MentSDet: concept of mobile-oriented multimodal information system for determining the patient's mental state*

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Abstract
Conducted analysis of the known methods and tools for determining mental state of patients revealed that despite the significant number of available methods and tools for determining mental state of patients, evidence-based methods and tools (for example, using the Diagnostic and Statistical Manual of Mental Disorders (DSM-5)) are currently underdeveloped. For the design and development of a mobile-oriented multimodal information system for determining patient's mental state, MentSDet, we will use the criteria for determining and classifying mental disorders (in particular, anxiety disorders, depression disorders, trauma- and stressor-related disorders, obsessive-compulsive disorders) using DSM-5. MentSDet, a mobile-oriented multimodal information system for determining the patient's mental state, developed in this article, offers a questionnaire(s) to the patient or his or her family to determine the presence of a specific mental disorder and, on the basis of the received answers, sends the patient, his/her family and psychiatrist notifications about the presence/absence of a particular mental disorder, and the mental disorder's type and severity, i.e., it allows not to miss the onset of the disease, the beginning of the exacerbation period, or to assess the effectiveness of treatment. The proposed information system is an automated and objective diagnostic tool for the early detection of mental disorders.

Keywords
Information system, multimodality, MentSDet mobile application, mental state, Diagnostic and Statistical Manual of Mental Disorders (DSM-5)

1. Introduction

Mental health (as a state of wellbeing where an individual is capable of fulfilling their potential and managing everyday stress effectively, work effectively and productively, and contribute to the life of their community [1]) affects the physical state of the body, social

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relationships, quality of life, etc. Talking about mental health can be difficult, but recognizing the problem means that there is a way to solve it. It is very important to get rid of the shame and fear that often accompany mental health topics, because this increases the likelihood that someone experiencing mental health issues will seek help when they need it. Taking care of mental health can increase productivity and self-esteem, improve relationships with people, and prevent the development of mental disorders [2]. In last years, the prevalence of mental health disorders has been steadily on the rise. The increasing prevalence of mental health disorders presents a significant challenge in today's world.

According to WHO estimates: around one in eight individuals worldwide experiences a mental health disorder, there are currently 970 million people with mental disorders, 129 million people have a disability due to mental disorders, every year around 1 million people take their own lives, and one in four families has at least one member living with a mental health disorder [3]. The COVID-19 pandemic has sparked a global mental health crisis, heightening both immediate and long-term stress factors and profoundly affecting the mental well-being of millions around the world – for example, anxiety and depressive disorders are estimated to have increased by more than 25% during the first year of the pandemic [3].

At this point in time, mental disorders are widespread, undertreated and under-resourced – Fig. 1 [3].

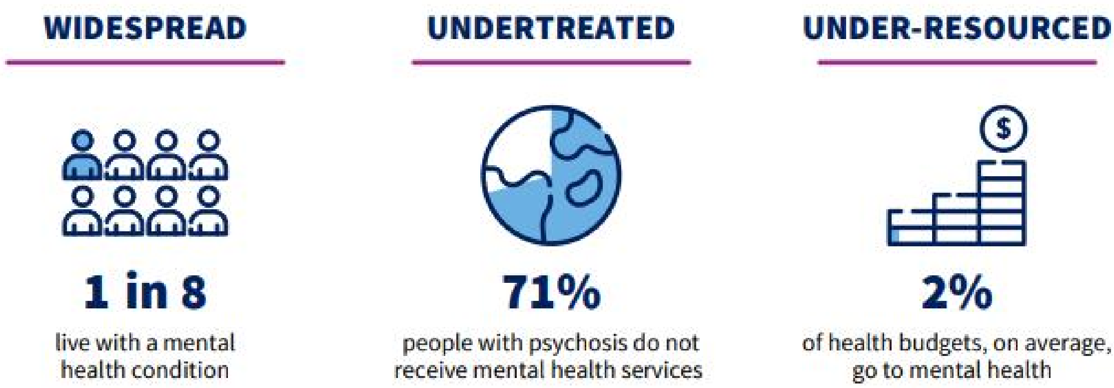

Figure 1: Widespreadness and resource-treated of treatment for mental disorders [3].

The widespreadness of mental disorders by their types in the world is shown in Fig. 2 [3]. It is clear that anxiety disorders (31%) and depressive disorders (28.9%) are the most prevalent.

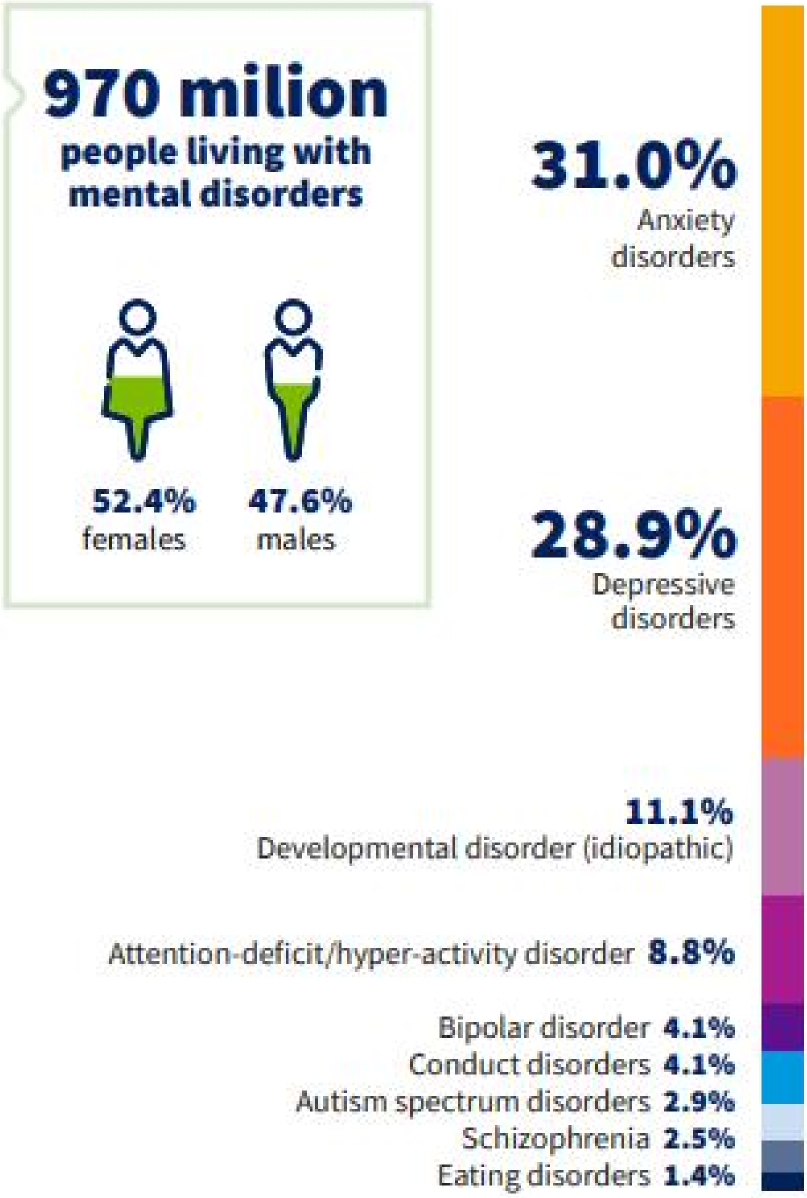

Figure 2: Widespreadness of mental disorders by their types [3].

