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MAPPING AFFECTIVE PROFILES IN DEPRESSION, BURNOUT, NORMAL SADNESS, AND EUTHYMIC STATE: A SELF-REPORT SCREENING TOOL DEVELOPED THROUGH A MACHINE LEARNING APPROACH

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SUMMARY

Background: *Modern post-industrial society is facing a complex of challenges, such as including epidemiological threats, high demands from employers, aggressive forms of corporations' management, stress at the work place, as well as geopolitical and economic instability worldwide. These factors bring a significant impact on mental health of the general population, contributing to an increased prevalence of mental disorders, particularly, affective states. The aim of this study was to develop a sensitive screening tool based on a self-questionnaire approach for accurate differentiation of affective spectrum state, from preclinical / at-risk to severe clinical conditions. To achieve this goal, we focused on identifying key affective symptoms' domains and application of machine learning (ML) methods to perform a comprehensive data analysis on classifying the respondents into preclinical and clinical subgroups.*

Subjects and methods: *The study consisted of two stages. At the first stage, we developed and conducted an online survey among the experimental population consisting of university staff and students. This survey version included 19 questions. The study was interrupted to make adjustments. At the second stage, the survey was finalized based on data analysis (descriptive and inferential) and classification tasks. The revised survey was redistributed with additional criteria for inclusion and exclusion of the respondents applied to the study design. The final version contained 34 questions, excluding unreliable questions characterized by $p > .05$. 381 individuals (269 employees and 112 students) were interviewed, of whom 99 showed signs of depression, normal sadness or emotional burnout. We conducted correlation, descriptive, and inferential analyses and classification of respondents using ML-based methods.*

Results: *The results confirmed the presence of significant differences ($p < .001$) between the groups with euthymia, normal sadness, emotional burnout and depression. However, there were no statistically significant differences for respondents with a pre-known emotional state and for respondents whose condition has been classified using machine learning technologies. The final distribution by category was as follows: euthymia - 38.8%, normal sadness - 27.3%, emotional burnout - 25.2%, depression - 8.7%. Our developed self-report tool has demonstrated statistical benefit, but requires further clinical research to clarify sensitive symptoms' domains for updating its items content.*

Conclusions: *ML-based analysis of the self-report screening tool-related data demonstrated its sensitivity to classify affective states spectrum onto the separate states of depression, emotional burnout, normal sadness and euthymia (i.e. affective or emotional profiles of the respondents) with 100% accuracy at the final iteration. The problem of assessing mental health lies in the difficulty of obtaining fast, accurate, and emotionally neutral determination of the affective state in individual respondents and across populations. Development of a sensitive self-questionnaire / screening benefits from the the integration of clinical assessments along with the modern ML-based algorithms, as well as targeting the approach that helps to reduce costs and increase the diagnostic accuracy of existing psychometric tools.*

Key words: *affective disorders - big data - burnout - depression - euthymic state - machine learning - self-report screening tool - stress at workplace - symptoms domains*

Abbreviations: *AI - Artificial Intelligence; BAD - bipolar affective disorder; DALY - disability-adjusted life years; EB – Emotional Burnout; ES - euthymic state; GAD - generalized anxiety disorder; GBD - Global Burden of Disease; HPA - hypothalamic-pituitary-adrenal axis; MBI - Maslach Burnout Inventory; ML - Machine Learning; NS - normal sadness; PTSD - post-traumatic stress disorder; YLD - years lived with disability; WHO - World Health Organization*

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INTRODUCTION

Modern society is facing a progressive deterioration of mental health, which is particularly evident in the context of the post-industrial crisis and the exponential growth of the global economy (Asmolov et al. 2020). According to the latest Global Burden of Disease (GBD) study for 2021, mental and neurological disorders rank first and third in terms of Years Lived with Disability (YLD) and Disability-Adjusted Life Years (DALY), respectively (Dar'in, Ambartsumyan, & Pitel 2021). The most common are depression of various origins (e.g., stress-related, unipolar depression), anxiety disorders, bipolar affective disorder (BAD), and post-traumatic stress disorder (PTSD) (Figure 1).

Over the past decade, there has been an increase in the incidence of mental disorders in absolute and relative terms, especially during the COVID-19 pandemic and in subsequent years (see Figure 2, left). According to the large-scale multidisciplinary projects, the prevalences of depression, anxiety disorders and suicidality risks have been increased in the majority of countries that experienced pandemic-related lockdown, including Russia (Fountoulakis et al. 2022a, Syunyakov et al. 2022, 2024). Younge people, health care professionals, lonely people and those with unstable financial income demonstrated vulnerability toward affective states in response to psychosocial stressors and life habits changes such as sleep disturbances, increased use of social media, time spent in reading news online (Fountoulakis et al. 2022b, Smirnova et al. 2021). Elevated suicidality risks in many low- and middle-income countries are also related to alcohol use (alcohol craving often masks dipsomania type of depression), easy access to alcohol in comparison to mental health care (which is often stigmatized in the community), and bring financial problems, especially in men (Bellman & Namdev 2022).

YLD assesses the impact of mental disorders through the loss of healthy years of life due to symptoms and functional impairments. This metric, along with DALY, is used in healthcare and economics to analyze costs, quality-of-life reductions, and other key indicators. The global economic damage from mental disorders is estimated at around $1 trillion and 12 billion days annually (Cookson 2024), while in the Russian economy, the losses are estimated at $ 16 billion per year (Domnina et al. 2018). The current situation is driven by structural changes in the economy related to post-industrialization, declining employment in traditional industries, focusing on AI-related jobs, increasing social instability, emotional imbalance and developing stress-related reactions of depression, anxiety, asthenia /fatique / burnout, as well as relapse of mental disorders in those people who previously experienced the history of mental disturbances. The contemporary social environment is also characterized by destructive perfectionism, lack of social support, social exclusion, dehumanization, bullying, violence rise, and loss of direction in life due to sociocultural changes in modern community, which together bring depression to daily life and the work environment, especially for the vulnerable populations of the young and the elderly (Kholmogorova & Garanyan 2024, Kholmogorova et al. 2019, Mihaljević et al. 2015).

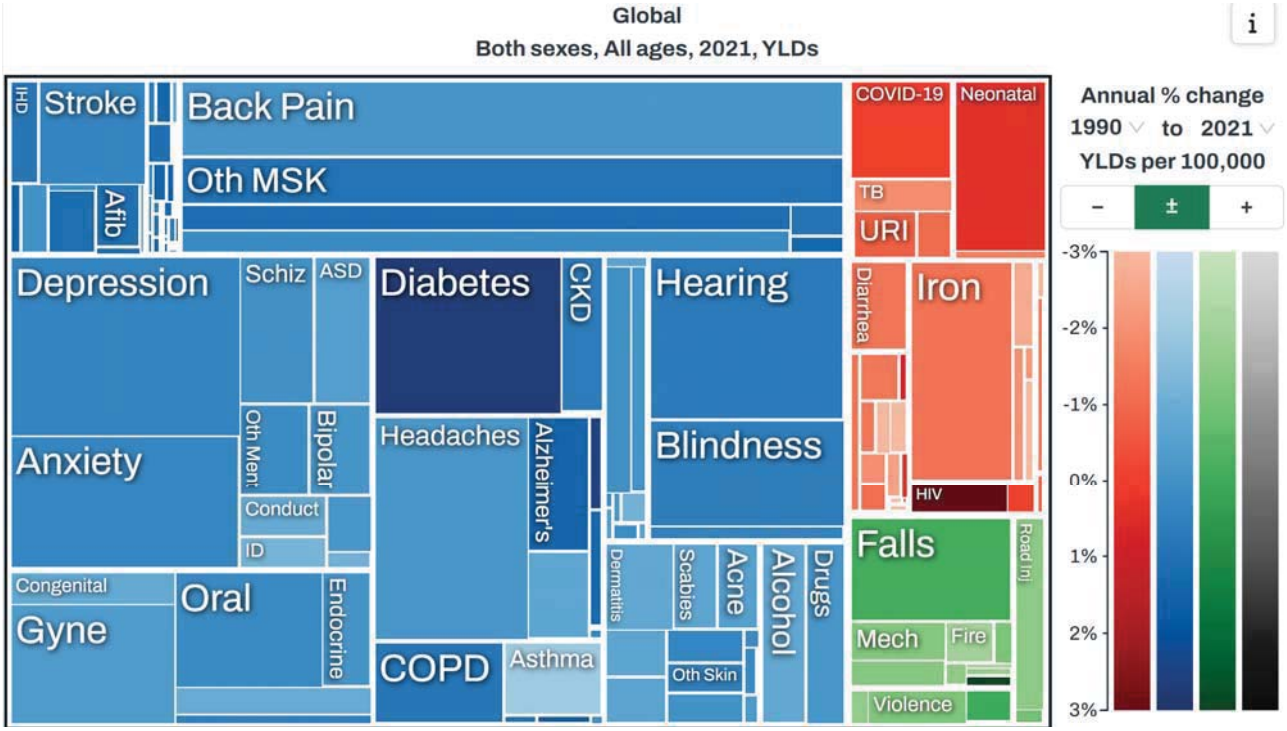
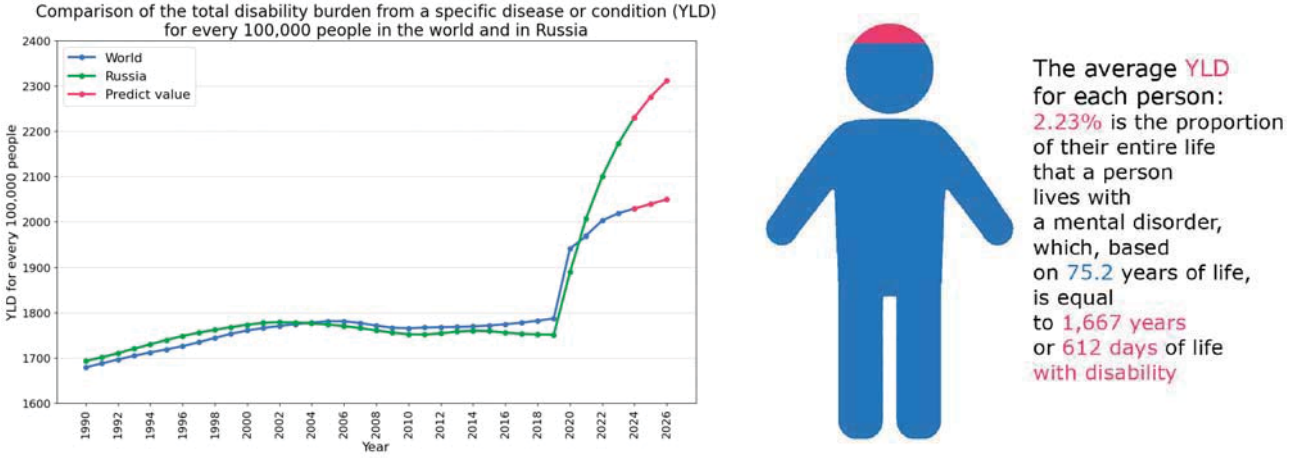


