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EEG Alpha Band Characteristics in Patients with a Depressive Episode within Recurrent and Bipolar Depression

Характеристики альфа-ритма ЭЭГ у больных с депрессивным эпизодом в рамках рекуррентной и биполярной депрессии

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Original research

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ABSTRACT

BACKGROUND: The search for biological markers for the differential diagnosis of recurrent depression and bipolar depression is an important undertaking in modern psychiatry. Electroencephalography (EEG) is one of the promising tools in addressing this challenge.

AIM: To identify differences in the quantitative characteristics of the electroencephalographic alpha band activity in patients with a depressive episode within the framework of recurrent depression and bipolar depression.

METHODS: Two groups of patients (all women) were formed: one consisting of subjects with recurrent depressive disorder and one with subjects experiencing a current mild/moderate episode (30 patients), and subjects with bipolar affective disorder or a current episode of mild or moderate depression (30 patients). The groups did not receive pharmacotherapy and did not differ in their socio-demographic parameters or total score on the Hamilton depression scale. A baseline electroencephalogram was recorded, and the quantitative characteristics of the alpha band activity were analyzed, including the absolute spectral power, interhemispheric coherence, and EEG activation.

RESULTS: The patients with recurrent depressive disorder demonstrated statistically significantly lower values of the average absolute spectral power of the alpha band (z=2.481; p=0.042), as well as less alpha attenuation from eyes closed to eyes open (z=2.573; p=0.035), as compared with the patients with bipolar affective disorder.

CONCLUSION: The presented quantitative characteristics of alpha activity are confirmation that patients with affective disorders of different origins also display distinctive electrophysiological features which can become promising biomarkers and could help separate bipolar depression from the recurrent type.

АННОТАЦИЯ
ВВЕДЕНИЕ: Поиск биологических маркеров для дифференциальной диагностики рекуррентной и биполярной депрессии является важной задачей современной психиатрии. Электроэнцефалография (ЭЭГ) выступает одним из перспективных инструментов для решения данной задачи.

ЦЕЛЬ: Выявить различия количественных характеристик альфа-ритма электроэнцефалограммы у пациентов с депрессивным эпизодом в рамках рекуррентной и биполярной депрессии.

МЕТОДЫ: Выделены две группы пациентов (женщин): с рекуррентным депрессивным расстройством, текущий эпизод легкой/средней степени тяжести (30 пациентов) и с биполярным аффективным расстройством, текущий эпизод легкой или умеренной депрессии (30 пациентов). Группы пациентов не получали фармакотерапию и не различались по социально-демографическим показателям и суммарной оценке по шкале депрессии Гамильтона. Проводилась запись фоновой электроэнцефалограммы и анализировались количественные характеристики альфа-ритма: абсолютная спектральная мощность, межполушарная когерентность и реакция активации.

РЕЗУЛЬТАТЫ: У пациентов с рекуррентным депрессивным расстройством по сравнению с пациентами с биполярным аффективным расстройством обнаружены статистически значимо меньшие показатели усредненной абсолютной спектральной мощности альфа-ритма (z=2,481; p=0,042), а также меньшая степень депрессии альфа-ритма при открывании глаз (z=2,573; p=0,035).

ЗАКЛЮЧЕНИЕ: Представленные количественные характеристики альфа-активности подтверждают, что больные с аффективными расстройствами различного генеза имеют свои отличительные электрофизиологические особенности, которые могут стать перспективными биомаркерами для различения биполярной и рекуррентной депрессии.

Keywords: *electroencephalogram; alpha rhythm; recurrent depression; bipolar depression; biomarkers*
Ключевые слова: *электроэнцефалограмма; альфа-ритм; рекуррентная депрессия; биполярная депрессия; биомаркеры*

INTRODUCTION

Differential diagnosis of recurrent and bipolar depression, i.e., depressive episodes in recurrent depressive disorder (RDD) and bipolar affective disorder (BAD), presents challenges in practice, despite their obvious clinical features and differences [1, 2]. For example, the clinical guidelines for the diagnosis and treatment of BAD published by the Ministry of Health of the Russian Federation in 2021 [3] state that the diagnostic criteria for a depressive episode in BAD and RDD do not differ; however, certain signs, such as an onset at a younger age (as young as 25 years) or in the postpartum period; acute onset (days or hours) of symptoms and their rapid resolution; features of atypical depression with hyperphagia, hypersomnia, inverted circadian rhythm, etc.; the presence of psychotic symptoms; a prolonged course of the disease; and low susceptibility to antidepressant therapy, are more typical of depression in BAD. However, in clinical practice, the above-mentioned signs of an atypical depressive episode of BAD remain undetected in many cases [4, 5]. At the same time, differentiating between recurrent and bipolar depression is key in the choice of treatment. In the absence of surefire clinical criteria, the neurobiological characteristics of depressive conditions may come to play an important role, although their studies have so far been relatively disappointing and in some cases even economically unjustified [6–9].

One of the objectives in clinical neurophysiological studies is to identify reliable markers that could not only detect changes in the functioning of the nervous system in various diseases, but also contribute to an objective diagnosis of the diseases themselves, including differential diagnosis. Electroencephalography (EEG) might be the most promising tool so far in this endeavor. It is a non-invasive, low-cost, and objective method for recording brain neural activity. Unlike neuroimaging methods, EEG provides a continuous assessment of the neural activity associated with a particular stimulus or reaction with high temporal resolution, even when no external changes in behavior are observed. Consequently, EEG parameters can be useful as biological markers of a mental illness that trace back to specific pathophysiological mechanisms. Data accumulated to date from high-caliber studies [10–12], including the results of our own studies [13, 14], suggest various EEG markers that can be used to differentiate between unipolar and bipolar depression. However, the question of how well they hold up to scrutiny remains open.

A trove of data seems to indicate that the development of depressive conditions is accompanied by a change in the patterns of all EEG frequency ranges [15–17]. These changes mostly affect the main EEG rhythm; the alpha rhythm. According to a number of studies, the generation of the alpha rhythm is associated with impulses that spread in the intercortical and thalamocortical neural networks and its magnitude synchronizes the functional brain activity and determines the interplay between information received from the afferent system and the mechanisms of working memory, thereby regulating adaptive processes in the body [18, 19]. Therefore, the EEG alpha frequency traditionally attracts the attention of researchers due to its high sensitivity to various external influences and the subtle changes that take place in the functional state of the cerebral cortex. Meanwhile, both the neurophysiological mechanisms and the functional significance of the alpha rhythm are still the subjects of debates. According to some studies, the quantitative characteristics of the alpha rhythm can only be fully understood after one takes into account the spectral power and activation intensity (inhibition of the alpha rhythm after one opens their eyes, the Berger effect) [18, 19]. Considerable data now exists on the changes that take place in the alpha power in depressive disorders of various origins [10–17]. However, only a few studies into the activation reaction in patients with depressive disorders can be found in the literature [20].

The objective of this study was to search for differences in the quantitative characteristics of the EEG alpha rhythm in patients with a depressive episode within the framework of recurrent depression and bipolar depression.

METHODS

Setting

The selection of patients for the study was carried out at the 3rd Clinical Psychiatric Department (Department of Affective Conditions) of the Clinic of the Mental Health Research Institute of the Tomsk National Research Medical Center. The EEG study was carried out at the Laboratory of Molecular Genetics and Biochemistry of the Mental Health Research Institute of the Tomsk National Research Medical Center.

Participants

The study sample included a total of 60 female patients (age, years: median 32, interquartile range 27 and 53) admitted for treatment with a diagnosis from the cluster of mood disorders: RDD, current episode mild/moderate (F33.0, F33.1 according to ICD-10, n=30) and BAD, and current episode mild or moderate depression (F31.3 according to ICD-10, n=30). Diagnostic assessment and clinical qualification of the disorder were carried out by psychiatrists according to the ICD-10 criteria and using the Hamilton Depression Rating Scale (HDRS-17) for the assessment of the severity of symptoms. The medical history was collected, including the age of the patient, the duration of the disease in years, the total number of depressive episodes, and the duration of the current episode in months.

Inclusion criteria: patient consent for the study, established diagnosis of an affective disorder (F31.3 or F33.0-1) according to the ICD–10, age 18–60 years.

Exclusion criteria: refusal to participate in the study, dementia, mental retardation, other severe organic brain diseases with severe cognitive impairment (encephalitis, meningitis, sequelae of traumatic brain injury, etc.), and acute or chronic decompensated somatic diseases requiring intensive treatment.

All patients were examined during hospitalization (before the main course of treatment), usually on days 2–3 after admission to the hospital.

The control group consisted of 30 mentally and somatically healthy women (age, years: median 35, interquartile range 25 and 53) who were examined using the same exclusion criteria (The Kruskal-Wallis test (2, N=90)=6.689, p=0.158 for comparisons of the RDD, BAD, and control groups).

EEG recording and processing procedure

The EEG was performed in an electrically screened room with dim light. During the study, the patients were in a state of calm, relaxed wakefulness, and in the sitting position. Two functional tests were performed: a baseline study with closed eyes and a test with open eyes. All patients remained under physician supervision during the EEG recording, and the recording was discontinued if the patient started falling asleep or EEG signs of drowsiness were detected. The EEG was recorded using a 16-channel encephalograph (Neuropolygraph, LLC Neurocor, Moscow) according to the international 10–20 system, in monopolar configuration, with a sampling rate of 1 kHz and Fz as the ground electrode. Reference electrodes (A1 and A2) were positioned on the ear lobes.

The average duration of the EEG recording was 5 minutes. The obtained EEG recordings were band-pass-filtered from 1 to 40 Hz. First, each EEG was cleaned of artifacts (ballistocardiogram, oculographic and electromyographic potentials) based on a visual assessment by a qualified EEG technician. The cleaned EEG recording was subjected to a quantitative analysis using the Neuropolygraph Software package. Topographic maps of the alpha band were constructed to illustrate the gradient changes in the alpha band maxima: dominance region — brain regions with the maximum amplitude (usually in the occipital regions); preserved regional differences — differences in the magnitude of the alpha rhythm in the leads; and assessment of the fronto-occipital gradient — decreasing alpha activity from the occipital to the frontal leads. Average values of the absolute spectral power (μV²) and interhemispheric coherence (AvCOH) of the alpha rhythm in the standard frequency range (8–13 Hz) with closed and open eyes were calculated for all EEG leads. The magnitude of the activation reaction (the Berger effect) was determined using the following formula:

$$M_a = \frac{P_{ec} - P_{eo}}{P_{ec} \times 100\%},$$

where M_a is the magnitude of the activation reaction, P_{ec} and P_{eo} are the spectral power of the alpha band averaged over all EEG leads with eyes closed and eyes open, respectively (μV²).

Statistical analysis

Statistical processing of the obtained data was carried out using the Statistica 12 Software package (StatSoft). The distribution was tested for normality using the Shapiro-Wilk test. The obtained data demonstrated a non-normal distribution. Data are presented as medians and interquartile ranges: Me [Q1; Q3]. The Mann-Whitney test was used to compare the demographic and clinical characteristics between the two groups of patients. The Kruskal-Wallis test (ANOVA) and the automatic *a posteriori* pairwise comparison procedure using Dunn's test were used to compare quantitative alpha band characteristics between the control and patient groups. The Spearman rank correlation test was used to assess the presence, level, and direction of the correlations of demographic, clinical, and EEG variables. Differences were considered statistically significant at p <0.05.

Ethical approval

Our study was conducted in full compliance with the Declaration of Helsinki of 1964, as amended in 1975–2013, and was approved by the Local Ethics Committee at the Mental Health Research Institute of the Tomsk National Research Medical Center (Minutes No. 154 dated June 17, 2022, case No. 154/1.20.22). All study subjects provided written informed consent to participate in the study and allow the processing of their personal data.

RESULTS

The socio-demographic and clinical characteristics of patients are given in Table 1.

A comparative analysis of the averaged absolute spectral powers of the EEG alpha band between the control group and patients with BAD and RDD revealed statistically significant differences. Patients with RDD demonstrated a reduced alpha rhythm compared with the control group (z=3.223; p=0.003) and patients with BAD (z=2.399; p=0.042).

Table 1. Socio-demographic and clinical characteristics of patients

Parameter	Patients with BAD *n*=30	Patients with RDD *n*=30	U	*p*
Age, years	36 [23; 53]	37 [26; 52]	1819	0.749
Disease duration, years	7 [4; 13]	7 [3; 11]	1763	0.381
Duration of the current episode, months	6 [3; 10]	3 [2; 8]	1597	0.137
Number of previous episodes	3 [2; 7]	4 [3; 8]	1711	0.501
Total HDRS-17 score	19 [16; 24]	20 [17; 25]	1608	0.277

Note: p is the level of statistical significance for inter-group comparisons using the Mann-Whitney test.

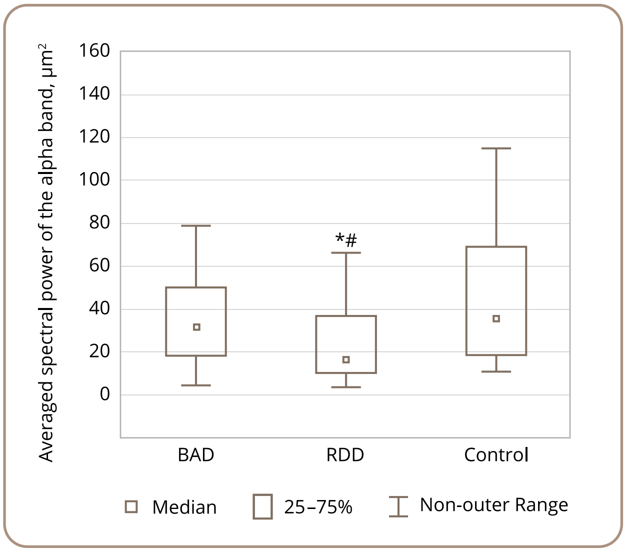

Figure 1. Averaged spectral powers of the alpha band in the study groups of healthy individuals and patients with BAD and RDD.

Note: * statistically significant differences with *p* <0.05 between the RDD and control groups; # statistically significant differences with *p* <0.05 between the RDD and BAD groups using the Kruskal-Wallis test (ANOVA).

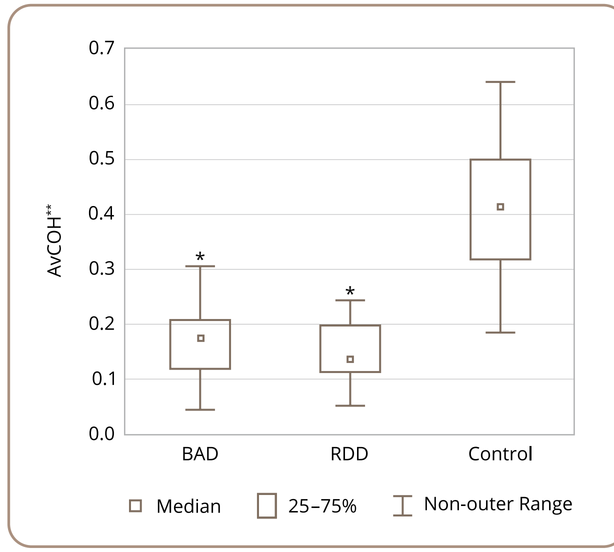

Figure 2. Averaged interhemispheric coherence values of the alpha band in the study groups of healthy individuals and patients with BAD and RDD.

Note: * statistically significant differences with *p* <0.05 between the control group and patients with BAD and RDD revealed using the Kruskal-Wallis test (ANOVA). ** AvCOH is an average interhemispheric coherence (no dimensionality)

There were no statistically significant differences between patients with BAD and the control group (z=0.976; p=0.986) (Figure 1).

The AvCOH values of the study groups revealed markedly decreased (z >7.121; p <0.001) relationships in all patients compared with the control group (Figure 2). No statistically significant differences were found between patients with BAD and patients with RDD (z=0.951; p=0.961).

According to the visual assessment of EEG recordings (Figure 3), a decrease in the generation of the alpha rhythm in patients with RDD led to a decrease in the fronto-occipital gradient and decreased regional EEG differences, but the highest alpha amplitudes were still observed in the occipital regions in the EEG recordings of patients with RDD. The topographic map of the alpha band distribution in patients with BAD was similar to that in the control group.

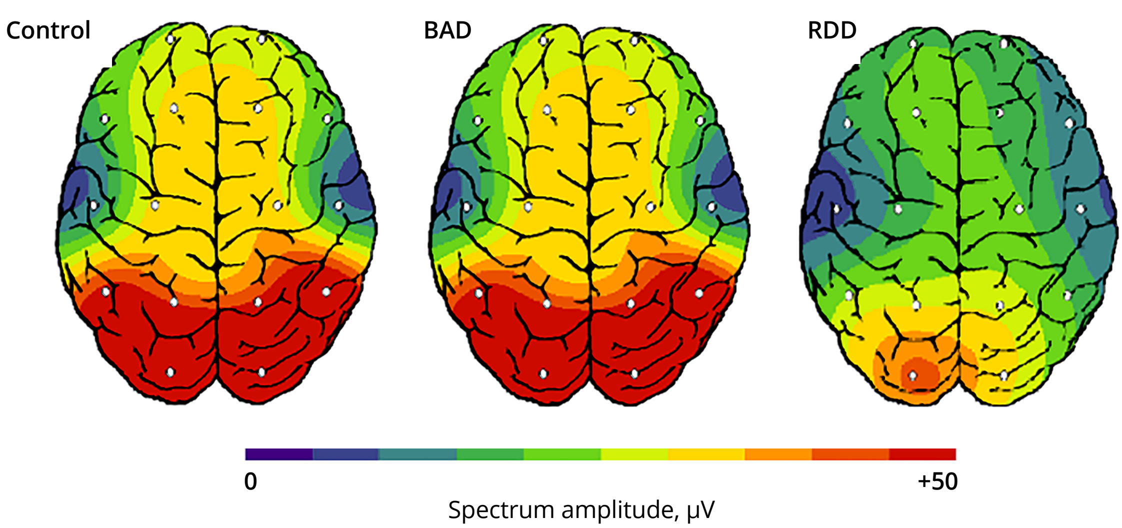

Figure 3. Topographic maps of the alpha band distribution in the control group and in patients with BAD and RDD.

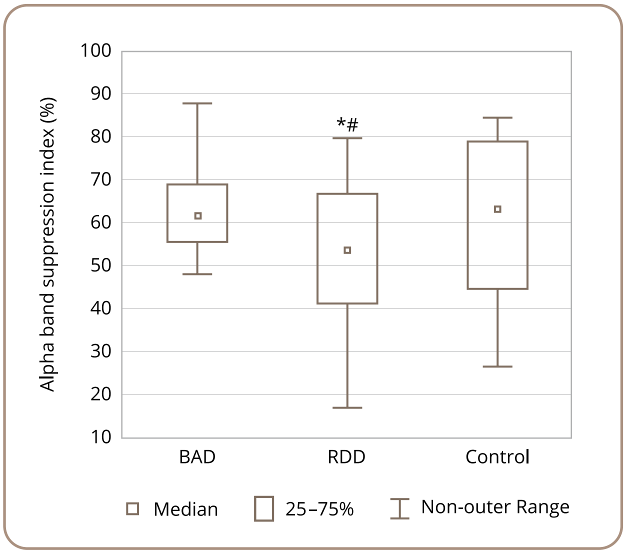

Figure 4. Averaged alpha band suppression indices (%) from eyes closed to eyes open in the study groups of healthy individuals and patients with BAD and RDD.

Note: * statistically significant differences with *p* <0.05 between the RDD and control groups; # statistically significant differences with *p* <0.05 between the RDD and BAD groups using the Kruskal-Wallis test (ANOVA).

The degree of alpha rhythm suppression upon opening of the eyes (the Berger effect) was statistically significantly lower in the group of patients with RDD compared with the control group (z=2.481; p=0.042) and patients with BAD (z=2.573; p=0.035) (Figure 4). We found no statistically significant differences between patients with BAD and the control group either (z=0.442; p=0.991).

We could not find statistically significant correlations of the spectral power, AvCOH of the alpha band and the activation reaction with the age and clinical characteristics of the patients in any of the groups (p >0.05) (Tables S1 and S2 in the Supplementary).

DISCUSSION

In this study, we assessed the quantitative characteristics of the EEG alpha rhythm in patients with BAD and RDD who had an ongoing mild/moderate depressive episode. Both the non-specific physical parameters of the waves (power and coherence) and physiological features of the alpha oscillations (response to visual stimulation after opening of the eyes) were evaluated.

The obtained results revealed that each study group of patients possessed their own distinctive electrophysiological features. In particular, patients with RDD typically had a low absolute spectral power of the alpha band, as well as a less pronounced activation reaction compared to patients with BAD. According to current concepts, EEG recordings reflect the neurophysiological mechanisms of excitation and inhibition [22]. On the one hand, low alpha power values indicate increased excitation in the central nervous system of patients with RDD, as compared with BAD. On the other hand, low spectral power values of the alpha band in patients with RDD indicate less synchronization (dysfunction) of the thalamocortical connections [22]. This was additionally confirmed by an AvCOH value that was lower than that in the controls.

A decreased alpha power in response to the opening of the eyes (the Berger effect) is one of the informative signs of stability of the activation reaction and, together with the magnitude of desynchronization (alpha rhythm suppression percentage), is associated with information processing [18, 23], which reflects the transition from a relatively restful state to the state of wakefulness. The magnitude of the alpha power reduction correlates with the intensity of the activation processes. Thus, patients with RDD typically have a decreased intensity of the activation process compared with relatively healthy controls and patients with BAD. In patients with BAD, the magnitude of the activation reaction was the same as that in the control group.

Thus, the study of the EEG alpha rhythm using a spectral and coherent analysis revealed that patients with BAD and RDD have specific bioelectrical brain activity patterns, something that may subsequently allow a differentiated approach to the assessment of the functional activity of the brain during the first depressive episode based on the quantitative characteristics of the alpha rhythm.

In addition to looking for differences in the alpha rhythm characteristics between patient groups, we also assessed the correlations of the alpha rhythm characteristics with clinical data. However, we were unable to find any statistically significant correlations, probably due to the fact that subclinical manifestations of depression in both groups required a more subtle phenomenological analysis than the duration of the disease/episode and the Hamilton score.

