An Intelligent Psychiatric Recommendation System for Detecting Mental Disorders

Esma Nur Ucar, Sedat Irgil, Salih Tutun, Nilay Aras and Ilker Yesilkaya

April 27, 2021

An Intelligent Psychiatric Recommendation System for Detecting Mental Disorders

Esma Nur Ucar[1,3], Sedat Irgil[1], Salih Tutun[2], Nilay Aras[1], Ilker Yesilkaya[3]

[1] Balikesir Guven Private Health Laboratory Services Limited Company, Balikesir, Turkey
psk.esmaucar@gmail.com, drsirgil@gmail.com, nilaykocak3500@gmail.com

[2] Olin Business School at Washington University in St. Louis, Clayton, Missouri, USA
salihtutun@wustl.edu

[3] WeCureX AI Research Lab, DNB Analytics, Balikesir, Turkey
ilkeryesilkaya@dnbanalytics.com

KEYWORDS - Recommendation System, Feature Selection, Machine Learning, Psychiatric Diagnosis, Mental Health Disorder, Differential Diagnosis

ABSTRACT

Despite the remarkable recent developments in mental healthcare, many uncertainties in the diagnosis process remain. Even a detailed, well-timed, and closely followed psychiatric interview may not be sufficient to produce an accurate differential diagnosis. At the same time, an insufficient number of specialists and the resultant heavy workloads impede diagnostic efforts, making it very difficult to receive appropriate medical services and manage the treatment process. Such problems underscore the need for auxiliary systems to help experts in making diagnoses, saving both labor and time. For this reason, we propose a new intelligent psychiatric recommendation system with the Comprehensive Psychiatric Differential Diagnosis Test (CPDDT), which we created to screen and differentiate among psychiatric diagnoses. To guide expert in using the system, we included axis one and axis two diagnosis groups, which respectively refer to clinical and personality disorders in the DSM-4. The goal was to measure areas affecting the course of an illness and the treatment plan developed by a specialist, including functionality, memory, and suicidal thoughts. The CPDDT can detect 48 different diagnostic groups from the answers to 319 questions. The system was subjected to an online test of 676 users via a web system developed by DNB Analytics. Psychiatrists evaluated the results in a clinical setting. The test results were then evaluated by the evolutionary simulation annealing LASSO logistic regression model. After determining the importance of each question on the scale, the algorithm eliminated the questions with the least impact and the test was reduced to 147 questions, producing a .93 level of accuracy. In addition, the algorithm found the probability of each patient suffering from a disorder. In summary, the new machine learning-based CPDDT was finalized to include 147 questions; the algorithm is presented here as a useful suggestion system for experts engaging in the diagnostic process.

1 INTRODUCTION

Mental disorders often begin in childhood, experience a development period, and have continued effects throughout life. Studies have shown that they can negatively impact functionality, socialization, and even academic and business success [20]. In addition to their individual effect on a person's life, mental illnesses have also been found to reduce the overall quality of family life [19]. It has been shown that an individual’s mental illness increases the susceptibility of their children to such illness by up to four times the regular rate [12]. These various issues underscore the importance of the accurate diagnosis of mental illnesses and necessity of effective treatment. Yet, according to a 2017 report by the National Council for Behavioral Health, treatment can often be significantly delayed, due to a lack of access to mental health services, leading to adverse outcomes and increased costs. The main source of such delays is a shortage of experts. Experts often must operate under heavy workloads, and as a result, are unable to allocate sufficient time to their patients [11].

Moreover, the fact that different diagnostic groups share similar characteristics can create conflicts in the diagnostic process [7]. Issues can arise even when highly structured comprehensive assessments are followed closely [21]. It is essential that the right diagnostic decisions be made because the first step in effective psychiatric treatment (as in every health-related field) is an accurate differential diagnosis and a corresponding treatment approach [13]. In pursuit of such goals, studies have shown that self-report scales can help experts with the psychiatric diagnosis process and offer a solution to this problem [22].

