Lecture Notes on Data Engineering
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Sergii Babichev
Volodymyr Lytvynenko *Editors*

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Contents

Machine Learning Method to Identifying Early Factors Leading to Burnout Among Medical Professionals

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Abstract. The issue of professional burnout syndrome (PBS) among medical professionals is a pressing global concern. Utilizing machine learning methods presents a promising avenue for enhancing the precision and effectiveness of PBS diagnosis. This research introduces an innovative statistical model that combines machine learning techniques with a flexible framework for visualizing and troubleshooting intricate models. Employing survey data from the Maslach Burnout Inventory (MBI), the proposed model aims to pinpoint prepathological conditions among medical personnel across different specialties and the broader population. The study yielded informative criteria for classifying respondents into distinct groups based on their burnout risk. These findings can help medical professionals recognize early warning signs of PBS, enabling timely interventions to prevent its development. The proposed model has the potential to revolutionize PBS diagnosis, allowing for more targeted and effective preventive measures. The study's results provide valuable insights into the complex factors contributing to PBS among medical personnel. By leveraging machine learning techniques, this approach can help identify prepathological conditions earlier, enabling proactive interventions to mitigate the risk of burnout. This novel approach has far-reaching implications for improving healthcare quality and patient safety, as well as promoting resilience and well-being among medical professionals. In summary, this research underscores the capacity of machine learning methodologies in forecasting PBS occurrences among healthcare professionals.

Keywords: professional burnout syndrome · Maslach Burnout Inventory · prepathological conditions · machine learning

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1 Introduction and Literature Review

Burnout among medical professionals has emerged as a critical issue impacting healthcare systems worldwide, necessitating early detection and intervention [6,22]. This pervasive problem not only affects the well-being of healthcare workers but also compromises patient care quality and organizational efficiency. Burnout is characterized by emotional exhaustion, depersonalization, and a diminished sense of personal accomplishment, which can lead to severe physical and mental health consequences [22–24]. The increasing demands of the medical profession, including long working hours, high patient loads, and administrative burdens, exacerbate this issue. Furthermore, the high-stress environment, often coupled with insufficient support and resources, contributes significantly to the development of burnout. Early identification of burnout symptoms and understanding its contributing factors are essential for implementing effective preventive measures. We seek to provide a comprehensive analysis of the factors leading to burnout. Our research highlights the urgent need for targeted interventions and support systems to mitigate this widespread issue. Ultimately, addressing professional burnout is crucial for fostering a healthier, more resilient healthcare workforce and ensuring the delivery of high-quality patient care.

The literature review suggests a promising application of machine learning (ML) techniques across diverse fields [29], including medicine [30], finance, environment [25], marketing [31], safety, and industry [16,33].

In the medical domain, machine algorithms and data analysis techniques are extensively employed in automated diagnostic programs. These algorithms assimilate numerous diagnosed samples gleaned from medical test reports, coupled with expert diagnoses, to aid healthcare professionals in predicting and diagnosing diseases more effectively in subsequent cases. The integration of machine learning (ML) holds the potential to enhance the reliability, performance, and precision of diagnostic systems across various illnesses [7].

Different strategies and techniques have been suggested for forecasting heart strokes. This research employs a range of machine learning models, such as support vector machine (SVM), decision tree algorithm (DT), K-nearest neighbor (KNN) method, and logistic regression (LR). The proposed model compares these algorithms concerning accuracy and identifies the most effective model for predicting heart strokes with the highest precision. Additionally, it visualizes data across diverse parameters. The findings indicate that SVM outperforms others with an accuracy of 89.95% [32]. The use of the io-BERT (BERT for Biomedical Text Mining) model made it possible to reduce the time for literary analysis of scientific data on the incidence of Covid-19 and to get high informativeness of the obtained results [26]. The results of detecting testlet effects (Detecting Testlet Effects in Cognitive Diagnosis Models) in cognitive diagnosis models are published [20]. Transformer-based linguistic models (LM) for predicting psychometric properties [19]. A method based on neural network of back propagation for classification of benign or malignant stage [28] is proposed.