The main limitation of this study was the relatively small size of the study sample and the absence of males in the groups. However, it should be noted that we aimed to balance the groups based on their socio-demographic and clinical data. Another limitation of the study was that, although we evaluated both the nonspecific physical parameters of the waves and the physiological features of alpha oscillations, the selected quantitative characteristics of the alpha rhythm did not cover the full spectrum of possibilities of quantitative EEG assessment. The quantitative characteristics of the alpha rhythm are highly variable and can hardly be fully captured through linear methods of investigation [24]. Unlike other studies [11, 12, 16, 19, 20, 24], our analysis minimized inter-regional differences by averaging the spectral power and EEG alpha rhythm coherence values. Nonetheless, this approach is well justified and is used in many studies [25, 26]. Although our patients were examined during hospitalization (before the main course of treatment), we did not take into account the effect of maintenance therapy, which may well have affected the EEG, another limitation of this study.

CONCLUSION

The data collected in this study provide additional evidence of the specificity of the functional activity of the brain of patients with affective disorders. The differences identified between the patient groups in this study can serve as a starting point for a further search for biomarkers that can help separate recurrent depression from bipolar depression. Using larger groups sizes, as well as including men in the sample, in further studies will help determine whether these differences represented the random occurrence that can often be observed in relatively small groups.

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Supplementary data

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Computational Psychiatry Approach to Stigma Subtyping in Patients with Mental Disorders: Explicit and Implicit Internalized Stigma

Вычислительная психиатрия в типологии стигматизации у пациентов с психическими расстройствами: эксплицитная и имплицитная интернализованная стигма

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Original research

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ABSTRACT

BACKGROUND: Psychiatric stigma has potentially controversial effects on patients' health-related behaviors. It appears that both stigmatization and motivation in psychiatric patients are heterogeneous and multi-dimensional, and that the relationship between stigma and treatment motivation may be more complex than previously believed.

AIM: To determine psychiatric stigma subtypes as they relate to treatment motivation among inpatients with various mental disorders.

METHODS: Sixy-three psychiatric inpatients were examined by the Treatment Motivation Assessment Questionnaire (TMAQ) and the Russian version of Internalized Stigma of Mental Illness scale (ISMI). K-Means cluster and dispersion analysis were conducted.

RESULTS: Cluster 3 (25 subjects) was the least stigmatized. Cluster 1 (18 subjects) showed an "explicit stigma." Cluster 2 (20 subjects) showed an "implicit stigma" that took the form of the lowest treatment motivation compared to other clusters. "Implicitly" stigmatized patients, in contrast to "explicitly" stigmatized individuals, showed a decline in 3 out of 4 TMAQ factors (Mean dif.=1.05–1.67).

CONCLUSION: Cooperation with doctors, together with reliance on one's own knowledge and skills to cope with the disorder, might be the way to overcome an internalized stigma for patients with mental disorders.

АННОТАЦИЯ

ВВЕДЕНИЕ: Психиатрическая стигма имеет потенциально противоречивое влияние на поведение пациентов, связанное со здоровьем. Похоже, что стигматизация и мотивация пациентов с психическими расстройствами являются гетерогенными и многогранными характеристиками, и взаимосвязь между внутренней стигмой и мотивацией к лечению может быть более сложной, чем рассматривалось ранее.

ЦЕЛЬ: Определить подтипы психиатрической стигмы в их связи с терапевтической мотивацией у пациентов стационара, имеющих различные психические расстройства.

МЕТОДЫ: Было обследовано 63 пациента психиатрического стационара с помощью опросника оценки мотивации к лечению (TMAQ) и русскоязычной версии шкалы интернализованной стигмы психических заболеваний (ISMI). Выполнены дисперсионный и кластерный анализ методом k-средних.

РЕЗУЛЬТАТЫ: Кластер 3 (25 человек) оказался наименее стигматизированным. Кластер 1 (18 человек) показал эксплицитную стигму. Кластер 2 (20 человек) показал имплицитную стигму, проявляющуюся, в частности, через самую низкую мотивацию к лечению среди других кластеров. Имплицитно стигматизированные пациенты, в отличии от эксплицитно стигматизированных, в структуре мотивации к лечению демонстрировали снижение по 3-м из 4-х факторов TMAQ (Mean dif.=1,05–1,67).

ЗАКЛЮЧЕНИЕ: Существует категория пациентов с психическими расстройствами, которые преодолевают психиатрическую стигму за счет сотрудничества с врачами и опоры на собственные знания и навыки в преодолении болезни.

Keywords: *patient engagement; motivation; mental disorders; stigma; prejudice*
Ключевые слова: *вовлеченность пациента; мотивация; психические расстройства; стигма; предубеждение*

INTRODUCTION

The development of mental disorders is often associated with a change in a person's attitude towards themselves and a reassessment of their relationships with those closest to them. In literature, identity transformation in psychotic patients is usually discussed in terms of role reorganization and social maladjustment, self-stigmatization, symptomatic (morbid) personality change, cognitive impairment, as well as opportunities for personal growth [1]. It is of note that the psychological effects of demoralization are not unique to those suffering from psychotic disorders, but in over 20% of cases they are a common response to any serious health challenge [2]. The clinical consequences in this case are associated not only with social maladjustment, but also with psychosomatic, anxiety, and depressive disorders [3]. The consequences of stigmatization as a clinical phenomenon related to demoralization are thus likely to become a "second disease" for some health service users. For patients with mental disorders, the internalization of perceived stigma, developing as a response to social stigma, is particularly common and is associated with impaired recovery, decreased energy capacity, lower self-confidence, and self-efficacy [4, 5]. On the other hand, targeted interventions designed to prevent patients from internalizing perceived stigma and negative social attitudes have shown to be effective with respect to their coping strategies and recovery trajectory [6]. However, the relationship between internalized stigma (IS), feelings of social inadequacy, and low quality of life is being debated, and even when taken together, these factors may not be fully predictive of the breadth of self-stigmatized patients' behavioral repertoire within the therapeutic process [4]. In particular, adherence to treatment is also largely determined by motivation and the level of one's insight into the illness [7, 8]. Previous studies have shown higher IS to be associated with poorer treatment adherence across all groups of psychiatric patients [9, 10]. At the same time, in one study, a higher self-rated severity of the illness proved to be a predictor of better adherence to medication, despite the detrimental effect of stigma [11]. It appears that both stigmatization and treatment motivation in psychiatric patients are heterogeneous and multi-dimensional factors, and that their interrelationship may be more complex than previously believed.

Our study aim was to determine the phenomenological subtypes (clusters) of psychiatric stigma as they relate to treatment motivation among inpatients with various mental disorders using a computational approach.

Investigation tasks: (1) to explore IS across its subtypes; and (2) to explore typical associations between types of treatment motivation and IS subtypes.

We tested a hypothesis holding that there is a category of psychiatric patients who can withstand stigma by building a specific structure of treatment motivation. The second assumption was that patients with psychotic disorders and different manifestations of stigmatization present different clinical characteristics.

METHODS

Study design

To address our goal, an observational cohort study design was chosen. Cross-sectional psychosocial variables were used to digitally phenotype groups of patients in a data clustering procedure.

Sample

Patients were recruited from an inpatient unit of the V.M. Bekhterev National Medical Research Centre for Psychiatry and Neurology. Patients were included if they were aged between 18 and 65; were undergoing psychopharmacological treatment for an exacerbation of psychotic, affective, or anxiety disorders or a decompensation of personality disorders (a sample of patients with severe mental disorders [4, 7, 12, 13] for whom the expected levels of psychiatric stigma are the highest); and were close to achieving remission and demonstrated the ability to understand and consent to comply with the research procedures. Patients were excluded if they were unable to participate in assessments due to low cognitive performance, or withdrew consent at any stage.

Ethical approval

Participation in the current study was voluntary and was based on the principles of the Helsinki declaration, confirmed by RIB/IEC (No. 72 EK-I-105/18, dated September 25, 2018).

Measurements

Medical records were used to obtain information about the socio-demographic, clinical, and anamnestic parameters of the patients: sex, age, family status, children, education, occupation, duration of illness, and the number of previous hospitalizations.

All patients in the sample underwent an assessment of treatment motivation and that of the level of IS. Treatment motivation was assessed using The Treatment Motivation Assessment Questionnaire (TMAQ) — based on the patient's motivation for the psychopharmacotherapy scale, developed at the Department of Integrative pharmaco-psychotherapy [8]. The questionnaire includes 20 items. The mathematical algorithm for their evaluation allows one to extract five standardized indicators in Z-Scores. Structurally, the questionnaire represents 4 motivational factors: (1) reliance on one's own knowledge and skills to cope with the disorder, (2) insight into treatment necessity, (3) insight into the psychological mechanisms of morbid maladjustment, and (4) willingness to actively participate in the treatment process. All items are rated on a five-point Likert scale (from 1 [strongly disagree] to 5 [strongly agree]), where higher scores reflect higher levels of treatment motivation, with the exception of level 1, where the items are reversely coded. The final internal consistency of TMAQ was found to be good (Cronbach's alpha 0.842). The convergent, concurrent, and discriminatory validity of the questionnaire was confirmed and described in previous publications [14, 15].

Self-stigmatization was measured using the Russian version of the Internalized Stigma of Mental Illness scale (ISMI) [16]. The validation of the Russian translation of ISMI is currently underway, with findings of the preliminary analysis consistent with the five-factor structure described in the original English version (alienation, stereotype endorsement, perceived discrimination, social withdrawal, and stigma resistance). The original ISMI instrument includes 29 items, each rated on a 4-point scale that ranges from 1 (strongly disagree) to 4 (strongly agree). The results of these questionnaires were used to test the primary hypothesis about the relationship between stigma typology and treatment motivation across the entire sample. The response rate for this part of the study with self-administered questionnaires was 100%. The second hypothesis was tested only in patients with psychotic disorders (schizophrenia, organic mood (with manic features) and schizophrenia-like disorders: codes F2, F06.3, and F06.2 according to ICD-10). The current clinical state of patients was evaluated using the most common psychometric instruments, which also have validated Russian versions: The Brief Psychiatric Rating Scale (BPRS) [17], The Scale for the Assessment of Negative Symptoms (SANS) [18], and The Global Assessment of Functioning scale (GAF) [19]. The response rate for scales application was 93.6%.

Statistical analysis

Analysis of such heterogeneous and dimensional research parameters requires specific statistical tools.

The first stage of the study involved an exploratory analysis with a description of the sample, assessment of the normality of the obtained distributions (using Kolmogorov-Smirnov's z-test with Lilliefors correction for significance), and a description of the measures of central tendency.

The next step involved the application of a cluster analysis of the sample using the k-means method (IBM SPSS Statistics) for subscales of ISMI (previously standardized using Z-Scores), and factors of the TMAQ (have only Z-Scores measurement) in accordance with accepted statistical and methodological practices [20] commonly applied in practice [12, 21].

Next, a comparison of the socio-demographic and clinical characteristics of the patients within the obtained clusters was performed. The core research analysis was conducted using one-way analysis of variance (ANOVA) and Student's t-test for parametric data, Kruskal–Wallis H-test and Mann–Whitney U-test for non-parametric data, as well as Pearson's chi-square test or Fisher's exact test for nominal scales.

Subsequently, for each obtained cluster, a separate assessment of the nature of the data distribution for the included patients was conducted and measures of central tendency were described using methods similar to those mentioned above.

The next step involved a comparison of the means (or mean ranks, depending on the results of the assessment of the distribution normality) for subscales of IS and subscales evaluating the structure and strength of the treatment motivation of patients, similarly using dispersion analyses. For clarity and consistency, all results were presented as mean values (SD). Differences were considered significant at $p \leq 0.05$.

RESULTS

Sample characteristics

The sample included 63 psychiatric inpatients (ICD-10 diagnostic codes: F2, *n*=41 (65%); F3, *n*=8 (13%); F4/F6, *n*=8 (13%); F06, *n*=6 (9%)). The mean age of patients was 34±13 years, the mean illness duration was 12±11 years, and 67% of patients were female.

Average values of the main characteristics of interest in the whole sample were as follows. The sum Z-Score of TMAQ (the intensity of motivation for treatment) –0.29 (0.88) and TMAQ factors: reliance on one's own knowledge and skills to cope with the disorder –0.04 (0.98); insight into treatment necessity -0.08 (0.95); insight into the psychological mechanisms of morbid maladjustment –0.01 (0.92); and willingness to actively participate in the treatment process –0.09 (1.0). The sum score of ISMI (the intensity of self-stigmatization) was 2.47 (0.49); ISMI subscales scores: alienation 2.46 (0.75); stereotype endorsement, 2.12 (0.56); perceived discrimination, 0.11 (0.64); social withdrawal, 2.23 (0.71); and stigma resistance, 3.44 (0.63).

Patients' clusters based on ISMI and TMAQ scores

Cluster analysis of the ISMI scores and TMAQ factors identified three clusters of patients. That enabled us to subtype IS depending on the structure of therapeutic motivation into "explicitly self-stigmatized" (Cluster 1), "implicitly self-stigmatized" (Cluster 2), and patients without specific self-stigmatization marks, i.e., with "minimal self-stigma" (Cluster 3). The results of the cluster analysis are described in Figure 1.

Clinical and demographic characteristics of the patients in clusters

Subjects from the two clusters with self-stigmatization (Cluster 1 and Cluster 2) showed significant differences in all time-associated parameters: age (Cohen's d=1.1), illness duration (Cohen's d=2.1), and history of hospitalizations (Cohen's d=1.3) (Figure 2).

The three resulting clusters of patients showed no differences in main sociodemographic and clinical characteristics, with the exception of the prevalence of negative symptoms and social maladjustment, as well as gender (Table 1 and Table 2).

Characteristics of internalized stigma and treatment motivation in patients' clusters

According to ANOVA with post-hoc tests, 18 patients in Cluster 1 (29% of the sample) had higher levels of total IS score (Mean dif.=0.90, S.E.=0.089, sig. <0.001) due to a higher level of alienation (Mean dif.=1.20, S.E.=0.17, sig. <0.001), stereotype endorsement (Mean dif.=0.81, S.E.=0.14, sig. <0.001), social withdrawal (Mean Dif.=1.09, S.E.=0.14, sig. <0.001), and discrimination experience (Mean dif.=1.09, S.E.=0.17, sig. <0.001) compared to 25 subjects from Cluster 3 (40% of the sample). The features of stigma structure in Cluster 1 was defined as an "explicit" self-stigmatization.

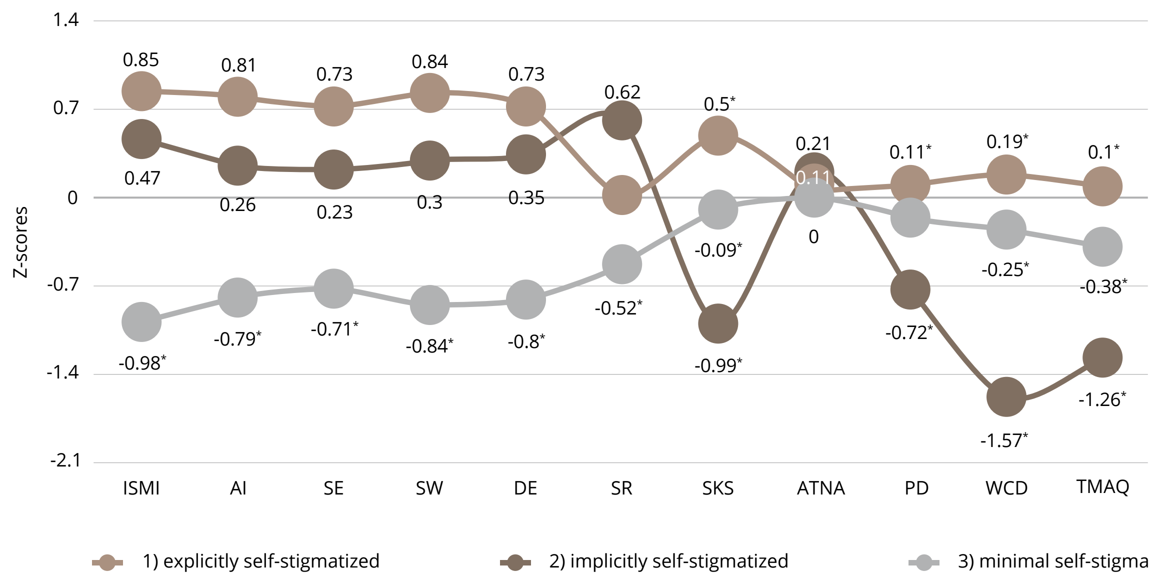

Figure1. Three clusters of IS in connection with treatment motivation in psychiatric inpatients.

Note: * average indicators for a cluster of patients relative to which the indicated numerical values without asterisk differ at *p* ≤0.05; only values with statistically significant differences are numerically marked. ISMI parameters: ISMI — sum. score, AI — alienation, SE — stereotype endorsement, SW — social withdrawal, DE — discrimination experience, SR — stigma resistance. TMAQ parameters: SKS — reliance on one's own knowledge and skills to cope with the disorder, ATN — awareness of the treatment necessity, APD — awareness of the psychological mechanism of maladaptation, WCD — willingness to cooperate with doctor, TMAQ — sum. score.

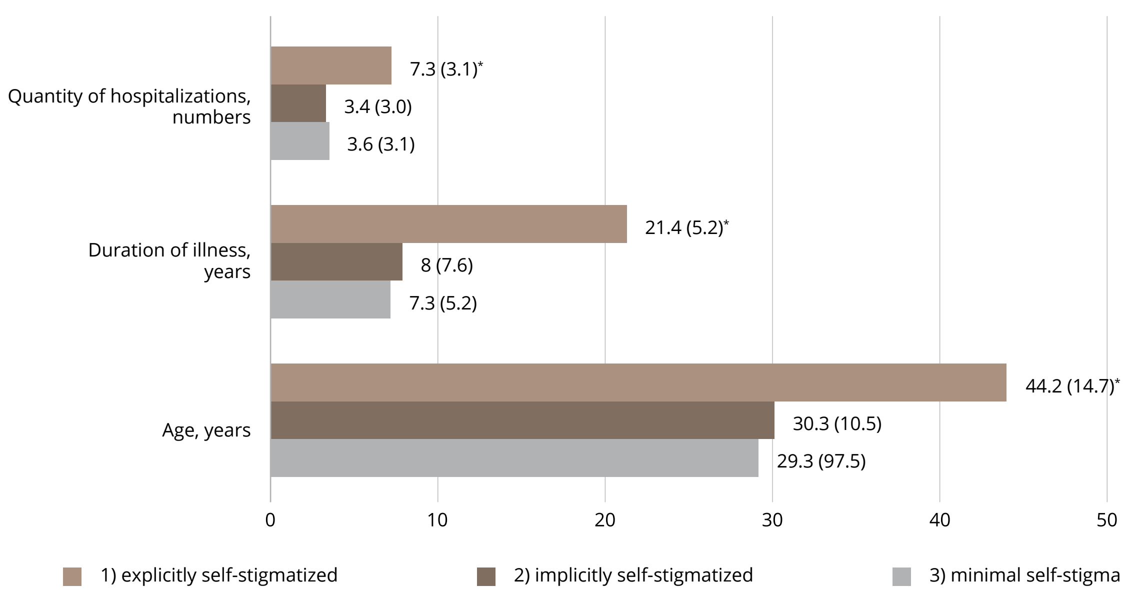

Figure 2. Statistically significant differences between clusters.

Note: * *p* ≤0.05.

Table 1. Sociodemographic and clinical characteristics of studied clusters

Characteristics		Prevalence in Cluster, N(%)			χ²(df)
		Cluster 1, *n*=18	Cluster 2, *n*=20	Cluster 3, *n*=25	
Sex	Male	3 (4.8)	13 (20.6)	5 (7.9)	13.3 (2)***
	Female	15 (23.8)	7 (11.1)	20 (31.8)	
Family	Married	6 (9.5)	6 (9.5)	9 (14.3)	0.2 (2)
	Single	12 (19.1)	14 (22.2)	16 (25.4)	
Children	Yes	7 (11.1)	4 (6.4)	11 (17.5)	3.0 (2)
	No	11 (17.5)	16 (25.4)	14 (22.2)	
Education	Primary	4 (6.4)	10 (15.8)	5 (7.9)	6.0 (4)
	Secondary	5 (7.9)	3 (4.8)	5 (7.9)	
	High	9 (14.3)	7 (11.1)	15 (22.7)	
Occupation	Employed	8 (12.8)	4 (6.4)	11 (17.5)	3.4 (2)
	Unemployed	10 (15.8)	16 (25.4)	14 (22.2)	
ICD-10	F2	12 (19.1)	15 (22.7)	14 (22.2)	4.8 (6)
	F3	3 (4.8)	1 (1.6)	3 (4.8)	
	F4+F6	1 (1.6)	2 (3.2)	6 (9.6)	
	F0	2 (3.2)	2 (3.2)	2 (3.2)	

Note: * *p* ≤0.05; ** *p* ≤0.01; *** *p* ≤0.001.

Table 2. Psychometric characteristics of patients with psychotic disorders (F2, F06)

Characteristics		Prevalence in Cluster, N(%)			χ²(df)
		Cluster 1, *n*=14	Cluster 2, *n*=17	Cluster 3, *n*=16	
BPRS	≥60 points	2 (4.3)	3 (6.4)	5 (10.6)	2.2 (4)
	40–60 points	9 (19.1)	11 (23.4)	8 (17.0)	
	≤40 points	1 (2.1)	2 (4.3)	3 (6.4)	
SANS	≥60 points	6 (12.8)	6 (12.8)	1 (2.1)	9.9 (4)*
	30–60 points	4 (8.5)	6 (12.8)	5 (10.6)	
	≤40 points	2 (4.3)	4 (8.5)	10 (21.3)	
GAF	≤40 points	4 (8.5)	6 (12.8)	3 (6.4)	13.2 (4)**
	40-60 points	7 (14.9)	9 (19.1)	4 (8.5)	
	≥ 60 points	1 (2.1)	1 (2.1)	9 (19.1)	

Note: * *p* ≤0.05; ** *p* ≤0.01; *** *p* ≤0.001.

Twenty patients from Cluster 2 (32% of the sample) were more self-stigmatized (Mean dif.=0.71, S.E.=0.09, sig. <0.001) compared to subjects from Cluster 3 due to a lower level of resistance to self-stigmatization (Mean dif.=-0.71, S.E.=0.17, sig. <0.001). The stigma subtype of Cluster 2 patients was defined as an "implicit" stigma.