We propose an intelligent system to assist experts in the diagnostic process by offering a practical means of obtaining a comprehensive body of information. The Comprehensive Psychiatric Differential Diagnosis Test (CPDDT) was created to serve as a self-report scale for examining in detail the mental health of prospective patients. This scale includes two diagnostic groups, axis one and axis two, which reference clinical and personality disorders outlined in the DSM-4, respectively. The goal was to measure areas affecting the course of a disease and the related treatment plan, such as functionality, memory, attention, and suicidal thoughts. We also developed an intelligent psychiatric recommendation system that served to shorten and further established this scale at a high level of accuracy; experts can now use an online platform to practically apply the recommendation system to detect mental disorders. This research is an introductory study of the proposed algorithm and illustrates its adaptability to many healthcare services.

2 RELATED WORK

Evaluation in the field of psychiatry includes examining whether a person has a mental illness, and if so, determining its effects and level of severity. Although such decisions are often based on experts’ subjective judgments, the completeness of such clinical judgment is supported when the evaluation is based on objective conclusions drawn from psychiatric tests [2].

Some of the scales commonly used in this field are listed in Table 1. Generally, the scales used in clinical and personality disorders are separate. The MMPI is the most researched and oft-used scale for personality measurements. It consists of 566 questions and includes 10 clinical symptom pattern subscales [9]. Another test used for personality disorders is the Rorschach test. This is a projective test in which the patient is asked to interpret ink blots [1]. However, this test is only rare employed because it requires detailed training, takes substantial time for application and analysis, and projective tests in general are scientifically controversial [8].

In terms of clinical disorders, the majority of scales are designed to measure a single disease. For example, the Beck Depression Inventory [16] is frequently used to measure depression, and the Beck Anxiety Inventory [5] is commonly applied as an anxiety scale. The ADHD Self-Report Scale is often employed to measure attention deficit and hyperactivity disorders in adults [6]. These are just a few of the many scales created to facilitate psychiatric diagnoses.

Scales for multiple clinical disorders are less common. The most widely used is the SCL-90R, a Likert-type self-report scale that includes nine basic subscales and 90 questions [3]. Another, the Brief Psychiatric Screening Scale, consists of 18 questions, roughly inquiring as to the frequency of one symptom for each question [4]. However, these scales are not comprehensive and tend to be impractical. For this reason, they are rarely applied clinically, and instead are reserved for research.

Table 1 Examples of Scales Used in Psychiatry

Name Of The Scale	**Number Of Questions**	**Disorders or Structures Measured By The Test**	**Reference**
Beck Depression Inventory	21	Depression	[16]
Beck Anxiety Inventory	21	Anxiety	[5]
ADHD Self Report Scale	18	Attention Deficit Hyperactivity Disorder	[6]
Maudsley Obsessive Compulsive Inventory	37	Obsessive-Compulsive Disorder	[15]
Liebowitz Social Anxiety Scale	24	Social Anxiety Disorder	[10]
The Michigan Alcoholism Screening Test	25	Alcohol Use Disorder	[14]
Minnesota Multiphasic Personality Inventory	566	Hypochondriasis Depression Hysteria Psychopathic Deviate Masscculinity/Femininity Paranoia Psychasthenia Schizophrenia Hypomania Social Introversion	[9]

SCL-90R	90	Somatization Obsessive-Compulsive Interpersonel sensitivity Depression Anxiety Hostility Phobic Anxiety Paranoid Ideation Psychoticism	[3]

To address the need for a comprehensive scale applicable in clinical practice, we created the CPDDT. A specialist can send this test to the patient via a digital platform and have the results analyzed by artificial intelligence, thus providing the expert with comprehensive information about the subject in a practical and efficient way. This work fills a gap in the literature through the holistic perspective it provides.

