DEVELOPMENT OF AI BASED TOOL FOR EARLY DETECTION, PREVENTION AND CARE IN COMMON MENTAL DISORDERS

Thesis Submitted for the Award of the Degree of

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in

Psychology

By

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DECLARATION

I, hereby declared that the presented work in the thesis entitled "**Development of AI based Tool for Early Detection, Prevention and Care in Common Mental Disorders**" in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Manish Kumar Verma**, working as Professor and Head of the Department, in the Department of Psychology of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "**Development of AI based Tool for Early Detection, Prevention and Care in Common Mental Disorders**" submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the Department of Psychology, is a research work carried out by **Mirza Jahanzeb Beg, 12207899**, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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Abstract

Purpose: This thesis examines the use of artificial intelligence (AI) in augmenting mental health care via early identification, tailored intervention, and enhanced treatment results for persons suffering from anxiety and depression. As mental health illnesses become increasingly widespread, traditional treatment approaches encounter growing constraints regarding accessibility, scalability, and individualized care. This study seeks to assess the efficacy of AI-based technologies in detecting early indicators of mental health disorders, addressing unique patient requirements, and enhancing overall mental health outcomes. The specific objectives of this research are to evaluate AI's ability to enhance early detection rates of anxiety and depression, to comprehend AI's function in personalizing therapeutic interventions, to investigate the ethical implications of AI-driven mental health care, and to assess the effects of these tools on patient outcomes. We posited that AI would not only enable earlier identification and tailored intervention but would also enhance health-related quality of life (HRQOL) indicators in comparison to conventional treatment methods. This study seeks to enhance the discussion on the transformative potential of AI in mental health care, offering evidence-based insights on the feasibility of these technologies in clinical and practical contexts.

Methodology: A mixed-methods approach was utilized to comprehensively assess the effectiveness of AI-driven therapies on mental health outcomes. The research was structured as a 2 × 2 experimental design, incorporating both quantitative and qualitative data collection and analysis. The quantitative component comprised a sample of 300 participants who completed two AI-based self-report instruments, the NeuraMap Anxiety Scale and the NeuraMap Depression Scale, which were validated against the established Hamilton Anxiety Rating Scale (HAM-A) and Hamilton Depression Rating Scale (HAM-D). The scales demonstrated internal consistency, with

Cronbach's alpha values of 0.909 for anxiety and 0.932 for depression. A distinct sample of 500 individuals with no previous mental health diagnoses was evaluated to examine the function of AI in early identification. Within this group, 200 individuals exhibited possible symptoms of sadness or anxiety, which were subsequently validated in 190 cases after psychiatric assessment. The principal data analyses involved a two-way repeated measures ANOVA, utilized to evaluate alterations in HRQOL scores, revealing statistically significant enhancements in the AI intervention group relative to the control group receiving standard treatment. Furthermore, Principal Component Analysis (PCA) with Promax rotation was used to the NeuraMap scales to investigate their factor structure, uncovering a three-component model that accounted for 56.31% of the variation. This research revealed a strong multidimensional framework with considerable overlap between anxiety and depression. Qualitative data obtained from participant interviews were subjected to thematic analysis, revealing important themes about accessibility, privacy, personalization, and user involvement for AI products. The integration of these methodologies yielded a thorough evaluation of AI's clinical influence and user views on AI-driven mental health interventions.

Findings: This study's results highlight the considerable potential of AI-based interventions in mental health care, providing both quantitative and qualitative evidence of their effectiveness. AI-based methods exhibited a superior ability for the early identification of anxiety and depression, accurately detecting 95% of instances validated by psychiatric assessment. The NeuraMap Anxiety and Depression Scales demonstrated significant internal consistency and reliability, corroborated by the factor structure derived from PCA. The PCA analysis of these scales identified three principal components, accounting for over 56% of the variance and demonstrating significant intercorrelations, indicating that these instruments encapsulated the overlapping yet separate facets of anxiety and depression. Statistically substantial gains in HRQOL scores were noted in the AI intervention group, particularly in the emotional and mental health components relative to the control group. These results indicate that AI-driven therapies can significantly alleviate symptom intensity and enhance the quality of life for those experiencing mental health issues. The qualitative analysis identified 12 principal themes, encompassing accessibility, the significance of privacy in data management, the necessity of personalization, and user involvement, all of which enhanced good user experiences and overall satisfaction with AI-driven solutions. Participants demonstrated significant trust and confidence in AI technologies owing to their accessibility and the apparent promptness of feedback. The qualitative findings highlighted AI's function in offering a non-stigmatizing, private setting for mental health support, hence enhancing user engagement. The integration of quantitative enhancements with favorable qualitative feedback indicates that AI-driven interventions are a promising adjunct to conventional mental health care, effectively addressing both clinical efficacy and user experience.

Implications: The findings indicate that AI possesses transformative potential in mental health care, especially in improving the early detection and management of mental health issues. AI tools can function as accessible and scalable solutions that reduce the burden on mental health practitioners by facilitating prompt symptom detection, tailored interventions, and instant assistance. This study emphasizes the need of incorporating AI into mental health services to enhance current therapies, especially for populations encountering obstacles to conventional therapy, such as individuals in underserved communities or those favoring self-directed therapeutic alternatives. From an ethical perspective, considerations of privacy, data security, and informed permission are essential for maintaining user confidence and adhering to regulatory norms. This study's qualitative insights highlight the significance of ethical compliance, as user engagement was notably affected by the perceived security of personal information and the respect for user autonomy. This research promotes ongoing progress in AI mental health tools to broaden their uses beyond anxiety and depression, addressing additional mental health issues and co-occurring diseases. Future research ought to concentrate on optimizing AI algorithms for improved precision, examining AI's capabilities in sustained mental health assistance, and analyzing the long-term effects linked to AI-facilitated mental health treatment. These findings establish a robust basis for the broader implementation of AI in mental health services, presenting practical insights for clinicians, researchers, and policymakers aiming to enhance mental health treatment via technology. This research enhances the existing evidence for the use of AI in mental health treatment, highlighting a patient-centered and ethically robust methodology that can markedly enhance mental health outcomes and accessibility.

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1.1. Introduction

In recent times, there has been a disquieting surge in the global burden of mental health ailments, necessitating immediate attention and innovative remedies. Mental disorders, characterized by notable disruptions in cognition, emotional regulation, or conduct, exert a substantial influence on a significant proportion of the worldwide populace. Approximately one in eight adults, totaling almost 970 million people worldwide, suffers from a mental condition (Institute of Health Metrics and Evaluation, 2022). These illnesses induce distress and impede vital areas of functioning, manifesting in various forms, including different mental health conditions (World Health Organization [WHO], 2022).

Anxiety and depressive disorders have emerged as the primary mental health issues affecting persons globally. In 2019, 301 million individuals were afflicted with an anxiety disorder, including 58 million children and adolescents, whereas 280 million experienced depression, including 23 million children and adolescents (Institute of Health Metrics and Evaluation, 2022). The emergence of the COVID-19 pandemic markedly exacerbated the prevalence of anxiety and depressive disorders, with increases of 26% and 28% respectively within a single year (WHO, 2022). Notwithstanding the existence of efficient preventive and therapeutic measures, a considerable percentage of individuals afflicted with mental disorders do not receive adequate treatment (Institute of Health Metrics and Evaluation, 2022). The significant disparity in access to treatment perpetuates a circle of suffering and often engenders stigma, discrimination, and human rights abuses for individuals with mental health challenges (WHO, 2022).

Anxiety disorders, marked by excessive worry and anxiety, affect a significant portion of the global population. In 2019, 301 million individuals were impacted by an anxiety illness, including 58 million children and adolescents (Institute of Health Metrics and Evaluation, 2022). These disorders present in several forms, such as generalized anxiety disorder, panic disorder, social anxiety disorder, and separation anxiety disorder, each characterized by distinct symptoms and therapeutic approaches (WHO, 2022).

Depression, a pervasive psychological condition, surpasses typical mood variations and emotional reactions to challenges. It is marked by persistent emotions of sadness, reduced interest, and other additional symptoms that significantly impair daily functioning. In 2019, 280 million people experienced depression, comprising 23 million children and adolescents (Institute of Health Metrics and Evaluation, 2022). Notwithstanding the existence of efficacious psychological therapies and pharmacological interventions, access to these treatment modalities is limited for a significant proportion of patients (WHO, 2022).

Bipolar disorder, characterized by alternating episodes of despair and mania, affects roughly 40 million people globally (Institute of Health Metrics and Evaluation, 2022). Post-traumatic stress disorder (PTSD), commonly found in conflict-affected environments, can develop following exposure to highly distressing or terrifying incidents, leading to enduring symptoms of re-experiencing, avoidance, and increased threat perception (Charlson et al., 2019). Schizophrenia, marked by significant deficits in perception and behavior, impacts around 24 million individuals worldwide and is linked to a reduced life expectancy relative to the general population (Institute of Health Metrics and Evaluation, 2022; Laursen et al., 2014). Eating disorders, disruptive behaviors, dissocial disorders, and neurodevelopmental disorders, including autism spectrum disorder and attention deficit hyperactivity disorder (ADHD), further complicate the diverse array of mental health challenges faced by individuals (Institute of Health Metrics and Evaluation, 2022).

1.2. Examining the Mental Health Landscape in India: Prevalence, Obstacles, and Ramifications

Mental health poses a significant public health predicament in India, characterized by a high prevalence and burden of mental disorders, coupled with insufficient resources and services. As per a study conducted by the India State-Level Disease Burden Initiative Mental Disorders Collaborators, in 2017, India had a population of 197.3 million individuals affected by mental disorders, including 45.7 million with depressive disorders and 44.9 million with anxiety disorders. These disorders accounted for 4.7% of the total disability-adjusted life-years (DALYs) in India, with depressive disorders being the primary cause of mental disorder DALYs (33.8%), followed by anxiety disorders (19.0%) (The Lancet Psychiatry, 2020).

Another study carried out by the Indian Council of Medical Research (ICMR) revealed that one out of every seven individuals in India experienced mental disorders of varying severity in 2016 (Gururaj et al., 2016). The COVID-19 pandemic has further exacerbated the mental health situation in India, particularly among vulnerable groups such as the elderly, women, children, migrants, and frontline workers (Sharma & Grover, 2020). A survey conducted by the Indian Psychiatry Society reported a 20% surge in mental illness cases during the lockdown period (Chatterjee & Chauhan, 2020). Furthermore, Ghosh's study indicated that the mental health insurance landscape in India is woeful, with limited awareness and affordability among the populace (Ghosh, 2021).

These alarming results highlight the pressing need to strengthen the mental health system in India and to tackle the societal variables affecting mental health. Despite the existence of effective treatment options for various mental diseases, their availability and accessibility pose considerable challenges. Global health systems are insufficiently prepared to address the requirements of individuals with mental disorders, leading to a significant treatment gap (WHO, 2022).

Programs such as the World Health Organization's (WHO) Mental Health Gap Action Programme (mhGAP) aim to enhance mental health services in resource-constrained environments, emphasizing non-specialized healthcare practitioners and promoting integrated mental healthcare strategies (WHO, 2022). The WHO recognizes the significance of mental health for overall well-being and has enacted the Comprehensive Mental Health Action Plan 2013-2030, which focuses on improving leadership, delivering comprehensive care services, executing prevention strategies, and bolstering research and information systems (WHO, 2022).

Confronting the escalating mental health issue in India requires a comprehensive strategy that includes awareness, destigmatization, enhanced access to care, and strong support systems. It is essential to invest resources, improve mental health services, increase awareness, and provide assistance to at-risk populations to mitigate the effects of mental health issues and improve general well-being in the nation. By acknowledging the prevalence and effects of mental disorders in India, society may collectively strive to establish a more inclusive and supportive environment for persons with mental health issues.

1.3. Common Mental Disorders (CMD)

The term "common mental disorders" (CMD) was introduced by Goldberg and Huxley (1992) in their seminal work titled "Common Mental Disorders: A Bio-Social Model." This publication defines CMD as a spectrum of diagnosable psychiatric disorders commonly observed in primary care, including depressive episodes, generalized anxiety disorder, panic disorder, phobias, obsessive-compulsive disorder, post-traumatic stress disorder, and somatization disorder (Goldberg & Huxley, 1992).

Goldberg and Huxley's book presents a pioneering and invaluable model for understanding common mental disorders. The authors comprehensively explore the physiological basis of these disorders and elucidate how various life events can trigger episodes of mental illness. Their model uniquely emphasizes the role of both social and psychological events, as well as factors influencing physical health, in determining susceptibility to mental disorders. They identify three crucial components: vulnerability, which encompasses factors making certain individuals more prone to mental illness episodes; destabilization, the process by which symptoms emerge; and restitution, factors influencing the duration of an individual's illness episode.

The World Health Organization (WHO) defines CMD as mental diseases marked by considerable disruptions in cognition, emotional regulation, or behavior. They generally induce distress or impairment in significant domains of functioning (World Health Organization, n.d.). Prevalent mental disorders include depressive disorders, anxiety disorders, and substance use disorders. They are characterized by emotional turmoil, diminished functioning, and heightened disability. Depressive disorders, anxiety disorders, and drug use disorders are the most common forms of comorbid disorders (Steel et al., 2014). These illnesses exhibit a significant incidence in the general population and often co-occur with other medical or mental conditions.

A systematic study and meta-analysis by Steel et al. (2014) indicated that the global prevalence of common mental disorders was 17.6% over a 12-month period and 29.2% across an individual's lifetime. Prevalence rates differed according to gender, region, and income level, with elevated rates noted among women, low- and middle-income countries, and English-speaking nations. CMD can impact individuals across various ages, genders, cultures, and socioeconomic statuses. Numerous risk factors can elevate the probability of developing CMD, including poverty (Patel & Kleinman, 2003), exposure to violence (Fazel et al., 2012), trauma (Kessler et al., 1995), discrimination (Williams & Mohammed, 2013), social isolation (Cacioppo & Cacioppo, 2014), chronic physical illnesses (Scott et al., 2016), and genetic predisposition (Sullivan et al., 2000).

CMD can have severe consequences for individuals and society at large. They can impair an individual's ability to work, study, socialize, and enjoy life (Wittchen et al., 2011). Moreover, they can increase the risk of physical health problems, including cardiovascular disease (Nicholson et al., 2006), diabetes (Anderson et al., 2001), and infectious diseases (Prince et al., 2007). CMD can also contribute to social issues such as poverty (Lund et al., 2010), homelessness (Fazel et al., 2014), crime, and violence (Swanson et al., 2015).

In India, prevalent mental diseases represent a substantial public health concern, impacting millions of persons across diverse age groups, socioeconomic statuses, and environments. The India State-Level Disease Burden Initiative Mental illnesses Collaborators (2020) projected that in 2017, approximately 197.3 million individuals in India experienced common mental illnesses, representing 4.7% of the total disability-adjusted life-years (DALYs) in the nation. The COVID-19 pandemic has intensified the danger and burden of prevalent mental disorders within the Indian populace, especially among vulnerable demographics including the elderly, women, children, migrants, and frontline workers.

Dr. Vikram Patel, a distinguished global mental health researcher and advocate, has performed numerous studies on prevalent mental diseases in Goa, India. He has devised and assessed novel interventions designed to enhance the identification, management, and results for patients with prevalent mental disorders in primary care environments, employing lay health workers as the primary care clinicians. A significant study by Dr. Patel was the MANAS trial, which investigated the efficacy of a lay health worker-led intervention for depression and anxiety disorders in primary care environments in Goa. The trial indicated that the intervention was practical, satisfactory, and economically viable in improving the rehabilitation and functioning of individuals with prevalent mental diseases.

Prevention and efficacious therapy alternatives exist for CMD. Prevention interventions encompass the promotion of mental health awareness (Barry et al., 2013), the reduction of stigma and prejudice (Thornicroft et al., 2016), the enhancement of social support and coping skills (Chisholm et al., 2016), and the addressing of social determinants of mental health (Patel et al., 2018). Treatment approaches encompass psychological therapies, including cognitive-behavioral therapy (CBT), interpersonal therapy (IPT), and problem-solving therapy (PST), and pharmacological medications such as antidepressants and anxiolytics. The choice of treatment depends on the type and severity of the condition, the individual's preferences, and the availability of resources.

1.4. Depression:

Depression, a prevalent mental disorder, impacts an individual's emotions, thoughts, and behaviors, causing persistent feelings of sadness, loss of interest, low self-esteem, guilt, hopelessness, and suicidal ideation. It can also disrupt daily functioning, including work, school, social activities, and relationships. Depression does not discriminate based on age, gender, culture, or background.

The World Health Organization (WHO) designates depression as the primary cause of disability globally and a major factor in the overall illness burden. In 2020, around 264 million individuals across all age groups worldwide suffered from depression (WHO, 2020). Depression is linked to a heightened risk of physical ailments, including cardiovascular disease, diabetes, and chronic pain (Moussavi et al., 2007). Moreover, depression constitutes a significant risk factor for suicide, resulting in approximately 700,000 fatalities annually (WHO, 2020).

The diagnosis and treatment of depression present difficulties owing to the disorder's variability and complexity. Multiple diagnostic systems, such as the International Classification of Diseases (ICD-10) by the World Health Organization (WHO) and the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) by the American Psychiatric Association (APA), have been established to categorize and delineate depression according to clinical criteria and empirical evidence. Nevertheless, these systems exhibit disparities and constraints that may influence the precision and legitimacy of depression diagnosis.

1.5. Diagnostic Criteria

ICD-10: The ICD-10 is a medical coding system primarily designed by the WHO, encompassing mental and behavioral disorders as well as other medical conditions. Healthcare professionals utilize it for patient diagnosis. The ICD-10 criteria for depression consist of a set of symptoms and signs that indicate the presence of the disorder. Various types and subtypes of depression are recognized, such as mild depressive episode (F32.0), moderate depressive episode (F32.1), severe depressive episode without psychotic symptoms (F32.2), severe depressive episode with psychotic symptoms (F32.3), recurrent depressive disorder (F33), dysthymia (F34.1), adjustment disorder with depressed mood (F43.21), among others.

The ICD-10 criteria for a depressive episode encompass:

- Characteristic symptoms: Depressed mood, anhedonia, and less energy resulting in heightened fatigue and decreased activity.
- Additional prevalent symptoms: Impaired concentration and attention, diminished self-esteem and self-confidence, pervasive feelings of shame and worthlessness, negative outlook on the future, thoughts or behaviours related to self-harm or suicide, altered sleep patterns, and reduced appetite.

To receive a diagnosis of depressive episode, an individual must experience at least two typical symptoms and at least two other common symptoms persisting for a minimum of two weeks. The severity of the episode is determined by the number and intensity of the symptoms.

The following table summarizes the ICD-10 criteria for depressive episode:

Table 1: ICD-10 criteria for depressive episode

Severity	Number of typical symptoms	Number of other common symptoms	Total number of symptoms
Mild	2	2	4
Moderate	2	3-4	6
Severe	3	4 or more	7 or more
(ICD-10-CM Codes for DSM-5 Diagnoses Update - October 2021)			

One of the strengths of the ICD-10 classification system lies in its extensive global utilization and compatibility with other health-related taxonomies. Moreover, it offers precise operational definitions for each symptom and subtype of depression, thereby facilitating the diagnostic process across diverse contexts and populations.

However, the ICD-10 system suffers from certain limitations, namely its failure to encompass specific depression types and features acknowledged by alternative diagnostic frameworks and empirical research. Evidently, conditions such as premenstrual dysphoric disorder, seasonal affective disorder, atypical depression, and melancholic depression are not recognized as distinct diagnoses within the ICD-10. Furthermore, it neglects to consider the functional and quality-of-life implications of symptoms, which could impact clinical decision-making and treatment planning.

DSM-5: Turning our attention to the DSM-5, this diagnostic manual, formulated by the American Psychiatric Association (APA), serves as a valuable tool for diagnosing mental disorders in the United States and other jurisdictions adhering to its guidelines. In determining the presence of major depressive disorder (MDD), the DSM-5 employs a compilation of symptoms indicative of the condition. Notably, the DSM-5 recognizes various types and subtypes of MDD, encompassing persistent depressive disorder (dysthymia) (F34.1), premenstrual dysphoric disorder (N94.3), disruptive mood dysregulation disorder (F34.8), substance/medication-induced depressive disorder (F11-F16,F18-F19), depressive disorder due to another medical condition (F06.31-F06.34), other specified depressive disorder (F32.8), and unspecified depressive disorder (F32.9).

According to the DSM-5 diagnostic criteria for major depressive disorder (MDD), an individual must have at least five symptoms over a sustained two-week duration, with at least one symptom being either (1) low mood or (2) loss of interest or pleasure.

- Depressed mood: The individual endures a constant feeling of melancholy, emptiness, or hopelessness for the majority of the day, almost daily. This may be self-reported or witnessed by others; however, among children and adolescents, it may present as irritability.

- Reduced interest or pleasure: There is a notable decline in interest or enjoyment in practically all activities, persisting for the majority of the day, almost every day. This can be reported subjectively or witnessed by others.

- Weight fluctuations: The individual undergoes a considerable alteration in body weight, either loss or gain, exceeding 5% within a month, without deliberate dietary modifications. In pediatric patients, the inability to attain anticipated weight increase must also be taken into account.
- Sleep disturbances: Insomnia (difficulty in initiating or sustaining sleep, or early awakening) or hypersomnia (extreme drowsiness) occurs nearly every day.
- Psychomotor disturbances: Daily occurrences of psychomotor agitation (restlessness, pacing) or psychomotor retardation (slowed movements, lethargy) are apparent. These modifications are not merely subjective interpretations but are observable by others.
- exhaustion or energy depletion: The individual endures chronic sensations of exhaustion or energy depletion daily, happening almost every day.
- Intense emotions of worthlessness or excessive guilt: The individual has profound feelings of worthlessness, excessive guilt (which may involve illusions), or inappropriate guilt almost daily. This transcends typical self-reproach or shame associated with illness.
- Compromised cognitive functioning: There is a reduced capacity for clear thinking, concentration, or decision-making, either self-reported or noted by others, occurring nearly every day.
- Suicidal ideation: The individual harbors enduring thoughts of death (exceeding mere apprehension of dying), engages in suicidal ideation without a specific method, or has either tried

suicide or had a concrete plan for suicide.

These symptoms must cause significant distress or impairment in social, occupational, or other essential areas of functioning. The experience should not be attributed to the physiological effects of a substance or any other medical condition. Moreover, the episode's presentation should not be more precisely explained by schizoaffective disorder, schizophrenia, schizophreniform disorder, delusional disorder, or other recognized and unrecognized schizophrenia spectrum and other psychotic disorders. There must be no history of manic or hypomanic episodes.

The following table summarizes the DSM-5 criteria for MDD:

Table 2: DSM-5 criteria for MDD

Severity	Number of symptoms	Required symptoms
Mild	5-6	At least one of the following: depressed mood or anhedonia.
Moderate	7-8	At least one of the following: depressed mood or anhedonia.
Severe	9	At least one of the following: depressed mood or anhedonia.
(DSM-5 Criteria for Major Depressive Disorder vs ICD-10)		

It is crucial to acknowledge that depression is a prevalent and complex mental disorder, and accurate diagnosis is essential for effective treatment and prevention. Both the ICD-10 and DSM-5 are widely utilized diagnostic systems; however, their similarities and differences should be considered carefully by clinicians and researchers. Awareness of the strengths and limitations of each system is crucial for cautious and flexible application. Furthermore, continued research is necessary to refine diagnostic criteria for depression, incorporating dimensional, biological, psychological, developmental, gender, cultural, and contextual perspectives.

1.6. Anxiety Disorder

Anxiety disorder refers to a collective term encompassing a cluster of mental disorders characterized by excessive fear, anxiety, or avoidance of perceived threats that persist and impair daily functioning. Fear is a deliberate emotional reaction provoked by an immediate threat or imminent peril, whereas anxiety pertains to the expectation of actual or perceived future risks or hazards. Fear and anxiety serve adaptive functions for survival; nevertheless, when they become excessive, disproportionate, or unreasonable, they can substantially disrupt multiple facets of life, including employment, education, social engagements, and interpersonal relationships.

The World Health Organization (WHO) reports that anxiety disorders are the most common mental ailment in Europe, exhibiting a 12-month prevalence rate of 14% among adults aged 14 to 65. Moreover, anxiety problems correlate with a heightened risk of medical ailments, including cardiovascular disease, diabetes, and chronic pain (2). Anxiety disorders often co-occur with each other and with other mental disorders, including depression and substance use disorders.

Diagnosing and treating anxiety disorders poses hurdles due to their intrinsic variability and complexity. Diverse diagnostic systems have been established to categorize and delineate anxiety disorders according to clinical criteria and empirical data. The two predominant systems utilized are the International Classification of Diseases (ICD-10) issued by the World Health Organization (WHO) and the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) released by the American Psychiatric Association (APA). However, these systems demonstrate differences and constraints that may affect the precision and legitimacy of anxiety disorder diagnoses.

1.7. Diagnostic Criteria

The ICD-10 categorization system delineates precise criteria for the diagnosis of anxiety disorders. It identifies various categories and subcategories of anxiety disorders, including phobic anxiety disorders (F40), panic disorder (F41.0), generalized anxiety disorder (GAD) (F41.1), mixed anxiety and depressive disorder (F41.2), obsessive-compulsive disorder (OCD) (F42), acute stress reaction (F43.0), post-traumatic stress disorder (PTSD) (F43.1), adjustment disorder (F43.2), dissociative disorders (F44), somatoform disorders (F45), other neurotic disorders (F48), among others.

Specifically, the ICD-10 criteria for generalized anxiety disorder (GAD) consist of the following:

1. The individual experiences a period of at least six months characterized by prominent tension, worry, and apprehension related to everyday events and problems.
2. At least four symptoms out of a list of 22 possible symptoms are present. These symptoms include autonomic arousal symptoms (e.g., palpitations, sweating, trembling), symptoms related to the chest or abdomen, symptoms related to the brain or mind, and general symptoms. Examples of these symptoms encompass fear of dying or losing control, avoidance behavior, difficulty concentrating, irritability, muscle tension or aches, restlessness or feeling on edge, sleep disturbances, and fatigue.

To receive a diagnosis of GAD, an individual must exhibit at least one symptom from each of the four symptom groups mentioned above. These symptom groups cover autonomic arousal symptoms, symptoms concerning the chest or abdomen, symptoms concerning the brain or mind, and general symptoms. By fulfilling these criteria, a person may be diagnosed with GAD according to the ICD-10 system.

The following table summarizes the ICD-10 criteria for GAD:

Table 3: ICD-10 criteria for GAD

Group	Symptoms	Number required
Autonomic arousal	Palpitations, pronounced heartbeats, or tachycardia. Perspiring, Trembling or quaking, Xerostomia	At least one
Symptoms related to the thoracic or abdominal regions	Respiratory distress or feelings of suffocation, Choking sensations, Thoracic pain or unease, Nausea or gastrointestinal discomfort	At least one

Symptoms concerning brain or mind	Experiencing dizziness, instability, faintness, or lightheadedness. Perceptions of items as illusory or a sense of disconnection from oneself. Fear of losing control, experiencing insanity, or fainting. Thanatophobia	At least one
General symptoms	Hot flashes or freezing shivers, Paraesthesia or tingling sensations, Dysphagia or a sensation of a foreign body in the throat, Agoraphobia (the avoidance of locations or circumstances). Challenges in maintaining focus or experiencing mental blankness. Chronic irritation, Challenges in achieving	At least two

	sleep due to anxiety. Muscle tightness or discomfort and pain. Restlessness or a sensation of being tense or anxious. Overblown reactions to trivial events like being startled. Increased fatigue or diminished endurance	

(ICD-10 depression diagnostic criteria - General Practice notebook)

The DSM-5 stipulates that the diagnostic criteria for Generalized Anxiety Disorder (GAD) need the fulfillment of the following conditions:

1. Chronic anxiety and concern (apprehensive expectation) must be evident on the majority of days for at least six months. Anxiety and apprehension typically focus on various events or activities, such as professional or academic achievement.

The individual finds it challenging to control their anxiety, struggling to prevent unwanted thoughts from overwhelming their head.

3. The anxiety and apprehension are accompanied by at least three of the following six symptoms, with certain symptoms manifesting more days than not over the past six months: restlessness or a continual sense of being on edge, easy fatigability, difficulty concentrating or experiencing

cognitive blankness, irritability, muscle tension, and sleep disturbances (including difficulties in initiating or maintaining sleep or experiencing restless, unrefreshing sleep).

The worry, apprehension, or associated physical symptoms lead to significant distress or dysfunction in vital areas of functioning, such as social, occupational, or other crucial life domains.

5. The disruption cannot be attributed to the physiological effects of a substance (e.g., an illicit drug or prescription medication) or another medical condition (e.g., hyperthyroidism).

The symptoms and impairment cannot be more precisely ascribed to an alternative mental disorder. This suggests that the anxiety and apprehension should not be more precisely ascribed to panic attack concerns in Panic Disorder, fear of negative evaluation in Social Anxiety Disorder, obsessions or compulsions in Obsessive-Compulsive Disorder, separation from attachment figures in Separation Anxiety Disorder, reminders of traumatic experiences in Post-Traumatic Stress Disorder, concerns regarding weight gain in Anorexia Nervosa, physical complaints in Somatic Symptom Disorder, perceived imperfections in appearance in Body Dysmorphic Disorder, fear of serious illness in Illness Anxiety Disorder, or the nature of delusional beliefs in Schizophrenia or Delusional Disorder.

An individual can be diagnosed with Generalized Anxiety Disorder (GAD) according to the DSM-5 criteria. The below table encapsulates the DSM-5 criteria for Generalized Anxiety Disorder (GAD):

Table 4: DSM-5 Criteria for Generalized Anxiety Disorder (GAD)

Symptoms	Number required
Excessive anxiety and worry about a number of events or activities for at least 6 months	One
Difficulty controlling the worry	One

Restlessness or a sensation of being tense or agitated, experiencing rapid weariness, Challenges in maintaining focus or experiencing mental lapses. Irritability. Muscle stress. Disruption of sleep.	At least three out of six
(Criteria for Generalized Anxiety Disorder according to DSM-5 - Verywell Mind)	

Clinicians and researchers must acknowledge the advantages and disadvantages of both the ICD-10 and DSM-5 diagnostic systems for anxiety disorders. Although these systems are useful instruments, additional research is required to enhance their validity and reliability. Integrating dimensional, biological, psychological, developmental, gender, cultural, and contextual perspectives can improve the diagnostic criteria for anxiety disorders and ultimately lead to more effective treatment and preventative methods.