Figure 1. Disease burden structure ratio for the YLD indicator (Institute for Health Metrics and Evaluation, based on HealthDataHub (https://vizhub.healthdata.org/gbd-compare/)



Figures 2. YLD trend for mental disorders, predicted using ARIMA for three years ahead (figure on the left); visualization of the burden of mental disorders in terms of lost years of life (figure on the right)

One may experience different manifestations of violence, hard work pressure, and lack of empathy in daily life communication, which together are triggering for problematic affective states. However, providing psychosocial interventions across educational institutions, local community groups, and practicing the concept of civilization of empathy can improve mental health for vulnerable populations (Jakovljević 2024). Moreover, depression and other affective states, undergo psychosocial pathomorphosis extending over decades, manifesting in incapacity to verbalize feelings or emotional complaints, language changes due to social networks use, and increased prevalence of somatic complaints (Krasnov et al. 2023). Consequently, mental health care professionals are calling for the development of up-to-date screening tools that are able to capture emotional symptoms in population via novel and comprehensive screening tools.

Timely identification of mental symptoms is hindered by a number of factors, including the high cost of consulting qualified specialists, the lack of time for potential clients, social barriers (e.g., stigmatization of depression, mental health care and psychiatrists), and other factors (Krupchanka et al. 2017, O'Donnell & Faran 2024). Regular (monthly or quarterly) examination is recommended for assessing and monitoring the psychological climate at the workplace. These methods are cost-effective, time-saving, and allow for the analysis of the mental state of both employees and the social group as a whole, which helps to identify critical conditions early, prevent crisis situations in the workplace, and manage the preventive training / consultations (Mamat & Anderson 2023). Systematic self-reflection also allows individuals to monitor their mental health and identify the dynamics and factors that affect their mental, in general, or, in particular, emotional state (Duan-Porter et al. 2018).

Mental disorders are often characterized by gradual aggregation of symptoms and phases, from the onset of the first symptoms to the critical stage of the disease in case of intermittent course of the disorder, such as bipolar depression, dysthymia, recurrent depression, chronic stress-related states like neurasthenia. There is also a possibility of transformation of one state into another when taking into account the time perspective, or chronic course, and elevated severity overtime, such as normal sadness or burnout condition may predispose towards mild depression, which may be observed in those with an early history of major depressive disorder or other serious conditions. Euthymic state (ES), normal sadness (NS), emotional burnout (EB), stress disorder, depressive disorder, and generalized anxiety disorder (GAD) are various psychopathological conditions that may manifest with similar unspecific clinical signs, such as decreased work productivity, sleep disturbances, increased irritability, and cognitive dysfunctions such as attention deficit (Smirnova et al. 2024). ES is characterized as a stable emotional balance, NS as a short-term emotional response to external events in the absence of clinical symptoms, depression as an acute state of chronic disorder with a predominance of hypothymia and anhedonia, ES refers to professional maladjustment and exhaustion due to stress arising from threatening factors, and GAD designates a persistent state of anxiety and tension (Smirnova et al. 2024).

Chronic stress at the workplace activates the hypothalamic-pituitary-adrenal (HPA) system, increasing cortisol levels and causing allostatic stress (Bayes et al. 2021). This condition disrupts the neuroendocrine, immune, and metabolic systems (Gajewski et al. 2017). Stress reduces the activity of the brain's reward system and increases sensitivity to otherwise reinforcing or motivational stimuli. In response, employees may resort to unhealthy habits such as substance abuse, poor diet, and decreased physical activity (Da Silva et al. 2025). Compulsive buying behavior is a contemporary marker of stress, showing a consistent and significant positive correlation with overall perceived stress (Thomas et al., 2024). These actions exacerbate the risk of anxiety and depression, cognitive impairment, decreased motivation, and poor mental health (du Prel et al. 2024). At the same

time, maladaptive perfectionism (incongruence) predicts increased levels of depression, anxiety, and stress, as well as decreased life satisfaction, while adaptive perfectionism (high standards), although associated with increased stress, is also associated with higher life satisfaction and does not increase anxiety. In contrast, maladaptive perfectionism clearly burdens mental health and is a robust predictor of anxiety-depressive conditions and EB in clinical populations and professional groups (Simon et al. 2025).

To identify the described conditions, we developed a self-report questionnaire based on questions from the most commonly used and clinically significant scales. For each diagnostic area, we selected a reference test, and the questionnaires were compared based on their diagnostic accuracy, subjective difficulty of answering the questions, straightforwardness, and volume (see Table 1).

We have also taken into account the following disadvantages of self-report-based questionnaires (as described below), aiming to improve reliability of the self-report screening tool. (i) The subjective impression of sensitivity and complexity of questions, which implies their degree of ambiguity and the need for reflection to compose and answer, can lead to distortion of results due to dissimulation or cognitive processes associated with anxiety and stress (Schwarz & Clore 1983, Fazio 1990). (ii) The straightforwardness of questions, which implies a direct clarification about the presence of the symptom/disorder being studied, can also be challenging in the context of mass surveying, where minimizing the time required to complete the survey and reducing the level of stress in respondents is critically important. (iii) The length of questionnaires, which can be extensive and calling for considerable time to complete, can be tiring for respondents, and may thus reduce the accuracy of their responses. (iv) Questions that are correlated with each other may duplicate information, which can also make the self-reporting process more difficult. (v) Privacy is equally important, as direct questions about personal life can be uncomfortable and therefore reduce the sincerity of the respondents' responses (Schwarz 1999). Modern sociological studies that are adjusted to the Russian sociocultural context often do not take into account the transformational processes caused by the post-industrial stage of society's development (Bell, 1973/2004). This requires a revision of the methods used to formulate questions to ensure their relevance and compliance with current sociocultural realities. When conducting large-scale surveys, it is necessary to take into account the cognitive and cultural differences between various social and demographic groups, which will help minimize cognitive biases and ensure that respondents understand the content of the questions clearly.

SUBJECTS AND METHODS

Instrument Development and Pilot Testing

The preliminary questionnaire comprised 19 items based on the scales from Appendix A: 11 core (mandatory) and 8 supplementary /clarifying questions, and was worded for two target populations (students and employees; see Appendix A). The survey was distributed via the Internet, social networks and in the work team in the IT company. Convenience sampling precluded a formal evaluation of sample representativeness. After 56 employee and 93 student responses had been recorded, the survey was suspended. Inspection of pilot data revealed missing response options and insufficient coverage of group-specific characteristics.

