch pressure, to discern patterns of behavioural reaction to app use. All these

multimodal data streams enable a comprehensive picture of daily behavior using passive smartphone monitoring.

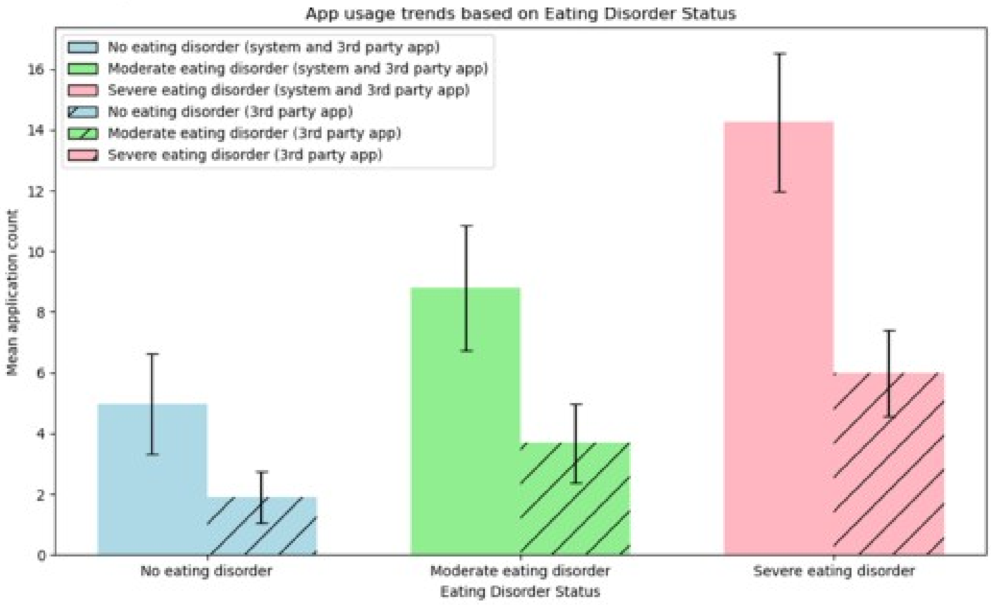

Figure 5.1 Comparative Analysis of App Usage Trends Based on Eating Disorder Severity

Figures 5.1 present comparison of eating disorder status, the persons without a disorder used the least amount of apps, followed by persons with moderate eating disorders who used more apps, and finally, those with severe eating disorders used the most. Those with severe eating disorders use roughly twice as many apps compared to the ones with no disorder.

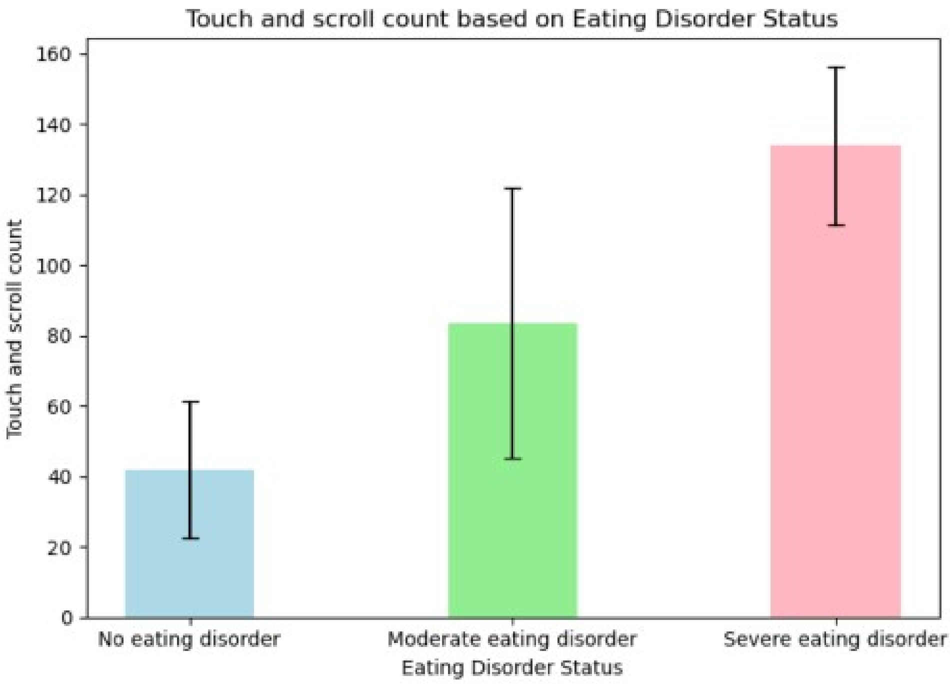

Figure 5.2. Comparison of User Engagement in Touch and scroll Activity Across Different Eating Disorder Statuses

The Figure 5.2 shows that individuals with severe eating disorders or poor mental well-being have higher smartphone interaction—measured by touch and scroll frequency—compared to those with moderate or no symptoms. This suggests that increased app usage may be linked to mental health severity and could serve as a digital indicator for monitoring these conditions.

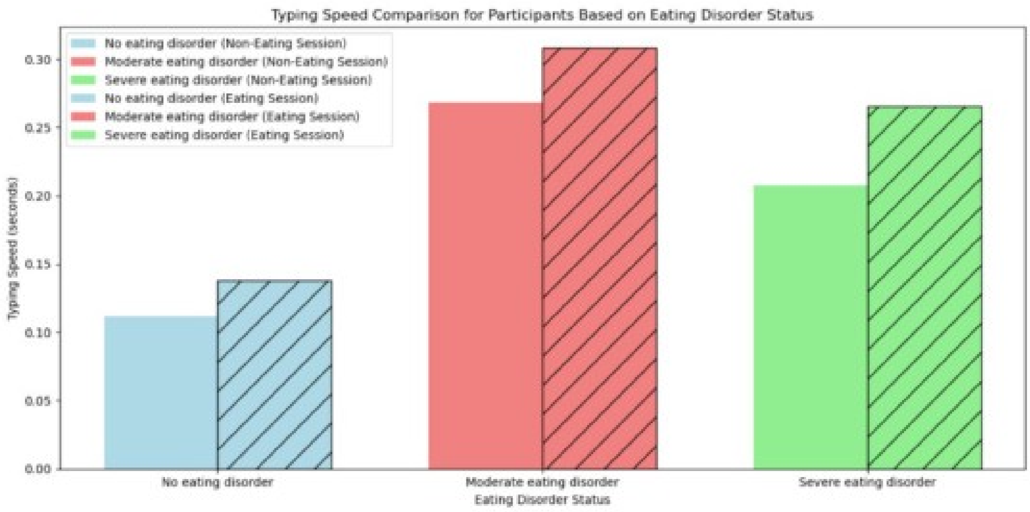

Figure 5.3: Comparing Typing Speed Between Individuals With and without eating disorders

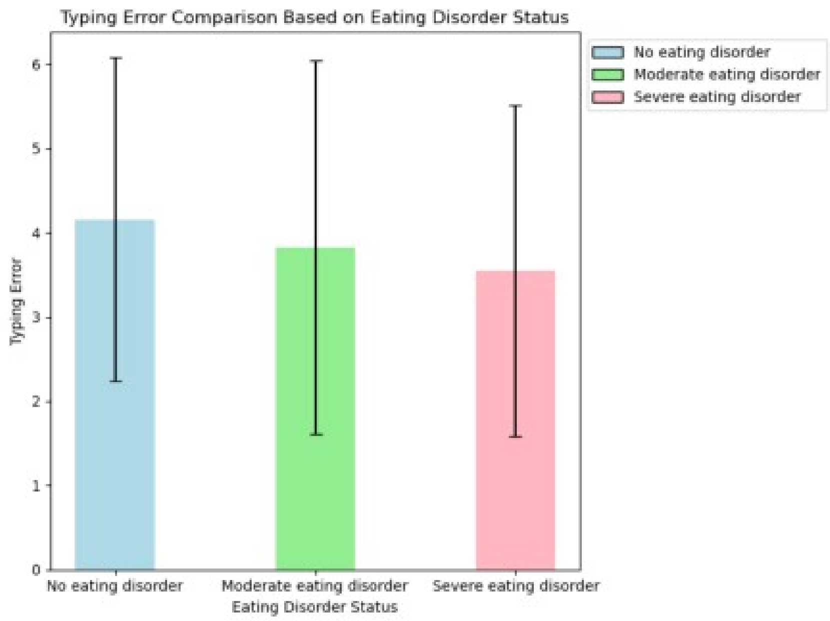

Figure 5.4: Comparison of Typing error Between Individuals with and without eating disorder

The Figure 5.4 depicts the correlation between the number of typing errors and the presence of an eating disorder. The study participants were categorised into three groups: no eating disorder, moderate eating disorder, and severe eating disorder. According to the graph, individuals with severe eating disorders commit the highest number of typing errors, followed by those with moderate eating disorders. Conversely, people with no eating disorder make the fewest typing errors. In summary, the trend indicates that the severity of the eating disorder is directly proportional to the number of typing errors made.

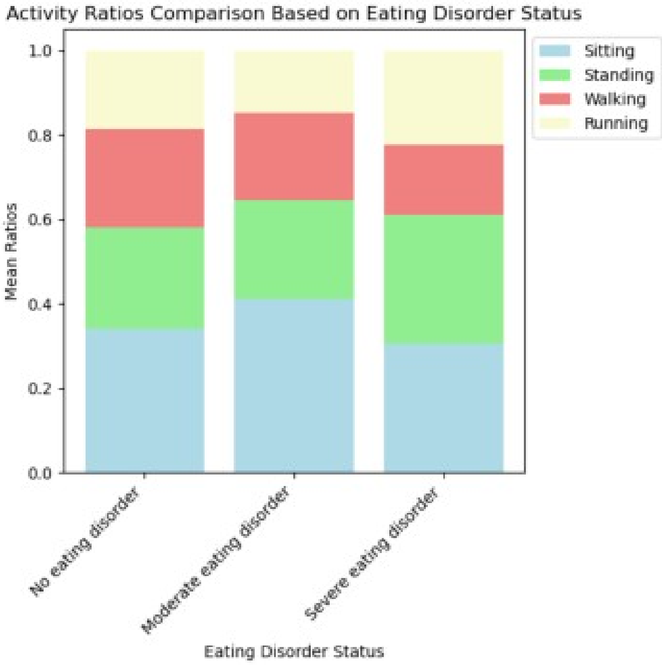

Figure 5.5: Bar chart of Activity Ratios comparison among Different conditions between individuals with and without eating disorder

The Figure 5.5 illustrates a comparison of activity levels among individuals with different types of eating disorders. The y-axis represents the average activity levels, while the x-axis indicates the severity of the eating disorder (no eating disorder, moderate eating disorder, severe eating disorder). Each group consists of three bars that depict the levels of activity: sitting, standing, walking, and running.

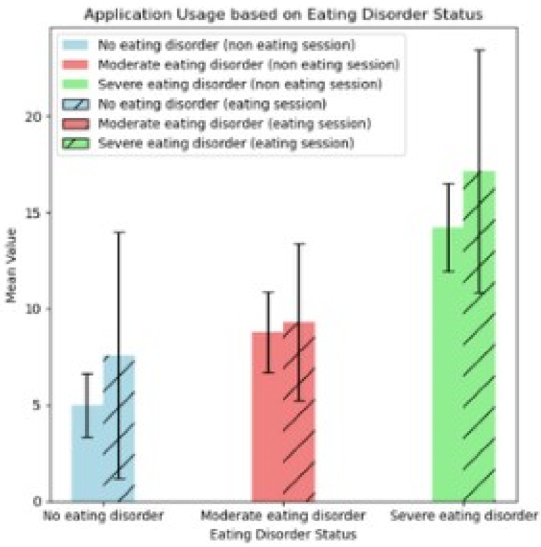

Figure 5.6: Comparison of Application Usage based on Eating Disorder Status during Eating and Non-Eating Sessions

Figure 5.6 depicts the use of applications among individuals with varying levels of eating disorders during eating and non-eating sessions. It shows that application usage increases as the severity of the eating disorder increases, both during eating and non-eating sessions. This suggests that individuals with more severe eating disorders tend to use applications more frequently, especially during eating sessions.

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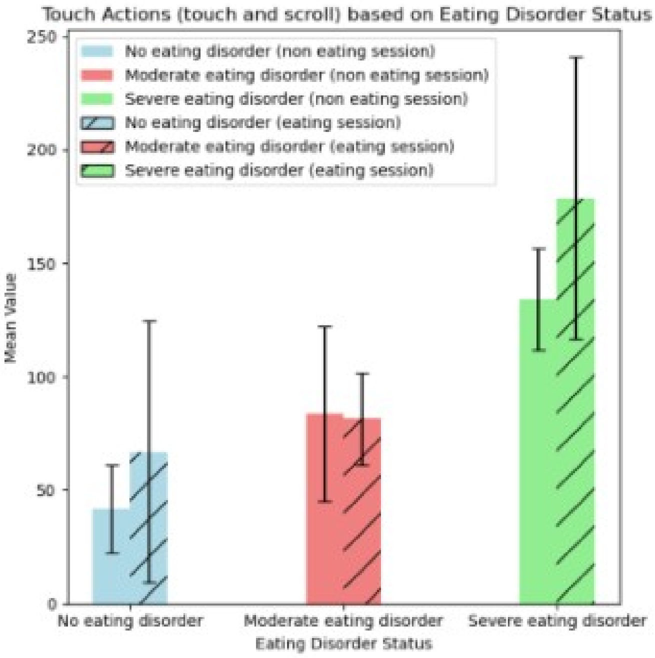

Figure 5.7: Comparison of Touch Actions (Touch and Scroll) among Individuals with No, Moderate, and Severe Eating Disorders during Non-Eating and Eating Sessions

Figure 5.7 represents the mean values of touch actions, including tapping and scrolling, observed during both non-eating and eating sessions across three distinct categories of eating disorder status: individuals with no eating disorder, those with a moderate eating disorder, and those with a severe eating disorder. Notably, the group classified as having no eating disorder exhibits the lowest mean values of touch actions, while the moderate eating disorder group shows marginally higher mean values. Moreover, the severe eating disorder group displays the highest mean values of touch actions. It is important to note that all groups demonstrate increased touch actions during eating sessions compared to non-eating sessions.

Figure 5.8 compares typing speeds among participants based on their eating disorder status during non-eating and eating sessions. Participants without an eating disorder exhibited the highest typing speeds, while those with a moderate eating disorder demonstrated lower typing speeds. Additionally, participants with a severe eating disorder displayed even lower typing speeds.

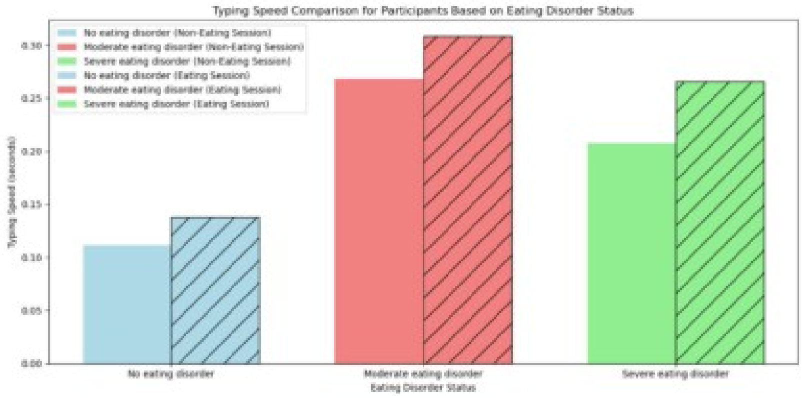

Figure 5.8: Comparison of Typing Speed by Eating Disorder Status and Session Type

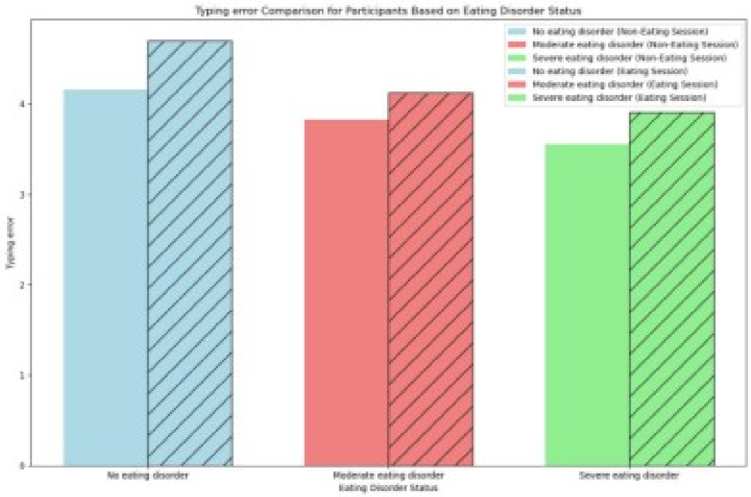

Figure 5.9: Bar Graph of Typing Error Rates by Eating Disorder Status and Session Type

Figure 5.9 visually represents the association between the frequency of typing errors and the severity of eating disorders. It compares individuals with no eating disorders, those with moderate eating disorders, and those with severe eating disorders during both non-eating and eating sessions. It's worth noting that individuals with severe eating disorders exhibited the highest number of typing errors in both sessions, while participants without an eating disorder displayed the fewest errors.