Therefore, machine learning refers to tools that are widely used in various fields, including medicine. Consequently, machine learning is indicative of technologies that find extensive application across diverse domains, notably in the medical sector. This facilitates the resolution of diagnostic challenges prevalent in numerous medical disciplines [17], encompassing medical imaging, cancer detection, and others. Employing contemporary methodologies to scrutinize crucial clinical metrics, such as procuring medical data and forecasting illnesses along with their progression, aids in devising and upholding patient care strategies. Moreover, leveraging machine algorithms facilitates efficient health surveillance through proficient data examination and issuance of insightful notifications when deemed essential [13].

Therefore, modern approaches based on the collaboration of the technical and medical fields can be effective in the rapid diagnosis of predictors of the development of diseases, rapid decision-making and the implementation of prophylactic methods, first of all, to prevent diseases that are currently more widespread in the world.

In contemporary society, amid rapid economic and technological advancement, there's a notable uptick in professional competition alongside challenges concerning psychological development and the shaping of personal attributes. The individual's character undergoes professional evolution due to the proliferation of various detrimental innovations within their field [10].

Those whose work directly involves interactions with others are particularly susceptible to such alterations. Professional stress detrimentally impacts employees' performance, diminishing productivity and worsening interpersonal dynamics.

The concept of occupational health encompasses the intricate interplay between individuals and their professional environments, serving as a gauge for aligning societal needs with human capabilities within the context of work [18]. It's important to emphasize that only when a worker's professional attributes align with job requirements, and their physical, mental, and social well-being are maintained, can high labor efficiency, optimal social and industrial adaptation, and reduced healthcare costs for the workforce be ensured [37].

The frequency and intensity of syndrome manifestation can also be influenced by a range of factors, including professional aspects (work schedules, psychological atmosphere in the team), personal factors (individual health condition, age, family, individual traits), socio-economic factors (social protection of pharmacy professionals, salary levels, decent work), and cultural factors (personal development level) [27].

The aim of this research is to propose and validate a machine learning-based model for the early detection and prevention of PBS among medical professionals.

Also, the importance of understanding and managing workplace stress is crucial, especially in fields where the risk of professional burnout is high. Stress reactions can play a significant role in the psychological well-being of employees, so it is important to develop strategies and programs to support and prevent such burnout in the workplace. Research also indicates that the issue of burnout is relevant not only in the workplace but also in society at large - military conflicts, social instability, and economic crises can significantly increase stress levels and contribute to professional burnout [11].

2 Materials and Methods

Over the past decade, the issue of chronic fatigue among workers in high-intensity and high-stress work environments has gained significant attention within the realm of global medical science. The escalation of neuro-emotional strain during work processes engenders a state of tension and frequently leads to overexertion of the body's functional capacities, a phenomenon often recognized as the development of professional stress and chronic fatigue syndrome [15].

Presently, in the consensus of most scholars, the phenomenon of burnout syndrome (originally termed by H. Freudenberg in 1974) and the concept of professional exhaustion are viewed as outcomes of prolonged engagement in high-intensity and high-stress work, serving as the breeding ground for various psychosomatic pathologies, neurological disorders, borderline mental health conditions, arterial hypertension, and so forth (see Fig. 1) [12].

In 2010, during its 307th session, the Administrative Council of the International Labor Organization (ILO) endorsed a revised catalog of occupational diseases. For the first time, psycho-emotional and behavioral disorders were incorporated into the ILO List, provided there was evidence establishing a direct correlation between the impact of a particular factor and the development of psycho-emotional or behavioral disorders in the employee [2,4].

As per the World Health Organization (WHO), burnout syndrome (PBS) is acknowledged as an outcome of prolonged stress in the workplace, occurring after the depletion of adaptive and protective mechanisms. Employees combat stress by psychologically disengaging from work, leading to the development of apathy and cynicism, which manifest through several indicators: a sensation of motivational or physical exhaustion, an increasing mental detachment from professional duties, feelings of negativism or cynicism towards professional responsibilities, diminished work capacity, and a sense of reduced personal accomplishment [3,6].