The war, in which Ukraine has been living for 10 years, takes away people's lives and health, separates them, forces them to leave their homes and jobs, and completely changes their daily routine. Because of the war, people have the experience of unavoidable losses, living under occupation, being in captivity, and being subjected to violence. All this affects their mental state. The problem of mental health is even more acute for combatants and veterans. According to WHO estimates, one in five people in Ukraine already lives with some form of mental disorder [2]. According to statistics, 15 million Ukrainian citizens are in need of professional psychological assistance, including 3-4 million who need medication [4]. In addition, 90% of veterans and their family members need psychological assistance, including about 30% who have posttraumatic stress disorder (PTSD) and obsessive-compulsive disorders.

Mental disorders need to be detected at an early stage to prevent negative health consequences and to find effective treatment quickly [5]. Incorrect diagnoses and treatment delays can lead to the development of conditions such as major depressive disorder and bipolar disorder. Misdiagnoses may result in unsuitable therapies, while delays in treatment can worsen symptoms, hinder daily functioning, and reduce the effectiveness of interventions. If mental health problems are recognized at an early stage, they can be dealt with more quickly and easily. In this case, they are less likely to affect a person's relationships with loved ones, work or school, or disrupt daily life [6, 7]. In addition, the sooner a person receives qualified support for mental health conditions, the more likely they are to be able to cope with their condition. Early detection of mental health disorders is important for preventing the worst outcomes, reducing the risk of suicide, increasing the effectiveness of therapy, improving overall well-being, and providing cost-effective treatments [8, 9]. Mental health screening involves a comprehensive approach that includes: observation of the patient, history taking from the patient, history taking from those around the patient, and the results of additional screening methods [10-12].

Given that information systems and technologies make modern medicine more accessible, qualitative and functional, and that they provide patients with greater opportunities for accurate diagnosis and monitoring of their health (including mental health) [13-15], that medical information systems and technologies facilitate the possibility of continuous monitoring of patients' health status as needed [16-18], that Conventional diagnostic methods largely depend on psychiatrists' subjective evaluations, highlighting the crucial need for developing automated and objective diagnostic tools [19-21], then for the early detection of mental disorders, a mobile-oriented information system is *relevant*, which will offer the patient a test to assess his or her mental state, which will vary depending on the diagnosis (since the system is designed not so much for self-diagnosis as for cooperation with a psychiatrist), send notifications to the patient, his or her relatives and the psychiatrist about the beginning of the exacerbation period, and evaluate the effectiveness of treatment (assess whether the symptoms have disappeared after the start of treatment).

2. Review of existing methods and tools

Let's examine the established methods, tools, which used for determining the mental state of patients.

Paper [19] presents novel computer aided depression detection system IntervoxNet, which is designed for analyzing the interview audio with using the convolutional neural network (BERT-CNN). IntervoxNet is an effective and efficient tool designed for the rapid screening of depression through interviews. The paper [22] discusses the application of BERT, an innovative deep-learning transformer model, for detecting depression levels using textual data as input. Meanwhile, the study in paper [23] evaluates the effectiveness of three natural language processing models – BERT, GPT-3.5, and GPT-4 – by comparing their performance on three distinct datasets for identifying depression from text data. The research [24] shows the use of machine learning-based models for accurate depression diagnosis. The primary goal of this research is to improve early diagnosis, risk assessment, and patient care in the field of depression detection utilizing predictive models. The paper [25] presents a novel approach for the automatic identification of early-stage adolescent depression using advanced deep multimodal learning techniques. The unimodal features are extracted from electroencephalography(EEG), electrocardiogram(ECG), speech signals and subsequently fused into a comprehensive multimodal feature set for binary classification.

The paper [26] introduces a new method for detecting and preventing student depression using machine learning techniques, which focuses on face recognition using Convolutional Neural Networks (CNN) and voice recognition. The proposed system analyzes students' facial expressions and voice patterns to identify signs of depression.

Using pretrained language models is critical in data-scarce research areas, such as early detection of mental health issues. Pretrained language model MentalHealthBERT use the content about anorexia, depression and self-harm from Reddit social media [27].

The paper [28] examines the use of various techniques based on natural language processing and transformer-based techniques, such as TF-IDF, n-grams, BERT, RoBERTa, and ALBERT, foe analyzing the textual data from diverse social media platforms towards mental health and stress prediction.

The paper [29] explores two machine learning algorithms (K-nearest neighbors (KNN) and Recurrent Neural Networks (RNN)) for mental health prediction based on the data analysis on mental health patients' demographics, health, and long-term habits.

Using advanced artificial intelligence techniques and machine learning algorithms (LSTM and SVM), the system developed in [30] effectively analyzes users' social media behavior for determination of depression, is a tool designed for the early detection of mental health issues, providing valuable insights into individuals' mental well-being through the analysis of textual emotional intelligence. The study [31] introduces a new machine-learning model called AL-BTCN for identifying suicide risk based on posts from social media platforms such as Twitter (X) and Reddit, utilizing both natural language processing and advanced deep learning techniques. In study [32], text classification models are developed to predict the severity of suicidal ideation, alongside a prototype web application designed to evaluate ideation severity and support self-therapy using cognitive behavioral therapy. Furthermore, research in [33] presents a framework for detecting suicidal ideation on social media, utilizing machine learning and genetic algorithms.

The authors of [34] introduce LLMental, a tool designed to classify mental disorders such as depression, excessive stress, and social phobia through the analysis of social media posts using modified large language models (including PHI-2, Mistral, Flan-T5, and LLaMA 2).

In diagnosing epilepsy, electroencephalography (EEG) signals are utilized. However, the human analysis and interpretation of these signals for the early detection of epilepsy can lead to errors. The study in [35] explores the analysis of EEG signals related to epileptic seizures using proposed automated methods, FCM-PSO-LSTM and PSO-LSTM, aimed at improving the early detection of stress and anxiety-induced seizures.