Figure 5.10 shows the average light intensity for participants categorised by their eating disorder status during non-eating and eating sessions. The participants were grouped into three categories: no eating disorder, moderate eating disorder, and severe eating disorder. It's important to note that the average light intensity rises as we move from no eating disorder to severe eating disorder in both non-eating and eating sessions. However, the increase is more significant during eating sessions

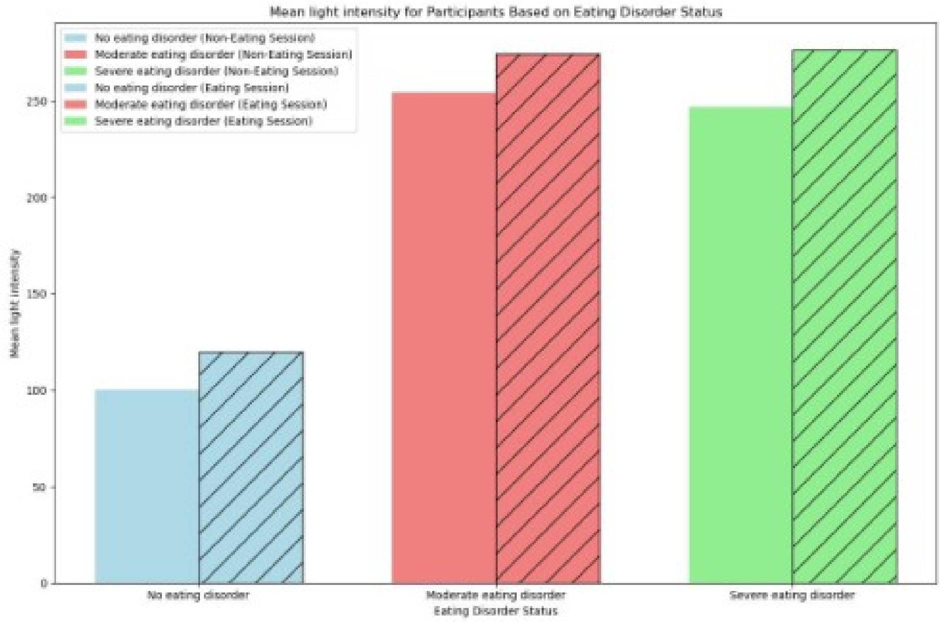

Figure 5.10: Comparison of Mean Light Intensity for Participants with Different Eating Disorder Statuses During Non-Eating and Eating Sessions

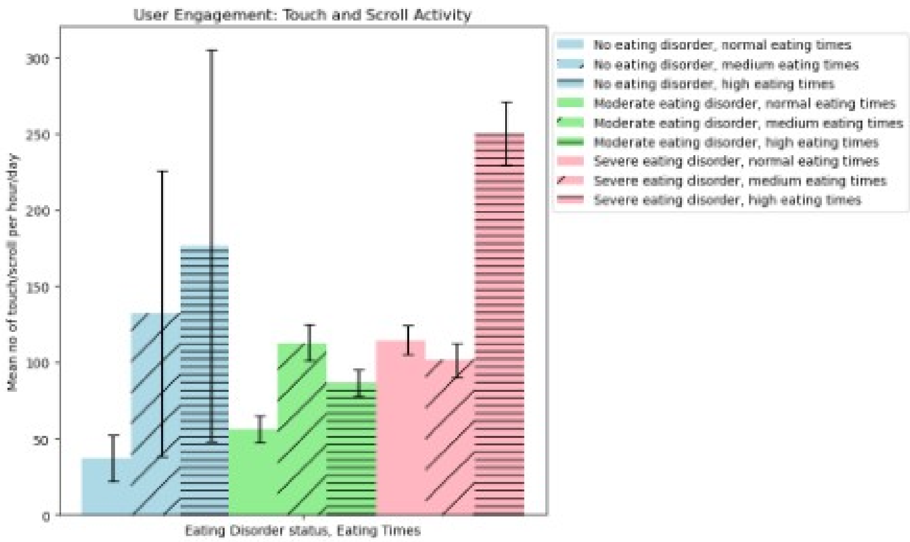

Figure 5.11: Graph of User Engagement based on Touch and Scroll Activity for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.11 depicts the average number of touch and scroll interactions per hour for various groups according to their eating disorder status and eating times. The findings show that people without eating disorders, particularly those who eat normally, are less likely to engage in touch and scroll activities. Individuals with severe eating disorders engage in more touch and scroll interactions, particularly during peak eating times.

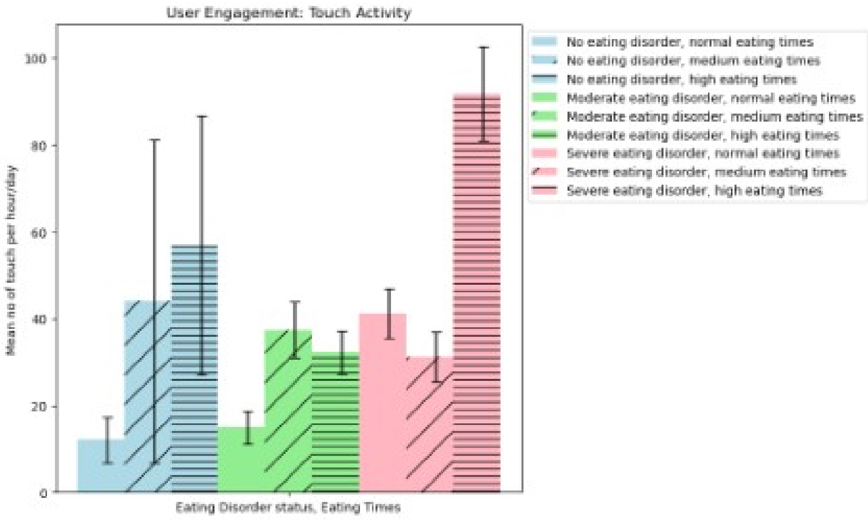

Figure 5.12: Graph of User Engagement based on Touch Activity for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.12 depicts the average number of touch interactions per hour for various groups according to their eating disorder status and eating times. The findings show that people without eating disorders, particularly those who eat normally, are less likely to engage in touch activities. Individuals with severe eating disorders engage in more touch interactions, particularly during peak eating times.

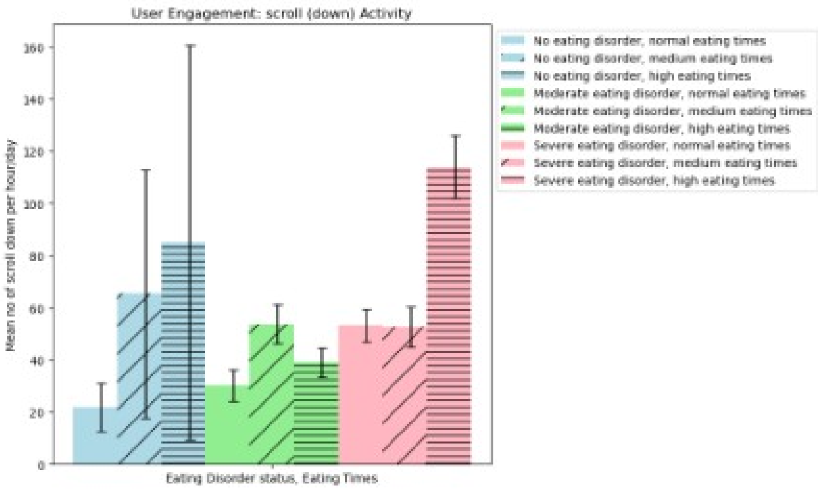

Figure 5.13: Graph of User Engagement based on Scroll (down) Activity for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.13 depicts the average number of scroll (down) interactions per hour for various groups according to their eating disorder status and eating times. The findings show that people without eating disorders, particularly those who eat normally, are less likely to engage in scroll (down) activities. Individuals with severe eating disorders engage in more scroll (down) interactions, particularly during peak eating times.

Figure 5.14: Graph of User Engagement in Scroll (Up) Activity for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.14 depicts the average number of scroll (up) interactions per hour for various groups according to their eating disorder status and eating times. The findings show that people without eating disorders, particularly those who eat normally, are less likely to engage in scroll (up) activities. Individuals with severe eating disorders engage in more scroll (up) interactions, particularly during peak eating times.

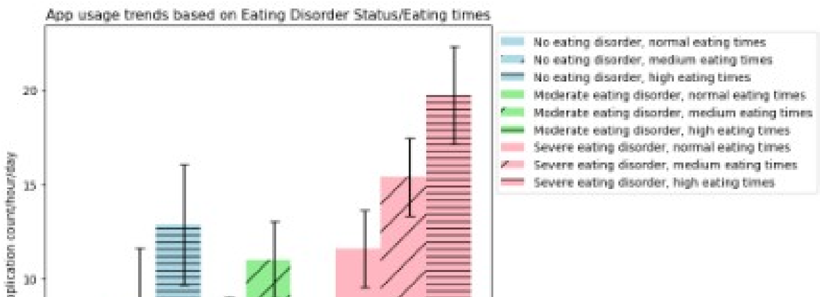

Figure 5.15: Comparison of Mean Application Count per Hour for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.15 illustrates how app usage varies according to eating disorder status and eating times. It shows the average number of times the app is used per hour per day across various groups. People without eating disorders are more likely to use the app as their eating habits progress from normal to medium to high. This pattern is even more noticeable in people with moderate to severe eating disorders.

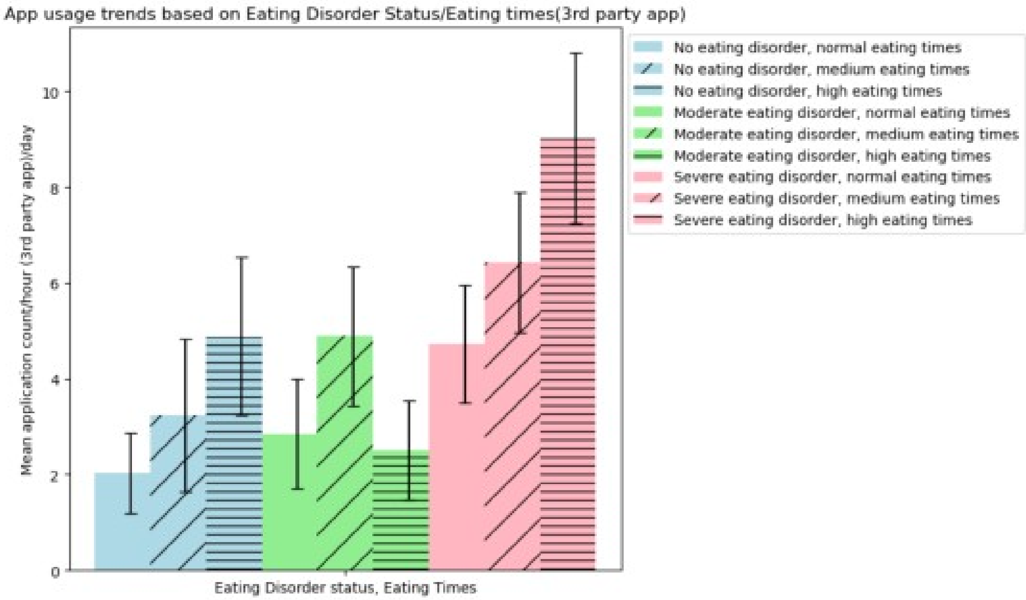

Figure 5.16: Comparison of Mean Application (3rd party app) Count per Hour for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.16 depicts how app usage (3rd party app) changes depending on eating disorder status and eating times. It shows the average number of times the app is used per hour per day across various groups. People without eating disorders are more likely to use the app as their eating habits progress from normal to medium to high. This pattern is even more noticeable in people with moderate to severe eating disorders.

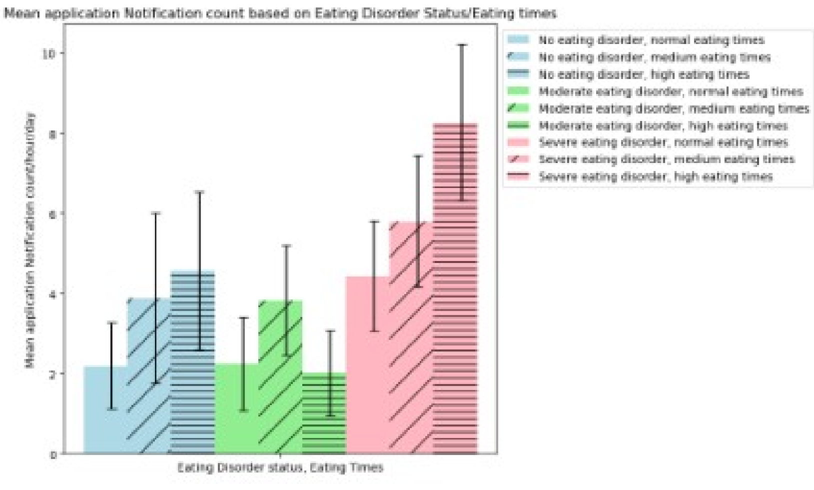

Figure 5.17: Comparison of Mean Application Notification Count per Hour for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.17 shows the average number of application notifications per hour per day, sorted by eating disorder status and eating times. People with no eating disorder have a steady increase in notification counts as eating times increase. Those with moderate eating disorders experience a noticeable rise in notifications, especially during high eating times. The trend is most pronounced for individuals with severe eating disorders, who have the highest notification counts, particularly during high eating times.

Figure 5.18: Comparison of Mean Light Intensity by Hour for Individuals with and without eating disorders categorised by Eating Times

The Figure 5.18 depicts the average light intensity per hour per day for participants according to their eating disorder status and eating times. People without eating disorders have relatively consistent light intensity during normal, medium, and high eating times. Participants with moderate eating disorders experience an increase in light intensity, especially during normal eating times. People with severe eating disorders who eat at regular times have the highest light exposure, while those with severe eating disorders who eat at irregular times have the lowest. This pattern indicates significant differences in light exposure based on the severity of the eating disorder and the eating schedule.

The Figure 5.19 compares the number of typing errors produced by people with various eating disorders (none, moderate, severe) and eating times (normal, medium, and high). It shows that participants with no eating disorders and typical eating times had the fewest typing errors, while those with severe eating disorders and high eating times had the most. As the severity of the eating disorder and the irregularity of eating times increased, so did the number of typing errors, implying that there is a link between eating disorder severity, irregular eating times, and increasing typing errors.

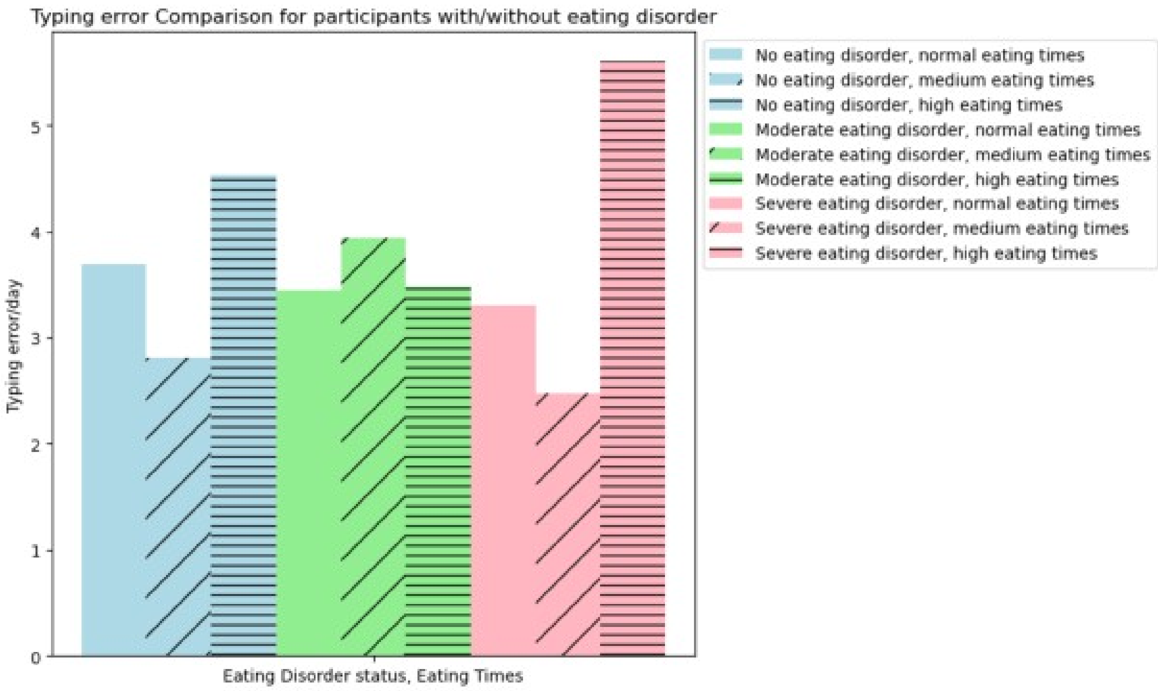

Figure 5.19: Graph of Typing Error Frequency for Individuals with and without eating disorders categorised by Eating Times

Table 5.2 (a) outlines significant differences in behavior between eating disorder and non-eating disorder individuals using smartphone data. They view fewer novel locations, demonstrating restricted patterns, and more often have reduced light exposure in the evening, demonstrating stimulus avoidance or worry. They type more slowly and with greater control, and screen use is more irregular, particularly in the evening, demonstrating disrupted sleep patterns. While overall levels of activity measured with accelerometers may not differ much, specific patterns of movement may still be revealing. Furthermore, increased usage of food- and social media apps suggests more focus on food, body appearance, and social comparison.