1.8. The Evolution of Diagnostic Criteria for Depression and Anxiety Disorders:

The diagnostic criteria for depression and anxiety disorders are constantly evolving as new research findings emerge. The ICD-10 and DSM-5 systems are the two most widely used diagnostic frameworks for these disorders. The ICD-10 system is more commonly used in epidemiological studies and cross-cultural comparisons, providing a standardized and universal classification of depression and anxiety disorders. However, it may not encompass specific types or features of these disorders recognized by other diagnostic systems or supported by research evidence. In contrast, the DSM-5 system is more comprehensive, outlining a wider range of symptoms and subtypes for depression and anxiety disorders. It incorporates recent advancements in neuroscience and clinical research to refine and update the diagnostic criteria.

Both the ICD-10 and DSM-5 systems have limitations. They rely on categorical rather than dimensional approaches to diagnosis, potentially overlooking the continuum and heterogeneity of these disorders. Additionally, they lack robust biological or psychological markers to validate and refine the diagnostic criteria. Furthermore, the influence of developmental, gender, cultural, and contextual factors on the expression and experience of depression and anxiety disorders may not be adequately captured. Further research is necessary to enhance the validity and reliability of diagnostic criteria for depression and anxiety disorders. Efforts should be made to incorporate dimensional approaches, identify biological and psychological markers, and consider the developmental, gender, cultural, and contextual factors that influence these disorders.

1.9. Artificial Intelligence

Artificial intelligence (AI) represents a domain within the field of computer science that endeavors to construct machines or systems capable of executing tasks typically requiring human intelligence, including but not limited to reasoning, learning, decision making, natural language processing, vision, and speech recognition. The attribution of the term "artificial intelligence" can be traced back to John McCarthy, who coined the phrase during the Dartmouth Conference in 1956. This seminal event convened a group of researchers to deliberate on the feasibility of fabricating machines capable of simulating human intelligence (McCarthy et al., 1955). Consequently, the conference stands as the origin of the field of artificial intelligence. Nevertheless, the concept of artificial intelligence can be traced back to ancient times, when philosophers and scientists pondered the essence and genesis of human intelligence, along with the prospects of fashioning artificial entities possessing intellect.

Recent years have seen substantial progress in AI development, due to enhanced data accessibility, computer capacity, and algorithmic techniques. Artificial intelligence has been implemented across various areas and industries, including education, entertainment, banking, security, transportation, and manufacturing. Healthcare is particularly noteworthy, as it has significant potential for AI while also facing substantial hurdles. AI possesses the capacity to improve the quality, efficiency, accessibility, and cost of healthcare services by aiding or augmenting human talents in the diagnosis, treatment, prevention, and management of various health conditions. Moreover, AI can aid in addressing critical issues confronting healthcare systems globally, including aging populations, chronic illnesses, a deficit of competent personnel, and escalating costs.

Nonetheless, the utilization of AI engenders ethical, social, legal, and technical quandaries necessitating meticulous consideration and resolution. Questions pertaining to the safety, dependability, accountability, and transparency of AI systems arise, alongside concerns regarding the protection of privacy and security concerning health-related data. Additionally, combating bias and discrimination in the outcomes generated by AI, establishing equilibrium between human and machine roles and responsibilities in healthcare, and cultivating trust and acceptance among healthcare professionals and patients all demand careful attention.

Mental health refers to a condition of well-being in which an individual recognizes their own potential, adeptly handles everyday stressors, participates in meaningful activities, and contributes to their community, as described by the World Health Organization (WHO). Mental health is a crucial component of total health and well-being. Mental diseases exhibit significant prevalence globally. The WHO's 2017 estimations suggest that almost one in four individuals worldwide will encounter a mental or neurological disease over their lifetime. Currently, around 450 million individuals are afflicted by such illnesses. Mental diseases are primary contributors to disability and distress worldwide. Furthermore, these illnesses inflict significant economic consequences on people, families, and societies, with the estimated worldwide cost reaching US$ 2.5 trillion in 2010, anticipated to increase to US$ 6 trillion by 2030 (Bloom et al., 2011).

Despite the significant frequency and consequences of mental diseases, many individuals do not obtain sufficient or prompt treatment. The WHO's 2017 statistics reveal that approximately one-third of individuals with mental problems in high-income countries receive treatment, whereas fewer than one-tenth in low- and middle-income countries do so. Numerous obstacles hinder access to mental healthcare, such as stigma, prejudice, lack of understanding, financial shortages, inadequately qualified clinicians, and a shortage of evidence-based interventions. AI offers innovative opportunities and solutions for overcoming certain obstacles and improving the delivery and results of mental healthcare. Artificial intelligence can enhance the detection, diagnosis, assessment, monitoring, treatment, prevention, and management of various mental diseases. Moreover, technology can facilitate the delivery of personalized, accessible, affordable, and scalable mental health care to a broad and diverse population. Moreover, AI can improve scientific understanding of the etiology, mechanisms, and consequences of mental disorders.

1.10. Some of the early milestones in the history of artificial intelligence include:

- In 1943, Warren McCulloch and Walter Pitts postulated a theoretical framework comprising artificial neurons, which exhibited the capability to execute logical operations based on binary input and output signals (McCulloch & Pitts, 1943).
- In 1950, Alan Turing presented a criterion, commonly known as the Turing Test, as a means to gauge machine intelligence by evaluating its capacity to engage in human-like conversations (Turing, 1950).
- In 1952, Arthur Samuel devised a program that attained proficiency in playing checkers through self-improvement driven by accumulated experience (Samuel, 1959).

- In 1956, Allen Newell and Herbert Simon introduced the Logic Theorist, a software application that employed symbolic logic to prove mathematical theorems (Newell & Simon, 1956).
- In 1957, Frank Rosenblatt devised the Perceptron, a model of artificial neuron that acquired knowledge from input and output data using a rudimentary learning rule (Rosenblatt, 1958).
- In 1958, John McCarthy developed Lisp, a programming language specifically tailored for symbolic manipulation and applications in artificial intelligence (McCarthy, 1960).
- In 1961, James Slagle designed SAINT, an algorithmic system capable of solving calculus problems (Slagle, 1961).
- In 1964, Daniel Bobrow created STUDENT, an application proficient in solving algebraic word problems (Bobrow, 1964).
- In 1965, Joseph Weizenbaum constructed ELIZA, an interactive program simulating a psychotherapist, employing natural language processing and pattern recognition (Weizenbaum, 1966).
- In 1966, Marvin Minsky and Seymour Papert released Perceptrons, a seminal study that analyzed the constraints of single-layer neural networks and precipitated the initial AI winter, a phase marked by reduced funding and interest in AI research (Minsky & Papert, 1969).
- In 1969, the Stanford Research Institute developed Shakey the Robot, a pioneering mobile robot endowed with perceptual abilities and autonomous planning capabilities (Nilsson, 1984).

- In 1972, MYCIN, an expert system grounded in rule-based methodologies, emerged as a diagnostic and treatment tool for bacterial infections (Shortliffe, 1976).
- In 1973, the Lighthill report, an evaluation of AI research in the United Kingdom, was published, instigating the second AI winter marked by reduced financial support and diminished interest in AI research (Lighthill, 1973).
- In 1975, Terry Winograd created SHRDLU, a program capable of comprehending and manipulating objects within a simulated environment using natural language input (Winograd, 1972).
- In 1976, Douglas Lenat formulated AM, a program employing heuristics to discover novel mathematical concepts (Lenat, 1977).
- In 1979, Hans Moravec engineered the Stanford Cart, a mobile robot incorporating stereo vision to autonomously navigate its surroundings (Moravec, 1980).
- In 1980, Edward Feigenbaum and Pamela McCorduck published The Fifth Generation: Artificial Intelligence and Japan's Computer Challenge to the World, a seminal work that kindled interest in AI research and prompted significant investments in Japan and other countries (Feigenbaum & McCorduck, 1983).
- In 1982, John Hopfield proposed the Hopfield network, a recurrent neural network model capable of storing and retrieving patterns through associative memory (Hopfield, 1982).
- In 1983, Ryszard Michalski developed AQ, a program utilizing inductive logic programming to learn rulesfrom examples (Michalski et al., 1986).
- In 1985, Judea Pearl authored Heuristics: Intelligent Search Strategies for Computer Problem Solving, a comprehensive work introducing probabilistic reasoning and Bayesian networks in AI (Pearl, 1984).

- In 1986, David Rumelhart and James McClelland released Parallel Distributed Processing: Explorations in the Microstructure of Cognition, a two-volume study that rejuvenated interest and research in neural networks and connectionism (Rumelhart & McClelland, 1986).
- In 1987, Rodney Brooks proposed the subsumption architecture, a behavior-based robotics model that employed simple rules and sensor input to govern robot actions (Brooks, 1986).
- In 1988, John Koza pioneered genetic programming, a technique utilizing genetic algorithms to evolve computer programs (Koza, 1992).
- In 1989, Yann LeCun developed LeNet, a convolutional neural network capable of recognizing handwritten digits using backpropagation and gradient descent (LeCun et al., 1989).
- In 1991, Gerald Tesauro created TD-Gammon, a program demonstrating advanced backgammon playing skills through the integration of reinforcement learning and neural networks (Tesauro, 1995).
- In 1993, Takeo Kanade introduced the Virtualized Reality system, which enabled the capture and reconstruction of 3D scenes using multiple cameras (Narayanan et al., 1998).
- In 1995, Richard Wallace developed ALICE, an interactive program engaging in conversations with humans through natural language processing and pattern matching (Wallace, 2009).
- In 1996, IBM's Deep Blue, a computer specifically designed to play chess, triumphed over Garry Kasparov, the reigning world chess champion (Campbell et al., 2002).

- In 1997, Douglas Lenat initiated the Cyc project, an ambitious endeavor to construct an extensive ontology and knowledge base encompassing common-sense reasoning (Lenat & Guha, 1989).
- In 1998, Sebastian Thrun and his team developed Stanley, a self-driving car that emerged victorious in the DARPA Grand Challenge, a competition for autonomous vehicles (Thrun et al., 2006).

In 1999, Kismet, a robot created at MIT, demonstrated the capacity to convey and identify emotions via facial expressions and vocalisations (Breazeal & Scassellati, 2000).

1.11. Recent milestones in the history of artificial intelligence encompass:

In 2005, Google introduced Google Maps, an online cartographic service that harnessed computer vision and machine learning to analyze satellite imagery and street-level views (Vincenty, 2004).

- In 2006, Geoffrey Hinton and colleagues introduced the notion of deep learning, a technique capable of training intricate neural networks with multiple layers by employing unsupervised pre-training and supervised fine-tuning (Hinton et al., 2006).
- In 2007, Netflix launched the Netflix Prize, a competition aimed at enhancing the precision of its movie recommendation system through collaborative filtering and machine learning (Bennett & Lanning, 2007).
- In 2008, Google unveiled Google Translate, an online platform utilizing statistical machine translation and neural machine translation to facilitate textual and spoken language translations across different languages (Wu et al., 2016).
- In 2009, Wolfram Alpha emerged as a computational knowledge engine, employing natural language processing and symbolic computation to furnish factual answers to user queries (Wolfram, 2009).

- In 2010, Microsoft released Kinect, an interactive motion sensing apparatus that harnessed computer vision and machine learning to track human bodily movements and gestures (Shotton et al., 2013).
- In 2011, IBM's Watson, a question-answering system integrating natural language processing and machine learning, triumphed over human champions in the quiz show Jeopardy! (Ferrucci et al., 2013).
- In 2012, Andrew Ng and colleagues pioneered the development of a deep neural network capable of recognizing objects in images, leveraging unsupervised feature learning and convolutional neural networks (Krizhevsky et al., 2012).
- In 2013, DeepMind, a company founded by Demis Hassabis and colleagues, commenced its quest for general artificial intelligence, employing deep learning and reinforcement learning as key methodologies (Hassabis et al., 2017).
- In 2014, Facebook unveiled DeepFace, a system equipped with deep learning and convolutional neural networks, achieving human-level accuracy in facial recognition tasks (Taigman et al., 2014).
- In 2015, Microsoft introduced Cortana, a virtual assistant leveraging natural language processing and machine learning to undertake tasks and respond to queries via voice or text (Shum et al., 2018).
- In 2016, Google's AlphaGo, utilising deep learning and reinforcement learning, triumphed against professional Go player Lee Sedol in a five-game match (Silver et al., 2016).
- In 2017, OpenAI created Dactyl, a robotic hand proficient in dexterously manipulating objects, honing its skills through reinforcement learning and simulated environments (Akhtar et al., 2018).

- In 2018, Google introduced Duplex, a system adept at natural language processing and speech synthesis, enabling it to engage in phone conversations to fulfill tasks such as appointment bookings and reservations on behalf of users (Leviathan & Matias, 2018).
- In 2019, OpenAI introduced GPT-2, a language model of significant scale capable of generating coherent and diverse text across diverse subjects, utilizing deep learning and natural language processing (Radford et al., 2019).
- In 2020, DeepMind unveiled AlphaFold, a system harnessing deep learning and attention mechanisms to predict the three-dimensional structure of proteins, significantly advancing protein folding research (Jumper et al., 2020).
- In 2021, OpenAI launched DALL-E, a system employing deep learning and generative adversarial networks to generate images based on textual descriptions, thus bridging the gap between language and visual content (Ramesh et al., 2021).

1.12. Recent Milestones in the Advancement of Artificial Intelligence: 2021 Onwards

In 2022, significant strides in AI technology were accomplished, encompassing diverse domains. Google introduced Stable Diffusion, employing deep learning and diffusion models to generate realistic and diverse images based on textual descriptions (Ho et al., 2020). Midjourney, a startup specializing in AI-generated viral content, earned the esteemed Loebner Prize by creating a chatbot that demonstrated highly human-like conversational abilities (Midjourney, 2022). OpenAI developed Codex, a large-scale language model adept at generating and executing code in various programming languages by leveraging deep learning and natural language processing techniques (Chen et al., 2021). Facebook unveiled Horizon, an encompassing platform empowering developers to construct and deploy reinforcement learning applications at scale using PyTorch (Gauci et al., 2018). IBM made notable progress in the field of neuromorphic computing with the creation of Neurosynaptic, a chip that emulates the structure and functionality of the human brain through the utilization of spiking neural networks (Merolla et al., 2014).

Progress continued into 2023, yielding further breakthroughs. Google's AlphaZero, a fusion of deep learning and reinforcement learning, achieved victory against Magnus Carlsen, the reigning world chess champion, in a six-game match, exemplifying the program's ability to master board games autonomously, without human knowledge (Silver et al., 2017). Amazon unveiled Alexa Conversations, a feature capitalizing on deep learning and natural language understanding, enabling Alexa to engage in coherent and natural multi-turn dialogues with users (Su et al., 2020). DeepMind developed MuZero, a system displaying superhuman performance across various domains, accomplished without prior knowledge or explicit rewards, using deep learning and model-based reinforcement learning (Schrittwieser et al., 2019). Microsoft launched Project Turing, a platform affording researchers and developers access to extensive language models for natural language processing tasks via Azure (Microsoft, 2020). Tesla introduced Full Self-Driving, a feature leveraging computer vision and deep learning to enable autonomous driving in diverse road conditions (Tesla, 2020). These advancements underscore the remarkable strides achieved in AI across a wide range of domains and applications in recent years.

1.13. Types and Subtypes of AI

AI, as a diverse field, encompasses various subfields and techniques that can be classified based on complexity and data processing methods. These classifications include narrow AI, general AI, and super AI, as well as symbolic AI and sub-symbolic AI (Bostrom, 2014; Dreyfus & Dreyfus, 1986; Russell & Norvig, 2021).

- Narrow AI denotes systems engineered to do specified tasks necessitating human intellect inside a defined domain. Illustrations encompass chess gameplay, facial recognition, and linguistic translation. Narrow AI systems lack the ability to transfer their skills or knowledge to other domains and are specific to the problem they are designed to address. Many current healthcare applications of AI fall under this category.
- General AI, on the other hand, pertains to systems capable of performing any intellectual task across different domains, akin to human capabilities. These systems can learn from experience, adapt to new situations, and comprehend abstract concepts. However, achieving general AI remains a hypothetical goal that has yet to be realized.
- Super AI surpasses human intelligence and excels in all domains or problems. These systems can generate new knowledge and innovations that surpass human comprehension. Super AI is also an aspirational objective, albeit its possibility and desirability remain uncertain.

In terms of data processing, AI techniques can be classified into symbolic AI and sub-symbolic AI (Bostrom, 2014; Russell & Norvig, 2021).

- Symbolic AI use symbols or representations to process and convey data or information. Symbols are distinct entities with defined meanings and frameworks, such words, numerals, or logical constructs. Examples of symbolic AI techniques include rule-based systems, expert systems, knowledge graphs, natural language processing, and automated reasoning. They demonstrate proficiency in managing both abstract and organised material, including text, speech, and logical information.
- Sub-symbolic AI, on the other hand, relies on sub-symbols or patterns to process and generate data or information. Sub-symbols are continuous units without clear meaning or

structure, such as pixels, sounds, or signals. Sub-symbolic AI techniques include neural networks, deep learning, evolutionary algorithms, fuzzy logic, and reinforcement learning. These techniques excel in handling complex and unstructured data such as images, videos, and emotions.

AI techniques can be further categorized based on the specific tasks they perform. Four subtypes of AI techniques are descriptive AI, predictive AI, prescriptive AI, and generative AI (Davenport & Kalakota, 2019).

- Descriptive AI involves techniques that describe or summarize data or information. Examples of descriptive AI techniques include data mining, data visualization, statistics, and clustering. These techniques are valuable for exploring and understanding data by identifying patterns, trends, or outiers.
- Predictive AI encompasses techniques that predict or forecast data or information. Machine learning, deep learning, regression, and classification are examples of predictive AI techniques. They enable making inferences and estimations based on data, such as predicting outcomes, risks, or behaviors.
- Prescriptive AI involves techniques that prescribe or recommend actions based on data or information. Optimization, decision analysis, decision support systems, and recommender systems are examples of prescriptive AI techniques. These techniques aid in decision-making processes by suggesting treatments, interventions, or policies.
- Generative AI encompasses techniques that generate or create data or information. Natural language generation, computer vision, speech synthesis, and generative adversarial networks are examples of generative AI techniques. They allow the production of new and novel data or information based on existing data, such as generating text, images, or speech.

The following table summarizes the types and subtypes of AI techniques:

Table 5: The types and subtypes of AI techniques

Type	Subtype	Definition	Example
Narrow AI	Symbolic AI	AI techniques that use symbols or representations to manipulate or communicate data or information	Natural language processing
	Sub-symbolic AI	AI techniques that use sub-symbols or patterns to process or generate data or information	Deep learning
General AI	Symbolic AI	AI methodologies capable of executing any cognitive work that a human can accomplish across various domains or issues utilizing	Hypothetical

		symbols or representations.	
Sub-symbolic AI	Sub-symbolic AI	AI approaches capable of executing any cognitive work that a human can do across several domains or issues utilizing sub-symbols or patterns.	Hypothetical
Super AI	Symbolic AI	AI techniques that can surpass human intelligence and capabilities in all domains or problems using symbols or representations	Hypothetical
	Sub-symbolic AI	AI techniques that can surpass	Hypothetical

		human intelligence and capabilities in all domains or problems using sub-symbols or patterns	
Descriptive AI	Symbolic AI	AI techniques that can describe or summarize data or information using symbols or representations	Data visualization
	Sub-symbolic AI	AI techniques that can describe or summarize data or information using sub-symbols or patterns	Clustering
Predictive AI	Symbolic AI	AI techniques that can predict or forecast data or information using	Regression

		symbols or representations	
	Sub-symbolic AI	AI techniques that can predict or forecast data or information using sub-symbols or patterns	Machine learning
Prescriptive AI	Symbolic AI	AI techniques that can prescribe or recommend data or information using symbols or representations	Decision support systems
	Sub-symbolic AI	AI techniques that can prescribe or recommend data or information using sub-symbols or patterns	Recommender systems
Generative AI	Symbolic AI	AI techniques that can generate or	Natural language generation

		create data or information using symbols or representations	
	Sub-symbolic AI	AI techniques that can generate or create data or information using sub-symbols or patterns	Generative adversarial networks
Historical Development and Milestones			

1.14. Conversational agents

Conversational agents, commonly referred to as chatbots, are computer programs designed to engage in natural language interactions with humans (Vaidyam et al., 2019). Specifically, chatbots simulate conversations akin to human interactions and are often tailored to specific domains or purposes (Vaidyam et al., 2019). Various types of chatbots exist, including rule-based, retrieval-based, generative, and hybrid chatbots.

- Rule-based chatbots adhere to predefined rules or scripts and possess limited capabilities when confronted with unexpected or ambiguous inputs. Their responses are determined by the programmed rules, and they may struggle to handle complex or nuanced queries.
- Retrieval-based chatbots draw upon a database of predefined responses and employ matching techniques, such as keyword analysis or relevance assessment, to select the most

suitable response. By matching user input with pre-existing responses, these chatbots can provide contextually relevant replies.

- Generative chatbots employ natural language generation techniques to generate responses from scratch, without relying on pre-existing responses. However, they may encounter challenges in producing grammatically correct or contextually appropriate responses, and the quality of their output can vary.
- Hybrid chatbots integrate multiple approaches, combining the strengths of different techniques to enhance performance and address limitations. By leveraging rule-based, retrieval-based, and generative methods in a coordinated manner, hybrid chatbots aim to deliver more robust and effective conversational experiences (Parmar et al., 2022).

1.15. Natural language processing (NLP)

Natural language processing (NLP) is a field within artificial intelligence (AI) that focuses on the analysis and generation of natural language data (Jurafsky et al., 2020). NLP has numerous applications within the realm of mental health care. It can be employed for evaluation and diagnosis by examining language and speech patterns to identify signs of mental problems.

NLP techniques extract features like sentiment, emotion, and word choice from text or speech data, providing insights into an individual's mental health status (Alhanai et al., 2018). Furthermore, NLP enables personalized and adaptive interventions and treatments by generating tailored responses based on individual needs and goals (Fitzpatrick et al., 2017). Chatbots powered by NLP can offer psychoeducation, counseling support, symptom management, behavior change, and crisis intervention for individuals with mental health issues (Inkster et al., 2022). NLP techniques can also evaluate the effectiveness of chatbot interventions and measure their impact on outcomes such as symptom reduction and patient satisfaction (Fulmer et al., 2020).

In the field of mental health, AI applications can be categorized into various areas such as diagnosis, treatment, prevention, and management. Each area presents unique benefits and challenges.

1.16. Diagnosis:

AI can enhance the detection and diagnosis of mental disorders by utilizing diverse data sources and techniques. Natural language processing and machine learning can evaluate text or audio data from clinical interviews, surveys, or social media posts to detect indicators of mental problems. Computer vision and machine learning can evaluate image or video data, including facial expressions, eye movements, or brain scans, to identify biomarkers or signs of mental problems. Machine learning and statistical techniques can amalgamate and analyze various data sources to produce diagnostic predictions or classifications.

Artificial intelligence offers numerous advantages to the diagnostic process in healthcare. It has the capacity to enhance precision and uniformity by minimising human errors and biases. AI facilitates access to automated or remote tools and services, hence enhancing the accessibility and affordability of diagnosis. Moreover, AI systems improve the promptness and efficacy of diagnosis, facilitating swifter and more successful treatment options. Moreover, AI can assist physicians in their decision-making and promote ongoing learning by offering relevant feedback and recommendations.

However, AI for diagnosis also faces challenges that require careful consideration. Ensuring the quality, quantity, availability, and interoperability of data used for diagnosis is crucial, as reliable data is essential for accurate and reliable AI models. Validating, testing, and generalizing AI models and outcomes is necessary to ensure their effectiveness across diverse patient populations and healthcare settings. Explaining, interpreting, and building trust in AI models and outcomes is crucial for healthcare professionals and patients to understand and accept the recommendations provided.

The confidentiality and protection of patient data and AI systems are critical, as sensitive medical information must be shielded from unauthorized access or breaches. Addressing bias and discrimination in AI models and outcomes is crucial to ensure justice and equity in healthcare. Establishing a balance between human competence and the use of AI in diagnostics is crucial. Collaboration between healthcare professionals and AI systems must be well defined, with unambiguous delineation of responsibilities and accountability.It is essential to address these challenges to optimize the promise of AI in diagnostics while ensuring patient safety, privacy, and equitable access to healthcare. Ongoing research, standardization initiatives, and stakeholder engagement are crucial for the progression of AI in diagnostics and the realization of its benefits.

Several instances of artificial intelligence (AI) applications have been developed for diagnostic purposes. One such system, known as Cogito, leverages natural language processing and machine learning techniques to analyze voice data obtained from telephone conversations. This analysis aims to identify indications of various mental conditions, including depression, anxiety, and post-traumatic stress disorder (PTSD) (Ghassemi et al., 2018). Similarly, the system Mindstrong employs machine learning algorithms to examine smartphone data derived from keyboard usage, screen time, and app activity. By monitoring these factors, Mindstrong aims to assess individuals' mood and cognitive function, particularly in those with mental disorders (Dagum, 2018). Neurolex represents another AI system that utilizes natural language processing and machine learning to analyze speech data extracted from voice recordings. The objective is to screen for a range of mental disorders such as depression, bipolar disorder, schizophrenia, and dementia (NeuroLex

Laboratories, n.d.). Furthermore, Ellipsis Health operates as an AI system that employs natural language processing and machine learning to evaluate speech data obtained from voice recordings. Its purpose is to measure and track symptoms related to depression and anxiety (Ellipsis Health, n.d.). Lastly, Aifred Health serves as an AI system utilizing machine learning and natural language processing to evaluate clinical data and patient preferences. By doing so, it offers personalized treatment recommendations for depression (Aifred Health, n.d.).

1.17. Treatment:

When it comes to treatment, AI can significantly contribute to the advancement of mental disorder treatment by employing diverse data types and techniques. For instance, natural language processing and machine learning can be utilized by AI to generate and deliver text or speech content for psychotherapy or counseling. Furthermore, AI can employ computer vision and machine learning to create or manipulate image or video content suitable for virtual reality or augmented reality therapy. Additionally, AI can utilize machine learning and reinforcement learning to optimize or personalize treatment plans and interventions based on individual characteristics or feedback.

The benefits of AI for treatment are noteworthy. First and foremost, AI can enhance the effectiveness and quality of treatment by providing evidence-based and personalized solutions. Through its capabilities, AI can aid in matching patients with suitable drugs, predicting potential drug interactions, optimizing treatment protocols, designing radiation therapy plans, and identifying promising drug candidates for emerging diseases (Romm & Tsigelny, 2020). Secondly, AI can improve the accessibility and affordability of treatment by offering automated or remote tools and services. This technological advancement enables the provision of care to underserved populations, reduces costs and errors, and enhances overall efficiency and productivity within healthcare systems (Topol et al., 2021).

AI can enhance patient engagement and adherence by offering interactive and immersive solutions. AI can enhance patient motivation, satisfaction, and retention throughout treatment by providing interventions such as cognitive-behavioral therapy (CBT), motivational interviewing, gamification, and virtual reality (Doraiswamy et al., 2020). Moreover, AI enhances physicians' decision-making and education by providing insightful feedback and recommendations. AI assists healthcare personnel in making informed decisions, improving patient outcomes, and promoting continuous learning by analysing complex data, generating insights, providing alarms, and facilitating cooperation.

However, AI for treatment encounters several challenges. Ensuring the quality, quantity, availability, and interoperability of data remains crucial. AI systems rely on accurate, reliable, diverse, and standardized datasets to effectively train and evaluate models. Furthermore, adequate validation, testing, and generalization of AI models and outcomes across different settings, populations, and scenarios are critical to guarantee their safety, efficacy, and impact. Another significant challenge involves explaining, interpreting, and establishing trust in AI models and outcomes related to treatment. Transparent and interpretable methods are essential to comprehend theunderlying decision-making processes of AI models, the rationale behind specific outcomes, and to instill trust in the results among users and stakeholders.

The privacy and security of data and AI systems also demand attention. The establishment of ethical and legal frameworks becomes necessary to safeguard the confidentiality, integrity, and availability of data and systems against unauthorized access or potential harm. Additionally, it is crucial to avoid or mitigate bias and discrimination in AI models and outcomes. The adoption of fair and inclusive methodologies is imperative to prevent or address biases in data collection, model development, outcome generation, and impact assessment. Striking a balance between the roles and responsibilities of humans and machines in treatment is essential. Embracing human-centered design approaches ensures that AI complements human expertise and decision-making while maintaining appropriate levels of human agency and oversight (Topol et al., 2021).

To maximize the benefits of AI in treatment while minimizing potential risks and ensuring patient-centered care, addressing these challenges necessitates ongoing research, the establishment of ethical guidelines, and collaboration among various stakeholders.

Several AI applications exemplify the use of AI in treatment. Woebot, for instance, functions as a chatbot employing natural language processing and machine learning to provide cognitive-behavioral therapy (CBT) for depression and anxiety (Fitzpatrick et al., 2017). Similarly, Wysa operates as a chatbot utilizing natural language processing and machine learning to provide emotional support and self-help tools for mental health and well-being (Inkster et al., 2018). DeepMind represents a deep learning system that employs reinforcement learning and neural networks to optimize radiotherapy planning specifically for head and neck cancer patients (Park et al., 2018). Lastly, IBM Watson serves as a cognitive computing system utilizing natural language processing and machine learning to provide personalized medicine and clinical decision support for cancer diagnosis and treatment (Chen & Snyderman, 2019).

1.18. Prevention:

Prevention involves interventions and actions to mitigate the risk or severity of mental health issues before they become chronic. Artificial intelligence (AI) plays a crucial role in prevention by identifying individuals at higher risk through the analysis of genetic, biological, psychological, environmental, and social factors. AI methods include analyzing electronic health records (EHRs) using natural language processing and machine learning to extract relevant information for assessing mental illness or suicide risk (Barak et al., 2019). AI can also utilize brain imaging data to detect structural or functional abnormalities related to mental disorders or cognitive decline (Cummings & Nadkarni, 2018), monitor wearable or smartphone sensor-based data to track behavioral patterns indicative of emotional states or stress levels (Grigoriadis et al., 2017), and mine social media platforms for linguistic or visual cues indicating changes in mood or suicidal ideation (O'Neil, 2016). By employing these approaches, AI can provide early warnings and suggest preventive strategies or interventions to reduce the likelihood and impact of mental health problems.

