Cyber-physical system for determining the condition of patients with depression based on motion activity fixation

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Abstract

The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation is a modern approach to monitoring psycho-emotional health, combining sensor technologies, data processing tools, and algorithms for analyzing behavioral markers. The scientific relevance of such a system lies in the creation of a new paradigm for monitoring mental health, which is based on objective data on motion activity and the use of analysis algorithms, and is capable of significantly improving the effectiveness of early diagnosis, individualization of treatment, and reduction of the socioeconomic consequences of depression. The conducted review of the literature showed that most of the known solutions are aimed at studying the onset and fixation of manifestations of depression for various reasons, but little attention is paid to the study of objective behavioral markers, one of which is a decrease in motion activity. Therefore, this study will focus on the design and development of the cyber-physical system for determining the condition of patients with depression based on the motion activity fixation using sensor technologies and real-time data processing methods, with the aim of ensuring early diagnosis, timely intervention, and improving the effectiveness of psychiatric care. The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation allows for continuous, non-invasive, and objective monitoring of the condition of patients with depression, contributes to the early detection of exacerbation, and increases the effectiveness of treatment through timely intervention. The use of wearable sensors in combination with data analysis algorithms allows for the early detection of risks of deterioration in psycho-emotional state, which is critically important for the timely referral of patients to narrow-profile specialists and the prevention of serious consequences. Automatic generation of reports and notifications simplifies the work of doctors, allows for quick decision-making, and optimizes patient routing. Thus, the proposed cyber-physical system combines digital technologies, sensor devices, and data analysis algorithms for the early detection of depression, ensuring continuous monitoring and improving the effectiveness of psychiatric care.

Keywords

Cyber-physical system, wearable sensor devices, condition of patients with depression, motion markers of depression, fixation of motion activity.

1. Introduction

The digitization of the medical sector is a strategic direction for the modernization of the healthcare system, as today's conditions require efficiency, accuracy, and consistency in management and clinical decision-making. The use of information technology in medicine opens up opportunities for comprehensive data collection, processing, and analysis, improved communication between patients and doctors, and increased efficiency, accessibility, and transparency of medical services [1, 2].

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The use of digital tools allows for the implementation of electronic medical records, telemedicine services, remote patient monitoring systems, and software solutions for automated analysis. This helps reduce bureaucratic burdens, optimize the working time of medical staff, and provides opportunities for early detection of pathologies, individualization of treatment, and efficient use of financial and material resources [3, 4]. On a global scale, the digital transformation of medicine shapes the resilience and competitiveness of the healthcare system, making it ready for emergency challenges and capable of providing continuous, high-quality, and safe medical care [5].

Among the fields that need automation and digitalization, psychology, in particular psychodiagnostics, occupies a special place. In this context, the use of specialized information and cyber-physical systems for psychodiagnostic research is becoming increasingly important [6, 7].

Depression is one of the most common mental disorders in the world, significantly affecting a person's quality of life, work capacity, and social relationships [8, 9]. According to the WHO, approximately one in eight people worldwide experience mental disorders. Currently, the number of people suffering from depression reaches about 970 million, of whom 129 million live with disabilities caused by these conditions. Every year, nearly 1 million people take their own lives, and one in four families has at least one member with a mental disorder [10].

Depression is recognized by the World Health Organization as one of the leading causes of disability and reduced quality of life [10]. According to researchers' estimates, depressive disorders are on the rise globally, affecting increasingly wider age and social groups, which makes the problem not only medical but also social. Depressive disorders are among the leading causes of disability and loss of working capacity, as confirmed by data from the World Health Organization [10]. The problem is complicated by a high level of latency — a significant number of cases remain undetected due to social stigma and insufficient access to professional help. This necessitates the introduction of objective diagnostic methods that do not depend on the subjectivity of the patient or doctor.