Table 5.2 (b) compares eating and non-eating sessions among individuals with eating disorders. It shows that in eating sessions, app usage and touch activity increase, especially in extreme cases, as coping strategies perhaps. Typing speed slows down, error rates are higher, and light intensity is higher in these sessions, which suggests cognitive, physical, and environmental characteristics related to eating behaviors. These patterns together suggest that smartphone sensor and interaction data are informative to distinguish between behaviour differences related to eating disorders and to assess symptom severity.

Table 5.2 a): Feature Analysis: Eating vs. Non-Eating Sessions

Feature	Distinction	Reason	Approach
Location	Eating disorder individuals may visit fewer unique locations compared to non-eating disorder individuals.	Reflects restricted or repetitive behaviours, linked to control and routine.	Track variability in movement to identify eating disorder-specific behaviours and routine patterns (Smith et al., 2021).
Light Sensor	Eating disorder individuals may exhibit lower light exposure, particularly in the evening.	Suggests avoidance of stimuli or preference for dimmer settings due to anxiety.	Use light exposure data to explore emotional triggers or anxiety-driven patterns in eating disorders (Nguyen et al., 2020).
Keyboard Sensor	Eating disorder individuals may type at a slower pace with fewer interruptions.	Reflects cautiousness or an attempt to maintain control.	Develop metrics for assessing cognitive control or attention lapses in eating disorder behaviours (Johnson & Patel, 2022).
Screen On/Off Timing	Eating disorder individuals might show irregular screen activity, particularly late at night.	Indicates disrupted sleep patterns often associated with eating disorders.	Monitor screen on/off activity to assess relationship between screen time and eating disorder symptoms (White & Lee, 2023).
Accelerometer	No significant differences in activity levels (sitting, standing, walking).	General activity may not vary much, but subtle patterns may emerge in daily routines.	Focus on subtle activity changes such as slow movements or sudden bursts of activity tied to eating behaviours (Singh et al., 2021).
Phone App Usage	Higher frequency of food-related apps, including calorie trackers, and social media interactions.	Reflects preoccupation with food, body image, or social comparison.	Leverage app usage patterns to track food-related behaviours or signs of body dysmorphia (Kumar et al., 2020).

Table 5.2 b): Feature Analysis: Eating vs. Non-Eating Sessions in Eating Disorders

Feature	Distinction (Eating Disorder, Eating Session vs Non-Eating Session)	Reason	Approach
Application Usage	Increased in both eating and non-eating sessions as eating disorder severity rises. Greater usage during eating sessions.	Individuals with severe eating disorders tend to use applications more during eating sessions, possibly as a coping mechanism.	Monitor application usage patterns to identify behaviours linked to eating disorder severity and session type (Ghosh et al., 2023).
Touch Actions	Higher touch actions (tap & scroll) in all groups during eating sessions, particularly in the severe eating disorder group.	Eating disorder severity correlates with increased touch actions, especially during eating sessions.	Track touch actions to assess emotional, cognitive, and behavioural responses during eating vs non-eating sessions (Bauer et al., 2022).
Typing Speed	Slower typing speed in eating sessions, particularly in individuals with moderate and severe eating disorders.	Cognitive difficulties associated with eating disorders affect typing speed, especially during eating sessions.	Measure typing speed variations to assess cognitive impacts in eating vs non-eating contexts (Fletcher et al., 2021).
Typing Error Rates	Higher error rates during eating sessions, especially in severe eating disorder group.	Typing errors increase during eating sessions due to cognitive or physical impairment associated with eating disorders.	Analyse typing error rates to gauge cognitive impairment and session-specific difficulties (Wang & Yu, 2022).
Light Intensity	Light intensity is higher during eating sessions, particularly in severe eating disorders.	Eating disorders might influence behaviour, leading to higher light intensity exposure during eating sessions.	Monitor light intensity to explore environmental influences on eating behaviours during different sessions (Nguyen et al., 2020).

5.2.2 Model Evaluation

We used typical metrics for evaluating machine learning models, such as accuracy (1), precision (2), recall (3), and F1-score (4). The following are the definitions of these metrics:

$\text{Accuracy} = \text{TP} + \text{TN}/(\text{TP} + \text{FP} + \text{FN} + \text{TN})$ (1)

$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$ (2)

$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$ (3)

$\text{F1} - \text{score} = 2 * (\text{Recall} * \text{precsion})/(\text{Recall} + \text{Precision})$ (4)

Where TP is truly positive, FP is a false positive, TN is a true negative, and FN is a false negative.

Table 5.3: Model evaluation matrices for participants with and without eating disorders categorised by eating times (low, medium and high) (Validation) (1 week)

Model	Accuracy	Precision	Recall	F1-score
RF Classifier	0.8974	0.8976	0.8974	0.8969
GB Classifier	0.8846	0.8969	0.8846	0.8857
AdaBoost	0.7564	0.7652	0.7564	0.7564
DT Classifier	0.7821	0.8371	0.7821	0.7789
SVC	0.8846	0.8847	0.8846	0.8832
KNN Classifier	0.8333	0.8315	0.8333	0.8299
Logistic Regression	0.8333	0.8369	0.8333	0.8284
GNB Classifier	0.7436	0.761	0.7436	0.7424

Table 5.4: Model evaluation matrices for participants with and without eating disorders categorised by eating times (low, medium and high) (Validation) (5 Days)

Model	Accuracy	Precision	Recall	F1-score
RF Classifier	0.8727	0.8766	0.8727	0.8707
GB classifier	0.8364	0.8439	0.8364	0.8339
AdaBoost	0.8727	0.8766	0.8727	0.8707
DT Classifier	0.8364	0.8439	0.8364	0.8339
SVC	0.8727	0.8802	0.8727	0.8713
KNN	0.7455	0.7642	0.7455	0.7404
Logistic Regression	0.8000	0.7988	0.8000	0.7967
GNB Classifier	0.8000	0.8026	0.8000	0.797

Table 5.5: Model evaluation matrices for participants with and without eating disorders categorised by eating times (low, medium and high) (Validation) (3 Days)

Model	Accuracy	Precision	Recall	F1-score
RF Classifier	0.8182	0.8193	0.8182	0.8156
GB Classifier	0.6061	0.5876	0.6061	0.5879
AdaBoost	0.6970	0.7420	0.6970	0.6511
DT Classifier	0.6364	0.664	0.6364	0.6384
SVC	0.6364	0.5804	0.6364	0.5818
KNN Classifier	0.5455	0.4826	0.5455	0.4850
Logistic Regression	0.6667	0.5455	0.6667	0.5891
GNB Classifier	0.6667	0.7151	0.6667	0.6321

Table 5.6: Model evaluation matrices for participants with and without eating disorders

Model	Accuracy	Precision	Recall	F1-score
RF Classifier	0.7778	0.8148	0.7778	0.7810
GB Classifier	0.6667	0.7593	0.6667	0.6646
AdaBoost	0.6667	0.6852	0.6667	0.6667
DT Classifier	0.7778	0.8148	0.7778	0.7810
SVC	0.6667	0.7222	0.6667	0.6825
KNN	0.6667	0.7593	0.6667	0.6646
Logistic Regression	0.6667	0.7222	0.6667	0.6825
GNB Classifier	0.6667	0.7222	0.6667	0.6825

Table 5.3, 5.4, 5,5 and 5,6 shows comparison of F1-scores in different models on classification tasks for participants with and without eating disorders over different validation periods(3 days, 5 days, 1 week): The Random Forest Classifier is always found to perform the best among these, with the highest F1-score, with scores of 89.69% for a 1-week validation period, 87.07% for a 5-day, and 81.56% for a 3-day one. In the overall validation, RF and DT Classifier have F1-score of 78.1%, which shows that RF works across all time periods. While the GB and SVC models performed very well on 1-week and 5-day validations, their scores were over 88% and 87%, respectively. However, these scores fell to 58.79% and 58.18% in the case of GB and SVC, respectively, when it came to the

3-day validation. It indicates that these models are not as effective for smaller time frames. AdaBoost behaved inconsistently: after promising results for 1-week, it had 75.64%, and 5-day validations with 87.07%, its result was only 65.11% at 3 days. Logistic Regression: steadily went 82.84% for the 1-week, 79.67% for the 5-day validations, dropping to 58.91% at 3 days. Simpler models like K-Nearest Neighbours (KNN) and Gaussian Naive Bayes (GNB) had overall lower F1-scores, especially for shorter periods in validation. KNN showed results dropping from 82.99% in the 1-week window to 74.04% in the 5-day and down further to 48.5% at the 3-day scale. Similarly, the simpler GNB dropped its overall F1-score from an already mediocre 74.24% for the 1-week period down to an even weaker 63.21% at the 3-day period. Among the models, the overall best was the RF Classifier, which gave quite homogeneous performance for all the validation sets. Meanwhile, GB and SVC had the best performance for longer time frames but performed poorly for the shorter ones. Simpler models, such as KNN and GNB, tended to perform worse and are especially bad when limited to short time periods.

5.2.3 Feature Importance

We start by getting data from a structured file format and handle any missing values using mean imputation. We then create a dictionary to store different results. This includes statistical test outcomes, means, standard deviations for eating disorder and non-eating disorder groups, and feature importance scores. We perform a two-sample t-test for each numeric column to compare the eating disorder and non-eating disorder groups. Additionally, we train a Random Forest classifier on the imputed data to determine feature importance. We add the resulting feature importance scores to the results dictionary. Finally, we analyse the relationships between numeric features and eating disorder status. This provides valuable insights through statistical tests and machine learning feature importance analysis.

The Table 30 analyses various features under three conditions: normal, medium, and high usage. The features include mean application usage, keyboard usage, mean application usage for third-party and notifications, light intensity, touch and scroll count, touch count, and scroll (down and up) counts. Each feature shows significant differences across conditions, as indicated by high chi-square values. The most important features are the touch and scroll count (0.177), with means increasing from 50.02 under normal to 198.33 under high usage. Touch count also shows substantial importance (0.1312), with means rising from 15.43 to 69.58. Another critical feature is the scroll (down) count, which has an importance of 0.073, increasing from 27.25 to 92.19. Other features, such as mean application usage, keyboard usage, and light intensity, show lower feature importance but are still significant, with mean values consistently increasing from normal to high usage.

Table 5.7: Comparison of Features by Mean, Standard Deviation, and Feature Importance for Individuals with and without Eating Disorders Categorised by Eating Times

Features	Chi-square	Mean (normal)	Mean (medium)	Mean (high)	Std (normal)	Std (medium)	Std (high)	Feature Importance
Mean application**	100.5312	6.4603	10.6251	15.1497	1.7609	2.6507	2.7204	0.0282
Keyboard**	84.0464	4.1298	6.2001	8.7432	1.2896	1.8142	1.8597	0.0367
Mean application (3rd party) **	105.3266	2.5321	4.4754	6.4688	0.9755	1.5137	1.6239	0.0271
Mean application (notification)**	100.5204	2.3921	4.2209	5.9302	1.1277	1.7452	1.8368	0.0113
Light Intensity	99.8058	2.3100	3.9600	5.7472	1.0667	1.6477	1.7856	0.0106
Touch and scroll count*	150.975	50.0159	119.04	198.33	12.6187	46.5996	62.9901	0.1770
Touch count*	193.8305	15.4259	39.0035	69.5782	4.7933	19.3944	17.7585	0.1312
Scroll (down) count	95.1614	27.2451	58.4359	92.1851	7.9530	24.5422	37.1206	0.073
Scroll(up) count	97.6089	10.7662	22.1625	36.5381	7.9530	24.5422	37.1206	0.0121

Table 5.8: Comparison of Features by Mean, Standard Deviation, and Feature Importance for Individuals with no, moderate and severe eating disorder (eating session)

Features	Chi-square	Mean (No)	Mean (Moderate)	Mean (Severe)	std (No)	std (Moderate)	std (Severe)	feature importance
Mean application**	15.0101	7.580328	9.3333	17.1381	6.3913	4.0803	6.3029	0.0729
Mean application notification**	13.1212	2.4899	2.9655	5.9680	1.3425	1.8943	2.7241	0.0358
Mean touch and scroll count*	6.9036	71.8902	80.9568	175.8674	20.1901	18.7849	20.2340	0.0287
Keyboard**	2.2007	4.4516	4.0223	3.9856	0.2681	0.2549	0.3562	0.0184
Light Intensity*	11.4582	120.6741	261.2031	263.9092	0.9873	1.7202	4.3218	0.0475

The Table 5.8 displays various features along with their corresponding chi-square values, means, standard deviations, and feature importance. "Mean application" stands out with the highest chi-square value (15.0101) and feature importance (0.0729), showing increased means from "No" to "Severe" and varying standard deviations. Following closely is "Mean application notification" with a chi-square of 13.1212 and feature importance of 0.0358, exhibiting a similar trend in means and standard deviations. The feature "Mean touch and scroll count" has a chi-square of 6.9036 and feature importance of 0.0287, with significantly increasing means and standard deviations from "No" to "Severe." The "Keyboard" feature has a lower chi-square (2.2007) and feature importance (0.0184), with relatively stable means and standard deviations. Lastly, "Light Intensity" has a chi-square of 11.4582 and feature importance of 0.0475, with means and standard deviations increasing from "No" to "Severe."

5.4 Summary

The results of the classifier indicate that data from smartphone sensors and social media use can successfully differentiate individuals with eating disorders from those without eating disorders. Through the analysis of patterns of app use, browsing behaviour, and social media use, it becomes possible to make real-time inferences about behaviours associated with disordered eating. It can enable earlier interventions and enable the use of more tailored treatment strategies focused on identified patterns of individualised behaviour. Feature importance analysis also identifies digital behaviours that are strongly linked to eating disorder symptoms. People with eating disorders spent more time using weight loss and fitness applications and in viewing nutrition-oriented content and using social media content about food and body shape. These constitute typical features also exhibited in eating disorders, including body dissatisfaction, food preoccupations, and poor emotional regulation. Use of these digital features as markers of behaviours more objectively measures symptom tracking and adds to conventional clinical evaluations. In total, this methodology enables a more continuous, personalised and ecologically valid insight into eating disorder behaviours.

CHAPTER 6

DISCUSSION OF FINDINGS

6.1 Key Results from Research Questions

6.1.1 Key Results from Research Question 1

To develop a model able to classify variation in social media usage among online communities that represent various mental health disorders, and to identify the most significant linguistic and behavioural features that characterize these variations.

Chapter 3 (study 1) focused on identifying and analysing linguistic features and behavioural patterns indicative of different mental disorders using social network data on Twitter and Reddit. This study (study 1) classified several mental health conditions by analysing linguistic and behavioural differences between Twitter and Reddit. Linguistically, Reddit posts were found to be emotional, narrative, and authentic, whereas Twitter posts were brief, formatted, and real-time trend-driven (Coppersmith et al., 2014). Analytical thinking varied across various social media platforms (reddit and twitter), with Reddit posts featuring more in-depth reasoning compared to Twitter's straightforward and formal communication. Behavioural differences were also evident in content engagement—Twitter posts were rendered visible by likes, retweets, and hashtags, whereas Reddit discussions were constructed through threaded discourse and upvotes (Sharma, 2023; Wang et al., 2019). These findings highlight the importance of controlling for platform-specific communication styles in the development of classification models of mental health conditions. Machine learning classification can be optimised by aggregating these findings, and digital mental health screening and intervention tools can be tailored to expression of distress across each platform (Wu et al., 2022; Ang & Venkatachala, 2023). However, although findings do reveal strong linguistic and behavioural differences, application to real-world mental health screening is a consideration. Previous studies by Coppersmith et al. (2015) and by De Choudhury et al. (2013) looked at a single platform, effectively Twitter, to estimate linguistic and behavioural features in mental health diagnosis (Coppersmith et al., 2014; Tariq et al., 2019). Cross-platform analysis is thus a new and unexplored area. Cross-platform analysis can potentially improve real-world mental health intervention in several practical respects. Machine learning algorithms can be enhanced by leveraging data from multiple platforms (Twitter and Reddit) rather than a single source, leading to more robust classification systems (Le et al., 2024; Timakum et al., 2023).