Questionnaire Revision

Within this approach, both the qualitative and quantitative content of the questionnaire was revised, which led to a reduction in the number of emotional profiles studied. We found that the boundaries between anxiety, EB, and depression were unclear due to the moderate correlations between anxiety and both EB ($r = 0.46$) and depression ($r = 0.52$) (Koutsimani et al. 2019). Because anxiety often manifests through somatic and cognitive fatigue, which may obscure burnout or depressive symptoms, we removed the anxiety profile from the subsequent differentiation.

Table 1. Overview of the Relevant Tools Targeting the Diagnosis of Investigated Mental Disorders

Diagnostic Tool	Target	Accuracy	Complexity	Straightforwardness	Number of questions / Time consumption
Beck Depression Inventory (BDI)	Evaluates the severity of depression	High - 87% (Beck, Steer, & Carbin, 1988)	Low	Direct	21 questions, 5-10 min.
Maslach Burnout Inventory (MBI)	Evaluates professional burnout	High - 90% (Wickramasinghe, Dissanayake, & Abeywardena, 2018)	Average	Indirect	22 questions, 10-15 min.
Perceived Stress Scale (PSS)	Evaluates the stress level	Average - 70-80% (Cohen, Kamarck & Mermelstein, 1983)	Low	Indirect	10-14 questions, 5-10 min.
Spielberger-Khanin Anxiety Scale	Measures situational and personal anxiety	High - 82-92% (Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983)	Low	Direct	40 questions, 1 5-20 min.

Table 2. Second Revision of the Novel Self-Report Questionnaire Developed for Screening Purposes (including mandatory and clarifying questions)

N	Question	Mandatory/ clarifying	Source
1	Consent to the processing of personal data	mandatory	Socio-demographic characteristics of the respondent.
2	How old are you	mandatory	Socio-demographic characteristics of the respondent.
3	Marital status	mandatory	Socio-demographic characteristics of the respondent.
4	Your gender	mandatory	Socio-demographic characteristics of the respondent.
5	Your professional field	mandatory	Socio-demographic characteristics of the respondent.
6	What is your current mood: 1 - bad, 5 - neutral, 10 - excellent	mandatory	Spielberger's scale of assessment of the level of reactive and personal anxiety.
7	Do you have enough rest per week	mandatory	Sato et al. (2020). Mental health effects of long work hours, night and weekend work, and short rest periods; Roskams et al. (2021). Job demands-resources model: Its applicability to the workplace environment and human flourishing.
8	Do you currently need to rest	mandatory	Need for Recovery Scale.
9	Are you experiencing negative emotions after your last long rest	mandatory	Sonnentag & Fritz (2007). The Recovery Experience Questionnaire: development and validation of a measure for assessing recuperation and unwinding from work.
10	Do you feel the need for a long rest	mandatory	MFI-20 (Multidimensional Fatigue Inventory); FAS (Fatigue Assessment Scale).
11	Evaluate your productivity: 1 - unproductive, 5 - productive, 10 - maximally productive	mandatory	Beck Depression Scale.
12	Do you have additional employment in the form of other work or studies	mandatory	Yusuf et al. (2023). Impact of work environment on job satisfaction and stress among hemodialysis staff in Klang Valley. Bruns et al. (2019). Multiple Job Holding and Mental Health among Low-Income Mothers.
13	The decision to combine several types of activities is forced or voluntary	clarifying	Bruns et al. (2019). Multiple Job Holding and Mental Health among Low-Income Mothers; Burr et al. (2018); international COPSOQ Network. The Third Version of the Copenhagen Psychosocial Questionnaire.
14	Does this affect your mental health	clarifying	MBI (Maslach & Jackson, 1981, 1996).
15	Do you find your job emotionally difficult	mandatory	MBI (Maslach & Jackson, 1981, 1996).
16	Are you planning to change your occupation	clarifying	CTI (Career Transition Inventory).
17	How many people do you have to interact with on average: 1 - rarely, 5 - at the household level, 10 - often	mandatory	COPSOQ III.
18	How often do you ask other people to do your job: 1 - never, 5 - sometimes, 10 - always	mandatory	Scale of perceived stress, PSS-10 (Cohen, Kamarck, & Mermelstein, 1983).
19	Do you often have to help or perform other people's tasks: 1 - never, 5 - sometimes, 10 - always	mandatory	MBI (Maslach & Jackson, 1996).
20	Frequency of other people's tasks: 1 - never, 5 - sometimes, 10 - always	mandatory	ROS (Role Overload Scale); S. Bekker (2021). Role Overload: Examining the Definition and Measurement of a Common Work Stressor.

Table 2. Continues

N	Question	Mandatory/ clarifying	Source
21	How would you rate your emotional state now: 1 - bad, 5 - neutral, 10 - excellent	mandatory	Spielberger's scale of assessment of the level of reactive and personal anxiety
22	How often do you have to answer the question "How are you?" with answers that do not correspond to your current state: 1 - never, 5 - sometimes, 10 - always	mandatory	ELS (Emotional Labour Scale)
23	How often do you hide your true emotions from your loved ones: 1 - never, 5 - sometimes, 10 - always	mandatory	EEESS (Emotion Experience and Expressive Suppression Scale)
24	Do you have enough support from your loved ones	mandatory	MSPSS (Multidimensional Scale of Perceived Social Support)
25	At the moment, you need support from your loved ones or psychologists.	clarifying	Scale of perceived stress, PSS-10 (Cohen & Williamson, 1988)
26	Do you consider yourself a perfectionist	mandatory	Simon et al. (2025). The distinct link of perfectionism with positive and negative mental health outcomes.
27	Do your values align with your goals	mandatory	Cao & Ma (2024). Establishing self-concordant goals: a longitudinal study on the influence of ego identity on goal self-concordance.
28	How often do you compare yourself to others: 1 - never, 5 - sometimes, 10 - always	mandatory	Beck Depression Scale
29	Do you often buy things that you know you don't need or haven't used since you bought them?: 1 - never, 5 - sometimes, 10 - always	mandatory	Thomas et al. (2024). Stress and compulsive buying-shopping disorder: A scoping review.
30	Does alcohol help you cope with emotions/feelings	mandatory	DMQ-R (Drinking Motives Questionnaire, Revised)
31	Do you think you drink alcohol a lot	clarifying	Clarification of question No. 31
32	How often do you drink alcohol: 1 - never, 5 - sometimes, 10 - often	clarifying	Clarification of questions No. 31-32
33	Do you use narcotic or illegal substances	mandatory	CRAFFT 2.1 (Car, Relax, Alone, Forget, Friends, Trouble) DAST-10 (Drug Abuse Screening Test of the 10-item)
34	Here you can share your feelings or experiences	clarifying	Socio-demographic characteristics of the respondent

The final version contained 34 items (27 mandatory, 7 supplemental). Newly added items assessed addictive behaviors and perfectionism, aiming to capture additional determinants of emotional state based on the scales described in from Table 2. Items with nonsignificant discrimination ($p > 0.05$) were excluded.

Participants

The updated questionnaire was published online on a specialized survey platform and distributed to target groups. The respondents were selected according to pre-established inclusion and exclusion criteria: (a) adults aged 18–65 years from the working population and student body with no documented mental-health condition (n = 282) and (b) adults aged 18–65 years who self-reported clinician-diagnosed depression, NS, or EB (n = 99). The combined dataset comprised 381 respondents (269 employees, 112 students). Sociodemographic characteristics and descriptive statistics for all study variables appear in Table 3.

Data Preprocessing

Data were cleaned up / preprocessed and transformed prior to analysis as follows:

- Occupational titles were Label Encoded to explore psychological-profile distributions across professions;
- Implausible ages, inconsistent comments, and extreme mean scores were removed as outliers;
- Free-text self-descriptions were manually coded as negative/pessimistic, neutral, or positive and then Label Encoded;
- Encoding binary responses using One-Hot Encoding;
- Default values were imputed for missing supplemental-item responses.

Table 3. Sociodemographic characteristics of the respondents and surveys applied in the study design of the project targeting development of the novel self-report screening tool

Variable	Questionnaire version 1 (N=149)	Questionnaire version 2 (N=381)
Men/Women	59/90	185/196
Employees/students	56/93	269/112
Average age ± SD	30.3 ± 10.2	41.7 ± 8.1
Mandatory/clarifying questions	11/8	27/7
Average transit time	2 min 21 sec	2 min 39 sec

Statistical Analyses

Pearson's r quantified associations between continuous variables; rank-biserial correlations were applied to continuous–dichotomous pairs, and Cohen's κ to dichotomous pairs (see Appendix B). Only strong ($|r| \geq 0.70$) and very strong ($|r| \geq 0.90$) correlations were interpreted because weaker effects explain < 49% of variance ($R^2 < 0.49$). A binary indicator of addiction showed a very strong correlation with frequency of alcohol use ($r = 0.98$, $R^2 = 0.96$) and was retained as the more parsimonious measure. Mood ratings correlated positively with self-reported emotional state ($r = 0.77$, $R^2 = 0.59$). Alcohol-use frequency was excluded from subsequent modeling because it served solely as a validation variable.