Annually, experts from the Centers for Disease Control (CDC) in Atlanta, United States of America, along with those from the National Institute for Occupational Safety and Health (NIOSH), diligently review and update the roster of professional fields aimed at monitoring and mitigating the prevalence of chronic fatigue, commonly referred to as "burnout", while also formulating preventive measures [1].

It is known that the frequency of occurrence of PBS among employees of "helping", socially significant professions, namely, medical and pharmaceutical workers, pedagogical workers, employees of banks, social assistance centers, and company managers is quite high, which is associated with the specialist's significant involvement in interpersonal communication, constant ability to empathize and understand the problems of another person [37].

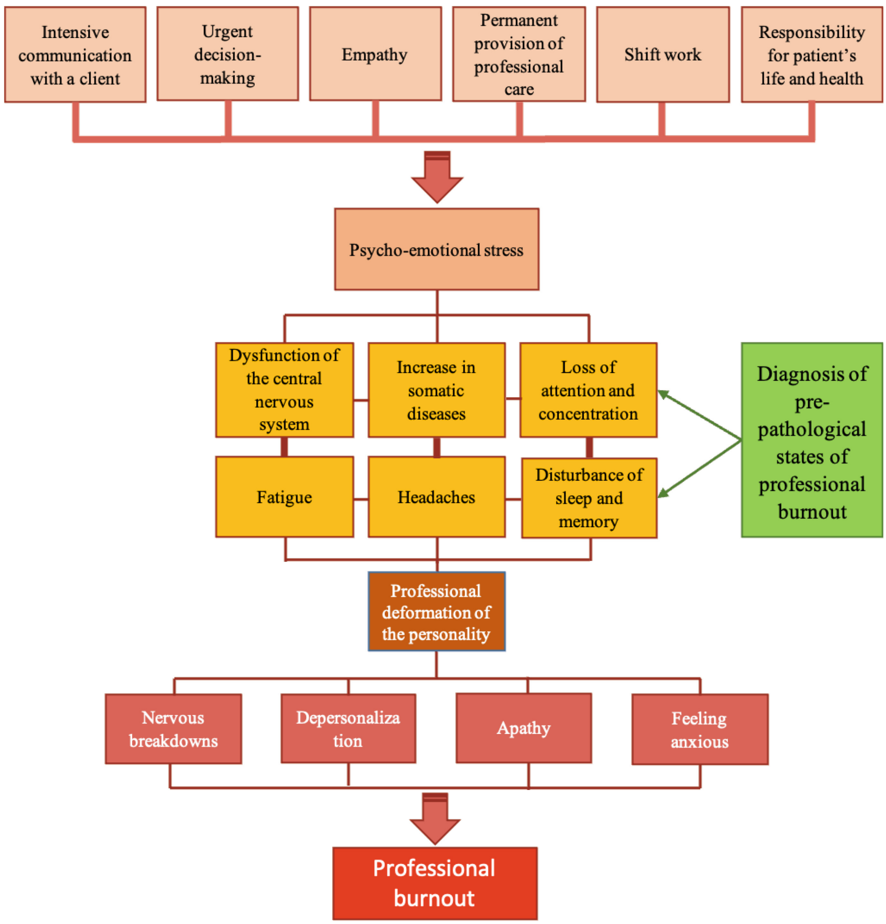

Fig. 1. General diagram of the development of the syndrome of professional burnout (PBS)

Evidence indicates a notable elevation in the occurrence of burnout syndrome (PBS) among professionals in "helping" and socially significant occupations, including healthcare and pharmaceutical personnel, educators, bank employees, staff at social assistance centers, and company managers. This increased prevalence is linked to the substantial involvement of specialists in interpersonal interactions, their ongoing requirement for empathy, and their ability to understand the challenges encountered by others [34].

The defining aspect of the professional duties of healthcare practitioners entails a demanding work pace attributed to numerous factors including a large patient volume, substantial intellectual and emotional demands, ineffective management strategies, persistent structural alterations, extensive paperwork with redundant data entry into electronic systems, insufficient governmental backing, inadequate material and technical resources, as well as shortages in medication supplies, among other challenges [36].