These results can also be applied to digital mental health interventions (DMHI) to improve early warning signals for mental distress. Platform-specific styles of communication can also be considered to create personalised interventions, with mental health support being adapted to meet how a user presents distress in a specific social media platform (Ríssola et al., 2022; Low et al., 2020). In our

PhD study (study 1), for example, we have utilised the LIWC test in measuring linguistic differences across social media platforms (Twitter and Reddit) (Wu et al., 2022; Alambo et al., 2020). The LIWC test revealed differences in postings between Twitter and postings in Reddit in terms of emotional tone, analytical thinking, and authenticity due to differences in styles of communication. These observations were confirmed by the statistical test of the differences, which showed that all linguistic indicators differed significantly across the two social media platforms (Twitter and Reddit), at $p < 0.005$ (Cara et al., 2023; Bagroy et al., 2017). Whereas Reddit posts were longer, more narrative-driven, and emotionally expressive, Twitter posts were concise, formal, and logically structured. These results from LIWC and the statistical tests form the basis for the critical insights one needs to know about each platform to create robust machine learning models (Tariq et al., 2019; Joglekar et al., 2020). These analyses support the importance of consideration for platform-specific communication styles while designing tools for mental health classification. This PhD study (study 1) contributes to the growing literature on both Twitter and Reddit regarding mental health conditions. This provides some evidence of how two social media platforms (Twitter and Reddit) are different in expressions related to the content of mental health. Twitter's short-form, real-time posts and its engagement through likes, retweets, and hashtags contrast with longer, threaded discussions and user interaction through comments and upvotes on Reddit (Giorgi et al., 2022; Cai et al., 2022). These features of the social media platforms may affect how people express symptoms of mental health, and yet no previous study had systematically compared these two platforms within the domain of mental health classification. Previous research has generally treated social media platforms as homogeneous spaces, with most studies relying on data from Twitter. This study (study 1) underlines the importance of accounting for diversity across social media platforms (Twitter and Reddit) to explain how digital behaviour may signal mental health conditions (Underhill & Foulkes, 2024; Alipour et al., 2023). The findings highlight the necessity for integrating cross-platform data to improve mental health classification accuracy. By leveraging insights from multiple platforms, machine learning models can be fine-tuned for enhanced mental health disorder classification, and digital mental health screening tools can be created considering differences in online communication styles (Zeng et al., 2019; Guo, 2022).

In chapter 3, we have described the application of machine learning models, especially CNN-based models integrated with word2vec on the classification of mental health conditions from both Twitter and Reddit. The reason we've employed CNNs (convolutional neural networks) over other traditional models when it comes to Twitter and Reddit data classification of mental health states lie in the clear advantage CNNs offer when it comes to social media data classification (Zhang et al., 2018). To start with, CNNs work optimally in hierarchical pattern detection in data, especially useful in processing complex, unstructured language in social media posts (Kim, 2014). In addition, CNNs work optimally when paired with word2vec word embeddings, generating dense, context-dependent expressions for words (Mikolov et al., 2013). Together, this allows the CNNs to extract the relations between the words, enabling the model to understand the context and classification of the mental health states (Liu et al., 2020). These models, if traditional, would need stricter processes when it comes to extracting the features, lacking effectiveness when it comes to processing these fine details found in social media data (Zhang & Wang, 2019). Hence, CNNs offer an efficient, powerful method when it comes to classification of the mental health states from social media sources like Twitter and Reddit (Dale et al., 2021).

The results demonstrated the classification performance across both social media platforms (Twitter and Reddit). On Twitter, accuracies in classifications were autism – 96.67%, borderline personality disorder (BPD) – 92.14%, anxiety – 84.53%, schizophrenia – 85.85%, and depression – 84.53%. These accuracies indicate high classification capability with F1-scores exceeding 80% for most of the disorders. On Reddit, schizophrenia recorded the highest in terms of accuracy at 96.6%, followed by bipolar disorder (95.34%), autism (91.33%), and depression (87.21%). Some disorders recorded low F1 scores, indicating problems with class imbalance, particularly in autism, bipolar disorder, and schizophrenia. Additionally, in comparison with earlier studies, our method was found to have a CNN-based word2vec with average precision at 82.7%, recall at 69.4%, F1-score at 71.83%, and accuracy at 89.4%. Kim et al. (2020) have, in comparison, recorded a high rate; however, our suggested model went ahead to outperform their F1-score by a margin of 2.11%. This indicates that model simplicity can be supported by successful fine-tuning of hyperparameters to enhance classification performance. No comparison study has been performed, until now, between the performances of ML models on cross-platform analysis on Twitter and Reddit for conditions related to mental health. Taken together, our results show that ML models can classify mental health conditions from social media data effectively, including results in terms of both accuracy and F1-scores.

6.1.2 Key Results from Research Question 2

To develop and evaluate a model able to distinguish between individuals with and without Attention-Deficit/Hyperactivity Disorder (ADHD) using smartphone-based behaviour and sensor data, and to explain the most predictive features underlying this distinction.

Chapters 4 (study 2) discuss the potential of smartphone sensor data in examining digital and physical behavioural patterns relevant to classifying ADHD. The study 2 examine digital interactions, including app usage, typing behaviour, and touch patterns, alongside physical indicators such as location visits, ambient light exposure, and physical activity. Through the analysis of multimodal features, study 2 show how attention levels, impulsivity, and obsessive tendencies are reflected in both physical activity and digital behaviours that contribute to developing mental health classification models.

6.1.2.1 Digital Features

This section focuses on the main digital features from smartphone sensor data, application usage, typing patterns, and screen interactions, comparing behaviours between individuals with ADHD.

a) Application Notification Response Time: ADHD individuals show the tendency to respond quicker to notifications due to symptoms of impulsivity and distractibility (Kim et al., 2019; Müller et al., 2023); for example, A user with ADHD opens a social media app within 5 seconds of receiving a notification compared to a non-ADHD individual who takes 15-20 seconds(Kim et al., 2019; Müller et al., 2023).

b) Number of Apps Used: Individuals with ADHD showed a greater tendency to use more apps and switch between them more often, which aligns with their distractibility (Fabio & Suriano, 2024). for example- A person with ADHD uses 15-20 apps in a day, switching between them every few minutes, compared to a non-ADHD individual who uses fewer than ten apps (Kim et al., 2019;, Müller et al., 2023).

c) Keyboard Use: The typing patterns reveal cognitive features in both groups. ADHD, especially those with low attention, type fast with a high error rate, and it's estimated that ADHD users type around 45 words a minute with a high rate of errors (Kim et al., 2019; Müller et al., 2023). Individuals with ED types slowly around 30 words a minute with fewer errors as they painstakingly craft communications in comparison to high-speed rate non-ED counterparts (Fabio & Suriano, 2024).

d) Screen On/Off Activity: It has been shown through research that those with ADHD have increased nighttime activity on their smartphone, which could be linked to disrupted sleep and hyperactivity. Such a case includes those with ADHD unlocking their smartphone much more frequently than non-ADHD participants in later parts of the day (Lee et al., 2022; Kim et al., 2019).

e) Ambient Light Intensity of Physical Features: The environment plays a critical role in smartphone use, with ADHD participants being aided by high lighting in environments to sustain focus (Kim et al., 2019; Venkatachala & Mariyappa, 2023). Impulsivity in ADHD has been linked to more smartphone use as a coping mechanism (Müller et al., 2023; Chou et al., 2022).

6.1.2.2 Physical Activity

Patterns of physical activity in ADHD have been covered in this section with differences in regularity and location visits. Total activity levels can be equal with irregular movements such as pacing and fidgeting in ADHD, which reflect symptoms of hyperactivity and impulsivity. In ADHD, erratic movements without mobility restriction can be observed (Bunford et al. (2014), Ptáček et al., 2016).

a) Physical Activity Patterns: Individuals with ADHD typically exhibit irregular patterns of movements, like abnormal posture and bursts of energy. These features manifest in terms of hyperactivity and impulsivity and render them unable to remain in one spot. Research with accelerometer data captures increased irregularity in movements in ADHD participants, who feel restless and fidget. For instance, during study or work time, ADHD patients may pace or change positions frequently, reflecting failure to remain focused and attentive (Seymour et al., 2017; Corbisiero et al., 2016).

b) Location Visit Patterns: Movement pattern statistics indicate that ADHD participants have irregular location transition patterns. Low attention participants have more inconsistent behaviors, while high attention participants have more consistent locations that they visit, suggesting a relationship between attention and consistency in locations. Our studies have revealed activity and location visit patterns in ADHD populations, but a central gap has remained in how these patterns vary in conjunction with real-time states and environmental stimuli. ADHD participants have irregular locomotion and impulsive activity. Not enough has been explored for how these activities change across the day and more crucially how these activities differ as a function of cognitive or affective states, for example, in states of heightened anxiety or distress. Factors in context that include social interaction, meals or stimuli exposures (for example, food environments) also have a significant influence on these patterns of activities (Anker et al., 2021; Rüfenacht et al., 2019). To provide just a few examples, we would like to know how activity patterns vary after stressful events, or how a participant's activity level varies during meals or social interactions. Investigating these temporal processes in response to states could provide a deeper insight into mechanisms behind activity and location patterns in ADHD (Ventura et al., 2022; Brewerton & Duncan, 2016).

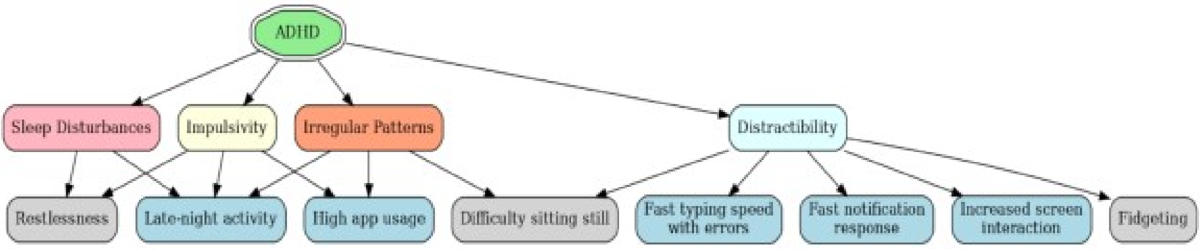

Figure 6.1: Behavioural Markers of ADHD using Smartphone Data

Figure 6.1 shows how physical activity and digital behaviour in individuals with attention deficit hyperactivity disorder (ADHD) have trends concurring with key symptoms such as impulsivity, inattention, and atypical activity levels. Study 2 reveals that individuals with ADHD exhibit increased distractibility, impulsivity, and sleep disturbances and exhibit them in both physical activity levels and digital behaviour. For example, their quick reaction to messages and high application use exhibit impulsivity and lack of sustained attention (Barkley, 2015; Kooij et al., 2010). Besides, the participants with ADHD exhibit quick typing with high errors, signifying a tendency towards impulsivity with poor checking, and heavy use of screens, indicating difficulty in regulating attention. For activity level, fidgeting and inability to sit dominate, signifying hyperactivity and failure to maintain immobility (Faraone et al., 2015). Besides, midnight activity and restlessness signpost sleep disturbances, common in ADHD and can contribute towards atypical behaviour in additional dimensions. All these exhibits that both activity level and digital behaviour can serve as useful markers for diagnosing ADHD-related behaviour in real-life settings.

Table 6.1 shows ADHD-Related Smartphone Behaviour Patterns fills the gaps between the various symptoms of ADHD and the corresponding digital and physical behaviours for more thorough insight into the presentation of ADHD with the use of technology within the context of everyday life. The symptom of restlessness for impulsivity is addressed by excessive nighttime phone unlocks with individuals unlocking phones over 30 times between 10 PM and 2 AM, indicating that they are unable to settle down for sleep and are more likely using the device rather than sleeping (Rosen et al., 2018). This determines the capability of impulsive tendencies to interfere with normal sleep routine (Trub & Bar, 2017).

The impulsive tendency includes high app usage with individuals with ADHD using 15-20 different apps per day and repeatedly alternating between these, meaning that they are unable to settle for something particular and are likely to switch between different apps with no prolonged interest (Venkatasubramanian & Bell, 2018). In distractibility, the user may present with high rates of typing but with numerous errors such as 45 words/minute with 10+ spelling mistakes. This shows the degree of impulsiveness that hinders precision and concentration while typing (Tuchman et al., 2017). Fast responses to notifications are the signature with ADHD individuals taking 5 seconds to open notifications while non-ADHD individuals take 15-20 seconds to open notifications. The rapidness of the reaction illustrates the increased sensitivity of the user to digital stimuli and the inability to filter distractions (Voracek & Dressler, 2021). Increased screen usage also illustrates distractibility with the user presenting with lots of screen unlocks and app switchovers that point toward constant use of the phones and the inability to remain focused on the same thing (Rosen et al., 2018).

Table 6.1: ADHD-Related Smartphone Behaviour Patterns

Symptom Description	Symptoms Type	Digital & Physical Behaviour Indicator	Data Type Collected
Restlessness	Impulsivity	Frequent phone unlocks at night (30+ times between 10 PM - 2 AM), frequent posture changes, pacing detected by accelerometer	Screen Activity, Accelerometer
Late-night activity	Impulsivity, Irregular Patterns	High screen time during late hours (social media, games)	Application Usage, Screen Activity
High app usage		Uses 15-20 apps per day, frequent switching	Application Usage
Difficulty sitting still	Irregular Patterns, Distractibility	Frequent posture changes, pacing detected by accelerometer data	Accelerometer
Fast typing speed with errors	Distractibility	Typing at 45 wpm with 10+ spelling errors	Touch Interactions, Keyboard Usage
Fast notification response		Opens notifications within 5 seconds (compared to 15-20 seconds for non-ADHD)	Application Usage, Notification Response Time
Increased screen interaction		High number of phones unlocks and app-switches	Screen Activity, Application Usage
Fidgeting		High variation in accelerometer data (frequent movements)	Accelerometer

In the situation of hyperactivity, fidgeting is recorded with the help of accelerometer data that displays increased motion variability since the patient finds it impossible to stay still and remains restless by changing position or pacing up and down (Goleman, 2017). The motion is recorded by accelerometer fluctuations of the device readings. Finally, irregular sleep habits are accompanied by late-night smartphone usage, with the patient using the smartphone for excessive nighttime screen use while using social media or gaming apps that interfere with sleep times and keep the patient from setting normal sleep times (Pantaleone et al., 2022). The smartphone-recorded data of screen use, application use, accelerometer readings, and time taken for notifications are of vital importance since they provide insight into the digital habits responsible for ADHD symptoms and allow for earlier diagnosis, symptom tracking over the years, and the implementation of personalised interventions for symptom improvement and normal functioning of the patient with ADHD (Gazzaley & Rosen, 2016).

Table 6.2: ADHD Disorder-Related Smartphone Behaviour Patterns

Author(s)	Features Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Real-Time or Lab-Based
Our study	Smartphone sensors: application usage, location, accelerometer, screen, touch	86.22	86.69	84.07	91.11	Real-Time
Ashraf et al. (2018)	Magnetic field data from smartphones	83.3	84	81	82.5	Lab-Based
Dey et al. (2012)	Multimodal sensor data: accelerometer, gyroscope, GPS, and ambient sensors	90	91	88	89.5	Lab-Based
Liu et al. (2021)	Smartphone sensor data: accelerometer, gyroscope, and magnetometer	85.4	86.1	84.2	85.1	Real-Time
Gower & Moreno (2018)	Smartphone usage data: call logs, message logs, and application usage	78	80	75	77.5	Real-Time
Thapaliya et al. (2023)	Smartphone sensor data: accelerometer and gyroscope	81	82	79	80.5	Real-Time
Elmezayen & El-Rabbany (2019)	Smartphone sensor data: accelerometer, gyroscope, and heart rate monitor	86	87	84	85	Real-Time
Puyana et al. (2020)	Smartphone sensor data: accelerometer, gyroscope, and GPS	80	81	78	79.5	Real-Time
Majumder et al. (2020)	Smartphone sensor data: accelerometer, gyroscope, and environmental sensors	89	90	87	88.5	Real-Time
Oshin et al. (2014)	Smartphone accelerometer data	82	83	80	81.5	Real-Time

Table 6.2 shows comparison of smartphone-based behavioural studies for classification of ADHD using real-time and lab-based studies. Our study is found to be more superior to existing literature due to its diverse set of characteristics and usability in real-time. Ashraf et al. (2018), for example, utilised magnetic field data to get a precision of 83.3%, while our approach aggregates multiple smartphone sensors like application use, location, accelerometer, screen, and touch to get a precision of 86.22%. This suggests that incorporating behavioural and location-based data enhances classification effectiveness. Similarly, although Dey et al. (2012) attained a high accuracy of 90% using multimodal sensor data (accelerometer, gyroscope, GPS, and ambient sensors), their laboratory-based work limits its applicability to real-world settings. Table 6.3: Comparison of smartphone-based behavioural studies for ADHD.