Cluster 2 patients demonstrated the lowest treatment motivation compared to the subjects in Clusters 1 and 3 (Mean dif.=-1.53, S.E.=0.20, sig. <0.001; Mean dif.=-1.14, S.E.=0.19, sig. <0.001) due to the lowest TMAQ factor 1 (reliance on one's own knowledge and skills to cope with the disorder; Mean dif.=-1.67, S.E.=0.22, sig. <0.001; Mean dif.=-1.31, S.E.=0.21, sig. <0.001) and factor 4 (willingness to cooperate with the doctor; Mean dif.=-1.19, S.E.=0.29, sig.=0,01; Mean dif.=-1.13, S.E.=0.26, sig. <0.001).

Explicitly and implicitly stigmatized patients differed from each other in TMAQ factor 3 (awareness of the psychological mechanism of maladjustment), which was lower in the implicitly stigmatized group (Mean dif.=-1.05, S.E.=0.27, sig.=0,01).

DISCUSSION

In this study, the cumulative proportion of patients with psychiatric disorders who had pronounced IS was 60%, which is higher than the prevalence of psychological demoralization reactions (24%) known for patients with non-psychiatric disorders [3].

Three clinically different manifestations of psychiatric stigma internalization with bearing on treatment motivation were observed in a sample of psychiatric inpatients. This result confirmed the first hypothesis about the existence of psychiatric patients capable of withstanding stigma by building a specific structure of treatment motivation.

The most favorable type of reaction to mental disorders was found in the largest portion of the sample with minimal self-stigma measured by ISMI and a favorable treatment motivation structure measured by TMAQ (Cluster 3, 40%). Patients in Cluster 1 (29%) and Cluster 2 (32%) displayed effects of alienation, stereotype endorsement, social withdrawal, and discrimination experiences according the ISMI scale. Nonetheless, patients in Clusters 1 and 2 displayed different health-related behavior due to the differences in treatment motivation.

Patients from Cluster 1 could withstand stigma thanks to cooperation with doctors and reliance on their own knowledge and skills in coping with their illness (according to TMAQ). Therefore, because of the ability of patients in this cluster to show good coping skills in the treatment process, we called self-stigmatization in that category of psychiatric inpatients "explicit self-stigmatization."

Patients in Cluster 2 exhibited the highest scores on the reversely coded stigma resistance subscale of ISMI. As a result, they passively accepted the role of "mentally ill person" and showed minimal treatment motivation, which was confirmed by the results on the TMAQ scale — patients showed the lowest intensity of treatment motivation and low awareness of the psychological mechanism of maladjustment. Therefore, because of the absence of any active pushback against internalization of stigma, patients in this cluster were categorized as "implicitly self-stigmatized."

The levels of morbid maladjustment and negative symptomatology (according to the GAF and SANS scales, respectively) in patients with schizophrenia, organic mood (with manic features), and schizophrenia-like disorders in Cluster 1 and Cluster 2 were comparable. They displayed pronounced negative symptoms (SANS score over 60 points) and moderate negative symptoms (SANS score between 40 and 60 points). Social maladjustment was predominantly characterized by moderate levels of GAF scores (scoring between 40 and 60 points). Patients from Cluster 3 had rare maladjustment according to the GAF scale and a low prevalence of negative symptomatology on the SANS scale. The number of patients with schizophrenia, organic mood (with manic features), and schizophrenia-like disorders was comparable in Clusters 1, 2, and 3. Therefore, this result partially confirms the second hypothesis of the study: differences in clinical characteristics among patients with different types of stigmatization are apparent between self-stigmatized (Cluster 1 and Cluster 2) and minimally-stigmatized (Cluster 3) patients, but not between patients with two types of IS with or without lack of treatment motivation (Cluster 1 and Cluster 2). This finding is in accordance with a large body of evidence showing that reducing self-stigma in psychiatric rehabilitation work not only comes with an increase in compliance, but also with symptomatic improvement [22] and reductions in social maladjustment [13].

The two subtypes of stigmatized patients (Clusters 1 and Cluster 2) had differences in clinical and sociodemographic characteristics. Cluster 1 (comprising individuals motivated for treatment and experiencing stigmatization) included older patients with longer illness duration and repeated hospitalizations. The most vulnerable group were the patients from Cluster 2 who, unlike patients from Cluster 1, had IS without building intensive treatment motivation. These patients were younger, they had a shorter duration of the illness, fewer hospitalizations, and were predominantly male.

Strengths and limitations

There are several limitations in this study. The first limitation is the sample size. However, pilot studies in the field of the stated topic quite often rely on small samples: out of the 111 articles included in review [23], around 15% had comparable or smaller sample sizes. The second limitation is the cross-sectional, rather than longitudinal, design of the study, which creates a need to confirm the identified patterns in further observational studies.

The observational nature of this study also determines the nosological heterogeneity of the sample, which, nevertheless, reflects the natural appeal for inpatient psychiatric care at the National Medical Research Centre and is quite common in studies on the psychology of the treatment process [4, 9, 10].

A significant general methodological limitation is the uncertainty of the construct of IS or self-stigma. In this regard, we applied one of the most widely used psychometric tools (ISMI), due to its prevalence, known to be a consensus method of assessing the stigma phenomenon [16]. The literature also describes substantial differences in the prevalence, perception, and internalization of psychiatric stigma across cultures [5]. This underlines the relevance and necessity of expanding transcultural research initiatives into the psychological responses of people with mental illness, with the aim of identifying universal protective factors in relation to self-stigma.

The primary strength and central practical outcome of this study lie in the identification of individuals exhibiting implicit self-stigma (Cluster 2), revealing notably reduced treatment motivation within the realm of all self-stigmatized patients. These observations, detached from disparities in nosology or positive symptomatology between Cluster 2 patients and those categorized in the other two groups (Clusters 1 and Cluster 3), emphasize the potential impact of patients' personal traits and the disease course on the internalization of stigma. Further research into the psychological mechanisms and clinical factors driving the self-stigmatization phenomenon, especially in terms of motivated and nonmotivated treatment attitudes, holds the promise of forging more tailored and person-centered approaches in the psychiatric rehabilitation of individuals with severe mental disorders.

CONCLUSION

Three clinically different types of reaction to mental disorders were observed in a sample of psychiatric inpatients, which enabled us to identify different psychiatric self-stigmatization subtypes, depending on the type of treatment motivation. The tendency of patients with psychiatric disorders to develop self-stigma is associated with a more pronounced morbid maladjustment and severe negative symptoms, but not positive symptoms. The formation of a favorable or less favorable subtype of IS is mediated predominantly by the disease course and the patients' gender, but not diagnosis and symptoms severity. Identification of transnosological phenomena such as stigma and motivation toward psychiatric treatment affords us a promising opportunity to develop a personal, rather than nosologically oriented, approach (personalized approach) to patient rehabilitation. Two subtypes of psychiatric stigma were identified depending on health-related behavior. The "explicit" subtype of self-stigmatization can be considered more favorable than the "implicit subtype," due to a constructive type of treatment attitude with intensive therapeutic motivation among patients with explicit self-stigmatization.

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Level of Patient Satisfaction with Online Psychiatric Outdoor Services

Удовлетворенность пациентов телепсихиатрической помощью

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Original research

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ABSTRACT

BACKGROUND: The COVID-19 global pandemic exposed gaps in the treatment of common physical and mental disorders that had to do with things like lockdowns, poor convenience, fear of contracting COVID, and economic constraints. Hence, to address these treatment gaps while also limiting exposure to the COVID-19 infection, telemedicine in the form of telephone and internet consultations has increasingly become the recourse around the world. Our center adopted this trend and also launched a telepsychiatry initiative in order to better cater to the needs of patients with pre-existing mental health disorders and to ensure regular follow-ups and compliance with prescription regiments.

AIM: The present study aimed to assess the level of patient satisfaction with the online psychiatric services/telepsychiatry.

METHODS: The sample consisted of 100 patients with pre-existing mental health disorders. This was a cross-sectional study lasting 6 months. The DigiDoc app by Hospital Information Software (HIS) software, which is used to manage a patient's appointment schedule, relevant clinical and lab details, along with follow-up prescriptions, was used to follow the selected patients for the purpose of this study. This software also provides a digital platform for video calls for online consultation. The Client Satisfaction Questionnaires-8 (CSQ-8) was employed to collect patient data for analysis.

RESULTS: The mean total CSQ-8 score of the study sample was 21.01±5.80 (8–32), which corresponds to a low-to-moderate level of satisfaction with online psychiatric services/telepsychiatry. Most patients (45%) reported low satisfaction levels, followed by 37% who reported moderate levels of satisfaction. Only 18% of patients reported higher satisfaction with telepsychiatry.

CONCLUSION: Despite the psychiatrists ability to provide adequate professional advice and psychoeducation through online psychiatric services, patients' level of satisfaction proved moderate-to-low. This suggests a need to design standard protocols and guidelines in the search and provision of consultation services on online psychiatric service platforms that could help enhance patients' levels of satisfaction.

АННОТАЦИЯ

ВВЕДЕНИЕ: Глобальная пандемия COVID-19, в частности, такие факторы как необходимость соблюдения режима ограничения по перемещению граждан (локдаун), неудобство оказания помощи, боязнь заражения коронавирусной инфекцией и экономические трудности, выявили слабые места в ведении пациентов с распространенными соматическими и психическими заболеваниями. Для устранения этих слабых мест, а также для ограничения контакта с инфекцией COVID-19, во всем мире все чаще прибегают к телемедицинским технологиям в виде телефонных и онлайн-консультаций. Наш центр последовал примеру и также запустил программу телепсихиатриической помощи, чтобы лучше удовлетворять потребности пациентов с ранее диагностированными психическими расстройствами, обеспечивать регулярное наблюдение и соблюдение назначенных схем лечения.

ЦЕЛЬ: Данное исследование ставило целью оценку уровня удовлетворенности пациентов работой онлайн-службы психиатрической помощи/телепсихиатрии.

МЕТОДЫ: Выборка включала 100 пациентов с ранее диагностированными психическими расстройствами. Данное исследование было кросс-секционным с одной точкой исследования. Набор участников исследования осуществлялся на протяжении 6 месяцев. Данные были собраны с помощью приложения DigiDoc, являющегося частью программного обеспечения Hospital Information System, которое использовалось для записи пациентов на прием пациентов, просмотра важных клинических и лабораторных данных, а также врачебных назначений. В данном приложении также имелась платформа для видеозвонков для проведения онлайн-консультаций. Для сбора данных использовался Опросник удовлетворенности клиентов (CSQ-8).

РЕЗУЛЬТАТЫ: В исследуемой выборке средний балл по опроснику CSQ-8 составил 21,01±5,80 (8–32), что свидетельствует о низком или среднем уровене удовлетворенности от работы онлайн-службы психиатрической помощи/телепсихиатрии. У большинства пациентов (45%) уровень удовлетворенности по данным опроса был низким; 37% сообщили о среднем уровне удовлетворенности. Лишь у 18% пациентов уровень удовлетворенности психиатрической помощью в формате телепсихиатрии был высоким.

ЗАКЛЮЧЕНИЕ: Несмотря на доступность информации и возможность врача-психиатра предоставить адекватную профессиональную консультацию с помощью онлайн-технологий, уровень удовлетворенности пациентов оказался умеренным или низким. Это свидетельствует о необходимости разработки стандартных протоколов и руководств по поиску и предоставлению телепсихиатрических консультационных услуг, которые могли бы способствовать повышению уровня удовлетворенности пациентов.

Keywords: *level of patient satisfaction; telepsychiatry; telemedicine; online psychiatry; digital psychiatry*
Ключевые слова: *уровень удовлетворенности пациентов; телепсихиатрия; телемедицина; онлайн-психиатрия; цифровая психиатрия*

INTRODUCTION

COVID-19 has been declared a global pandemic by the World Health Organization since 2019. Even 2 years after the start of the pandemic, COVID-19 continues to spread in waves across different geographical areas of the world. To help check the spread of the virus, most countries have adopted specific protocols such as social distancing, home quarantine, closure of nonessential businesses, and intermittent travel restrictions[1]. Due to the adoption of COVID-19-weighted behavior, many aspects of people's lives have been affected, including the healthcare needs of those who are suffering from chronic medical, surgical, or mental illnesses due to difficulty in accessing healthcare services and the reduced availability of healthcare professionals who are themselves trying to avoid COVID-19 self-infection [1]. This has resulted in the breakdown of the traditional in-person, face-to-face physical consultation model, which has resulted in a global explosion in online consultation.

1 WHO Director-General's opening remarks at the media briefing on COVID-19. [Internet]. 2020 March 11. [cited 2021 Nov 10]. Available from: https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

To close this treatment gap while minimizing exposure to the COVID-19 infection, online psychiatry consultation/telepsychiatry has been adopted to cater to the needs of patients with mental health disorders [2].

Patient satisfaction is a general psychological condition that results from emotions surrounding the expectations, coupled with the prior experiences of patients, as they interface with healthcare services [3]. In the past few decades, patients' satisfaction with healthcare services has gained importance for patients with mental illness, seeing as it is an important aspect of management protocol, which positively affects treatment adherence and overall outcomes [4]. This also points to weaknesses and flaws in the delivery of healthcare and helps as we explore the determinant of quality in healthcare, which is important as policymakers seek to design more effective mental health programs [5]. Therefore, the level of satisfaction with healthcare services is considered a reliable indicator of improvement and change in the existing healthcare provision infrastructure [6] and could be beneficial as we explore new ways of providing healthcare services, such as online psychiatric services.

Although a good deal of studies [7–10] have revealed good levels of client satisfaction as relates to in-person, face-to-face psychiatric services, there is a dearth of information regarding the state of play as regards online psychiatric services/telepsychiatry in India. Although there is a study that assesses the level of satisfaction with telepsychiatry in India, the sample in that study consisted of only patients with substance-abuse disorders [11]. Similarly, another study during the covid pandemic assessed the level of client satisfaction using semi-structured scales, with a sample consisting of both psychotic and neurotic disorders [12].

In this era of accelerated spread of digital technologies, online consultation/telepsychiatry would, theoretically, seem to be an easier, more convenient, and cost-effective way of providing medical services to remotely located populations. It could also be considered a good alternative for consultations and follow-up for psychiatric patients, who usually require years of treatment [13]. This highlights the importance of the present study, the findings of which could be helpful to policymakers in designing tools and guidelines for online Psychiatric services/telepsychiatry.

During the pandemic, online psychiatric services were launched at the Study Center, using video conferencing and the mobile application DigiDoctor App of Hospital Information Software (HIS). This raised the question of the level of patient satisfaction relative to the newly introduced online psychiatric services/telepsychiatry. This led, in turn, to the launch of a study designed to assess the level of satisfaction of those suffering from psychiatric disorders who were consumers of our online psychiatric services. The primary objective was to assess their level of satisfaction as patients using the Client Satisfaction Questionnaire (CSQ-8).

METHODS

Study design

This study had a cross-sectional design. Data was collected during six months.

Setting

After the start of the COVID-19 pandemic in 2019, all patients with psychiatric disorders who had enrolled in the previous two years using the HIS software were informed via text message and phone calls by the department of electronic medical record about the availability of online psychiatric services for the purpose of consultation and follow-up, with the goal of minimizing instances of discontinuation of ongoing psychiatric treatment.

Those patients, who had until then been consulted in-person at the Department of Psychiatry, were asked to download the mobile application of the HIS from Google Play store and advised to log in with their registered mobile number or with their old registration number, which had already been sent to them via text messages. Following that, the patient was instructed to book an appointment with their consulting psychiatrist from Monday to Saturday between 9 am and 2 pm.

The DigiDoctor App of HIS was designed and developed by Criterion Tech Pvt Ltd. This App covers most aspects related to patient care, from the registration of patient, to out-patient department (OPD)/in-patient department (IPD) care, and follow-up. This involves the registration of patients, patient sociodemographic and clinical details, options for offline and online (video) consultation, lab reports generation, imaging reports generation, billing, pharmacy, referrals to other specialists, prescription filling, and dietary management for each patient.

After the launch of online psychiatric services/telepsychiatry, an influx of patients seeking follow-up care ensued. The recruitment of patients as per the study protocol began on March 1, 2021 and ended on August 30, 2021.

Through the psychiatrist on duty, on three specified days (Monday, Wednesday, and Friday), all scheduled patients seeking online consultation were screened as per the predesigned selection criteria. During the assessment, the on-duty psychiatrist was advised not to wear a face mask or headgear while conducting the online consultations. This was in keeping with the view that masks might conceal facial expression, scramble a voice, or negatively affect the quality of the consultation, which would be an important factor in determining the level of satisfaction of the patient. This was made possible by sanitizing the rooms where OPD videoconferencing was taking place and requiring only one individual in the room at a time, so as to avoid contact/spread of COVID-19. No such instructions were applied to patients/informants.

Participants

A total of 110 patients were screened, out of which 10 were excluded during the study procedure. Of the excluded patients, 6 refused to provide verbal consent while the remainder had comorbid substance abuse disorders.

Inclusion criteria: (a) a patients with follow-up cases of major depressive disorder, bipolar disorders, anxiety disorders, obsessive compulsive disorder, or tension-type headaches with subsyndromal psychiatric symptoms who had undergone in-person face-to-face consultation at the Study Center and were willing to provide verbal consent to be part of the study and (b) reliable family member/overseers.

Exclusion criteria: patients with mental retardation, psychosis (acute psychosis, schizophrenia, mood disorder with psychosis), substance-abuse disorders, bipolar disorder current episode mania, and lacking a reliable family member/overseer. Patients who refused to provide verbal consent were also excluded.

Procedure

Patients between 18–60 years of age, males and females, who met the inclusion criteria were selected for further assessment after providing verbal informed consent. The informed consent form designed for the study was approved by the Ethics Committee of the Study Center, where it was mentioned that, due to the ongoing COVID-19 pandemic, the only way to secure the informed consent was through a verbal response by the participant, after the participant had been made to read and understand the risks and benefits of the study.

After a participant had provided her/his verbal consent to be included in the study, a text message stating 'You have given your informed consent to participate in the study' was sent to their mobile phone number for record purposes. The recruited patients had been promised that after completing the research study and after the lockdowns/isolation orders had been lifted, they would be allowed to choose between in-person and online consultations. Patients were also informed that regardless of whether they completed the study, neither their right to both types of consultations nor the management protocol for their illness would be affected in the future.

As per scheduled appointment, a psychiatrist consulted the patient remotely using the HIS software mobile application. The duration of each consultation was set at 15–20 minutes. The consultation protocol consisted in an adequate psychiatric assessment that included history, a brief mental status examination, psychoeducation and professional advice, and prescription of medications. During the online consultation, patients were probed by the Psychiatrist. A semi-structured proforma was used to collect information regarding the socio-demographic and clinical profiles of the patient. After completion of the very first online consultation, the patient was given a second online appointment for follow-up consultation, usually 2 weeks later. On the second scheduled online follow-up consultation, besides the assessment of any clinical progress, the Client Satisfaction Questionnaire-8 (CSQ-8) scale [14] was administered by the Psychiatrist to gauge the level of satisfaction of the patient with the online psychiatric services/telepsychiatry experience. The reason the CSQ-8 was introduced during the second scheduled online consultation was that the two-week time interval allowed the patient to become familiar with the technical aspects of online provision of psychiatric services, and his level of satisfaction with such a service could reasonably be assessed. Thus, the patient was now in a better position to use the CSQ scale to rate the quality of the service provided him. In theory, it is reasonable to assume that patient satisfaction after the first appointment may not be as high as that after the second appointment, when the patient is expected to have become comfortable and more familiar with the online delivery of psychiatric services.

The CSQ-8 has shown high internal consistency, along with high reliability and relevance [12]. Patients' responses were recorded on an eight-point Likert scale, and the scoring was categorized as low satisfaction (8–20), medium satisfaction (21–26), and high satisfaction (27–32).

The semi-structured proforma for the collection of patient-related data and CSQ-8 scores were converted into Google Forms for an easier and contactless assessment of the recruited patients. Patients' data were converted in the Excel format for an analysis of the results. Relevant statistical tests were used to analyze the data; e.g., continuous variables were analyzed using Pearson correlation coefficients; means and standard deviations were compared using the unpaired t-test and One-way ANOVA.

RESULTS

Sample characteristics

The sample consisted of 100 patients, of which 40 suffered from major depressive disorders (MDD); 31 — from anxiety spectrum disorder (ASD); 18 — from obsessive–compulsive disorder (OCD), and 11 patients — from tension-type headaches with subsyndromal depressive symptoms. The average age of the sample was 31.0±11.56 (95% CI: 28.71 to 33.29).

Main results

Although there was a positive correlation between the age of the patient and level of satisfaction, it was weak and insignificant (Pearson correlation '*r*'=0.16, df=02, P=0.12). Further, there was an approximately equal male/female ratio in the sample, with the mean CSQ-8 score of males being around 20.75±5.73 and that of females being around 21.30±6.01. Statistically, there was no significant difference in the level of satisfaction between the male and female participants (t=0.46, df=98, P=0.65). Similarly, there was no difference in the level of satisfaction as per religion (t=1.0399, df=98, P=0.31), marital status (t=1.36, df=98, P=0.18), years of formal education (F=2.18, df: 02, P=0.12), occupation (F=0.40, df=02, P=0.68), or type of family setup (t=0.30, df=98, P=0.76). The other socio-demographic variables where the level of satisfaction significantly differed were place of residence and income level. Patients from urban areas were more satisfied than those in rural areas (t=2.32, df=98, P=0.02), and, similarly, patients in the low- and higher-income groups were more satisfied than those in the middle-income group (F=4.04, df=02, P=0.02). The sociodemographic characteristics of the sample are displayed in Table 1.

The mean total CSQ-8 score of the sample was 21.01±5.80 (range: 8-32; 95% CI: 19.85 to 22.17), which meant a moderate level of satisfaction with the online delivery of psychiatric services/telepsychiatry. The majority of patients (45%) reported low satisfaction with online psychiatric services (16.16±4.11; 95% CI: 14.92 to 17.39), while 37% reported moderate satisfaction (22.73±1.3; 95% CI: 22.29 to 23.16). Only 18% reported a higher level of satisfaction (29.61±2.03; 95% CI: 28.60 to 30.62). One-way ANOVA was utilized to analyze the differences between these three levels- lower, moderate, and higher levels of client satisfaction. The analysis revealed a statistically significant difference between the three groups' means± (F=138.58, P=0, DF=2) Table 2.