3 METHODOLOGY

3.1 General structure of the test

The CPDDT is a test that examines in detail the mental state of a prospective patient. It was created to assist specialists in the psychiatric examination of individual subjects. The test uses 319 questions to measure 48 sub-diagnoses (see Table 2). In addition to conditions such as the personality and anxiety disorders listed in the DSM IV and V, subscales for symptoms such as suicidal thoughts, which are considered important for the treatment process, were also included. The response options for the 5-point Likert-type scale range from 0 to 4, reflecting the answers of "Never," "Rarely," "Sometimes," "Often," and "Always," respectively.

Table 2 Diagnostic Groups Included in the Comprehensive Psychiatric Differential Diagnostic Test

• Paranoid Personality • Schizoid Personality • Schizotypal Personality • Antisocial Personality • Borderline Personality • Histrionic Personality • Narcissistic Personality • Avoidant Personality • Dependent Personality • Obsessive-Compulsive Personality • Introvert Structure • Sociopathy • Decrease in Functionality • Decreased Insight • Cognitive Impairment(Memory) • Movement Disorders • Suicidal Thoughts	• Generalized Anxiety Disorder • Panic Disorder • Separation Anxiety Disorder • Agoraphobia • Social Phobia • Posttraumatic Stress Disorder • Acute Stress Disorder • Psychotic Disorder • Paranoid Schizophrenia • Dissociation • Sleeping disorders • Sexual Disorders • Lack of Attention • Impulsiveness • Alcohol Use Disorder • Substance Use Disorder	• Obsessive-Compulsive Disorder • Body Dysmorphic Disorder • Hoarding Disorder • Trichotillomania (Hair Pulling Disorder) • Misophonia • Illness Anxiety Disorder • Conversion Disorder • Somatic Symptom Disorder • Orthorexia Nervosa • Depressive Episode • Manic Episode • Seasonal Affective Disorder • Premenstrual Dysphoric Disorder • Hostility • Psychological Rigidity

3.2 Test Creation Phase

The first draft of the CPDDT was created after a comprehensive literature review. The scales and sources used to determine the questions were as follows: the DSM IV and V, SCL90R, MMPI, Five-Factor Personality Test, Beck Depression Scale, Hamilton Depression Rating Scale, Seasonal Pattern Assessment Questionnaire, Beck Anxiety Scale, Adult ADHD Self-Report Scale, Panic Disorder Severity Scale, Liebowits Social Anxiety Scale, Dissociative Experiences Scale, Social Functioning Scale, Yale-Brown Obsessive Compulsive Scale, Michigan Alcoholism Screening Test, Positive Symptom Rating Scale, and Negative Symptom Rating Scale. The draft was forwarded to 15 psychiatrists and one assessment and evaluation specialist and their opinions were collected. The second draft, prepared in response to their feedback, was then forwarded to a language expert for language evaluation. Subsequently, the necessary final arrangements were made, and the draft was finalized.

3.3 Data Collection Phase

A website created by DNB Analytics was used during the data collection phase. A total of 676 people who came to a psychiatry clinic were registered on this website by an expert and a CPDDT was distributed to them. Subjects completed their tests by clicking on a link sent to them via text message. Artificial intelligence analyzed the test results and sent a report to the expert. The information and test results were kept confidential and never shared, and their data were protected by recording all details in the system according to protocol numbers.

3.4 The Optimized LASSO Logistic Regression Model

The goal of the proposed model was to optimize the logistic regression (LR) coefficients by using a combination evolutionary strategy (ES) and simulated annealing (SA) algorithm. SA, a random search technique that uses single-base optimization, explores the neighborhoods of the primary solutions and searches for the appropriate solution space. Although the starting point can be determined randomly in this algorithm, it is trapped in the local optima because it scans the primary solutions at nearby points.

In the model we propose, an ES meta-heuristic optimization is used to determine the primary solution. Unlike SA, when ES is used to find the primary solution, it is possible for the algorithm to go beyond the local optimum, allowing for more accurate solutions. Thus, the best model can be found by optimizing the coefficients with this hybrid meta-heuristic optimization approach.