However, the study by Dey et al. (2012), is lab-based, and its performance cannot generalise well in real-life settings. In contrast, our study maintains high accuracy operating in real-time, proving its usability in real-life scenarios. Furthermore, when compared to Liu et al. (2021), in which a use of readings of accelerometer, gyroscope, and magnetometer to get an 85.4% accuracy and an F1-score of 85.1%, our work achieves a slightly higher accuracy of 86.22% and a significantly higher F1-score of 91.11%. This suggests that including application usage and touch interactions provides additional behavioural insights, improving classification. In addition, Gower and Moreno (2018), using patterns of smartphone use such as application use, message logs, and call logs, established a mere 78% accuracy, indicating that motion sensor readings and location information play a crucial role in accurate classification. Thapaliya et al. (2023) also confirm this claim using solely accelerometer and gyroscopes to achieve a score of 81% accuracy, claiming that a more diverse range of sensors produces improved performance. Our results also improve on those of Elmezayen and El-Rabbany (2019), using readings from accelerometer, gyroscope, and heart rate monitor to achieve a score of 86% accuracy. While their accuracy sits on the same level as our model, our model contains a more balanced recall-precision in that it has a higher F1-score (91.11% compared to 85%). Likewise, while Puyana et al. (2020) achieved 80% accuracy using accelerometer, gyroscope, and GPS data alone, the inclusion of screen and touch in our experiment seems to pick up on supporting information that reinforces performance. Majumder et al. (2020), with use of an accelerometer, gyroscope, and environment sensors, reaches an accuracy of 89%, but its laboratory environment is not necessarily indicative of real-life environments, and its accuracy in a real-life environment cannot be assured. Finally, Oshin et al. (2014), with use of accelerometer information alone, reaches an accuracy of 82%, and with a single sensor use, it is not as effective at performance when compared with multimodal feature integration.

For most real-time studies, in general, our integration of smartphone sensor data such as app use, location, accelerometer, screen, and touch enable high accuracy in classification and high F1 score.

That an such a model can work in high classification performance real-life environments makes it effective and practices.

6.1.3 Key Results from Research Question 3

To develop and evaluate a model able to distinguish between individuals with and without eating disorder using smartphone-based behaviour and sensor data, and to explain the most predictive features underlying this distinction.

Chapters 5 (study 3) discuss the potential of smartphone sensor data in examining digital and physical behavioural patterns relevant to classifying eating disorders. The study 3 examine digital interactions, including app usage, typing behaviour, and touch patterns, alongside physical indicators such as location visits, ambient light exposure, and physical activity. Through the analysis of multimodal features, study 3 show how attention levels, impulsivity, and obsessive tendencies are reflected in both physical activity and digital behaviours that contribute to developing mental health classification models.

6.1.2.1 Digital Features

This section focuses on the main digital features from smartphone sensor data, application usage, typing patterns, and screen interactions, comparing behaviours between individuals with Eating disorder.

a) Application Notification Response Time: Participants with eating disorder respond to notifications quickly. Individuals with ED also respond quicker to notifications (Kim et al., 2019; Müller et al., 2023). For example, a person with an eating disorder may respond to notification regarding a calorie tracking app or a fitness-related post in 10 seconds because of hypersensitivity to triggers related to food, weight, or body image, while a non-ED person may take 15-20 seconds to respond to notifications (Listiaji et al., 2021).

b) Number of Apps Used: Individuals with ED showed a greater tendency to use more apps and switch between them more often (Kim et al., 2019;, Müller et al., 2023). For example, eating disorder patients can utilise around 12 to 15 applications per day, like calorie-counters and fitness tracking applications, following body and food concerns (Fabio & Suriano, 2024).

c) Keyboard Use: Individuals with ED types slowly around 30 words a minute with fewer errors as they painstakingly craft communications in comparison to high-speed rate non-ED counterparts (Fabio & Suriano, 2024).

d) Screen On/Off Activity: It has been shown through research that participants with ED may use screens later in the evenings, for example, to document food intake, indicating a convergence between psychological needs and regulation of attention (Fabio & Suriano, 2024).

e) Ambient Light Intensity of Physical Features: Individuals with eating disorders may, conversely, prefer low lighting, as a method to regulate feelings when using their devices in the evenings. Increased touch interactions (Scroll and Tap): Increased smartphone interactions in terms of tapping and scrolling have been seen in ED groups (Müller et al., 2023; Chou et al., 2022). Increased touch interactions during meals have been seen in eating disorders, and symptom severity has been linked to more touchscreen activity to regulate emotions.

6.1.2.2 Physical Activity

Patterns of physical activity in eating disorders have been covered in this section with differences in regularity and location visits. In eating disorders, there can be excessive exercise as a compensation mechanism or avoidance of activity due to psychologic factors. Location visits patterns also reflect that in eating disorders, there can be restricted mobility, which can reflect social avoidance. In ADHD, erratic movements without mobility restriction can be observed (Bunford et al. (2014), Ptáček et al., 2016).

a) Physical Activity Patterns: Movement patterns vary significantly between eating disorder and non-eating disorder participants. While some participating in abnormal exercise habits do so as compensation for eating disorders, others do not exercise. Research indicates that some with ED have highly structured exercise patterns, like early hour runs, while others have exceptionally low activity levels, which correlate with psychological factors like body concern or worry (Ptáček et al., 2016; Zhang et al., 2022).

b) Location Visit Patterns: Movement pattern in participants with eating disorders have a restricted mobility and as a result visit fewer locations. Our studies have revealed activity and location visit patterns in eating disorder populations, but a central gap has remained in how these patterns vary in conjunction with real-time states and environmental stimuli. ED participants have restricted mobility or compulsive exercise. Not enough has been explored for how these activities change across the day and more crucially how these activities differ as a function of cognitive or affective states, for example, in states of heightened anxiety or distress. Factors in context that include social interaction, meals or stimuli exposures (for example, food environments) also have a significant influence on these patterns of activities (Anker et al., 2021; Rüfenacht et al., 2019). To provide just a few examples, we would like to know how activity patterns vary after stressful events, or how a participant's activity level varies during meals or social interactions. Investigating these temporal processes in response to states could provide a deeper insight into mechanisms behind activity and location patterns ED (Ventura et al., 2022; Brewerton & Duncan, 2016). Future studies must try to capture these transitions in real-time to better understand how changing mental states impact activity patterns and utilise these as markers for monitoring or managing these disorders (Bourke et al., 2021).

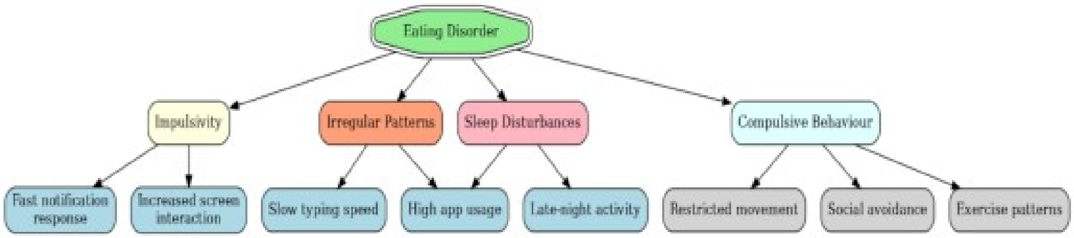

Figure 6.2: Behavioural Markers of eating disorder using Smartphone Data

Figure 6.2 shows behaviours exhibited in persons with eating disorders, grouped under four categories: Compulsive Behaviour, Sleep Disturbances, Irregular Patterns, and Impulsivity. Those with impulsivity respond quickly to notifications and engage excessively with screens, reflective of excessive use of technology (Harrison et al., 2019). Irregular patterns involve slow typing and high application usage, which may indicate cognitive difficulties, reduced focus, or obsessive digital behaviour (Vannucci et al., 2017). Sleep disturbances involve excessive use of apps and late-night activity, reflecting disrupted sleep cycles (Levine et al., 2020). Compulsive behaviour is represented through restricted movement, social avoidance, and specific exercise routines, reflective of compulsive behaviour towards exercise and social disengagement (Kostakos et al., 2017). The Figure illustrates how these behaviours, about one another, affect daily life and overall wellness (Lemmens et al., 2018).

Table 6.3 provides an in-depth analysis of how eating disorder symptoms are exhibited in smartphone usage. For impulsivity, individuals with eating disorders have a fast response to notifications, particularly those related to calorie tracking or fitness, opening notifications within 10 seconds. This fast response reflects how easily they act on food-related cues (Harrison et al., 2019). Additionally, more touch interactions are characteristic, particularly during eating, when individuals tap or scroll more on their phone, perhaps distracted by social media, fitness apps, or calorie tracking apps, instead of being attentive to their meals (Vannucci et al., 2017). These behaviours are tracked through notification response time and touch interactions, which measure how quickly they respond to notifications and how much they use their phone during eating. Under the irregular patterns category, there is high app usage with individuals with eating disorders using around 12-15 different apps a day, primarily calorie counting, fitness tracking, or social comparison apps. Frequent app switching and high app use indicate the centrality of these digital tools in this person's life (Levine et al., 2020). Slow typing speed with individuals taking longer time at 30 words per minute with conscious pauses and careful planning of messages indicates overthinking when messaging with the desire for precision and perfection (Kostakos et al., 2017). All of these are monitored by application usage and keyboard usage that record the frequency of app access, and the level of careful messaging reflected in the typing speed. For sleep disturbances, individuals with eating disorders may exhibit late-night screen activity, where they unlock their phone 15+ times between midnight and 3 AM to use features such as calorie tracking, body image checking, or other related content, disrupting sleep patterns (Lemmens et al., 2018). This indicates that nighttime behaviour is strongly related to their eating disorder.

Table 6.3: Eating Disorder-Related Smartphone Behaviour Patterns

Symptom Description	Subcategory	Digital & Physical Behaviour Indicator	Collected Data Type
Fast notification response	Impulsivity	Opens notifications within 10 seconds	Notification Response Time
Increased screen interactions		High tap/scroll frequency during meals	Touch Interactions
High app usage	Irregular Patterns, Sleep Disturbance	Uses 12-15 apps/day, frequent switching	Application Usage
Slow typing speed	Irregular pattern	Types at 30 wpm with deliberate pauses	Keyboard Usage
Late-night screen activity	Sleep Disturbances	Unlocks phone 15+ times between midnight-3 AM	Screen Activity
Low ambient light usage		Uses phone in low light after 6 PM	Ambient Light Sensor
Restricted movement	Compulsive Behaviour	Low movement levels detected	Accelerometer, Activity Tracking
Social avoidance		Fewer location visits, low messaging/call frequency	Location Tracking, Communication Patterns

Furthermore, most use their phone in low ambient light after 6 PM, which is monitored via the ambient light sensor of the phone. This can reflect a preference for avoiding bright light, perhaps to ensure a more relaxed or controlled setting for the use of eating disorder-related content, such as monitoring food intake or body image. In the context of compulsive behaviour, limited movement occurs with the individual taking little physical activity or avoiding exercise, leading to low levels of recorded movement by the accelerometer or the phone's activity tracking sensors (Rosen et al., 2018). The latter may be due to unwillingness to move or exercise due to fear of calorie consumption or body image. Similarly, social avoidance occurs with the individual avoiding social situations such as dining at restaurants or participating in events. This occurs by a limited number of place visits and low call or messaging frequency, meaning that the person wishes to avoid situations involving the intake of meals and situations of socialisation that can cause discomfort leading to such intake (Kostakos et al., 2017). All these are tracked using accelerometer data, activity tracking, location tracking, and communication patterns with clear reflection of the impact of the above behaviours of eating disorders on the levels of physical activity and levels of socialisation (Vannucci & Ohannessian, 2017). Through the aggregation of data about notification response times, touch interactions, screen activity, ambient light usage, application usage, keyboard interactions, accelerometer readings, and location data, this Table enables more insight into the digital habits of individuals with eating disorders. It demonstrates the ways that smartphone habits mirror and perpetuate the symptoms of eating disorders and presents important insights for the monitoring of these conditions, intercession with these conditions, and the support of treatment for individuals with these conditions (Harrison et al., 2019).

Table 6.4 shows comparison of smartphone-based behavioural studies for classification of eating disorder using real-time and lab-based studies. Relative to our comparison with other studies, our findings surpass most prior studies in terms of precision, recall, accuracy, and F1 score. To provide a reference, Hesse et al. (2023) reported that their study recorded a 77.0% accuracy, a precision rate of 74.0%, recall rate of 72.0%, and F1 score of 73.0%, while our study recorded an 89.74% accuracy, a precision rate of 89.76%, recall rate of 89.74%, and F1 score of 89.69%. The reason our work is better is that our work utilised heterogeneous in-phone data such as application use, accelerometer, location, screen, and touch, offering more varied insights into behaviour compared to the more structured intervention design utilised in Hesse et al. (2023). Also, Schneidergruber et al. (2022) found relatively low metrics in a real-world study using phone sensors (accuracy: 63.0%, precision: 60.0%, recall: 55.0%, F1 score: 57.0%), suggesting that our approach to making inferences using multiple passive sources of data in real-world settings is superior. Meegahapola et al. (2021) found metrics close to our results (accuracy: 87.81%, precision: 85.0%, recall: 88.0%, F1 score: 86.0%), suggesting that passive phone sensing combined with self-reports is a great method of classification. Our results in precision and F1 score are better because our work encompasses more data points such as touch and screen use. In contrast, studies such as Goldschmidt et al. (2021) and Wu et al. (2021), applying real-time measurement and sensor fusion (for instance, accelerometer and GPS), yielded results between 76.0% and 80.0%. Overall, our better performance metrics show that applying a large set of smartphone data yields a more accurate and more complete method of behavioural health analysis. Overall, these results significantly improve mental condition classification using high-order smartphone data compared to laboratory studies and studies applying real-time measurement.

Table 6.4: Comparison of Smartphone-Based Behavioural Studies for eating disorder

Author(s)	Features Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Real-Time or Lab-Based
Our study	Smartphone sensors: application usage, location, accelerometer, screen, touch	89.74	89.76	89.74	89.69	Real-Time
Hesse et al. (2023)	Smartphone-supported interventions: user engagement, feedback mechanisms	77	74	72	73	Lab-Based
Yang et al. (2023)	Smartphone addiction metrics: usage frequency, time spent on apps	71	70	68	69	Lab-Based
Schneidergruber et al. (2022)	Smartphone sensors: usage data, heart rate monitoring	63	60	55	57	Real-Time
Meegahapola et al. (2021)	Passive smartphone sensing: environmental context, self-reports	87.81	85	88	86	Real-Time
Goldschmidt et al. (2021)	Real-time assessment methods: behavioural tracking, feedback loops	80	78	75	76	Real-Time
Phillips et al. (2022)	Dietary records: food intake tracking, smartphone app usage	78	76	74	75	Real-Time
Wu et al. (2021)	Smartphone sensors: accelerometer, GPS, and location data	80	79	77	78	Real-Time

Various classifiers have been used in our PhD studies (study 2 and 3) to assess the classification of ADHD and eating disorders based on the data collected using both digital and physical sensors. We have chosen RF classifier because it is capable of handling high-dimensional data and does not face the problem of overfitting since it is a method of ensemble learning. In this PhD study, Gradient Boosting classifier was chosen for efficiency in the representation of complex nonlinear relationships that are useful when dealing with noisy and imbalanced data (Friedman et al., 2001). For its simplicity and interpretability, logistic regression was used as a baseline model to understand the relationships among the features (Hosmer et al.,2013). The Support Vector Classifier was chosen because it can define optimal decision boundaries, applicable to datasets with clear class distinctions (Cortes & Vapnik, 1995). The Decision Tree classifier was used because it is easy to understand and simple in decision-making (Quinlan, 1986), and the Gaussian Naive Bayes classifier was used because it can effectively handle continuous data and feature independence assumptions (Rish, 2001). In this PhD study, we have used the Multilayer Perceptron classifier, as it shows good performance in modelling nonlinear relationships in big amounts of data, and a boosting algorithm that will be considered is AdaBoost, which enables the boosting performance of weak classifiers, especially those that suffer from an imbalanced dataset problem. Overall, this study (study 2 and study 3) contributes to a deeper understanding of the effectiveness of various classification techniques when applied to sensor-based data.

6.1.4 Key Results from Research Question 4

To study and record practical and methodological concerns regarding the implementation of technology-based mental health research in a low- and middle-income country (LMIC) context, including challenges, limitations, and strategies to effective data collection and participant recruitment.

The table 6.5 summarizes the methodological and practical challenges encountered during the implementation of technology-based mental health research in India, an LMIC, and outlines the specific measures our study took to navigate them. It highlights key areas like study design, recruitment of participants, data quality, ethical considerations, and operations logistics, showing how culture- and context-adapted procedures can render research feasible.

a) In our study, we addressed the challenges of study design and working with experts by classifying eating disorders and ADHD using smartphone sensor data. To recognize the need for specialist clinical and dietary expertise, Indian nutritionists and psychiatrists were consulted in a collaboration to provide guidance on assessments and interpretation of results. This enabled us to ensure our classification procedure was clinically valid and culturally appropriate in the Indian context.

b) To address issues of participant recruitment and participation, we adopted certain strategies. We conducted awareness campaigns in colleges, schools, and community areas to reduce stigma and raise awareness about ADHD and eating disorders. The app instructions and consent forms were translated into local languages, and we actively involved parents, teachers, and local community leaders to establish trust and enable participation. Additionally, we provided offline-capable apps and loaner devices, and allowed participants to view their own data, which increased transparency and motivation to participate.