Each portion of the CSQ-8 scale was ranked from highest to lowest to illustrate in which area the patients were most satisfied and in which they were least. The highest satisfaction rates were observed when the patient was asked "*If you were to seek help again, would you come back to our service?*" (72%) and *"If a friend needed similar help, would you recommend our service to him or her?"* (67%), followed by the question "*to what extent has our service met your needs?*", for which 52% of patients recorded satisfaction. In addition, 52% of patients answered positively when asked "*Did you get the kind of service you wanted*?", but only 42% said they were satisfied with the amount of help received when asked "*How satisfied are you with the amount of help you received?*".

The lowest satisfaction level came with the question "*Have the services you received helped you to deal more effectively with your problems?"* in the last two weeks, to which 61% of patients responded in the negative, followed by 55% of patients responding in the negative to the question "*How would you rate the quality of service you received?"*. Some 53% of patients said that they were not satisfied or somewhat satisfied when asked "*In an overall, general sense, how satisfied are you with the service you received?"*. (Table 3)

DISCUSSION

To the best of this author's knowledge, this is one of the few studies on the level of patient satisfaction with online psychiatric services in India. The study indicates that the majority of patients have a moderate-to-low level of satisfaction with online psychiatric services/telepsychiatry. This finding is in line with another study from India which revealed that although clinicians' satisfaction is higher as regards online psychiatric services, patients' level of comfort and satisfaction with such services remain low [12]. Similarly, a recent study comparing telepsychiatry with in-person consultation of patients with substance-use

Table 1. Sociodemographic Details of Patients and its relation to CSQ-8 (*n*=100)

Characteristic	Statistic	Mean CSQ±SD	Statistics
Mean Age±SD (Range) in years	31.0±11.56; 95% CI: 28.71 to 33.29; R: 14-68	21.01±5.80; 95% CI: 19.85 to 22.17; R: 8-32	* r=0.16. df=98 P=0.12
Gender			
Male	53	20.75±5.73	** t=0.4623 df=98 P=0.65 95% CI: -2.87 to 1.79
Female	47	21.30±6.01	
Religion			
Hindu	68	21.43±5.86	** t=1.04 df=98 P=0.31 95% CI: 1.18 to 3.79
Muslim	32	20.13±5.79	
Marital Status			
Married	62	21.63±5.82	** t=1.36 df=98 p=0.18 95% CI: -0.75 to 4.01
Unmarried	38	20.0±5.81	
Place of residence			
Urban	62	22.05±5.24	** t=2.32 df=98 **P=0.02** 95% CI: 0.40 to 5.07
Rural	38	19.32±6.42	
Education			
Up to 08 Years	35	2.4571±1.1464	*** F=2.18 P=0.12 df: 02
Up to 12 Years	35	2.6286±0.7702	
Graduation & above	30	2.9333±0.7849	
Occupation			
Homemakers & Unemployed	33	20.58±7.0	*** F=0.40 P=0.68 df=02
Employed	40	21.65±5.34	
Students	27	20.60±5.07	
Type of family			
Joint	32	20.75±7.62	** t=0.30 df=98 P=0.76 95% CI: -2.88 to 2.11
Nuclear	68	21.13±4.85	
Total monthly family income (Indian rupee)			
≤ 10,000/-	50	22.18±5.99	*** F=4.04 **P=0.02** DF: 2
10,001–20,000/-	31	18.61±5.82	
> 20,000/-	19	21.84±4.34	

Note: * Pearson Correlation; ** Unpaired t-test; *** One-way ANOVA.

Table 2. Distribution of cases and CSQ-8 scores based on the level of Client Satisfaction (CSQ-8)

S. no	Score Range	Level of satisfaction	Number of cases	Mean±SD	Statistics (One way ANOVA)
1.	<20	Low satisfaction	45	16.16±4.11 (95% CI: 14.92 to 17.39)	F-value: 138.58 P-value: 0 DF: 2
2.	21–26	Medium satisfaction	37	22.73±1.3 (95% CI: 22.29 to 23.16)	
3.	27–32	High Satisfaction	18	29.61±2.03 (95% CI: 28.60 to 30.62)	
4	8–32	Total Score (Overall Satisfaction)	100	21.01±5.84 (95% CI: 19.85 to 22.17)	

Table 3. Domain scores for the Client Satisfaction Questionnaire (CSQ-8) Scale

S. no	Domains	Score (number of patients)				Mean±SD (95% CI)
		1	2	3	4	
1.	How would you rate the quality of service you received?	10	35	34	21	2.66±0.92 (2.48 to 2.84)
2.	Did you get the kind of service you wanted?	19	29	37	15	2.48±0.97 (2.29 to 2.67)
3.	To what extent has our service met your needs?	15	37	31	17	2.5±0.95 (2.31 to 2.69)
4.	If a friend needed similar help, would you recommend our service to him or her?	17	16	36	31	2.81±1.06 (2.60 to 3.02)
5.	How satisfied are you with the amount of help you received?	20	38	26	16	2.38±0.98 (2.19 to 2.57)
6.	Have the services you received helped you to deal more effectively with your problems?	11	28	46	15	2.65±0.87 (2.48 to 2.82)
7.	In an overall, general sense, how satisfied are you with the service you received?	13	34	36	17	2.57±0.92 (2.39 to 2.75)
8.	If you were to seek help again, would you come back to our service?	9	19	39	33	2.96±0.94 (2.77 to 3.15)
Mean Total Score±SD (Range)		21.01±5.84 (8-32) 95% CI: 95%CI: 19.85 to 22.17				

Note: Each domain is rated on 4 points scale where the level of satisfaction increases from Likert rating of 4 to 1 in domains 1, 3, 6, 7; and in the rest of the domains (2, 4, 5, 8), the level of satisfaction increases from Likert rating 1 to 4.

disorders in India revealed a lower level of therapeutic relation, empathy, and satisfaction with teleconsultation than with in-person consultation [11].

On the contrary, another Indian study that assessed the satisfaction level of psychiatric patients with telepsychiatry pre-COVID-19 revealed a higher level of patient satisfaction [16]. Similarly, studies in developed nations assessing patient satisfaction with telepsychiatry have also revealed higher levels of patient satisfaction [9, 10, 17, 18]. The ability of people from developed nations to effectively use digital technology may be the reason for this.

However, the findings of the studies conducted to assess the level of patient satisfaction in face-to-face psychiatric consultation are in contrast with the present study, which has revealed an above-average level of satisfaction (50–65%) [7, 8]. The level of satisfaction also varies with the diagnostic category, as it was highest for patients with depression, followed by those with anxiety and bipolar disorder. It was lowest for patients with schizophrenia [7]. In the present study, the level of client satisfaction was assessed for people with neurotic disorders only, and due to the smaller number of patients in each diagnostic subgroups, intra-diagnostic differences in the level of client satisfaction were not analyzed.

Moreover, the satisfaction level of patients with telepsychiatry also turned out to depend on the psychiatrist's satisfaction with telepsychiatry [19]. Studies that have assessed the level of satisfaction have revealed that clinicians are more satisfied with the online delivery of psychiatric services than patients are [9, 12].

A recent review revealed that telepsychiatry was adopted as the platform of choice to provide mental health services to patients with pre-existing mental health disorders during the COVID-19 pandemic, but that there is a limited amount of information comparing the benefit and feasibility of telepsychiatry over face-to-face consultation [2].

In the present study, sociodemographic factors did not show correlation with the level of satisfaction, except for the fact that the patients from an urban background were more satisfied than those from a rural background, while patients in the lower and higher income groups were more satisfied than those in the middle income group. The reason may be that patients from an urban background are more aware of and may have had prior exposure to online psychiatric services or telemedicine in general. Why patients in the lower income group reported high levels of satisfaction is unclear, but it may be that during the COVID-19 pandemic, these were the patients who could least afford convenience and, hence, a free online consultation may have been a valuable option for them. This finding is in contrast with a recent study conducted in a developed country which revealed that younger age, female gender, and first-time-visitor patients are associated with a lower level of patient satisfaction [18]. The present study did not include naive patients.

In the present study, various unexplored factors could have been responsible for the moderate-to-low satisfaction levels with online psychiatric services/telepsychiatry we uncovered, as this is an emerging practice in developing nations like India. Likewise, there is a lack of awareness among the general population as to how to contact and seek consultations from clinicians through online platforms.

In the present study, despite the moderate-to-low satisfaction level with online delivery of psychiatric services, more than half of the patients agreed that they received the kind of service they wanted, and that online psychiatric services provided the approximate extent of help they needed. Fortunately, about two-thirds of patients agreed to recommend our online services to friends/acquaintances and were also ready to again seek help for themselves. It is a hardship for many patients to travel miles for a consultation that lasts a few minutes, especially for a follow-up, when the patient is stable on prescribed medication. In that scenario, telepsychiatry could be a lifeline [19]. Hence, referred satisfaction to friends or another patient may be understood to be the highest.

Overall, 53% of the patients in our study reported being either not or less satisfied. This may be due to the fact that about 61% of them reported that the consultations received from online psychiatric services providers were either marginally or ineffective in dealing with their problems. Further, 55% of effective patients had a negative view of the quality of online psychiatric services.

The other reasons for the low levels of satisfaction with online delivery of psychiatric services may be the culture. Generally, patients in South Asian countries do prefer to see clinicians in person for a physical examination of their ailments, at least through touching or looking at them; e.g., palpation of radial arterial beats, chest auscultation, etc. This may be due to the ancient cultural belief in the general population that clinicians are second-to-God, as they possess the healing touch/eyes, beside the medications they prescribe. Although there is a lack of research on the subject, the presumed consensus in the general population regarding the satisfaction that comes from being consulted in person is that the patient should be seen and listened to by the naked eye/ear and in person, and so, he must be physically examined. These cultural beliefs regarding medical consultation seem to have positive psychological effects on patients and their families and may also be responsible for the higher levels of patient satisfaction regardless of the afferent medical benefits during in-person face-to-face consultations.

The important characteristic of this study is that it was conducted using a mobile-based application, which not only provided audio consultation (telephonic) between patients and Psychiatrists, but also audio-video consultation, where patient and psychiatrist could interact as during a face-to-face physical consultation. Theoretically, the videoconferencing practiced in the present study is thought to be more satisfying for both the patients and psychiatrists. What is more, in the present study, consultations were conducted by psychiatrists for the need of patients, along with simultaneous assessment of patients' satisfaction. This was not simply a survey where patients were invited, after undergoing a procedure, to rate their satisfaction with the said procedure. We also assessed patient satisfaction upon the second consultation, not upon the first one. This might have given patients time to assess in details the different aspects of teleconsultation before being able to appropriately rate the procedure in the different portions of the CSQ-8 scale.

Strengths and limitations

Although this is an important area of investigation, since teleconsultation is becoming a more common means of providing psychiatric services, the sample size was arbitrarily chosen and most subjects had diagnoses of anxiety disorder, depression, OCD, etc; hence, the findings could not be generalized, as the nature of these disorders may themselves influence the responses to the satisfaction questionnaires. Furthermore, this case may not reflect the regular psychiatric population covering a variety of diagnoses. In addition, the sample consisted of people with follow-up cases only, which may have been biased towards online psychiatric services based on their previous experience of in-person consultation. Also, there is a real possibility of falsely interpreting the emotional response and facial expression of the patient being consulted through videoconferencing by the interviewing psychiatrist, as compared to in-person consultation. This possible erroneous perception by psychiatrists may also stand in the way of an appropriate reciprocation of satisfaction and emotional response from patients. Unfortunately, CSQ-8 was used for research purposes only in this study and had not previously been used at the Center to study a similar sample, making it impossible to compare data on patients' levels of satisfaction with traditional and online consultation. There was also no data that could allow us to compare physician and patient levels of satisfaction (although there was an oral positive response from the consulting physician after completion of the study, and it was not scored on the standardized satisfaction scale). Hence, these results are clearly not sufficient for a discussion and comparison with data from other studies.

CONCLUSION

Despite psychiatrists' ability to provide an adequate psychiatric assessment, professional advice, and psychoeducation in this study, the patient level of satisfaction remained stuck at moderate-to-low. Although online consultation appeared to partially meet patient expectations in this study, there appears to be a need to develop guidelines around telepsychiatry that could help improve the level of client satisfaction before the procedure can be introduced in routine practice, given that awareness about online consultation has now been raised in the Indian population.

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Current Status, Challenges and Future Prospects in Computational Psychiatry: A Narrative Review

Современное положение, вызовы и перспективы развития вычислительной психиатрии: нарративный обзор

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Review

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ABSTRACT

BACKGROUND: Computational psychiatry is an area of scientific knowledge which lies at the intersection of neuroscience, psychiatry, and computer science. It employs mathematical models and computational simulations to shed light on the complexities inherent to mental disorders.

AIM: The aim of this narrative review is to offer insight into the current landscape of computational psychiatry, to discuss its significant challenges, as well as the potential opportunities for the field's growth.

METHODS: The authors have carried out a narrative review of the scientific literature published on the topic of computational psychiatry. The literature search was performed in the PubMed, eLibrary, PsycINFO, and Google Scholar databases. A descriptive analysis was used to summarize the published information on the theoretical and practical aspects of computational psychiatry.

RESULTS: The article relates the development of the scientific approach in computational psychiatry since the mid-1980s. The data on the practical application of computational psychiatry in modeling psychiatric disorders and explaining the mechanisms of how psychopathological symptomatology develops (in schizophrenia, attention-deficit/hyperactivity disorder, autism spectrum disorder, anxiety disorders, obsessive-compulsive disorder, substance use disorders) are summarized. Challenges, limitations, and the prospects of computational psychiatry are discussed.

CONCLUSION: The capacity of current computational technologies in psychiatry has reached a stage where its integration into psychiatric practice is not just feasible but urgently needed. The hurdles that now need to be addressed are no longer rooted in technological advancement, but in ethics, education, and understanding.

АННОТАЦИЯ

ВВЕДЕНИЕ: Вычислительная психиатрия — это область научных знаний, которая находится на пересечении нейронауки, психиатрии и информатики, использующая математические модели и вычислительные симуляции для понимания имеющихся сложностей в моделировании психических расстройств.

ЦЕЛЬ: Цель данного нарративного обзора — дать представление о текущем положении дел в области вычислительной психиатрии, обсудить ее существенные вызовы, а также потенциальные возможности для развития этой области.

МЕТОДЫ: Авторы провели обзор научной литературы, опубликованной по теме вычислительной психиатрии. Поиск литературы проводился в базах данных PubMed и eLibrary. Для обобщения опубликованной информации о теоретических и практических аспектах вычислительной психиатрии был использован описательный анализ.

РЕЗУЛЬТАТЫ: в статье описано развитие научного подхода в вычислительной психиатрии с середины 1980-х годов. Обобщены данные о практическом применении методов вычислительной психиатрии для моделирования психических расстройств и объяснения механизмов развития психопатологической симптоматики (при шизофрении, синдроме дефицита внимания/гиперактивности, расстройствах аутистического спектра, тревожных расстройствах, обсессивно-компульсивном расстройстве, расстройствах вследствие употребления психоактивных веществ). Обсуждаются проблемы, ограничения и будущие перспективы вычислительной психиатрии.

ЗАКЛЮЧЕНИЕ: Возможности современных вычислительных технологий в психиатрии достигли той стадии, когда их интеграция в психиатрическую практику не только возможна, но и крайне необходима. Препятствия, которые сейчас необходимо преодолеть, связаны не с технологическим прогрессом, а с этикой, образованием и пониманием технологий.

Keywords: *computational psychiatry; artificial intelligence; machine learning; ethics; education; diagnosis of psychiatric disorders*

Ключевые слова: *вычислительная психиатрия; искусственный интеллект; машинное обучение; этика; образование; диагностика психических расстройств*

INTRODUCTION

Computational psychiatry (CP), a rapidly evolving field, is often defined in various ways across the literature. For the purposes of this review, we align with the definition proposed by Montague et al., viewing CP as an interdisciplinary field that leverages mathematical models and computational algorithms to understand, predict, and enhance mental health [1]. This broad scope encompasses the modeling of neurobiological processes, the application of machine learning in the predicting of psychiatric states, and the development of computational tools to aid clinical practice. Under this umbrella, 'aspects of computational psychiatry' in our review refer to any research or applications that employ these approaches in the study of mental health.

In this narrative review, we aim to offer an insight into the current landscape of CP, discussing its significant challenges, as well as the potential opportunities for the field's growth. By highlighting the essential role of interdisciplinary collaboration and ethical safeguards, we hope to contribute to the ongoing discourse surrounding the responsible development and application of computational approaches in psychiatry.

It is important to stress that overcoming these challenges will be a demanding, yet crucial endeavor. The potential of computational psychiatry to transform mental health care inspires us to confront these obstacles and facilitate the field's progression with care, diligence, and due consideration for ethical implications.

METHODS

The authors have carried out a narrative review of the scientific literature published on the topic of CP. Both theoretical articles and published research results up to and including May 2023 were considered in the review. The literature search was performed in the PubMed and eLibrary databases, as well as PsycINFO and Google Scholar to ensure a comprehensive review. The following keywords were used to search for the scientific literature: "computational psychiatry", "digital psychiatry", "digital mental health", "computers in psychiatry", "artificial intelligence in psychiatry", "AI in psychiatry", "machine learning in psychiatry".

The evaluation of articles was performed by two independent reviewers, who assessed the publications based on predefined inclusion and exclusion criteria. Any disagreements between the reviewers were resolved through discussion until a consensus was reached. Articles were deemed to fulfil the inclusion criteria if they focused on aspects of CP and the full text of the article was available to the authors. In addition to articles, books that proved significant contributions to the field were also considered.

Additional search was conducted in the reference lists of the articles included in the analysis.

A descriptive analysis was used to summarize the published information on the theoretical and practical aspects of CP. In total, our review includes 54 publications, providing a broad overview of the current state of CP.

RESULTS

In our exploration of the field of CP, we have identified several key themes that recur in the literature. These themes include the definition and scope of CP, the challenges and ethical considerations it presents, the role of interdisciplinary collaboration, the recognition and growth of the field, its application to specific psychiatric disorders, and potential future directions. These themes provided the framework for our discussion of the literature and helped to highlight the key points made by various authors. In the following sections, we present a summary of our findings for each theme, aiming to provide a balanced overview of the current state of CP.

Definition and scope of computational psychiatry

Computational psychiatry is an emerging interdisciplinary field that aims to integrate computational modeling, empirical data, and theoretical insights from various fields, such as psychology, neuroscience, computer science, and mathematics, in order to better understand psychiatric disorders and their underlying mechanisms [1, 2]. The central goal of this field is to develop quantitative models that can link neurobiological processes, cognitive functions, and clinical symptoms to improve diagnostic accuracy, identify novel therapeutic targets, and predict individual treatment responses [3, 4].

To achieve these aims, CP researchers employ a variety of approaches, including reinforcement learning [5], Bayesian inference [6], dynamical systems theory, information theory [7, 8], and large-scale data analysis and network modeling [9, 10]. These approaches help in the investigation of the complex and dynamic nature of psychiatric disorders, dysfunctions in learning and decision-making processes, and the interactions between different brain regions and genetic and environmental factors.

A key challenge in CP is to develop computational models that effectively reproduce the complexity of psychiatric disorders and account for individual differences in symptomatology and treatment response [11]. This process often follows a generalized schema that includes stages such as data collection, preprocessing, modeling, testing, interpretation, and ethical considerations. A detailed illustration of this process can be found in Figure 1.

The integration of various computational approaches can enable researchers to develop more sophisticated models and test specific hypotheses regarding the mechanisms underlying psychiatric disorders [12]. Moreover, CP benefits from advances in machine learning and artificial intelligence (AI), providing novel ways to analyze and interpret complex psychiatric data and offering potential avenues for personalized treatment [13]. The application of computational approaches to neuroimaging data further advances our understanding of the neural basis of various psychiatric disorders [14].

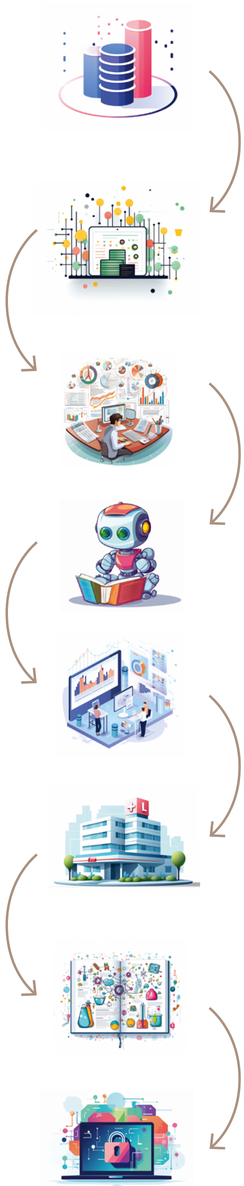
The success of CP ultimately depends on close collaboration between computational scientists, neuroscientists, and clinicians, as well as the development of rigorous model validation and evaluation techniques [15]. By providing a quantitative framework for understanding mental disorders, CP helps to bridge the gap between clinical observations and neurobiological mechanisms, ultimately contributing to the development of more targeted and effective interventions [2, 16].

Interdisciplinary collaboration

Interdisciplinary collaboration is a cornerstone of CP, as it blends insights from various fields such as psychology, neuroscience, computer science, and mathematics to better understand psychiatric disorders and their underlying mechanisms [1, 2]. This cooperation is not without its challenges. For instance, the integration of different methodologies and theoretical frameworks can be complex and requires a deep understanding of multiple disciplines [16]. However, the potential benefits of such teamwork are significant: it allows for the development of more comprehensive models of psychiatric disorders, which can lead to improved diagnostic tools and treatment strategies [17–19].

Moreover, interdisciplinary efforts extend beyond the scientific community. They also involve the education and training of mental health professionals. This includes not only equipping them with the necessary computational skills, but also fostering an understanding of the potential benefits and limitations of computational approaches [20–22].

The essence of interdisciplinary work in CP is also reflected in the research practices within the field, especially in the context of omics technologies. These include genomics,



1. Data collection
Preparation: Defining the goals and parameters of the research, including selecting relevant variables and metrics.
Gathering: Collecting clinical data, neuroimaging, genetic samples, and other relevant data from patients and control groups.

2. Data preprocessing and cleaning
Noise and Artifact Removal: Elimination of noise and artifacts.
Normalization and Standardization: Standardizing and normalizing the data.
Handling Missing Values: Dealing with missing data.

3. Data analysis and methods selection
Algorithm Selection: Determining the suitable algorithm or combination of methods (e.g., machine learning, statistical analysis).
Data Splitting: Dividing the data into training and testing sets.