Regularization methods have been proven effective at resolving the overfitting problem that exists with traditional LR models.

$$F_x = \frac{1}{1 + e^{-(\beta_{n+1} + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n)}} \qquad (1)$$

The x values in Eq. (1) represent each question on the test. Since there were 314 questions, the value of n is 314. The β variable is a value between 0 and 1, indicating the severity of each question.

In this equation, β is unknown and the algorithm determines the value. For example, if as a result of the algorithm the value of β_1 is 0, x_1, the 1st question, does not contribute to the test and can be excluded. A value of β close to 1 indicates that the importance of the question is high. The ES algorithm was used when first determining the ß values in this formula. The values that were not attached to the local optima given by SA were later developed with LR and finalized. The importance of each question was determined in the most optimal way.

$$min_{\beta_0,\beta_1,\beta_2,\beta_3,\ldots\beta_n}\left(\frac{1}{2N}\sum_{i=1}^{N}\left(Y_i-(F_{Xi})\right)^2+\lambda\sum_{j=1}^{p}\left|\beta_j\right|\right. \tag{2}$$

The mathematical formula of the LASSO algorithm is given in Eq. (2). Here, N is the number of test questions, Yi is the response in the test, and Xi is the datapoint. While λ is a non-negative regression parameter, β is the coefficient value of the regression model. Since the formulation as an objective function is not linear with absolute and square values, the ES-based SA algorithm is used to optimize the formulation.

To summarize the proposed model, feature selection is done first, and the best feature subset is selected by using the filter and wrapper feature selection methods together. After determining the LASSO-LR formulation for the problem, the SA model is begun with the help of the ES algorithm. Then, as the model is optimized, the coefficients of the LASSO model are adjusted using the SA-based hybrid evolution strategy. In the end, the most suitable solution is chosen, and using the LASSO model, the most distinctive items on the test are estimated with optimal coefficients [17].

4 RESULTS

This research is an initial study of the proposed algorithm. Two separate results can be obtained from the algorithm: the severity of each question and probability of the patient suffering from a disorder. In the present work, the first two-thirds of the 676 data points were used to train the model. The remaining data were used in the test phase to determine whether the algorithm worked. During the training phase, the accuracy was 0.93 for 450 data points. The 226 data points not included in the training were used in the test phase. The algorithm was found to predict if respondents suffered from a disorder at an accuracy level of 0.71.

The β value in Eq. (1) was calculated separately for each question to determine the importance. Questions with an importance value of 0.000 were removed because they did not create a discriminatory effect on the scale. The weight values of the remaining 147 questions are given in Table 3.

Table 3 Distinct Question Severity Levels of the 147 Questions

Question Number	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**	**Question Number**	**Weight Value**
2	0.010	**51**	0.002	**86**	0.007	**142**	0.003	**180**	0.004	**225**	0.002	**259**	0.004	**296**	0.003
8	0.013	**53**	0.020	**90**	0.001	**143**	0.005	**181**	0.007	**228**	0.007	**260**	0.004	**297**	0.012