Paper [36] reviews various deep learning algorithms for EEG analysis, focusing especially on Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) for early-stage detection and assessment of mental stress.

The study in [37] proposes a machine learning approach to detect stress in natural settings using wearable sensors that track vital signs, such as heart rate and physical activity. Additionally, the study [38] investigates the effects of applying two common text representation techniques – Term Frequency-Inverse Document Frequency (TF-IDF) and Bag-of-Words (BoW) – to the task of stress detection.

The research presented in [39] introduces an innovative technology known as Effective Stress Detection. This technology leverages ontology to identify signs of stress among social media users. By employing ontology, it can comprehensively analyze user-generated content for indicators of stress. Additionally, this approach initiates necessary preventive measures that could help prevent users from falling into severe depression or even contemplating suicide.

In [40], the authors collected data on patients with current depressive symptoms using a detailed digital mental health questionnaire, based on the World Health Organization's World Mental Health Composite International Diagnostic Interview. They trained and validated gradient-boosted tree algorithms to identify key predictors of misdiagnosis, providing a machine learning-based perspective on the complex factors that may lead to diagnostic errors.

Paper [41] presents a dialogue system (chatbot) developed in collaboration with a clinical psychiatrist. This system assesses individuals' mental states and provides personalized feedback tailored to the severity of their mental health issues.

The review [42] examines the mobile-based applications with cognitive tests for dementia early detection. In paper [43], dementia is predicted using MRI images, for which three distinct datasets of MRI images have been compiled. To enhance prediction accuracy, several machine learning models are employed, including K-Nearest Neighbors, XGBoost, Support Vector Machine, Random Forest Algorithm (RFA), and Convolutional Neural Network (CNN). The performance of these models is validated through statistical analysis. Authors of [44] propose a methodology for late-life depression automated classification based on an advanced diffusion tensor imaging segmentation framework and artificial intelligence for early detection late-life depression and dementia.

The authors of [45] developed an Adaptive Multi-End Fusion Attention Mechanism tailored for extracting information about the human body within a deep learning framework. This mechanism relies on human expressions, postures, and environmental factors to effectively assess an individual's mental health.

Paper [46] examines human personality by utilizing the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria to evaluate depressive episodes, along with Eysenck's personality traits questionnaire, which consists of 66 questions organized into six forms for assessing personality traits. Multiple machine learning models (in particular, the effective Support Vector Machine classifier) are used for questionnaire results processing and predictions forming.

An analysis of existing methods and tools for assessing patients' mental state revealed that, despite the wide range of available options, evidence-based approaches (such as those utilizing the Diagnostic and Statistical Manual of Mental Disorders (DSM-5)) remain insufficiently developed.

3. Criteria for determining and classifying the mental disorders using DSM-5

Before creation of the system for determining the mental state of patients based on evidence-based psychiatry, let's look at the basics of determining and classifying mental disorders. The

Introduction identifies anxiety disorders and depression as the most prevalent, with post-traumatic stress disorder and obsessive-compulsive disorder also being significant in the context of Ukraine. Therefore, the criteria for diagnosing these four mental disorders using the DSM-5 [47] will be examined. The Diagnostic and Statistical Manual of Mental Disorders (DSM) provides a classification system for mental disorders with specific criteria aimed at improving the reliability of diagnoses.

Depression disorders can be of varying severity. For example, the criteria for determining major depressive disorder are shown in Fig. 3 [47]. Similarly, [47] provides criteria for the determination of persistent depressive disorder (dysthymia), disruptive mood dysregulation disorder, substance/medication-induced depressive disorder, premenstrual dysphoric disorder, depressive disorder due to another medical condition, other specified depressive disorder, unspecified depressive disorder, etc.

Anxiety disorders can manifest in various forms. For instance, the criteria for diagnosing social anxiety disorder (social phobia) are shown in Fig. 4 [47]. Similarly, [47] provides criteria for the determination of selective mutism, separation anxiety disorder, panic disorder, specific phobia, agoraphobia, panic attack specifier, substance/medication-induced anxiety disorder, generalized anxiety disorder, anxiety disorder due to another medical condition, other specified anxiety disorder, unspecified anxiety disorder, etc.

Obsessive-compulsive disorders come in different forms. For example, the criteria for diagnosing obsessive-compulsive disorder are illustrated in Fig. 5 [47]. Similarly, [47] provides criteria for the determination of hoarding disorder, body dysmorphic disorder, excoriation (skin-picking) disorder, trichotillomania (hair-pulling disorder), obsessive-compulsive and related disorder due to another medical condition, substance/medication-induced obsessive-compulsive and related disorder, other specified obsessive-compulsive and related disorder, unspecified obsessive-compulsive and related disorder, etc.

Trauma- and stressor-related disorders can take various forms. For instance, the criteria for diagnosing post-traumatic stress disorder are shown in Fig. 6 [47]. Similarly, [47] provides criteria for the determination of disinhibited social engagement disorder, reactive attachment disorder, adjustment disorders, acute stress disorder, other specified trauma- and stressor-related disorder, unspecified trauma- and stressor-related disorder, etc.

To design and develop a mobile-oriented multimodal information system, MentSDet, for assessing a patient's mental state, we will utilize the DSM-5 criteria for diagnosing and classifying mental disorders, including anxiety disorders, depression, trauma- and stressor-related disorders, and obsessive-compulsive disorders.

Major Depressive Disorder

Diagnostic Criteria

A. Five (or more) of the following symptoms have been present during the same 2-week period and represent a change from previous functioning; at least one of the symptoms is either (1) depressed mood or (2) loss of interest or pleasure.

Note: Do not include symptoms that are clearly attributable to another medical condition.

1. Depressed mood most of the day, nearly every day, as indicated by either subjective report (e.g., feels sad, empty, hopeless) or observation made by others (e.g., appears tearful). (**Note:** In children and adolescents, can be irritable mood.)
2. Markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day (as indicated by either subjective account or observation).
3. Significant weight loss when not dieting or weight gain (e.g., a change of more than 5% of body weight in a month), or decrease or increase in appetite nearly every day. (**Note:** In children, consider failure to make expected weight gain.)
4. Insomnia or hypersomnia nearly every day.
5. Psychomotor agitation or retardation nearly every day (observable by others, not merely subjective feelings of restlessness or being slowed down).
6. Fatigue or loss of energy nearly every day.
7. Feelings of worthlessness or excessive or inappropriate guilt (which may be delusional) nearly every day (not merely self-reproach or guilt about being sick).
8. Diminished ability to think or concentrate, or indecisiveness, nearly every day (either by subjective account or as observed by others).
9. Recurrent thoughts of death (not just fear of dying), recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.