4. Model building
Training: Training the model based on the selected algorithm, using training data.
Tuning: Optimizing the model's parameters to enhance its efficiency and accuracy.

5. Testing and validation
Evaluation: Assessing the model using test data.
Cross-Validation: Possibly using cross-validation to gauge the model's reliability.

6. Interpretation and application
Analysis: Analyzing results to identify significant patterns and insights.
Integration: Integrating the model into clinical practice to improve diagnosis, prediction, and treatment.

7. Documentation and communication
Recording: Documenting all steps and results for reproducibility.
Communication: Communicating the results with other specialists and potentially publishing in scientific journals.

8. Ethical considerations
Confidentiality: Ensuring patient data's confidentiality and security.
Compliance: Adhering to all regulatory and ethical standards in the research.

Figure 1. A generalized schema for computational model development in psychiatry: an overview.

Note: Images were created by the Midjourney neuronet, Creative Commons Noncommercial 4.0 Attribution International (CC 4.0).

as well as emerging fields such as lipidomics, proteomics, and transcriptomics. Polygenic disease genetics, for example, is one of the omics models, with approaches like polygenic risk scores at the forefront. The application of these multimodal approaches, in conjunction with big data analysis, is mainstream in computational research, significantly contributing to the modeling of mental illnesses [23–26]. This integrative approach is essential for the advancement of CP and its application in clinical practice [27–29].

Challenges and ethical considerations

Despite the promising potential of CP, the field faces several intricate challenges. One primary hurdle is the development and interpretation of computational models that accurately reproduce psychiatric disorders, accounting for individual differences in symptomatology and treatment response [11]. Integration of various computational approaches can lead to more sophisticated models but brings forth difficulties in double-checking, verification in independent studies, comparison in multi-center studies, and across populations, possibly resulting in inaccurate or tainted conclusions [30].

Furthermore, mathematical models, particularly those using big data and machine learning, calculate probability values, such as risk degrees [31]. Misunderstanding these probabilities can lead to societal judgments, especially when personal data leakage occurs, equating risk with diagnosis and potentially leading to stigmatization [32].

The complexity of these models also necessitates the development of stringent guidelines and standards, which becomes crucial in the context of CP [33]. The preconceptions and apprehensions surrounding computational technologies must be overcome. Emphasizing model transparency and biological plausibility can facilitate more widespread acceptance and use [11, 12]. Addressing these challenges, including ethical considerations, will be vital for the continued growth and success of CP in mental health care [28].

Recognition and growth of computational psychiatry

Computational psychiatry, lying at the intersection of neuroscience, psychiatry, and computer science, has been recognized as a significant area of scientific knowledge since the mid-1980s [1, 17]. Despite the complexities and challenges associated with the integration of computational technologies into practical healthcare, the field has seen substantial growth over the past few decades [34]. The evolution of CP heavily relies on the synergy between computational scientists, neuroscientists, and clinicians. This interdisciplinary collaboration is essential to develop a comprehensive understanding of mental disorders, improve diagnostic accuracy, identify novel therapeutic targets, and predict individual treatment responses [1, 2, 16].

The potential of computational technologies in psychiatry has been recognized since the pioneering work of Hedlund et al. (1985) [34], who were among the first to highlight both the potential and challenges associated with this integration. Despite the more than decade that has passed since the first mention of computational psychiatry in publications [1], substantial changes in the field appear to be minimal. However, the advancement of computational psychiatry heavily relies on the synergy between computational scientists, neuroscientists, and clinicians.

The recent integration of machine learning and AI into computational psychiatry has only served to intensify this sense of potential and novelty, offering unparalleled means to dissect complex psychiatric data [13]. However, there is still a palpable misunderstanding within both the literature and professional communities about these technologies. In particular, the apprehensions surrounding the utilization of computers by specialists persist, including the use of modern technologies in psychiatry education [21]. Despite these challenges, the capacity of current computational technologies has reached a stage where its integration into psychiatric practice is not just feasible but urgently needed.

Computational psychiatry in practice: applications to specific disorders

Computational psychiatry has shown significant potential in modeling and the understanding of various psychiatric disorders. The application of computational methods has been explored in the context of schizophrenia, attention-deficit/hyperactivity disorder, autism spectrum disorder, anxiety disorders, obsessive-compulsive disorder, and substance use disorders [35–41].

In schizophrenia, the 'Jumping-to-Conclusions' bias, a tendency to make decisions based on insufficient evidence, has been modeled using Bayesian principles [35]. Similarly, the disruption of reward prediction errors in psychosis has been linked to the substantia nigra/ventral tegmental area [36]. In the context of negative symptoms, the failure to represent the expected reward value of actions has been explored using computational models [37].

In autism spectrum disorder, predictive coding theories have been used to explain the social deficits observed in these individuals [42]. Theories of anhedonia, a core symptom of depression, have been mapped onto reinforcement learning models [39].

In obsessive-compulsive disorder, specific frontostriatal circuits have been identified that are associated with impaired cognitive flexibility and goal-directed planning [43]. The tendency towards habitual behavior, a characteristic of compulsive disorders, has been modeled using computational methods [44].

In substance use disorders, the computational anatomy of addiction has been explored, with a focus on the role of uncertainty and anticipation in anxiety [45]. The application of CP in these disorders has not only provided a deeper understanding of their underlying mechanisms, but also opened up new avenues for their diagnosis and treatment [46, 47].

However, it is important to note that while these applications have provided valuable insights, they also highlight the complexity and heterogeneity of psychiatric disorders. Each disorder presents unique challenges that require tailored computational approaches.

Future directions and potential

Computational psychiatry is a rapidly evolving field with immense potential for future growth. The integration of computational technologies into psychiatric practice is not just feasible but urgently needed [48]. The development of more sophisticated mathematical models and computational simulations will continue to improve our understanding of mental disorders [49, 50].

The use of machine learning and big data in psychiatry is expected to revolutionize the way we predict and treat mental disorders [51]. Network analysis, for instance, offers an integrative approach to the understanding of the structure of psychopathology [52].

The field also faces challenges in terms of stigma and social adaptation, particularly among patients with first-episode schizophrenia [20]. The introduction of artificial companions to older adults with cognitive impairment, for example, may raise some concerns.

The future of CP also lies in interdisciplinary collaboration. The integration of neuroscience, psychiatry, and computer science will be crucial in advancing the field [34, 53]. The educational needs of mental health specialists will also need to be addressed to ensure the successful integration of computational methods into clinical practice [21–23]. Finally, the potential of computational psychiatry in genetic research cannot be ignored. The identification of risk loci with shared effects on major psychiatric disorders represents a significant breakthrough in the field [54].

In conclusion, while the future of CP is promising, it is also fraught with challenges.

DISCUSSION

Upon reviewing the literature concerned with the application of computational technologies in psychiatry, one may perceive an apparent impedance in its integration into practical healthcare. Despite more than a decade since the first mention of computational psychiatry in various publications [1], substantial changes in the field remain minimal. Nonetheless, the advancement of CP heavily relies on the synergy between computational scientists, neuroscientists, and clinicians. This interdisciplinary collaboration is essential to develop a comprehensive understanding of mental disorders and improve diagnostic accuracy, as well as to identify novel therapeutic targets and predict individual treatment responses. This potential of computational technologies in psychiatry has been recognized since the pioneering work of Hedlund et al. (1985) [34], who were among the first to shed light on both the potential and challenges associated with this integration.

Reflecting on the evolution of CP, it’s important to acknowledge the revolutionary shift that has occurred in the field. The advent of advanced computational tools and the increasing acceptance of technology in research have significantly expanded the capabilities of CP. This shift has not only enabled researchers to explore new avenues, but also to revisit existing concepts with a fresh perspective. Despite its 30 years of progress, there is still a palpable misunderstanding within both the literature and professional communities about these technologies. In particular, the tiptoeing around the utilization of computers by specialists persist. The recent integration of machine learning and AI into computational psychiatry has only served to intensify this sense of potential and novelty, offering unparalleled means to dissect complex psychiatric data. However, this area of scientific knowledge currently faces limitations as regards its development. Revisiting the key points discussed in the results section, it’s clear that the field of CP is marked by its interdisciplinary nature, the recognition and growth it has received, and its application to specific psychiatric disorders. Each of these aspects presents unique challenges but also hints at potential future directions for the field. The discussion of these key points in light of the extant literature not only provides a comprehensive overview of the current state of CP, but also sets the stage for future research.

Computational psychiatry has the potential to transform mental health care, laying the groundwork for personalized treatment approaches. The field of psychiatry, unfortunately, has been stigmatized due to limited understanding about the etiology of mental disorders, as well as misunderstandings related to the use of mathematical models. For instance, models that calculate probability values, such as risk degrees, can be misconstrued. When a personal data leak occurs or the essence of risks and probabilities is misunderstood, the risk of a mental disorder might be equated with a diagnosis, potentially leading to further stigmatization [30–32, 55]. This lack of comprehensive knowledge is one of the factors that fuel prejudice. Addressing this, CP strives to construct more intricate models of mental disorders [53]. This process requires the integration of a multitude of data sources, including neuroimaging [48], genetics [54], and behavioral data [1], and necessitates examining these data at different levels of analysis, from the molecular to the cellular and systems level [23]. This multi-modal and multi-level approach empowers researchers to untangle the complex interactions between the genetic [24], environmental [25], and neurobiological factors [26] that contribute to the onset and progression of psychiatric disorders. Importantly, this approach also facilitates the identification of biomarkers and endophenotypes [27], which can serve as essential tools for early diagnosis, prognosis, and the deployment of targeted interventions.

Ensuring the validity and reliability of computational models is crucial for their successful application in clinical practice. The discussion can emphasize the importance of rigorous model validation and evaluation techniques, which can help determine the accuracy and generalizability of these models across diverse patient populations. Access to large-scale, high-quality datasets is vital in this process, as it enables researchers to thoroughly test and refine their models based on real-world data. Encouraging the sharing of data and resources among researchers can facilitate model validation and promote reproducibility in CP.

The application of computational models in clinical decision-making raises several ethical concerns that need to be addressed. These include the potential for stigmatization or discrimination against certain patient groups, breaches of privacy, and misuse of sensitive patient data. It's crucial to develop ethical guidelines and best practices to ensure that computational psychiatry adheres to the highest standards of patient care and confidentiality. Addressing these concerns is key for building trust among patients and clinicians and fostering the responsible growth of the field.

Three major ethical concerns emerge within the realm of computational methods in psychiatry, pertaining to screening, diagnosis, monitoring of conditions, and recommendations for therapy and rehabilitation. First, the security of patients' personal data is a significant issue, albeit not unique to CP, as it extends to all digital workflows [30, 31]. Second, the potential stigmatization of patients is a common concern across the psychiatric field, where computational methods might inadvertently reinforce stereotypes or misconceptions [32, 55]. Finally, the misuse of sensitive information, which is closely related to the first challenge, necessitates stringent measures to ensure data privacy and integrity. These ethical considerations require thoughtful attention and the development of guidelines and best practices to foster responsible conduct in CP and safeguard patients' rights and welfare.

The integration of CP into practical health care demands specialized education and training programs. That being said, it should be noted that in some countries psychiatrists still harbor concerns about the use of computers by professionals, including the use of modern technology in psychiatry training [23]. Meanwhile, more and more work is devoted to the reflection on the use of CP and digital methods in the education of psychiatrists [22, 56], noting both the possible advantages of this approach and its limitations, primarily ethical ones. The research, in the meantime, shows a high level of interest and demand in young psychiatrists for education in psychiatry, including scientific training [57], which may indirectly indicate the potential success in targeting educational programs in CP, specifically for this professional group. Education and training programs on CP must foster interdisciplinary collaboration, ensuring that specialists from various fields can communicate effectively and understand the common language of computational models and tools. Special emphasis should be placed on training clinicians to comprehend the applicability limits of AI-based models, integrating these tools into existing practices with consideration of data security measures and legal aspects [22]. Moreover, it's essential to develop educational programs for patients to demystify the capabilities and limitations of computational psychiatry. This comprehensive educational approach will not only bridge the gap between computational scientists, neuroscientists, clinicians, and patients, but also pave the way for a more coherent and effective application of CP in mental health care.

Furthermore, enhancing the interpretability of models by making them more transparent and biologically plausible can foster their widespread adoption and improve their clinical utility. This emphasis on transparency and plausibility not only augments understanding, but can also contribute to a reduction in the stigmatization of computational psychiatry and its associated technologies.

It is important to also acknowledge the limitations and challenges inherent in CP, such as the need for more biologically plausible models, generalizability across diverse patient populations, and the integration of different levels of analysis. By identifying these limitations, the discussion can outline potential future directions for the field, such as refining existing models, exploring novel computational approaches, and fostering interdisciplinary collaboration. Addressing these challenges will be essential for the continued growth and success of CP in improving mental health care.

The main limitation of this article lies in its narrative review format, as opposed to a systematic review. While this approach allows for a broad overview of CP, it's worth mentioning that potentially insightful articles that could have offered a more comprehensive understanding may not have been included in the search results. Therefore, the scope of our review may be inherently limited by the articles we have accessed. The breadth of the literature reviewed is also a major strength of the article. The authors hope that the literature review presented will generate interest in CP among psychiatrists, which in turn could lead to an increase in the number of studies in this field, as well as a willingness from professionals to use CP methodology in their work and clinical practice, which will be an example of the practical application of the scientific work done by the authors.

CONCLUSION

The field of computational psychiatry is a rapidly evolving discipline that integrates computational modeling, empirical data, and theoretical insights from various fields such as psychology, neuroscience, computer science, and mathematics. It aims to better understand psychiatric disorders and their underlying mechanisms. This interdisciplinary approach has led to significant advances in the field, including the development of novel diagnostic and therapeutic tools. However, the broad scope of CP also presents several challenges. These include the need for rigorous ethical guidelines to govern the use of computational models in psychiatric research and practice. The integration of computational methods into psychiatric research also requires a high degree of interdisciplinary collaboration, which can be challenging to achieve in practice.

Despite these challenges, the field of CP has seen significant growth and recognition over the past decade. This growth is evident in the increasing number of publications on the topic and the expanding range of psychiatric disorders to which computational methods are being applied. The application of computational methods to specific psychiatric disorders has yielded promising results. For example, computational models have been used to better understand the neurobiological mechanisms underlying disorders such as schizophrenia and depression. However, further research is needed to fully realize the potential of these methods in clinical practice.

Looking forward, the field of CP holds significant potential for advancing our understanding of psychiatric disorders and improving patient care. However, realizing this potential will require continued interdisciplinary collaboration, rigorous ethical oversight, and ongoing research to refine and validate computational models. While computational psychiatry is a promising field, it is also a complex one, with many challenges to overcome. However, with continued research, collaboration, and ethical oversight, it has the potential to significantly advance our understanding of psychiatric disorders and improve patient care.

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Machine Learning Techniques in Diagnostics and Prediction of the Clinical Features of Schizophrenia: A Narrative Review

Использование методов машинного обучения в диагностике и прогнозировании клинических особенностей шизофрении: нарративный обзор литературы

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Review

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ABSTRACT

BACKGROUND: Schizophrenia is a severe psychiatric disorder associated with a significant negative impact. Early diagnosis and treatment of schizophrenia has a favorable effect on the clinical outcome and patient’s quality of life. In this context, machine learning techniques open up new opportunities for a more accurate diagnosis and prediction of the clinical features of this illness.

AIM: This literature review is aimed to search for information on the use of machine learning techniques in the prediction and diagnosis of schizophrenia and the determination of its clinical features.

METHODS: The Google Scholar, PubMed, and eLIBRARY.ru databases were used to search for relevant data. The review included articles that had been published not earlier than January 1, 2010, and not later than March 31, 2023. Combinations of the following keywords were applied for search queries: “machine learning”, “deep learning”, “schizophrenia”, “neural network”, “predictors”, “artificial intelligence”, “diagnostics”, “suicide”, “depressive”, “insomnia”, and “cognitive”. Original articles regardless of their design were included in the review. Descriptive analysis was used to summarize the retrieved data.

RESULTS: Machine learning techniques are widely used in the functional assessment of patients with schizophrenia. They are used for interpretation of MRI, EEG, and actigraphy findings. Also, models created using machine learning algorithms can analyze speech, behavior, and the creativity of people and these data can be used for the diagnosis of psychiatric disorders. It has been found that different machine learning-based models can help specialists predict and diagnose schizophrenia based on medical history and genetic data, as well as epigenetic information. Machine learning techniques can also be used to build effective models that can help specialists diagnose and predict clinical manifestations and complications of schizophrenia, such as insomnia, depressive symptoms, suicide risk, aggressive behavior, and changes in cognitive functions over time.

CONCLUSION: Machine learning techniques play an important role in psychiatry, as they have been used in models that help specialists in the diagnosis of schizophrenia and determination of its clinical features. The use of machine learning algorithms is one of the most promising direction in psychiatry, and it can significantly improve the effectiveness of the diagnosis and treatment of schizophrenia.

АННОТАЦИЯ

ВВЕДЕНИЕ: Шизофрения является тяжелым психическим расстройством, которое влечет за собой значительные негативные последствия. Раннее выявление шизофрении и ее лечение благоприятно влияют на клинический прогноз и качество жизни пациента. В этом контексте методы машинного обучения открывают новые возможности для более точной диагностики и прогнозирования клинических особенностей данного расстройства.

ЦЕЛЬ: Данный обзор литературы направлен на поиск информации о применении методов машинного обучения в прогнозировании и диагностике шизофрении и ее клинических особенностей.

МЕТОДЫ: Поиск материала был осуществлен в базах данных Google Scholar, PubMed, eLIBRARY.ru. В обзор включались работы, опубликованные не раньше 1 января 2010 г. и не позже 31 марта 2023 г. Поисковые запросы формировались путем комбинации ключевых слов: “machine learning”, “deep learning”, “schizophrenia”, “neural network”, “predictors”, “artificial intelligence”, “diagnostics”, “suicide”, “depressive”, “insomnia”, “cognitive”. В обзор включались оригинальные исследования независимо от их дизайна. Для обобщения полученных данных использовался описательный анализ.

РЕЗУЛЬТАТЫ: Методы машинного обучения широко применяются в функциональной диагностике шизофрении. Их используют в распознавании данных от МРТ, ЭЭГ, актиграфии. Также модели, созданные с помощью алгоритмов машинного обучения, могут анализировать речь, поведение, творчество людей для диагностики психических расстройств. Было установлено, что различные модели, построенные на основе машинного обучения, способны помогать специалистам прогнозировать и диагностировать шизофрению, основываясь на анамнестической, генетической, эпигенетической информации. Методы машинного обучения также успешно применяются для построения моделей, которые способны помогать специалистам диагностировать и прогнозировать клинические проявления и осложнения шизофрении, такие как бессонница, депрессивные проявления, риск суицида, агрессивное поведение, динамика когнитивных функций.

ЗАКЛЮЧЕНИЕ: Применение методов машинного обучения играет важную роль в психиатрии, с их помощью разработаны модели, помогающие специалистам в диагностике шизофрении и ее клинических особенностей. Применение алгоритмов машинного обучения является одним из наиболее перспективных направлений в психиатрии, это может значительно повысить эффективность диагностики и лечения шизофрении.

Keywords: *machine learning; schizophrenia; neural network; artificial intelligence; predictors*
Ключевые слова: *машинное обучение; шизофрения; нейронная сеть; искусственный интеллект; предикторы*

INTRODUCTION

The previous decades have been marked by rapid developments in artificial intelligence (AI). The number of scientific articles on the use of AI techniques is increasing. Machine learning is a fundamental area of AI that allows a computer to analyze data and extract information without explicit programming. Unlike the traditional approach, where it is necessary to write a special code to solve a specific problem (e.g., determining an image of a cat), in machine learning a model is generated with a large amount of data (e.g., images of cats and images of non-cats) and is allowed to "learn" based on this generated data. Following that, the model is able to predict or aporton new data (e.g., determine whether the new image is a cat) that were not used in the original dataset [1]. In scientific papers, machine learning is used as a tool with many practical applications, including pattern recognition, data analysis, event prediction, and much more [2, 3]. Models created using machine learning techniques are used in many fields of the sciences, such as physics, chemistry, mathematics, economics (forecasting financial markets [4]) and in bioinformatics for the analysis of biological data, such as genomes, proteomes, and metabolomes [5]. Models created using machine learning techniques are also used in medicine; they can help specialists in decision-making, in diagnosing and predicting the development of diseases, in monitoring patients' health using mobile applications, in predicting epidemic outbreaks, etc. [6–8].

Machine learning algorithms have also found use in the diagnosis of schizophrenia. Schizophrenia is a chronic, progressive psychiatric disorder with an incidence of 4 to 6 per 1,000 population. The prevalence of schizophrenia is quite identical in females and males and is slightly higher in residents of urban communities compared to residents of rural areas [9–11]. The diagnosis of schizophrenia, according to the DSM-5 criteria, is based solely on clinical signs [12]. This may make it difficult to accurately diagnose disorders that are similar in some cases, such as schizophrenia and autism spectrum disorders [13], or schizophrenia and bipolar disorder [14]. To increase the likeliness of a good prognosis and a high quality of life for patients with schizophrenia, it is crucial to quickly and accurately detect the clinical symptoms of the disease and prescribe treatment in a timely manner [15, 16]. In the context of schizophrenia, machine learning techniques open up new opportunities for more accurate diagnosis and prediction of the clinical features of the illness. One of the advantages of using machine learning techniques is the ability to process large amounts of data, as well as the ability to analyze information that is diverse in nature [17]; e.g., individual clinical manifestations, neuroimaging test findings, patient's history data, genetic data, the patient's voice, etc. Based on these data, both diagnostic and prognostic models have been generated. Diagnostic models help specialists identify the disease more accurately, and prognostic models can help predict the development course of schizophrenia [18], as well as its clinical manifestations and complications, including the risk of suicide [19]. Furthermore, machine learning can help identify new biomarkers associated with schizophrenia, which can improve our understanding of the mechanisms underpinning this disorder and contribute to the development of more effective therapeutic methods [20, 21].

There has been a significant increase in the number of studies that seek to evaluate the diagnosis of schizophrenia and predict its clinical course using machine learning techniques. However, the field is characterized by a wide variety of topics and multiple publications, which requires a systematic review of available information. First, a literature review on this topic allows one to identify the most effective machine learning techniques used to predict and diagnose schizophrenia; second, it allows one to also identify promising areas of future research into the use of AI in psychiatry.