Table 6.5: Challenges and Study Approaches for ADHD and Eating Disorder Research in India

Domain	Challenges / Limitations for conducting research in India	Our Approach in the Study
Study Design & Expert Collaboration	Need for clinical and nutritional expertise for accurate classification	a. Conducted study on classification of ADHD and eating disorders using smartphone sensor data b. Collaborated with psychiatrists and nutrition experts from India to guide assessment and interpretation
Participant Recruitment & Engagement	a. Stigma around mental health b. Low awareness of ADHD and eating disorders Language diversity c. Gender norms affecting participation d. Socioeconomic disparities in smartphone access e. Cultural factors influencing willingness to participate	a. Conducted awareness campaigns in schools, colleges, and communities b. Translated app instructions and consent forms into regional languages c. Engaged parents, teachers, and local cultural/community leaders to build trust and encourage participation d. Provided offline-capable apps and loaner devices; participants could view their own data, enhancing trust
Data Quality & Standardization	a. Device heterogeneity (low-end vs. high-end smartphones) b. Intermittent internet connectivity c. Sensors occasionally disabled d. Variations in daily routines, meals, and festivals	a. Developed preprocessing pipelines for missing/noisy data b. Standardized feature extraction across devices c. Adjusted models to account for cultural routines and behavioral variability d. Developed the app to run background data collection so sensors remained active even when the app was not open. e. Provided participants with clear instructions and guidance on keeping sensors enabled.
Ethical & Privacy Concerns	a. Low digital literacy b. Concerns about data privacy c. Limited regulatory framework in LMICs	a. Used culturally appropriate consent procedures b. Ensured data anonymization and security c. Obtained approvals from University in India
Operational & Logistical Limitations	a. Long-term engagement challenges b. Device battery, storage, and maintenance issues c. Limited technical support in rural areas	a. Maintained engagement via reminders, incentives, and flexible schedules b. Provided technical support through phone and community volunteers c. Scheduled data collection to accommodate exams, festivals, and work commitments

c) For standardization and quality of data, we employed preprocessing pipelines to manage noisy or missing data and standardized feature extraction across different devices to manage hardware variability. Our models were also made to include cultural routines and behavioral variation, and the app itself was made to capture background data even if it was not open. Instructions and reminders were also given to participants regarding leaving sensors on, so as to ensure high-quality, consistent data.

d) We addressed ethical and privacy concerns through culturally appropriate consent procedures, anonymization and secure storage of the data, and Indian ethics board approvals within Indian Council of Medical Research (ICMR) guidelines. These steps ensured participants' privacy, enhanced trust, and preserved conformity with local ethics.

e) To deal with operational and logistics limitations, we employed methods to maintain long-term participation, including reminders, incentives, and flexible scheduling. We provided technical support in the form of telephone and local area volunteers and organized data collection to keep away from exams, festivals, and work. These strategies minimized interruptions and maintained smooth participation during the study.

6.1.5 How can multimodal smartphone data, including sensor, usage, and behavioural patterns, be utilised to enhance the classification of mental health conditions such as ADHD and eating disorders?

In studies 2 and 3 (Chapters 4 and 5), data were collected from various smartphone sensors such as application usage logs (digital), accelerometers (physical), touch, and screen interaction (digital), and location tracking (physical). While existing literature explores data from individual sensors about ADHD and eating disorders, very few studies incorporate multi-modal data from multiple sensors. Most of the studies have been done on either depression or anxiety, never fully incorporating both physical and digital data sensors with multi-modal data (Beard et al., 2019). Therefore, this gap is addressed in our PhD study, providing a novel approach in the classification of mental health. Because no prior study had investigated mental health monitoring (ADHD and eating disorders) in this population, we could not compare our results to the literature directly.

One of the defining symptoms of ADHD, impulsivity, can occur in both in terms of a person's use of phone (digital activity) and terms of activity level (physical activity level). The integration of digital and physical data sources, such as app usage patterns (digital), accelerometer data (physical), screen and touch interaction (digital), and location data (physical), enables the comprehensive analysis of behavioural patterns that are not always detectable using single sensor. For example, impulsivity related to ADHD might be detected by frequent app switching during times when an individual is detected as in a state of rest using digital data, whereas complementary insights are given with the physical data of movement recorded through accelerometers (Smith et al., 2020; Chan et al. 2019). Symptoms of ADHD are not the same throughout the day or across environments. With the ability to monitor digital behaviour (e.g., the use of a smartphone) and physical behaviour (e.g., movement), it is easier to properly classify likelihood of ADHD.

a) Interpreting Behaviour within Context

Some behaviours may seem like symptoms of ADHD when viewed alone but are not enough to classify ADHD. It is hard to differentiate ADHD from other problems like stress or anxiety. When viewed with other behaviours, specifically from a different context within life, their meaning is clearer (Sankesara et al., 2023). Two behaviours that, when combined, may provide stronger indications of ADHD are frequent app switching and physical fidgeting.

- Frequently switching between apps: It might seem like the individual is acting impulsively while switching apps back and forth. It does not necessarily point towards ADHD because the individual might be switching apps either out of boredom or because he or she is multitasking.
- Physical Fidgeting: Some people are highly mobile and are constantly moving around, but this may be associated with exercising, stress, or habit and not with ADHD-related hyperactivity. Not only does the person switch apps repeatedly but also fidget excessively. When combined, these behaviours serve as a stronger indicator. This is because digital behaviour (app switching) and physical behaviour (fidgeting) both reflect impulsive and hyperactivity, two core symptoms of ADHD (Sankesara et al., 2023).

To classify ADHD accurately, digital and physical behaviours need to be considered. For example, if someone swipes through apps quickly and walks around a lot at the same time, this behaviour might be a better predictor of ADHD (Sankesara et al., 2023).

b) Time and Situation-Dependent Changes in Symptoms

Symptoms of ADHD are not consistent across the day. They can change with the time of day, the environment, or the activity the individual is performing (Sankesara et al., 2023). Two common variations are seen in the evening and during the day.

- Evening behaviour: An individual may also present with signs of distractibility in the evenings with excessive social media scrolling or random internet surfing. It could be a sign of poor focus ability, but it could also be a symptom of fatigue after a long day.
- Daytime behaviour: The same individual may wander about extensively during the day, constantly arising from the bed, walking, or pacing. This may be a sign of hyperactivity but could also be caused by overall restlessness.

By looking at behaviour over time and not simply at a point in time, it is possible to gain a better comprehension of ADHD symptoms.

c) Avoid misclassification.

When a machine model is trained with a single source of data (e.g., smartphone use alone), it could misdiagnose unrelated behaviours as symptoms of ADHD (Sankesara et al., 2023). For example, a person who is working late into the night might switch apps back and forth and seem distractible. The model could misdiagnose them with ADHD simply by looking at how the person is using their phone. When the motion data reflects the person is sitting and not walking around with their phone, this shows the person is simply working late and not displaying ADHD-related hyperactivity. By combining various sources of data (physical and digital), it is easier to confirm whether a behaviour pattern reflects ADHD. This reduces false positives and increases accuracy (Sankesara et al., 2023).

To understand symptoms of ADHD on a deeper level, both digital and physical information together reveal a complete picture of a person's behaviour. For example, participant A reveals constant, focused behaviour with fewer app-switches, constant typing pace, and fewer mistakes, with little physical activity, depicting calm and regulated behaviour with no hyperactivity and impulsivity, and no symptoms of ADHD. participant B reveals fewer app use, average accuracy in typing, and constant reaction to notifications, with even physical activity during the entire day, depicting a balanced life with no apparent symptoms of ADHD. participant C, in contrast, reveals high app-switches, fast typing with numerous typing mistakes, and high physical activity, depicting restlessness and impulsivity, with unpredictable behaviour and inattention, all traditional symptoms of ADHD. By combining both digital information, such as app use and typing behaviour, with physical information, such as accelerometer activity, multi-dimensional analysis can reveal complete picture of symptoms of ADHD, distinguishing between participants with and without symptoms of the disorder.

Eating disorders are manifested through digital and physical behaviour and change with time based upon situational and environmental factors. Eating disorders are not fixed mental illnesses but are a dynamic interaction between habits, compulsions, and coping mechanisms whose expression changes with context. It is essential to recognise these changes for appropriate detection and classification.

d) Capturing Physical and Digital Behaviours' Variation

Individuals with eating disorders typically exhibit a pattern of behaviours including their digital behaviours and physical activities. The behaviours are not consistent around the clock but change with factors like the time of meals, the level of stress, and social interaction. Two key areas where these variations are observed are digital behaviour and physical activity.

- Digital behaviour may involve the person repeatedly visiting diet websites, reading about fasting plans, or employing weight loss apps. The behaviour may be increased later in the night, as a preoccupation with body image before bed or planning the food restriction strategies for the following day.

- Physical Activity: Some may exhibit reduced physical activity levels throughout the day, e.g., longer sitting periods after meals. Others may employ compensatory behaviours, e.g., excessive physical activity following meals, as a counterbalance for perceived caloric intake.

The combined pattern of digital behaviour and physical behaviour can determine the normal lifestyle habits and separate them from eating disorder symptoms. For instance: An individual who surfs weight loss content at night and exhibits a pattern of physical inactivity during the day may be involved with disordered eating behaviours. In contrast, a person who exercises regularly but also searches for radical dieting strategies might be engaging in compensatory behaviours that are not healthy (Levinson et al., 2020). By looking into digital and physical behaviours across different time periods, researchers are better able to understand the way eating disorders arise and are sustained.

e) Contextualising Changes in Physical Activity

Physical activity is crucial when evaluating eating disorders. It is critical to distinguish between physical activity as a healthy lifestyle and physical activity for disordered eating behaviour. Some individuals engage in excessive amounts of exercise for overall fitness, but others use excessive exercise as compensation for food intake. Below are two distinct types of physical activity related to eating behaviours.

- Healthy physical activity: A person who exercises or plays sports on a regular basis for the sake of remaining healthy follows a normal and healthy routine. Their physical activity pattern is typically structured, regular, and unrelated to food intake.
- Compensatory physical activity: An individual who excessively exercises as compensation for food intake may be evidencing an eating disorder. The behaviour is typically compulsive, increases after food intake and is linked with guilt or fear after skipping.

If the person is very physically active and watching content online promoting extreme dieting or unsafe weight-reduction strategies, it is a sign of a potential eating disorder. A good example is the individual who looks for "how to burn 500 calories fast" immediately after eating and then undertakes heightened physical activity. The combination of the two is a risk indicator for disordered eating (Levinson et al., 2022). Positioning physical activity within the digital behaviour context provides a better method for the identification of abnormal patterns since it separates normal and disordered behaviours.

f) Distinguishing Between Normal and Disorder-Linked Behaviour

Most behaviours related to eating disorders, including frequent internet searches for weight loss or excessive physical exercise, are also found within the normal population. The most critical factor differentiating normal behaviour from behaviour related to eating disorders is the identification of clusters of activities instead of individual behaviours alone. The following examples highlight the differences

- Single behaviour: Late-night surfing the fitness blogs or watching weight loss videos does not automatically indicate the existence of an eating disorder. Running every day as part of a training schedule is not inherently problematic.
- Clustered Behaviour: When a person searches extensively late into the night for extreme dieting and increases exercise and skips meals, all these actions combined make up a pattern which may indicate the existence of an eating disorder.
- Non-disordered individual: A person who exercises and eats a balanced diet regularly may occasionally read healthy eating or weight control literature but whose behaviour is otherwise within normal limits. Potential Eating Disorder Signals: If someone regularly spends time on pro-anorexia websites, monitors every morsel he or she eats and exercises excessively regardless of injury or exhaustion, these actions collectively point toward the possibility of an eating disorder.

By combining digital behaviour and physical movement data, researchers can increase classification accuracy and avoid the misclassification of healthy behaviours as disordered behaviours (Levinson et al., 2020).

g) Evolution of eating habits over time

Symptoms of eating disorders are not stable and change with various external factors such as time of day, mood, and social setting. It is difficult to determine the existence of an eating disorder from isolated observations. The following examples illustrate how external influences can affect eating behaviours and their expression.

- Some people limit their food consumption during the day but binge-eat during the night.
- Others eat normally within social settings but restrain their food when alone.
- Higher online engagement with diet content or higher compensatory physical activity could be brought about by stress.
- One who restricts food intake before social events and compensates with excessive physical

activity might present symptoms of situational eating disorder.

- Digital behaviour such as late-night searches for fasting techniques could be linked with breakfast-skipping behaviour the next day.

Symptoms of eating disorders evolve with time and are influenced by the external environment. Disordered behaviour may be seen in some environments and not others. Real-time tracking of digital and physical behaviour is thus critical. It is through the detection of the changes that interventions and support mechanisms can be developed.

A person may have minimal interaction with food-related content online during meals but increased dieting-related searches later in the evening, suggesting perhaps restrictive eating or binge behaviour. Observing these fluctuations longitudinally (digitally and in real-world settings) gives a more accurate picture of eating disorder behaviour, and combining multiple data sources captures the full range of symptoms (Levinson et al., 2022). Reducing false positives and improving classification accuracy a false positive can occur if someone presents with symptoms that resemble an eating disorder but are caused by another factor. An example is: An individual seeking nutrition advice could be doing so out of healthy motives, and not because of an eating disorder. But if they also have intense physical exercise behaviours (e.g., compensatory exercise), it suggests the presence of an eating disorder. By combining digital behaviour (searching for diet content) and physical behaviour (exercise patterns), multimodal data sharpens the categorisation and reduces the likelihood of misinterpretation (Levinson et al., 2020).

A combination of behaviour indicators drawn from various sources, such as application usage patterns, typing behaviour, response to notifications, and physical activity information, may provide a comprehensive picture of a person's mental and physical well-being. Digital behaviours, including application use, typing speed, typing errors, and reaction times for pop-ups, can say a lot about a state of mind and an individual's coping mechanism. For example, participant A shows focused and controlled behaviour with fewer app-switches, steady typing speed, and minimal mistakes, along with little physical activity, indicating calm behaviour without hyperactivity, and no signs of an eating disorder. Participant B has a moderate use of apps, average typing accuracy, and a balanced reaction to app notifications, with normal physical activity throughout the day, suggesting a balanced life with no apparent eating disorder symptoms. Participant C has high app switching, quick and frequent errors in typing, and high physical activity, suggesting eating and body image obsession behaviours, with restrictive or excessive exercise behaviours, typical in eating disorder. By comparison between digital behaviours, like app use and typing behaviours, and physical activity, a clear difference can be identified in those with and without eating disorders, with differences in activity and behaviour between participants.

A more precise characterisation of eating disorders can be drawn up using physical activity and digital behaviour patterns. Cognitive and affective states information can be found using digital information, i.e., app usage, notification reaction timings and typing patterns, while knowledge about physical activities, i.e., activities and location data, can provide information on a person's experience and engagement in the environment (Levine et al., 2020).Together, a more comprehensive characterisation of a person's behaviour can be assessed, enabling the detection of subtle symptoms of eating disorders that may not be discerned through a single source of information alone (Dale et al., 2021).

CHAPTER 7

DISCUSSION OF IMPLICATIONS AND CONCLUSION

7.1 Implications

7.1.1 Implications for Healthcare Practitioners

Implications primarily relate to the potential for early identification of ADHD and eating disorders. The use of digital analysis in practice can be very useful to mental health practitioners in low- and middle-income countries (LMIC), where resources are generally scarce to respond to mental health demands. Digital analysis can fill in gaps between limited resources and mounting pressures for mental health patients. This can particularly be useful in settings with limited access to traditional mental health centres. Early identification through digital means allows clinicians to recognise symptoms sooner and initiate timely interventions before conditions become severe.

Continuous monitoring using digital technologies, such as smartphone-based behavioral monitoring, can provide real-time data on attention, sleep patterns, and other symptoms unique to both ADHD and eating disorders. Such early detection enables clinicians to create personalized treatment plans, more effectively monitor progress, and prevent complications that may arise from delayed diagnosis. Digital tools are very effective in rural settings as the health services in these areas are not easily accessible because of the distance and limitations in infrastructure. Behavioural data using smartphones can help in meeting the mental needs in areas lacking conventional services. Digital interventions can plug the gaps by enabling remote consultations and monitoring and thereby expanding the coverage of mental health services. With the patient's consent, the app—operated on a smartphone—employs machine learning to analyse patterns of activities.

In urban Indian settings, despite relatively easier access to mental health services, such systems still face overcrowding and unsustainable demand. Digital interventions can reduce such pressures by allowing remote monitoring of patients and thus increasing system efficiency. Data like activity levels, sleep patterns, and communication behaviours can offer objective information about patients' mental health states. This can enable a more accurate classification of disorders such as depression, anxiety, ADHD, and eating disorders. Furthermore, health practitioners can add such data to electronic health records to offer a more holistic view of patients' health. Such innovations can enable early intervention and personalised treatment plans, and mental health care can be more proactive and not reactive.