In the current conditions of war and socio-economic instability [8, 9], depressive disorders are becoming particularly relevant for Ukrainians. Statistics show that about 15 million Ukrainian residents need qualified psychological support, with 3–4 million of them also requiring medication [11]. In addition, 90% of veterans and their families need psychological support. High levels of stress, traumatic experiences, and chronic psychological strain on the population create additional challenges for the healthcare system. Therefore, remote and automated monitoring tools that reduce the burden on doctors and increase the availability of care are of exceptional importance.

Depression often remains undiagnosed or is detected too late because patients do not always seek help in the early stages. Traditional diagnostic methods are based mainly on subjective questionnaires and clinical interviews, which depend on the patient's willingness to talk openly about their condition. The issue of access to psychiatric care is also particularly important. In most countries, including Ukraine, there is a shortage of mental health professionals, which complicates timely diagnosis and treatment.

Early detection of mental disorders is essential for preventing negative health consequences and quickly selecting effective treatment [12]. An incorrect diagnosis can lead to inappropriate treatment, and delayed treatment can lead to worsening symptoms, functional impairments, and reduced treatment effectiveness [13, 14]. Early recognition of mental health problems plays a key role in reducing the risk of fatal outcomes, preventing suicide, increasing the effectiveness of therapeutic measures, improving the overall condition of patients, and applying cost-effective treatment methods [15, 16].

Traditional methods of diagnosing and treating depression rely primarily on subjective patient assessments and clinical questionnaires, which significantly complicates the timely detection of pathology. At the same time, depression has objective behavioral markers, one of the most important being a decrease in motor activity [17–19]. Decreased physical activity, increased periods of inactivity, changes in sleep patterns and circadian rhythms are validated markers of depressive disorders [20–22]. The use of motor activity indicators as an indicator of psycho-emotional state is of particular importance. Therefore, the use of wearable sensor devices (accelerometers, fitness bracelets, smart watches) allows for continuous and non-invasive collection of data on physical activity, sleep, and lifestyle, which makes it possible to detect early signs of deterioration in psycho-emotional state, i.e., opens up new prospects for early detection of the disease and assessment of treatment dynamics. This necessitates the use of modern sensor technologies and cyber-physical systems capable of continuously collecting and analyzing motor activity indicators in order to objectify the diagnostic process.

Thus, a cyber-physical system for determining the condition of a patient with depression based on the fixation of motion activity is relevant due to its ability to combine digital technologies, sensor devices, and data analysis algorithms for the early detection of depression, ensuring continuous monitoring, and improving the effectiveness of psychiatric care. The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation is a modern approach to monitoring psycho-emotional health, combining sensor technologies, data processing tools, and algorithms for analyzing behavioral markers. The relevance of such a system also lies in its ability to process large volumes of data received in real time, which allows for the creation of individual risk models, the prediction of exacerbation, and the provision of personalized recommendations. Such a cyber-physical system can also partially compensate for the shortage of mental health professionals by automating data collection and initial analysis processes, reducing the workload on doctors and shortening the response time to changes in the patient's condition. So, the scientific relevance of such a system lies in the creation of a new paradigm for monitoring mental health, which is based on objective data on motion activity and the use of analysis algorithms, and is capable of significantly improving the effectiveness of early diagnosis, individualization of treatment, and reduction of the socioeconomic consequences of depression.

2. Literature review

Let’s review the literature on known tools for determining the condition of patients with depression.

Study [23] focuses on the use of electroencephalography to detect depression as one of the promising methods of early diagnosis. The approach is based on recording individual characteristic patterns of neural activity, which manifest themselves in the form of cluster microstates.

In [24], machine learning models and explanatory artificial intelligence methods were used to analyze the relationships between chronic pain, psychological distress, and their simultaneous manifestation in young people. The use of explanatory AI made it possible to identify the perception of one's own health and sleep disturbances as key factors associated with all the conditions studied. At the same time, the associations varied depending on whether the conditions manifested simultaneously or separately: some factors contradicted each other, while others combined to form clear patterns of comorbidity.