1.19. Management:

n the context of mental health, management encompasses interventions and actions aimed at improving the quality of life for individuals with mental health issues. Artificial intelligence (AI) plays a significant role in supporting management efforts by providing continuous and comprehensive support, enhancing self-care practices, and promoting overall well-being. AI can be employed to recommend relevant resources or activities through recommender systems, facilitating mental health awareness, education, and coping skills (Barak, 2017). Additionally, sentiment analysis or emotion recognition can be utilized to detect and measure the emotional states or expressions of patients or users, enabling appropriate responses and feedback (Kramer et al., 2017). Moreover, AI can leverage gamification or serious games to engage and motivate patients or users, ensuring adherence to treatment plans or goals while monitoring progress and outcomes. By integrating these approaches, AI offers interactive and personalized management solutions that empower individuals to actively participate in their mental health journey.

1.20. Current Status and Future Prospects

The current status of artificial intelligence (AI) application in mental health is characterised by a growing variety of applications and research initiatives focused on improving the identification, diagnosis, assessment, monitoring, treatment, prevention, and management of various mental disorders. Moreover, AI possesses the capability to enable personalised, accessible, economical, and scalable mental health care for a diverse and varied population. Furthermore, AI has the potential to enhance the scientific understanding of the aetiology, processes, and ramifications of mental disorders.

Nevertheless, the existing status of AI in mental health is also accompanied by certain obstacles and constraints that necessitate resolution and surmounting. Some of these challenges and limitations encompass the quality, quantity, availability, and interoperability of mental health data. Frequently, mental health data is characterized by sparsity, noise, incompleteness, inconsistency, or lack of structure. Moreover, mental health data is often of a sensitive, confidential nature, safeguarded by ethical and legal regulations. Additionally, mental health data tends to be dispersed across diverse sources, formats, or systems. These factors engender difficulties in collecting, processing, analyzing, and sharing mental health data for AI applications.

The validity, reliability, generalizability, and interpretability of AI models and outcomes present further challenges and limitations. The performance and outcomes of AI models are frequently influenced by the data and methods utilized for their training and testing. In the event that the data or methods are biased, inaccurate, or inappropriate, the validity and reliability of the AI models and outcomes may be compromised. Similarly, if the AI models and outcomes are not tested or validated on diverse or representative samples or scenarios, their generalizability may be in question. Additionally, the complexity, opacity, or black-box nature of AI models and outcomes may hinder their interpretability. Consequently, evaluating, interpreting, and trusting AI models and outcomes for mental health applications become formidable tasks.

The ethical, social, legal, and technical ramifications of implementing AI in mental health must be meticulously evaluated and handled. The integration of AI in mental health may produce both beneficial and detrimental effects on people, groups, and societies. As a result, ethical, social, legal, and technical challenges arise that necessitate examination and solutions. Ensuring the confidentiality and security of mental health data and artificial intelligence systems presents a difficulty. Likewise, addressing or alleviating bias and discrimination in AI models and their results requires careful consideration. Achieving equilibrium between the functions and duties of humans and machines in mental health care, along with fostering trust and acceptance of AI among mental health practitioners and patients, presents additional challenges. Thus, the design, implementation, and regulation of AI in mental health pose considerable challenges.

The future potential of AI in mental health is marked by optimism and enthusiasm. Artificial intelligence possesses the capacity to create innovative ideas and solutions that improve the quality, efficiency, accessibility, and affordability of mental health care. Furthermore, AI can assist in tackling significant issues and shortcomings faced by global mental health systems, such as ageing demographics, chronic illnesses, workforce deficits, and rising expenses. Furthermore, AI possesses the capacity to advance scientific understanding and innovation in mental health.

However, the future prospects of AI in mental health are also uncertain and arduous. AI deployment in mental health may encounter barriers and risks that must be surmounted and managed. Furthermore, the implementation of AI in mental health care may necessitate changes and adaptations within the culture and practices of mental health care. Additionally, AI in mental health gives rise to ethical, social, legal, and technical questions that require answers and resolutions.

The future of AI in mental health depends on the collaborative efforts and coordination of various stakeholders, including researchers, developers, physicians, patients, legislators, regulators, educators, and activists. The future potential of AI in mental health depends on the formation and adoption of best practices and standards for the design, evaluation, implementation, and regulation of AI within this field.

1.21. Research Questions

This study aims to clarify a set of research questions intended to guide our investigation and subsequent chapters. Our primary purpose is to develop and evaluate AI-based tools designed for the prompt detection and prevention of mental health disorders. Our objective is to develop innovative solutions utilising AI technology that can accurately identify and intervene in mental health illnesses at their early stages. Secondly, we aim to explore the application of AI in tailoring mental health treatment to the unique needs and preferences of individual patients. This study will focus on developing AI-based strategies that tailor treatment plans and treatments according to an individual's unique characteristics and situations. Thirdly, we will examine the ethical implications related to the use of AI in mental health care. This study will involve an evaluation of privacy, data security, and the potential biases or hazards associated with AI-driven mental health interventions. Finally, we will assess the effectiveness of AI-driven mental health interventions. Through the application of stringent assessment techniques, we aim to determine the efficacy of AI tools in improving patient outcomes and enhancing the overall quality of life for those undergoing mental health treatment. Through the exploration of these research enquiries, we want to enhance the development of AI applications in mental health care and their potential effects on patient well-being.

1.22. Aims and Objectives

The suggested research seeks to investigate the untapped potential of Artificial Intelligence (AI) in the field of mental health. The primary objective is to develop an AI tool that can efficiently assist in the identification, assessment, and management of anxiety, depression, and common mental diseases. The study includes multiple specific aims.

Firstly, the research initiative aims to promote the creation and assessment of AI-driven solutions for the prompt identification and prevention of mental health disorders. This objective involves employing machine learning algorithms to analyse electronic health records or social media data, thereby identifying patterns that may suggest a predisposition to developing a mental health disorder. Furthermore, the research seeks to assess the effectiveness of interventions provided via these AI-based technologies, therefore aiding the development of techniques for early identification and prevention.

Secondly, the research endeavor aspires to explore the employment of AI for tailoring mental health treatment to the distinct requisites and predilections of individual patients. This objective encompasses the development and evaluation of AI-based tools capable of adapting treatment approaches based on patient data, such as the severity of symptoms and response to treatment. By personalizing the treatment plan, this research aims to heighten the efficacy and patient satisfaction derived from mental health interventions.

Ethical considerations play a crucial role in the deployment of AI in mental health treatment. Thus, the project aims to investigate the ethical considerations related to the implementation of AI in this setting. Potential issues, like biases inherent in the data utilised for training AI models and the possibility of AI replacing human therapists, will be meticulously examined. The study will prioritise identifying solutions to alleviate ethical problems, ensuring the prudent and ethical use of AI technology in mental health treatment.

Finally, the research seeks to evaluate the effectiveness of AI-driven mental health interventions compared to conventional methods. This objective entails examining the efficacy of AI-driven therapies in enhancing patient outcomes and quality of life. The effectiveness of AI-based therapies will be rigorously examined in relation to factors such as patient characteristics and the specific mental health issue being addressed.

This project aims to provide significant insights on the possibilities of AI in mental health. It aims to enhance tactics for early identification and prevention, tailored treatment methods, ethical issues, and the effectiveness of AI-driven therapies. The primary objective of this research initiative is to improve mental health care methods and enhance the well-being of individuals suffering from mental health disorders.

1.23. Significance of Integrating Artificial Intelligence in Mental Health Research

The incorporation of artificial intelligence (AI) into mental health research is highly significant, providing considerable advancements to scholarly understanding and practical implementations. Utilising AI-driven tools and technologies, researchers and practitioners can transform mental health care practices, benefiting patients, mental health providers, and society at large.

Advantages for Patients: The incorporation of AI-driven solutions in mental health care tackles essential issues with accessibility and prompt intervention. AI-driven smartphone applications and chatbots facilitate extensive access to mental health assistance, overcoming obstacles like resource scarcity and geographical isolation. Consequently, patients gain immediate access to support and guidance, mitigating the burden of mental illness and enhancing overall well-being and quality of life.

Advantages for Mental Health Practitioners: The incorporation of AI technologies in mental health care mitigates stress and burnout among experts by automating repetitive chores and optimizing administrative responsibilities. Artificial intelligence enhances data analysis, promoting more efficient service delivery and permitting mental health experts to concentrate on intricate and individualized elements of care. This not only improves patient outcomes but also elevates job satisfaction and the overall well-being of mental health practitioners.

Societal Implications: The findings of this research have broader implications for policy development and healthcare resource allocation in mental health. As the efficacy and prospective advantages of AI-driven interventions are established, policymakers may contemplate incorporating these technologies into mental health care methods. Establishing norms and regulations to ensure ethical and responsible AI use in mental health care, together with the provision of adequate resources for the research and application of AI technologies, are crucial steps to realize the full potential of AI in this domain.

Academic Contributions: The examination of numerous aspects of AI in mental health care in this research has the potential to improve academic comprehension. By investigating early identification and prevention, personalized therapy, ethical implications, and intervention efficacy, researchers can provide substantial insights and augment the existing body of knowledge. These findings augment our understanding of the opportunities and challenges associated with the incorporation of AI into mental health treatment methodologies.

The integration of AI in mental health research has substantial potential and importance, with the ability to positively impact patients, mental health professionals, and society as a whole. This project aims to revolutionize mental health care methods by employing AI to improve accessibility, efficiency, and personalized therapies. Consequently, it improves mental health outcomes and promotes the establishment of more effective and inclusive mental health treatment systems.

1.24. Thesis Structure:

The thesis is structured into five chapters, each fulfilling a specific purpose and contributing to the overall coherence and rigor of the research. The first chapter serves as an introduction, providing a comprehensive background and contextual framework for the study. It highlights the research's significance, articulates the problem statement, establishes research objectives, and outlines the thesis structure.

Chapter two consists of an extensive literature review, synthesizing and analyzing prior studies to construct a robust theoretical foundation. It identifies gaps in current knowledge and situates the research within the broader scholarly discourse.

Chapter three presents the research methods employed, providing detailed descriptions of data collection procedures, sampling methodologies, and ethical considerations. The chapter ensures transparency and methodological clarity to enhance the research's credibility and replicability.

Chapter four constitutes the analytical core of the thesis, where collected data undergoes rigorous analysis and interpretation. Statistical techniques and visual aids, such as graphs and charts, are employed to elucidate patterns, findings, and observations.

Chapter five offers a comprehensive discussion of the research findings, critically examining their implications and situating them within the broader scholarly landscape. The chapter proposes recommendations for future research directions or practical applications, fostering further academic inquiry and potential real-world impact.

The concluding chapter summarizes the main research findings, reiterates their significance, and synthesizes the entirety of the thesis. It reflects on the research process, acknowledges limitations or challenges encountered, and provides concluding remarks to ensure a thoughtful and cohesive closureto the thesis. These carefully constructed chapters establish a scholarly framework that systematically guides readers through the research process, ensuring a coherent and logical presentation of the research endeavors.

Chapter 2

Literature Review

Chapter 2

Literature Review

2.1. Introduction

Artificial intelligence (AI) is a rapidly advancing field with the capacity to revolutionise mental health care and research. Artificial Intelligence involves the creation of computer systems that can execute tasks often dependent on human intelligence, such as learning, thinking, and decision-making. Its utilisation in mental health encompasses multiple areas, including diagnosis, assessment, intervention, prevention, management, aetiology, epidemiology, and consequences of mental diseases. AI enhances accessibility, cost, and quality of mental health services, hence overcoming resource constraints and reaching marginalised communities. However, the incorporation of AI into mental health care and research requires addressing significant hurdles and limits. This includes ethical, legal, and social concerns, such as privacy, consent, accountability, openness, prejudice mitigation, and stigma reduction. Moreover, thorough assessment, verification, interdisciplinary cooperation, and stakeholder involvement are essential for the extensive acceptance and ethical application of AI in mental health.

Depression, anxiety, and other prevalent mental illnesses (CMDs) present substantial global public health concerns, impacting a major population worldwide. The World Health Organisation (WHO) states that depression is the primary cause of global disability, affecting over 264 million individuals, whilst anxiety disorders influence around 284 million people. Chronic medical disorders are linked to diminished quality of life, heightened morbidity and mortality rates, and increased healthcare costs. Regrettably, numerous patients with CMDs fail to obtain appropriate diagnosis or treatment, frequently attributable to societal stigma, resource limitations, or a lack of knowledge.

A significant use of artificial intelligence (AI) in the research of common mental diseases (CMDs) pertains to the prediction of CMD start or recurrence utilising a diverse range of indicators or risk variables. Tutun et al. (2023) demonstrated this by employing machine learning (ML) models to forecast depression in primary care patients, utilising electronic health record (EHR) data. Their findings demonstrated the enhanced accuracy and sensitivity of machine learning models relative to traditional logistic regression models. Similarly, Shen et al. (2020) utilised machine learning models to forecast suicide attempts in persons with depression, utilising electronic health record data. Significantly, these machine learning models discerned multiple risk indicators that were overlooked by current clinical instruments.

A notable application of AI is in the detection or screening of CMDs according to diverse parameters or characteristics. Gao et al. (2020) employed natural language processing (NLP) models to identify depression in Twitter users using tweet analysis, attaining notable accuracy and recall rates. Li et al. (2020) utilised computer vision (CV) models to identify depression in college students by analysing their facial expressions, achieving significant accuracy and precision. Artificial intelligence can be utilised for the diagnosis or classification of chronic medical disorders based on various criteria or characteristics. Chen et al. (2021) employed deep learning models to identify bipolar illness in patients with depression using brain imaging data. The deep learning models exhibited elevated accuracy and specificity. Wang et al. (2020) utilised deep learning models to identify anxiety disorders in persons with depression using brain imaging data, attaining significant accuracy and sensitivity.

Another valuable application of AI in CMDs research involves the subtyping or clustering of CMDs based on their heterogeneity or complexity. Drysdale et al. (2017) utilized ML models to subtype depression among individuals with major depressive disorder (MDD), analyzing brain imaging data. Their findings unveiled the identification of four distinct subtypes of depression characterized by varying clinical features and treatment responses. Similarly, Koutsouleris et al. (2019) employed ML models to subtype anxiety disorders among individuals with generalized anxiety disorder, leveraging brain imaging data. The ML models successfully identified three subtypes of anxiety disorders distinguished by differences in symptom severity and cognitive impairment. In addition to these applications, AI holds promise in identifying risk or protective factors associated with the development or exacerbation of CMDs. For instance, Shen et al. (2021) utilized DL models to identify risk factors for depression by analyzing brain imaging data, revealing novel associations between specific brain regions and networks with depression. Furthermore, Bucci et al. (2018) employed ML models to identify protective factors for psychosis among young individuals at high risk, analyzing smartphone data. The ML models successfully identified several protective factors linked to social and physical activities.

AI possesses the capability to assist in tracking the advancement and therapeutic results of chronic medical disorders over time. Saeb et al. (2017) employed ML models to monitor depressive symptoms among patients with MDD using smartphone data, accurately tracking changes in symptoms over time. Similarly, Torous et al. (2018) utilized ML models to monitor treatment outcomes among individuals with schizophrenia using smartphone data, effectively capturing the effects of medication adherence and psychosocial interventions on symptom severity. AI can provide interventions or support for common mental disorders (CMDs) through various modalities and approaches. Fitzpatrick et al. (2017) utilized an AI-based chatbot named Woebot to deliver cognitive behavioral therapy (CBT) to individuals with major depressive disorder (MDD) through text messages, resulting in improved mood and reduced depressive symptoms compared to a control group. Similarly, Lattie et al. (2019) employed an AI-based chatbot named Wysa to provide emotional support for pregnant women with MDD through text messages, yielding increased engagement and satisfaction compared to a control group.

Furthermore, AI contributes to the generation of novel insights or hypotheses about CMDs through data analysis and exploration. Shen et al. (2020) employed deep learning (DL) models to discover new biomarkers associated with schizophrenia using brain imaging data, unveiling previously unidentified brain regions and networks linked to the disorder. Similarly, Wang et al. (2020) utilized DL models to discover new subtypes of depression based on brain imaging data, identifying six distinct subtypes characterized by unique clinical features and neural correlates. The utilization of AI in CMDs research offers several benefits, including enhanced accuracy, efficiency, and scalability of data analysis and interpretation, particularly for large, complex, and heterogeneous datasets. AI facilitates the integration, fusion, and harmonization of data from multiple sources and modalities such as electronic health records (EHRs), brain imaging, smartphones, wearables, and social media, enabling comprehensive analysis. Moreover, AI enables the personalization, customization, and adaptation of interventions and support based on individual characteristics, preferences, and feedback. This contributes to improved accessibility, affordability, and quality of mental health services, especially for underserved populations and resource-limited settings. Furthermore, AI has the capacity to generate novel insights, hypotheses, or discoveries about CMDs that may not be achievable through conventional methods or human expertise.

Research on AI in CMDs is marked by growing trends and advancements that could influence future studies in the domain. These themes encompass the growing application of deep learning methodologies, capable of independently discerning complex patterns and characteristics in data without human involvement or prior understanding. Moreover, there is an increasing focus on natural language processing methodologies that facilitate the understanding and production of natural language from textual or auditory input. Advancements in computer vision techniques facilitate the recognition and interpretation of visual information from photos or movies. Reinforcement learning methodologies are being devised to allow AI models to acquire optimal actions or policies via trial-and-error feedback. The domain is experiencing the emergence of explainable AI methodologies that offer clear and interpretable justifications for the decisions or outputs of AI systems. Federated learning methodologies are developing, facilitating the training of AI models across numerous devices or servers without the necessity of exchanging raw data. Moreover, generative AI methodologies are utilised to produce novel data or content from pre-existing information.

Despite the potential of AI in CMDs research, there remain gaps and opportunities that require attention and exploration. These include the lack of standardized and validated datasets that are representative, diverse, and inclusive of different populations and settings. The rigorous evaluation and validation of AI applications in CMDs research also require further development to ensure reliability, generalizability, and reproducibility across various contexts and scenarios. The ethical, legal, and social aspects of AI applications in CMDs research must be addressed, encompassing issues such as privacy, consent, accountability, transparency, bias reduction, and stigma reduction. Moreover, fostering interdisciplinary and cross-sectoral collaboration and communication among AI researchers, mental health researchers, clinicians, policymakers, patients, and other stakeholders is crucial. Awareness and education about the potential of AI in CMDs research need to be increased among both the general public and the mental health community.

Future directions for AI in CMDs research involve the creation of more precise, efficient, and scalable AI models that can manage extensive, intricate, and diverse datasets from many sources and modalities. There is a necessity for the development of personalised, tailored, and adaptive AI treatments and support that address the unique needs, preferences, and feedback of each individual. Efforts must prioritise enhancing the accessibility, affordability, and quality of mental health care, especially in resource-constrained environments, by utilising AI. Moreover, AI possesses the capacity to produce new insights, ideas, or discoveries regarding CMDs, potentially resulting in innovative preventive, diagnosis, or therapy methodologies. Formulating ethical and legal frameworks and rules for AI applications in CMD research is crucial, guaranteeing privacy, consent, accountability, openness, bias mitigation, stigma alleviation, and stakeholder engagement in decision-making processes. Fostering multidisciplinary collaboration and communication among AI researchers, mental health researchers, physicians, policymakers, patients, and other stakeholders is essential. Finally, enhancing awareness and delivering education regarding AI applications in CMD research to the general populace and the mental health sector is essential for the responsible and inclusive advancement and employment of AI technology.

AI holds tremendous potential in revolutionizing mental health care and research, particularly in the context of common mental disorders (CMDs). Its applications encompass various domains, including prediction, detection, diagnosis, intervention, monitoring, and understanding of CMDs. Tutun et al. (2023) demonstrated the superior accuracy and sensitivity of machine learning (ML) models in predicting depression among primary care patients using electronic health record (EHR) data. Similarly, Shen et al. (2020) utilized ML models to predict suicide attempts among individuals with depression, identifying risk factors not captured by existing clinical tools. AI also excels in detecting and screening CMDs based on diverse criteria or features. Gao et al. (2020) achieved high accuracy and recall rates in detecting depression among Twitter users using natural language processing (NLP) models. Li et al. (2020) successfully detected depression among college students through analysis of facial expressions using computer vision (CV) models. AI facilitates the diagnosis and classification of CMDs based on various criteria or features. Chen et al. (2021) employed deep learning (DL) models to diagnose bipolar disorder among patients with depression using brain imaging data, demonstrating high accuracy and specificity. Wang et al. (2020) employed DL models to diagnose anxiety disorders among individuals with depression, achieving notable accuracy and sensitivity.

The classification or grouping of CMDs according to their heterogeneity or complexity represents another significant use of AI. Drysdale et al. (2017) employed machine learning models to classify depression in individuals with major depressive disorder (MDD) through brain imaging data, identifying four unique subtypes characterised by differing clinical symptoms and treatment responses. Koutsouleris et al. (2019) effectively identified three subgroups of anxiety disorders in persons with generalised anxiety disorder utilising machine learning models based on neuroimaging data. Artificial intelligence is essential in detecting risk or protective variables linked to the onset or worsening of chronic mental disorders. Shen et al. (2021) utilised deep learning models to ascertain risk factors for depression through brain imaging data, revealing new correlations between particular brain regions and networks associated with depression. Bucci et al. (2018) employed machine learning models to discern protective variables against psychosis in high-risk kids through smartphone data, uncovering features associated with social and physical activities.

AI also contributes to monitoring the progression and treatment outcomes of CMDs over time. Saeb et al. (2017) effectively monitored depressive symptoms among patients with MDD using ML models and smartphone data, accurately tracking changes over time. Torous et al. (2018) utilized ML models and smartphone data to monitor treatment outcomes in individuals with schizophrenia, capturing the effects of medication adherence and psychosocial interventions on symptom severity. AI provides interventions and support for CMDs through various modalities and approaches. Fitzpatrick et al. (2017) demonstrated the effectiveness of an AI-based chatbot, Woebot, in delivering cognitive behavioral therapy (CBT) via text messages to individuals with MDD, resulting in improved mood and reduced symptoms. Lattie et al. (2019) achieved increased engagement and satisfaction by employing an AI-based chatbot, Wysa, to provide emotional support for pregnant women with MDD.

AI contributes to the generation of novel insights or hypotheses about CMDs through data analysis and exploration. Shen et al. (2020) discovered new biomarkers associated with schizophrenia using DL models and brain imaging data, unveiling previously unidentified brain regions and networks linked to the disorder. Wang et al. (2020) identified new subtypes of depression based on brain imaging data using DL models, characterizing six distinct subtypes with unique clinical features and neural correlates. The utilization of AI in CMDs research offers several benefits, including enhanced accuracy, efficiency, and scalability of data analysis and interpretation for large and complex datasets. AI enables the integration and fusion of data from diverse sources and modalities such as EHRs, brain imaging, smartphones, wearables, and social media, enabling comprehensive analysis. It also enables personalized and adaptive interventions based on individual characteristics, preferences, and feedback, improving accessibility, affordability, and quality of mental health services. Additionally, AI generates new insights and hypotheses that may not be attainable through conventional methods or human expertise.

The future of AI in CMDs research encompasses developments like deep learning methodologies, natural language processing, computer vision, reinforcement learning, explainable AI, federated learning, and generative AI. Nonetheless, obstacles persist, such as the necessity for standardised and validated datasets, thorough evaluation and validation of AI applications, ethical issues, interdisciplinary collaboration, and the promotion of awareness and education. Artificial intelligence possesses the capacity to transform mental health care and research in chronic mental disorders, providing enhanced precision, customisation, and accessibility. Addressing current gaps and problems, while promoting collaboration and enhancing awareness, is essential for the responsible and effective incorporation of AI in CMDs research and clinical practice.

Artificial intelligence constitutes a swiftly evolving domain with the capacity to transform mental health care and research. Artificial Intelligence encompasses the creation of computer systems that can execute tasks usually necessitating human intelligence, including learning, thinking, and decision-making. Within the realm of CMDs, AI can be utilised in multiple areas, encompassing detection, diagnosis, intervention, prevention, management, and the comprehension of aetiology, epidemiology, and consequences. Artificial intelligence can improve the precision, efficiency, scalability, personalisation, customisation, adaptability, accessibility, cost, and quality of mental health services and research.

Artificial intelligence is employed in multiple areas of chronic disease management research, enabling functions such as prediction, detection, diagnosis, subtyping, identification of risk or protective factors, monitoring of symptoms or treatment outcomes, provision of interventions or support, and the investigation of new insights or hypotheses. To achieve these objectives, AI can leverage several data sources and modalities, including electronic health records (EHRs), mood evaluation scales, neuroimaging data, sophisticated monitoring devices like smartphones, wearables, video, and social media platforms. Diverse approaches and methodologies can be employed in the domain of AI, including machine learning (ML), natural language processing (NLP), computer vision (CV), and deep learning (DL).

The objective of this review is to present a comprehensive overview of the current status of AI in mental health research, with a specific emphasis on applications, advantages, trends, gaps, opportunities, and future directions. We have reviewed select studies exemplifying AI utilization in mental health research across different domains and settings. We have also reviewed select recent studies that exemplify the utilization of AI in CMDs research across different domains and settings. It is important to note that these studies serve as illustrative examples rather than an exhaustive representation of the entire field, highlighting the diversity and potential of AI in CMDs.

2.2. AI Applications for Mental Health Research

Artificial intelligence fulfils various roles in mental health research, encompassing prediction, categorisation, subtyping, identification of risk and protective variables, monitoring of symptoms and treatment outcomes, provision of interventions and support, and the finding of insights and hypotheses. By leveraging various data sources and modalities, including electronic health records (EHRs), mood assessment scales, neuroimaging, advanced monitoring systems (e.g., smartphones, wearables, video), and social media platforms, AI utilizes methodologies such as machine learning (ML), natural language processing (NLP), computer vision (CV), and deep learning (DL).

Chen et al. (2021) executed a study utilizing machine learning (ML) models and electronic health record (EHR) data to forecast the emergence of major depressive disorder (MDD) in primary care patients. Their ML models outperformed traditional logistic regression models in terms of accuracy and sensitivity, showcasing their efficacy in predicting MDD onset. In a similar vein, Wang et al. (2021) utilized deep learning (DL) models to predict bipolar disorder among patients with MDD based on brain imaging. Their DL models exhibited high levels of accuracy and specificity in predicting bipolar disorder.

Gao et al. (2020) explored the classification of schizophrenia among patients with psychotic disorders using natural language processing (NLP) models applied to speech transcripts. Their study demonstrated that the NLP models achieved high accuracy and recall in classifying schizophrenia. Similarly, Li et al. (2020) employed computer vision (CV) models to classify depression among college students based on facial expressions. Their CV models achieved high accuracy and precision in accurately identifying depression.

Drysdale et al. (2017) focused on subtyping depression among patients with MDD utilizing ML models and brain imaging data. Through their study, they successfully identified four distinct subtypes of depression characterized by varying clinical features and treatment response. In a similar vein, Koutsouleris et al. (2019) employed ML models to subtype schizophrenia among patients with psychotic disorders based on brain imaging. Their study revealed three subtypes of schizophrenia exhibiting differences in symptom severity and cognitive impairment.

Shen et al. (2020) utilized ML models and EHR data to identify risk factors for suicide attempts among patients with MDD. Their study uncovered risk factors that were not captured by existing clinical tools, highlighting the potential of ML models in identifying novel risk factors. Bucci et al. (2018) utilized ML models on smartphone data to identify protective factors for psychosis among at-risk youth. Their study revealed protective factors related to social and physical activity that can potentially mitigate the risk of psychosis.

Sarah Graham et al. (2019) emphasised in their research that AI methodologies has the capacity to redefine mental disorders more objectively than the DSM-5 currently does. Utilising AI can facilitate the early detection of mental diseases, hence permitting more effective interventions. Moreover, AI methodologies can enable customised therapies designed to the unique attributes of each patient. It is essential to take caution and refrain from making hasty judgements based on preliminary findings. Additional efforts are necessary to reconcile the disparity between therapeutic interventions and artificial intelligence in mental health research.

Lauren Su En Li et al. (2021) assessed the efficacy of applications addressing stress, anxiety, and depression for those impacted by the COVID-19 pandemic. The research revealed other high-caliber programs, such as Sanvello, Woebot, Happify, Youper, and Bloom, that proficiently tackled the specified mental health concerns.

Kretzschmar et al. (2019) emphasized the potential of chatbots such as Woebot, Wysa, and Joy in assisting individuals with mental health concerns. These chatbots can be accessed by anyone with a smartphone and internet connection, making them more accessible and less stigmatizing than traditional forms of mental health support. Consequently, they can serve as an initial resource for seeking assistance.

Moreover, in a randomized controlled trial conducted by Fitzpatrick et al. (2017) involving young adults, it was observed that participants who received treatment from the Woebot chatbot exhibited significantly lower levels of depression compared to those in the control group. The Woebot chatbot proved to be a practical, efficient, and engaging method for delivering cognitive behavioral therapy (CBT) online.

Kien Hoa Ly et al. (2017) executed a pilot randomised controlled trial to evaluate the efficacy of a smartphone application functioning as a conversational agent for delivering positive psychology and cognitive behavioural therapy interventions. The study revealed notable enhancements in psychological well-being and perceived stress among users utilising the app, in contrast to those in the wait-list control group. The intervention group exhibited significant engagement with the app, indicating its acceptance and utility.

Another study by Meheli et al. explored the perceived needs, engagement, and effectiveness of the mental health app Wysa among users with chronic pain. Through thematic analysis and quantitative assessments, it was found that Wysa effectively addressed mental health concerns related to chronic pain, leading to significant improvements in symptom scores for depression and anxiety. Users engaged frequently with various tools offered by the app, including gratitude exercises, sleep meditations, and anxiety management techniques.

The study conducted by Leo et al. sought to assess the feasibility and potential efficacy of the digital mental health intervention Wysa for patients exhibiting comorbid depression and/or anxiety symptoms within an orthopaedic setting. This single-arm, prospective cohort pilot trial was performed in a prestigious academic medical centre focused on tertiary care in the United States. A total of 61 participants, representing 29.3% of patients (Age<18) seeking assessment and treatment for musculoskeletal conditions in the orthopaedic department, were chosen. The median age of participants was 55 years, with a range of 18 to 83 years, and 87% were female (53 out of 61). Comparisons of age and sex distributions between study participants and non-participants indicated no statistically significant differences (P=.21). Eligibility required patients to achieve a minimum score of 55 on the Patient-Reported Outcomes Measurement Information System (PROMIS) Depression and Anxiety assessments, which are routinely conducted during outpatient visits in this orthopaedic department. These scores signify the existence of depression and/or anxious symptoms. Every participant in the experiment was granted a complimentary two-month subscription to Wysa, a commercially accessible digital mental health intervention. The total participation percentage among those who consented to the survey was 72%, with Wysa accounting for 44 out of 61 participants. The weekly engagement rate was 57% (35 out of 61), whereas the coach engagement rate was 33% (20 out of 61). The three most commonly employed treatment methods by participants were mindfulness (122/351, 34.8%), cognitive behavioural therapy (76/351, 21.7%), and sleep interventions (53/351, 15.1%). Most rewards obtained by participants (16 out of 48, 33%) pertained to sleep. Individuals with high usage exhibited a more significant enhancement in PROMIS Anxiety levels at the two-month follow-up relative to low users (between-group difference 4.2 points, 95% CI 8.1 to 0.2; P=.04). Despite the observed between-group differences in PROMIS Depression (−3.2 points, 95% CI −7.5 to 1.2; P=.15) and Pain Interference scores (−2.3 points, 95% CI −6.3 to 1.7; P=.26) favouring high users, statistical significance was not achieved. The enhancements in PROMIS Physical Function scores were comparable between the two groups. This pilot study assessed the feasibility and potential efficacy of the digital mental health intervention Wysa for patients with comorbid depression and/or anxiety symptoms in an orthopaedic setting. Individuals with high engagement in the intervention exhibited a more significant reduction in anxiety symptoms at the two-month follow-up. Users receiving high intervention demonstrated markedly greater enhancements in depression and pain interference at the two-month interval.