B. The symptoms cause clinically significant distress or impairment in social, occupational, or other important areas of functioning.

C. The episode is not attributable to the physiological effects of a substance or to another medical condition.

Note: Criteria A–C represent a major depressive episode.

Note: Responses to a significant loss (e.g., bereavement, financial ruin, losses from a natural disaster, a serious medical illness or disability) may include the feelings of intense sadness, rumination about the loss, insomnia, poor appetite, and weight loss noted in Criterion A, which may resemble a depressive episode. Although such symptoms may be understandable or considered appropriate to the loss, the presence of a major depressive episode in addition to the normal response to a significant loss should also be carefully considered. This decision inevitably requires the exercise of clinical judgment based on the individual's history and the cultural norms for the expression of distress in the context of loss.[1]

D. The occurrence of the major depressive episode is not better explained by schizoaffective disorder, schizophrenia, schizophreniform disorder, delusional disorder, or other specified and unspecified schizophrenia spectrum and other psychotic disorders.

E. There has never been a manic episode or a hypomanic episode.

Note: This exclusion does not apply if all of the manic-like or hypomanic-like episodes are substance-induced or are attributable to the physiological effects of another medical condition.

Figure 3: Criteria for determining major depressive disorder [47].

Obsessive-Compulsive Disorder

Diagnostic Criteria **300.3** (F42)

A. Presence of obsessions, compulsions, or both:

Obsessions are defined by (1) and (2):

1. Recurrent and persistent thoughts, urges, or images that are experienced, at some time during the disturbance, as intrusive and unwanted, and that in most individuals cause marked anxiety or distress.
2. The individual attempts to ignore or suppress such thoughts, urges, or images, or to neutralize them with some other thought or action (i.e., by performing a compulsion).

Compulsions are defined by (1) and (2):

1. Repetitive behaviors (e.g., hand washing, ordering, checking) or mental acts (e.g., praying, counting, repeating words silently) that the individual feels driven to perform in response to an obsession or according to rules that must be applied rigidly.
2. The behaviors or mental acts are aimed at preventing or reducing anxiety or distress, or preventing some dreaded event or situation; however, these behaviors or mental acts are not connected in a realistic way with what they are designed to neutralize or prevent, or are clearly excessive.

Note: Young children may not be able to articulate the aims of these behaviors or mental acts.

B. The obsessions or compulsions are time-consuming (e.g., take more than 1 hour per day) or cause clinically significant distress or impairment in social, occupational, or other important areas of functioning.

C. The obsessive-compulsive symptoms are not attributable to the physiological effects of a substance (e.g., a drug of abuse, a medication) or another medical condition.

D. The disturbance is not better explained by the symptoms of another mental disorder (e.g., excessive worries, as in generalized anxiety disorder; preoccupation with appearance, as in body dysmorphic disorder; difficulty discarding or parting with possessions, as in hoarding disorder; hair pulling, as in trichotillomania [hair-pulling disorder]; skin picking, as in excoriation [skin-picking] disorder; stereotypies, as in stereotypic movement disorder; ritualized eating behavior, as in eating disorders; preoccupation with substances or gambling, as in substance-related and addictive disorders; preoccupation with having an illness, as in illness anxiety disorder; sexual urges or fantasies, as in paraphilic disorders; impulses, as in disruptive, impulse-control, and conduct disorders; guilty ruminations, as in major depressive disorder; thought insertion or delusional preoccupations, as in schizophrenia spectrum and other psychotic disorders; or repetitive patterns of behavior, as in autism spectrum disorder).

Specify if:

With good or fair insight: The individual recognizes that obsessive-compulsive disorder beliefs are definitely or probably not true or that they may or may not be true.

With poor insight: The individual thinks obsessive-compulsive disorder beliefs are probably true.

With absent insight/delusional beliefs: The individual is completely convinced that obsessive-compulsive disorder beliefs are true.

Specify if:

Tic-related: The individual has a current or past history of a tic disorder.

Figure 5: Criteria for determining obsessive-compulsive disorder [47].

Social Anxiety Disorder (Social Phobia)

Diagnostic Criteria **300.23** (F40.10)

A. Marked fear or anxiety about one or more social situations in which the individual is exposed to possible scrutiny by others. Examples include social interactions (e.g., having a conversation, meeting unfamiliar people), being observed (e.g., eating or drinking), and performing in front of others (e.g., giving a speech).

Note: In children, the anxiety must occur in peer settings and not just during interactions with adults.

B. The individual fears that he or she will act in a way or show anxiety symptoms that will be negatively evaluated (i.e., will be humiliating or embarrassing; will lead to rejection or offend others).

C. The social situations almost always provoke fear or anxiety.

Note: In children, the fear or anxiety may be expressed by crying, tantrums, freezing, clinging, shrinking, or failing to speak in social situations.

D. The social situations are avoided or endured with intense fear or anxiety.

E. The fear or anxiety is out of proportion to the actual threat posed by the social situation and to the sociocultural context.

F. The fear, anxiety, or avoidance is persistent, typically lasting for 6 months or more.

G. The fear, anxiety, or avoidance causes clinically significant distress or impairment in social, occupational, or other important areas of functioning.

H. The fear, anxiety, or avoidance is not attributable to the physiological effects of a substance (e.g., a drug of abuse, a medication) or another medical condition.

I. The fear, anxiety, or avoidance is not better explained by the symptoms of another mental disorder, such as panic disorder, body dysmorphic disorder, or autism spectrum disorder.

J. If another medical condition (e.g., Parkinson's disease, obesity, disfigurement from burns or injury) is present, the fear, anxiety, or avoidance is clearly unrelated or is excessive.

Specify if:

Performance only: If the fear is restricted to speaking or performing in public.

Figure 4: Criteria for determining social anxiety disorder (social phobia) [47].

Posttraumatic Stress Disorder

Diagnostic Criteria **309.81** (F43.10)

Posttraumatic Stress Disorder

Note: The following criteria apply to adults, adolescents, and children older than 6 years. For children 6 years and younger, see corresponding criteria below.

A. Exposure to actual or threatened death, serious injury, or sexual violence in one (or more) of the following ways:

1. Directly experiencing the traumatic event(s).
2. Witnessing, in person, the event(s) as it occurred to others.
3. Learning that the traumatic event(s) occurred to a close family member or close friend. In cases of actual or threatened death of a family member or friend, the event(s) must have been violent or accidental.
4. Experiencing repeated or extreme exposure to aversive details of the traumatic event(s) (e.g., first responders collecting human remains; police officers repeatedly exposed to details of child abuse).

Note: Criterion A4 does not apply to exposure through electronic media, television, movies, or pictures, unless this exposure is work related.