Thus, this literature review aimed to probe for information on the use of machine learning techniques in predicting and diagnosing schizophrenia and trying to identify its clinical features, as well as generalizing data and identifying key findings that can provide a better understanding of the current state of research in this field.

METHODS

Scientific papers were searched in the Google Scholar, PubMed, and eLIBRARY.ru databases, and the publications included in the lists of references of thematic reviews were also analyzed. Search queries included various combinations of the following words: "machine learning", "deep learning", "schizophrenia", "neural network", "predictors", "artificial intelligence", "diagnostics". The following keywords were used to search for papers devoted to the identification of the clinical features and complications of schizophrenia: "suicide", "depression", "insomnia", cognitive". These keywords were combined to create search queries; e.g., "machine learning", "predictors" AND "schizophrenia".

The review included studies into the use of various AI technologies in the context of schizophrenia diagnosed according to the DSM-IV, DSM IV-TR, DSM-5, ICD-10, and ICD-11 criteria published no earlier than January 1, 2010, and no later than March 31, 2023, without any language restrictions. This time interval was chosen because of the substantial increase in the number of publications on this topic from 2010 to the present. The review included original studies, regardless of their design, evaluating the use of various machine learning techniques in the diagnosis of schizophrenia and determination of its clinical features in patients with both a first episode of schizophrenia and the chronic form of the disease. Descriptive analysis was used to summarize the retrieved data.

RESULTS

Based on the search results, 38 papers were included in the review. Then the sections containing information on the use of different AI technologies in the functional testing (electroencephalography (EEG) and magnetic resonance imaging (MRI), actigraphy) of patients with schizophrenia, the analysis of their mental capacities (speech, behavior, creativity), the evaluation of their history and genetic data, as well as the prediction of complications, outcomes of the disease, and its individual manifestations, were determined. Each of the listed aspects of the use of AI technologies is reviewed below.

Machine learning techniques in the functional assessment of patients with schizophrenia

In addition to psychiatric interviews and neuropsychological testing, other investigative (EEG, MRI) techniques are used in the diagnosis of schizophrenia to rule out the presence of other disorders, as well as for research purposes. In a study by Di Lorenzo et al., the authors revealed that people with schizophrenia demonstrated lower alpha rhythms on EEG in the frontal and central regions of the brain compared to the control groups. The level of the alpha rhythm is known to be associated with mental processes, such as attention and memory. The authors suggested that a low level of alpha rhythm may be associated with cognitive impairment and impaired mental abilities in patients with schizophrenia [22]. In another study, scientists found that in people with schizophrenia, interhemispheric connectivity was significantly lower in the frontal and parietal lobes compared to the control group [23].

Despite the fact that EEG is not used to diagnose schizophrenia in routine clinical practice, machine learning techniques can improve the accuracy of the diagnosis of schizophrenia based on EEG findings. In an article by Sun et al., researchers concerted EEG signals into a series of images then a hybrid deep neural network was built and trained, which could help distinguish the EEG signals of a healthy person from those of a person with schizophrenia with 99.22% accuracy [24]. In another, similar study in which a convolutional neural network was used, the accuracy was also high, reaching 98.07% [25]. Neural networks are widely used in the classification of EEG signals, and scientists also suggest that neural networks trained to classify EEG findings can be useful in early detection of schizophrenia [26–28].

Neural networks are being relied upon with increasing frequency in the analysis of 3D MRI images of the brain. In a study by Chen et al., the researchers trained a convolutional neural network to classify MR images of people with schizophrenia with a probability of 85%. Likewise, with the help of a neural network, suspected biomarkers of schizophrenia were identified: namely, abnormal structural changes in the cerebellum, fusiform gyrus, and the temporal, occipital, and frontal brain lobes [29]. In another study, researchers analyzed MR images of people with schizophrenia, bipolar disorder, and mentally healthy people. As a result, models based on machine learning algorithms were built to distinguish an image of a person with schizophrenia from that of a healthy person with an average accuracy of 90%, and from a person with bipolar disorder with an accuracy of 88% [30]. In a study by Oh et al., the authors successfully used a convolutional neural network to classify MR images of patients with schizophrenia with an accuracy of 84.15~84.43% and they revealed that the most significant brain regions were the low and middle temporal lobes [31]. In another paper that pursued the same objective, the researchers applied the M3 method (multimodal imaging and multi-level characterization with multi-classifier) and achieved an accuracy of 83.49% [32].

There are models that have been created using machine learning techniques that can be used to diagnose schizophrenia using actigraphy. In one study, scientists collected data from Actiwatch bracelets that recorded the acceleration amplitude of the sensor, thereby reflecting the motor activity of the participants during the day. Using a convolutional neural network, the researchers successfully distinguished patients with schizophrenia from those suffering from mood disorders against the control group patients. At the same time, patients with schizophrenia showed the lowest motor activity [33]. In another study, researchers analyzed the patterns of nocturnal activity in individuals at risk of developing schizophrenia, people with bipolar disorder, and healthy people. Using various machine learning algorithms, the scientists created models that could identify a respondent at risk of schizophrenia and bipolar disorder [34].

Machine learning techniques in the analysis of speech, behavior, and creativity in people with schizophrenia

Machine learning is used to analyze written and spoken speech. In a study by Bae et al., the authors used a neuronal network to analyze the linguistic patterns of people with and without schizophrenia on the Reddit social network. On this social platform, people can create different topics, discuss them, and share something important. Researchers compared the topics created about schizophrenia with topics about humor, fitness, meditation, parenting, etc. It turned out that people describing their mental issues used fewer singular first and third person pronouns, and, vice versa, a greater number of impersonal pronouns, plural second, and third person pronouns. It has also been observed that people with mental illnesses are less likely to use the past tense as well as words describing positive emotions, and that they are more likely to use words associated with negative emotions [35]. In a study evaluating the linguistic characteristics of people with schizophrenia on the Twitter social network, it was found that people diagnosed with schizophrenia more often used interpersonal pronouns in their texts and were more likely to put less emphasis on friendship and more on biological needs [36].

Neural networks are also capable of processing audio information. In a study by Fu et al., researchers created a Sch-net neuronal network which was able to distinguish the speech of a person with schizophrenia from that of a mentally healthy person with 97.68% accuracy [37]. In a study by Tahir et al., researchers used a system based on machine learning algorithms to automatically predict the presence of “negative symptoms” of schizophrenia based on the speech characteristics. This also could identify the voice of a person with schizophrenia with 81.3% accuracy [38].

There is also data in the literature on the use of the SchiNet convolutional neural network in the analysis of facial behavior during psychiatric interviews of people with schizophrenia. Researchers have concluded that automated identification of facial behavioral patterns is a reliable means of identifying “negative symptoms” of schizophrenia [39]. In another study, a convolutional neuronal network could recognize people with schizophrenia by video recordings. The recording of the face was carried out following various types of emotional stimulation; based on the information collected, the neural network determined a person with schizophrenia with 89% accuracy [40].

A study conducted by Vasilchenko and Usov published the results of the use of a convolutional neural network in the classification of drawings made by people with schizophrenia based on the images of a human face drawn by them; the accuracy in providing correct answers amounted to 82% [41]. In a study by Shen et al., the authors evaluated the categorization of color drawings created by people with schizophrenia and control group subjects using a convolutional neural network. The study showed that people with schizophrenia were more likely to use fewer colors in their drawings, draw irregular lines, and draw more lines near the center of the image compared to the control group. The accuracy demonstrated by the neural network was 90%. Using a neural network analysis, the investigators could reliably predict the results of the Positive and Negative Syndrome Scale (PANSS) assessment using drawings made by people with schizophrenia. The model could predict high scores both in the general scale and the subscales [42].

Diagnosis of schizophrenia based on genetic information using artificial intelligence

There are psychiatric disorders that come with similar symptoms, such as schizophrenia and bipolar disorder, as well as schizophrenia and autism spectrum disorders. This may make the diagnosis of such disorders difficult and result in the use of inadequate therapy. Machine learning techniques-based models can use genetic data to help alleviate this problem. For example, in a study by Karthik et al., researchers used genetic information to teach a neural network how to separate schizophrenia from bipolar disorder. Models based on machine learning techniques helped identify genetic patterns consisting of 75 genes for schizophrenia and 67 genes for bipolar disorder; the probability of correct assumptions by the constructed neural network stood at 95.65% and 97.01%, respectively [43]. In a study by Sardaar et al., researchers compared the genome architecture of schizophrenia and autism spectrum disorders in order to look for "nodal" genes for these disorders. Using a model based on the regularized "gradient boosted machine" (GBM) technique, researchers separated patients with these diseases with an accuracy of 86–88%. They were also able to identify the "nodal" genes responsible for the transmembrane ion transport, neurotransmitter transport, and the processes in the cytoskeleton associated with schizophrenia [44]. In another study, a neural network used information on 792 genetic markers to allocate respondents to a control group and people with schizophrenia with an accuracy of 87.9% [45]. The research conducted by Gunasekaraet al., was also aimed at identifying schizophrenia in the study subjects. In that study, the authors used a SPLS-DA machine learning technique to successfully identify schizophrenia based on epigenetic data: namely, the methylation of various DNA sites [46]. In another study, scientists pointed at the possibility of distinguishing people with and without schizophrenia using G72 gene single-nucleotide polymorphisms, as well as the plasma level of the G72 protein. A naive Bayes classifier turned out to be the best model (AUC=0.9356) [47]. Aguiar-Pulido et al. studied single-nucleotide polymorphisms in the HTR2A and DRD3 genes. They employed neural network analysis of genetic information to identify the genotypes of people with schizophrenia, and the accuracy in the exercise ranged from 78.3 to 93.8% [48].

Analysis of patient's history data using machine learning techniques in the early diagnosis and prevention of schizophrenia

In a large study by Raket et al., researchers used information obtained from the electronic medical records (4,899 events) of the control group (N=72,860) and people with schizophrenia (N=72,860) to predict the development of the first episode of psychosis within one year before its onset. To create a model capable of solving such a problem, the method of recurrent neural network analysis was selected and the probability of a correct predication was 0.774 [49]. Fusar-Poli et al. used machine learning techniques to create a model to predict the development of a psychotic episode in people with a clinically high risk of psychosis. The authors identified the following most significant predictors: high scores on the scales for positive and negative symptoms and disorganization on the Brief Psychiatric Rating Scale, Expanded (BPRS-E), and a small number of years of formal education [50]. Then, the model was improved with the addition of other predictors such as tearfulness, poor appetite, weight loss, cannabis use, cocaine, guilt, hopelessness, irritability, delusion, sleep disorders, lack of insight, arousal, and paranoia. The accuracy of the model based on the Harrell's C-index was 0.085 [51]. In another study, 500 health records of patients with psychosis were analyzed using deep learning of the neural network. This neural network was able to identify the health record of a person with schizophrenia with an accuracy of 92.5%. The most important factor in detecting the disease was age [52].

Predicting the clinical features of schizophrenia

In addition to the main symptoms, the clinical symptoms of schizophrenia may include insomnia, depressive, anxiety, suicidal thoughts, and other symptoms [53–55]. These additional symptoms of schizophrenia may aggravate its course, making treatment more difficult [56, 57].

Insomnia often accompanies schizophrenia exacerbations and may herald an emergent psychotic episode. Insomnia also complicates the course of schizophrenia exacerbation and worsens the clinical prognosis and quality of life of patients [58, 59]. Its diagnosis is of great clinical importance. Kalinich et al., developed an application using machine learning which not only assumed the presence of schizophrenia in the respondent, but also predicted the development of insomnia and neurocognitive deficit. In that application, the subjects were asked to answer several questions and play a mini-game [60]. We have also constructed and trained a neural network capable of predicting the development of insomnia during hospitalization with 72% accuracy based on a patient's medical history and statistical data [61].

One of the most unfortunate complications of schizophrenia is suicide, which can result from symptoms of depression. With the help of AI, scientists have the opportunity to predict the development of depressive manifestations in a person with schizophrenia [62]. Hettige et al., used models created using machine learning techniques to identify individuals with schizophrenia and suicidal attempts. The authors used social, cultural, statistical, medical history, and clinical data from their medical records as input data. The most significant factors in determining suicidal behavior were age, the results of the Childhood Trauma Questionnaire (CTQ) "emotional abuse” subscale, the total CTQ score, the duration of the disease, and the scores on the neuroticism scale in the NEO Five Factor Inventory (NEO-FFI) [63]. In another study, which also used machine learning techniques, the most significant predictors of suicide attempts were sexual abuse in childhood and the knowledge that one is suffering from a mental disorder [64].

An important aspect of the clinical manifestations of schizophrenia is aggressive, violent behavior. It is known that the risk of committing violent crimes in female and male patients suffering from the schizophrenic spectrum disease is 1 in 20 and 1 in 4, respectively [65]. Scientists from Switzerland tried to establish the factors associated with violent behavior using machine learning techniques. The authors concluded that a large number of stress factors affect the frequency of violent crimes by people with schizophrenia. The most important factors included social isolation in adulthood, involuntary psychiatric treatment, unemployment, estrangement from family, and failure in school. The model based on classification trees determined a person who had committed a violent crime with 91.57% accuracy [66].

Kanchanatawan et al. used neural network predictions to demonstrate that the severity of “negative” symptoms, symptoms of mannerism, arousal, and hostility are very accurate predictors of affective and psychosomatic symptoms in schizophrenia [67]. Models based on machine learning techniques can also predict the outcomes of schizophrenia. In a study by Lin et al., low scores on the quality-of-life scale were associated with the severity of “negative” and depressive symptoms and low results on the global functioning assessment scale were associated with the severity of “positive” and “negative” symptoms in schizophrenia. Cognitive impairment was also evaluated in that study. Researchers were able to predict changes over time in cognitive functions using machine learning techniques based on test results and the analysis of cognitive domains; the most significant predicting factor was the speed of information processing [68]. In another study, the significant factors able to predict the state of neurocognitive functions were memory disorders, executive dysfunction, as well as disorders of concentration and fluency of speech [69].

DISCUSSION

Our analysis of published literature included articles relating to the use of AI for the development of the diagnostic and prognostic models used in the context of schizophrenia. Diagnostic models are used to more accurately identify schizophrenia by analyzing EEG signals, MRI scans, mental abilities (speech, voice, emotions, visual art), and genetic and epigenetic information. Predictive models created with the help of AI technologies can be used for early identification of persons at high risk of psychosis, including the first episode of schizophrenia, as well as for predicting the outcomes of schizophrenia. Prognostic models are able to predict individual clinical symptoms and complications in schizophrenia.

Based on the information provided so far, it can be predicted that in the near future various methods may find wider application in psychiatric practice. Some algorithms have already been approved by the U.S. Food and Drug Administration (FDA) [70]. In this regard, many doctors and scientists are concerned about the ethical question of AI use in medicine and, particularly, in psychiatry. Researchers are concerned about the confidentiality of information, the accuracy of calculations, the safety of the use of algorithms, and possible disregard for the individual characteristics of a patient [70, 71].

AI algorithms, including those based on machine learning, are only as good as the data they were trained on [72]. If the training data is biased, incomplete, or of poor quality, then the operation of the AI system may be disrupted, which will lead to inaccurate or unreliable results. Therefore, it is very important to check the results obtained with the help of AI technologies using traditional diagnostic methods to ensure their accuracy. Also, models may be sensitive to input bias and models may make mistakes in situations that are very different from those on which they were trained, which makes the model less reliable. Therefore, some scientists propose to introduce tools into AI-based models that can shore up their reliability; for example, by comparing the training set against each new instance introduced into the model [73]. It can be difficult to understand the decisions made by some models based on machine learning techniques; e.g., deep neural networks. Such models are called “black box” models in the literature [74, 75]. In this regard, there arises a question on the ethics of entrusting the patient’s health to the “internal logic” of AI, which is not controlled by humans [76]. In our opinion, machine learning techniques should be used with extreme caution in clinical practice, only in conjunction with the main diagnostic tests, checking the results provided by AI and, of course, informing patients if recommendations based on the use of machine learning techniques are used.

The limitations of this review included a nonsystematic search for information, continuous inclusion of any type of studies, and lack of any assessment of the quality of the included studies. Also, the small sample size in a number of studies does not allow one to extrapolate the results to all people with schizophrenia.

There are several aspects of practical significance in the obtained results.

First, the use of models based on machine learning techniques in the diagnosis of schizophrenia makes it possible to achieve a more accurate and reliable qualification of this mental illness. An accurate diagnosis is key in providing the patient with adequate medical care.

Second, predictive models created using AI technologies can help with early identification of individuals at high risk of developing psychotic episodes, including the first episode of schizophrenia. This can be especially useful because early detection of schizophrenia can help prevent or reduce the severity of this mental illness. Moreover, prognostic models can predict the outcomes of schizophrenia, which can help clinicians and patients choose the most appropriate treatment and plan long-term care.

Third, the ability to predict individual clinical symptoms and complications of schizophrenia using prognostic models is of great importance for an individualized approach to treatment. This means that clinicians can predict what symptoms and complications may occur in specific patients and choose treatment according to their individual needs. This personalized approach can improve the effectiveness of treatment and clinical outcomes. However, no model can ensure a perfect result, which may be explained by the inability to include all patient features contributing to the final outcome in the prognostic or diagnostic model. In addition, models “overloaded” with input data can become unstable and produce poorer results compared to balanced models.

In general, the results of this review indicate the significant potential of machine learning techniques in the field of diagnosis and prediction of schizophrenia and its clinical features. These methods can significantly improve our understanding, diagnosis, and treatment of this psychiatric disorder, which ultimately can lead to an improvement in the lives of people with schizophrenia and lessen the state’s economic burden associated with this disease.

CONCLUSION

Machine learning techniques are used both to identify schizophrenia (diagnostic algorithms) and to predict the manifestation of the disease or the clinical features of a known illness (prognostic algorithms).

So far, the ethical issues associated with the use of these techniques remain unresolved and the clinical reliability of these models remains unclear, which limits, at this point, our ability to use these algorithms in clinical practice. Nevertheless, the use of machine learning algorithms remains one of the most promising areas in psychiatry, and it can significantly improve the effectiveness of diagnosis and treatment when dealing with schizophrenia.

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Equivalence of the Autism Spectrum Disorders Diagnostics in Children in Telemedicine and Face-to-Face Consultations: A Literature Review

Эквивалентность диагностики расстройств аутистического спектра у детей в рамках телемедицинских и очных консультаций: обзор литературы

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Review

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ABSTRACT

BACKGROUND: The use of remote forms of mental health care has become widespread during the period of epidemiological restrictions due to the COVID-19 pandemic. Methodological and organizational issues remain insufficiently developed, including the level of equivalence of the use of telemedicine technologies in the diagnosis of autistic spectrum disorders.

AIM: Study of the equivalence of diagnostic tools in the framework of telemedicine and face-to-face consultations in children with autistic spectrum disorders according to modern scientific literature.

METHODS: A descriptive review of scientific studies published between January 2017 and May 2023 was carried out. The papers presented in the electronic databases PubMed, Web of Science, and eLibrary were analyzed. Descriptive analysis was used to summarize the obtained data.

RESULTS: The conducted analysis convincingly indicates sufficient equivalence of remote tools used in different countries for level I screening, assessment scales, and structured procedures for diagnosing autistic spectrum disorders with a high level of specificity from 60.0 to 94.4%, sensitivity from 75 dog 98.4%, and satisfaction of patients and their legal representatives.

CONCLUSION: The widespread use of validated telemedicine diagnostic systems in clinical practice contributes to the early detection of autistic spectrum disorders, increasing the timeliness and effectiveness of medical, corrective psychological, pedagogical, and habilitation interventions.

АННОТАЦИЯ

ВВЕДЕНИЕ: Применение дистанционных форм оказания психиатрической помощи получило большое распространение в период эпидемиологических ограничений в связи с пандемией COVID-19. Недостаточно разработанными остаются методологические и организационные вопросы, включая уровень эквивалентности применения телемедицинских технологий в диагностике расстройств аутического спектра.

ЦЕЛЬ: Изучение эквивалентности диагностических инструментов в рамках телемедицинских и очных консультаций у детей с расстройствами аутистического спектра по данным современной научной литературы.

МЕТОДЫ: Проведен описательный обзор научных исследований, опубликованных в период с января 2017 по май 2023 года. Были проанализированы работы, представленные в электронных базах данных PubMed, Web of Science и eLibrary. Для обобщения полученных данных был использован описательный анализ.

РЕЗУЛЬТАТЫ: Проведенный анализ убедительно свидетельствует о достаточной эквивалентности применяемых в разных странах дистанционных инструментов для скрининга I уровня, оценочных шкал и структурированных процедур диагностики расстройств аутического спектра с высоким уровнем специфичности от 60,0 до 94,4%, чувствительности от 75 до 98,4% и удовлетворенности пациентов и их законных представителей.

ЗАКЛЮЧЕНИЕ: Широкое использование в клинической практике валидизированных телемедицинских диагностических систем способствует раннему выявлению расстройств аутистического спектра, повышению своевременности и эффективности медицинских, коррекционных психолого-педагогических и абилитационных вмешательств.

Keywords: *telemedicine; equivalence of telemedicine consultations; autism spectrum disorders; childhood*
Ключевые слова: *телемедицина; эквивалентность телемедицинских консультаций; расстройства аутистического спектра; детский возраст*

INTRODUCTION

Limitations on the availability and timeliness of specialized psychiatric care are a reality across the globe. This mainly has to do with the high prevalence of mental disorders and the shortage of staff in the specialized services of health care systems, especially in small settlements and those geographically remote from large medical and diagnostic centers, not to mention the obstacles involved in seeking the help of specialists because of the pervasive issue of stigmatization [1].

Autism spectrum disorder (ASD) is currently among the most challenging problems in pediatric psychiatry, due to its increasing rate of detection in recent decades, poorly defined etiopathogenetic factors, its diagnostic framework, and the therapeutic approaches used, as well as the need for long-term intensive complex treatment and rehabilitation. There are significant issues related to the scarcity of medical and diagnostic resources for families in rural or remote areas with a lower socioeconomic status [1, 2]. In such cases, ASD is diagnosed with a significant delay [3].

The active use of remote forms of assistance, including telemedicine consultations (TMCs), expanded during the epidemiological restrictions that came with COVID-19 around the world [4–6]. Russian specialists have accumulated sufficient experience in conducting TMCs in the “doctor-doctor” format, with remote interaction between healthcare professionals, including in psychiatry [7, 8]. At the same time, due to the multifactorial limitations relating to the availability of specialized medical care, the “patient-doctor” TMC format using video conferencing (VC) seems to be more in demand. A wide range of organizational and methodological issues related to medical care during remote interaction between healthcare professionals and patients or their legal representatives having to do with the regulation of the scope of medical intervention, the use of examination and treatment methods, quality assurance, information and clinical security remain unresolved [9, 10].