Research has uncovered burnout within numerous medical fields, encompassing surgeons, oncologists, and mental health professionals. Notably, American palliative care physicians exhibit some of the highest rates of burnout globally, ranging from 40% to 65%. Similarly, burnout among medical staff in infectious disease departments in Beijing reaches 76.9%. According to the 2020 Medscape National Physician Burnout and Suicide Report, the overall burnout rate stands at approximately 43%. Furthermore, Medscape's 2020 National Report on Physician Burnout and Suicide identifies urology (54%), neurology (50%), and nephrology (49%) as the specialties most commonly affected by burnout. Conversely, general surgery (35%), psychiatry (35%), and orthopedics (34%) demonstrate lower rates of burnout. Anesthesiology ranks 16th with 41%, emergency medicine ranks 14th with 43%, and critical care ranks 10th (44%) [9].

Burnout is associated with reduced work efficiency, poor health, mental illness of staff, high staff turnover, increased medical errors, and a concomitant decrease in patient satisfaction [21,35].

Despite the abundance of published literature examining the structure, characteristics, frequency, and manifestations of burnout syndrome (PBS) across different professional cohorts, there remains a dearth of consensus regarding the core essence of this phenomenon. Furthermore, there lacks a theoretically grounded and methodologically justified model elucidating its onset and progression, as well as a thoroughly developed and empirically tested approach to prevent and rectify the professional distortions experienced by specialists. Along with this, the study of the issue of early diagnosis of occupational burnout, taking into account the data of the general hygienic assessment of work based on the indicators of the production environment and factors of the labor process, medical-psychological and psychophysiological studies, socio-demographic characteristics of workers of socially significant professions, is extremely limited. For today, there are no standardized and generally accepted procedures for the diagnosis of PBS [6]. Thus, an important aspect of modern health care is to pay attention to this phenomenon and quickly identify emotional exhaustion in medical workers, along with the development of sound individual and organizational strategies to overcome this phenomenon. Therefore, preventive activities to preserve the health of employees are of great practical importance and are recognized as an important state mission in the prevention of chronic psychosomatic diseases.

Creation of a methodologically sound model for the early revealing of professional burnout at the stage of the absence of objective manifestations, namely prepathological conditions, a method of determining criterion-significant statements according to the questionnaire for psychological diagnosis of professional burnout "Maslach Burnout Inventory – General Survey" (MBI-GS) has been developed [22].

The Maslach Burnout Inventory – General Survey (MBI-GS) consisted of 16 items divided into burnout risk scales: "emotional exhaustion" (ee), "depersonalization/cynicism" (zy) and "professional efficiency" (ef).

Respondents were asked to provide answers to each statement using a point scale from 0 points (never) to 6 points (every day). The mean of points on each of these scales shows the degree of expressiveness of "professional burnout" and is defined as low, moderate/average or high (see Table 1) [23].

Table 1. Assessment of PBS levels

Scale	The degree of expressiveness		
	Low	Average	High
Emotional exhaustion	≤2,00	2,01–3,19	≥3,20
Depersonalization/cynicism	≤1,00	1,01–2,19	≥2,20
Work efficiency	≤4,00	4,01–4,99	≥5,00

In the procedure presented here a new approach is tried out. In contrast to the original methodology from Maslach a point on a scale were added together and evaluated. Based on these coefficients the levels of burnout were new determined for each of the scales of MBI-GS (see Table 2).

Table 2. New recording of burnout scales

Scale	New degree of expression		
	Low	Average	High
Emotional exhaustion	0–12	13–20	21–30
Depersonalization/cynicism	0–3	4–9	10–30
Work efficiency	25–36	21–24	0–20

Professional burnout is recorded if there are high scores on the "ee" and "zy" scales against the background of low scores on the "ef" scale, i.e., a high level of reduction in personal achievements.

A medical and psychological survey was conducted in medical institutions of the city of Kharkiv. The participants of the survey were medical workers from various clinical institutions, including 73 anesthesiologists from the intensive care and anesthesiology departments of the Municipal Non-commercial Enterprise "City Clinical Hospital of Emergency Medical Care named after Prof. O.I. Meshchaninov" of Kharkiv City Council, 37 oncology doctors from the clinic of State Institution "Institute of Medical Radiology and Oncology named after S. P. Grigoryev of the National Academy of Medical Sciences of Ukraine", as well as 88 medical workers from the departments of the Municipal Non-commercial Enterprise “Center for Emergency Medical Assistance and Disaster Medicine” of the Kharkiv Regional Council. The work was performed on the basis of the Kharkiv National Medical University by researchers of the Department of Hygiene and Ecology No. 2 with cooperation Otto von Guericke University of Magdeburg, Germany.