Descriptive statistics (mean, median, variance, and standard deviation for continuous variables; mode, frequency, and percentage for categorical variables) were computed. Continuous variables followed log-normal or normal distributions, whereas categorical variables were either evenly distributed (e.g., sex) or skewed (e.g., non-use of illicit substances) (see Appendix C). Group-level differences are summarized in Table 4. Independent-samples t tests and multivariate analyses of variance (MANOVAs) were conducted to compare psychological profiles across groups ($\alpha = .05$) (see Appendix D); statistically significant differences were observed.

Machine-Learning Classification

The labeled subset was randomly stratified into training (85%) and test (15%) stratified subsamples. Hyperparameters were optimized via grid search, and 5-fold cross-validation was used to guard against overfitting. Model performance was evaluated with the weighted F1 score to accommodate class imbalance. A gradient-boosting algorithm implemented in CatBoost achieved the highest performance (F1-weighted = 1.00) (see Appendix E). The final model was built on a complete set of labeled data and applied to the unlabeled cases. Follow-up inferential testing revealed no significant differences between newly classified and previously labeled groups ($p > 0.05$ for both t tests and MANOVAs), supporting the quality of automated labeling (see Appendix F). Feature-importance rankings are illustrated in Appendix G.

RESULTS

The study revealed statistically significant differences between groups of survey respondents with different emotional states. Machine learning (ML) algorithms demonstrated significant differences ($p < 0.001$) between the groups with euthymia, normal sadness, emotional burnout, and depression. At the same time, there were no statistically significant differences ($p > 0.05$) between these groups and respondents with already established emotional states. This indicates the high accuracy of the classification, which confirms the quality of the automated analysis.

An analysis of the final distribution by category showed that 38.84% of respondents had euthymia, 27.30% had normal sadness, 25.20% had emotional burnout, and 8.66% had depression. The high accuracy of the questionnaire and the absence of false positive results indicate its good sensitivity and specificity (Figure 3).

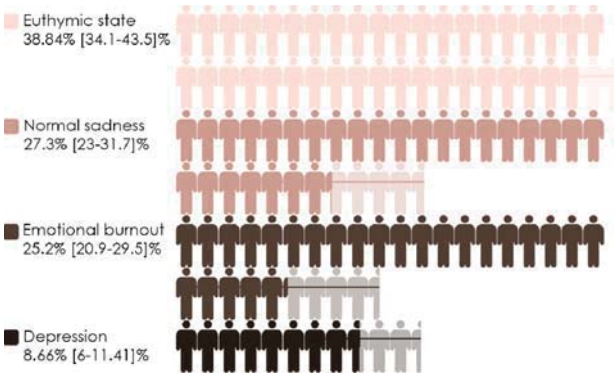


Figure 3. Distribution of emotional profiles among the respondents of the studied population of employees and students

When developing the questionnaire, the relationships between anxiety, depression and emotional burnout were underestimated due to insufficient consideration of the components of anxiety. The exclusion of the alarm domain from the survey indicates the need to develop specific questions to assess this condition.

The development of a sensitive self-report questionnaire should integrate of knowledge based on clinical practice and modern data ML-driven analysis methods. This approach may reduce costs at the diagnostic stage of interventions and increase the reliability of existing psychometric tools (see Appendix H).

Table 4. Characteristics of the groups identified using novel self-report questionnaire via machine learning- based data analysis

Signs & Symptoms' Domains	The group with ES signs	The group with NS signs	The group with EB signs	The group with depression signs
Mood	The average mood is elevated, and a neutral assessment is acceptable.	The rating is closer to neutral, indicating a good or slightly lower mood.	On average, a reduced or bad mood is allowed, as well as a neutral assessment.	There is no mood, and the assessment is as pessimistic as possible, fluctuating around the lower limit.
The need for rest	This group generally gets enough rest during the week, but additional rest is acceptable.	On average, this group is more likely to feel the need for rest, as they do not get enough rest during the week.	The group needs rest, and they don't get enough rest during the week.	The group needs rest, and they don't get enough rest during the week.
Negative rest	Respondent did not have any negative emotions after his last vacation.	Some respondents have negative emotions after their last vacation.	Respondent mostly doesn't feel negative emotions after my last vacation.	Respondent mostly doesn't feel negative emotions after his last vacation.
Productivity	Respondents rate their productivity above average and consider themselves productive.	Respondents rate themselves as moderately productive.	Productivity is below average, and they rate themselves as unproductive.	Productivity is at the lower end of the scale, indicating complete inefficiency.
Emotional assessment of work	A minority of respondents consider their work to be emotionally challenging, often interact with people, and do not plan to change their occupation. Two-thirds also have additional employment.	Half of the respondents consider their work to be emotionally demanding. They interact with people relatively often, do not plan to change their occupation, and mostly do not have additional employment.	More than half of the respondents consider their work to be emotionally demanding. They interact with people relatively often, and most of them plan to change their occupation and take on additional employment.	More than half of the respondents consider their work to be emotionally demanding. They interact with people relatively rarely, and most of them plan to change their occupation and take on additional employment.
Emotional state	On average, a high self-assessment of the emotional state.	On average, the emotional state is quite good, with a slight bias towards neutrality.	The score is below average, and they are more pessimistic than neutral.	The assessment is biased towards the lower end of the scale, and people rate their condition as poor.
Hiding emotions	Sometimes respondents hide their emotions, but they are mostly sincere with their loved ones.	Respondents often hide their emotions and may not be completely sincere with their loved ones.	Respondents often hide their emotions and may not be completely sincere with their loved ones.	Respondents often hide their emotions and may not be completely sincere with their loved ones.
A tendency towards perfectionism	Most of the respondents do not have a tendency towards perfectionism.	The group is not prone to perfectionism.	Most of the respondents have a tendency towards perfectionism.	Most of the respondents do not have a tendency towards perfectionism.
Comparing yourself with others	Sometimes respondents compare themselves with others.	Sometimes respondents compare themselves with others.	More often than average, they compare themselves with others.	More often than average, respondents compare themselves with others.
Tendency to oniomania	Respondents rarely give in or are not prone to impulsive purchases.	Respondents are relatively rare or not prone to impulsive purchases.	Respondents are relatively rare or not prone to impulsive purchases.	Respondents are relatively rare or not prone to impulsive purchases.

Note: ES – euthymic state; NS – normal sadness; EB – emotional burnout

Table 4. Continues

Signs & Symptoms' Domains	The group with ES signs	The group with NS signs	The group with EB signs	The group with depression signs
Alcohol addiction	Respondents do not have a penchant for alcohol.	A small number of respondents turn to alcohol as a means of coping with their emotions.	The group has a pronounced tendency to drink alcohol, especially in emotionally challenging situations.	A small number of respondents turn to alcohol as a means of coping with their emotions.
Addiction to psychoactive substances	Respondent does not have a tendency to use psychoactive substances.	Respondent has no inclination towards drugs, but 5% of the group uses them.	Respondent has no inclination towards drugs, but 3% of the group uses them.	Respondent has no inclination towards drugs, but 3% of the group uses them.

Note: ES – euthymic state; NS – normal sadness; EB – emotional burnout

DISCUSSION

The results of our survey are consistent with global reports that the COVID-19 pandemic and the broader post-industrial crisis have led to increased levels of anxiety, depression, and EB across populations (Daly & Robinson 2021). According to WHO, in the first year of the pandemic, the prevalence of anxiety and depression increased by 25%, while burnout among medical professionals reached 28%, and symptoms of depression and anxiety increased by 44-46% (Fountoulakis et al. 2022a, Lluch et al. 2022, Syunyakov et al. 2022, World Health Organization 2022).

Consistent with previous evidence that chronic occupational stress, workaholism, and socio-economic instability contribute to adverse mental health outcomes (Bellman & Namdev 2019, Cookson 2024), our data demonstrated statistical differences between euthymia, NS, EB, and depression. But not so definitely with anxiety disorder (du Prel et al. 2024). The MBI study showed a weak association of anxiety with EB, which indicates that anxiety symptoms are censored in classical questionnaires. Anxious individuals are more vulnerable to EB, which in turn increases anxiety. Moderate correlations between anxiety and EB, and depression, revealed during the revision of the methodology, confirm the view that traditional questionnaires can censor anxiety-related burnout, thereby complicating differential diagnosis (Koutsimani et al. 2019).