15	0.004	**55**	0.017	**98**	0.019	**149**	0.018	**184**	0.007	**230**	0.027	**261**	0.005	**299**	0.016
16	0.007	**57**	0.002	**107**	0.002	**150**	0.028	**185**	0.008	**231**	0.020	**262**	0.002	**301**	0.013
20	0.010	**60**	0.006	**110**	0.002	**153**	0.008	**186**	0.005	**232**	0.002	**265**	0.002	**302**	0.001
21	0.006	**61**	0.004	**113**	0.004	**154**	0.001	**190**	0.016	**233**	0.006	**266**	0.001	**304**	0.008
22	0.010	**63**	0.017	**115**	0.002	**156**	0.006	**192**	0.010	**235**	0.004	**267**	0.003	**306**	0.003
23	0.005	**64**	0.003	**116**	0.002	**158**	0.013	**199**	0.004	**236**	0.011	**272**	0.006	**307**	0.008
26	0.004	**66**	0.009	**117**	0.006	**160**	0.006	**200**	0.018	**238**	0.005	**273**	0.013	**309**	0.001
28	0.007	**68**	0.005	**121**	0.006	**163**	0.001	**202**	0.008	**239**	0.003	**275**	0.006	**311**	0.002
30	0.002	**69**	0.015	**122**	0.011	**165**	0.015	**203**	0.002	**242**	0.004	**279**	0.005	**312**	0.005
31	0.005	**71**	0.004	**125**	0.002	**169**	0.006	**205**	0.001	**245**	0.007	**280**	0.002	**313**	0.008
33	0.005	**75**	0.007	**126**	0.015	**170**	0.012	**207**	0.003	**246**	0.005	**281**	0.005	**317**	0.011
35	0.001	**79**	0.003	**129**	0.012	**171**	0.005	**210**	0.007	**247**	0.003	**283**	0.006	**319**	0.004
40	0.004	**80**	0.003	**131**	0.010	**172**	0.003	**215**	0.002	**248**	0.004	**284**	0.008		
42	0.004	**81**	0.001	**132**	0.004	**173**	0.016	**216**	0.001	**249**	0.002	**285**	0.012		
46	0.003	**83**	0.006	**137**	0.002	**176**	0.007	**217**	0.007	**252**	0.001	**286**	0.004		
47	0.019	**84**	0.005	**139**	0.004	**177**	0.008	**219**	0.014	**255**	0.008	**290**	0.004		
48	0.11	**85**	0.013	**140**	0.002	**178**	0.006	**221**	0.010	**258**	0.006	**293**	0.002		

In summary, as a result of the algorithm, the CPDDT was reduced from 314 to 147 questions, with an accuracy level of 0.93. In addition, the model would found to predict at an accuracy level of 0.71 whether an individual suffered from a disorder.

5 DISCUSSION AND FUTURE WORK

In a world where digitalization continues to increase on a global scale, modernization of the application and analysis of psychiatric tests is inevitable. Of course, experts will always be needed to evaluate the analysis results presented by artificial intelligence. The goal is not to remove experts from the system, but rather to provide mental health services to more people by offering a practical, helpful system that will reduce experts' workloads. In a system in which the number of patients is high and experts are few, it is essential in terms of both time and cost to offer tests online and analyze the results automatically. The digital advancement of psychiatric tests will also eliminate the need for certain types of applications and analyzes and create a common level of use at the national level, making more accurate results and comparisons possible.

One drawback of both digital and traditional methods is that Likert-type scales are used to quantify individual responses. In contrast to performance measures, on psychiatric scales, it is generally accepted that the respondent is correct. On a digital platform, recording the time spent per question, selections changed, and mouse movement through the website are useful means of overcoming this weakness. These records will automatically provide experts with information such as the person's tendency to lie, provide haphazard responses, or spend excessive time on the test.

Moreover, when paper tests are used, test results must manually be individually entered into the system. In a well-structured study, the higher the number of participants, the greater the workload. In the proposed system, test results from tens of thousands of respondents can remain anonymous and ready for analysis, without the need for extra data entry. The coexistence of many test results about a particular person also makes it possible to evaluate that person more integrally. It is also very important for epidemiological research that tests be easy to deliver and the results interpreted automatically. The goal of epidemiology is to improve health and reduce disease by interpreting and applying large bodies of information [18]. This system is capable of breaking new ground in epidemiology research by providing a practical means of collecting and analyzing substantial bodies of data.

The literature review revealed that scales for psychiatric disorders are generally specific to a single disease, and thus there is a need for a more comprehensive scale. This study is pioneering in terms of providing a holistic perspective and means of evaluating diagnoses with factors affecting treatment, such as functionality. However, it should be noted that although many diagnosis and sub-diagnosis groups are included in this test, there are diagnoses that have been omitted so as not to increase the number of questions to an unreasonable level. In the first draft, the total number of questions was 314. The current version has 147 questions. Determining which diagnoses were not added to draft, creating a second scale that includes all diagnoses in the DSM are opportunities for development in this field. Creating a more complete body of diagnoses will close the current gap, and a CPDDT 2 is planned in which these diagnoses will be added.