When it comes to diagnosing depression, the Patient Health Questionnaire-9 (PHQ-9) and its shorter versions, PHQ-8 and PHQ-2, are widely used as online screening tools. Studies [25, 26] have focused on the development and implementation of psycho-emotional screening systems based on these and other questionnaires.

The aim of the systematic review [27] was to create a tool for assessing adherence to evidence-based recommendations for the treatment of depression, identifying factors that influence adherence, and determining ways to improve it. The review provided a comprehensive analysis of the current state of implementation of recommendations for the treatment of depression and outlined directions for initiatives aimed at improving the quality of treatment.

The study [28] focused on examining seasonal fluctuations in depression and the relationship between weather conditions, physical activity, and the severity of depressive symptoms in 428 participants in a longitudinal mobile study. Mediation analysis showed that air temperature and daylight duration significantly influenced the severity of depression, which in turn indirectly affected the participants' level of physical activity.

Study [29] focused on developing the CLARION (Consolidated AppRoach to Intervention adaptatiON) approach for adapting interventions that promote self-management of depression. CLARION identified a number of advantages: clear definition of key components before making decisions about modifications, involvement of a diverse steering committee of experts, including patient partners and developers of the initial intervention, which allowed for a balance between contribution and effectiveness, and establishment of clear rules for decision-making by the committee using specific criteria and a 75% supermajority.

In [30], various mobile applications were developed to support healthcare workers and reduce their anxiety. The aim of the study was to evaluate the effect of using such self-help applications on reducing anxiety in healthcare workers. The results showed that mobile medical applications, their content, and the selected intervention strategies have a positive effect on reducing anxiety. In addition, the interventions were effective in reducing other mental disorders, such as anxiety, stress, depression, and the risks of drug and psychotropic substance abuse among healthcare workers.

Digital phenotyping is becoming increasingly important for organizing remote mental health monitoring. A study [31] used a personalized approach involving anomaly detection and neural network-based clustering methods to predict relapses in patients with psychotic disorders. The results showed the potential of self-learning algorithms in detecting atypical changes in patient behavior using objective data obtained from granular, continuous biosignals collected via convenient wearable devices.

The aim of the study [32] was to study latent patterns of response to symptom severity, as assessed by the Brief Symptom Inventory (BSI), and limitations in daily functioning, as recorded by the PROMIS extended bank of questions “Ability to Participate in Social Roles and Activities,” among outpatient psychiatric patients. Four profiles were identified that provide a clinically meaningful basis for understanding self-reported psychosocial dysfunction, allowing patients to be distinguished by key outcomes such as suicidal ideation and participation in occupational activities. This approach facilitates the adaptation of interventions, the prioritization of therapeutic goals, and the efficient allocation of resources based on shared patterns of characteristics.

Study [33] aimed to identify factors influencing the intentions of users with depression to use AI-based medical assistants, as well as to deepen the understanding of the mechanisms of acceptance of this technology. It was found that perceived trust is closely related to expected performance and behavioral intention, while reducing perceived risk. In turn, a high level of perceived risk negatively affects intentions to use the technology.

The authors [34] investigated the impact of different sources and forms of emotional support on the prediction of symptoms of depression and anxiety in older adults. Identifying the benefits and availability of different aspects of social support allows for the prediction of mental health outcomes and guides clinical decisions when selecting appropriate treatment methods.

A study [35] analyzed the relationship between self-neglect, depression, social networks, and health literacy in older adults. The results showed that health literacy, depressive symptoms, and social networks are key predictors of self-neglect, with social networks and health literacy partially mediating the relationship between depression and self-neglect. Based on these findings, it can be concluded that improving health literacy and strengthening social support systems are effective strategies for reducing the effects of depression and preventing self-neglect in older adults.