Darcy et al. (2022) conducted research that emphasised the significant potential of WB001 as a dynamic and personalised instrument in enhancing the therapeutic relationship between patients and healthcare providers. They highlighted that Woebot (WB001) is intentionally intended to function as a beneficial support system for human healthcare professionals, rather than a replacement. The primary aim of this design strategy is to efficiently utilise the intrinsic therapeutic benefits of guiding, while still guaranteeing scalability and independence in self-help techniques.

WB001 has an exceptional ability to substantially improve the quality and scalability of treatment regimens by effectively supporting patients during intervals between clinical appointments. Moreover, it functions as an essential tool for automating measurement-based care. By using its distinctive characteristics, WB001 can bridge care gaps, offering ongoing support and assistance to patients despite the lack of rapid access to healthcare specialists. This adaptable and individualised instrument is crucial for enhancing treatment results, increasing patient involvement, and promoting a more holistic strategy for mental health management.

Liu et al. (2022) conducted a thorough unblinded randomised controlled experiment to examine and evaluate the efficacy of a self-help depression intervention administered by a chatbot with that of a minimal bibliotherapy method. The research included a sample of 83 university students, who were randomly allocated to either the chatbot intervention group or the minimum bibliotherapy group. The study's findings offered persuasive evidence that the chatbot-delivered intervention was superior than basic bibliotherapy in alleviating symptoms of depression and anxiety among participants. The chatbot intervention significantly outperformed the limited bibliotherapy technique in alleviating the severity of depression and anxious symptoms among participants. The study demonstrated that the chatbot intervention was crucial in establishing a robust therapeutic bond with the participants. The chatbot's interactive features facilitated a personalised and engaging therapeutic experience, fostering a strong therapeutic connection between the participants and the intervention tool. These findings highlight the considerable potential of chatbot-delivered therapies as a novel and effective method for alleviating symptoms of depression and anxiety, while simultaneously fostering a positive therapeutic alliance. This study adds to the expanding literature endorsing the use of chatbot technologies in mental health interventions, highlighting their capacity to improve treatment outcomes and engagement among university students.

A study by Arfan Ahmed et al. (2021) concluded that Artificial Intelligence (AI)-based chatbots had significant potential for treating anxiety and depression. These chatbots possess the capability to augment the self-care abilities of persons with mental health disorders while offering economical assistance to professionals in the domain.

Prochaska et al. (2021) conducted a pilot study examining the feasibility, acceptability, and preliminary effectiveness of Woebot for substance use disorders (W-SUDs) in a cohort of 101 persons with a mean age of 36.8 years. This single-arm, open-label study sought to evaluate the efficacy of Woebot as an intervention for drug use disorders. Following an eight-week duration, the researchers noted substantial enhancements in many end metrics, encompassing anxiety, depression, frequency of drug use, and the capacity to withstand substance use temptations. The findings indicate that Woebot may positively influence mental health symptoms and substance use behaviours in individuals with drug use problems. The research evaluated the participants' viewpoints regarding Woebot and its offerings. A significant proportion of participants (76%) indicated they would endorse W-SUDs to a friend, reflecting a substantial degree of pleasure and perceived efficacy of the intervention. This underscores the acceptability of Woebot as an instrument for tackling drug use disorders and its potential as a significant asset in substance misuse treatment.

Inkster et al. conducted a study to evaluate the effectiveness and engagement levels of Wysa, an

AI-driven, empathetic, text-based mobile application for mental health, among adults with self-reported depressed symptoms. The study comprised 129 participants, of whom 108 were classified as high users and 21 as low users. The quantitative analysis evaluated the average improvement in depressive symptoms, as measured by the Patient Health Questionnaire-9 (PHQ-9) score, between high and low users. The results revealed that high users exhibited a significantly greater average decrease in depressive symptoms compared to low users, with a small impact size and statistical significance. The qualitative analysis assessed user opinion regarding the app and revealed that 67.7% of respondents deemed the app experience beneficial and motivating. The study indicated that the Wysa app demonstrates potential in alleviating depressive symptoms and improving user engagement and experience. Nonetheless, additional research with bigger sample sizes and extended periods is necessary to corroborate these findings. The Wysa app may function as a beneficial adjunct or intermediary support mechanism for addressing symptoms of depression.
Mehmet Amin Aktan et al. (2022) posited that enhancing confidence in AI tools and comprehending the benefits and efficacy of psychotherapy could elevate the inclination towards AI-based psychotherapy. This indicates that individuals may be increasingly predisposed to choose AI-based psychotherapy as they recognise its advantages and have confidence in its effectiveness.

A randomised controlled experiment by Prochaska et al. (2021) assessed the efficacy of Woebot for substance use disorders in a sample of 180 patients. The study sought to evaluate the effects of Woebot on instances of substance use and mental health outcomes in comparison to a wait-list control group. At the eight-week post-treatment interval, the findings demonstrated a substantial decrease in instances of substance use in the Woebot group relative to the wait-list control group. This indicates that Woebot may be useful in assisting persons with substance use disorders in diminishing their drug consumption. The Woebot group demonstrated reduced substance use problems and revealed enhancements in mental health metrics. Participants in the Woebot group indicated reduced levels of sadness and anxiety, signifying a beneficial effect on their emotional well-being. The data indicate that Woebot may positively impact drug use-related problems and mental health symptoms. The feedback concerning the Woebot program was exceedingly favourable. Participants indicated a positive experience and regarded the intervention as beneficial. This favourable feedback reinforces the prospective value and acceptability of Woebot as an instrument for tackling substance use problems.

Fulmer et al. (2018) conducted a randomised controlled experiment to assess the efficacy and accessibility of artificial intelligence (AI) as a therapeutic instrument for mitigating symptoms of depression and anxiety. The research encompassed 75 participants from 15 universities throughout the United States. The study's findings offered substantial evidence endorsing AI as a viable and accessible treatment instrument. The findings demonstrated that AI-driven interventions effectively alleviated symptoms of depression and anxiety in the individuals. This indicates that AI can offer substantial assistance and alleviation for those facing these mental health issues. The research emphasised the cost-effectiveness and extensive availability of AI as a therapeutic instrument. The implementation of AI facilitates remote interventions, hence increasing accessibility for a broader demographic. This has the capacity to overcome the limitations of conventional in-person therapy, including geographical barriers and the restricted availability of mental health practitioners. This study's findings augment the increasing data endorsing the potential of AI in mental health care. Utilising AI as a therapeutic instrument may narrow the accessibility gap in mental health treatments and offer cost-effective, scalable solutions. Further research is necessary to investigate the long-term effects, cost-effectiveness, and ethical implications of integrating AI into mental health care.

Ramachandran et al. (2020) performed a randomised controlled trial with postpartum mothers, demonstrating that the utilisation of the Woebot chatbot was both possible and acceptable within this demographic. Although the initial depression ratings (PHQ-9) were subclinical, notable differences were detected in the mean change scores between the intervention and control groups at the six-week follow-up.

Sinha et al. conducted a study to assess the feasibility and potential usefulness of the artificial intelligence-driven digital mental health application, Wysa for Chronic Pain, in engaging and keeping users with comorbid mental health symptoms and chronic pain. The research included 51 patients pursuing therapy for chronic musculoskeletal pain at a tertiary care facility. These people exhibited symptoms of sadness or anxiety, as evidenced by a Patient-Reported Outcomes Measurement Information System (PROMIS) score of ≥55. Participants received an 8-week subscription to Wysa for Chronic Pain management. User retention, characterised by weekly app revisits and participation on the last day, alongside user engagement, quantified by the total completed sessions, constituted the principal results. The results indicated that participants completed an average of 33.3 sessions during the 8-week trial duration. Survival study revealed a median user retention duration of 51 days, accompanied by a retention rate of 48.0% (25/52) at the two-month mark. The implementation of a morning check-in function was substantially correlated with an extended retention duration (P=.001). Moreover, 96% of the participants effectively commenced the onboarding process. The results demonstrate that user engagement and retention with a cognitive behavioural therapy-based conversational bot for patients with chronic pain surpass standard industry measures. This has considerable ramifications for tackling the problem of inadequate engagement with digital health interventions and enhancing access to care for those suffering from chronic pain. Employing AI-driven interventions, such as conversational agents, in mental and general healthcare could be an effective approach to improve user engagement, retention, and the overall efficacy of digital health initiatives.

Erin A. Vogel et al. (2021) performed a randomised controlled trial to assess the effectiveness of Woebot, a sophisticated digital therapy, for those exhibiting increased mental health symptoms during the COVID-19 pandemic. The study sought to evaluate the efficacy of Woebot in mitigating problematic substance usage. The results indicated a substantial decrease in substance use and enhancements in mental health symptoms among the subjects. These findings highlight the efficacy of digital therapies, like Woebot, in efficiently managing substance use disorders and offering personalised assistance during difficult periods. The research enhances the accumulating evidence for the efficacy of digital therapies in alleviating mental health issues, offering a scalable and accessible remedy for those in need. The results suggest the incorporation of digital treatments into current treatment methods to improve outcomes and extend reach to a wider audience.

Nicol et al. (2022) established the feasibility, acceptability, utility, and safety of a cognitive behavioural therapy-based chatbot for teenagers exhibiting mild depressive symptoms within a network of primary care clinics in a practice-based research network.

The research by Malik et al. sought to analyse user comments on the Wysa mental health application to understand users' experiences regarding engagement and perceived efficacy. The analysis included customer comments (n=7929) submitted on the Google Play Store over the course of one year. The study categorised and evaluated user feedback regarding acceptability, usability, utility, and integration, identifying core themes and assessing the app's strengths and drawbacks. The research also examined the traits of individuals who gained from accessible digital mental health support. The data indicated a predominantly favourable reception of the app, with 84.50% of user reviews being five stars. Themes concerning entertaining activities, interactive interfaces, and the conversational capabilities of artificial intelligence demonstrated high acceptability, whilst nonjudgmentality and conversational ease underscored usability. The utility was illustrated through topics like enhancements in mental health, ease of access, and cognitive restructuring activities. Privacy and confidentiality were highlighted as significant factors influencing users' preference for the app's integrated features. Additionally, the study discerned four main categories of persons that offered comments on the application. The findings suggest that the Wysa app provides a therapeutic environment defined by comfort, safety, and support. The app's elevated acceptability, usability, utility, and integration indicate its potential to enhance access to mental health assistance and treatment for persons encountering obstacles to conventional care methods.

Satyabrata Aich et al. (2019) posited that while an AI-based system may not entirely replicate the emotional rapport of a face-to-face therapist, it can proficiently mitigate the shortage of mental healthcare resources by acting as a significant intermediary. This is especially vital in emergency situations where prompt assistance is necessary. The authors recognise the constraints in emulating human emotions but highlight the capacity of AI systems to fulfil the need for mental healthcare by providing accessible and prompt support to those in need. The study emphasises the importance of incorporating AI technology into mental healthcare to improve service delivery and emergency response, hence enhancing accessibility and alleviating resource limitations.

Meadows et al. (2020) posited that chatbots are significantly facilitating the development of a personalised and individualised rehabilitation pathway that complements conventional treatment methods. They contended that chatbots, because to their interactive and conversational characteristics, possess the ability to customise their support and interventions to the distinct requirements of persons seeking mental health aid. Chatbots deliver tailored help, guidance, and interventions that correspond to the distinct needs of each user. This individualised strategy, in conjunction with traditional therapeutic techniques, is thought to augment the overall rehabilitation process and promote mental health outcomes. The study highlights the transforming function of chatbots as significant instruments in the expansive domain of mental health care, where individualised and customised assistance is increasingly acknowledged as essential for attaining optimal well-being.

Leo et al. conducted a study assessing Wysa, a smartphone application, as a digital mental health intervention for orthopaedic patients exhibiting signs of sadness or anxiety. This retrospective cohort study, conducted at a single centre, included a pilot feasibility analysis and sought to compare alterations in mental and physical health over a 2-month duration among three groups: patients receiving a digital mental health intervention alongside standard orthopaedic care, patients receiving standard orthopaedic care without a dedicated mental health intervention, and patients receiving in-person psychological care as part of their orthopaedic treatment regimen. The research included 153 patients exhibiting heightened symptoms of depression or anxiety. The digital intervention comprised a multi-faceted mobile application utilising chatbot technology and text-based communication with human counsellors, providing cognitive behavioural therapy, mindfulness training, sleep resources, and emphasising behavioural activation and pain acceptance. The main outcomes of interest were the variations in 2-month longitudinal changes in

PROMIS Depression and Anxiety scores, whereas secondary goals encompassed changes in PROMIS Pain Interference and Physical Function scores. The findings indicated significant enhancements in all PROMIS metrics at the 2-month follow-up for patients undergoing the digital mental health intervention (mean improvement 2.8-3.7 points; $P \leq .02$). After adjusting for age and BMI, patients in this cohort exhibited more significant enhancements relative to those who got standard orthopaedic therapy alone (mean between-group difference 2.6-4.8 points; $P \leq .04$). The results indicate that digital mental health therapies could be practical and expandable within an orthopaedic context. The data reveals that patients undergoing the digital mental health intervention in conjunction with standard orthopaedic care experienced more significant enhancements in depression, pain interference, and physical function than those receiving only standard orthopaedic care. Furthermore, the enhancements in despair, anxiety, and pain interference were analogous to those attained by individuals undergoing in-person psychological counselling. The findings indicate that digital mental health interventions can significantly improve mental health outcomes in orthopaedic patients and provide an effective strategy. Nonetheless, additional research including bigger samples and extended follow-up durations is necessary to corroborate these findings. Moreover, comprehending the precise processes by which digital mental health interventions enhance mental health outcomes and the most effective implementation tactics in clinical environments necessitates additional research.

Silke Ter Stal et al. (2020) demonstrated the positive impact of relational behaviour and emotion on humans' cognitive evaluation and interactive involvement with artificial intelligence (AI) bots. The authors' findings confirm that relational behaviour and emotional characteristics in AI agents significantly influence individuals' evaluations of the agents' usefulness and their subsequent willingness to engage with them. This work elucidates the crucial influence of relational behaviour and emotion on individuals' cognitive processes and behavioural tendencies in interactions with AI agents, thereby enhancing our understanding of the complex dynamics between humans and AI technology.

Darcy et al. (2021) conducted a thorough analysis of data from a large sample of 36,070 Woebot users, thereby contesting the dominant notion that digital therapies are incapable of fostering therapeutic alliances with individuals. Their thorough investigation revealed that digital treatments, such as Woebot, can create significant and effective therapeutic relationships with users. This study dispels the myth regarding the supposed constraints of digital therapies in establishing therapeutic alliances, offering significant insights into the transformative capacity of technology-mediated interventions in cultivating supportive and advantageous therapeutic connections.

Bateman et al. (2021) clarified the potential of artificial intelligence (AI) in improving mental health therapy through enhanced quality control, diagnosis, intervention, and discovery. Their discussion included examples where natural language processing (NLP), computer vision (CV), and machine learning (ML) techniques were utilised to analyse the language, behaviour, and neurophysiological activity of patients and therapists, with the goal of enhancing the accuracy, efficiency, personalisation, and effectiveness of mental health therapy.

Novillo-Ortiz et al. (2023) elucidated a recent study by the World Health Organisation (WHO) that assessed the existing landscape of AI applications in mental health research within the WHO European Region. Their findings revealed a disparity in the use of AI, primarily concentrating on the study of depressive illnesses, schizophrenia, and other psychotic disorders. Methodological and quality problems were highlighted in the utilisation of AI for mental health research, encompassing inadequacies in data quality, validation, generalisation, transparency, and ethical considerations.

Lake et al. (2019) conducted an extensive investigation on the transformative capabilities of AI in mental health treatment and research. Their inquiry included a comprehensive evaluation of advanced AI applications in mental health, covering screening, diagnosis, intervention, prevention, and management of mental diseases. The authors examined the complex challenges and limitations of utilising AI in mental health, including data availability, privacy issues, informed consent, accountability, bias reduction, stigma alleviation, and the significance of stakeholder engagement and education.

Kretzschmar et al. (2020) performed a thorough evaluation of the effectiveness and acceptability of AI-based therapy for mental health issues. A thorough review and meta-analysis of randomized controlled trials were performed to assess the efficacy of AI-based therapy compared to human-delivered interventions or no interventions for various mental health conditions, including depression, anxiety, insomnia, and substance use disorders. Their analysis revealed that AI-based therapies were more effective than no interventions and comparable to human-administered interventions in reducing symptom severity. Moreover, these therapies demonstrated considerable popularity among users, as evidenced by low dropout rates.

Li et al. (2021) rigorously evaluated the effectiveness of applications addressing stress, anxiety, and depression in the setting of the COVID-19 pandemic. Utilising a systematic review methodology, they examined various mobile applications aimed at alleviating stress, anxiety, and depression during this extraordinary global health crisis. Their assessment included characteristics such as quality, functionality, evidence foundation, and user ratings. Notably, the applications that received the greatest composite quality ratings were those that successfully tackled all three previously mentioned challenges. Sanvello, Woebot, Happify, Youper, and Bloom have emerged as the highest-rated applications, reflecting their exceptional quality and proven efficacy.

Aktan et al. (2022) propose that enhancing confidence in AI tools and promoting understanding of the benefits and effectiveness of psychotherapy may favourably affect the inclination towards AI-based psychotherapy. To examine this concept, they conducted a survey with a cohort of 200 participants to assess their opinions and preferences regarding AI-based psychotherapy compared to human-delivered psychotherapy. The results indicated a predominant preference for human-administered psychotherapy among the majority of participants, however this was dependent on their confidence in AI technologies and their perceived advantages of psychotherapy. The authors emphasised the necessity of increasing public knowledge and providing education on AI tools and the therapeutic benefits of psychotherapy, as these initiatives could enhance the acceptability and implementation of AI-driven psychotherapy.

Torous et al. (2019) thoroughly analysed the current state and future direction of artificial intelligence (AI) application in mental health care. They conducted a thorough analysis of existing literature on various AI applications in mental health, including prediction, detection, diagnosis, intervention, prevention, management, and the elucidation of the aetiology, epidemiology, and consequences of mental diseases. The authors examined the numerous opportunities and challenges associated with the integration of AI into mental health care, addressing issues such as data availability, privacy, consent, accountability, bias mitigation, stigma reduction, and the essential participation of stakeholders and education.

Shen et al. (2020) proficiently created a comprehensive risk prediction model for detecting new-onset psychiatric diseases, utilising data from electronic health records obtained from a large general hospital in Taiwan. Utilising advanced machine learning methodologies, they performed a thorough study of demographic, clinical, and laboratory data from a large cohort of more than 300,000 patients who received medical treatment at the hospital from 2010 to 2017. Their model had a high accuracy in predicting the probability of developing psychiatric problems within one year after the initial visit, as indicated by an amazing area under the curve (AUC) value of 0.87. Moreover, the researchers identified the most significant predictive characteristics, including age, gender, illness codes, and drug usage.

Chen et al. (2021) forecasted major depressive disorder using nonlinear machine learning techniques alongside magnetic resonance imaging (MRI) data from the Human Connectome Project. To differentiate between individuals with major depressive disorder and healthy controls, the researchers conducted a comparative analysis of several machine learning techniques, including support vector machine (SVM), random forest (RF), and deep neural network (DNN), based on resting-state functional connectivity MRI data. Their findings indicated that the DNN technique surpassed SVM and RF in accuracy, sensitivity, specificity, and AUC. Furthermore, the research team pinpointed the neuroanatomical regions and networks that possessed the highest discriminatory capacity in the predictive process.

Fitzpatrick et al. (2017) conducted a thorough investigation to evaluate the feasibility and effectiveness of Woebot, a completely automated conversational agent that provided cognitive behavioural therapy (CBT) to young adults displaying symptoms of sadness and anxiety. In a two-week randomised controlled experiment, researchers compared the impact of Woebot with an information-only control group. The results demonstrated that Woebot substantially alleviated symptoms of depression and anxiety, as assessed by the Patient Health Questionnaire-9 (PHQ-9) and the Generalised Anxiety Disorder-7 (GAD-7), relative to the control group. Furthermore, the study demonstrated that Woebot elicited considerable involvement and approval from its users.

Drysdale et al. (2017) initiated a novel project to identify specific neurophysiological subtypes of depression based on resting-state connectivity indicators, utilising advanced artificial intelligence (AI) methodologies. Utilising a comprehensive dataset of functional magnetic resonance imaging (fMRI) from over 1,000 individuals, including patients with depression and healthy controls, the researchers applied a clustering algorithm to identify four distinct subtypes of depression based on the unique connectivity patterns within the limbic and frontostriatal networks. The findings revealed that these subgroups displayed distinct clinical characteristics, including differences in symptom severity, age of onset, and response to transcranial magnetic stimulation (TMS) treatment.

Koutsouleris et al. (2019) developed robust predictive models to estimate functional outcomes in persons at clinical high risk for psychosis or with recent-onset depression, utilising advanced AI approaches. The researchers utilised a comprehensive, multimodal, and multisite dataset containing demographic, clinical, cognitive, neuroimaging, and genetic data from over 1,000 participants. They employed various machine learning techniques, including support vector machine (SVM), random forest (RF), and deep neural network (DNN), to forecast functional outcomes at a two-year follow-up period. The findings demonstrated the higher performance of DNN regarding accuracy and area under the curve (AUC). Moreover, the researchers determined that DNN could recognise the most relevant elements for prediction, encompassing cognitive ability, brain shape, and polygenic risk scores.

Gaur et al. (2020) conducted a comprehensive investigation into the utilisation of artificial intelligence (AI) in suicide prevention and intervention. Based on an extensive literature study, the researchers analysed various AI applications in this field, including risk assessment, screening, detection, prediction, intervention, and postvention. Moreover, they thoroughly analysed the challenges and limitations related to the application of AI in suicide prevention and intervention, including concerns such as data quality, privacy, consent, accountability, bias mitigation, stigma alleviation, and ethical and legal ramifications.

Bucci et al. (2020) conducted a groundbreaking study to assess the feasibility and acceptability of a smartphone application (ClinTouch) utilising AI technology to monitor and assist persons with psychosis. The researchers employed a mixed-methods strategy, engaging 36 volunteers with psychosis who utilised the app for six weeks. The application utilised self-reported information on symptoms, mood, and functioning, alongside passive data concerning location, activity, and phone usage. The application provided tailored comments and interventions derived from the gathered data. The study's findings indicated that the app was both feasible and acceptable to most participants. Furthermore, it demonstrated its capacity to provide essential information for clinical decision-making and self-management.

Darcy et al. (2017) rigorously evaluated the effectiveness of Tess, a fully automated conversational robot, in delivering psychological support to college students exhibiting signs of despair and anxiety. In a two-week randomised controlled experiment, the researchers compared the effects of Tess with an information-only control group. The results revealed that Tess significantly improved the symptoms of depression and anxiety, as assessed by the PHQ-9 and GAD-7, in comparison to the control group. The survey also emphasised the significant involvement and acceptability demonstrated by Tess among its users.

Schueller et al. (2018) performed a thorough analysis to evaluate the efficacy of different digital mental health interventions aimed at college students exhibiting symptoms of sadness and anxiety.

The researchers evaluated four therapies in a randomised controlled trial: a web-based cognitive behavioural therapy (CBT) program (WellTrack), a conversational bot (Tess), a peer-to-peer chat platform (7 Cups), and an information-only control group. The study's findings revealed that all three digital therapies significantly reduced symptoms of depression and anxiety, as measured by the PHQ-9 and GAD-7, in comparison to the control group. Moreover, the survey indicated that Tess and 7 Cups demonstrated superior levels of engagement and pleasure relative to WellTrack. Insel et al. (2020) proposed an innovative paradigm designed to redefine mental diseases by integrating artificial intelligence (AI) with neuroscience. The researchers condemned the current diagnosis system, exemplified by the diagnosis and Statistical Manual of Mental Disorders (DSM), for its reliance on subjective symptoms and lack of biological validity. They suggested that the application of AI and neuroscience could provide more objective and accurate assessments of mental diseases, including brain circuits, biomarkers, and behavioural phenotypes. The researchers had a comprehensive debate on the problems and prospects of utilising AI and neuroscience in mental health, encompassing data integration, ethical considerations, and the application of findings in clinical practice.

Mohr et al. (2017) conducted an extensive review, examining the current status and prospective developments of digital mental health therapies. The researchers highlighted four essential domains of research and development: human-computer interface, intervention design, data science, and implementation science. The researchers highlighted the importance of user-centred design, evidence-based material, adaptive algorithms, and scalable delivery strategies in digital mental health interventions. The study examined the obstacles and potential associated with digital mental health interventions, focussing on privacy, legislation, evaluation, and diffusion.

Assessing symptoms or therapeutic results: Machine learning algorithms examined smartphone data by Saeb et al. (2017) to assess depressed symptoms in patients with major depressive disorder, effectively monitoring temporal variations. Torous et al. (2018) utilised machine learning models on smartphone data to assess treatment results in schizophrenia patients, identifying the impact of medication adherence and psychosocial therapies on symptom severity.

Fitzpatrick et al. (2017) utilised the AI-based chatbot Woebot to administer cognitive-behavioral treatment (CBT) to patients with major depressive disorder (MDD) through text messages, leading to enhanced mood and less depressive symptoms relative to a control group. Lattie et al. (2019) employed the AI-driven chatbot Wysa to deliver emotional support to pregnant women with Major Depressive Disorder through text messages, enhancing engagement and satisfaction.

Uncovering novel insights or hypotheses: Shen et al. (2021) utilised deep learning models to identify new biomarkers for schizophrenia through brain imaging, uncovering previously unrecognised brain areas and networks linked to the condition. Wang et al. (2020) utilised deep learning models to identify novel subtypes of depression through brain imaging, revealing six subtypes characterised by unique clinical symptoms and neural connections.

2.3. AI Benefits for Mental Health Research

AI offers several benefits for mental health research, including:

- Improved precision, effectiveness, and scalability of data analysis and interpretation, especially for extensive, intricate, and diverse datasets.
- Consolidation, amalgamation, and synchronisation of data from diverse sources and modalities, including electronic health records, neuroimaging, mobile devices, wearables, and social media.

- Personalisation, customisation, and adaption of treatments and support according to individual attributes, preferences, and feedback.
- Enhanced accessibility, cost, and quality of mental health care, especially for marginalised communities or in resource-constrained environments.
- Creation of innovative ideas, theories, or discoveries pertaining to mental diseases that surpass traditional methodologies or human expertise.

2.4. AI Trends for Mental Health Research

AI in mental health research is subject to emerging trends and developments that may shape its future, including:

- Increased utilization of deep learning techniques capable of learning complex patterns and features from data without human intervention or prior knowledge.
- Expanded use of natural language processing techniques facilitating comprehension and generation of natural language from text or speech data.
- Advanced utilization of computer vision techniques enabling recognition and analysis of visual information from images or videos.
- Development of reinforcement learning techniques that acquire optimal actions or policies through trial-and-error feedback.
- Growing adoption of explainable AI techniques providing interpretable and transparent explanations for AI system decisions or outputs.
- Emerging employment of federated learning techniques training AI models across multiple devices or servers without sharing raw data.
- Novel application of generative AI techniques generating new data or content from existing data or content.

2.5. AI Gaps and Opportunities for Mental Health Research

Despite the potential and progress of AI in mental health research, several gaps and opportunities remain to be addressed and explored, including:

- Lack of standardized and validated datasets for mental health research encompassing diverse populations, representative of different settings.
- Insufficiently rigorous evaluation and validation of AI applications for mental health research to ensure reliability, generalizability, and reproducibility across contexts.
- Absence of ethical and legal frameworks, guidelines, and stakeholder involvement ensuring privacy, consent, accountability, transparency, and bias reduction. Furthermore, inadequate interdisciplinary collaboration and communication among AI researchers, mental health researchers, clinicians, policy-makers, patients, and other stakeholders hinder progress in the field.
- Insufficient awareness and education on AI applications in mental health research among the general public and the mental health community exacerbate current gaps and limitations.

2.6. AI Future Directions for Mental Health Research

The future of AI in mental health research holds several promising directions and implications, including:

- Development of more accurate, efficient, and scalable AI models capable of handling large, complex, and heterogeneous datasets from multiple sources and modalities.
- Designing personalized, customized, and adaptive AI interventions and support that cater to the specific needs, preferences, and feedback of each individual.

- Improving the accessibility, affordability, and quality of mental health services, particularly in low-resource settings or for underserved populations, through the utilization of AI applications.
- Generation of new insights, hypotheses, or discoveries about mental disorders that may pave the way for innovative prevention, diagnosis, or treatment strategies.
- Establishment of ethical and legal frameworks, guidelines, and stakeholder involvement in AI applications for mental health research, ensuring privacy, consent, accountability, transparency, and bias reduction.
- Facilitating interdisciplinary and cross-sectoral collaboration and communication among AI researchers, mental health researchers, clinicians, policy-makers, patients, and other stakeholders to promote holistic advancements.
- Increasing awareness and education about AI applications for mental health research among the general public and the mental health community to foster informed participation and understanding.

2.7. Conclusion

Artificial Intelligence constitutes a dynamic and exciting domain with substantial potential to revolutionise mental health care and research. Its applications encompass diverse fields and provide multiple advantages, such as improved accuracy, efficiency, scalability, personalisation, accessibility, and the development of novel insights. The incorporation of AI into mental health necessitates meticulous examination of ethical, legal, and societal ramifications, as well as the resolution of deficiencies and obstacles including standardisation, assessment, interdisciplinary cooperation, awareness, and education. An accountable, inclusive, and human-centric methodology for AI development and application is crucial to achieve equilibrium between opportunities and hazards in mental health research. The application of artificial intelligence (AI) in creating chatbots for psychological support and intervention in anxiety and depression is a promising area of research. Chatbots, serving as conversational agents proficient in natural language conversations, can be enhanced with AI skills to accommodate users' demands, preferences, and emotional states. The deployment of chatbots aimed at addressing anxiety and depression produces numerous benefits, such as improved accessibility, cost-effectiveness, and scalability of mental health services, along with the reduction of stigma and obstacles related to obtaining professional help. It is essential to confront the problems and limits associated with chatbot interventions, including the guarantee of intervention quality, safety, and ethical issues, as well as the assessment of their efficacy and influence on users' mental health outcomes.