A newly developed self-report (i.e., self-analysis) questionnaire, enhanced with ML-based approach in selecting items, provided excellent internal consistency and excellent classification efficiency based on available data. The statistical difference between the groups was $p < .001$, and the classification accuracy was 100% during final iteration of analysis. -These results illustrate how ML technologies can enhance screening sensitivity/ reliability by modeling complex nonlinear patterns of signs, symptoms and symptoms' domains. This trend wass already evident in prior ML applications that predict depression and post-traumatic stress disorder based on electronic medical records, physiological data, and behavioral markers (Islam et al. 2024). The absence of statistical discrepancies between automatically flagged cases and cases confirmed by clinicians further confirms the correctness of the model, but still requires accuracy in interpretation of the findings, and should also take into account ethical requirements: targeting mandatory confidentiality, preventing algorithmic bias, and ensuring that automated results are interpreted in partnership with qualified clinicians.

Despite these advantages, a number of limitations should be considered. Convenient sampling through online channels and a single corporate network has limited representativeness, and cross-analysis does not allow us to draw a causal conclusion about the temporal dynamics between symptom domains. Moreover, anxiety indicators were excluded from the final version, which limits the capabilities of the tool for detecting concomitant / comorbid disorders associated with anxiety and EB. Future research should include longitudinal studies to identify cause-effect relationships, the inclusion of target-related assessment scales (GAD-7 for anxiety, PHQ-9 for depression, MBI for burnout) and the analysis of overlapping symptoms to exclude the background of anxiety.

This study offers a novel approach in developing a sensitive self-screening questionnaire capable to disentangle the states of euthymia, normal sadness, emotional burnout, and depression on a continuum of socially significant preclinical and clinical mental states with high accuracy. Further clinical validation and integration into long-term monitoring systems are important. Next steps should be made towards reliable early detection of affective spectrum conditions in a changing landscape of occupational stressors and factors affecting public health.

CONCLUSIONS

The present study confirmed statistically significant differences between euthymia, normal sadness, emotional burnout, and depression when using a self-report-based classifier linked with a ML-based approach ($p < 0.001$). The results of data-based classifications coincide with previously established emotional states (p

> 0.05), which confirms the accuracy of the model. The distribution of states obtained as a result of the analysis was: euthymia - 38.8%, normal sadness - 27.3%, emotional burnout - 25.2%, depression - 8.7%, which is in accordance to average epidemiological data. These data demonstrate the high sensitivity and specificity of the questionnaire, as well as the absence of false positive results.

However, the initial version of the tool does not fully take into account the symptoms of anxiety, the interaction of which with emotional burnout and depression requires a more detailed assessment. In future studies, it is recommended to include questions aimed at detecting anxiety and to conduct longitudinal validation in groups of patients with clinically confirmed disorders to assess the predictive value of the questionnaire. The combination of clinical experience with modern data analysis makes this questionnaire an effective tool for self-completion, allowing you to quickly and accurately assess mental health. This can reduce the cost of assessment and increase the effectiveness of existing psychometric methods.

Limitations

In the first iteration of the study, the number of respondents with mental disorders was not recorded and differentiated, and anonymous identifiers were used. This makes it difficult to compare data from the same respondent between two surveys. In the second study, the sample of respondents with mental disorders and the control group were formed on the basis of an anamnesis provided by the respondents themselves, without additional clinical examination and the use of validation scales. This could have detrimentally affected the quality of the final algorithm. Despite the high statistical significance of the differences between the groups ($p < 0.001$) and the completeness of profile recognition ($F1 = 1.0$), additional studies with the participation of qualified clinicians are required for a more objective assessment of the developed questionnaire. Further clinical studies involving groups of respondents with established diagnoses and long-term follow-up are needed to assess the predictive ability of the questionnaire. Current work is a demonstrative example of the use of modern machine learning technologies and data analysis in combination with classical medical approaches.

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Appendix A

Table A. First version of the Questionnaire used in the experiment

N	Question	Mandatory/ clarifying	Source
1	What is your current mood: 1 - bad, 5 - neutral, 10 - excellent	mandatory	Spielberger's scale of assessment of the level of reactive and personal anxiety (adapted by Khanin)
2	Do you have enough rest per week	mandatory	Beck Depression Scale
3	How many hours a week do you rest	clarifying	Sato et al. (2020). Mental health effects of long work hours, night and weekend work, and short rest periods
4	How much rest per week do you need	clarifying	Janse (2019). Job Demands-Resources Model
5	How many hours a week do you work	mandatory	Lin et al. (2021). Long working hours and burnout in health care workers: Non-linear dose-response relationship and the effect mediated by sleeping hours-A cross-sectional study.
6	Evaluate your productivity: 1 - unproductive 5 - productive 10 - maximally productive	mandatory	Beck Depression Scale
7	Is there additional employment in the form of other work or studies	mandatory	Yusufa & Yeeb (2022). Impact of work environment on job satisfaction and stress among hemodialysis staff in Klang Valley; Bruns & Pilkauskas (2019). Multiple Job Holding and Mental Health among Low-Income Mothers.
8	The decision to combine several types of activities is forced or voluntary		Bruns & Pilkauskas (2019). Multiple Job Holding and Mental Health among Low-Income Mothers; Burr et al. (2019); international COPSOQ Network. The Third Version of the Copenhagen Psychosocial Questionnaire.
9	Does this affect your mental health		The questionnaire of professional "burnout" (Maslach & Jackson (1981, 1996).
10	How would you rate your emotional state now: 1 - bad, 5 - neutral, 10 - excellent	mandatory	Spielberger's scale of assessment of the level of reactive and personal anxiety (adapted by Khanin)
11	Do you find your job emotionally difficult	mandatory	The questionnaire of professional "burnout" (Maslach & Jackson (1981, 1996), adapted by Vodopyanova). Beck Depression Scale
12	Are you planning to change your occupation	clarifying	CTI (Career Transition Inventory)
13	Do you have enough support from your loved ones	mandatory	MSPSS (Multidimensional Scale of Perceived Social Support)
14	On average, how many people do you have to interact with: 1 - rarely, 5 - at the household level, 10 - often	mandatory	COPSOQ III
15	Your gender	mandatory	Socio-demographic characteristics of the respondent
16	How old are you	mandatory	Socio-demographic characteristics of the respondent
17	Your professional field	clarifying	Socio-demographic characteristics of the respondent
18	At the moment, you need support from your loved ones or psychologists	clarifying	Scale of perceived stress, PSS-10 (Cohen & Williamson, adaptation by Zolotarev)
19	Here you can share your feelings or worries	clarifying	Socio-demographic characteristics of the respondent