B. Presence of one (or more) of the following intrusion symptoms associated with the traumatic event(s), beginning after the traumatic event(s) occurred:

1. Recurrent, involuntary, and intrusive distressing memories of the traumatic event(s).
   Note: In children older than 6 years, repetitive play may occur in which themes or aspects of the traumatic event(s) are expressed.
2. Recurrent distressing dreams in which the content and/or affect of the dream are related to the traumatic event(s).
   Note: In children, there may be frightening dreams without recognizable content.
3. Dissociative reactions (e.g., flashbacks) in which the individual feels or acts as if the traumatic event(s) were recurring. (Such reactions may occur on a continuum, with the most extreme expression being a complete loss of awareness of present surroundings.)
   Note: In children, trauma-specific reenactment may occur in play.
4. Intense or prolonged psychological distress at exposure to internal or external cues that symbolize or resemble an aspect of the traumatic event(s).
5. Marked physiological reactions to internal or external cues that symbolize or resemble an aspect of the traumatic event(s).

C. Persistent avoidance of stimuli associated with the traumatic event(s), beginning after the traumatic event(s) occurred, as evidenced by one or both of the following:

1. Avoidance of or efforts to avoid distressing memories, thoughts, or feelings about or closely associated with the traumatic event(s).
2. Avoidance of or efforts to avoid external reminders (people, places, conversations, activities, objects, situations) that arouse distressing memories, thoughts, or feelings about or closely associated with the traumatic event(s).

D. Negative alterations in cognitions and mood associated with the traumatic event(s), beginning or worsening after the traumatic event(s) occurred, as evidenced by two (or more) of the following:

1. Inability to remember an important aspect of the traumatic event(s) (typically due to dissociative amnesia and not to other factors such as head injury, alcohol, or drugs).
2. Persistent and exaggerated negative beliefs or expectations about oneself, others, or the world (e.g., "I am bad," "No one can be trusted," "The world is completely dangerous," "My whole nervous system is permanently ruined").
3. Persistent, distorted cognitions about the cause or consequences of the traumatic event(s) that lead the individual to blame himself/herself or others.
4. Persistent negative emotional state (e.g., fear, horror, anger, guilt, or shame).
5. Markedly diminished interest or participation in significant activities.
6. Feelings of detachment or estrangement from others.
7. Persistent inability to experience positive emotions (e.g., inability to experience happiness, satisfaction, or loving feelings).

E. Marked alterations in arousal and reactivity associated with the traumatic event(s), beginning or worsening after the traumatic event(s) occurred, as evidenced by two (or more) of the following:

1. Irritable behavior and angry outbursts (with little or no provocation) typically expressed as verbal or physical aggression toward people or objects.
2. Reckless or self-destructive behavior.
3. Hypervigilance.
4. Exaggerated startle response.
5. Problems with concentration.
6. Sleep disturbance (e.g., difficulty falling or staying asleep or restless sleep).

F. Duration of the disturbance (Criteria B, C, D, and E) is more than 1 month.

G. The disturbance causes clinically significant distress or impairment in social, occupational, or other important areas of functioning.

H. The disturbance is not attributable to the physiological effects of a substance (e.g., medication, alcohol) or another medical condition.

Figure 6: Criteria for determining posttraumatic stress disorder [47].

4. Concept of mobile-oriented multimodal information system for determining the patient's mental state

Let's create the concept for a mobile-oriented multimodal information system aimed at assessing a patient's mental state.

Considering the classic and well-known principles of designing and operating information systems [18], let's outline the structure of MentSDet, the mobile-oriented multimodal information system for patient's mental state determining (Fig. 7).

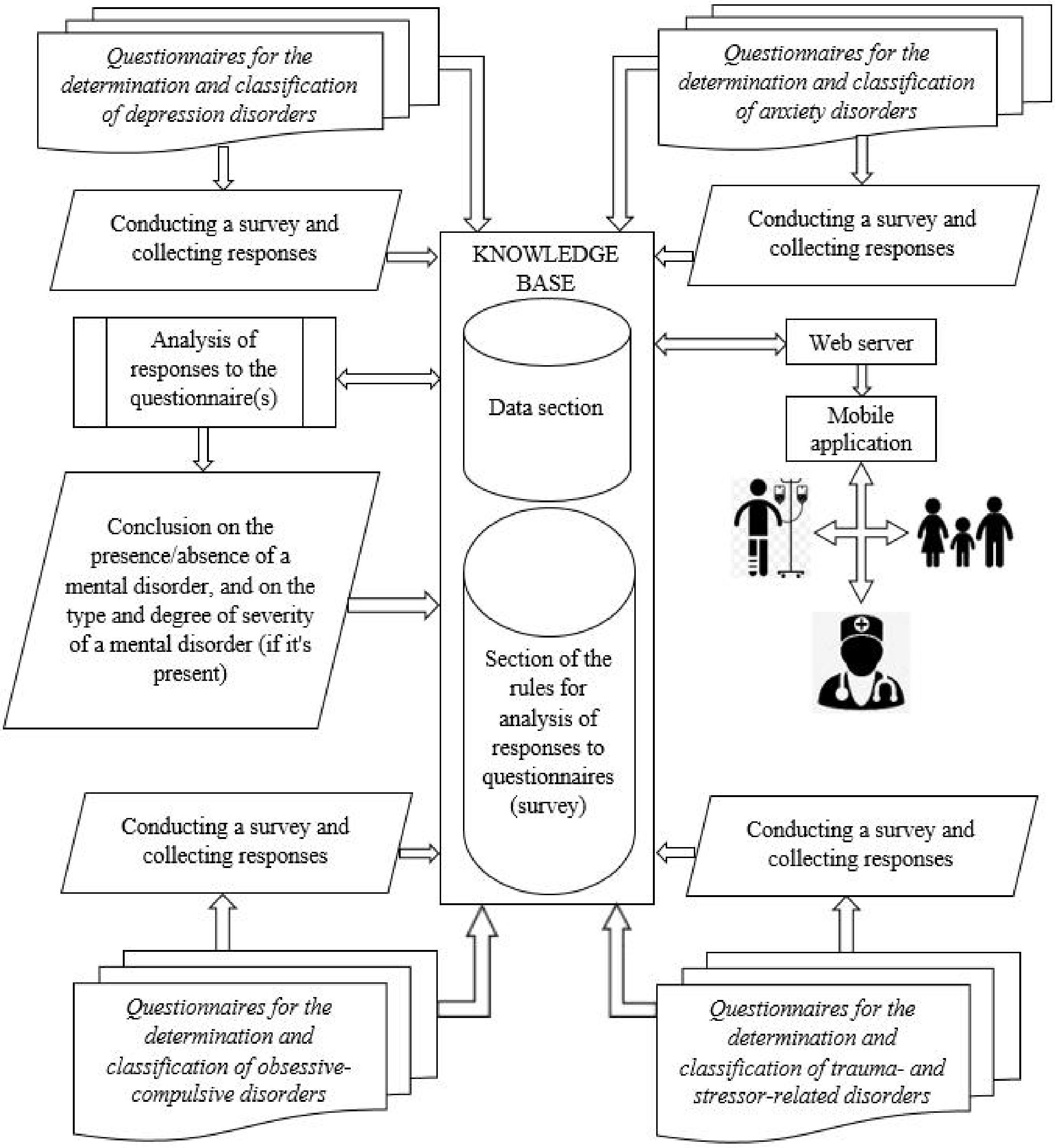

Figure 7: MentSDet: mobile-oriented multimodal information system for patient's mental state determining.