3 Experiment and Results

3.1 Exploratory Data Analysis (EDA)

198 medical workers of different categories took part in the study: oncology doctors, anesthesiologists and emergency medical workers. Among them, 149 people (75.3%) belonged to the medical staff, and 39 (19.7%) – to the paramedic category. The gender distribution was almost equal, with 47% men and 53% women. The average age of the study participants was 38.96 ± 0.94 years, and the average length of service was 14.71 ± 0.91 years. These data indicate that mainly middle-aged persons with significant professional experience perform medical activities in this field. The analysis of the distribution by gender and length of service within certain professions showed the following. With a mean age of 39.75 ± 1.28 years and a mean length of service of 14.19 ± 1.30 years, workers specializing in resuscitation were divided between men (48%) and women (52%). In the group of oncology doctors, women predominated (54%), and the average age was 46.51 ± 2.23 years, while the average length of service was 22.47 ± 2.20 years. EMS professionals were the youngest of all study participants, with the average age of 35.13 ± 1.44 years and the average length of service of 11.88 ± 1.35 years. This group included 42 men (48%) and 46 women (52%).

According to the MBI-GS, 57 (28.8%) respondents had a high level of emotional exhaustion among medical workers (see Fig. 2), high levels of cynicism were deter-mined in 72 (36.4%) medical workers (see Fig. 3), and the reduction of personal achievements had high levels in 56 (28.3%) survey participants (see Fig. 4)

Using the logistic regression method, all study participants were divided into three groups (healthy individuals, a group of prepathology of the development of professional burnout, and a group of individuals with signs of burnout). So, the group of prepathology was 43 (21.7%) people among the general sample of medical workers. Principal component (pc) visualization represents all groups in the form of scatter plot (see Fig. 5).

The next stage was to determine the informative questions from the MBI-GS, which were specific to the group of the prepathological state. With an accuracy factor of 0.84 ± 0.17, questions from the scales “depersonalization/cynicism” and “emotional exhaustion” (see Table 3) were set as informative indicators, namely:

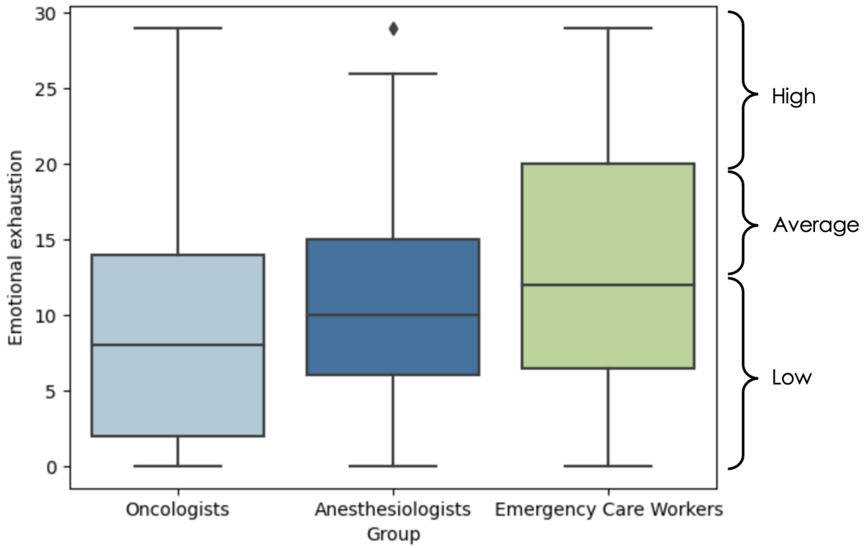

Fig. 2. Scheme of the general distribution of medical workers according to the "emotional exhaustion" scale