Appendix B

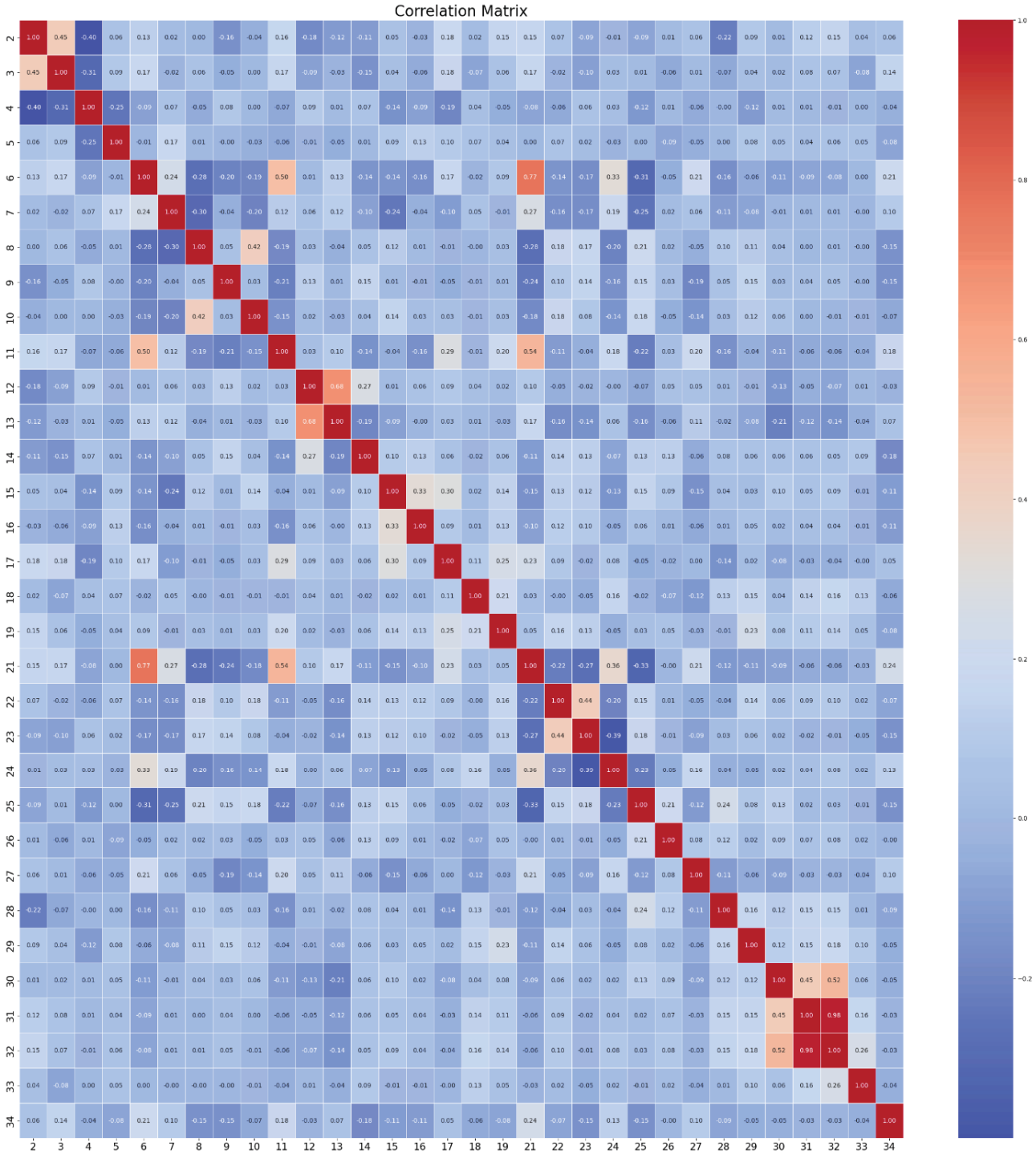

Figure B1. A full correlation analysis of the respondents' data on 32 of the 34 questions of the latest version of the questionnaire was carried out. The Pearson correlation coefficient was used for quantitative samples, the rank-biserial correlation coefficient was used for quantitative binary samples, and the Kappa Cohen agreement coefficient was used for binary data

Appendix C

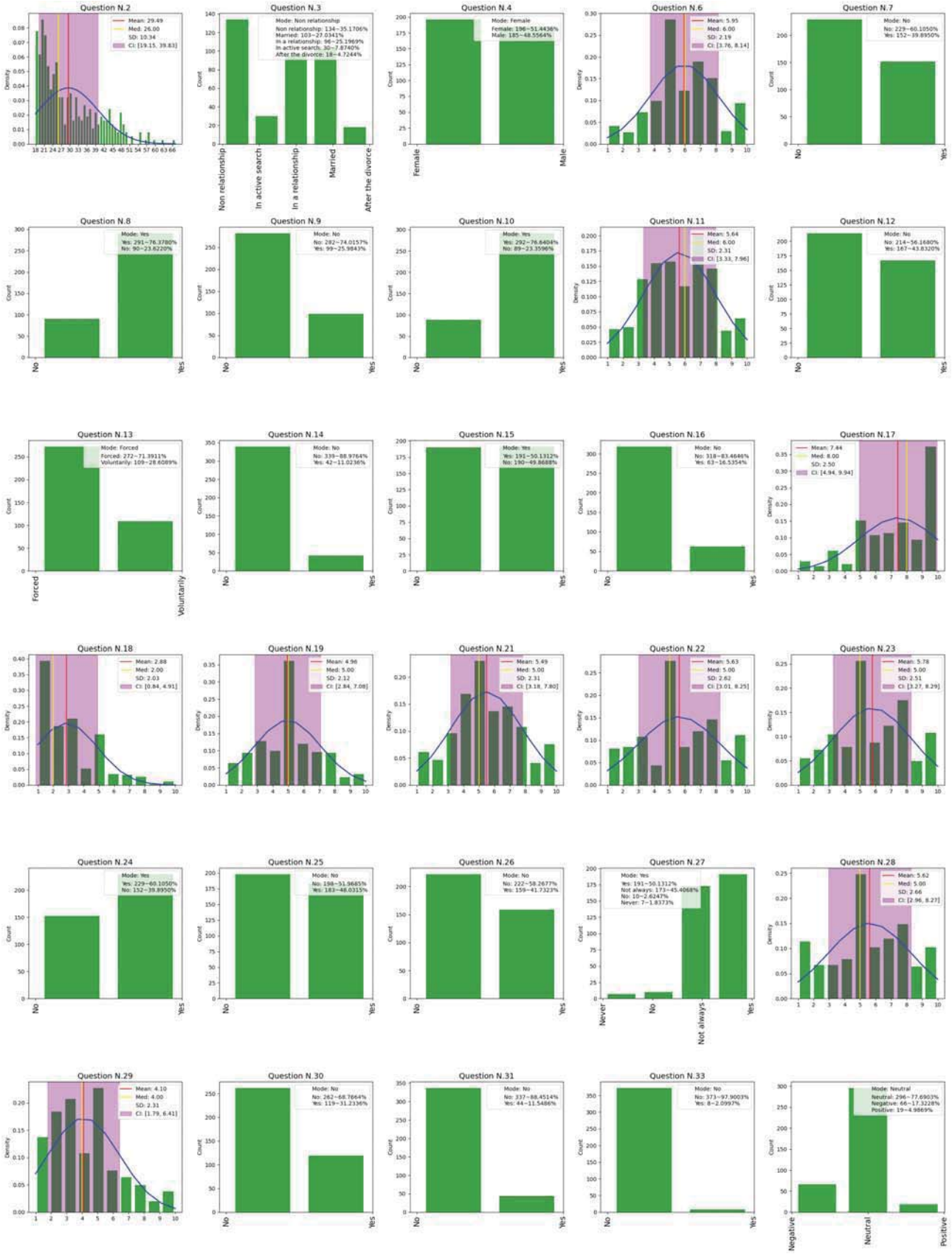

Figure C1. A comprehensive descriptive analysis of respondents' responses to 30 of the 34 questions from the latest version of the questionnaire, including an assessment of the data distribution, calculation of the mean and median values, as well as the construction of a 95% confidence interval

Appendix D

Table D1. Statistical comparison of groups of euthymia and normal sadness using T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables

Question n.	Euthymia	NS	t-criterion	p-value	Cohen's d
6	7.54	6.38	5.06	< 0.001	0.82
7	0.63	0.35	3.53	< 0.001	0.57
8	0.59	0.81	-3.09	0.002	-0.51
9	0.11	0.22	-1.84	0.068	-0.29
10	0.66	0.73	-0.96	0.336	-0.16
11	7.64	5.93	10.1	< 0.001	1.69
12	0.61	0.34	3.49	< 0.001	0.57
13	0.50	0.20	4.03	< 0.001	0.67
14	0.06	0.09	-0.87	0.384	-0.14
15	0.29	0.53	-3.17	0.002	-0.51
16	0.09	0.12	-0.66	0.513	-0.1
17	8.07	7.46	1.68	0.094	0.27
18	2.99	2.98	0.03	0.976	0
19	4.91	4.92	-0.01	0.992	0
21	7.79	5.44	10.66	< 0.001	1.71
22	4.14	5.60	-3.96	< 0.001	-0.63
23	4.07	6.15	-6.79	< 0.001	-1.04
24	0.87	0.56	4.55	< 0.001	0.71
25	0.24	0.36	-1.65	0.100	-0.26
26	0.41	0.28	1.71	0.089	0.28
27	2.63	2.44	2.13	0.035	0.33
28	5.07	5.39	-0.78	0.436	-0.13
29	3.77	4.13	-1.01	0.313	-0.16
30	0	0.27	-5.58	< 0.001	-0.82
31	0	0.09	-2.95	0.004	-0.43
33	0	0.05	-2.04	0.045	-0.30
34	1.10	0.86	3.88	< 0.001	0.60
MANOVA				< 0.001	

Table D2. Statistical comparison of groups of normal sadness and emotional burnout using T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables.