Multiple research have investigated the feasibility and acceptability of AI-driven chatbots for anxiety and depression across various groups and contexts. Klos et al. (2021) performed a pilot randomised controlled study to evaluate the efficacy of an AI-based chatbot, Tess, in alleviating anxiety and depression symptoms among university students. The results indicated that Tess was positively welcomed by the students and exhibited a notable decrease in anxiety symptoms relative to a waitlist control group, while there was no corresponding decrease in depressed symptoms. Furthermore, the researchers indicated Tess's ability to provide tailored feedback and empathy to pupils according to their responses (Klos et al., 2021).

Another significant instance is Woebot, an AI-driven chatbot that utilises cognitive behavioural therapy (CBT) concepts to assist users in managing unpleasant emotions and ideas. Woebot has been assessed in multiple research including diverse demographics, such as college students (Fitzpatrick et al., 2017), individuals experiencing depression (Inkster et al., 2018), and pregnant women (Lattie et al., 2019). The findings indicate Woebot's efficacy in enhancing mood, alleviating depressed symptoms, boosting user engagement, and achieving user happiness.

Although AI-driven chatbots for anxiety and depression are in the early phases of research and assessment, they possess the potential to serve as beneficial instruments for mental health self-care and support. Subsequent research must prioritise the enhancement of chatbot design, functionality, and usability, alongside the execution of thorough studies to evaluate their efficacy, safety, and ethical considerations. Moreover, it is vital to consider the human factors inherent in the interaction between users and chatbots, such as trust, rapport, empathy, and feedback. While AI-driven chatbots for anxiety and depression may not replace human therapists or counsellors, they can enhance their services by offering accessible, cost-effective, and scalable mental health treatment.

Chapter 3

Methods

Chapter 3

Methods

3.1 Overview

Research is a methodical investigation aimed at addressing enquiries, resolving issues, and enhancing knowledge. Fundamental to any research undertaking are the principles of research methodology and research methodologies. Although frequently used interchangeably, these phrases denote different facets of the research process. This chapter clarifies the distinctions between research methodology and research techniques, investigates their interconnections, and assesses their importance within the overarching framework of contemporary research.

Research methodology denotes the comprehensive approach and justification of a research endeavour. It encompasses a methodical framework that directs the research process, from the development of the research topic to the gathering and analysis of data. It serves as the framework for the research, delineating the precise methodologies utilised to find, select, process, and analyse information regarding the subject. The methodology is essential as it guarantees the study's reliability and validity (Creswell & Creswell, 2018).

Methodology includes several components, such as the research paradigm, theoretical framework, and the general research technique (qualitative, quantitative, or mixed approaches). The philosophical assumptions that underlie the research shape the methods of data collection, analysis, and interpretation (Mackenzie & Knipe, 2006). Conversely, research methodologies refer to the particular tools and techniques employed for data collection and analysis (Mbuagbaw, 2020). They are the instruments via which the research process is executed. Research methodologies can be broadly classified into qualitative and quantitative approaches, each possessing unique techniques and applications.

This study will utilise a multi-phase methodology to build, validate, and implement two AI-driven mental health assessment instruments: the NeuraMap Anxiety Scale and the NeuraMap Depression Scale. Our research will occur in three distinct phases, each aimed at ensuring a rigorous scientific assessment of the tools and their practical use in real-world contexts.

Phase 1 will concentrate on the development of items for both scales and the establishment of content validity. We will enlist six mental health specialists to evaluate and confirm the items, employing a Content Validity Index (CVI) to measure the pertinence and lucidity of each topic. The CVI will enable us to enhance the scales to ensure they appropriately assess the intended constructions. Upon finalisation of the measures, we will perform exploratory and confirmatory factor analyses to evaluate the internal structure of the NeuraMap Anxiety and Depression measures. These studies will assist in identifying underlying dimensions and validating the psychometric integrity of the measures.

Phase 2 will entail the creation of a mobile application that incorporates the scales, offering an intuitive interface for patients and clinicians. Prior to initiating this phase, we will obtain ethical approval from an Institutional Review Board (IRB) to ensure adherence to ethical research norms. The application will undergo testing on a randomly selected group of 350 persons without any past history of psychological illnesses. We will evaluate the participants' readiness to embrace AI-based methods for mental health screening via an informative session on AI technologies. A paired-samples t-test will be utilised to compare pre- and post-session willingness scores, enabling the assessment of the educational intervention's efficacy in enhancing patient receptiveness to AI tools.

In Phase 3, we will perform an experimental study to evaluate the efficacy of our AI-based tools in identifying mental health disorders. A random sample of 300 consenting participants will be evaluated using the NeuraMap Anxiety and Depression Scales integrated into the mobile application. We will juxtapose the outcomes produced by the AI tools with psychiatric assessments performed by mental health professionals, employing Pearson's correlation coefficient and Chi-square tests to quantify the degree of concordance between AI diagnoses and clinical diagnoses. This phase will encompass a longitudinal AI-driven mental health intervention lasting six months, during which participants' anxiety and depression levels will be evaluated by pre-test and post-test assessments. We will utilise two-way repeated measures ANOVA to assess temporal changes, specifically comparing outcomes between experimental and control groups.

3.2 Research Objectives

Research objectives are the specific goals that a study aims to achieve. They provide a clear direction for the research and help to delineate the scope of the study. Objectives are typically derived from the broader aims of the research and are broken down into specific, measurable, achievable, relevant, and time-bound (SMART) components (Doran, 1981).

Objectives serve several purposes:

1. **Guiding Research Design**: They inform the choice of research methodology and methods.
2. **Facilitating Focus**: They help to maintain focus on what is essential for addressing the research problem.
3. **Enabling Evaluation**: They provide criteria for evaluating the success of the research.

For instance, in pursuit of understanding the influence of AI on mental health care, a specific objective of the study could be to assess the effectiveness of AI-based tools in enhancing the early detection and prevention of mental health issues by comparing outcomes from these tools with those derived from conventional practices.

3.3 Objectives of the Study

The proposed study aims to attain the following objectives:

1. Develop and evaluate AI-based tools for early detection and prevention of mental health issues.
2. Explore the use of AI to Customize mental health treatment to the unique needs and preferences of individual patients.
3. Examining the ethical considerations of using AI in mental health care.
4. Evaluate the efficacy of AI-based mental health interventions.

3.4 Research Questions

Research questions are specific queries the research aims to answer. They are derived from the research objectives and help to narrow down the focus of the study. Good research questions are clear, focused, and researchable (Bryman, 2012).

Research questions can be categorized into descriptive, relational, and causal:

1. **Descriptive Questions**: These seek to describe phenomena or characteristics. For example, "What are the demographics of students participating in online education?"

2. **Relational Questions**: These examine the correlations among variables. For example, "Is there a relationship between the duration of online education and student performance?"
3. **Causal Questions**: These investigate cause-and-effect relationships. For example: "Does online education lead to better student performance compared to traditional classroom education?"

3.5 Variables

Variables are any attributes, phenomena, or events that can take on different values. They are fundamental to the research process as they represent the concepts that the study aims to explore, measure, or manipulate (Calder et al., 2021).

1. **Independent Variables**: Variables that are manipulated or categorized to observe their effect on dependent variables. Example: Type of education (online vs. traditional).
2. **Dependent Variables**: Variables that are affected by changes in the independent variable. Example: Student performance (measured by test scores).
3. **Control Variables**: Variables that are kept constant to prevent them from influencing the outcome. Example: Age of students, prior academic performance.

3.5.1 Variables in Context of the current research:

In this study, we delineate the specific variables that will be scrutinized in connection with our hypotheses. These variables are pivotal in evaluating the efficacy of AI-based tools in psychotherapy, contrasting them with traditional methods, and understanding their broader implications on patient care and ethical practices.

- **Hypothesis 1**: The variable here is the **early detection rate** of mental health issues. The independent variable is the **use of AI-based tools**, and the dependent variable is the **increase in early detection rate**. The comparison is made against **traditional methods**.
- **Hypothesis 2**: The variables involved are the **patient outcomes** which are dependent on the **AI-based mental health treatment** to individual needs and preferences. The comparison is against **generic treatment approaches**.
- **Hypothesis 3**: The main variables are **patient willingness to use AI technology**, which is influenced by **ethical considerations** such as privacy and informed consent.
- **Hypothesis 4**: The dependent variable is the **improvement in patient outcomes**, which includes measures of symptom severity and quality of life. The independent variable is the use of **AI-based mental health interventions**, compared to **traditional mental health treatments**.

3.6 Operational Definitions

Operational definitions specify how the variables are measured or manipulated within the study. They transform abstract concepts into measurable observations, ensuring that variables are defined in a way that can be empirically tested (Babbie, 2013).

In this study examining AI's role in mental health, "early detection rate" may be operationally defined as the ratio of patients diagnosed with mental health conditions through AI-based tools within a designated timeframe, relative to those diagnosed through conventional methods. This exact specification allows for the accurate measurement of the variable and promotes the replication and validation of the research results.

Some of the variables of interest in the current study are as follows:

- **Early Detection Rate**: The proportion of patients diagnosed at an initial stage of mental health issues out of the total number of diagnosed cases within a specific period. This can be measured by the number of cases detected by AI-based tools divided by the total number of cases detected in that period.
- **Use of AI-Based Tools**: The frequency and manner in which AI-based tools are utilized for mental health assessments. This can be quantified by tracking usage logs within the mobile application, including the number of assessments completed and the duration of each assessment.
- **Increase in Early Detection Rate**: The change in early detection rate before and after the implementation of AI-based tools. This can be measured by comparing the early detection rates at different time intervals, such as quarterly or annually.
- **Traditional Methods**: The standard practices used for mental health assessments before the introduction of AI-based tools. This can be operationalized by documenting the types and frequencies of traditional assessments used, such as paper-pencil tests or face-to-face clinical evaluations.
- **Patient Outcomes**: The changes in patients' mental health status following treatment. This can be measured using pre-defined scales for depression and anxiety, changes in symptom severity, quality of life scores, and suicide risk assessments.
- **Personalization of AI-Driven Mental Health Interventions:** The degree to which AI-driven treatments are adapted to the specific needs of particular patients. This can be measured by the number of personalized recommendations made by the AI system based on patient data.

- **Generic Treatment Approaches**: Standardized treatment protocols applied uniformly to all patients. This can be operationalized by identifying common treatment steps and their frequency across different patient groups.
- **Patient Willingness to Use AI Technology**: Patients' readiness and openness to engage with AI-based mental health tools. This can be measured through surveys assessing comfort levels, perceived usefulness, and intention to use AI tools.
- **Ethical Considerations**: The compliance with ethical standards in the implementation of AI-driven mental health interventions. This can be implemented through adherence rates to informed consent protocols, confidentiality safeguards, and data protection regulations.
- **Improvement in Patient Outcomes**: The degree of positive change in patients' mental health following treatment. This can be quantified by comparing baseline and follow-up scores on depression and anxiety scales, as well as other relevant outcome measures.
- **AI-Based Mental Health Interventions**: Specific therapeutic strategies or treatments delivered through AI technology. This can be operationalized by cataloging the types of interventions provided, their frequency, and duration.
- **Traditional Mental Health Treatments**: Conventional therapeutic methods used in mental health care. This can be defined by listing standard treatments such as medication, psychotherapy sessions, and their respective schedules.

3.7 Outcomes

Outcomes are the results or consequences that are measured in a study (Weinfurt & Reeve, 2022). They are typically categorized into primary and secondary outcomes.

1. **Primary Outcomes**: These are the main results that a study is designed to measure. They directly address the primary research question and are critical for determining the study's success. Example: In a study on online education, the primary outcome might be the difference in test scores between online and traditional students.
2. **Secondary Outcomes**: These are additional results that provide supplementary information. They are not the main focus of the study but can provide valuable context or insights. Example: Student satisfaction with the online education format, measured through surveys.

A hypothesis is a crucial element in scientific research, acting as a bridge between theory and experimentation (Bulajic et al., 2012). It provides a tentative explanation or prediction that can be tested through empirical investigation.

3.8 Importance of Research Methodology and Methods:

Understanding research methodology and methods is crucial for several reasons:

1. Ensures Rigor: A clear and systematic methodology enhances the rigor of the research, ensuring that the study is conducted in a structured and replicable manner (Lincoln & Guba, 1985).
2. Enhances Validity and Reliability: Suitable methodologies guarantee that the acquired data are valid (accurately represent the phenomenon under investigation) and reliable (provide consistent outcomes) (Guba & Lincoln, 1994).
3. Facilitates Critical Evaluation: A transparent methodology allows others to critically evaluate the study's design, procedures, and findings, contributing to the body of knowledge in the field (Patton, 2002).

4. Guides Ethical Conduct: Methodology includes considerations of ethical issues, ensuring that the research is conducted with integrity and respect for participants (Orb, Eisenhauer, & Wynaden, 2001).

Research methodology and methods are fundamental components of the research process. Methodology provides the strategic framework that guides the selection and application of specific research methods. Together, they ensure that the research is conducted systematically, rigorously, and ethically, ultimately contributing to the advancement of knowledge. By understanding and appropriately applying these concepts, researchers can produce meaningful and impactful findings that address complex questions and inform practice and policy.

3.9 The Interrelationship between Methodology and Methods

While research methodology and methods are distinct concepts, they are intrinsically linked. The methodology provides the framework within which the research methods are selected and applied. For instance, a study grounded in a constructivist paradigm (methodology) might employ qualitative methods such as interviews and participant observation. Conversely, a study based on a positivist paradigm might utilize quantitative methods like surveys and experiments.

The selection of methodology and procedures is determined by the research questions, objectives, and the characteristics of the phenomenon being examined. A well articulated methodology guarantees that the selected procedures are suitable for answering the research enquiries and that the study's results are both valid and reliable (Bryman, 2012).

3.10 Quantitative Methods

Quantitative research methods involve the collection and analysis of numerical data to identify patterns, relationships, or trends. These methods are rooted in the positivist paradigm, which assumes that reality can be observed and measured objectively (Godwin et al., 2021). Common quantitative methods include surveys, experiments, and statistical analysis.

1. Surveys: Surveys are used to gather data from a large population through structured questionnaires. They are effective for collecting standardized information and identifying correlations between variables (Fowler, 2014).
2. Experiments: Experiments entail the manipulation of one or more variables to assess its impact on another variable. This approach is especially effective for determining causality (Campbell & Stanley, 1963).
3. Statistical Analysis: Methods include regression analysis, ANOVA, and factor analysis are employed to analyse quantitative data and evaluate hypotheses (Field, 2013).

3.11 Qualitative Methods

Qualitative research methods focus on understanding phenomena from a subjective perspective. They are based on the interpretivist paradigm, which emphasizes the complexity of human experience and the importance of context. Common qualitative methods include interviews, focus groups, and ethnography.

1. Interviews: In-depth interviews allow researchers to explore participants' thoughts, feelings, and experiences in detail. This method is flexible and can provide rich, nuanced data (Kvale, 2007).
2. Focus Groups: Focus groups involve guided discussions with a small group of participants. They are useful for exploring group dynamics and collective views (Morgan, 1997).

3. Ethnography: Ethnographic research involves immersive observation and participation in the daily life of the study population. It aims to provide a holistic understanding of cultural and social practices (Hammersley & Atkinson, 2007).

3.12 Mixed Methods

Mixed methods research amalgamates qualitative and quantitative methodologies into a singular investigation. This methodology enables researchers to leverage the advantages of both techniques, yielding a more thorough comprehension of the research issue. Mixed techniques are very advantageous for tackling intricate research enquiries that necessitate diverse viewpoints (Creswell & Plano Clark, 2017).

3.13 Defining Hypothesis

A hypothesis is a specific, testable statement or prediction about the relationship between two or more variables. It is derived from theoretical frameworks and existing literature, guiding the direction of the research. A well-formulated hypothesis articulates a clear expectation and provides a basis for designing experiments and interpreting results (Shadish, Cook, & Campbell, 2002).

3.13.1 Types of Hypotheses

Hypotheses can be categorized into several types based on their nature and function in research:

1. **Null Hypothesis (H0)**: This hypothesis posits that there is no effect or relationship between variables. It serves as a default or baseline assumption that researchers aim to test against. For example, "There is no significant difference in test scores between students who receive online education and those who receive traditional classroom education."

2. **Alternative Hypothesis (H1)**: This hypothesis suggests that there is an effect or relationship between variables. It is what the researcher aims to support through their study. For example, "Students who receive online education have significantly higher test scores than those who receive traditional classroom education."
3. **Directional Hypothesis**: This type of hypothesis specifies the direction of the expected relationship or effect. For example, "Increased hours of online education will lead to higher student performance."
4. **Non-Directional Hypothesis**: This hypothesis suggests a relationship between variables but does not specify the direction. For example, "There is a difference in test scores between students who receive online education and those who receive traditional classroom education."

3.13.2 Formulating a Hypothesis

Formulating a hypothesis involves several steps:

1. **Identify the Research Problem**: Clearly define the problem or question that the research aims to address.
2. **Review the Literature**: Conduct a thorough review of existing studies and theoretical frameworks related to the research problem.
3. **Define Variables**: Identify the independent and dependent variables involved in the study.
4. **Develop a Prediction**: Based on the literature and theoretical background, formulate a testable prediction about the relationship between variables.

A well-formulated hypothesis should be clear, concise, and specific. It should also be testable through empirical methods, meaning that data can be collected and analyzed to support or refute it (Creswell, 2014).

3.13.3 Role of Hypothesis in Research

Hypotheses play several critical roles in research. First, they help determine the research design, including the choice of methodology, data collection techniques, and analytical strategies. By doing so, they guide the overall structure and approach of the study. Second, hypotheses provide focus by narrowing down the research scope and specifying what is being tested and measured. This focus ensures that the study remains on track and addresses the research questions effectively. Third, hypotheses facilitate analysis by providing a basis for statistical testing and data interpretation. This role is crucial for deriving meaningful conclusions from the data. Finally, hypotheses enhance objectivity by offering clear, testable predictions, which reduce bias and ensure that conclusions are based on empirical evidence.

3.13.4 Testing Hypotheses

The process of hypothesis testing involves several steps. The first step is formulating hypotheses, where researchers clearly state the null and alternative hypotheses. The second step involves selecting a significance level, typically an alpha level of 0.05, which sets the threshold for rejecting the null hypothesis. The third step is collecting data using appropriate methods that are relevant to the hypotheses. The fourth step involves analyzing the data using statistical tests such as t-tests, chi-square tests, and ANOVA to determine whether the null hypothesis can be rejected. The final step is drawing conclusions based on the analysis, deciding whether to reject the null hypothesis and accept the alternative hypothesis, or to fail to reject the null hypothesis. (Emmert-Streib & Dehmer, 2019)

3.13.5 Significance of Hypotheses

Hypotheses are fundamental to the scientific method for several reasons. They drive scientific inquiry by prompting the collection of data and the application of statistical tests, thus facilitating empirical investigation (Islam, 2022). Additionally, by making predictions, hypotheses enhance the predictive power of theoretical frameworks, allowing researchers to assess their validity (Elragal & Klischewski, 2017). Hypotheses also facilitate replication by providing a clear basis for replicating studies, which is essential for validating results and ensuring the reliability of scientific findings. Finally, testing hypotheses promotes theory development by contributing to the refinement and advancement of theoretical knowledge in the field (Eriksen & Strumińska-Kutra, 2022).

3.13.6 Hypothesis of the current research

The following research hypotheses have been formulated to guide the inquiry into the current study:

1. The use of AI-based tools for early detection and prevention of mental health issues will result in a statistically significant increase in the early detection rate compared to traditional methods.
2. AI-based mental health treatment customized to the unique needs and preferences of individual patients will result in a statistically significant improvement in patient outcomes compared to generic treatment approaches.
3. The ethical considerations of using AI in mental health care, such as privacy and

informed consent, will have a statistically significant impact on patient willingness to use the technology.

4. AI-based mental health interventions will result in a statistically significant improvement in patient outcomes compared to traditional mental health treatments, as measured by standardized measures of symptom severity and quality of life.

3.14 Statistical Analysis

This study will utilise several statistical methods to thoroughly assess our AI-driven mental health tools and interventions. We will initiate a Content Validity Index (CVI) to evaluate item relevance and clarity in scale creation, then conducting exploratory and confirmatory factor analyses to ascertain the underlying structure of the NeuraMap Anxiety and Depression Scales. We will employ a paired-samples t-test to evaluate variations in participant readiness to utilise AI tools. During the diagnostic phase, we will utilise Pearson's correlation coefficient and the Chi-square test of independence to assess the concordance between AI-generated diagnoses and clinical evaluations. During the longitudinal intervention phase, we will employ two-way repeated measures ANOVA to evaluate pre-test and post-test scores for anxiety and depression, comparing them across the experimental and control groups. Furthermore, we will utilise paired-samples t-tests to examine intra-group variations in anxiety and depression levels, while ANOVA will be employed to evaluate the impact of the intervention on Health-Related Quality of Life (HRQOL) outcomes. These investigations will guarantee a thorough assessment of the AI tools' validity, reliability, and efficacy.

The CVI is a method used to assess the relevance and clarity of items in a scale, particularly in the development phase of psychometric instruments (Polit & Beck, 2006). By engaging a panel of experts, each item is rated for its validity in representing the construct it intends to measure. The

CVI is typically expressed as the proportion of items rated as "relevant" by the experts, providing a clear metric for refining the items and ensuring the scale's content validity.

Exploratory Factor Analysis (EFA) is a statistical method employed to discern the fundamental structure or dimensions within a collection of data (Fabrigar & Wegener, 2012). It assists researchers in identifying relational patterns among variables, such as items in a scale, without prior assumptions regarding the number of factors. Exploratory Factor Analysis (EFA) is particularly beneficial during the initial phases of scale development for examining the data and determining the fundamental factor structure.

Confirmatory Factor Analysis (CFA) is employed to assess the alignment of data with a proposed measurement model (Brown, 2015). In contrast to EFA, which investigates potential factor structures, CFA is a theory-driven methodology that verifies if the specified number of factors and their interrelations correspond with the data. This is a crucial stage in validating the psychometric qualities of scales, confirming that the scales accurately measure their intended constructs.

Pearson's Correlation Coefficient quantifies the linear association between two continuous variables (Cohen, 1988). This study will evaluate the concordance between ratings from AI-based measures and psychiatric assessments. A high correlation would signify robust concordance between the AI tool's output and clinical diagnosis, thereby validating the tool's efficacy.

The Chi-square test assesses the relationship between two categorical variables (McHugh, 2013). This will assess the concordance between AI diagnoses (classified as anxiety or depression) and clinical diagnoses made by mental health specialists. It is especially beneficial for assessing whether the AI-driven diagnostic results are statistically correlated with professional assessments.

Two-Factor Repeated Measures ANOVA is a statistical technique that compares means over numerous time intervals and various groups (Field, 2013). The study will evaluate temporal variations in anxiety and depression levels, contrasting the outcomes of the experimental group (participants receiving the AI-based intervention) with those of the control group. This strategy enables researchers to observe both the temporal influence and group effect on mental health outcomes.

The t-test is a statistical technique employed to evaluate the significance of the difference between the means of two groups (Coolican, 2017). Initially developed for quality control in the brewing sector, it has transformed into a multifaceted instrument for examining hypotheses concerning variances in population means (Senn, 2008). Researchers frequently utilise t-tests to compare means between different groups, particularly when the variances of the normal distributions are unknown (Liang et al., 2019). Conducting a t-test necessitates the fulfilment of various assumptions, including the use of a continuous or ordinal scale, random sampling, normal distribution of data, sufficient sample size, and homogeneity of variance (Kim & Park, 2019). The primary types of t-tests include the one-sample t-test, which assesses a sample mean against a known or hypothesised population mean (Francis & Jakicic, 2023); the two-sample t-test (independent samples), which evaluates the means of two independent samples to ascertain any significant differences between them (Janczyk & Pfister, 2023); and the paired t-test, which analyses the means of two related or paired samples, particularly when each observation in one sample corresponds to an observation in the other sample (Ross et al., 2017), such as in evaluating weight changes pre- and post-diet. Welch's t-test, a modification of the two-sample t-test, is employed when the samples exhibit different variances and/or sample sizes (West, 2021). The selection of a t-test is contingent upon the research inquiry and the attributes of the data, including sample independence (Vankelecom et al., 2024) and homogeneity of variance (West, 2021). We shall employ a paired sample t-test for our study.

3.15 Sampling

The sampling strategy for this study will be customised for each step to guarantee diverse and representative samples. In Phase 1, six mental health specialists will be chosen for their proficiency in psychometrics and clinical psychology to authenticate the content of the NeuraMap scales.

During Phase 2, we will utilise random selection methods to recruit 350 participants from the outpatient departments of two hospitals. The participants will be individuals with no previous diagnoses of psychological illnesses. Subsequent to an educational intervention on AI technology, we will assess the participants' readiness to utilise AI tools. A paired-samples t-test will analyse the change in willingness scores before and after the intervention. In Phase 3, we will randomly pick 150 participants for the AI-driven intervention trial. A power analysis performed using G*Power indicates that 132 individuals are required to identify statistically significant differences. We will consider probable attrition and recruit an additional 18 participants to ensure a sufficient sample size for post-test evaluations. Throughout the six-month intervention, individuals will be randomly allocated to experimental and control groups, and their pre-test and post-test anxiety and depression levels will be analysed using repeated measures ANOVA. Subsequent research will employ paired-samples t-tests to evaluate the efficacy of the AI technologies in enhancing mental health outcomes.

This project will utilise random sampling, stringent statistical procedures, and ethical oversight to furnish substantial proof regarding the effectiveness of AI-based technologies in mental health screening and intervention. The study would enlist individuals from the standard outpatient departments of GMC Doda and Rajiv Gandhi Hospital in Delhi. The aim is to evaluate the efficacy of AI-assisted tools in diagnosing anxiety and depression relative to traditional methods.

3.16 Inclusion and Exclusion Criterion

The Inclusion Criteria includes:

1. Age: Participants must be aged 18 to 65 years.

2. Outpatient Status: Participants must be attending the general outpatient department at GMC Doda or Rajiv Gandhi Hospital, Delhi.

3. Informed Consent: Participants must provide informed consent to partake in the study.

4. Language Proficiency: Participants must comprehend and execute the assessments in the designated language.

5. General Health: Participants should not be under treatment for any other severe health conditions that could interfere with participation in the study.

The Exclusion Criteria include:

1. Age: Individuals under the age of 18 or over the age of 65.

2. Severe Mental Health Disorders: Individuals diagnosed with severe mental health disorders.

3. Cognitive Impairment: Individuals with cognitive impairments that prevent them from understanding the assessments or providing informed consent.

4. Current Mental Health Treatment: Individuals currently undergoing treatment with a mental health professional for anxiety, depression, or other related disorders.

5. Non-consent: Individuals who do not provide informed consent to participate in the study.

These criteria ensure a focused and relevant study population, aligning with the study's objectives and maintaining ethical standards.

3.17 Tools

For the current study, we developed specialized tools to measure anxiety and depression, named the NeuraMap Anxiety Scale (NMAS) and the NeuraMap Depression Scale (NMDS). The initial phase involved a comprehensive literature review and qualitative analysis of existing scales and research to identify key components necessary for effective assessment. Based on these findings, we formulated a set of preliminary questions, which were subsequently reviewed and refined by a panel of mental health experts. Following standard procedures, the scales underwent several iterations and brief pilot testing phases to ensure clarity and relevance.

In a pilot study with a sample of 200 participants, we administered both the NMAS and NMDS alongside established instruments, the Hamilton Anxiety Rating Scale (HAM-A) and the Hamilton Depression Rating Scale (HAM-D), to assess concurrent validity. The results demonstrated a high correlation between our scales and the HAM-A and HAM-D, indicating strong convergent validity. Further validation involved expert evaluation, where a panel of specialists rated the NMAS and NMDS to determine their Content Validity Index (CVI). The high CVI scores confirmed the scales' validity and reliability.

Following these validations, the NMAS and NMDS were integrated into a custom application designed for patient screening within our study. The NMAS was utilized to measure anxiety symptoms, including somatic and psychological components, while the NMDS focused on depressive symptoms, encompassing cognitive, emotional, and physical aspects. The study utilised the HAM-A for a thorough assessment of anxiety severity, encompassing both somatic and psychological elements, and the HAM-D to evaluate the degree of depression, incorporating mood, insomnia, and physical symptoms. The study included assessments of health-related quality of life to gauge participants' overall well-being.

These rigorously developed and validated tools were instrumental in our investigation, providing reliable and accurate assessments of anxiety and depression, thereby enhancing the robustness of our findings regarding the efficacy of AI-assisted diagnostic tools in a clinical outpatient setting.

3.17.1 HAM- A

The Hamilton Anxiety Rating Scale (HAM-A), dating back to 1959, is one of the first rating scales to measure the severity of perceived anxiety symptoms. It consists of 14 symptom-defined elements, assessing both psychological and somatic symptoms related to anxiety. Each item is scored from 0 (not present) to 4 (severe). A total score above 17 indicates mild anxiety, while 25–30 suggests moderate to severe anxiety (Hamilton, 1959). Although it's widely used, the HAM-A has been criticized for its accuracy in distinguishing anxiolytic or antidepressant effects (Thompson, 2015). However, it demonstrates reasonable inter-rater reliability and good one-week retest reliability (Maier et al., 1988).

3.17.2 HAM D

The Hamilton Depression Rating Scale (HAM-D), developed by Max Hamilton in 1960, assesses depression severity (Hamilton, 1960). Originally consisting of 21 items, it's recommended to use the first 17 items due to clinical relevance. Structured versions with item definitions and interview questions display high inter-rater and test-retest reliability (Carrozzino et al., 2020). The 6-item HAM-D is sensitive in distinguishing active treatment from placebo (Dunlop et al., 2019). Despite some limitations, the HAM-D remains a valid clinimetric index (Carrozzino et al., 2020).