The goal of this review is to study how diagnostic tools compare to each other in the framework of telemedicine and in-person consultation as they apply to children with ASD. Our effort was based on a review of the extant scientific literature.

METHODS

We analyzed papers available on the PubMed, Web of Science, and eLibrary electronic databases for a period ranging from January 2017 to May 2023. Search terms included keywords such as “telemedicine diagnostics”, “telemedicine consultations”, “equivalence of telemedicine consultations”, “autism spectrum disorder”, and “children and teenagers”. Studies were considered eligible for analysis if they assessed the comparative validity of telemedicine (remote) and in-person consultations for the purpose of diagnosis, as well as the quantitative and qualitative assessment of ASD in children. Ninety-five articles were reviewed, and 43 of them were selected for analysis. In addition, we analyzed a number of related articles in Google Scholar and reviewed earlier longitudinal studies (up to 2017) and publications on diagnostic tools adapted for use in a remote format.

Descriptive analysis was used to summarize the obtained data.

RESULTS

Even before the COVID-19 pandemic hit, there was interest in developing and testing new remote forms of care for patients with ASD to improve access to diagnosis, treatment, and rehabilitation, as well as to increase the role and involvement of patients' parents in the assessment procedures [11]. The relevance and growth of the research into the use of telemedicine in medical care for children and adolescents with ASD is evidenced by the change in the number of publications in systematic reviews. The publication by Sutherland et al. in 2018 [12], contains an analysis of the results of 14 studies, and the most recent review by Ellison et al. [13], conducted just 3 years after the previous one, already included 55 peer-reviewed articles.

The obtained data on the use of a remote format for diagnosing autistic disorders in childhood shall be divided into three parts: 1) ASD risk screening, 2) qualitative and quantitative diagnostics using standardized rating scales and procedures, and 3) clinical (clinical and psychopathological) examination. The distinction between the 2nd and 3rd options can be made only with some degree of conditionality, since in most of the analyzed studies, clinical diagnostics included the use of standardized assessment tools, which in many countries are provided for by the standards of medical care.

Telemedicine risk screening for autistic disorders

Most of the screening tools used are questionnaires in which the total scores obtained are compared against predetermined thresholds. The first level of screening assessment involves an initial survey in the general population of children in order to identify the risk ("red flags", i.e., alarms) of ASD. First-level screening tools do not require special training, take minimal time, are conducted by parents or primary medical care professionals, but at the same time they have high sensitivity and low specificity, and therefore the probability of false positive is relatively high. The most popular and most studied first-level screening tool for assessing the risk of ASD validated around the world is The Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT-R/F) for children aged 16–30 months [14, 15].

Second-level screening tools have higher specificity, require special training and more time to interpret the results, and, accordingly, are used by trained specialists. These include the Social Communication Questionnaire (SCQ) [16] and the Checklist for Autism Spectrum Disorder (CASD) [17].

The high relevance of and potential demand for remote primary ASD risk screening have been noted in many studies in connection with the significant time gap between the onset of symptoms and the age of diagnosis [18]. According to Constantino et al. [19], the median age of diagnosis in the United States is above 4 years and 27% of children with ASD are not diagnosed by the age of 8 years, while the median age of diagnosis has not decreased in more than 15 years.

According to Qiu et al. [20], remote application of the Chinese version of the Checklist for Autism in Young Children CHAT-23-A for ASD screening showed a sensitivity and specificity of 0.92 and 0.90, respectively. It is believed that it is possible to replace the time-consuming, ineffective and expensive routine offline screening procedure in China with a telemedicine option on the web resource of the Network Center for Early Diagnosis of ASD[1] based on the WeChat platform.

An Indian study by Kadam et al. [21] compared the results of remote screening of 39 children for ASD (M-CHAT-R/F, analysis of 1–2 min home videos) and traditional in-person examination in accordance with DSM-5 diagnostic criteria. Remote assessment showed a correlation of 94.87% with the final diagnosis verified after 3 months as part of an in-person examination. Video-scoring agreement between two independent clinicians had a kappa correlation of 0.803, which was qualified as significant agreement.

A study by Colombo et al. [22] presented the result of an investigation of the first Italian online tool for using CHAT in 1,250 children via a mobile application using the

1 http://gdz.fenghuaxinxi.com/admin/login

LAMP platform for outpatient pediatricians called Web Italian Network for Autism Spectrum Disorder (WIN4ASD). It demonstrated effectiveness, efficiency, and sustainability of online screening in the primary health care system.

Remote diagnosis of autism spectrum disorder using rating scales and structured procedures

Prior to the COVID-19 pandemic, the development of special tools for remote diagnosis of ASD was rather slow; they have acccelerated in the last 2–2.5 years.

Conventional autism spectrum disorder diagnosis tools

The basic diagnosis of autistic disorders generally includes a structured observation of the child, learning their medical history data from parents, assessment of cognitive, speech and social adaptive functions, as well as a physical examination. Currently, TMC involves using the so-called "gold standard" tools for diagnosing ASD, which include a semi-structured interview with parents as assessment tools for in-person diagnosis: The Autism Diagnostic Interview-Revised (ADI-R) [23] and Structured Child Observation: Autism Diagnostic Observation Schedule (ADOS) [24].

A study by Reese et al. [25] described one of the first experiences with the use of videoconferencing for assessment procedures using ADI-R and ADOS (module 1) vs. a similar in-person assessment. Nearly 100% inter-specialist agreement (20 out of 21 cases) of diagnoses was shown; there were some difficulties in the assessment of socially directed pointing gesture and eye contact with the parent; the survey noted a high level of parental satisfaction.

Synchronous and asynchronous diagnostic approaches

Literature sources outside Russia commonly classify remote diagnostic approaches as synchronous or asynchronous according to the methods used to coordinate the actions of specialists and those receiving care [26, 27]. Synchronous options for remote ASD diagnosis involve monitoring a child's spontaneous or stimulus-induced behavior in real time in the form of an online video conference. Asynchronous options are usually based on the analysis of video recordings of the child's behavior. With asynchronous TMC, the transfer of information by the patient (legal representatives) and its processing by specialists occur at different times. Compared to online synchronous TMCs, such organization of interaction minimizes the difficulties of coordinating the schedules of care users and specialists; parents can record videos at convenient days and hours and record the most striking manifestations in the child's behavior without being limited in time.

The article by Narzisi [26] presents a detailed and comprehensive model of telemedicine diagnostic and corrective care, using both synchronous and asynchronous algorithms for the interaction of a child and his legal representatives with specialists (Appendix 1 in the Supplementary). One of the essential components of this model is the algorithm for parents that describes the preparation of short videos illustrating the peculiarities of the child's behavior at home. The scenarios included in this algorithm (spontaneous and directed play alone, with parents, siblings, eating together, problematic behavior) with some variations are universal for most tools of remote assessment of ASD manifestations. Video recordings should be made on different days for a more comprehensive understanding of the child's behavior.

A study by Sutantio et al. [28] concerned the clarification of the validity of diagnosing ASD in children aged 18–30 months based on video recordings according to a protocol that included established scenarios. Diagnostic agreement with in-person consultations was 82.5%, sensitivity was 91.3%, and specificity was 70.6%. This has proved the significant reliability of remote assessment by video recordings vs. the in-person diagnosis of ASD.

According to the article by Riva et al. [29], the most popular structured tools for asynchronous remote assessment of ASD are the Naturalistic Observation Diagnostic Assessment (NODA), The Systematic Observation of Red Flags (SORF), and Brief Observation of Symptoms of Autism (BOSA) (Appendix 2 in the Supplementary).

In a pilot study of the NODA methodology by Nazneen et al. [30], parents easily used the system without prior training to record video materials, 96% of which were found to be clinically relevant for the diagnosis of autism. In 91% of cases, the diagnosticians using NODA Connect confidently (mean score 4.5 on a 5-point scale) arrived at a diagnostic result that aligned with the previous in-person examination of children by other specialists. Smith et al. [31] showed a diagnostic agreement between NODA and in-person diagnosis of 88.2%, sensitivity was 84.9%, and specificity was 94.4%.

At Florida State University, Dow et al. [32] investigated the psychometric properties of their proposed SORF technique in 228 children aged 18 to 24 months with ASD, with developmental delay and with typical development. Specificity and sensitivity were 63% and 73% for social communication and interaction disorders and 54% and 70% for manifestations of stereotypical forms of behavior. The most informative parameters were limited eye contact, looking into an adult's face, pointing gesture, predominance of interest in non-living objects, adherence to certain non-functional objects, and actions. Pileggi et al. [33] tested SORF as a screening tool for early detection of ASD risk in 122 one-year-old younger siblings of children with confirmed autism. ASD was confirmed in younger siblings at the age of 24 months. With an optimal Composite threshold of 18, sensitivity was 0.77 and specificity was 0.76.

NIDA, Italy's largest network of interdisciplinary services for observational research and early screening of ASD, has developed the TeleNIDA telemedicine tool for children aged 18–30 months. Parents provide 5-minute videos of their child's behavior during free play, organized play with parents, eating, and book activities. The tool also has good psychometric properties compared to the "gold standard" in-person assessment [29].

In synchronous remote diagnostics, the tools for assessing the behavior of infants which cause difficulties even during in-person examination are of particular interest. Talbott et al. [34, 35] investigated the possibility of remote detection of ASD risk in 41 infants (mean age 10.51 months) using the Telehealth Evaluation of Development for Infants (TEDI). Inter-rater reliability ranged from 0.88 to 0.94 for most evaluation criteria, and retest reliability was 0.75, p <0.001 (mean interval between 2 tests 1.5 weeks, range 5–41 days).

A study by Kryszak et al. [36] evaluated the Autism Detection in Early Childhood-Virtual (ADEC-V) tool in 121 children aged 18–47 months. It showed high sensitivity (0.82) and specificity (0.78), significant correlation with the results of assessments using other standardized tools (CARS 2, ADI-R), and acceptable internal consistency (α=0.77).

Appendix 2 (in the Supplementary) provides a brief description of other structured tools for remote diagnosis of ASD manifestations based on the materials of the review by Berger et al. [37].

One of the most discussed ones, the TELE-ASD-PEDS (TAP) tool, was specifically developed for remote assessment of ASD in children without phrase speech under the age of 3 years before the COVID-19 pandemic. Currently, work is underway to validate the methodology and preliminary studies have shown a sufficient level of acceptability and convenience for both accompanying persons and specialists [38]. Authors in a separate study [39] compared parents' perceptions of TAP possibilities with the Screening Tool for Autism in Two-Year-Olds (STAT) adapted for the videoconferencing format [40]. STAT includes assessment of a number of communicative actions when an adult initiates a joint game with a ball or a toy car, the presence of a request/demand of a child when presenting food, repetition of movements, and simple actions. The version for remote use of TELE-STAT contains additional instructions for certain experimental actions with the child, and the presence of eye contact is specified with the parents. Most parents found remote assessment using TAP and TELE-STAT convenient and meaningful, and they separately noted the advantage of these remote ASD assessment tools in the participation of specialists on only "one side of the screen", which expands their availability and scalability.

The latest publication [39] of a project comparing the use of TAP and TELE-STAT with in-person assessment presents the results of a survey of 144 children aged 17 to 36 months, showing diagnostic agreement in 92% of cases. Diagnostic discrepancies were more often associated with a lesser severity of autistic symptoms or younger age of the children. A large study by McNally Keehn et al. [41] investigated the relationship between the clinical characteristics of 335 children aged 14 to 78 months and the effectiveness of remote diagnosis of ASD using TAP. For 85% of the examined children, including those with speech underdevelopment, the TMC format was sufficient to detect the symptoms of ASD; the presence of specific stereotypical behavior predicted the diagnosis to a greater extent.

We did not find information on remote diagnosis of ASD in Russia using rating scales and structured procedures in the available literature for the specified period.

Remote diagnosis of autism spectrum disorder and the possibilities of artificial intelligence

Developing tools for remote diagnosis of ASD using artificial intelligence (AI) algorithms seems promising [42–45].

For several years, the Cognoa laboratory (Palo Alto, USA) has been gradually validating an ASD screening tool using AI in the form of the Cognoa ASD mobile application [46, 47] — the Child Behavior Checklist to a novel mobile-health screening tool developed by Cognoa. Data for machine learning was collected from several repositories of the ADI-R and ADOS protocols; in an automatic mode and in a short time, the program evaluates the behavioral characteristics of children according to separate questionnaires for parents, specialists, and two short home videos. Abbas et al. [46] showed that the second-generation Cognoa advanced screening tool provided higher accuracy than standard screening tools (M-CHAT-R/F, SRS-II, SCQ) in the same age range. Sensitivity and specificity of 90% and 60% showed the potential of AI-based technology to improve and accelerate the detection of ASD in young children. The latest publication on a double-blind, multicenter, prospective cohort study [48] shows the results of testing the Cognoa tool vs. the diagnostic agreement of two or more independent specialists in a cohort of children aged 18–72 months with developmental delay (*n*=425, 29% prevalence of ASD). For the 31.8% of participants with a definite result (presence or absence of ASD), the positive predictive value was 80.8%, and the negative predictive value was 98.3%; sensitivity was 98.4%, and specificity was 78.9%. In the group with an "indeterminate" result due to insufficient detail of the input data, 91% of the children had one or more complex neurodevelopmental disorders. Thus, for almost a third of the sample, the Cognoa screening tool allowed timely, rapid diagnostic evaluation with a high degree of accuracy.

Clinical (clinical and psychopathological) remote diagnosis of autism spectrum disorder

In most of the studies, clinical diagnosis involved the use of some of the standardized assessment tools described above. A review of studies on the use of telemedicine diagnosis of ASD by Stavropoulos et al. [49] obtained data on the equivalence of diagnostic assessments compared with in-person consultations in the range of 80-91%. Six of the ten studies yielded a degree of sensitivity ranging from 75% to 100%, while five of the six studies demonstrated specificity values ranging from 68.75% to 100%.

Juarez et al. [50] used TMC to diagnose ASD in 62% of 45 children; in 13% of the cases, autism disorders could not be confirmed or excluded remotely. Matthews et al. [51] investigated the acceptability of diagnosing ASD in children, adolescents, and adults as part of a TMC deployed at an autism center in the U.S. Southwest during the COVID-19 pandemic. One hundred and two (84%) patients out of 121 completed the 6-month remote diagnosis program; for 91% (93 out of 102), it was sufficient to use only telemedicine procedures. In-person assessment was required for nine participants; according to surveys of specialists and parents of patients, the telemedicine model for diagnosing ASD was acceptable for most of the respondents.

The relevance of remote assessment of children aged 18–30 months with M-CHAT-R pre-set ASD risk based on video recordings with certain scenarios according to DSM-5 criteria was compared with similar in-person clinical diagnoses [52]. Diagnostic agreement was 82.5%, sensitivity was 91.3%, and specificity was 70.6%. The positive predictive value was 80.7%, and the negative predictive value was 85.7%.

In a comparative RCT of remote and in-person consultations for 23 patients with ASD aged 4 to 16 years, the diagnosis and treatment recommendations aligned in 96% of cases [53]. There were no differences in the satisfaction of patients and parents, 26% of children preferred the remote format, and 91% of parents preferred videoconferencing without the need to travel long distances for in-person psychiatric visits.

In the Russian-speaking segment, we found only a description of a pilot comparative ASD diagnosis study within the framework of TMC and in-person consultations, which was conducted at the Moscow State Budgetary Healthcare Institution "Scientific and Practical Center for Mental Health of Children and Adolescents named after G.E. Sukhareva of the Moscow Department of Health" [54]. There were 84 patients in the TMC group and 310 patients in the in-person consultations group. All consultations were conducted by one specialist and had a stable clear structure and duration. Mandatory blocks included observation and assessment of the child's spontaneous behavior, structured situations of interaction with parents, with specialists (attending physician, psychologist, speech therapist, defectologist), and with a remote consultant. Fundamental differences were revealed only in the assessment of the interaction of a child with a remote consultant: the difficulty of assessing eye contact "through the screen," the degree of subjective attitude of the patient to the consultant, the presence/absence of non-verbal reactions to the background visual, sound, and other stimuli that are not noticeable to the consultant due to fragmented image and sound from the patient and his/her environment (family members, animals, electronic gadgets, and much more). The TMC scenario includes additional clarification questions and actions (tests).

DISCUSSION

The remote format of interaction between specialists and consumers of diagnostic services coincides to the maximum extent with the tasks of ASD screening. Online screening allows one to conduct a primary examination in a much larger group of children aged 16–30 months thanks to the fact that it is easily accessible when placing simple tools with high sensitivity on various web resources; it does not require special training on the part of its users (parents, teachers, or specialists of the primary medical network). Studies conducted in different countries suggest the possibility and expediency of using the telemedicine format instead of the time-consuming and expensive routine offline screening procedure with limited productivity [20–22].

The COVID-19 pandemic has significantly accelerated and scaled up the development of special tools for remote diagnosis of ASD. The analysis of the publications presented in this review convincingly indicates a sufficient equivalence between assessment scales and structured procedures for the remote diagnosis of ASD and in-person examination with a high level of specificity, from 60.0 to 94.4%, sensitivity from 75 to 98.4%, and satisfaction of patients and their legal representatives. Most diagnostic tools are for children over 18 months of age, but tools are also available for the remote diagnosis of ASD in infants 6–12 months of age [34, 35].

Synchronous variants of clinical and psychopathological and remote diagnosis of ASD based on standardized tools are as close as possible to the in-person interaction between specialists and consumers of medical care; however, they require coordinated schedules of care recipients and specialists. There was an almost 100% consistency level between the online and offline formats of the so-called "gold standard for autism diagnosis" ADI-R and ADOS [25].

Asynchronous models of remote assessment of ASD symptoms use video recordings of the child's behavior in their usual home settings, are free from organizational difficulties in coordinating the schedule of consultations, and provide video recording of the most characteristic manifestations at a convenient time for the required period of time. Typically, recommended video recording scenarios include focusing on the child's spontaneous and directed play both alone and with parents and siblings, eating together, making requests, imitating actions, and problematic behavior. A number of studies have noted some difficulties in the remote assessment of a pointing gesture and eye contact in the videoconferencing mode, which requires additional clarification of the details of the corresponding manifestations by the persons accompanying the child [36, 39, 54].

A limitation of this review is the fact that a number of studies on the topic under consideration may have been omitted, because a systematic search strategy was not used in the selection of publications. In addition, the methodology and data quality of a number of studies were not sufficiently homogeneous.

CONCLUSION

These authors reviewed publications comparing a remote format for diagnosing autistic disorders in childhood as part of ASD risk screening and clinical diagnosis including the use of standardized rating scales and procedures.

We analyzed various structured tools for a qualitative and quantitative assessment of ASD symptoms developed and validated in different countries for use in the TMC format. A large number of studies have confirmed their acceptable equivalence to in-person diagnosis and sufficient applicability in young children, including infants in their first year of life. At the same time, the availability of these tools in Russian pediatric psychiatry practice is limited; one of the reasons is the need to purchase expensive licenses from copyright holders, which increases the relevance of developing domestic analogues. The introduction and widespread use of validated telemedicine diagnostic systems in clinical practice will contribute to the early detection of ASD and increase the timeliness and effectiveness of medical, corrective psychological, pedagogical, and habilitation interventions.

The active use of the remote diagnostic format can mitigate the limitations in the availability and timeliness of specialized care for children with ASD, which are among the most difficult problems of modern pediatric psychiatry.

In Russia, the "patient-doctor" format of TMC in the case of remote interaction between healthcare professionals and patients and/or their legal representatives has yet to take root, and, therefore, the various organizational, legal, clinical, and methodological aspects of remote care for ASD require further development. One of the relevant issues is the selection of valid diagnostic tools for remote symptom assessment with an evaluation of their agreement with the traditional face-to-face assessment procedures.

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Supplementary data

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Impact of Online Dating on the Adolescent Population: A Brief Review of the Literature with Special Reference to the Indian Scenario

Влияние онлайн-знакомств на подростков: краткий обзор литературы с учетом текущей ситуации в Индии

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Review

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ABSTRACT

BACKGROUND: Online dating is becoming more and more popular not only among the adult population, but also among adolescents, which comes with its own advantages and disadvantages. Adolescents are more vulnerable to a number of issues connected with online dating, including online grooming, bullying, emotional abuse, revenge porn, harassment, and lack of social interaction.

AIM: We aimed to briefly review the available literature exploring the impact of online dating on adolescents, with special reference to the current Indian Scenario.

METHODS: A brief literature search was conducted in PubMed and Google Scholar in September 2022 with no date limits. Keywords included various combinations of terms such as "online dating", "dating applications", "social media", "mental illness", "psychiatric disorders", "adolescents", and "mental health". Original studies and review articles exploring the impact of online dating on adolescents and published in English were reviewed in our work. A descriptive strategy was used to summarise the findings.

RESULTS: The impact of online dating on adolescents is discussed in the light of (1) issues associated with online dating among adolescents, (2) the international context, and (3) Indian context.

CONCLUSION: Since the beginning of the COVID-19 pandemic, online dating has grown in popularity among adolescents, which has led to a number of worrying situations, including increased risk of sexually transmitted infections, dating violence, and mental health issues. All of these issues are described in the literature in the context of unsupervised use of technology, peer pressure, and desire to fit into the society. Data from India remain scarce on this topic, highlighting the need for research exploring the influence of online dating on adolescents.

АННОТАЦИЯ

ВВЕДЕНИЕ: Онлайн-знакомства становятся все более популярными не только среди взрослых, но и среди подростков. Такая тенденция имеет как положительные, так и отрицательные стороны. Подростки чаще становятся жертвами онлайн-груминга (формирование доверительных отношений с несовершеннолетними для их дальнейшей сексуальной эксплуатации), травли, эмоционального насилия, порномести, домогательств и недостатка социального взаимодействия.

ЦЕЛЬ: Провести краткий обзор имеющейся литературы, посвященной влиянию онлайн-знакомств на подростков, с учетом текущей ситуации в Индии.