Question n.	NS	EB	t-criterion	p-value	Cohen's d
6	6.38	4.63	10.68	< 0.001	1.58
7	0.35	0.22	1.82	0.071	0.30
8	0.81	0.93	-2.27	0.025	-0.36
9	0.22	0.38	-2.05	0.043	-0.36
10	0.73	0.95	-3.93	< 0.001	-0.60
11	5.93	4.70	4.90	< 0.001	0.93
12	0.34	0.50	-1.91	0.058	-0.33
13	0.20	0.28	-1.14	0.257	-0.20
14	0.09	0.18	-1.50	0.137	-0.26
15	0.53	0.67	-1.67	0.097	-0.28
16	0.12	0.23	-1.77	0.079	-0.31
17	7.46	7.22	0.60	0.548	0.10
18	2.98	2.97	0.03	0.978	0
19	4.92	5.38	-1.33	0.186	-0.23

Table D2. Countinues

Question n.	NS	EB	t-criterion	p-value	Cohen's d
21	5.44	4.20	6.62	< 0.001	1.02
22	5.60	6.15	-1.35	0.178	-0.23
23	6.15	6.05	0.24	0.808	0.04
24	0.56	0.47	1.16	0.248	0.20
25	0.36	0.68	-3.97	< 0.001	-0.67
26	0.28	0.67	-4.89	< 0.001	-0.83
27	2.44	2.38	0.48	0.632	0.08
28	5.39	6.13	-1.81	0.072	-0.30
29	4.13	4.37	-0.67	0.503	-0.11
30	0.27	0.58	-3.89	< 0.001	-0.67
31	0.09	0.28	-2.83	0.006	-0.51
33	0.05	0.03	0.42	0.677	0.07
34	0.86	0.70	2.03	0.044	0.34
MANOVA				< 0.001	

Table D3. Statistical comparison of groups of emotional burnout and depressive using T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables.

Question n.	EB	Depression	t-criterion	p-value	Cohen's d
6	4.63	1.92	13.35	< 0.001	3.94
7	0.22	0.19	0.26	0.799	0.06
8	0.93	0.96	-0.56	0.577	-0.12
9	0.38	0.38	-0.01	0.991	0
10	0.95	0.88	0.94	0.356	0.26
11	4.70	1.96	9.44	< 0.001	1.72
12	0.50	0.42	0.65	0.519	0.15
13	0.28	0.23	0.51	0.611	0.12
14	0.18	0.19	-0.10	0.924	-0.02
15	0.67	0.58	0.77	0.444	0.19
16	0.23	0.35	-1.03	0.311	-0.25
17	7.22	6.31	1.31	0.198	0.35
18	2.97	2.85	0.21	0.833	0.05
19	5.38	4	2.84	0.007	0.66
21	4.20	1.65	13.6	< 0.001	3.19
22	6.15	6.42	-0.46	0.650	-0.11
23	6.05	6.27	-0.33	0.741	-0.08
24	0.47	0.27	1.80	0.078	0.40
25	0.68	0.77	-0.83	0.412	-0.19
26	0.67	0.42	2.09	0.042	0.50
27	2.38	2.38	-0.01	0.993	0
28	6.13	6.65	-0.74	0.464	-0.20
29	4.37	4.31	0.10	0.918	0.03
30	0.58	0.27	2.87	0.006	0.65
31	0.28	0.08	2.6	0.011	0.51
33	0.03	0.04	-0.11	0.91	-0.03
34	0.70	0.73	-0.29	0.775	-0.07
MANOVA				< 0.001	

Appendix E

Table E. Application of the grid hyperparameter search method to solve the problem of classifying emotional profiles. The paper presents the results, including the type of classification model, selected hyperparameters that provide the best performance, as well as the F-weighted quality metric

Model	Parameters	F-weighted
Logistic regression	1. The inverse of the regularization force is 1.02. 2. The type of regularization used is l1. 3. The algorithm for optimizing the loss function is Saga.	0.9185
The support vector method (SVM)	1. The regularization parameter is 11.12. 2. The radius of influence of the example is 0.01. 3. The core type is RBF.	0.8637
K-nearest neighbor (KNN)	1. The algorithm is a Ball Tree. 2. The measure of distance is the Manhattan distance. 3. The number of nearest neighbors is 23.	0.8339
Naive Bayes	1. Smoothing the variance of features - 1e-05.	0.7319
Decision trees	1. The criterion is Entropy. 2. The maximum depth of the tree is as long as the nodes will branch. 3. The minimum number of samples to create a sheet is 1. 4. The minimum number of samples to split a node is 2.	0.9464
Catboost	1. Number of iterations - 10000. 2. Learning rate - 0.01. 3. The maximum depth of the tree is 10. 4. The proportion of considered features is 0.25. 5. The loss function is for multiclass classification.	1.0000
Random Forest	1. The criterion is Entropy. 2. The maximum depth of the tree is 5. 3. The number of features taken into account - calculates the square of the total number of features. 4. The number of trees is 2500.	1.0000
LightGBM (Light Gradient Boosting Machine)	1. Learning rate - 0.01. 2. The maximum depth of the tree is 5. 3. The number of trees in the forest is 1,500.	0.9735
Extra-Trees	1. The criterion is Entropy. 2. The maximum depth of the tree is as long as the nodes will branch. 3. The number of features taken into account - calculates the square of the total number of features. 4. The number of trees is 600.	0.9454
XGBoost (eXtreme Gradient Boosting)	1. The proportion of randomly selected features is 0.8. 2. Learning rate - 0.01. 3. The maximum depth of the tree is 5. 4. Number of trees - 240. 5. The proportion of random samples of each tree is 1.	1.0000
Multi-layer perceptron	1. There are three hidden layers of 80, 40, and 40 neurons, respectively. 2. The activation function is tangential. 3. Optimization algorithm - Adam. 4. The regularization parameter is 0.05. 5. The learning rate is constant.	0.9725
Bagging	1. The criterion is Entropy. 2. The maximum depth of the tree is 9. 3. The number of considered tree features is 0.7. 4. The minimum number of examples for a sheet is 2. 5. The minimum number of examples for a node is 4. 6. The number of forest signs taken into account is 0.8. 7. The number of trees is 70.	1.0000

Appendix F

Table F1. Statistical comparison of two groups of euthymia: one marked up using machine learning methods, and the other, a reference group of euthymia (according to the respondent). The analysis was performed using the T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables

Question n.	Euthymia	Euthymia Control	t-criterion	p-value	Cohen's d
6	7.85	7.54	1.32	0.189	0.20
7	0.64	0.63	0.21	0.835	0.03
8	0.53	0.59	-0.74	0.462	-0.11
9	0.14	0.11	0.58	0.563	0.09
10	0.64	0.66	-0.17	0.862	-0.03
11	7.47	7.64	-0.78	0.439	-0.11
12	0.55	0.61	-0.87	0.388	-0.13
13	0.46	0.50	-0.50	0.621	-0.08
14	0.04	0.06	-0.55	0.581	-0.09
15	0.32	0.29	0.44	0.658	0.07
16	0.09	0.09	0.02	0.985	0
17	8.18	8.07	0.33	0.740	0.05
18	2.89	2.99	-0.31	0.760	-0.05
19	4.97	4.91	0.18	0.857	0.03
21	7.96	7.79	0.85	0.398	0.13
22	4.18	4.14	0.11	0.913	0.02
23	4.36	4.07	1.11	0.267	0.16
24	0.87	0.87	-0.12	0.908	-0.02
25	0.26	0.24	0.25	0.804	0.04
26	0.43	0.41	0.24	0.811	0.04
27	2.65	2.63	0.32	0.747	0.05
28	5.22	5.07	0.37	0.710	0.06
29	3.68	3.77	-0.25	0.805	-0.04
30	0.13	0	4	< 0.001	0.51
31	0.04	0	2.03	0.045	0.26
33	0	0			
34	1.09	1.10	-0.26	0.793	-0.04

Table F2. Statistical comparison of two groups of normal sadness: one marked up using machine learning methods, and the other, a reference group of normal sadness (according to the respondent). The analysis was performed using the T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables

Question n.	NS	NS Control	t-criterion	p-value	Cohen's d
6	6.41	6.38	0.18	0.859	0.02
7	0.36	0.35	0.18	0.856	0.02
8	0.8	0.81	-0.14	0.886	-0.02
9	0.25	0.22	0.46	0.648	0.06
10	0.74	0.73	0.23	0.819	0.03
11	5.84	5.93	-0.50	0.619	-0.06
12	0.36	0.34	0.36	0.717	0.05
13	0.22	0.2	0.29	0.77	0.04
14	0.10	0.09	0.18	0.858	0.02
15	0.53	0.53	0.06	0.949	0.01
16	0.14	0.12	0.39	0.698	0.05
17	7.28	7.46	-0.52	0.601	-0.07
18	2.82	2.98	-0.58	0.562	-0.08
19	5.05	4.92	0.46	0.645	0.06

Table F2. Continues

Question n.	NS	NS Control	t-criterion	p-value	Cohen's d
21	5.43	5.44	-0.04	0.964	-0.01
22	5.97	5.60	1.13	0.259	0.15
23	6.38	6.15	0.67	0.501	0.09
24	0.59	0.56	0.34	0.733	0.05
25	0.41	0.36	0.61	0.540	0.08
26	0.28	0.28	-0.09	0.931	-0.01
27	2.38	2.44	-0.64	0.524	-0.09
28	5.32	5.39	-0.20	0.838	-0.03
29	4.30	4.13	0.57	0.57	0.08
30	0.28	0.27	0.22	0.829	0.03
31	0.09	0.09	-0.16	0.874	-0.02
33	0.03	0.05	-0.48	0.630	-0.07
34	0.86	0.86	-0.01	0.991	0