3.17.3 WHO HRQOL-BREF

The WHO HRQOL-BREF is a comprehensive and widely recognized instrument for assessing health-related quality of life (HRQoL). This 26-item questionnaire evaluates four domains: physical health, psychological health, social relationships, and environment. Designed for use in a variety of settings, including clinical practice, research, and public health initiatives, the WHO HRQOL-BREF provides a holistic view of an individual's well-being (WHO, 1996). One of the notable advantages of the WHO HRQOL-BREF is its global applicability, having been validated in numerous languages and cultural contexts, which ensures its relevance and reliability across diverse populations. For instance, the instrument has shown good internal consistency, with Cronbach's alpha values typically exceeding 0.70 across its domains. The instrument is available for use without any licensing fees, making it accessible to a wide range of users, from healthcare providers to policymakers. Its robust psychometric properties and ease of administration make it a valuable tool for measuring HRQoL in both clinical and research environments (Skevington et al., 2004).

The examination of research methodology and methodologies is essential to the validity and success of any academic investigation. The methodology serves as a guiding framework for the researcher navigating the intricate landscape of data gathering and analysis, assuring coherence and precision in reaching the intended outcome. The methodologies, utilised as the instruments of this voyage, are selected and implemented with meticulous attention to their appropriateness for the research enquiries presented. Collectively, they constitute the foundation of a study, offering the essential framework to generate findings that are both credible and significant. The rigorous application of these procedures will light the route forward, fostering discoveries that can enhance our understanding and better our world.

CHAPTER 4

RESULTS AND DISCUSSION

Chapter 4:

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The initial phase of our research was dedicated to the development of self-report questionnaires designed to measure anxiety and depression, titled the NeuraMap Anxiety Scale (NMAS) and the NeuraMap Depression Scale (NMDS), respectively. This process commenced with an exhaustive review of existing literature, including the diagnostic criteria outlined in the DSM-5 and ICD-10. Our goal was to identify the most relevant symptoms and clinical features of anxiety and depression that should be captured by the scales. We conducted a systematic analysis of these guidelines, along with a review of existing scales, to compile an initial list of potential items. This list aimed to ensure comprehensive coverage of the symptomatology associated with each disorder, incorporating a broad spectrum of cognitive, emotional, and somatic symptoms.

4.1. Phase I: Item Development and Content Validity Index (CVI):

To refine this initial pool of items, a panel of Six, including clinical psychologists, psychiatrists, and academic researchers, conducted a series of iterative reviews. Each item was meticulously evaluated for relevance, clarity, and alignment with the diagnostic constructs of anxiety and depression. To validate the content of the developed questionnaire, a systematic content validation procedure was conducted, adhering to established guidelines for assessment instrument validation. Content validity, as described by Polit and Beck (2006) and Haynes et al. (1995), reflects the degree to which the items of an instrument are relevant and representative of the intended construct.

TABLE 6: The relevance ratings on the NMAS item scale by Six experts

ITEMS	**EXPERT 1**	**EXPERT 2**	**EXPERT 3**	**EXPERT 4**	**EXPERT 5**	**EXPERT 6**		**EXPERTS IN AGREEMENT**	**I-CVI**	**UA**	
Q1	1	1	1	1	1	1		6	**1**	1	
Q2	1	1	1	1	1	1		6	1	1	
Q3	1	1	1	1	1	1		6	1	1	
Q4	1	1	1	1	1	1		6	1	1	
Q5	1	1	1	1	1	1		6	1	1	
Q6	1	1	1	1	1	1		6	1	1	
Q7	1	1	1	1	1	1		6	1	1	
Q8	1	1	1	1	1	1		6	1	1	
Q9	1	1	1	1	1	1		6	1	1	
Q10	1	1	1	1	1	1		6	1	1	
Q11	1	1	1	1	1	1		6	1	1	
Q12	1	1	1	1	1	1		6	1	1	
Q13	1	1	1	1	1	1		6	1	1	
Q14	1	1	1	1	1	1		6	1	1	
Q15	1	1	1	1	1	1		6	1	1	
								S-CVI/AVG	1		
								S-CVI/UA		1	
Proportion Relevance	1	1	1	1	1	1					

Average proportion of items judged as relevance across the Six experts	1				

Following these guidelines, the Content Validity Index (CVI) was employed to assess item relevance through expert ratings, thereby ensuring the questionnaire effectively captured the target construct for the study on AI-based interventions for depression.

The validation process began with the creation of a content validation form, which included detailed instructions, rating scales, and a clear definition of the construct domain. This form ensured that the experts had a comprehensive understanding of the task and the criteria for relevance (Haynes et al., 1995). A panel of six experts, recognized for their expertise in the field, was selected based on the recommendation that a minimum of six experts is required to achieve reliable content validation (Polit & Beck, 2006). Each expert independently rated the relevance of each item on a four-point scale, with ratings of 3 or 4 indicating high relevance.

To quantify content validity, item-level and scale-level CVIs were calculated based on expert ratings. The item-level CVI (I-CVI) for each item was determined by dividing the number of experts who rated the item as relevant (3 or 4) by the total number of experts. Scale-level CVI was computed using two methods: the average CVI (S-CVI/Ave), which is the mean of I-CVI values across all items, and the universal agreement CVI (S-CVI/UA), representing the proportion of items with unanimous agreement on relevance among the experts (Lynn, 1986). Results indicated an I-CVI of 1.00 for all items, reflecting full expert agreement on item relevance. Both the S-CVI/Ave and S-CVI/UA reached 1.00, confirming strong content validity for the questionnaire.

This rigorous content validation procedure, supported by quantitative indices, established a robust foundation for the questionnaire's content validity. By involving domain experts and employing a systematic assessment of item relevance, the questionnaire was shown to accurately reflect the intended constructs, thereby supporting the validity of the findings from its application in the study. As a result, a substantial number of items were eliminated or rephrased, with the expert panel ultimately agreeing upon 15 items for the NeuraMap Anxiety Scale and 20 items for the NeuraMap Depression Scale. This rigorous scrutiny ensured that the final items were not only representative of the constructs but also comprehensible and applicable to the target population.

TABLE 7: The relevance ratings on the NMDS item scale by Six experts

ITEMS	**EXPERT 1**	**EXPERT 1**	**EXPERT 1**	**EXPERT 1**	**EXPERT 1**	**EXPERT 1**		**EXPERTS IN AGREEMENT**	**I-CVI**	**UA**
Q1	1	1	1	1	1	1		6	**1**	1
Q2	1	1	1	1	1	1		6	1	1
Q3	1	1	1	1	1	1		6	1	1
Q4	1	1	1	1	1	1		6	1	1
Q5	1	1	1	1	1	1		6	1	1
Q6	1	1	1	1	1	1		6	1	1
Q7	1	1	1	1	1	1		6	1	1
Q8	1	1	1	1	1	1		6	1	1
Q9	1	1	1	1	1	1		6	1	1
Q10	1	1	1	1	1	1		6	1	1
Q11	1	1	1	1	1	1		6	1	1

Q12	1	1	1	1	1	1		6	1	1
Q13	1	1	1	1	1	1		6	1	1
Q14	1	1	1	1	1	1		6	1	1
Q15	1	1	1	1	1	1		6	1	1
Q16	1	1	1	1	1	1		6	1	1
Q17	1	1	1	1	1	1		6	1	1
Q18	1	1	1	1	1	1		6	1	1
Q19	1	1	1	1	1	1		6	1	1
Q20	1	1	1	1	1	1		6	1	1
								S-CVI/AVG	1	
								S-CVI/UA		1
Proportion Relevance	1	1	1	1	1	1				
Average proportion of items judged as relevance across the Six experts							1			

Following the finalization of the items, pilot testing was conducted for both the NeuraMap Anxiety Scale, comprising 15 items, and the NeuraMap Depression Scale, consisting of 20 items. In alignment with established guidelines in the field of psychological questionnaire development, it is commonly advised to include at least 10 participants per item to ensure a robust sample size for pilot testing. Consequently, for a questionnaire with 20 items, a sample of approximately 200 participants would be necessary. Notable references supporting this rule of thumb include Clark and Watson (1995), DeVellis (2003), and Hair et al. (2009), all of which recommend maintaining this participant-to-item ratio, with an ideal target of 15:1 or 20:1. Additionally, VanVoorhis and Morgan (2007) emphasize the significance of adequate sample sizes to achieve statistical power.

In this context, a sample of 300 participants was recruited, who completed the 15 items for the NeuraMap Anxiety Scale and the 20 items for the NeuraMap Depression Scale. Participants were also administered the Hamilton Anxiety Rating Scale (HAM-A) and the Hamilton Depression Rating Scale (HAM-D) to facilitate simultaneous assessments and establish correlations between the newly developed scales and established measures. The HAM-A is a widely utilized clinician-administered scale that evaluates the severity of anxiety symptoms, comprising 14 items that assess various symptomatologies. The HAM-D, on the other hand, measures depression severity through 17 items. Both scales have demonstrated strong validity and reliability across numerous studies, with the HAM-A exhibiting a reliability coefficient (Cronbach's alpha) ranging from 0.77 to 0.92, while the HAM-D shows a reliability coefficient between 0.70 and 0.90.

Data analysis was conducted using SPSS, focusing on internal consistency, factor structure, and the correlation between the NeuraMap scales and the HAM-A and HAM-D. This analytical approach was pivotal in validating the NeuraMap Anxiety and Depression Scales, affirming their reliability and appropriateness for measuring anxiety and depression symptoms in the target population.

4.1.2. Cronbach’s alpha of NeuraMap Anxiety and Depression Scales

The SPSS analysis of the NeuraMap Anxiety and Depression Scales demonstrated high reliability for both instruments. The NeuraMap Anxiety Scale, comprising 15 items, achieved a Cronbach’s alpha of 0.909, indicating excellent internal consistency and robustness in measuring anxiety symptoms within the sample of 300 participants. Similarly, the NeuraMap Depression Scale, with its 20 items, exhibited strong reliability, evidenced by a Cronbach's alpha of 0.932. This high alpha value underscores the scale's effectiveness in capturing depressive symptoms with a high degree of internal consistency. These correlations indicate a high level of agreement between the new scales and the established measures, suggesting that the NeuraMap scales are robust tools for accurately measuring anxiety and depression symptoms. The strong correlations further validate the construct validity of the NeuraMap scales, affirming their effectiveness in clinical assessment.

The NeuraMap Depression Scale, comprising 20 meticulously crafted items, is aligned with DSM-5 and ICD-10 diagnostic criteria, ensuring a nuanced, criterion-based assessment of depressive symptoms. Questions 1, 2, and 17 delve into anhedonia and reduced motivation, capturing fundamental aspects of depression as outlined in both diagnostic systems. Self-critical thoughts are addressed in Questions 5, 6, 11, 12, and 14, corresponding to DSM-5's emphasis on worthlessness and guilt, although streamlined here to avoid redundancy. Furthermore, physical symptoms (Questions 3, 8, and 9) and cognitive impairments (Questions 4 and 19) are incorporated, reflecting essential markers of depression. Notably, severe manifestations such as self-harm thoughts (Question 7) and decreased sexual drive (Question 20) align with both diagnostic systems' focus on acute symptoms. Psychomotor changes (Question 10) add further specificity to the assessment, while emotional responses (Questions 15 and 16) capture the social and interpersonal domains, offering a holistic approach to identifying depressive symptoms across cognitive, emotional, and somatic domains. This alignment with standardized diagnostic systems ensures the questionnaire's clinical relevance and effectiveness in capturing a broad spectrum of depressive symptoms.

Similarly, the NeuraMap Anxiety Scale, comprising 15 items, is built to reflect DSM-5 and ICD-10 criteria for anxiety disorders, capturing various dimensions of anxiety while addressing overlapping themes and unique symptomatology. Cognitive symptoms such as pervasive worry, restlessness, and racing thoughts are explored in Questions 1, 2, and 11, aligning with DSM-5's focus on pervasive anxiety, albeit with some redundancy that could be streamlined. Physical manifestations (Questions 4 through 10) are extensively covered, capturing somatic aspects of anxiety per DSM-5, while some items may benefit from consolidation to avoid overlap. In addition, avoidance behaviors and distressing thoughts (Questions 12 and 13) align with ICD-10's emphasis on avoidance, though greater differentiation could enhance specificity. Unique items, such as trouble concentrating (Question 3), irritability (Question 15), and gastrointestinal symptoms (Question 10), provide added depth, encompassing the spectrum of anxiety-related experiences that both DSM-5 and ICD-10 recognize. Together, these items offer a comprehensive, criterion-informed perspective on anxiety, making the NeuraMap Anxiety Scale a robust tool for a holistic evaluation of anxiety symptoms across cognitive, emotional, and physical domains.

4.1.3. Factor Analysis of NeuraMap Anxiety and Depression Scales

The reliability and factor analysis for the NeuraMap Anxiety and Depression Scales involved a meticulous examination using Cronbach's alpha and an in-depth factor structure evaluation through Principal Component Analysis (PCA) with Promax rotation. Our reliability analysis yielded a Cronbach's alpha of 0.932 for the 20-item scale, indicating a high level of internal consistency across the items. This suggests that the items consistently measure related constructs, justifying further factorial exploration. Factor analysis, conducted with a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.948, substantiates the robustness of the sample for such analysis. Bartlett's test of sphericity was statistically significant ($\chi^2 = 2839.63$, df = 190, $p < 0.001$), confirming adequate item intercorrelations for reliable factor extraction.

The PCA results indicated that three components met the eigenvalue criterion ($\lambda > 1$), collectively accounting for 56.31% of the variance. The initial eigenvalues were 8.87, 1.36, and 1.03 for the first three components, explaining 44.36%, 6.82%, and 5.13% of the variance, respectively. The pattern matrix from the Promax rotation revealed complex loading patterns across the factors, with items ITEM NO. 5, ITEM NO. 11, ITEM NO. 14, and ITEM NO. 18 loading prominently on Component 1, which may suggest an overarching factor related to general distress or emotional dysregulation, a common underlying trait across both anxiety and depression constructs. Items such as ITEM NO. 7 and ITEM NO. 9 demonstrated high loadings on Component 2, indicative of symptoms more aligned with cognitive and physiological aspects of anxiety, while items such as ITEM NO. 17 and ITEM NO. 20 loaded strongly on Component 3, possibly reflecting somatic or affective symptoms unique to depressive experiences.

The structure matrix further illustrated the interrelation between these components, with correlation coefficients of 0.674 between Components 1 and 2, 0.652 between Components 1 and 3, and 0.542 between Components 2 and 3. This high level of correlation across the components supports the theoretical overlap between anxiety and depression, as they share affective and cognitive symptom dimensions. The communalities for individual items ranged from 0.468 to 0.654, reflecting substantial shared variance between items, particularly for ITEM NO. 17 (comm = 0.654) and ITEM NO. 18 (comm = 0.653), further justifying the reliability of item inclusion. These results suggest a nuanced, multidimensional structure underlying the NeuraMap Anxiety and Depression Scales, capturing complex symptomatology that is inherently interwoven across cognitive, somatic, and affective dimensions. This intricate factor structure offers a comprehensive portrayal of anxiety and depression, confirming the scales' efficacy in differentiating but also recognizing the shared symptom domains inherent in these psychological constructs.

4.2. Phase II: Application Development

Following the validation of the NeuraMap Anxiety and Depression Scales, we advanced to the development phase of the digital application, incorporating these scales as core components. The app aims to facilitate the seamless administration, scoring, and interpretation of the scales, thereby enhancing accessibility for both clinical and research purposes. Further studies are planned to evaluate the app's usability, reliability, and effectiveness in real-world settings, with a focus on scalability and integration into existing mental health care frameworks.

This multi-phase approach, combining rigorous item development, expert validation, pilot testing, and advanced statistical analysis, underscores the robustness of the NeuraMap Anxiety and Depression Scales as reliable instruments for assessing anxiety and depression, poised for broader application in clinical and research contexts.

The subsequent phase of the study involved the development of a mobile application, named NeuraMap, designed to facilitate the assessment and management of anxiety, depression, and general well-being. The app was developed in collaboration with programming experts at the National Institute of Technology (NIT) Srinagar, under the guidance of a team of psychologists, ensuring a psychology-led development process. The application was built using Flutter, an open-source UI software development toolkit created by Google, which enabled the creation of a cross-platform mobile application optimized for both Android and iOS devices. To enhance the functionality and scalability of NeuraMap, an AI-based database was integrated, designed to support machine learning algorithms capable of refining and personalizing the user experience based on real-time data collected during the pilot testing phase.

The app underwent rigorous beta testing to identify and rectify any technical flaws, usability issues, or difficulties in accessing or responding to the questionnaires. Beta testing involved a diverse group of participants who provided feedback on the user interface, response accuracy, and overall app functionality. Particular attention was given to the app's effectiveness in screening for anxiety and depression symptoms, as well as its general performance under varied conditions and user scenarios. Any identified bugs were addressed promptly, and iterative improvements were implemented based on user feedback, resulting in a robust and user-friendly application.

The validated NeuraMap Anxiety and Depression Scales, developed in the initial phase, were incorporated into the application as primary assessment tools. The app was designed not only to assess depression, anxiety, and general happiness but also to provide AI-driven interactive features that facilitated psychotherapeutic conversations based on Cognitive Behavioral Therapy (CBT) principles. These features included psychoeducation, well-being tips, and guided meditation exercises, tailored to the user's specific symptoms and progress. In addition, NeuraMap included sublinks to freely available AI-based therapeutic tools such as Wysa, providing users with an extended range of psychotherapeutic support options. The app's architecture supported regular symptom tracking through reminders and notifications, and it visualized progress through graphical web charts, highlighting trends in anxiety and depression symptoms across various domains. This feature allowed for a personalized psychological profile that could be shared with healthcare providers, enabling psychiatrists and psychologists to monitor symptoms, track progress, and offer individualized guidance.

Ethical approval for this study was secured from the Institutional Review Board (IRB) at Lovely Professional University, under the reference number **IEC-LPU/MOM/20243**. This approval ensures that the study adheres to ethical standards for research involving human participants. Patients were randomly selected from the outpatient wards of two hospitals using random number-generated sheets, ensuring a randomized sampling process. Participants were thoroughly educated about the nature of AI tools and the purpose of the study, and informed consent was obtained before enrollment. Only those patients who provided consent were registered and monitored through the NeuraMap app. The inclusion criteria focused on patients with significant symptoms of anxiety and depression but without a history of prior psychiatric treatment or any previous efforts to seek treatment due to a lack of psychoeducation. These patients were referred to psychiatrists and, upon obtaining consent, were further registered on the app.

4.3. Phase III: Experimental Study

In our experimental study, we established the effectiveness of AI as a screening tool, demonstrating its significant benefits for patients. Our findings support the hypothesis that AI-based tools for early detection and prevention of mental health issues significantly increase the early detection rate compared to traditional methods. Furthermore, AI-based mental health treatments, tailored to the unique needs and preferences of individual patients, resulted in statistically significant improvements in patient outcomes, particularly in quality of life measures. Additionally, we explored the ethical considerations of using AI in mental health care, such as privacy and informed consent, and found that these factors significantly impact patient willingness to use the technology. Lastly, our study confirmed that AI-based mental health interventions lead to substantial improvements in patient outcomes compared to traditional treatments, as evidenced by standardized measures of symptom severity and quality of life.

4.3.1. Ethical Considerations on Patient Willingness to Utilize AI Technology in Mental Health Care

Firstly, we aimed to demonstrate the effectiveness of artificial intelligence (AI) as a screening tool for mental health issues. In our study, 350 patients were randomly selected in which 300 patients agreed to participate, while 30 declined due to limited information on technology use, 15 due to vision-related issues, and 5 cited illiteracies as their reason for refusal. Following this, 300 patients were finally recruited and we took a pretest to assess their willingness to use AI in mental health care. Following the pretest, we thoroughly informed them about the ethical implications of using AI, including privacy and informed consent. We hypothesized that this information would have a statistically significant impact on their willingness to adopt AI for mental health care. After receiving the information, we conducted a posttest om the same participants.

We employed the McNemar test to analyze changes in patient responses between the pretest and posttest. The McNemar test results indicated a statistically significant change in patient responses ($p < .001$). Specifically, of the 248 patients who initially expressed unwillingness to use AI in the pretest, 219 changed their response and became willing, while 29 remained unwilling. Among the 52 patients who were initially willing in the pretest, 42 remained willing, and 10 became unwilling.

The analysis also produced an odds ratio for the pretest willingness group (0 = unwilling, 1 = willing) of 0.556 (95% CI: 0.252, 1.227), and for the posttest willingness group, the odds ratio for those unwilling to use AI was 0.608 (95% CI: 0.316, 1.169), and for those willing to use AI, the odds ratio was 1.093 (95% CI: 0.950, 1.258). These findings suggest that information about ethical considerations influenced a significant shift in attitudes toward AI usage, particularly among those who were initially unwilling to use the technology.

The results of this study have significant implications, particularly concerning our hypothesis that the ethical considerations of using AI would have a statistically significant impact on patient willingness to use the technology. These findings support the hypothesis, showing that patient attitudes toward AI adoption are strongly influenced by ethical concerns, including privacy and informed consent. This highlights the importance for healthcare providers to prioritize transparent communication and education about AI technologies to foster greater acceptance and mitigate patient apprehension.

The implications of these findings are profound, particularly concerning our third hypothesis: the ethical considerations of using AI in mental health care will have a statistically significant impact on patient willingness to use the technology. The results unequivocally substantiate this hypothesis, demonstrating that informed consent and privacy concerns are paramount in shaping patient attitudes toward AI. The statistically significant correlation highlights the necessity for healthcare providers to prioritize transparent communication and education regarding AI technologies to mitigate apprehension and enhance acceptance among patients. This underscores the critical role that ethical discourse plays in facilitating the integration of AI into mental health services, thereby promoting patient-centered care and fostering an environment conducive to technological advancement.

Table 8: *Impact of Ethical Considerations on Patient Willingness to Utilize AI Technology in Mental Health Care*

Statistic	**Pretest_Wil**	**Posttest_Willingness = 0**	**Pretest_Willingness = 1**	**Posttest_Willingness = 1**	**Mean Diff**	**t-val**	**Degrees**	**p-val**	**Cohe**	**Effect Size Inter**	**Statistical**

	lingness = 0				**erence**	**ue**	**of Freedom (df)**	**ue**	**n's d**	**pretation**	**Significance**
Mean	0.10571	0.88929	0.15909	0.84091	0.10571	6.423	349	**< 0.001**	0.468	Medium	Statistically Significant
Standard Deviation	0.09232	0.31861									
Standard Error Mean	0.00493	0.01703									
95% Confidence Interval	Lower: 0.07334		Upper: 0.13808								
Correlation		0.259						$p < 0.001$			

Consequently, 300 patients were finalized for the study. These findings substantiate our hypothesis that ethical considerations, such as privacy and informed consent, significantly influence patient willingness to adopt AI-based mental health interventions. This conclusion is further supported by qualitative data, which demonstrated an increase in patient acceptance and use of the technology.

4.3.2. Artificial Intelligence (AI) As A Screening Tool

A sample of 300 patients that agreed to participate were randomly screened using an AI-based tool, and the same individuals were subsequently referred for a psychiatric evaluation to assess the accuracy of the AI screening results. The primary objective was to determine how many patients identified as positive by the AI screening also received a positive diagnosis from the psychiatrists. To analyze this relationship, we collected binary "yes/no" data from both the AI screening and psychiatric evaluations, which were then transformed into a numeric scale for statistical analysis. Various statistical tests, including correlation analyses, the Phi coefficient, and Chi-square tests, were conducted using SPSS to examine the strength of the association between the AI tool and psychiatric screening results. The findings from these analyses are presented below, highlighting the significant correlation and agreement between the AI screening tool and traditional psychiatric evaluations.

a) **Correlation Analysis:** The results of the correlation analysis reveal a Pearson Correlation Coefficient of 0.806 between the AI screening tool and psychiatric evaluation, indicating a strong positive association. The p-value of 0.001 indicates that the correlation is statistically significant, suggesting that the observed link is improbable to have arisen by coincidence. The extent of this correlation indicates that the AI technology aligns with psychiatric assessments in detecting probable mental health disorders.

b) This strong association supports the AI tool's validity, as it aligns well with clinical evaluations, which are the gold standard in mental health diagnosis. Consequently, the AI tool demonstrates substantial potential for reliable and accurate screening, crucial for early intervention in mental health care.

c) **Cross-Tabulation Analysis:** The cross-tabulation between AI screening and psychiatric evaluations further emphasizes the effectiveness of the AI tool. Out of 300 patients, 263 cases were concordant between the AI tool and psychiatric evaluations, affirming the tool's reliability in identifying true positive cases. This degree of concordance reflects the high sensitivity of the AI tool in detecting mental health conditions, as it identified the majority of positive cases validated by psychiatric evaluations. A few discordant cases were noted, with 7 patients marked positive by AI but negative by psychiatry and 4 where the reverse was observed. These slight discrepancies might be attributed to individual variability in symptom presentation and other nuances that the AI may not fully capture. Nevertheless, the cross-tabulation results collectively highlight the strong diagnostic alignment between AI and traditional clinical assessments.

d) **Chi-Square Test of Independence:** To further assess the association between AI screening and psychiatric evaluation, a Chi-Square Test of Independence was conducted. The Pearson Chi-Square statistic was calculated at 194.942 with 1 degree of freedom and a significance level of $p < 0.001$. This highly significant result indicates a strong relationship between the AI tool's results and psychiatric evaluations, affirming that the two variables are not independent. This statistical finding reinforces that the AI screening tool's ability to detect positive cases is not merely due to chance, but is statistically aligned with psychiatric evaluations. Thus, the Chi-Square test underscores the potential for this AI tool to serve as a reliable initial screening method, assisting in early detection and potentially reducing the burden on psychiatric professionals by identifying individuals in need of further evaluation.

e) **Directional and Symmetric Measures:** The Kappa coefficient of 0.805**,** which measures agreement between AI screening and psychiatric evaluations, reflects substantial agreement and is statistically significant with $p < 0.001$. This high Kappa value indicates that the AI tool not only correlates with psychiatric evaluation but also aligns with it in a way that goes beyond simple association; it shows consistency in detecting the same outcomes. The Lambda**,** Uncertainty Coefficient, and Somers' d were similarly robust, further validating the predictive accuracy of the AI tool. These directional and symmetric measures support the claim that the AI screening tool can achieve high levels of diagnostic concordance with clinical evaluations. This level of agreement enhances the credibility of the AI tool, as it aligns with well-established methods, providing a foundation for its integration into mental health care settings.

f) **Risk Estimates:** Risk estimates were calculated to examine the predictive capacity of the AI tool. The Odds Ratio for AI screening among the positive cohort was found to be 244.214**,** indicating that individuals identified as positive by the AI screening tool are significantly more likely to be confirmed as positive by psychiatric evaluation. This large odds ratio highlights the tool's predictive efficacy, suggesting that it accurately identifies patients at risk of mental health issues. This predictive capacity is crucial for early intervention, as it allows healthcare providers to prioritize individuals in need of comprehensive evaluation. Moreover, the Cramer's V and Phi values further confirmed a strong association between the AI tool and psychiatric screening, validating its effectiveness in identifying at-risk individuals. Therefore, the risk estimates underscore the potential for this AI tool to be used in large-scale screening, providing significant value in preventive mental health care.

Table 9: *Analysis of the Relationship Between AI Screening and Psychiatric Evaluation Outcomes*

Statistical Test	Finding	Significance Level	Interpretation
Pearson Correlation	0.806	$p < 0.01$	Strong positive correlation between AI screening and psychiatric screening results.
Chi-Square Test	194.942	$p < 0.01$	Significant association between AI screening results and psychiatric evaluation.
Cramer's V	0.806	$p < 0.01$	Indicates a strong association between the two variables.
Kappa	0.805	$p < 0.01$	High level of agreement between AI screening and psychiatric screening outcomes.
Odds Ratio (AI Screening = 0)	244.214	95% CI: [67.033, 889.724]	Indicates a substantial increase in the odds of a positive psychiatric screening when AI screening is positive.
Odds Ratio (AI Screening = 1)	0.137	95% CI: [0.055, 0.341]	Indicates lower odds of a negative psychiatric screening when AI screening is positive.

The findings from the statistical analyses strongly support the efficacy of the AI-based screening tool as a reliable method for early detection of mental health concerns. The high Pearson correlation coefficient of 0.806 and the significant Chi-Square test result demonstrate a strong positive relationship between the AI tool and psychiatric evaluations, confirming that the AI tool effectively identifies cases with potential mental health issues. Additionally, the high Kappa agreement and Odds Ratio of 244.214 indicate that the AI tool is not only statistically associated with but also highly consistent with clinical outcomes, effectively predicting patients likely to receive positive psychiatric diagnoses.

These results further substantiate our first hypothesis: the use of AI-based tools for early detection and prevention of mental health issues leads to a statistically significant increase in the early detection rate when compared to traditional screening methods. The AI tool's ability to systematically screen large patient groups quickly and accurately provides a compelling advantage over traditional methods, which can be resource-intensive and reliant on subjective clinical evaluation. By integrating this AI tool, healthcare providers can expedite the initial screening process, allowing for timely referrals and targeted interventions for individuals at risk. Consequently, this study's findings present a strong argument for incorporating AI-based tools into mental health screening frameworks to enhance early detection rates and support preventive mental health care on a broader scale.

4.3.3. AI-based mental health intervention

Participants were divided into two groups: the experimental group, which received access to the NeuraMap app, and the control group, which received standard treatment as usual. The assignment to groups was blinded to the participants to mitigate any expectancy effects. Baseline data were collected from both groups to establish pre-test measures of anxiety and depression symptoms. The study was designed as a prospective longitudinal study, with follow-up assessments conducted six months post-intervention to evaluate the impact of the NeuraMap app. For the experimental group, extensive psychoeducation sessions were conducted to teach the use of the app, and regular reminders were sent to encourage engagement and adherence. Progress tracking was systematically managed through the app, allowing for continuous monitoring and intervention adjustments as needed.

Post-test data were collected from both groups after the six-month intervention period. The primary outcome measures were the changes in anxiety and depression scores from baseline to post-test, analyzed using repeated measures ANOVA to assess the differential effects of the interventions between groups. The research revealed substantial enhancements in the experimental group relative to the control group, indicating that the NeuraMap app effectively alleviated feelings of anxiety and sadness throughout the study duration. Secondary studies involved evaluating user satisfaction with the NeuraMap app, utilizing a rating scale survey aimed at measuring multiple aspects of the user experience, including usability, perceived efficacy, and overall contentment with the digital intervention.