Furthermore, digital tools help bridge gaps in resources and offer possibilities to provide care through real-time gathering and analysis of information. Such technologies offer accessible and scalable ways to bridge the mental health treatment gap in LMIC and enable health professionals to respond to changing patient circumstances in a timely fashion and improve mental health outcomes.

7.1.2 Implications for Researchers

Some key implications can be drawn from evidence on digital behaviour in mental health classification, especially for those who wish to conduct studies in low- and middle-income countries like India. Analysis of trends in digital behaviour, like smartphone sensor use, allows researchers to identify trends in mental health that would be unobservable otherwise. Gathering real-time information from such sources (smartphone sensor data) enables real-time monitoring of mental health, which proves to be effective in capturing environmental or social factors' impacts on mental health.

Digital monitoring and real-time data collection allow researchers to detect patterns of ADHD and eating disorder behaviours sooner than traditional observational or survey methods. This enables studies to capture changes in symptoms over time, improving the accuracy of research outcomes and providing evidence for early intervention strategies. For researchers to conduct studies in LMIC like India, integrating smartphone sensor data for monitoring ADHD presents multiple challenges and opportunities. One of them is recruitment, particularly in rural areas, as families may be hesitant to participate in studies for privacy and safety fears about data. Researchers may find it hard to obtain consent to collect digital data on children from parents or participants for fears about abuse of health information. To overcome this, researchers must prioritise transparent communication to ensure that participants are aware of how their information will be used, stored, and protected. This can be achieved through clear informed consent procedures, educational materials, and assurances about safety of data, including through end-to-end encryption.

Another challenge is technological limitations in rural areas with smartphone availability and coverage sometimes being inconsistent, causing smartphone lag or breakdowns in data transmission. Researchers may be forced to adapt methods to deal with technological heterogeneity by designing offline apps or by storing collected data locally on devices and synchronising when a network is available. Real-time monitoring of ADHD symptoms using smartphone sensors can drain the phone's battery quickly, especially in areas with limited charging points. Researchers can deal with this by designing energy-efficient applications that reduce sensor utilisation during off-peak hours or by using low-energy equipment designed for long-term monitoring. In addition to this, researchers will be restricted by sample size due to these barriers. Recruitment can be slow, and study participants can drop out in case the procedure is too complex, or they are experiencing technical challenges. To prevent this, researchers can encourage study participation using non-financial incentives, for instance, by providing access to free mental health treatment or counselling to parents on how to deal with ADHD symptoms using smartphone apps.

Digital interventions that are proven effective in high-income countries cannot be directly implemented in LMIC due to differences in digital literacy, technological infrastructure, and cultural attitudes towards mental health. Piloting and adapting interventions in the local setting ensures cultural appropriateness and responsiveness to the specific needs of the local population. By doing so, researchers can develop interventions that are not just effective but also scalable and sustainable in LMIC like India.

Collaboration with local communities and organisations is essential. Trust building is fundamental in bridging cultural gaps, particularly in regions where there is strong stigma related to mental health. Local health workers, community leaders, and organisations can act as intermediaries for the acceptance of digital tools and ensure that participants are comfortable with the utilisation of technology for mental health monitoring. These partnerships not only strengthen data collection but also improve long-term sustainability through the integration of these interventions within the local health systems.

7.1.3 Implications for Patients

Mental health digital tools may have a considerable influence on rural and urban patients, especially in low- and middle-income countries (LMIC). The digital tools provide accessible and ongoing care, particularly in areas with scarce traditional mental health services. With mobile health apps, smartphone sensors, and real-time monitoring, patients can receive personalised treatment plans and early interventions. In rural India, for instance, patients may use mHealth apps to monitor well-being by tracking stress levels and mood swings in real-time. This allows personalised interventions, such as cognitive behavioural therapy exercises, mindfulness activities, and mood-tracking reminders, reducing a burden on overloaded health systems. Furthermore, smartphone-based interventions provide anonymity, allowing patients to seek help without social repercussions. Telepsychiatry initiatives provide remote consultations to patients with limited access to specialists. Utilising smartphone sensor-derived data, mental health professionals can spot early warning indicators for ADHD, depression, or eating disorders. These digital tools enable early intervention by connecting patients with specialists before symptoms escalate, helping prevent severe mental health breakdowns.

Urban environments in LMIC present specific challenges and opportunities for digital mental health interventions. Despite improved accessibility, limitations such as long waiting times, economic constraints, and stigma continue to hinder early detection and intervention. Digital mental health interventions can bridge these gaps by offering self-monitoring and intervention strategies that supplement traditional health care services. In urban India, ADHD screening patients can use mobile apps to track attention, impulsivity, and multitasking behaviours. By observing behavioural trends over time, patients can detect changes and receive early interventions. Smartphone sensors also aid in monitoring eating behaviours where social pressures and lifestyles contribute to unhealthy patterns. Applications tracking body activity and eating behaviours can identify excessive exercise or restrictive eating, enabling early detection and healthier behaviours. Real-time sensing data can flag abnormal sleep habits or sudden activity fluctuations as potential indicators of depression, anxiety, or bipolar disorder, supporting early intervention prior to worsening symptoms.

Digital mental health tools in LMIC offer great value by ensuring confidentiality, accessibility, and real-time intervention. Smartphone applications provide discreet platforms for symptom tracking, self-help tools, and therapeutic counselling, reducing social stigma. Integrating digital input with conventional health practices enhances diagnostic accuracy and personalised care. Tracking sleep patterns, activity levels, and cognitive habits in real-time allows patients and clinicians to make timely interventions and lifestyle modifications, contributing to the management of ADHD and eating disorders. These technologies bridge gaps between limited mental health services and demands for continuous, personalised care, ensuring timely support and improving outcomes for patients in LMIC.

7.1.4 Implementation for Developers

To develop efficient and user-focused digital mental health interventions for low- and middle-income countries (LMIC), a careful consideration must be made for differences in cultures and in health. Data security is another critical concern influencing user trust in mental health apps, particularly in nations such as India with high anxieties about data misuse. Developers must adopt end-to-end security and clear use policies. Ensuring cross-platform compatibility and offline use can also have a powerful impact in expanding mental health interventions, particularly in rural areas with low smartphone penetration. Other strategies that aid in ensuring that digital mental health interventions meet local needs include iterative localisation and testing. It requires the feedback of clinicians, researchers, and even the users to make these applications better. Patient feedback can lead to making app user interfaces more in line with usability and cultural expectations, while researchers provide insight into effective mental health elements that can be integrated. For instance, research has pointed to tracking and feedback as being critical for ADHD patients, and app design must be modified to include such features accordingly. Similarly, clinicians can provide feedback to developers to minimise barriers to access and ensure app functions align with clinical standards, to improve patient outcomes in a digital health environment.

Battery power is also a major consideration for app creators. Continuous monitoring of activity in the form of attention levels, mobility status, and sleep patterns drains a lot of energy. App developers need to create energy-efficient apps using power-saving measures in the form of sensor optimisation or relying on intelligent algorithms that save data only when in use. Power-saving wearables in the form of smartwatches can also offload smartphone work while offering real-time monitoring. Finally, recruitment into studies becomes problematic due to digital literacy and infrastructural barriers to digital access. To counter these, developers need to provide user-centric interfaces having straightforward installation processes and in-app tutorials. Partnerships with local telemedicine centres or community health workers enable families to be taken through installation and use to facilitate maximum participation in ADHD studies.

Early identification of ADHD and eating disorders is a central implication for developers. Apps and wearable devices can capture behavioural patterns, attention levels, and activity data continuously, enabling timely detection of symptoms and personalised interventions. Incorporating features for early monitoring ensures that interventions are proactive rather than reactive, supporting better outcomes for patients in low-resource settings.

7.1.5 Limitations and Solutions for Researchers and Developers

a) Technological literacy and accessibility: Slow performance on smartphones, battery drain, and low smartphone penetration in rural areas may slow sensor data capture. Programme developers can build light and efficient programmes that run on low-end hardware and support data storage offline. Researchers can keep the applications simple to avoid technological literacy problems.

b) Concerns for Privacy and Data Security: Abuse of data and privacy may pose a barrier to recruitment in the diagnosis studies for ADHD. This may be overcome by both the developers and researchers through transparent means of collecting data, informing participants about safety measures in place and having secure cloud storage that is encrypted.

c) Sample Size and Recruitment Issues: Recruiting adequate sample sizes for studies of ADHD in urban and rural settings may prove to be challenging. Incentivization strategies for recruitment may be established in collaboration between developers and researchers. Incentivization strategies may include providing free management or consultation for ADHD as compensation for study participation. Encouragement of study participation for ADHD may also be promoted through local health centres and community healthcare workers.

7.2 Limitations and Suggestions for Future Research

By addressing these limitations, future studies can refine digital mental health tools to be more inclusive, accurate, and effective in managing mental health across diverse populations.

a) Demographic Representation and Small Sample Sizes

One of the primary limitations of our research is the use of relatively small and unrepresentative samples in many demographic sub-groups such as low socio-economic backgrounds, rural areas, old age groups, and poor accessibility to technology. It would lead to underrepresentation of diverse experiences and behaviours and thus less generalisable findings in the overall populace. A research study using data from smartphones to identify ADHD symptoms targeted mostly young urban university students aged 18-25 years who were tech-savvy and used high-end smartphones. Their patterns of usage in terms of technology and interaction with online resources would be very different from low-income or rural areas where accessibility to high-end smartphones and high-speed internet would be poor. Older individuals might be using low-end devices or have data capture problems due to poor connectivity. Such a lack of variety in the sample would lead to incorrect inferences about the presentation and monitoring of mental health symptoms in diverse populations. The findings from the research might not be generalisable to those with technological, socio-economic, or cultural barriers to accessibility and thus the research might draw incorrect inferences about digital mental health intervention in such populations. To improve the validity and applicability of future research work, research should be done with larger and diverse samples encompassing participants from diverse socio-economic backgrounds, rural areas, and old age groups. It would ensure that the effects of digital mental health intervention were tested in a broad range of populations and thus the findings would be closer to real-life settings.

b) Cultural, contextual, and technological differences

The identification of ADHD and eating disorders using smartphone sensor data was hindered by robust cultural barriers due to the varying digital habits and levels of technological accessibility in the different states in India. Smartphone behaviours are influenced by regional disparities in digital proficiency, socio-economic levels, language use, and cultural beliefs that affect the presentation of mental illness in online behaviours. In highly developed states such as Kerala, Karnataka, and Maharashtra, where there is high digital literacy, the use of smartphones becomes part of daily life to work, learn, and play. People use multiple apps frequently, such as work and study apps, educational platforms, and online payments systems. Frequent app switching, irregular use patterns on the screens, and midnight phone use might be easily detectable in such areas. High penetration levels on the internet allow social media to be used continuously and hence might offer better patterns of use to detect eating disorders in urban dwellers. Nevertheless, having scheduled routines because of work or study requirements might also affect the interpretation of mobile use and hence require demarcating work-related online activities from impulsive ADHD behaviours. In contrast to that, states like Bihar, Uttar Pradesh, and Madhya Pradesh in rural areas have low rates of penetration with smartphones and different patterns of online activities. The users here would be using voice calls and SMS and not app-based services and hence data availability to detect ADHD and eating disorder-related behavioural patterns would be low. Moreover, poor connectivity and cost factors induce variable and periodic usage of smartphones and thus regular behavioural markers would be hard to establish. ADHD symptoms in terms of restlessness or impulsive behaviours in such areas may not be reflected in quantifiable online activities because mobile usage would be functional in nature and not recreational in purpose. Similarly, eating disorder behaviours may not be detected in-app usage because exposure to dieting forums online or calorie counting apps would be low compared to urban areas.

Cultural conventions affect the use of smartphones differently in varying states. Smartphone use in West Bengal and Tamil Nadu, where social interaction with the community is high, will be centred on social media platforms popular in the region, news apps, and messaging platforms like WhatsApp and Telegram. The use of regional social media platforms and news apps may affect the detection of ADHD symptoms because users may not be app switching in the same way app-dense online cultures would anticipate. Likewise, eating disorder patients may have higher levels of private talk or talk within the home and not social media talk in public places, and detection through mobile phone use would be made difficult. In Haryana and Rajasthan, where gender roles are stronger, women's ability to access smartphones may be hindered through social expectations. Women in each family may share phones with others in the house with blended online traces that cover up personal patterns of behaviour. The limitation provides a significant hurdle in detecting ADHD because hyperactivity or inattention may not be seen in limited smartphone use. Disproportionally impacting women, eating disorders may not be detected if users have little engagement with social media forums regarding body image and eating behaviours. In the north-eastern states like Manipur, Meghalaya, and Assam, digital adoption remains in the infancy stage and users primarily employ regional languages or voice communication rather than text-based interaction. The communication and linguistic divide can limit the performance of app usage monitoring and text-based sentiment analysis since voice calls and regional dialect messaging may not be properly interpreted using machine learning models trained primarily on English- or Hindi-based conversations. The influence of tribal and indigenous cultural beliefs regarding mental illness expression may induce different patterns of speaking about or thinking about ADHD and eating disorders to impede the capacity of generic models to detect symptoms in such populations.

These disparities highlight the limitation in applying a standardised machine learning model to mental health classification through smartphones in India. A one-size-fits-all approach will lead to high levels of misclassification or exclusion of individuals whose online activities don't fall within patterns in urban tech-literate populations. To enhance the effectiveness in mental health detection through smartphones, future work should employ region-specific data sets to consider varying online habits, cultural expectations, and levels of technological penetration. Training models with a more representative data set with data from rural, urban, and semi-urban regions from several states would improve accuracy and equity and ensure successful deployment of online mental health interventions in the culturally diverse Indian context.

The social media research was greatly hindered in discovering culturally differentiated patterns in discussing mental health due to linguistic and conceptual differences in expressing mental distress in various societies. The algorithms were primarily trained using data from Western countries where mental talk commonly revolves around personal feelings and psychological states, such as personal struggles with depression, worry, or self-esteem. But in much of South Asia, including in India, mental health would generally be described in terms of bodily symptoms, social roles, or spirituality and not in terms of explicit emotional states. For example, in India, depressed individuals may not overtly express feelings of sadness, isolation, or hopelessness in the same way they come to be described in Western literature. Rather, they will express feelings of distress in terms of chronic tiredness, headaches, body aches, or gastrointestinal complaints—complaints that routinely get diagnosed as bodily ailments and not mental illness. Such somatisation happens in collectivist cultures where emotional complaints get suppressed either because they are stigmatised or because they violate social expectations. So, if an individual posts about chronic body aches or tiredness on social media rather than stating they feel sad or hopeless, the machine learning system—trained primarily on Western emotional reports—will fail to detect the mental illness.

Along with that, social and domestic responsibilities play a central role in Indian mental health discourse. Where a US or UK citizen might put down on paper that they feel overwhelmed individually or have low self-esteem, an Indian might frame his or her despair in terms of duty to work, family, or community. A message that says "I am not taking good enough care of my family, and I feel like a burden" can be a sign of depression, but models trained on Western-type statements like "I feel empty inside" will not pick up on such statements as relevant. Such phrasing can lead to severe underrepresentation of South Asian mental health concerns in machine-based classification models. In addition to that, religious and spiritual contexts influence the presentation of mental distress in Indian social media discourse. Someone with depression or anxiety symptoms may couch their struggles in terms of karma or destiny. Someone with persistent worry may say to us, "Maybe this is coming back to me because of my past karma," rather than reporting that they have anxiety. Similarly, religious or spiritual action in the form of temple attendance, fasting, or prayer is a normal reaction to mental distress in India, and talk about those behaviours will contain helpful mental health markers that Western models do not pick up on.