Based on the criteria for diagnosing and classifying depression disorders, anxiety disorders, obsessive-compulsive disorders, and trauma- and stressor-related disorders discussed in Section 3, questionnaires were developed to assess and categorize these conditions. The responses to these questionnaires serve as the primary source of information for the mobile-oriented multimodal information system used to determine a patient's mental state. Patients can choose to complete any of the surveys at their own discretion or upon recommendation by their psychiatrist. Additionally, family members who observe symptoms of mental disorders in the patient can also provide responses. Both the questionnaires and their answers are stored in the system's knowledge base.

The knowledge base also contains rules for diagnosing and classifying depression, anxiety, obsessive-compulsive, and trauma- and stressor-related disorders. These rules are built on the DSM-5 criteria discussed in Section 3.

The system analyzes the responses to the questionnaire(s) using the developed rules and forms a conclusion about the presence/absence of a certain mental disorder, and on the type and degree of severity of the mental disorder (if it's present), which is an information product of the system and is also stored in the system's knowledge base.

The generated conclusion is sent through the web server to the mobile application, through which it is issued to the patient, his relatives and the psychiatrist, if the patient is already under treatment. Thanks to such a conclusion, both the patient and his relatives, as well as the psychiatrist, can evaluate the effectiveness of the received treatment, because based on the conclusion of the system, it becomes clear whether the symptoms have disappeared or weakened as a result of the treatment. If the patient has not yet been observed by a psychiatrist, but the system has formed a conclusion about the presence of a certain mental disorder, then this is the reason for immediate consultation and treatment with a psychiatrist.

Thus, MentSDet, the mobile-oriented multimodal information system developed in this article for assessing a patient's mental state, provides questionnaires to the patient or their family to identify the presence of specific mental disorders. Based on the responses received, it notifies the patient, their family, and psychiatrist about the presence or absence of a particular mental disorder, as well as its type and severity. This functionality helps ensure that the onset of the condition or any exacerbation periods are not overlooked, and it allows for the evaluation of treatment effectiveness. The proposed information system serves as an automated and objective diagnostic tool for the early detection of mental disorders.

5. Results & discussion

Let's examine the functionality of MentSDet, the mobile-oriented multimodal information system designed to assess a patient's mental state. Currently, the mobile application is implemented exclusively in test mode, so it is not possible to provide screenshots of its operation.

A combatant who was demobilized due to injuries was constantly anxious, he was constantly tormented by memories and flashbacks, he did not want to see people, he considered himself guilty that he survived and his comrades died, he had no desire to live, he couldn't to sleep, etc. The wife, realizing that some kind of mental disorder is taking place, passed the survey of the information system regarding trauma- and stressor-related disorders, in particular, regarding posttraumatic stress disorder (Fig. 6).

As a result of such surveys, the following answers were chosen: A 1, 2, 4; B 1, 2, 3, 4, 5; C 2; D 2, 3, 4, 5, 6, 7; E 1, 3, 5, 6; F; G; H in the questionnaire for determining posttraumatic stress disorder (Fig. 6).

The system evaluated the responses to the questionnaire(s) using the established rules stored in the knowledge base's rules section and generated a conclusion regarding the presence of post-traumatic stress disorder 309.81 (F43.10), which is recorded in the system's knowledge base.

The formed conclusion that the patient has post-traumatic stress disorder 309.81 (F43.10) was sent to the mobile application, through which it was issued to the veteran's wife. Since the system formed a conclusion about the presence of a mental disorder, the wife persuaded the patient to immediately contact a psychiatrist for consultation and treatment.

It is obvious that the proposed MentSDet information system helped to detect post-traumatic stress disorder in the patient and prompted him to consult a psychiatrist.

6. Conclusions

Given that information systems and technologies make modern medicine more accessible, qualitative and functional, and that they provide patients with greater opportunities for accurate diagnosis and monitoring of their health (including mental health), that medical information systems and technologies facilitate the possibility of continuous monitoring of patients' health status as needed, that conventional diagnostic methods heavily depend on psychiatrists' subjective evaluations, highlighting the need for automated and objective diagnostic tools, then for the early detection of mental disorders, a mobile-oriented information system is relevant, which will offer the patient a test to assess his or her mental state, which will vary depending on the diagnosis (since the system is designed not so much for self-diagnosis as for cooperation with a psychiatrist), send notifications to the patient, his or her relatives and the psychiatrist about the beginning of the exacerbation period, and evaluate the effectiveness of treatment (assess whether the symptoms have disappeared after the start of treatment).

An analysis of the existing methods and tools for assessing patients' mental states revealed that, despite the large number of available options, evidence-based methods and tools – such as those utilizing the DSM-5 – are still underdeveloped.

For the design and development of a mobile-oriented multimodal information system for determining patient's mental state, MentSDet, we will use the criteria for determining and classifying mental disorders (in particular, anxiety disorders, depression disorders, trauma- and stressor-related disorders, obsessive-compulsive disorders) using DSM-5.

MentSDet, a mobile-oriented multimodal information system for determining the patient's mental state, developed in this article, offers a questionnaire(s) to the patient or his or her family to determine the presence of a specific mental disorder and, on the basis of the received answers, sends the patient, his/her family and psychiatrist notifications about the presence/absence of a particular mental disorder, and the mental disorder's type and severity, i.e., it allows not to miss the onset of the disease, the beginning of the exacerbation period, or to assess the effectiveness of treatment. The proposed information system is an automated and objective diagnostic tool for the early detection of mental disorders.

Areas for future research by the authors to further optimize and develop the system include: implementing the MentSDet information system as a fully functional mobile application (not just its test version); improving data analysis algorithms for more accurate analysis of questionnaire responses and other data sources; exploring the possibility of including biometric data (e.g., heart rate, stress level) to improve mental health assessment; personalizing recommendations for patients based on their responses and medical history; analyzing the relationships between different mental disorders to improve diagnosis and treatment; evaluating the effectiveness of treatment based on data collected through the system; exploring opportunities to include new features such as online consultations with psychiatrists; ensuring data privacy and security of patient data in the system; integrating with other medical systems to improve information exchange; study of patient and doctor satisfaction with the system to improve the interface and functionality.

7. Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] Mental Health, 2024. URL: https://www.who.int/health-topics/mental-health#tab=tab_1.

[2] Why it is important to take care of mental health, 2024. URL: https://moz.gov.ua/uk/chomu-vazhlivo-dbati-pro-psihichne-zdorovja.

[3] World mental health report, 2022. URL: https://iris.who.int/bitstream/handle/10665/356119/9789240049338-eng.pdf?sequence=1.

[4] After the war, about 15 million Ukrainians will need psychological help, 2023. URL: https://www.ukrinform.ua/rubric-health/3796563-pisla-vijni-blizko-15-miljoniv-ukrainciv-potrebuvatimut-psihologicnoi-dopomogi.html.

[5] P. Dhanalakshmi, N. N. Jyoshna, P. Eswar, P. Ashiq, M. H. Vardhan, Multi-Class Stress Detection Using Physiological Sensor Data, in: 2024 International Conference on Intelligent Systems for Cybersecurity (ISCS), IEEE, 2024. doi:10.1109/iscs61804.2024.10581331.

[6] A. D. Espinoza García, Early detection of mental health problems in university students, Rev. Fac. Medicina Humana 24.1 (2024). doi:10.25176/rfmh.v24i1.6080.

[7] M. Gulhane, T. Sajana, N. Shelke, S. Maurya, Development of a Temporal Analysis Model Augmented for Disease Progression Identification through Multiparametric Analysis, Int. J. Intell. Syst. Appl. Eng., 12 2 (2023) 620–634.

[8] S. Arora, P. Sahadevan, J. S. Sundarakumar, Association of Sleep Quality with Physical and Psychological Health Indicators among Overweight and Obese, Middle-aged and Older Rural Indians, Sleep Med. (2024) 100112. doi:10.1016/j.sleepx.2024.100112.

[9] P. Subba, P. Petersen Williams, N. P. Luitel, M. J. D. Jordans, E. Breuer, A qualitative study on the adaptation of community programmes for the promotion of early detection

and health-seeking of perinatal depression in Nepal, BMC Women's Health 24.1 (2024). doi:10.1186/s12905-024-03122-y.
[10] D. O. Iloma, G. E. Abikoye, M. U. Nnam, C. E. Ogbonnaya, Why we're distraught: a pre and post quasi-experimental approach and interventional strategy for tackling psychological distress among perinatal women, Curr. Psychol. (2023). doi:10.1007/s12144-023-05449-5.
[11] Y. Y. Chen, S. R. Ghazali, A. Said, Posttraumatic stress disorder, depressive and cardiovascular disease symptoms among young patients receiving medical treatment in a heart centre: A cross-sectional study, Malays. Fam. Physician 19 (2024) 42. doi:10.51866/oa.557.
[12] C. Viegas, R. Maxion, A. Hauptmann, J. Magalhães, The Seven Faces of Stress: Understanding Facial Activity Patterns During Cognitive Stress, in: 2024 IEEE 18th International Conference on Automatic Face and Gesture Recognition (FG), IEEE, 2024. doi:10.1109/fg59268.2024.10581960.
[13] T. Hovorushchenko, A. Herts, Ye. Hnatchuk, Concept of Intelligent Decision Support System in the Legal Regulation of the Surrogate Motherhood, CEUR-WS 2488 (2019) 57-68.
[14] T. Hovorushchenko, Ye. Hnatchuk, A. Herts, O. Onyshko, Intelligent Information Technology for Supporting the Medical Decision-Making Considering the Legal Basis, CEUR-WS, 2853 (2021) 72-82.
[15] T. Hovorushchenko, A. Moskalenko, V. Osyadlyi, Methods of medical data management based on blockchain technologies, J. Reliab. Intell. Environ. (2022). doi:10.1007/s40860-022-00178-1.
[16] P. Hryhoruk, S. Grygoruk, N. Khrushch, T. Hovorushchenko, Using non-metric multidimensional scaling for assessment of regions' economy in the context of their sustainable development, CEUR-WS 2713 (2020) 315-333.
[17] T. Hovorushchenko, A. Herts, Y. Hnatchuk, O. Sachenko, Supporting the Decision-Making About the Possibility of Donation and Transplantation Based on Civil Law Grounds, in: Advances in Intelligent Systems and Computing, Springer International Publishing, Cham, 2020, p. 357–376. doi:10.1007/978-3-030-54215-3_23.
[18] Y. Hnatchuk, T. Hovorushchenko, O. Pavlova, Methodology for the development and application of clinical decisions support information technologies with consideration of civil-legal grounds, Radioelectron. Comput. Syst. № 1 (2023) 33–44. doi:10.32620/reks.2023.1.03.
[19] H. Ding, Z. Du, Z. Wang, J. Xue, Z. Wei, K. Yang, S. Jin, Z. Zhang, J. Wang, IntervoxNet: a novel dual-modal audio-text fusion network for automatic and efficient depression detection from interviews, Front. Phys. 12 (2024). doi:10.3389/fphy.2024.1430035.
[20] T. Hovorushchenko, Ye. Hnatchuk, A. Herts, A. Moskalenko, V. Osyadlyi, Theoretical and Applied Principles of Information Technology for Supporting Medical Decision-Making Taking into Account the Legal Basis, CEUR-WS 3038 (2021)172-181.
[21] E. Zaitseva, T. Hovorushchenko, O. Pavlova, Y. Voichur, Identifying the Mutual Correlations and Evaluating the Weights of Factors and Consequences of Mobile Application Insecurity, Systems 11.5 (2023) 242. doi:10.3390/systems11050242.

[22] M. Kumari, G. Singh, S. D. Pande, Depressonify: BERT a deep learning approach of detection of depression, EAI Endorsed Trans. Pervasive Health Technol. 10 (2024). doi:10.4108/eetpht.10.5513.

[23] B. Hadzic, P. Mohammed, M. Danner, J. Ohse, Y. Zhang, Y. Shiban, M. Rätsch, Enhancing early depression detection with AI: a comparative use of NLP models, SICE J. Control, Meas., Syst. Integr. 17.1 (2024) 135–143. doi:10.1080/18824889.2024.2342624.

[24] K. Shah, U. Patel, Y. Kumar, Machine Learning-Based Approaches for Early Prediction of Depression, in: 2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), IEEE, 2024. doi:10.1109/iitcee59897.2024.10467234.