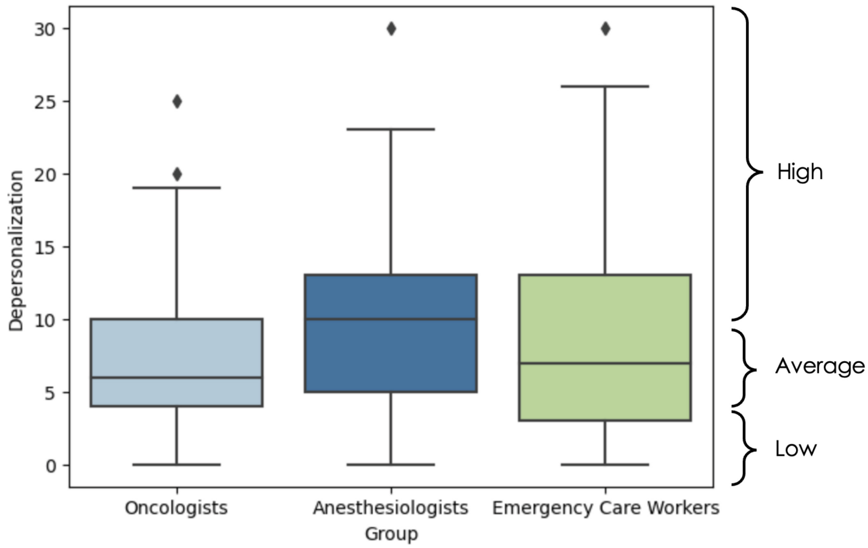

Fig. 3. Scheme of the general distribution of medical workers according to the "depersonalization/cynicism" scale

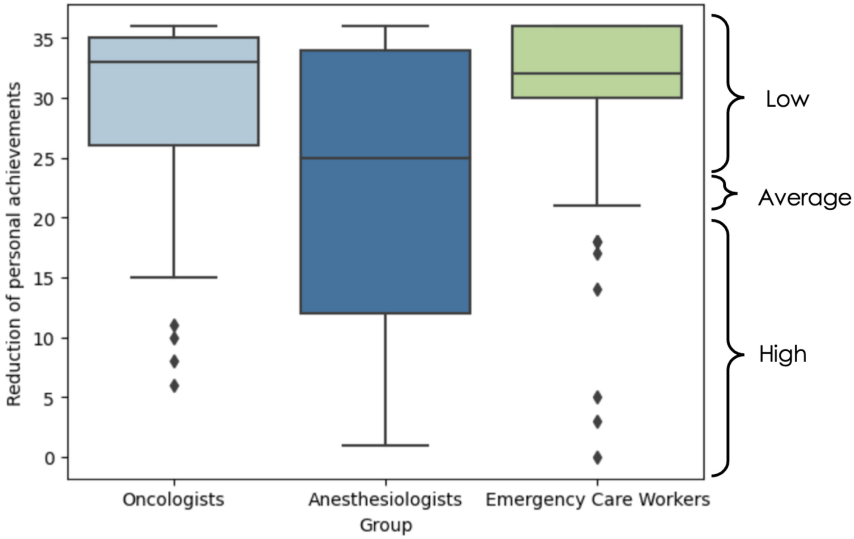

Fig. 4. Scheme of the general distribution of medical workers according to the scale of "professional efficiency"