The conducted review of the literature showed that most of the known solutions are aimed at studying the onset and fixation of manifestations of depression for various reasons, but little attention is paid to the study of objective behavioral markers, one of which is a decrease in motion activity. Therefore, this study will focus on the design and development of the cyber-physical system for determining the condition of patients with depression based on the motion activity fixation using sensor technologies and real-time data processing methods, with the aim of ensuring early diagnosis, timely intervention, and improving the effectiveness of psychiatric care.

3. Cyber-physical system for determining the condition of patients with depression based on motion activity fixation

Motion activity indicators as indicators of psychoemotional state [36] are presented in Table 1.

Table 1
Motion activity indicators as indicators of psychoemotional state

Indicator	Normal values	Typical changes in depression
Total Activity Counts (TAC) – total activity for the day	>2000 counts/min	<1200-1600 counts/min Daily activity <1500 counts/min is often associated with clinically significant depression
Mean Activity Level	High, variable throughout the day	Low, monotonous
Inactivity Periods	Short, intermittent	vProlonged, continuous (>30 min)
Sleep Fragmentation Index	<20–25%	>30%
Sleep Duration	6–8 hours/night	> 10 hours/day
Relative Amplitude of Circadian Rhythm	>0.6	<0.5
Day-to-Day Variability	High, rhythmic	Low, monotonous
Actigraphic Depression Score	Low score	Elevated score, correlates with MADRS/HAM-D
Correlation with Clinical Scales	Low scores on HAM-D, MADRS	High scores (severe depression)

The regular fitness bracelet and/or smartwatch can measure: total activity counts for the day using an accelerometer (number of steps, distance, active minutes, calories burned) and track dynamics over time (e.g., record a decrease in daily mobility); increase in periods of inactivity (most bracelets have a "reminder to move" function after registering how long the user has been sitting without moving, thus allowing easy analysis of the duration of "sedentary" periods); sleep fragmentation (sleep trackers determine sleep duration, phases, number of awakenings, and increase in sleep fragmentation); sleep duration (most devices automatically determine when the user fell asleep and woke up, and can also assess excessive sleep duration or sleep deprivation). Therefore, the developed cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity will use indicators such as activity, inactivity, and sleep collected from a fitness bracelet and/or smartwatch. The cyber-physical system requires the patient to wear a wearable device (fitness bracelet and/or smartwatch) and install a special mobile application on the smartphone of both the patient (and their family members) and their doctor.

The method of operation of a cyber-physical system for determining the condition of a patient with depression based on the fixation of motion activity consists of the following steps:

1. Collection of daily data from a wearable device (fitness bracelet and/or smartwatch) using a mobile application and transfer of data to the cloud. Collected data: number of steps/minutes of activity (intensity of movement, calories burned); duration of periods of inactivity; duration and structure of sleep (total duration, number of awakenings, phases).
2. Preliminary data processing: noise filtering (short movements, false sensor activations); averaging of activity per day; determination of dynamics of changes compared to the patient's individual norm (baseline).
3. Data analytics and calculation of indicators: daily activity *DA* (average number of counts per minute: *DA = total number of counts per day/1440*, counts); daily inactivity index *II* (average duration of periods without movement: *II = total inactivity time / number of periods of inactivity*, minutes); daily sleep duration *SD* (hours); daily sleep fragmentation index *SFI*: *SFI = (number of night time awakenings / total sleep time) ×100%.*
4. Accumulation of indicators: dynamics of weekly activity *DAD* – 7×4 matrix, where the elements $dad[i, 1]$, i = 1..7 contain DA values from Monday to Sunday, the elements $dad[i, 2]$, i = 1..7 contain *II* values from Monday to Sunday, the elements $dad[i, 3]$, i = 1..7 contain *SD* values from Monday to Sunday, the elements $dad[i, 4]$, i = 1..7 contain *SFI* values from Monday to Sunday, and monthly activity dynamics *WAD* – 31×4 matrix, where the elements $wad[i, 1]$, i = 1..31 contain *DA* values from the 1st to the 31st of the current month, the elements $wad[i, 2]$, i = 1..31 contain *II* values from the 1st to the 31st of the current month, the elements $wad[i, 3]$, i = 1..31 contain *SD* values from the 1st to the 31st of the current month, the elements $wad[i, 4]$, i = 1..31 contain *SFI* values from the 1st to the 31st of the current month.
5. Assessment of the patient's condition (based on basic indicators): if $dad[i, 1]$ (i = 1..7) < 1500 counts/min and if $dad[i, 2]$ (i = 1..7) > 30 min and if $dad[i, 3]$ (i = 1..7) > 10 hours and if $dad[i, 4]$ (i = 1..7) > 30%, then there is a suspicion of the onset or exacerbation of a depressive state in the patient.
6. Feedback and visualization: the patient's mobile app displays daily, weekly, and monthly graphs of their activity and sleep, as well as messages from the doctor with advice and recommendations; the mobile app for the patient's family members and doctor displays a report on the patient's physical activity, as well as warnings when there is suspicion of the onset or exacerbation of depression in the patient.
7. Comparison with activity recommendations: the doctor must set minimum physical activity goals for the rehabilitation and treatment of patients with depression, the fulfillment of which is also monitored by the cyber-physical system, which sends the patient reminders to follow the physical activity recommendations and sends the doctor reports on the patient's compliance with the recommendations.
8. Adaptation of the cyber-physical system: the system can update the baseline thresholds depending on the patient's personal dynamics, taking into account the doctor's recommendations for minimum physical activity for a specific patient with depression, then the patient's condition is assessed based on a comparison not with the baseline, but with the patient's individual indicators; if the patient increases their activity, the goals will increase, up to the baseline; if a significant drop in activity and increase in sleep is detected, even compared to individual indicators, the system alerts the doctor about a possible relapse.
9. Integration of the system with electronic medical records: all information about the patient's condition is promptly entered into their electronic medical record.

The developed method of operation of a cyber-physical system for determining the condition of a patient with depression based on the fixation of motion activity describes the operation of a system that evaluates data from a fitness bracelet/smart watch, calculates clinically significant indicators, allows assessing the severity of depression by the level of mobility, and simultaneously acts as a tool for behavior correction (activity as treatment).

The contextual diagram of the cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity is shown in Fig. 1.

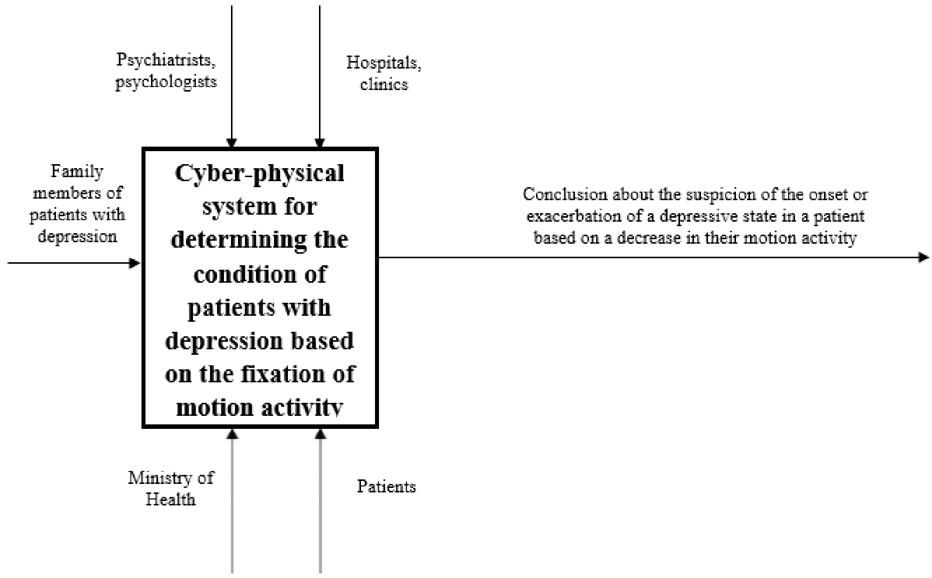

Figure 1: The contextual diagram of the cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity.