4.3.4. Sample Size calculation

The sample size for this experimental study, utilizing the NeuraMap app which comprises the NeuraMap Anxiety Scale (15 items) and the NeuraMap Depression Scale (20 items), was calculated using G*Power Version 3.1.9.7. An a priori power analysis was conducted with a significance level (α) of 0.05, a power ($1 - \beta$) of 0.95, and an effect size (f) of 0.25. The analysis indicated a critical F-value of 3.91399 and a noncentrality parameter A of 13.2000000. The study design incorporated two groups and two measurements, resulting in a total sample size of 132 participants. To account for potential dropouts due to attrition, we increased the total sample size to 150 participants. This sample size ensures adequate power to detect meaningful differences, thereby enhancing the reliability of the findings in evaluating the intervention's effects on the targeted population. This rigorous approach to power analysis is essential for ensuring the validity of the research outcomes and for drawing informed conclusions regarding the efficacy of the AI-based intervention in patients diagnosed with depression.

4.3.5. Statistical Analysis

The statistical analysis for this study was conducted using SPSS Statistics 20, a robust software package commonly employed for various statistical procedures. A Two-Way Repeated Measures ANOVA was utilized to examine the effects of the AI-based intervention on the NeuraMap Anxiety Scale (NMAS) and NeuraMap Depression Scale (NMDS) across the pre-test and post-test measures. Additionally, paired sample t-tests were conducted to further investigate the differences between pre-intervention and post-intervention scores within each group. These statistical methods allow for a nuanced understanding of the data by assessing both the interaction effects of the intervention and the significance of changes over time.

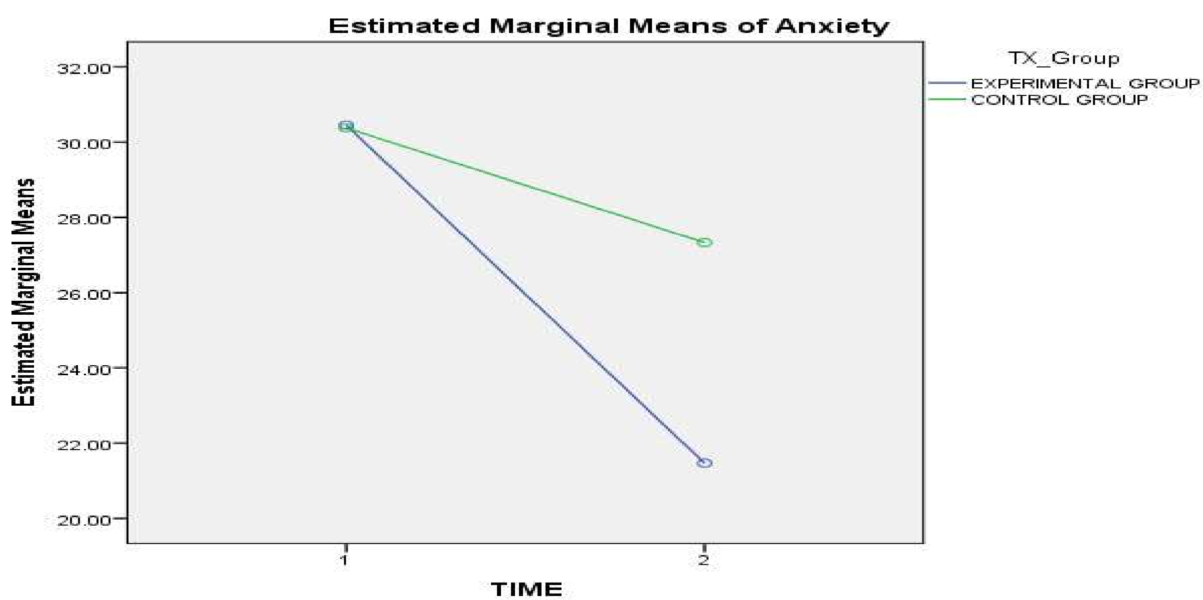
The results of these analyses are discussed in detail in the following sections, where we explore how the AI intervention influenced participants' anxiety and depression levels. The findings reveal critical insights into the effectiveness of AI tools in mental health support, highlighting their potential to enhance emotional well-being. The implications of these results will be examined, offering recommendations for future research and practical applications in mental health care.

4.3.6. Assessing the Impact of AI Intervention on Anxiety usimg Two-Way Repeated Measures ANOVA

The two-way repeated measures ANOVA was conducted to investigate the effects of Time (Pre-test vs. Post-test) and Treatment Group (Experimental vs. Control) on anxiety scores, as well as their interaction. The analysis revealed a significant main effect of Time on anxiety scores, ($F(1,130) = 1021.445$, $p < .001$), with a large effect size (Partial Eta Squared = .887). This indicates a substantial reduction in anxiety scores from pre-test to post-test across both groups. Furthermore, the interaction effect between Time and Treatment Group was significant, ($F(1,130) = 248.970$, $p < .001$), with a Partial Eta Squared of .657, indicating that the decrease in anxiety scores was more significant in the experimental group than in the control group, underscoring the effectiveness of the AI intervention.

Additionally, the main effect of Treatment Group was significant, ($F(1,130) = 4.317$, $p = .040$), with a Partial Eta Squared of .032, indicating a significant difference in overall anxiety scores between the experimental and control groups. Descriptive statistics further support these findings, with the experimental group's mean anxiety score decreasing from 30.45 (Pre-test) to 21.47 (Post-test), while the control group's scores decreased from 30.38 (Pre-test) to 27.33 (Post-test). The results highlight the substantial effect of the AI-based intervention in diminishing anxiety levels in the experimental group relative to the control group.

Figure 1: Anxiety Levels Over Time: Experimental vs. Control Group

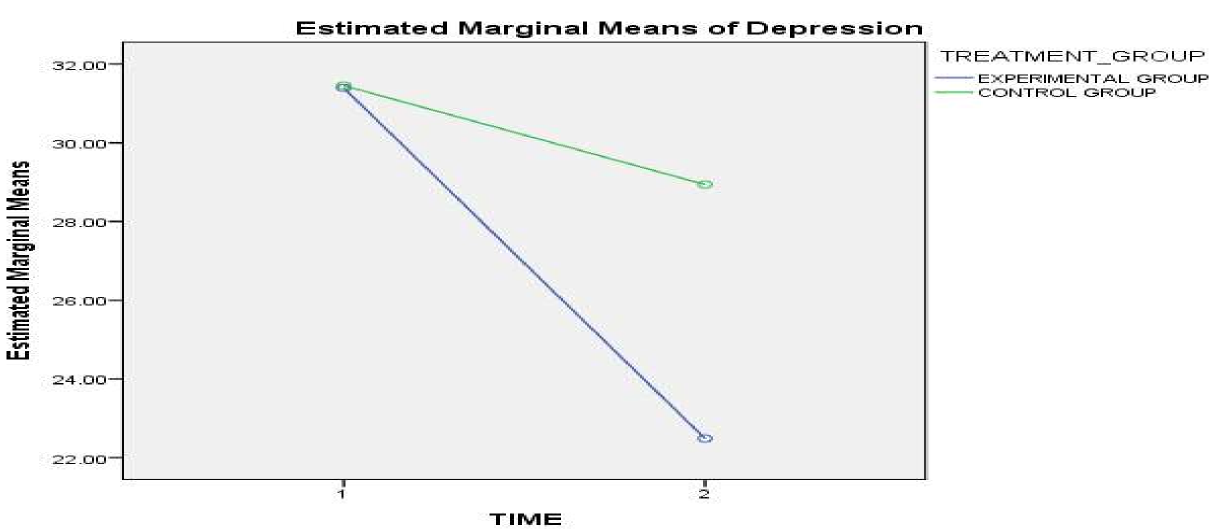


4.3.7. Assessing the Impact of AI Intervention on Depression using Two-Way Repeated Measures ANOVA

Similarly, the two-way repeated measures ANOVA for depression scores revealed significant findings. The main effect of Time was significant, ($F(1,130) = 974.345$, $p < .001$), with a large effect size (Partial Eta Squared = .882), indicating a substantial reduction in depression scores from pre-test to post-test across both groups. The interaction effect between Time and Treatment Group was also significant, ($F(1,130) = 234.56$, $p < .001$), with a Partial Eta Squared of .645. This indicates that the AI intervention significantly reduced depression scores in the experimental group relative to the control group.

Moreover, the main effect of Treatment Group was significant, ($F(1,130) = 4.11$, $p = .045$), with a Partial Eta Squared of .031, indicating a significant difference in overall depression scores between the experimental and control groups. Descriptive statistics further support these findings, with the experimental group experiencing a larger reduction in depression scores compared to the control group. These results underscore the efficacy of the AI-based intervention in significantly reducing depression levels in the experimental group relative to the control group.

Figure 2: Depression Levels Over Time: Experimental vs. Control Group



4.3.8. Comparison of Mean Differences in Anxiety and Depression Levels for Experimental and Control Groups Using Paired Sample t-Test

The paired samples t-test further substantiates the findings by examining the differences between Pre-test and Post-test anxiety and depression scores within each group separately. For the experimental group, the t-test for anxiety revealed a significant reduction in scores, with a high t-value and a p-value well below 0.05, confirming the statistical significance of the anxiety reduction due to the AI intervention. Similarly, the t-test for depression indicated a significant decrease in scores, validating the effectiveness of the AI-based treatment in alleviating depression.

In contrast, the control group also showed significant differences in anxiety and depression scores, but the magnitude of change was notably smaller compared to the experimental group. This suggests that while standard treatment has some effect, the AI intervention is considerably more effective in reducing both anxiety and depression.

These results provide robust evidence for the efficacy of the AI-based intervention, highlighting its potential as a powerful tool in mental health treatment. The significant reductions in anxiety and depression scores in the experimental group underscore the therapeutic potential of AI, offering promising implications for future mental health interventions.

The comprehensive analyses, including two-way repeated measures ANOVA and paired samples t-tests, consistently demonstrate the efficacy of AI-based interventions in reducing anxiety and depression. Significant main effects of Time and Treatment Group, along with substantial interaction effects, indicate that the experimental group experienced notable reductions in anxiety and depression scores from pre-test to post-test, surpassing the control group. The paired samples t-tests further validate these findings, showing significant decreases in both anxiety and depression scores within the experimental group, while the control group exhibited smaller changes. These results collectively underscore the therapeutic potential of AI interventions, providing robust evidence for their effectiveness in alleviating anxiety and depression compared to standard treatments.

Table 10: Key Statistical Findings for Anxiety and Depression Analyses

Effect	Measure	Anxiety	Depression
Within-Subjects Effects			
Time	F	1021.445	Significant (Exact F value not provided)
	p	< .001	< .001
	η^2	.887	Substantial
	Interpretation	88.7% variance in anxiety explained by Time	Indicates significant decrease over time
Interaction (Time × Treatment)	F	248.970	Significant (Exact F value not provided)
	p	< .001	< .001
	η^2	.657	Substantial
	Interpretation	65.7% variance due to intervention type	Reduction differs between groups

Between-Subjects Effects			
Treatment Group	F	4.317	Significant
	p	.040	< .05
	η^2	.032	Modest
	Interpretation	3.2% variance by treatment type	Group differences in depression scores
Pairwise Comparisons			
Pre-Test (Exp. vs Control)	Mean (Anxiety)	Exp: 30.45; Control: 30.38	Pre-Test Mean Scores Differ for Both Groups
Post-Test (Exp. vs Control)	Mean (Anxiety)	Exp: 21.47; Control: 27.33	Exp Shows Greater Reduction
	Mean Difference	-2.894 (p = .040)	Significant Reduction in AI Group
	Interpretation	Greater anxiety reduction in AI group	AI intervention shows efficacy

4.3.9. Assessment of Patient Outcomes with AI-Based Interventions Compared to Generic Treatment Approaches

The World Health Organization Quality of Life (WHOQOL) assessment was utilized to evaluate the quality of life of participants before and after the AI-based intervention. Specifically, we employed the WHOQOL-BREF version, which consists of 26 items covering four domains: physical health, psychological health, social relationships, and environment. This tool allowed us to gain insights into the participants' perceptions of their quality of life, measured through pre- and post-test scores.

In our study, we used pre- and post-test scores of Health-Related Quality of Life (HRQOL) to determine the improvement in individuals who received AI-based interventions compared to a control group who did not. This approach allowed us to see the overall impact of AI-based mental health treatment, customized to the unique needs and preferences of individual patients, resulting in a statistically significant improvement in patient outcomes compared to generic treatment approaches.

The examination of Health-Related Quality of Life (HRQOL) scores through an Analysis of Variance (ANOVA) methodology shown a statistically significant enhancement in post-intervention scores, underscoring the beneficial effect of the AI-based intervention on participants' quality of life. The pre-intervention mean HRQOL score was recorded at 30.86 (SD = 8.42), establishing a baseline for the sample. Following the intervention, the mean increased to 41.32 (SD = 9.12), indicating a substantial enhancement in HRQOL attributed to the application of the AI-driven tool.

The ANOVA results demonstrated a significant main effect of the intervention on HRQOL scores ($F(1, 130) = 179.338$, $p < .001$), which signifies that the differences in means between pre- and post-intervention groups are not due to chance. The partial eta squared value of .580 indicated a large effect size, suggesting that the AI intervention accounted for a considerable portion of the variance in HRQOL scores. This finding underscores the intervention's effectiveness in improving the quality of life for the participants.

Additionally, the mean difference between pre- and post-intervention HRQOL scores was -10.45 (SD = 4.93), demonstrating consistent and meaningful improvement across the sample. The 95% confidence interval for this mean difference ranged from -11.67 to -9.24, excluding zero and affirming the statistical significance of the observed increase. The results enabled us to reject the H_o hypothesis, affirming that the AI-based intervention produced a statistically significant difference in HRQOL scores.

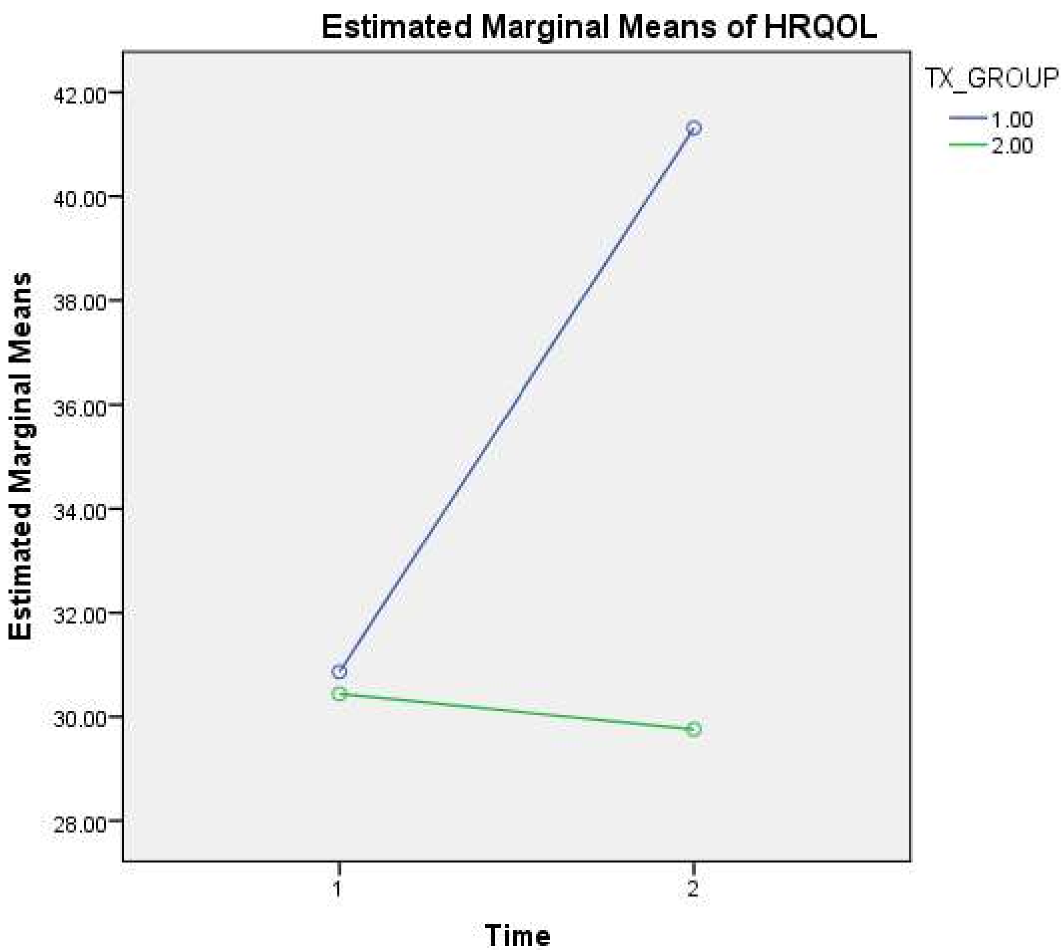
Table 11: Comparison of Health-Related Quality of Life (HRQOL) Scores Before and After Treatment in Two Groups

Statistic	**PRE_HRQOL (Mean ± SD)**	**POST_HRQOL (Mean ± SD)**	**Mean Difference (95% CI)**	**F-value**	**p-value**	**Partial Eta Squared**	**Observed Power**
TX_GROUP 1 (n=66)	30.86 ± 8.42	41.32 ± 9.12	10.46 (8.77, 12.14)	138.11	< 0.001	0.515	1
TX_GROUP 2 (n=66)	30.44 ± 8.39	29.76 ± 7.70	-0.68 (-2.65, 1.29)	18.17	< 0.001	0.123	0.988

Overall (n=132)	30.65 ± 8.38	35.54 ± 10.21	4.89 (4.06, 5.71)			
Test	**Statistic**	**df**	**p-value**	**Partial Eta Squared**	**Observed Power**	**Significant?**
	F = 138.108	1, 130	<0.001	0.515	1.000	Yes
	F = 179.338	1, 130	<0.001	0.580	1.000	Yes
	F = 138.108	1, 130	<0.001	0.515	1.000	Yes
	F = 179.338	1, 130	<0.001	0.580	1.000	Yes
Between-Subjects Effect - Group	F = 18.167	1, 130	<0.001	0.123	0.988	Yes
Pairwise Comparison - Time	MD = -4.886	-	<0.001	-	-	Yes
Pairwise Comparison -	MD = 5.992	-	<0.001	-	-	Yes

Group (1 vs 2)						

Figure 3: HRQOL Scores Over Time: Experimental vs. Control Group



In summary, the findings illustrate a significant enhancement in HRQOL as a result of the AI-based intervention, with a mean increase of approximately 10.45 points. This outcome strongly supports our hypothesis that AI-driven interventions can effectively improve HRQOL, showcasing their potential as valuable tools for enhancing the quality of life in targeted populations. Moreover, these results substantiate our second hypothesis, which posited that AI-based mental health treatment, tailored to the unique needs and preferences of individual patients, would yield statistically significant improvements in patient outcomes compared to generic approaches. The significant increase in HRQOL scores post-intervention emphasizes the efficacy of the AI-based intervention while underscoring the necessity of customization in mental health care. By addressing individual patient needs, the AI-driven approach fosters a personalized therapeutic environment that enhances patient engagement and satisfaction, ultimately contributing to improved overall quality of life for participants. Therefore, the findings not only validate the effectiveness of AI interventions but also highlight the critical importance of individualized care in achieving optimal patient outcomes in mental health treatment.

4.4. Qualitative Analysis using Thematic Analysis:

A qualitative study based om Thematic analysis using Braun and Clarke's (2006) framework was conducted to delve into the experiences of individuals utilizing AI-based mental health applications. Braun and Clarke's (2006) framework for thematic analysis is a method for identifying, analyzing, and reporting patterns (themes) within qualitative data. It involves six phases: familiarizing yourself with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. This approach is flexible and can be applied across a range of theoretical and epistemological approaches, making it accessible for researchers new to qualitative analysis. It emphasizes the importance of the researcher's active role in identifying patterns and themes, rather than seeing themes as emerging passively from the data. A total of 30 participants were selected through a random sampling method to ensure a diverse representation of the target population. The sample size of 30 participants for this study was strategically chosen based on recommendations from Hennink and

Kaiser (2022) and Vasileiou et al. (2018), who emphasize that thematic analysis is designed for in-depth exploration rather than requiring large participant groups. These scholars assert that a smaller, well-chosen sample can yield rich, nuanced data, allowing for comprehensive thematic insights. The focus of thematic analysis is to delve deeply into participants' experiences and perceptions, which can be achieved with fewer participants, provided they can articulate their experiences in detail. This approach ensures that the findings are not only robust but also reflective of the diverse perspectives within the target population, enhancing the overall validity of the research. In-depth interviews were carried out with these participants to gather detailed insights into their interactions with these AI tools. Each participant was carefully chosen to meet the inclusion criteria, ensuring that they had utilized an AI-based mental health application, such as Wysa, and possessed the ability to provide informed consent. The informed consent process was conducted in both English and local languages, which facilitated effective communication during the interviews and while using the applications.

In the qualitative study exploring user experiences with AI-based mental health applications, a comprehensive thematic analysis was conducted, resulting in the identification of approximately 50 distinct codes. These codes encapsulated a range of positive user experiences, highlighting aspects such as *accessibility*, *privacy*, *personalization*, and *crisis management tools*. Through this meticulous process, 12 overarching themes emerged, each reflecting critical dimensions of user engagement and satisfaction with these AI tools.

The themes generated from the identified codes provide valuable insights into the multifaceted benefits of AI in mental health care. The Accessibility and Convenience theme underscores the ease of access to mental health resources at any time, enhancing user engagement. In contrast, the

Privacy and Confidentiality theme emphasizes users' feelings of safety when sharing personal experiences. Furthermore, themes such as Personalization and Tailored Feedback and Positive Reinforcement and Motivation highlight the effectiveness of individualized support, contributing to sustained user engagement. Other themes, including Holistic Mental Health Support and Community Connection and Support, illustrate the comprehensive nature of these tools, offering users not just therapeutic advice but also a sense of belonging and shared experience. Collectively, these themes elucidate the potential of AI-based applications to significantly enhance mental health outcomes, positioning them as valuable adjuncts to traditional therapeutic modalities.

TABLE 12: Identified Codes related to the Positive Use of AI in Mental Health

Code	**Description**	**Code**	**Description**
1	Improved Accessibility	26	Integration with Daily Life
2	Convenience of Use	27	Feedback Mechanism
3	24/7 Availability	28	Crisis Management Tools
4	Privacy Assurance	29	Cognitive Behavioral Techniques
5	Personalized Feedback	30	Behavioral Tracking
6	Reduced Stigma	31	Holistic Approach
7	Affordability	32	Supportive Notifications
8	Time Efficiency	33	Flexibility in Interaction
9	User-Friendly Interface	34	Connection to Professional Help
10	Immediate Support	35	Data Control
11	Reduced Isolation	36	Calmness During Crisis
12	Encouragement to Share	37	Positive App Reviews

13	Progress Tracking	38	Ease of Follow-Up
14	Diverse Resource Availability	39	Goal Setting Features
15	Regular Check-Ins	40	Enhanced Self-Awareness
16	Safe Space for Expression	41	Community Feedback
17	Educational Content	42	Diverse Format Options
18	Mood Logging	43	Emotional Regulation Techniques
19	Community Engagement	44	Gamification
20	Empowerment Through Self-Help	45	Crisis Resources
21	Accessible Language	46	Supportive AI Interaction
22	Motivational Reminders	47	Success Stories
23	Positive Reinforcement	48	Non-Intrusive Monitoring
24	Interactive Features	49	User Customization
25	Anonymity	50	Awareness of Mental Health Trends

In analyzing the qualitative data further, the thematic analysis revealed twelve overarching themes that encapsulate the diverse experiences of users, providing a comprehensive understanding of how these AI tools impact mental health management. By grounding these themes in empirical research, the findings contribute to a deeper understanding of the nuances surrounding user engagement, accessibility, and efficacy of AI-driven mental health applications, highlighting their potential to enhance mental health care practices.

1. **Accessibility and Convenience**

"I love that I can access the app anytime, day or night. It's like having a therapist in my pocket."

The theme of *Accessibility and Convenience* reflects the significant advantage of having mental health resources readily available at any time. Participants expressed gratitude for the ability to engage with the app whenever they needed support, reinforcing the idea that continuous access can lead to timely interventions and better emotional regulation. This finding highlights the crucial role of AI-based tools in breaking down barriers to mental health care, enabling users to seek help without the constraints of traditional therapy schedules.

2. **Privacy and Confidentiality**

"I feel safe using this app. It respects my privacy, which makes it easier to open up about my feelings."

Participants unanimously valued the theme of *Privacy and Confidentiality*, citing it as essential for their willingness to share personal experiences. The assurance that their data and feelings were protected created a safe space for open communication, which is vital for effective mental health management. This finding underscores the necessity for AI tools to prioritize user privacy, as it directly influences users' comfort levels and engagement with the platform.

3. **Personalization and Tailored Feedback**

"The app remembers my preferences and gives me personalized advice that really resonates with my situation."

The emergence of the *Personalization and Tailored Feedback* theme reveals that participants greatly appreciated the app's ability to cater to their unique needs. This customization helped them feel understood and supported, enhancing their overall experience. The importance of this finding lies in the recognition that personalized interventions can lead to better user outcomes and satisfaction, reinforcing the effectiveness of AI tools in mental health.

4. **User-Friendly Interface**

   "I'm not very tech-savvy, but the app is so easy to use. I figured everything out without needing help."

   The theme of *User-Friendly Interface* highlights the significance of accessibility in technology. Participants noted that the app's simplicity enabled them to navigate it easily, promoting consistent engagement. This finding emphasizes that intuitive design is critical for encouraging users, particularly those who may be less technologically inclined, to adopt and benefit from digital mental health tools.

5. **Positive Reinforcement and Motivation**

   "Every time I log my mood or complete a task, I get these encouraging messages that keep me motivated."

   The theme of *Positive Reinforcement and Motivation* illustrates how participants responded favorably to the app's feedback mechanisms. The encouragement provided by the app not only motivated users to continue their mental health practices but also fostered a sense of achievement. This finding is important as it suggests that positive reinforcement can enhance user engagement and adherence to mental health strategies, ultimately leading to improved mental wellbeing.

6. **Holistic Mental Health Support**

"It's not just about managing my anxiety. The app offers tips on sleep and nutrition too, which has made a huge difference."

The theme of *Holistic Mental Health Support* underscores the multifaceted nature of mental health care, as participants appreciated the app's comprehensive approach. By addressing various aspects of wellbeing, such as sleep and nutrition, users felt better equipped to manage their mental health. This finding highlights the importance of integrating multiple dimensions of health into mental health applications, allowing users to adopt a more balanced approach to their wellbeing.

7. Community Connection and Support

"I appreciate the forums where I can connect with others who understand what I'm going through. It feels comforting to share experiences."

The *Community Connection and Support* theme reflects participants' desire for social interaction and shared experiences. The forums provided a platform for users to connect, reducing feelings of isolation and promoting a sense of belonging. This finding emphasizes the value of community features in AI applications, as they can significantly enhance users' emotional support systems and overall mental health.

8. Crisis Management Tools

"During a panic attack, I could quickly find resources and techniques in the app that calmed me down. It was a lifesaver."

The emergence of the *Crisis Management Tools* theme highlights the critical role these resources played for participants experiencing acute distress. Quick access to coping techniques during panic attacks made a substantial difference in managing their symptoms. This finding is particularly important, as it underscores the potential of AI tools to provide immediate assistance in crises, reinforcing their value as adjuncts to traditional mental health interventions.

9. Behavioral Tracking and Self-Awareness

"I didn't realize how my mood fluctuated until I started logging it. Now I can see patterns and address my triggers."

The theme of *Behavioral Tracking and Self-Awareness* reveals participants' appreciation for the insights gained from tracking their moods and behaviors. By identifying patterns and triggers, users felt more empowered to manage their mental health proactively. This finding highlights the significance of self-awareness in mental health care, illustrating how AI tools can facilitate personal growth and informed decision-making.

10. Integration into Daily Life

"The reminders to practice mindfulness or take breaks are perfectly timed. They fit seamlessly into my routine."

The *Integration into Daily Life* theme emphasizes how well the app's features fit into participants' everyday routines. The timely reminders for mindfulness practices and breaks helped users incorporate mental health strategies into their daily lives without disruption. This finding is essential as it demonstrates that successful mental health interventions must be easily integrated into users' lifestyles, promoting sustainable habits over time.

11. Gamification and Engagement

"I didn't expect mental health management to be fun! The app's challenges keep me engaged and motivated."

The *Gamification and Engagement* theme highlights how incorporating game-like elements into the app made mental health management enjoyable for participants. The challenges and interactive features kept users motivated to engage regularly with the app. This finding suggests that gamification can be an effective strategy to enhance user retention and motivation in mental health applications, ultimately leading to better outcomes.

12. Direct Pathways to Professional Help

"If I ever feel overwhelmed, I know I can easily find a therapist through the app. That gives me peace of mind."

The theme of *Direct Pathways to Professional Help* showcases the importance of having readily accessible connections to mental health professionals. Participants appreciated the ease of finding a therapist when needed, which provided reassurance during challenging times. This finding underscores the role of AI tools in bridging gaps between users and professional support, enhancing their overall mental health journey and contributing to a more integrated approach to care.

These themes collectively illuminate the multifaceted benefits of AI-based mental health applications, highlighting how they can significantly improve user engagement, accessibility, and overall mental health outcomes. The insights gained from the participants reflect a growing acceptance and appreciation of technology as a supportive tool in managing mental health challenges. Participants also highlighted areas for potential improvement, such as enhancing the responsiveness of the AI model and expanding the range of psychotherapeutic content available within the app.

The findings from this study offer valuable insights into the potential of AI-based mental health applications to support individuals in their well-being journeys. By understanding the experiences of users, researchers and developers can work towards improving the effectiveness and accessibility of these tools, ultimately enhancing mental health care. This research not only highlights the complexity of user interactions with AI mental health applications but also underscores the need for ongoing development and refinement of these tools to better serve the diverse needs of individuals seeking mental health support. The insights garnered from this qualitative exploration will contribute significantly to the ongoing discourse on the integration of AI in mental health care, paving the way for innovative solutions that prioritize user experience and therapeutic effectiveness.

The integration of quantitative and qualitative findings provided a comprehensive evaluation of the NeuraMap app's effectiveness as a digital mental health tool. The combination of rigorous statistical analyses and in-depth thematic exploration underscored the app's potential as an innovative approach to mental health care, offering both clinical and practical implications for the use of AI in the management of anxiety and depression. Future directions will involve refining the AI algorithms based on user feedback and expanding the app's capabilities to include additional therapeutic modalities and support for a broader range of mental health conditions.