МЕТОДЫ: В сентябре 2022 г. в базах данных PubMed и Google Scholar был выполнен краткий поиск литературы без ограничения по дате публикации. Ключевые слова включали различные сочетания терминов, такие как «онлайн-свидания», «приложения для знакомств», «социальные сети», «психическое расстройство», «психические расстройства», «подростки» и «психическое здоровье». В обзор включались оригинальные исследования и обзорные статьи на английском языке, освещающие влияние онлайн-знакомств на подростков. Для обобщения результатов применялся описательный подход.

РЕЗУЛЬТАТЫ: Влияние онлайн-знакомств на подростков обсуждается в свете (1) проблем, возникающих при знакомствах в интернете среди подростков; (2) международного контекста и (3) индийского контекста.

ЗАКЛЮЧЕНИЕ: С начала пандемии COVID-19 популярность онлайн-знакомств среди подростков возросла, что привело к ряду проблем, таких как увеличение риска заражения инфекциями, передающимися половым путем, насилие на свиданиях и психические расстройства. Все эти аспекты описаны в литературе с учетом их связи с бесконтрольным использованием технологий, давлением сверстников и желанием быть принятым в обществе. Данные по этой теме из Индии остаются немногочисленными, что подчеркивает необходимость проведения исследований, изучающих влияние онлайн-свиданий на подростков.

Keywords: *online; dating; adolescents; apps; India*
Ключевые слова: *онлайн; знакомства; подростки; приложения; Индия*

INTRODUCTION

The first use of the word “dating” in the American language appeared in the 1920s. As defined by various authors “dating” is a stage in a romantic relationship when two individuals engage in activities together, most often with the intention of weighing each other’s suitability as a partner for a future intimate relationship.[1] Historically, courtship used to be a matter of family and community interest.[2] However, around the time of the Civil War, it became a private matter for couples.[3] The protocols and practices of dating vastly differ across cultures, societies, and time periods. In India, dating is heavily influenced by the custom of arranged marriages [1]. “Arranged marriage” refers to a marriage negotiated by matchmakers or matrimony sites and agreed to by parents and relatives. Currently, there are strong indications that the marriage institution is undergoing a drastic transformation in India. Love marriages are becoming more common and accepted, especially among the urban populations, which is probably driven by the fact that India is becoming more and more integrated with the rest of the world.[3]

Since the beginning of the COVID-19 pandemic, online dating has increased in popularity due to the heightened feeling of loneliness that came along with the lockdowns. Online dating has been defined as a way of starting a romantic relationship on the internet using online dating platforms [1]. Online dating platforms, in turn, can be

1 Wikipedia [Internet]. Dating; c 2007-2023 [cited 2023 Apr 2023]. Available from https://en.wikipedia.org/w/index.php?title=Dating&oldid=1109272329

2 Hirsch E. The History of Dating and Communication. Communication Studies [Internet]. 2011 [cited 1 November 2022]. Available from: https://www.communicationstudies.com/the-history-of-dating-and-communication (accessed 12 September 2022).

3 India’s Arranged Marriage Traditions Live on in U.S. [Internet]. 2003 [cited 1 November 2022]. Available from: https://archive.nytimes.com/www.nytimes.com/uwire/uwire_APLJ050720039401343.html?ei=5034&en=be1a8b75099fc08d&ex=1130212800 (accessed 12 September 2022).

defined as social media platforms where people can find romantic partners and friends [2]. These platforms encompass dating websites, apps, and social media texting sites where people can interact with each other virtually. These applications can be easily accessed through devices like mobile phones, laptops, tablets, and computers. According to a survey conducted by Outlook India in 2022[4], around 83% of users professed interest in online dating during the pandemic. Overall, 63% of the users of online dating platforms reported being anxious regarding their future and around 70% claimed to have changed their attitude towards online dating as compared to the period preceding the COVID-19 outbreak. Furthermore, 81% of users claimed to be open to getting to know their matches at a deeper level, while 66% of users said that they were open to just chatting with their matches even if there was no prospect of a long-term relationship.

The adolescent population in India has free access to online dating platforms, since their use is not limited to adults. Within the past two years, almost all adolescents in India have used a smart device for educational purposes, something that contributed to a sudden explosion in unsupervised usage of social media and online dating applications. Although definitions vary considerably across the literature, an individual aged between 10–19 years can be described as an adolescent [2]. It is important to note that adolescence is a transitional period between childhood and adulthood when changes occur in the emotional, physical, social, and behavioural realms of an individual [3]. During this transitional stage, these individuals are more exposed to a number of issues having to do with online dating, including online grooming, bullying, emotional abuse, revenge porn, harassment, and lack of social interaction. In this regard, we aimed to briefly review the available literature exploring the impact of online dating on adolescents, with special reference to the current Indian Scenario.

METHODS

A brief literature search was conducted in PubMed and Google Scholar in September 2022 with no date limits. Keywords included various combinations of terms such as “online dating”, “dating applications”, “social media”, “mental illness”, “psychiatric disorders”, “adolescents”, and “mental health”.

Original studies and review articles exploring the impact of online dating on adolescents published in English were included in the review. A descriptive analysis technique was applied to summarise the findings.

RESULTS

Overall, 58 articles related to the topic of interest were found, out of which 19 were included in the review. The obtained results will be presented as follows: (1) issues associated with online dating among adolescents, (2) the international context, and (3) Indian context.

(1) Issues associated with online dating among adolescents

Development of a new technology comes with its own advantages and disadvantages. Online dating apps were intended to ease communication. Yet problems, such as absence of supervision, exposure to online grooming, harassment, and increased peer pressure have appeared along the way. Due to the increased desire to experiment in different aspects of life during adolescence, individuals in that age tranche may suddenly have to confront a spectrum of unique issues as a result of their use of online dating apps [4]. These issues are discussed below.

1. **Risk of contracting sexually transmitted diseases (STDs).** Due to unsupervised access to online dating apps, the lack of sex education, and easy access to pornography, a large number of adolescents are being drawn into unprotected sexual intercourses [5], increasing their risk of contracting STDs. The UNAIDS 2022 report (2000–2021 data) estimates that 160,000 individuals aged 10 to 19 are infected with the Human Immunodeficiency Virus (HIV).[5,6] Out of those, 56% are girls and 85% reside in sub-Saharan Africa.[6] Intercourses among male homosexuals is found to be one of the leading causes of the increased number of

4 Virtually: Is Digital Dating The New Normal? Outlook [Internet]. 2022 Sept 20 [cited 2023 Apr 17]. Available from: https://www.outlookindia.com/culture-society/love-virtually-is-digital-dating-the-new-normal-news-43423.

5 Dating apps prove factor in HIV rise among adolescents. BBC News [Internet]. 2015 Dec 6 [cited 2023 Apr 17]. Available from: https://www.bbc.com/news/health-34995811.

6 Adolescent HIV prevention. UNICEF DATA [Internet]. 2022 [cited 2023 Apr 17]. Available from: https://data.unicef.org/topic/hivaids/adolescents-young-people/.

HIV cases among adolescents, alongside other factors such as being sexually exploited in adolescence and youth engagement in sex work. Substance abusers and transgender adolescents are found to be at higher risk of contracting HIV.[6]

2. **Teen dating violence (TDV).** TDV refers to the physical, sexual, or emotional violence that occurs between adolescent dating partners interacting via online platforms [6, 7]. It includes psychological abuse [8, 9], stalking [10], harassment, and physical and sexual abuse [9, 11]. Online dating violence is linked to higher rates of suicide compared to offline dating, whereas higher levels of peer attachment and parental support were found to mitigate the risk of suicidal behavior [12]. Existing research shows that adolescents with authoritarian mothers are at higher risk of falling victim to online dating violence and that adolescent girls with authoritarian fathers are more susceptible to verbal-emotional violence [13]. A cross-sectional study from England and Wales which looked at dating and relationship violence among 16– to 19 year-old students found no significant gender differences but showed a high prevalence of dating and relationship victimization among adolescents in both males (two to eight times) and females (two to four times) [14]. The Oxford dictionary defines sexting as a process of "sending sexually explicit photographs, video-clips, or text messages to someone, typically via a mobile phone" [15]. A study conducted in Italy in 2016 found a relationship between dating violence and moderate-to-high use of sexting, highlighting the fact that male adolescents and non-heterosexuals were more often involved in sexting [16]. The study also reported that dating violence victimization and perpetration was predicted by sexting and by the duration of the relationship [16].
3. **Mental health issues.** A number of studies have been conducted to look for a relationship between body image issues and weight control behavior among adolescent Tinder users [17, 18]. It was found that Tinder users had higher levels of body image issues and unhealthy weight control behavior in comparison to non-users [17]. Although there are a few studies linking dating apps usage with disordered eating habits among adolescents, no study has reported any significant link between psychological distress and online dating [18]. It is possible to speculate that there might be a link between online dating and the level of stress among adolescents. But, to our knowledge, no published data is available to authenticate this.

(2) International context

Although the amount of data exploring the impact of online dating on adolescents remains limited, a survey conducted in the US in 2014 and 2015 by the National Pew Research Centre showed that around 35% of adolescents aged between 13 and 17 years had been romantically involved with or dated someone [19]. Although the majority of these relationships started offline (76%), online platforms was the most common method to engage romantically with others [19]. The survey also found that girls were more likely to be the recipients of uncomfortable flirtatious messages than boys [19]. In particular, around 35% of girls had blocked or unfriended someone for that reason compared to 16% of boys [19]. Although it was suggested that online platforms help adolescents feel closer to their partners and display affection, the platforms were also the reason for jealousy and uncertainty in relationships among 27% of users [19]. The most common ways of communicating and spending time with each other were texting, followed by calling, and meeting in person [19]. Overall, 88% of the adolescents expected to hear from their partners at least once a day and 15% expected their partner to check on them hourly [19]. Around 4–10% of adolescents involved in a relationship displayed potentially harmful or controlling behavior towards their current or an ex-partner [19]. This included having access to the partner's accounts, modifying their social media, impersonating their significant other, posting embarrassing photographs of their partner, and using a tracking program without the partner's knowledge [19]. Around 22% of adolescents experienced inappropriate behavior at the hand of their former partners, such as public shaming or posting derogatory comments against them once the relationship ended via social media platforms [19]. About 15% of adolescents reported that their former partners spread rumours about them using digital platforms [19]. Winstone et al. (2021) suggest that usage of online platforms has the potential to improve peer and family relations or exacerbate them [16, 17].

(3) The Indian context

The concept of adolescent romantic relationship has begun to attract increased attention from researchers in India.

It is believed that dating allows adolescents to explore their budding romantic feelings and bolster their social skills [20]. Furthermore, it helps to develop emotional feelings, form personal and social identities, and mitigate the feelings of loneliness and isolation [21]. Although dating has its obvious advantages, risky behaviors among adolescents involved in romantic relationships have been reported in various leading Indian newspapers on a regular basis in the context of getting married, engaging in unsafe sexual practices, and becoming pregnant. The affected adolescents contact child protection services such as government children homes of the Child Welfare Committee (CWC). They are offered psychosocial care and other child protection services, according to the guidelines of the Juvenile Justice (care and protection) Act of 2015. These services include institutional and non-institutional care, such as child line, foster care, sponsorship, shelter homes, promotion of family-based care, aftercare programs, adoption, education, vocational training, development programs, legal assistance, rehabilitation, etc. The Protection of Children from Sexual Offenses Act (POSCO 2012) makes sexual contact in any form with anyone below 18 years of age illegal and punishable under the law. This poses a threat to the sexual freedom of adolescents and imposes legal obligations on adolescents [18, 19].

Dating as a concept may not have been known to Indian adolescents two or three decades ago, but now, it is rather common [23]. Here are some of the reasons which have led to the rise of an adolescent dating culture in India:

1. **Westernization.** The increasing penetration of Western Culture has nudged urban Indians closer to the concept of open dating among adolescents. The older population may still not approve of adolescent romantic relationships, but they do accept and recognize its growing reality. Hence, the western influence has led to an increased popularity of dating among adolescents in India [23].
2. **Early Puberty.** In the last few decades, it has been the case that boys and girls experience puberty at a younger age than was the case in previous generations. In general, girls enter puberty between the ages of eight and 13 and reach menarche (first menstruation) several years later, while boys enter puberty between the ages of 9 and 14. Early puberty increases interest in sex, which makes adolescents seek out romantic partners more often [24]. This happens in the context of conflicting emotions and the social pressure brought about by the transition from childhood dependency to independent adulthood.
3. **Peer Pressure.** The Majority of adolescents try dating due to peer pressure. Not having a partner may increase the risk of being ridiculed by one's peers and can be a reason for non-acceptance into social circles [3].
4. **Media Influence.** Electronic and social media portray love/romantic relationships as an alluring experience, leading to the popularisation of dating among adolescents. Nowadays, demonstrating a new partner on social media, updating one's relationship status, and posting romantic pictures have become an integral part of adolescents' lives [25].

CONCLUSION

Since the beginning of the COVID-19 pandemic, online dating has grown in popularity among adolescents, which has led to the emergence of a number of challenges, including increased risk of sexually transmitted infections, dating violence, and mental health issues. All of these issues are described in the literature in the context of unsupervised use of technology, peer pressure, and desire to fit into society. However, data from India remain scarce on this topic, highlighting the need for research that explores the impact of online dating on adolescents.

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The Future of Psychiatry with Artificial Intelligence: Can the Man-Machine Duo Redefine the Tenets?

Будущее психиатрии с искусственным интеллектом: может ли союз человека и машины перевернуть парадигму?

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Short communication

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ABSTRACT

As one of the largest contributors of morbidity and mortality, psychiatric disorders are anticipated to triple in prevalence over the coming decade or so. Major obstacles to psychiatric care include stigma, funding constraints, and a dearth of resources and psychiatrists. The main thrust of our present-day discussion has been towards the direction of how machine learning and artificial intelligence could influence the way that patients experience care. To better grasp the issues regarding trust, privacy, and autonomy, their societal and ethical ramifications need to be probed. There is always the possibility that the artificial mind could malfunction or exhibit behavioral abnormalities. An in-depth philosophical understanding of these possibilities in both human and artificial intelligence could offer correlational insights into the robotic management of mental disorders in the future. This article looks into the role of artificial intelligence, the different challenges associated with it, as well as the perspectives in the management of such mental illnesses as depression, anxiety, and schizophrenia.

АННОТАЦИЯ

Ожидается, что в течение ближайшего десятилетия распространенность психических расстройств, которые носят наиболее существенный вклад в уровень заболеваемости и смертности, возрастет в три раза. Основными препятствиями в психиатрической помощи являются стигматизация, недостаточное финансирование, нехватка ресурсов и психиатров. Сегодняшние дискуссии сосредоточены на том, каким образом машинное обучение и искусственный интеллект могут повлиять на качество оказания помощи психиатрическим пациентам. Чтобы выявить актуальные проблемы, касающиеся доверия, конфиденциальности и автономии, необходимо изучить их социальные и этические аспекты. Более того, в работе искусственного интеллекта могут наблюдаться сбои и отклонения в «поведении». Глубокое философское понимание этих характеристик как человеческого, так и искусственного интеллекта может установить новые корреляции, проливающие свет на перспективы роботизированного лечения психических расстройств. В настоящей статье представлено описание роли искусственного интеллекта, различных сложностей и перспектив в лечении психических заболеваний, таких как депрессия, тревога, шизофрения.

Keywords: *AI & robotics; mental illness; virtual clinic; digital era; deep learning*

Ключевые слова: *искусственный интеллект и робототехника; психические заболевания; виртуальная клиника; цифровая эра; глубокое обучение*

INTRODUCTION

It appears that we have entered the era of the digital revolution, coming on the heels of the mechanical, electrical, and Internet eras. Today artificial intelligence (AI) tools are available for the diagnosis of behavioral issues, analysis of their manifestations, the prediction of the course of diseases, and the conduct of psychoeducation [1]. The global incidence of psychiatric disorders has skyrocketed in the past two decades. By some estimates, around 500 million individuals have struggled with one or another mental illness [2]. According to the World Health Organization (WHO), mental illnesses will surpass the ischemic heart disease as the biggest drivers of morbidity in the world in the coming years [3, 4].

AI and future technological breakthroughs are anticipated to improve access to care and the quality of the care available to patients suffering from psychiatric disorders. Nonhuman robotic or virtual applications in psychological care may become the preferred means for some, as those have the potential to minimize the feeling of embarrassment that may come with seeking care or adhering to a treatment regimen [5, 6]. The adoption of AI in mental health can also have the added benefit of helping to empower specific patient populations (for instance, those who are less accustomed to navigating the healthcare system), fostering greater transparency and trust between patients and the health care system. Plenty of AI applications are self-administered, enabling people who do not have a life-threatening medical condition to choose therapies without encountering the tedious process of being clinically evaluated and admitted to a health care facility. This is another significant benefit of AI applications [5, 7]. Last, but not least, there are additional advantages that come with having a virtual or robotic therapist who remains easily accessible, has inexhaustible patience and energy, remains aware at all times of what a patient has stated, and does not criticize or judge. Thus, AI could help by offering a service that is extremely trustworthy and, especially, beneficial to particular groups of patients [8].

AI-powered programs might deal with people with mild to moderate depressive disorder, anxiety, and other non-acute illnesses if they are incorporated into global health care services. This would allow medical professionals to devote themselves more to the harder-to-treat cases. These are significant advantages worth taking into account given the worldwide growing burden of mental illnesses and the limited resources available. Achieving maximal research and clinical practices for the cutting-edge treatment of psychological care in the near future mandates a deeper understanding of the ethical and social repercussions of integrated AI. As psychiatrists and psychologists, we must not shun AI, but embrace its present and foreseeable applications, and be ready to work hand-in-hand with AI when it becomes an established therapeutic tool [5, 6, 9].

AI AND PSYCHIATRY

In the technical language, the acronym "AI" indicates an algorithm that can justify, learn, and plan and exhibit actions that we observe with biologically intelligent systems. The term "machine learning" denotes a method of programming in computer science where an application can adjust itself (i.e., learning) according to its inputs in lieu of having all of its behavior dictated by the code. "Deep learning" is a unique kind of machine learning that frequently uses artificial neural networks as a model. The latter usually serves as the artificial neurons and entails interconnected nodes with an input layer, hidden layers, and an output layer. Data from the input layer is transformed multiple foists in the hidden layers. Since AI has the capacity to learn, it can perpetually get better [10].

Incorporating AI technology facilitates the generation of more accurate screening tools and risk models that gauge a person's propensity for or likelihood of being diagnosed with mental health problems. There are basically two types of prospective applications for AI in psychiatry. First is natural language processing, which permits systems to comprehend, decipher, and modify spoken words. Chatbots are a classic example of an AI-based application. These digital conversational agents can communicate via text, speech, or both to simulate human behavior. They serve as a way to offer psychological assistance to those who have trouble sharing their emotions with strangers or in places with limited access to medical facilities. The second application of AI is the combined evaluation of multiple biomarkers utilizing AI to categorize various diseases [11, 12].

CONUNDRUMS

Psychiatrists face challenges using such tools in the following six distinct avenues. The first pertains to the outlooks on AI by psychiatrists and psychologists. Their main problems are the unwillingness to entertain the possibility of employing AI in the coming years [10, 13].

The second is the feeling that, despite having knowledge, skills, experience, and expertise, one remains outdated. The third one is AI-inherent bias. Because of the prejudices of their programmers, AI systems can inadvertently become biased. Nevertheless, with the introduction of self-learning algorithms, AI systems might actually develop bias depending on the information it is gaining insight from [14]. The rampant use of social networking sites to express thoughts and emotions amid the backdrop of four-walled homes and hospitals is the fourth. The management of mental illnesses and the reliability of AI's nosology come together in the fifth. The acceptance of AI by the rural populace ranks sixth [15, 16].

The algorithms used to forecast or diagnose mental illnesses must be accurate and refrain from putting patients at a higher risk if responsible AI deployment is to be accomplished. The possibilities for AI-based neurotechnology to confine psychiatric patients within the neuroscientific principles might make it both theoretically advantageous and therapeutically pertinent, while also fraught [6, 17]. Thus, we contend that the latest technological innovations should only be incorporated into clinical practice if they satisfy each of the following three criteria: they must serve human purposes, they must respect individual identities, and they must foster interaction with humans. The ethical framework for AI applications extends beyond the humanitarian imperative. On the contrary, the core notion of humanity is the kernel of the other five concepts, which are accountability, information, transparency, consensus, and participation [18, 19].

FUTURE PERSPECTIVES

Research into the qualitative dimensions of AI in mental health, in addition to factual and theoretical studies on the relationship between innovation and societal transformation, from the spectrum of frontline deployment up to the domain of national policy making, must be conducted to address these issues. The cutting-edge character of AI will substantially transform the academic medicine's norm-setting, which will eventually be adapted. Since mental patients constitute a particularly vulnerable demographic, their privacy and ethical concerns will be the greatest hurdle [6, 10, 20].

A founding principle of clinical deontology and the vitality of the patient-practitioner relationship are opportunities to be highlighted here. The foundational teaching model should be a balance between the possible mitigation that AI platforms could provide and the addressing data privacy concerns [21]. Such tailored educational resources should be as practical as they are feasible at all times to be effective. Providing students with hands-on involvement with the development, utilization, as well as assessment of AI applications in psychiatry is one way to do that.

To reduce the problems with public health or evidence-based medicine, AI techniques can be highlighted as a primary option among several. Hackathons, which are small-team programming competitions with a specific theme, have recently become popular across every level of academia as a way to involve diverse groups of people (medical and engineering students, scientists, entrepreneurs, etc.) in an entirely novel format ensuring that medical innovation education is accessible and straightforward for curricular medical centers to adopt [10, 22]. Psychiatric departments must adopt multidisciplinary tools such as statistics, technology, and ethics or explore building such skills internally. It is an impediment to the training of future psychiatrists for AI.

CONCLUSION

This article has covered various pluses and minuses of AI as it relates to psychiatry. Changes to psychiatrists' responsibilities, professional status, and purview, which are inextricably tied to issues of socialization and training, have been addressed here. Viewing psychiatry as an integral part of a larger societal construct instead of operating within an academic "buble" may be extremely helpful in addressing these issues. Additionally, the continual development and evaluation of AI applications has laid the groundwork for a tremendous revolution, even though it isn't currently influencing mainstream practice.

Psychiatrists deserve to be permitted to engage with this paradigm shift. In the domains of health, finance, priority setting, resource allocation, and labor management, AI can supplement the job of managers and even substitute them in certain instances. We have to consider how AI could help shape our present and future worldview. The principles that will undergird our future autonomous health care system are currently being redefined, and we should seize the initiative rather than be simple bystanders.

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