The structural model of the cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity is shown in Fig. 2.

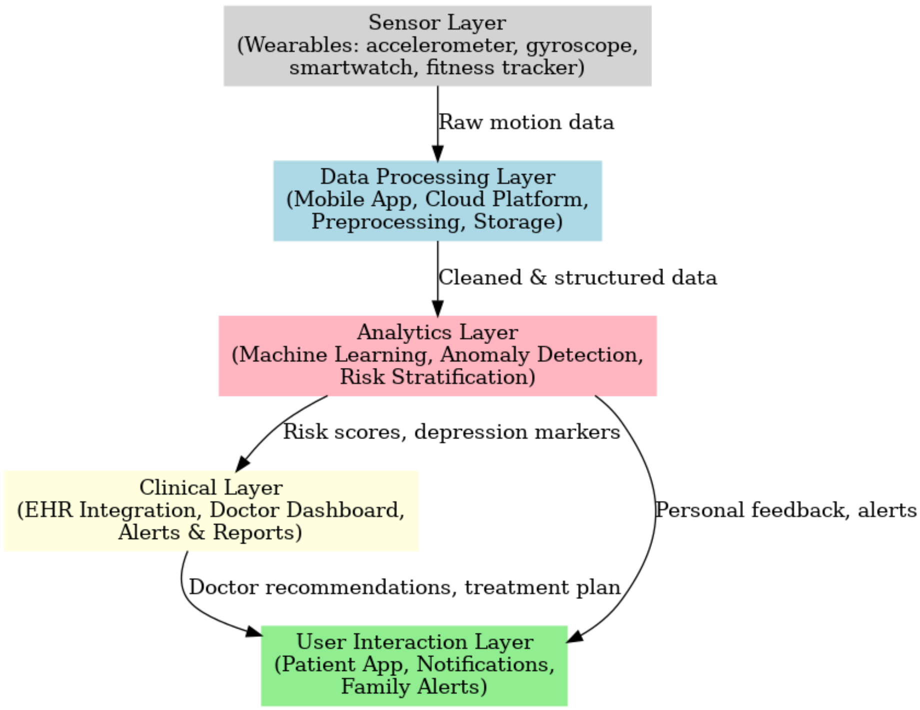

Figure 2: The structural model of the cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity.

The cyber-physical system for determining the condition of patients with depression based on the fixation of motion activity consists of a physical level, where wearable devices (fitness bracelets, smart watches, etc.) are used to continuously record the patient's motion activity indicators. The data is transferred to a digital environment — a mobile application and cloud platform — where it is pre-processed and stored. At the analytical level, data processing algorithms are used to identify deviations from individual motor activity norms. The management level of the system ensures integration with the patient's electronic medical record and generates reports for the doctor. If critical deviations are detected, the system automatically sends a message to the patient with recommendations and notifies the doctor and the patient's family members. The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation allows for continuous, non-invasive, and objective monitoring of the condition of patients with depression, contributes to the early detection of exacerbation, and increases the effectiveness of treatment through timely intervention.

Thus, a cyber-physical system for determining the condition of patients with depression based on fixation of motion activity increases the accessibility of psychiatric care. In conditions of war, social crises, and limited healthcare resources, it is important to have remote monitoring tools that ensure timely response from doctors and prevent the development of serious complications. The use of wearable sensors in combination with data analysis algorithms allows for the early detection of risks of deterioration in psycho-emotional state, which is critically important for the timely referral of patients to narrow-profile specialists and the prevention of serious consequences.

In addition, the integration of the system with electronic medical records makes it possible to form a complete picture of the patient's condition, increases the accuracy of diagnosis and personalization of treatment, and creates conditions for the formation of a comprehensive clinical profile of the patient, which contributes to improving the accuracy of diagnosis, personalization of therapy, and more efficient management of healthcare system resources. Automatic generation of reports and notifications simplifies the work of doctors, allows for quick decision-making, and optimizes patient routing.