Table F3. Statistical comparison of two burnout groups: one marked up using machine learning methods, and the other, a reference burnout group (according to the respondent). The analysis was performed using the T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables

Question n.	EB	EB Control	t-criterion	p-value	Cohen's d
6	4.51	4.63	-1.15	0.254	-0.17
7	0.26	0.22	0.62	0.533	0.10
8	0.89	0.93	-1.04	0.300	-0.16
9	0.35	0.38	-0.36	0.716	-0.06
10	0.90	0.95	-1.28	0.202	-0.20
11	4.45	4.70	-0.80	0.425	-0.13
12	0.45	0.50	-0.63	0.53	-0.10
13	0.24	0.28	-0.60	0.551	-0.10
14	0.18	0.18	-0.10	0.922	-0.02
15	0.61	0.67	-0.66	0.512	-0.11
16	0.22	0.23	-0.21	0.834	-0.03
17	7.07	7.22	-0.37	0.713	-0.06
18	2.96	2.97	-0.02	0.982	0
19	5.03	5.38	-1.01	0.317	-0.16
21	4.17	4.20	-0.23	0.819	-0.04
22	6.45	6.15	0.75	0.455	0.12
23	6.18	6.05	0.31	0.756	0.05
24	0.45	0.47	-0.23	0.821	-0.04
25	0.73	0.68	0.60	0.547	0.10
26	0.61	0.67	-0.66	0.512	-0.11
27	2.32	2.38	-0.56	0.575	-0.09
28	6.09	6.13	-0.10	0.921	-0.02
29	4.18	4.37	-0.54	0.591	-0.09
30	0.57	0.58	-0.13	0.899	-0.02
31	0.26	0.28	-0.31	0.757	-0.05
33	0.02	0.03	-0.45	0.651	-0.08
34	0.74	0.70	0.51	0.611	0.08

Table F4. Statistical comparison of two depression groups: one labeled using machine learning methods and the other. a reference depression group (according to the respondent). The analysis was performed using the T-test for each question and multivariate analysis of variance (MANOVA) for all dependent variables

Question n.	Depression	Depression Control	t-criterion	p-value	Cohen's d
6	2.06	1.92	0.55	0.586	0.14
7	0.18	0.19	-0.10	0.92	-0.03
8	0.97	0.96	0.17	0.868	0.04
9	0.39	0.38	0.07	0.943	0.02
10	0.88	0.88	-0.07	0.946	-0.02
11	2.42	1.96	1.72	0.092	0.43
12	0.39	0.42	-0.22	0.825	-0.06
13	0.18	0.23	-0.45	0.653	-0.12
14	0.18	0.19	-0.10	0.920	-0.03
15	0.61	0.58	0.22	0.825	0.06
16	0.39	0.35	0.37	0.711	0.10
17	6.85	6.31	0.66	0.512	0.17
18	2.82	2.85	-0.04	0.965	-0.01
19	4.30	4.00	0.54	0.594	0.14
21	1.88	1.65	0.98	0.330	0.25
22	6.24	6.42	-0.27	0.786	-0.07
23	6.42	6.27	0.21	0.833	0.06
24	0.27	0.27	0.03	0.977	0.01
25	0.79	0.77	0.17	0.867	0.04
26	0.42	0.42	0.01	0.993	0
27	2.36	2.38	-0.14	0.887	-0.04
28	6.82	6.65	0.20	0.842	0.05
29	4.33	4.31	0.04	0.969	0.01
30	0.24	0.27	-0.23	0.819	-0.06
31	0.06	0.08	-0.24	0.811	-0.06
33	0.03	0.04	-0.17	0.868	-0.04
34	0.70	0.73	-0.28	0.780	-0.07

Appendix G

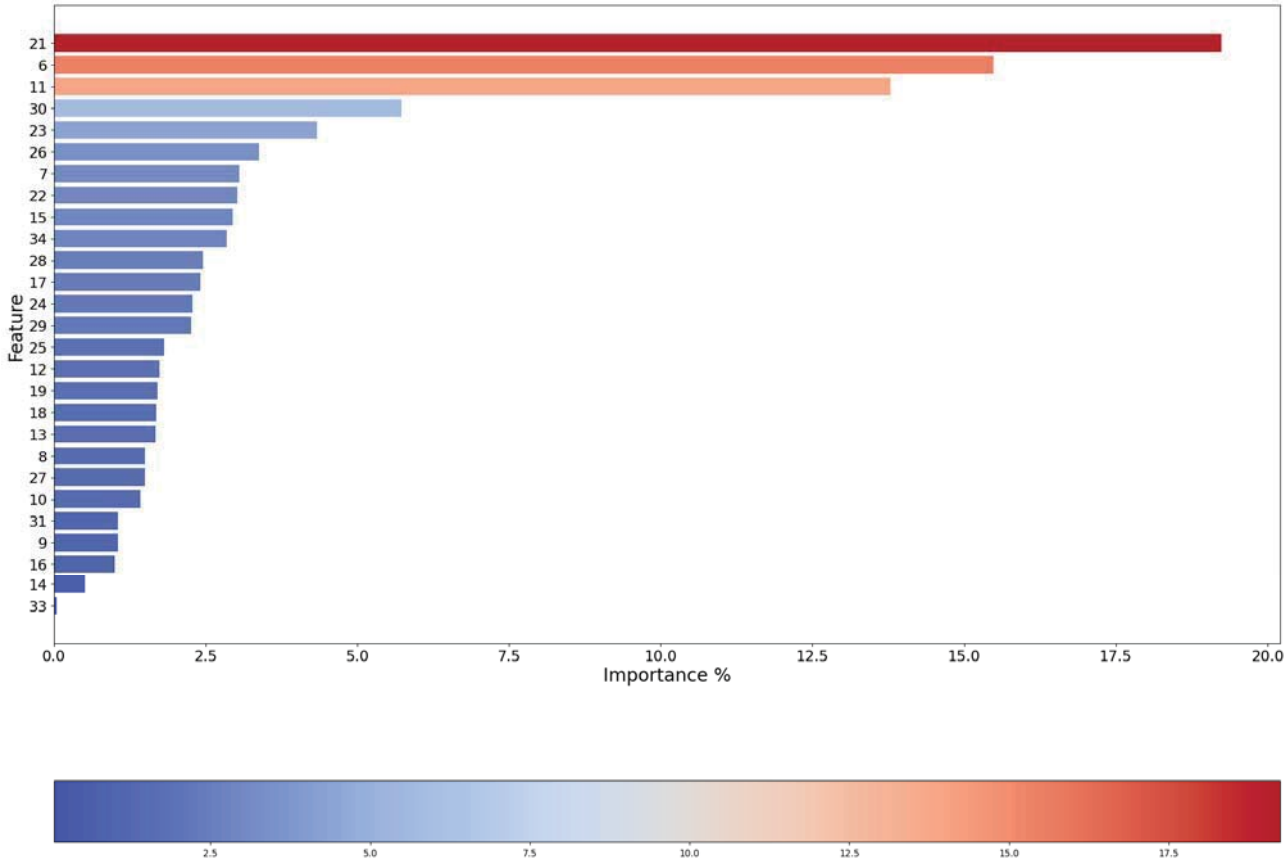

Figure G1. The distribution of the significance of features, characterizing the issues that had the most significant impact on the classification results using the CatBoost algorithm. At the same time, the signs that have demonstrated the greatest importance are highlighted in warmer shades

Appendix H

Table H. A comparative table of approaches to conducting surveys of respondents, including an analysis of classical methods and modern machine learning algorithms

The criterion being compared	The classical approach	Machine Learning Approach
Survey assessment methodology	Based on fixed, theoretically sound, and agreed-upon questions to obtain reliable and valid results.	Based on identifying patterns and regularities in data without the need for strictly consistent questions, implying the tracking of nonlinearly dependent data.
Administration	The questionnaire is filled out under the personal pretext of a specialist, psychologist, or clinician, during which either a questionnaire is filled out or a dialogue is conducted.	Questionnaires can be submitted via email, a form, or an app in written form for further digitization.
Data collection	The respondent fills out a questionnaire or answers questions, and the results are manually or automatically scored.	After receiving the compelted the questionnaire, a pre-trained model automatically labels the respondent.
Analysis of the results	The results are analyzed by a psychologist, clinician, or interviewer, who draws conclusions based on the total scores and threshold values.	Based on the data provided, the model classifies the respondent's condition.
Conclusions and recommendations	Based on the results of the questionnaire, the specialist provides an independent conclusion and recommendations for treatment and further actions, if necessary.	The model automatically generates an output that provides preventive advice and, if necessary, a recommendation to visit a specialist.

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