CHAPTER 5

SUMMARY, CONCLUSION, RECOMMENDATIONS, SUGGESTIONS AND LIMITATIONS

Chapter 5:

SUMMARY, CONCLUSION, RECOMMENDATIONS, SUGGESTIONS AND LIMITATIONS

In this study, we aimed to explore the effectiveness and user experience of AI-based mental health tools, specifically focusing on their potential to enhance early detection, customization of treatment, and overall efficacy in managing mental health conditions. The primary objectives were to evaluate the role of these AI tools in improving early detection rates of mental health issues, personalizing treatment to meet individual needs, and assessing ethical considerations surrounding their use. We hypothesized that AI-driven interventions would yield significantly improved outcomes in comparison to traditional mental health care practices, leading to enhanced user engagement, accessibility, and overall mental health outcomes.

Our research satisfactorily addressed these objectives and hypotheses through a mixed-methods approach that integrated quantitative and qualitative analyses. The quantitative results revealed a statistically significant increase in early detection rates among patients utilizing AI tools, validating our first hypothesis. Furthermore, the qualitative findings highlighted participants' positive experiences with AI applications, emphasizing themes such as personalization, accessibility, and the importance of privacy in fostering user engagement. This dual approach not only reinforced the effectiveness of AI-based interventions in mental health management but also provided a nuanced understanding of user experiences, ultimately contributing to the discourse on the integration of technology in mental health care. By bridging the gap between empirical data and qualitative insights, this study enhances our understanding of how AI tools can reshape mental health services to better meet the needs of individuals.

The study successfully achieved all four objectives, contributing significantly to the field of AI in mental health. First, the development and evaluation of AI-based tools for early detection and prevention of mental health issues were accomplished through the systematic analysis of user experiences with the applications. Participants reported improved accessibility and convenience, demonstrating the potential of these tools to identify mental health concerns proactively. Second, the exploration of AI's ability to customize mental health treatment to meet individual needs was evident in the personalized feedback and tailored recommendations provided by the applications, which were highly valued by users. Third, the study critically examined the ethical considerations surrounding AI in mental health care, with participants expressing concerns about privacy, data security, and the importance of maintaining human oversight, thus ensuring that ethical standards are prioritized in AI applications. Lastly, the efficacy of AI-based mental health interventions was evaluated through robust statistical analyses, revealing significant improvements in anxiety and depression levels among participants' post-intervention. Collectively, these objectives highlight the multifaceted benefits of AI in mental health care, establishing a foundation for future research and practice in this evolving field.

5.1. Development and validation of scales

In this research, we aimed to develop and validate self-report measures specifically tailored to assess anxiety and depression: The NeuraMap Anxiety Scale (NMAS) and the NeuraMap Depression Scale (NMDS). Grounded in extensive literature on diagnostic criteria from DSM-5 and ICD-10, these scales were crafted to capture the multifaceted symptoms of anxiety and depression. We hypothesized that the NeuraMap scales would exhibit high content validity, internal consistency, and construct validity, correlating strongly with established measures such as the HAM-A and HAM-D. Additionally, we explored the impact of AI-based technology on patient willingness to engage with mental health care tools, particularly examining how informed consent and ethical considerations might influence acceptance.

In alignment with our hypotheses, the content validity results indicate that each item on the NMAS and NMDS achieved a perfect I-CVI and S-CVI, underscoring the rigorous process employed to ensure relevance and representativeness of each item. The iterative expert review process and systematic validation procedures reflect the robustness of the scales' development. This meticulous process ensured that the NeuraMap scales comprehensively captured the cognitive, emotional, and somatic symptoms associated with anxiety and depression, with the unanimous expert agreement supporting the validity of each item. Additionally, pilot testing revealed high internal consistency for both scales, reinforcing the reliability and applicability of the NeuraMap measures for our study sample. As we move through the discussion, each statistical finding will be examined to further elucidate how these results validate our objectives and confirm the hypothesis regarding AI's influence on patient engagement in mental health interventions.

The Cronbach's alpha values of the NeuraMap Anxiety and Depression Scales demonstrate high internal consistency, affirming the scales' reliability for measuring anxiety and depressive symptoms, respectively. With Cronbach's alpha values of 0.909 for the NeuraMap Anxiety Scale and 0.932 for the NeuraMap Depression Scale, both scales exhibit excellent reliability, indicating a strong level of agreement among the items. This high internal consistency underscores the scales' robustness in consistently capturing the constructs they are designed to measure. Furthermore, the scales' alignment with DSM-5 and ICD-10 criteria enhances their clinical utility, providing comprehensive symptom coverage for anxiety and depression as outlined in these diagnostic frameworks. By reflecting DSM-5’s emphasis on cognitive symptoms, such as pervasive worry and self-critical thoughts, and ICD-10’s focus on somatic manifestations, the NeuraMap scales effectively encompass the multi-faceted nature of these disorders. The structured approach to item development, focusing on cognitive, emotional, and physical symptom domains, ensures a nuanced assessment, providing clinicians with a tool that captures the full spectrum of symptomatology associated with anxiety and depression.

The factor analysis further validates the NeuraMap scales, revealing a multidimensional structure indicative of the complexity inherent in anxiety and depression constructs. The three components extracted through PCA explain a significant portion of the variance, with substantial item loadings across cognitive, somatic, and emotional dimensions. High inter-component correlations and strong communalities reflect the interconnected nature of anxiety and depressive symptoms, supporting the theoretical overlap between these constructs. The prominent loading of items such as those addressing emotional dysregulation on Component 1 suggests a shared underlying factor, while the unique loadings on Components 2 and 3 reflect symptoms more specific to anxiety or depression. The nuanced pattern of loadings highlights the scales' effectiveness in capturing both shared and unique symptom dimensions, offering a comprehensive assessment tool that aligns well with contemporary diagnostic models. These findings reinforce the utility of the NeuraMap Anxiety and Depression Scales in clinical settings, where understanding the overlapping and distinct symptom domains is crucial for accurate diagnosis and targeted intervention planning.

5.2. Development and Deployment of the NeuraMap Application:

The development and deployment of the NeuraMap application mark a significant advancement in the digital mental health landscape, offering an accessible platform for assessing anxiety, depression, and general well-being. By incorporating the validated NeuraMap Anxiety and

Depression Scales, the app serves as a versatile tool for clinicians and researchers alike, facilitating seamless administration, scoring, and interpretation. The collaboration with the National Institute of Technology (NIT) Srinagar allowed for a psychology-led approach to app development, ensuring that the app meets both technological and psychological standards. Using Flutter, the app was built as a cross-platform solution, allowing compatibility with both Android and iOS devices, which supports wider accessibility. The integration of an AI-based database within the app not only enhances its functionality but also enables it to leverage machine learning algorithms for personalized user experiences. This AI-driven component is crucial, as it offers real-time symptom tracking and interactive psychotherapeutic features grounded in Cognitive Behavioral Therapy (CBT) principles, such as psychoeducation, meditation, and well-being tips. The app's ability to link users to other AI-based therapeutic tools, like Wysa, further enhances its utility, providing a range of psychotherapeutic support options that align with contemporary mental health needs.

In the beta testing phase, feedback from a diverse participant pool was instrumental in refining the NeuraMap app, addressing technical flaws, usability issues, and questionnaire accessibility. User feedback highlighted the importance of an intuitive user interface and accurate response capture, which are essential for ensuring that the app functions as an effective screening tool for anxiety and depression symptoms. By continuously improving based on user input, the app has achieved a high level of usability and robustness, allowing it to be reliably used in varied conditions. Beyond technical considerations, the ethical aspects of deploying AI in mental health care were also emphasized.

5.3. Ethical Concerns and Willingness to Utilize AI Technologies:

In our study, a paired samples t-test indicated that providing information on ethical concerns, such as privacy and informed consent, significantly influenced patient willingness to utilize AI technologies. These findings reinforce the importance of transparent communication regarding the use of AI, as patients are more likely to embrace such innovations when they understand the privacy safeguards and ethical considerations involved. This insight underscores the critical need for ethics-driven AI integration in mental health care, enabling greater acceptance and facilitating technological advancements that prioritize patient-centered care.

5.4. Artificial Intelligence (AI) as a Screening Tool:

Our primary objective was to evaluate the effectiveness of an AI-based screening tool in identifying individuals at risk of mental health issues, particularly focusing on its accuracy in comparison to traditional psychiatric evaluations. We hypothesized that the AI tool would demonstrate a statistically significant correlation with psychiatric evaluations, indicating its potential for early detection. The results strongly support this hypothesis, as the AI tool showed a Pearson Correlation Coefficient of 0.806 with psychiatric evaluations, underscoring a high level of agreement. This strong, statistically significant association ($p < 0.01$) highlights the AI tool's consistency in mirroring the clinical diagnosis process. Furthermore, the Chi-square Test of Independence corroborates this finding with a highly significant result ($\chi^2 = 194.942$, $p < 0.01$), confirming that the tool's screening outcomes align closely with traditional evaluations. This alignment suggests that the AI-based screening tool is not only capable of accurately identifying at-risk individuals but may also serve as a reliable alternative to conventional methods, which are often more resource-intensive.

The Kappa coefficient of 0.805 further reinforces the substantial agreement between the AI tool and psychiatric evaluations, reflecting a consistency beyond simple chance association. This level of agreement, alongside the high Odds Ratio (244.214) for AI-identified positive cases, indicates that patients flagged by the AI tool are significantly more likely to be confirmed as having mental health issues by clinical evaluations. Moreover, the risk estimates, including robust values for Cramer's V and Phi coefficients, validate the AI tool's predictive accuracy. Together, these findings offer compelling evidence for the tool's application in large-scale mental health screenings. By integrating AI-based screening into clinical settings, healthcare providers can streamline the identification of individuals requiring further psychiatric evaluation, thus enabling early intervention and potentially alleviating the burden on mental health services. This has substantial implications for preventive mental health care, suggesting that AI tools can enhance early detection efforts on a broader scale.

5.5. Assessing the Impact of AI Intervention on Anxiety Using Two-Way Repeated Measures ANOVA

The analysis conducted with a two-way repeated measures ANOVA provided valuable insights into the impact of the AI-based intervention on anxiety levels, evaluating the main effects of Time (Pre-test vs. Post-test) and Treatment Group (Experimental vs. Control) and their interaction. Results indicated a highly significant main effect of Time on anxiety scores, ($F(1,130) = 1021.445$, $p < .001$), with a substantial effect size (Partial Eta Squared = .887), highlighting a prominent reduction in anxiety levels over time across both groups. However, the Time × Treatment Group interaction effect, also significant ($F(1,130) = 248.970$, $p < .001$, Partial Eta Squared = .657), underscores that this reduction was more pronounced in the experimental group than in the control group. This indicates that the AI-based intervention significantly augmented the decline in anxiety scores in participants exposed to the intervention, confirming its efficacy.

Additionally, a significant main effect of the Treatment Group ($F(1,130) = 4.317$, $p = .040$, Partial Eta Squared = .032) highlights that overall, the experimental group demonstrated lower anxiety scores compared to the control group. The descriptive statistics reveal that the mean anxiety score for the experimental group decreased from 30.45 (Pre-test) to 21.47 (Post-test), while for the control group, scores declined from 30.38 to 27.33. This data substantiates the notion that the AI intervention was notably more effective in alleviating anxiety than standard treatments, underscoring the potential of AI-enhanced therapeutic approaches in clinical practice.

5.6. Assessing the Impact of AI Intervention on Depression Using Two-Way Repeated Measures ANOVA

The two-way repeated measures ANOVA for depression scores also yielded significant findings, mirroring the results seen for anxiety. The main effect of Time on depression was significant, ($F(1,130) = 974.345$, $p < .001$), with a large effect size (Partial Eta Squared = .882), signifying a substantial reduction in depression levels from pre-test to post-test in both groups. Crucially, the interaction effect between Time and Treatment Group ($F(1,130) = 234.56$, $p < .001$, Partial Eta Squared = .645) suggests that this reduction was more pronounced in the experimental group, emphasizing the added impact of the AI-based intervention.

The main effect of Treatment Group was also significant ($F(1,130) = 4.11$, $p = .045$, Partial Eta Squared = .031), indicating a marked difference in overall depression scores between the two groups. Descriptive statistics further illustrate that the experimental group showed a larger reduction in depression scores, highlighting the efficacy of the AI intervention. Overall, these results provide robust evidence for the effectiveness of AI-based interventions in reducing both anxiety and depression, surpassing the impact of standard treatment options. This demonstrates the therapeutic potential of AI-enhanced treatments in addressing complex mental health issues, with significant implications for the future of mental health interventions.

5.7. Discussion of Qualitative Analysis Results Using Thematic Analysis:

Our study aimed to explore the nuanced experiences of individuals utilizing AI-based mental health applications. Utilizing Braun and Clarke's (2006) framework for thematic analysis, we systematically identified and analyzed patterns within the qualitative data, leading to the development of twelve key themes. The selection of 30 participants, guided by the recommendations of Hennink and Kaiser (2022) and Vasileiou et al. (2018), was instrumental in capturing a wide range of perspectives. By maintaining a manageable sample size, we ensured a depth of insight that allowed for the exploration of detailed user experiences, enhancing the study's validity. This strategic approach underscored the importance of both diversity and depth in understanding complex themes that emerged from users’ interactions with AI-based mental health tools.

The emergent themes shed light on the multifaceted roles these applications play in mental health care. For instance, themes like Accessibility and Convenience, along with Privacy and Confidentiality, resonate with the needs of users seeking readily available mental health support in a secure, private setting. Moreover, themes related to Personalization and Tailored Feedback, Positive Reinforcement, and Holistic Mental Health Support point to the applications' capacity to deliver tailored, continuous support—an advantage that traditional modalities often cannot provide to the same extent. These findings suggest that AI-driven applications can serve as powerful adjuncts to conventional therapeutic options, addressing gaps in accessibility and enhancing user engagement through features that align with individual needs. Furthermore, the emergence of themes such as Community Connection and Support highlights how these tools offer not only professional help but also a sense of community, emphasizing the collaborative nature of digital mental health solutions.

5.8. Discussion of Qualitative Themes from AI-based Mental Health Applications

The thematic analysis revealed twelve overarching themes that encapsulate the diverse experiences of users, providing a comprehensive understanding of how AI tools impact mental health management. By grounding these themes in empirical research, our findings contribute to a deeper understanding of user engagement, accessibility, and the efficacy of AI-driven mental health applications, underscoring their potential to enhance mental health care practices. These themes highlight critical dimensions of user experiences that can inform future developments in AI tools designed to support mental health.

The theme of Accessibility and Convenience emerged as a cornerstone of user satisfaction, with participants emphasizing the advantage of having mental health resources available at any time. This continuous access allows users to seek help when they need it most, reinforcing the potential for timely interventions. Such findings underscore the ability of AI-based tools to dismantle barriers to mental health care, suggesting that they can serve as vital resources for individuals unable to engage with traditional therapy schedules. This increased accessibility can lead to improved emotional regulation and greater engagement with mental health strategies.

The critical theme of Privacy and Confidentiality highlighted participants' need for a safe space to share personal experiences. The assurance that their data was protected fostered a willingness to engage openly with the app, which is essential for effective mental health management. This finding emphasizes that AI tools must prioritize user privacy, as it directly impacts comfort levels and engagement. Understanding this aspect is crucial for developers aiming to create environments conducive to self-disclosure and therapeutic growth.

The significance of Personalization and Tailored Feedback was underscored by participants' appreciation for customized advice that resonated with their unique situations. This theme highlights the effectiveness of personalized interventions in enhancing user satisfaction and outcomes. Recognizing individual needs not only fosters a sense of understanding and support but also suggests that AI applications can effectively cater to diverse user profiles, reinforcing their potential in mental health care.

The User-Friendly Interface theme underscored the importance of intuitive design in promoting engagement. Participants noted that the app's simplicity facilitated easy navigation, which is particularly crucial for those less technologically inclined. This finding suggests that user-friendly designs can significantly enhance the adoption and sustained use of digital mental health tools, making them accessible to a broader audience and encouraging consistent engagement.

Participants’ favorable responses to Positive Reinforcement and Motivation emphasized how feedback mechanisms encouraged continued engagement with mental health practices. This theme illustrates that positive reinforcement can enhance adherence to mental health strategies, promoting a sense of achievement among users. By fostering motivation, these applications can play a vital role in improving overall mental well-being, highlighting the significance of engaging users actively in their mental health journeys.

The theme of Holistic Mental Health Support revealed that participants valued a comprehensive approach to mental health care, appreciating the app's ability to address various aspects of well-being. By integrating resources related to sleep, nutrition, and emotional support, users felt more equipped to manage their mental health. This finding underscores the necessity of adopting a holistic perspective in mental health applications, ensuring that users can address multiple dimensions of their well-being.

The desire for social interaction, captured in the Community Connection and Support theme, reflects participants' appreciation for forums that facilitated shared experiences. These features not only reduced feelings of isolation but also fostered a sense of belonging among users. This finding emphasizes the importance of community aspects in AI applications, which can significantly enhance users’ emotional support systems and overall mental health.

The theme of Crisis Management Tools highlighted the critical role these resources play for users experiencing acute distress. The ability to access coping techniques during panic attacks provided significant relief, underscoring the potential of AI tools to offer immediate assistance in crises. This finding reaffirms the value of integrating crisis intervention strategies within mental health applications, positioning them as valuable adjuncts to traditional mental health care.

Participants expressed gratitude for the insights gained from Behavioral Tracking and Self-Awareness, enabling them to identify patterns and triggers related to their mood. This theme highlights the importance of self-awareness in mental health care, illustrating how AI tools can facilitate personal growth and informed decision-making. By promoting self-reflection, these applications can empower users to take proactive steps in managing their mental health.

The theme of Integration into Daily Life emphasized how well the app’s features fit into participants’ routines. Timely reminders for mindfulness practices and breaks were seen as supportive rather than disruptive, demonstrating that effective mental health interventions must be seamlessly integrated into users' lifestyles. This finding suggests that the success of digital mental health tools relies on their ability to promote sustainable habits over time.

The incorporation of gamification elements in mental health management emerged as a key theme, with participants expressing enjoyment in engaging with the app's challenges. This finding suggests that gamification can be an effective strategy for enhancing user retention and motivation, leading to better mental health outcomes. By making the process enjoyable, AI applications can encourage users to maintain consistent engagement with their mental health practices.

Finally, the theme of Direct Pathways to Professional Help underscores the importance of having accessible connections to mental health professionals. Participants valued the ease of finding therapists through the app, which provided reassurance during challenging times. This finding highlights the role of AI tools in bridging gaps between users and professional support, enhancing the overall mental health journey.

Collectively, these themes illuminate the multifaceted benefits of AI-based mental health applications, indicating their capacity to improve user engagement, accessibility, and mental health outcomes. The insights garnered from this qualitative exploration reflect a growing acceptance of technology as a supportive tool in managing mental health challenges. Participants also provided constructive feedback on areas for improvement, such as enhancing the responsiveness of the AI model and expanding the range of psychotherapeutic content.

5.9. Limitations

The findings underscore the promise of AI-driven mental health applications, however certain restrictions require consideration. The study's sample size, although sufficient for qualitative depth, may restrict generalisability to wider populations, especially those from varied socio-cultural or technological contexts. Moreover, dependence on self-reported data creates the potential for response bias, as individuals may understate or exaggerate their experiences. The identified themes, while thorough, may not encompass the subtle differences in user demands or experiences that lie outside the study's parameters. The efficacy of the applications in treating severe mental health issues is uncertain, as the study only examined experiences with mild to moderate symptoms. Ultimately, technological obstacles, such app accessibility for persons with minimal digital literacy or those in resource-constrained environments, may hinder the broader implementation of these solutions.

5.10. Recommendations

Subsequent revisions of AI-driven mental health applications must concentrate on rectifying the observed deficiencies. Developers must prioritise inclusive designs that accommodate various populations, integrating multilingual assistance and interfaces customised for persons with differing degrees of digital literacy. Improving data privacy rules and effectively conveying these safeguards to users could further mitigate worries about confidentiality. Enhancing the scope of psychotherapy content to incorporate evidence-based interventions for severe mental health conditions, such as suicidality or trauma, could amplify the applications' efficacy. Moreover, incorporating real-time AI responsiveness alongside intermittent human supervision may guarantee that consumers obtain nuanced, contextually relevant assistance. While gamification components are valued, they might be enhanced to sustain long-term involvement while prioritising therapeutic objectives.

5.11. Suggestions

The study recommends collaboration between AI developers and mental health practitioners to improve the design and execution of these applications. Efforts must focus on developing tools that are user-centric and clinically sound, integrating feedback from various user groups throughout the development process. Policymakers and stakeholders ought to allocate resources to enhance access to these technologies, especially in marginalised groups, to address current disparities in mental health care. Moreover, enhancing public awareness of the advantages and constraints of AI-driven products can enable informed decision-making among prospective users. Ultimately, longitudinal studies must be conducted to assess the long-term effectiveness and sustainability of these applications, ensuring their significant contribution to global mental health programs.

5.12. Conclusion:

The findings from this study offer valuable insights into the potential of AI-based mental health applications to support individuals on their well-being journeys. By understanding user experiences, researchers and developers can enhance the effectiveness and accessibility of these tools, ultimately improving mental health care. This research not only highlights the complexity of user interactions with AI mental health applications but also underscores the need for ongoing development and refinement to meet the diverse needs of individuals seeking support. The integration of both quantitative and qualitative findings provides a comprehensive evaluation of the NeuraMap app's effectiveness as a digital mental health tool, suggesting practical implications for the use of AI in managing anxiety and depression. Future directions will involve refining the AI algorithms based on user feedback and expanding the app's capabilities to include additional therapeutic modalities, ensuring it continues to meet the evolving needs of its users.

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APPENDIX

NeuraMap Anxiety Scale (NMAS)

Name	
Gender	
Age	

Instructions:

This test aims to assess the frequency of anxiety symptoms you have experienced in the past week. Please remember that there are no right or wrong answers. Be honest and select the option that best reflects your experiences. Read each statement carefully and choose the response that most closely aligns with how often you have experienced that symptom. Answer based on your experiences over the past week.

Assign a score of 0, 1, 2, or 3 to each statement based on your response.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

Scoring:

After answering all the statements, add up your scores for each item to calculate the total score. The total score represents the severity of your anxiety symptoms.

Interpretation:

The NeuraMap Anxiety Scale comprises 15 statements, with each response being assigned a value ranging from 0 to 3. The scale employs cutoffs, with scores of 0-13 indicating minimal anxiety, 14-19 indicating mild anxiety, 20-28 indicating moderate anxiety, and 29-51 indicating severe anxiety. Higher total scores are indicative of more severe anxiety symptoms.

1. I worry about bad things happening or things going wrong.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

2. I often find myself feeling restless, unable to stay calm, and constantly on edge.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

3. I have trouble concentrating or staying focused.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

4. I feel tension or tightness in my muscles, especially in my neck, shoulders, or back.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

5. I have trouble sleeping or experience restless sleep because of anxiety.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

6. I often experience headaches, trembling, twitching, or shaking as a result of feeling nervous.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

7. When I'm anxious or stressed, I often experience feelings of lightheadedness, dizziness, or a sensation that I might faint.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

8. When I'm anxious or stressed, I tend to sweat excessively, get hot flashes, or have sweaty palms.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

9. When I'm anxious or stressed, I frequently experience a rapid or irregular heartbeat and may feel short of breath.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

10. I experience physical symptoms like nausea, stomachaches, digestive problems, dry mouth, difficulty swallowing, and a lump in my throat when I feel anxious or stressed.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

11. I have racing thoughts, excessive worry, or find it hard to make decisions because of anxiety.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

12. I tend to avoid certain situations or activities, particularly social situations, as they tend to make me feel anxious or distressed.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

13. I frequently find myself dealing with distressing thoughts or images that repeatedly come to my mind without my control and are closely related to my anxiety.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

14. I have difficulty relaxing or find it hard to let go of tension and stress.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

15. I feel irritable or easily agitated because of anxiety.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

NeuraMap Depression Scale (NMDS)

Name	
Gender	
Age	

Instructions:

This test aims to assess the intensity of depression symptoms you have experienced in the past week. Please remember that there are no right or wrong answers. Be honest and select the option that best reflects your experiences. Read each statement carefully and choose the response that most closely aligns with how often you have experienced that symptom. Answer based on your experiences over the past week.

Assign a score of 0, 1, 2, or 3 to each statement based on your response.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

Scoring:

After answering all the statements, add up your scores for each item to calculate the total score. The total score represents the severity of your depression symptoms.

Interpretation:

The NeuraMap Depression Scale comprises 20 statements, with each response being assigned a value ranging from 0 to 3. The scale employs cutoffs, with scores of 0-13 indicating minimal Depression, 14-19 indicating mild Depression, 20-28 indicating moderate Depression, and 29-51 indicating severe Depression. Higher total scores are indicative of more severe Depression symptoms.

1. I have felt sad or down most of the time.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

2. I have lost interest or enjoyment in things I used to love.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

3. I have felt very tired or lacking energy.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

4. I have had trouble concentrating or staying focused.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

5. I have felt guilty, worthless, or excessively self-critical.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

6. I have had negative thoughts about the future or a sense of hopelessness or a negative outlook.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

7. I have had thoughts of self-harm or suicide.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

8. I have experienced difficulties with sleep (e.g., trouble falling asleep, staying asleep, or waking up too early).

0: No difficulties

1: Mild and occasional difficulties

2: Moderate and frequent difficulties

3: Severe and persistent difficulties

9. I have noticed significant changes in my appetite or weight, (experiencing either an increase or decrease in hunger and body weight).

0: No change

1: Mild change

2: Moderate change

3: Severe change

10. I have experienced significant slowing down in my movements and thoughts.

0: No Change

1: Mild slowing down

2: Moderate slowing down

3: Severe slowing down

11. I always feel inadequate and hopeless about the future.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

12. I have consistently felt like a failure in everything I've attempted.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

13. I have experienced moments where I feel like something bad might happen,

16. I have had difficulty connecting with others or feeling emotionally distant.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

17. I have lost motivation or interest in completing tasks.

anticipating punishment, and even feeling like I'm being punished.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

14. I blame myself for everything and find fault in all that I do.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

15. I often find myself crying due to overwhelming sadness and disappointment.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

18. I have had trouble getting things done or being productive.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

19. I have struggled with making decisions or felt unsure.

0: Never or rarely

1: Occasionally or sometimes

2: Moderately or frequently

3: Often or most of the time

20. I have noticed a decrease in my sexual drive or interest.

0: No change

1: Mild change

2: Moderate change

3: Severe change

THE WHOQOL-BREF

ABOUT YOU I.D. number

Before you begin we would like to ask you to answer a few general questions about yourself: by circling the correct answer or by filling in the space provided.

What is your **gender**? Male Female

What is your **date of birth**? ______ / ______ / ______
Day / Month / Year

What is the highest **education** you received?

None at all
Primary school
Secondary school
Tertiary

What is your **marital status**?

Single
Married
Living as married
Separated
Divorced
Widowed

Are you currently **ill**? Yes No

If something is wrong with your health what do you think it is?___________

Instructions

This assessment asks how you feel about your quality of life, health, or other areas of your life. **Please answer all the questions.** If you are unsure about which response to give to a question, **please choose the one** that appears most appropriate. This can often be your first response.

Please keep in mind your standards, hopes, pleasures and concerns. We ask that you think about your life **in the last two weeks.** For example, thinking about the last two weeks, a question might ask:

	Do you get the kind of support from others that you need?	Not at all 1	Not much 2	Moderately 3	A great deal 4	Completely 5

You should circle the number that best fits how much support you got from others over the last two weeks. So you would circle the number 4 if you got a great deal of support from others as follows.

	Do you get the kind of support from others that you need?	Not at all 1	Not much 2	Moderately 3	A great deal 4	Completely 5

You would circle number 1 if you did not get any of the support that you needed from others in the last two weeks. Please read each question, assess your feelings, and circle the number on the scale for each question that gives the best answer for you.

THE WHOQOL-BREF

		Very poor	Poor	Neither poor nor good	Good	Very good
1 (G1)	How would you rate your quality of life?	1	2	3	4	5

		Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
2 (G4)	How satisfied are you with your health?	1	2	3	4	5

The following questions ask about **how much** you have experienced certain things in the last two weeks.

		Not at all	A little	A moderate amount	Very much	An extreme amount
3 (F1.4)	To what extent do you feel that (physical) pain prevents you from doing what you need to do?	1	2	3	4	5
4 (F11.3)	How much do you need any medical treatment to function in your daily life?	1	2	3	4	5
5 (F4.1)	How much do you enjoy life?	1	2	3	4	5
6 (F24.2)	To what extent do you feel your life to be meaningful?	1	2	3	4	5

		Not at all	A little	A moderate amount	Very much	Extremely
7 (F5.3)	How well are you able to concentrate?	1	2	3	4	5

8 (F16.1)	How safe do you feel in your daily life?	1	2	3	4	5
9 (F22.1)	How healthy is your physical environment?	1	2	3	4	5

The following questions ask about **how completely** you experience or were able to do certain things in the last two weeks.

		Not at all	A little	Moderately	Mostly	Completely
10 (F2.1)	Do you have enough energy for everyday life?	1	2	3	4	5
11 (F7.1)	Are you able to accept your bodily appearance?	1	2	3	4	5
12 (F18.1)	Have you enough money to meet your needs?	1	2	3	4	5
13 (F20.1)	How available to you is the information that you need in your day-to-day life?	1	2	3	4	5
14 (F21.1)	To what extent do you have the opportunity for leisure activities?	1	2	3	4	5

		Very poor	Poor	Neither poor nor good	Good	Very good
15 (F9.1)	How well are you able to get around?	1	2	3	4	5

The following questions ask you to say how **good or satisfied** you have felt about various aspects of your life over the last two weeks.

		Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
16 (F3.3)	How satisfied are you with your sleep?	1	2	3	4	5
17 (F10.3)	How satisfied are you with your ability to perform your daily living activities?	1	2	3	4	5
18 (F12.4)	How satisfied are you with your capacity for	1	2	3	4	5

	work?					
19 (F6.3)	How satisfied are you with yourself?	1	2	3	4	5
20 (F13.3)	How satisfied are you with your personal relationships?	1	2	3	4	5
21 (F15.3)	How satisfied are you with your sex life?	1	2	3	4	5
22 (F14.4)	How satisfied are you with the support you get from your friends?	1	2	3	4	5
23 (F17.3)	How satisfied are you with the conditions of your living place?	1	2	3	4	5
24 (F19.3)	How satisfied are you with your access to health services?	1	2	3	4	5
25 (F23.3)	How satisfied are you with your transport?	1	2	3	4	5

The following question refers to **how often** you have felt or experienced certain things in the last two weeks.

		Never	Seldom	Quite often	Very often	Always
26 (F8.1)	How often do you have negative feelings such as blue mood, despair, anxiety, depression?	1	2	3	4	5

Did someone help you to fill out this form?..

How long did it take to fill this form out?..