Social media mental health classification becomes even more challenging due to linguistic diversity. India alone has more than 20 prominent languages and numerous dialects and users code-switch among multiple languages in a post in many cases, especially Hindi-English code-switching (e.g., "Aaj kal bohot zyada stress ho raha hai, samajh nahi aa raha kya karu" meaning "I have been feeling too much stress lately, I don't know what to do"). Standard natural language processing (NLP) models trained on monolingual English corpora may not be effective in processing such code-switching expressions and hence may decrease accuracy in multilingual populations. Due to such linguistic and cultural barriers, machine learning models trained predominantly on Western data tend to overlook or label important mental health indicators among the South Asian populations. It leads to widespread underrepresentation of mental illnesses and makes it difficult to estimate the rates of conditions like depression, anxiety, ADHD, or eating disorders in the non-Western contexts. To enhance the accuracy and inclusiveness of machine learning models used to classify mental health in digital data, future work will need to integrate culturally diverse data sets that reflect regional patterns in expressing mental distress. It can be achieved through machine learning algorithmic training with multilingual social media data, the integration of culturally informed linguistic markers, and sentiment analysis tool customisation to identify indirect mental health expressions.

c) Performance on Devices, Battery Life, and Cross-Platform Consistency

One significant limitation of the research using the smartphone sensor-based approach (study 2 and study 3) involves the draining of battery life and inconsistency in device performance between models, compromising the practicality of continuous data collection. The participants, particularly in the eating disorder study, noted that intensive data collection using sensors such as the accelerometer, GPS, and gyroscope depleted mobile phone batteries and made prolonged participation difficult. The issue was worse among participants with old smartphones because they suffered from performance issues such as slow app performance and malfunctioning sensors, resulting in loss or unavailability of data. Other devices had hardware limitations where some sensors failed to capture data or were always not functional, resulting in data losses in behavioural monitoring. For instance, low-end smartphones with less responsive motion sensors were not effective in capturing minute motion patterns and inconsistencies in GPS accuracy resulted in losses in location-based behavioural data. The technical disparities introduced bias in the dataset because participants with high-end devices provided complete and better-quality data while participants with old devices provided fragmented or incomplete data and hence compromised the findings in the study. To address such limitations in future research, there should be a priority in improving the efficiency in utilising power through adjusting the frequency in data collection, utilising adaptive sampling techniques to only capture the most important data from sensors, and ensuring compatibility with a variety of devices to minimise data loss and improve the overall quality and accuracy in smartphone-based mental health assessments.

d) Lack of Long-Term Follow

One limitation in the current research is the application of short-term data collection, typically spanning one week. Even though such an approach gives insightful information about participants' mental well-being within a given time frame, it cannot capture the changes and fluctuations in mental well-being that may occur over time or in response to given events or situations. For instance, participants may have significant changes in mental well-being during examination periods or holiday seasons and semesters that would not be reflected in a short data collection period. For example, during examinations, the students have heightened stress and anxiety and sleeping patterns change. The periods have high concentration but with increased mental fatigue and burnout as well. Data collection before examinations, during examinations, and after examinations may provide information about the influence of stress on cognitive performance, emotional well-being, and levels of attention over time. A brief data collection may not be able to capture the transition and thus may not have a complete perspective regarding the influence of examination stress on mental well-being.

Similarly, social interaction heightens during festivals, routines get disrupted, and emotions rise and fall either in joy or in feelings of isolation or fear. Observation and data collection at different stages in a festival, i.e., the pre-event buildup phase, the event phase, and the post-event phase, would be useful in knowing the effects of social stress factors, emotional fluctuations, and changes in behaviour. Students may experience an uplift in the mood due to social interaction or feel alienated from others during the holiday if they are not with relatives or have very little social interaction. In addition, over the course of a term in school, students experience a typical rise and fall in mental well-being as they struggle with course requirements, social life, and personal growth. The demands of course work assignments and deadlines and extracurricular activities can produce fluctuations in mood, energy levels, and attention. Tracking data over the course of a term and not just a week would enable researchers to identify recurring patterns in mental illness related to the cycles of academics, such as heightened levels of stress in pre-deadline periods or social withdrawal after marathon study sessions.

Tracking data at sessional time intervals—before, during, and after such significant events—could be helpful in knowing about mental fluctuations over time in response to specific stressors. Scaling up the data to cover such diverse timeframes would offer a better and closer representation of mental well-being. It would allow better mental illness classification because patterns in attention, mood, and cognitive performance would be better attributed to the specific events or stressors involved. For example, if a participant has high levels of stress and low levels of attention during examination periods and high levels of mood and energy levels during holidays, the system can learn to differentiate between symptoms related to stress and those related to other mental conditions. Not only would this improve the precision with which the system classifies participants but would provide richer contextually relevant information that reflects real-life scenarios. The addition of sessional data points would enhance mental condition classification considerably through the presentation of a dynamic and time-sensitive picture of the influence of changing factors on well-being. The longer-term monitoring would additionally assist in the development of individually tailored interventions that would be better matched to changes in a person's mental well-being over time.

e) Methodological limitation

A methodological limitation of the research is using k-fold cross-validation instead of leave-one-out cross-validation (LOOCV) in measuring model performance. While k-fold cross-validation provides a reliable estimate of generalization and reduces computational complexity, it can cause moderate bias in performance estimates compared to LOOCV, which trains the model on each individual data point. LOOCV generally offers a better estimate in the case of small sample sizes, in that every sample gets to be used in both training and testing operations. The decision to use k-fold cross-validation was based on computational expense and convenience with the large volume of smartphone and sensor data collected; however, the method has a tendency to overestimate or underestimate the true predictive power of models at times.

f) Measuring Mental Health Involvement on Social Media

One of the drawbacks of Study 1 is that it was hard to determine whether users were indeed members of a community or just discussing about mental illness. The study assumed active participation on a website like Reddit or Twitter would mean that the person was interacting with a community and this may not always be true. Commenting or postings do not actually mean that one is active, connected to others, or feeling a sense of belonging. Posts can be from health professionals, celebrities posting about mental illness, awareness organizations, or news outlets sharing information and not from general community members. As a result, the study might have confused overall Internet use with genuine community participation. The data did not show evidence of the existence of deeper engagement, such as posting regularly, responding to others, or forming social connections. Therefore, it is hard to ascertain whether or not individuals were indeed participating in a community or merely using the site as a platform to post views. This limitation affects the interpretation of the findings in that they could be representing topic-based activity rather than true community engagement. This could be improved in future studies by looking at behavior or networks that show repeat contact, reciprocated reply, or a sense of belonging.

g) Limitations of Smartphone-Based Behavioural Classification

In this studies (study 2 and study 3), behaviour is considered quantifiable patterns of smartphone use captured by way of accelerometer data, GPS location, application use, notification response time, touchscreen and keyboard interaction, typing rate, and typing errors. While all participants were clinically diagnosed with an eating disorder or ADHD, labeling an individual as demonstrating the "same behaviour" as these groups remains in its boundaries because these measures are indirect markers of clinical features and do not include direct measures of cognitive, affective, or physiological signs. In addition, contextual and environmental influences—i.e., work, daily routine, social habits—may affect movement, location, use of apps, and typing behavior, introducing variability that can affect classification. Similarly, similarity in smartphone-derived behaviour identifies diagnosed groups but does not replace formal clinical assessment or apply to undiagnosed or subclinical individuals reliably.

7.3 Summary/Conclusion

Overall, the findings from study 1, study 2, and study 3 interface with one another in developing the current state of art regarding digital data usage for classification of various mental health disorders.

Study 1 focuses on social media platforms, such as Twitter and Reddit, to identify and classify posts related to mental health. Using machine learning algorithms incorporating CNN and word2vec, the study 1 successfully categorises social media content based on various types of mental health disorders without the use of specific mental health-related keywords. This study points out that there is great variation in the theme and sentiment across different platforms, and there is a need to integrate data across various social network platforms must achieve a better understanding of perceptions of mental health at large. The approach yields considerable insights into the linguistic patterns of mental health discussions and points to further real-time monitoring and cross-platform analysis.

This research demonstrates the potential of smartphone-derived sensor and behavioral data to provide fine-grained insights into ADHD and eating behavior in naturalistic settings. Study 2 introduced a novel ADHD classification approach using smartphone sensors with high accuracy in distinguishing between individuals with and without the condition, and Study 3 extended this approach to the classification of eating disorders. These studies confirm the possibility of non-invasive, real-time monitoring, and illustrate the value of continuous, objective data collection for affordable and scalable mental health assessment. By applying machine learning to patterns of behavior such as app use, typing dynamics, GPS location, accelerometer data, and response time to notifications, the research identifies the most predictive features of ADHD and eating disorder behaviors. These findings offer insight into the expression of mental health conditions in daily life as well as the potential for digital phenotyping to complement traditional clinical assessment. Further, the research establishes methodological frameworks for integrating smartphone-source sensor and behavioral data into prediction models with insights on intervention design as personalized interventions, adaptive mental health intervention, and public health strategies.

Despite these strengths, several limitations should be considered. Sample sizes were relatively small and non-representative, particularly in demographic sub-groups such as low socio-economic status, rural areas, older age groups, and populations with limited access to high-spec smartphones, which limits generalizability. Cultural, contextual, and technological disparities further constrained the detection of ADHD and eating disorder behavior: regional variations in digital literacy, online activities, gender roles, and linguistic diversity affected smartphone usage patterns, potentially undermining model accuracy. Device performance issues, battery drain, and cross-platform inconsistencies generated data gaps, while short-term monitoring limited insight into long-term behavior fluctuations according to academic, social, or seasonal cycles. Methodologically, the use of k-fold cross-validation rather than leave-one-out validation may have biased estimates of model performance. Furthermore, behaviorally measured by smartphone is an indirect index of clinical symptoms and perhaps confounded by context, and in social media research, even today it is hard to distinguish genuine community participation from peripheral or passive attendance. Future studies would involve larger and more representative groups, including rural, poor, and elderly cohorts, and account for regional, linguistic, and cultural differences to increase equity and model accuracy. Enhancing device compatibility, employing adaptive sensor sampling, and ongoing longitudinal follow-up would better capture temporal patterns in mental health. Combining culturally informed models with more representative data will improve detection of ADHD and eating disorder behavior and allow the creation of context-dependent, personalized, and real-time interventions. Overall, smartphone-based monitoring represents a low-cost and scalable route for mental health research that can be used to inform public health policy, intervention design, and clinical practice in diverse groups.

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Appendix

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

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.		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?					

Part A

7.	How often do you make careless mistakes when you have to work on a boring or difficult project?					
8.	How often do you have difficulty keeping your attention when you are doing boring or repetitive work?					
9.	How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?					
10.	How often do you misplace or have difficulty finding things at home or at work?					
11.	How often are you distracted by activity or noise around you?					
12.	How often do you leave your seat in meetings or other situations in which you are expected to remain seated?					
13.	How often do you feel restless or fidgety?					
14.	How often do you have difficulty unwinding and relaxing when you have time to yourself?					
15.	How often do you find yourself talking too much when you are in social situations?					
16.	When you're in a conversation, how often do you find yourself finishing the sentences of the people you are talking to, before they can finish them themselves?					
17.	How often do you have difficulty waiting your turn in situations when turn taking is required?					
18.	How often do you interrupt others when they are busy?					

Part B

Description:

The symptom checklist is a tool consisting of 18 criteria from the DSM-IV TR. Six of the 18 questions were found to be most predictive of ADHD symptoms. These six questions are the basis of the ASRS v1.1 checklist and are also part A of the symptom checklist. Part B of the symptom checklist contains the remaining 12 questions.

Scoring and Interpretation:

The symptom checklist is a tool consisting of 18 criteria from the DSM-IV TR. Six of the 18 questions were found to be most predictive of ADHD symptoms. These six questions are the basis of the ASRS v1.1 checklist and are also part A of the symptom checklist. Part B of the symptom checklist contains the remaining 12 questions.

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2. Experience sampling method (ESM)

Date:	Time:
Please rate the following items based on your experience right now or in the past hour using the scale provided (1-5):	
(1 = Not at all attentive/focused, 5 = Extremely attentive/focused)	
Questionnaire	Rating(1-5)
How attentive and focused do you feel at the moment?	
How often do you find your mind wandering or getting easily distracted?	
How often do you have difficulty sustaining attention in tasks or activities?	
How frequently do you feel restless or find it hard to sit still?	
How often do you have difficulty organizing tasks or activities?	
How often do you forget to do things or misplace important items?	
How often do you interrupt or talk excessively in conversations?	
How often do you feel impatient or have difficulty waiting for your turn?	
How frequently do you feel overwhelmed or have difficulty managing your time?	
How often do you engage in impulsive or risky behaviors without considering the consequences?	
How often do you experience difficulty in completing tasks or projects on time?	
How often do you struggle with following instructions or guidelines?	
How frequently do you feel easily frustrated or irritable?	
How often do you experience difficulty in prioritizing tasks or managing multiple responsibilities?	
How often do you feel that your mind is racing or overloaded with thoughts?	
How frequently do you find it challenging to start or initiate tasks?	
How often do you have difficulty staying organized or keeping track of important information?	
How frequently do you experience impatience or a need for immediate gratification?	
How often do you feel like you're constantly on the go or have difficulty relaxing?	
How frequently do you struggle with maintaining attention during conversations or lectures?	

Experience sampling method (ESM) to examine the impact of inattentive and hyperactive-impulsive ADHD symptoms on emotional well-being, activities and distress, cognitive impairment, and social functioning assessed in the daily lives of young adults. Researchers signaled the participants, administered the questionnaires, and time stamped and recorded the participants' responses. Participants were signaled to complete the ESM questionnaire daily (several times) between noon and midnight for 7 days [1],[2]

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3. **Binge Eating Scale (16 items)**

Instructions:
Below are groups of statements. Please read each group of statements carefully, and then pick out the one statement in each group that best describes the way you feel or act.

1.
A. I don't feel self-conscious about my weight or body size when I am with others.
B. I feel concerned about how I look to others, but it usually does not make me feel disappointed with myself.
C. I feel very concerned about how I look to others and I am often disappointed in myself for being overweight.
D. I feel so self-conscious about my weight and body size that I feel intensely ashamed and embarrassed when I am with others.

2.
A. I don't have any difficulty eating slowly in the proper manner.
B. Although I seem to "gobble down" foods easily at times, I don't feel that I lose control of my eating behavior.
C. At times, I tend to eat quickly and then feel as though I have eaten too much.
D. I have the habit of eating quickly and find myself eating too much before I realize what I am doing.

3.
A. I am usually aware of when I am hungry and when I am full.
B. Occasionally, I do not recognize my hunger and thus overeat.
C. I am frequently unaware of whether I am hungry or full.
D. I am almost always unaware of whether I am hungry or full and thus I overeat.

4.
A. I can feel comfortable eating with others even when I am dieting.
B. I feel self-conscious eating in front of other people, especially when I am trying to lose weight.
C. I feel very uncomfortable eating in front of others and will avoid eating in front of others whenever possible.
D. I feel so embarrassed when I eat in front of others that I will usually try to eat alone.

5.
A. I eat three meals a day with only an occasional snack.
B. I sometimes eat between meals, but these snacks don't really add up to much.
C. When I snack, I tend to eat large amounts of food whether I am hungry or not.
D. I eat so frequently during the day that I often lose track of how much I have eaten.

6.
A. I feel capable of controlling my eating urges when I want to.
B. I feel like I have some control over my eating, but I sometimes get into situations where I lose control.
C. I feel like I frequently lose control over my eating.
D. I feel so out of control with my eating that I sometimes feel like I am going crazy.

7.
A. I don't have any trouble stopping eating when I feel full.
B. I usually can stop eating when I feel full, but every so often I can't.
C. I frequently continue eating even after I feel full.
D. I almost always continue eating past the point when I feel full.

8.
A. I don't think much about trying to control unwanted thoughts about food.
B. I occasionally try to put food out of my mind, but I am usually successful.
C. I try to put food out of my mind a lot, but I usually am not successful.
D. I feel like I constantly have to struggle to keep from thinking about food.

9.
A. I usually know whether or not I am physically hungry.
B. Occasionally, I eat because I feel bored or lonely, even though I'm not really hungry.
C. I frequently eat when I'm bored or lonely, even though I'm not hungry.
D. I almost always eat when I'm bored or lonely, even though I'm not hungry.

10.
A. I only rarely feel guilty or self-critical after eating.
B. Sometimes I feel guilty or self-critical after eating.
C. Often I feel guilty or self-critical after eating.
D. Almost all of the time I experience strong guilt or self-hatred after I overeat.

11.
A. I don't lose total control of my eating when dieting even after periods when I overeat.
B. Sometimes when I eat a "forbidden food" on a diet, I feel like I "blew it" and eat even more.
C. Frequently when I overeat on a diet, I feel like I have failed, and I then eat even more.
D. I have a pattern of overeating, feeling like I have failed, and then overeating even more.

12.
A. I rarely eat so much food that I feel uncomfortably stuffed.
B. Sometimes I eat enough to feel uncomfortably stuffed.
C. I often eat so much that I feel uncomfortably stuffed.
D. Almost every time I eat, I tend to eat so much that I feel uncomfortably stuffed.

13.
A. I don't feel any need to hide my eating habits.
B. I sometimes feel I need to eat in private, but most of the time I don't.
C. I often feel I need to eat in private.
D. I feel a strong need to eat in private and will try to find a place where no one will see me.

14.
A. I eat sensibly in front of others and also when alone.
B. I eat sensibly in front of others but overeat when alone.
C. I overeat in front of others and when alone.
D. I overeat only when alone.

15.
A. I don't think much about food during the day.
B. I think about food a lot of the day.
C. I think about food most of the day.
D. I think about food all day long.

16.
A. I don't feel any embarrassment or disgust toward myself after I overeat.
B. Sometimes I feel embarrassed or disgusted with myself after I overeat.
C. I often feel embarrassed or disgusted with myself after I overeat.
D. Almost all the time I experience strong feelings of disgust or hatred toward myself after I overeat.

Scoring the BES:

Each item is scored 0, 1, 2, or 3 depending on the response (A = 0, B = 1, C = 2, D = 3).

Score interpretation:

- **0–17:** Non-binge eater
- **18–26:** Moderate binge eating behavior
- **27–46:** Severe binge eating behavior