It is also important to note that a portion of the data collection process overlapped with the onset of the Coronavirus pandemic, which may have affected the answers given to the questions related to obsessive-compulsive and anxiety disorders. For example, one item was: "I don't want to directly touch an object somewhere because I think other people have touched it before." In response to this question, someone who might have responded with "Never" before the pandemic could possibly answer "Often" today, considering that doing so would protect against the virus. For this reason, it is inevitable that Covid affected the data collected during this period.

Finally, this study reflects only a preliminary example of the proposed system. Although the test currently offers expert information on 48 different diagnoses, the algorithm is not examine individuals with regards to all of these. Since this is a preliminary study, the algorithm shortened the scale by determining the significance of each problem. Also, the algorithm is currently only able to determine if someone is suffering from a disorder by calculating the probability of that person being unwell. Moreover, while the accuracy level was 0.93 in the training phase (where 450 data points were used), it was 0.71 in the test phase (which utilized the remaining 226 data points). The data collection phase is currently ongoing. When the body of data increases to a sufficient extent, the accuracy of the test phase is expected to exceed 0.90. In future work employing a sufficient body of data, individuals found to be “sick” will be further examined for each of the 48 sub-diagnoses and a precise diagnosis delivered.

6 CONCLUSION

This system is recommended as means of assisting experts by providing a comprehensive screening test for use in the field of psychiatry. The test comprehensively examines respondents' mental health and this system can be used both alone and with other tests that will be integrated in the future. While the primary purpose is to assist experts, the sampling process makes it possible for health systems to digitalize their data, making the system more practical and capable of reaching more people. Thus, it is adaptable for use in various health areas in the future.

REFERENCES

[1] Beck, J. (n.d.). *The Rorschach Test and Personality Diagnosis*. 72–75.

[2] Burns, A., Lawlor, B., & Craig, S. (2002). Rating scales in old age psychiatry. *British Journal of Psychiatry, 180*(2), 161–167. https://doi.org/10.1192/bjp.180.2.161

[3] Derogatis, L. R., Rickels, K., & Rock, A. F. (1976). The SCL 90 and the MMPI: a step in the validation of a new self report scale. *British Journal of Psychiatry*, *128*(3), 280–289. https://doi.org/10.1192/bjp.128.3.280

[4] Dingemans, P. M. (1990). The brief psychiatric rating scale (BPRS) and the nurses' observation scale for inpatient evaluation (NOSIE) in the evalution of positive and negative symptoms. *Journal of Clinical Psychology*, *46*(2), 168–174. https://doi.org/10.1002/1097-4679(199003)46:2<168::AID-JCLP2270460207>3.0.CO;2-L

[5] Fydrich, T., Dowdall, D., & Chambless, D. L. (1992). Reliability and validity of the beck anxiety inventory. *Journal of Anxiety Disorders*, *6*(1), 55–61. https://doi.org/10.1016/0887-6185(92)90026-4

[6] Kessler, R. C., Adler, L., Ames, M., Demler, O., Faraone, S., Hiripi, E., Howes, M. J., Jin, R., Secnik, K., Spencer, T., Ustun, T. B., & Walters, E. E. (2005). The World Health Organization adult ADHD self-report scale (ASRS): A short screening scale for use in the general population. *Psychological Medicine*, *35*(2), 245–256. https://doi.org/10.1017/S0033291704002892

[7] Laura Pina-Camacho, M. P. & M. K. (n.d.). *Autism spectrum disorder and schizophrenia: boundaries and uncertainties | Enhanced Reader*. Retrieved April 8, 2021, from chrome-extension://dagcmkpagjlhakfdhnbomgmjdpkdklff/enhanced-reader.html?openApp&pdf=https%3A%2F%2Fwww.cambridge.org%2Fcore%2Fservices%2Faop-cambridge-core%2Fcontent%2Fview%2FA038239D14B3462832B5576D4B57E1B0%2FS2056467800001870a.pdf%2Fdiv-class-title-auti