[25] H. Yu, H. Shen, J. Zhang, Z. Liu, Early adolescent depression detection system based on the transformer model, in: 2024 International Conference on Future of Medicine and Biological Information Engineering (MBIE 2024), SPIE, 2024, p. 52. doi:10.1117/12.3048175.

[26] K. Sujigarasharma, M. L. Shri, K. Santhi, Smart Detection and Proactive Prevention of Student Depression: A DeepLearning Approach, in: 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT), IEEE, 2024, p. 1–4. doi:10.1109/tqcebt59414.2024.10545088.

[27] D. Maupomé, F. Rancourt, R. Belbahar, M.-J. Meurs, A Pretrained Language Model for Mental Health Risk Detection, CEUR-WS 3649 (2024) 101-111.

[28] A. Pandey, S. Kumar, Mental Health and Stress Prediction Using NLP and Transformer-Based Techniques, in: 2024 IEEE Symposium on Wireless Technology & Applications (ISWTA), IEEE, 2024, p. 61–66. doi:10.1109/iswta62130.2024.10651843.

[29] M. K. I. Zim, M. A. Hanif, H. Kaur, Prediction of personality for mental health detection using hybrid deep learning model, in: 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), IEEE, 2024. doi:10.1109/iatmsi60426.2024.10503423.

[30] N. B. Krishna, R. Y. Kumar, M. I. Bhanu, P. O. Reddy, R. Anjali, P. R. Reddy, Exploring Machine Learning Algorithms for the Detection of Depression, in: 2024 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES), IEEE, 2024. doi:10.1109/icsses62373.2024.10561447.

[31] S. L. Mirtaheri, S. Greco, R. Shahbazian, A self-attention TCN-based model for suicidal ideation detection from social media posts, Expert Syst. With Appl. (2024) 124855. doi:10.1016/j.eswa.2024.124855.

[32] P. Benjachairat, T. Senivongse, N. Taephant, J. Puvapaisankit, C. Maturosjamnan, T. Kultananawat, Classification of suicidal ideation severity from Twitter messages using machine learning, Int. J. Inf. Manag. Data Insights 4.2 (2024) 100280. doi:10.1016/j.jjimei.2024.100280.

[33] A. Basyouni, H. Abdelkader, W. S. Elkilani, A. Alharbi, Y. Xiao, A. H. Ali, A Suicidal Ideation Detection Framework on Social Media using Machine Learning and Genetic Algorithms, IEEE Access (2024) 1. doi:10.1109/access.2024.3454796.

[34] A. Nowacki, W. Sitek, H. Rybiński, LLMental: Classification of Mental Disorders with Large Language Models, in: Lecture Notes in Computer Science, Springer Nature Switzerland, Cham, 2024, p. 35–44. doi:10.1007/978-3-031-62700-2_4.

[35] K. K. Palanisamy, A. Rengaraj, Early Detection of Stress and Anxiety based Seizures in Position Data Augmented EEG Signal Using Hybrid Deep Learning Algorithms, IEEE Access (2024) 1. doi:10.1109/access.2024.3365192.

[36] Y. Badr, U. Tariq, F. Al-Shargie, F. Babiloni, F. Al Mughairbi, H. Al-Nashash, A review on evaluating mental stress by deep learning using EEG signals, Neural Comput. Appl. (2024). doi:10.1007/s00521-024-09809-5.

[37] M. Abd Al-Alim, R. Mubarak, N. M. Salem, I. Sadek, A machine-learning approach for stress detection using wearable sensors in free-living environments, Comput. Biol. Med. 179 (2024) 108918. doi:10.1016/j.compbiomed.2024.108918.

[38] K. Deulkar, M. Narvekar, P. Gandhi, D. Gada, S. Kamath, Evaluating the Influence of Text Representation techniques on Diverse Machine Learning Algorithms for Stress Detection in Social media users, in: 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE), IEEE, 2024. doi:10.1109/amathe61652.2024.10582212.

[39] E. Archana, A. Swaminathan, N. Sai, Comparative Analysis of Psychological Stress Detection: A Study of Artificial Neural Networks and Cat Boost Algorithm, Int. J. Intell. Syst. Appl. Eng. 12 1 (2023) 385–394.

[40] J. Benacek, N. Lawal, T. Ong, J. Tomasik, N. A. Martin-Key, E. L. Funnell, G. Barton-Owen, T. Olmert, D. Cowell, S. Bahn, Identification of Predictors of Mood Disorder Misdiagnosis and Subsequent Help-Seeking Behavior in Individuals With Depressive Symptoms: Gradient-Boosted Tree Machine Learning Approach, JMIR Ment. Health 11 (2024) e50738. doi:10.2196/50738.

[41] A. Abilkaiyrkyzy, F. Laamarti, M. Hamdi, A. E. Saddik, Dialogue System for Early Mental Illness Detection: Toward a Digital Twin Solution, IEEE Access 12 (2024) 2007–2024. doi:10.1109/access.2023.3348783.

[42] O. Vasileiou, H. Karanikas, Digital Cognitive Test for Early Detection of Dementia, in: Studies in Health Technology and Informatics, IOS Press, 2024. doi:10.3233/shti240404.

[43] A. Saini, S. Kumari, B. S. P. Ritik, B. S. P. Rajni, S. Hans, Prognosis of Dementia using Machine Learning, in: Disease Prediction using Machine Learning, Deep Learning and Data Analytics, BENTHAM SCIENCE PUBLISHERS, 2024, p. 80–91. doi:10.2174/9789815179125124010010.

[44] K. Siarkos, C. D. Katsis, G. Antonopoulos, E. Karavasilis, G. Velonakis, C. Papageorgiou, N. Smyrnis, N. Kelekis, E. Glavas, A. Politis, Late Life Depression Automated Detection by Means of Advanced Diffusion Tensor Imaging Segmentation and Artificial Intelligence, in: 2024 IEEE International Symposium on Biomedical Imaging (ISBI), IEEE, 2024, p. 1–4.

[45] X. Zhang, B. Li, G. Qi, A Multi-Featured Expression Recognition Model Incorporating Attention Mechanism and Object Detection Structure for Psychological Problem Diagnosis, Physiol. & Behav. (2024) 114561. doi:10.1016/j.physbeh.2024.114561.

[46] R. Krishna, R. Teja, N. Neelima, N. Peddi, Advanced machine learning models for Depression level categorization using DSM 5 and personality traits, Procedia Comput. Sci. 235 (2024) 2783–2792. doi:10.1016/j.procs.2024.04.263.

[47] Diagnostic and Statistical Manual of Mental Disorders, 5th Edition, American Psychiatric Publishing, Inc, 2013. doi:10.1176/appi.books.9780890425596.893619.