4. Results & discussion

Let’s consider an example of a cyber-physical system for determining the condition of a patient with depression based on fixation of motion activity at the moment when the patient's depressive state worsened while under medical supervision — Table 2.

Table 2
Dynamics of patient's weekly activity (over 2 weeks)

Day of the week	*DA*	*II*	*SD*	*SFI*
Monday	2350	10	7	23%
Tuesday	2180	12	7	24%
Wednesday	2220	10	7	25%
Thursday	2000	15	8	23%
Friday	1940	18	9	28%
Saturday	1830	20	9	27%
Sunday	1760	28	11	30%
Monday	1470	45	12	40%
Tuesday	1100	55	12	43%
Wednesday	1000	67	12	45%
Thursday	860	78	11	54%
Friday	600	87	13	56%
Saturday	540	89	13	59%
Sunday	450	99	13	63%

Therefore, it is evident that in the second week of observation, $dad[i, 1]$ $(i = 8..14) < 1500$ counts/min and $dad[i, 2]$ $(i = 8..14) > 30$ min and $dad[i, 3]$ $(i = 8..14) > 10$ hours and $dad[i, 4]$ $(i = 8..14) > 30\%$, so such data indicate an exacerbation of the depressive state in the patient who was under the supervision of a physician. The patient's mobile application displayed messages from the doctor with advice and recommendations; the mobile applications of the patient's family members and doctor displayed not only a report on the patient's physical activity, but also a warning about the exacerbation of the patient's depressive state. A note about the deterioration of the patient's condition was made in his electronic medical record.

The doctor set minimum physical activity goals for the patient's rehabilitation and treatment, and the cyber-physical system reminded the patient daily to follow the recommendations for physical activity and sent reports to the doctor on the patient's compliance with the recommendations. The cyber-physical system was adapted — the basic thresholds for the patient were updated, taking into account the doctor's recommendations.

Thus, the proposed cyber-physical system combines digital technologies, sensor devices, and data analysis algorithms for the early detection of depression, ensuring continuous monitoring and improving the effectiveness of psychiatric care.

5. Conclusions

The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation is a modern approach to monitoring psycho-emotional health, combining sensor technologies, data processing tools, and algorithms for analyzing behavioral markers. The scientific relevance of such a system lies in the creation of a new paradigm for monitoring mental health, which is based on objective data on motion activity and the use of analysis algorithms, and is capable of significantly improving the effectiveness of early diagnosis, individualization of treatment, and reduction of the socioeconomic consequences of depression.

The conducted review of the literature showed that most of the known solutions are aimed at studying the onset and fixation of manifestations of depression for various reasons, but little attention is paid to the study of objective behavioral markers, one of which is a decrease in motion activity. Therefore, this study will focus on the design and development of the cyber-physical system for determining the condition of patients with depression based on the motion activity fixation using sensor technologies and real-time data processing methods, with the aim of ensuring early diagnosis, timely intervention, and improving the effectiveness of psychiatric care.

The cyber-physical system for determining the condition of patients with depression based on the motion activity fixation allows for continuous, non-invasive, and objective monitoring of the condition of patients with depression, contributes to the early detection of exacerbation, and increases the effectiveness of treatment through timely intervention. The use of wearable sensors in combination with data analysis algorithms allows for the early detection of risks of deterioration in psycho-emotional state, which is critically important for the timely referral of patients to narrow-profile specialists and the prevention of serious consequences. Automatic generation of reports and notifications simplifies the work of doctors, allows for quick decision-making, and optimizes patient routing.

Thus, the proposed cyber-physical system combines digital technologies, sensor devices, and data analysis algorithms for the early detection of depression, ensuring continuous monitoring and improving the effectiveness of psychiatric care.

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.

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