[8] Lilienfeld, S. O., Wood, J. M., & Garb, H. N. (2000). The Scientific Status of Projective Techniques. *Psychological Science in the Public Interest*, *1*(2), 27–66. https://doi.org/10.1111/1529-1006.002

[9] Mathias, R. (1978). The Minnesota Multiphasic Personality Inventory (Book). *Journal of Personality Assessment*, *42*(3), 332–333. https://doi.org/10.1207/s15327752jpa4203_28

[10] Mennin, D. S., Fresco, D. M., Heimberg, R. G., Schneier, F. R., Davies, S. O., & Liebowitz, M. R. (2002). Screening for social anxiety disorder in the clinical setting: Using the Liebowitz Social Anxiety Scale. *Journal of Anxiety Disorders*, *16*(6), 661–673. https://doi.org/10.1016/S0887-6185(02)00134-2

[11] National Council for Behavioral Health. (2017). The Psychiatric Shortage: Causes and Solutions. *National Council for Behavioral Health*, 1–66. https://www.thenationalcouncil.org/wp-content/uploads/2017/03/Psychiatric-Shortage_National-Council-.pdf

[12] Pawlby, S., Sharp, D., Hay, D., & O'Keane, V. (2008). Postnatal depression and child outcome at 11 years: The importance of accurate diagnosis. *Journal of Affective Disorders*, *107*(1–3), 241–245. https://doi.org/10.1016/j.jad.2007.08.002

[13] Quevedo, A. S. (2017). *occurence of dermoid cyst in the FOM - the importance of differential diagnosis in pediatric patients*. *25*(3), 341–345.

[14] Selzer, M. L. (1971). The Michigan alcoholism screening test: the quest for a new diagnostic instrument. *The American Journal of Psychiatry*, *127*(12), 1653–1658. https://doi.org/10.1176/ajp.127.12.1653

[15] Sternberger, L. G., & Burns, G. L. (1990). Compulsive activity checklist and the maudsley obsessional-compulsive inventory: Psychometric properties of two measures of obsessive-compulsive disorder. *Behavior Therapy*, *21*(1), 117–127. https://doi.org/10.1016/S0005-7894(05)80193-5

[16] Teri, L. (1982). The use of the beck depression inventory with adolescents. *Journal of Abnormal Child Psychology*, *10*(2), 277–284. https://doi.org/10.1007/BF00915946

[17] Tutun, S., Khanmohammadi, S., He, L., & Chou, C. A. (2020). A meta-heuristic LASSO model for diabetic readmission prediction. *Proceedings of the 2016 Industrial and Systems Engineering Research Conference, ISERC 2016*, 2228–2233.

[18] Van Der Flier, W. M., & Scheltens, P. (2005). EPIDEMIOLOGY AND RISK FACTORS OF DEMENTIA. *J Neurol Neurosurg Psychiatry*, *76*, 2–7. https://doi.org/10.1136/jnnp.2005.082867

[19] Walton-Moss, B., Gerson, L., & Rose, L. (2005). Effects of mental illness on family quality of life. *Issues in Mental Health Nursing*, *26*(6), 627–642. https://doi.org/10.1080/01612840590959506

[20] Wittchen, H. U., & Jacobi, F. (2005). Size and burden of mental disorders in Europe - A critical review and appraisal of 27 studies. *European Neuropsychopharmacology*, *15*(4), 357–376. https://doi.org/10.1016/j.euroneuro.2005.04.012

[21] Zimmerman, M. (2012). Broadening the concept of bipolar disorder: What should be done in the face of uncertainty? *Postepy Psychiatrii i Neurologii*, *21*(2), 88–90.

[22] Zimmerman, M., & Mattia, J. I. (2001). A self-report scale to help make psychiatric diagnoses: The psychiatric diagnostic screening questionnaire. *Archives of General Psychiatry*, *58*(8), 787–794. https://doi.org/10.1001/archpsyc.58.8.787