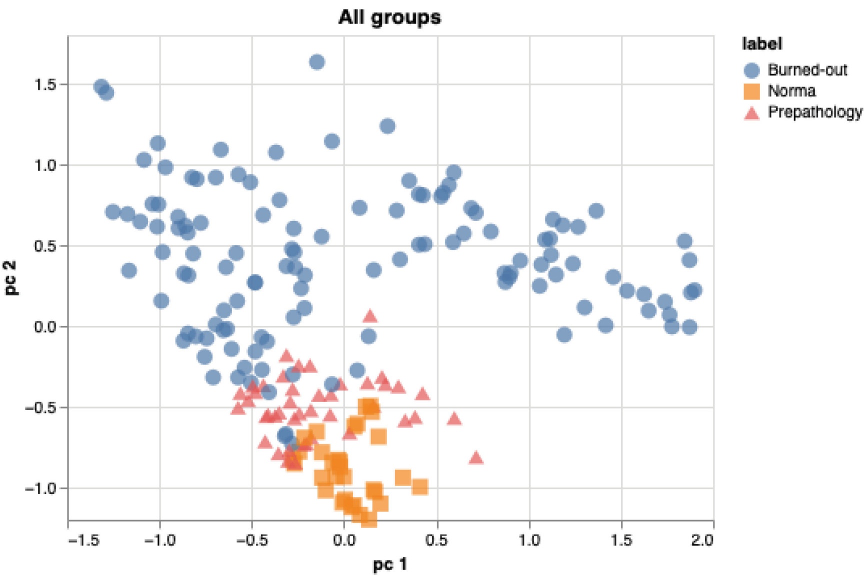

Fig. 5. Principal component (pc1, pc2) visualization of different groups among medical workers

– 6 ee – I feel burnt out from my work;
– 8 zy – I have become less interested in my work since I started this job;
– 13 zy – I just want to do my job and not be bothered;
– 14 zy – I have become more cynical about whether my work contributes anything.

Table 3. Results of the Eli5 explanation regarding the informativeness of questions from the MBI-GS among medical professionals

Weight	**Feature**
+0.615	MBI_13_zy
+0.454	MBI_11_ef
+0.400	MBI_16_ef
+0.376	MBI_12_ef
+0.228	MBI_03_ee
+0.157	MBI_04_ee
+0.142	MBI_02_ee
-0.098	MBI_01_ee
-0.188	MBI_07_ef
-0.203	MBI_10_ef
-0.210	BIAS
-0.244	MBI_05_ef
-0.265	MBI_15_zy
-0.386	MBI_09_zy
-0.480	MBI_14_zy
-0.483	MBI_06_ee
-0.814	MBI_08_zy

Therefore, taking into account the general distribution of medical workers according to the scales of the questionnaire and the informative criteria of this condition determined with help of the Eli5 explanation, no specific informative indicators were established for each specialty (oncology, anesthesiology and emergency medical care). Therefore, it was decided to conduct a deeper analysis. The results of the study on emotional well-being and risk of burnout in the study groups of health care professionals are presented in Table 4.

Healthcare professionals in general, especially those working in the intensive care of emergency conditions, are most susceptible to the impact of professional stress, considering the specific nature of their daily practices.

Table 4. Assessment of PBS levels

MBI scales	Degree of expressiveness	Emergency medical workers n = 88 (%)	Anesthesiologists n = 73 (%)	Oncology doctors n = 37 (%)
Emotional exhaustion	Low	36 (40.9%)	38 (52.1%)	23 (62.2%)
	Average	19 (21.6%)	19 (26.0%)	6 (16.2%)
	High	33 (37.5%)	16 (21.9%)	8 (21.6%)
Depersonalization/ cynicism	Low	31 (35.2%)	25 (34.2%)	16 (43.2%)
	Average	23 (26.1%)	19 (26.0%)	12 (32.4%)
	High	34 (38.6%)	29 (39.7%)	9(24.3%)
Labor efficiency	Low	11 (12.5%)	36 (49.3%)	9 (24.3%)
	Average	10 (11.4%)	8 (11.0%)	5 (13.5%)
	High	67 (76.1%)	29 (39.7%)	23 (62.2%)

Anesthesiologists, in particular, bear the highest emotional burden in their duties due to the elevated risk to patients' lives, especially during life support, treatment of acute and chronic pain syndromes, administration of resuscitation measures, and addressing postoperative complications in time-critical situations. Consequently, the result of such pressures is a low self-assessment of their professional effectiveness.

3.2 Group of Anesthesiologists

Among the anesthesiologists, 16 (21.9%) respondents had high levels of emotional exhaustion, cynicism – 29 (39.7%), and reduction of personal achievements – 36 (49.3%) survey participants (see Table 4).

The group of prepathology in this sample consisted of 10 doctors (see Fig. 6).

With an accuracy coefficient of 0.85±0.21 of logistic regression, anesthesiologists demonstrate a high level of reduction of personal achievements and cynicism on the scales "professional effectiveness", "depersonalization/cynicism" (see Table 5).

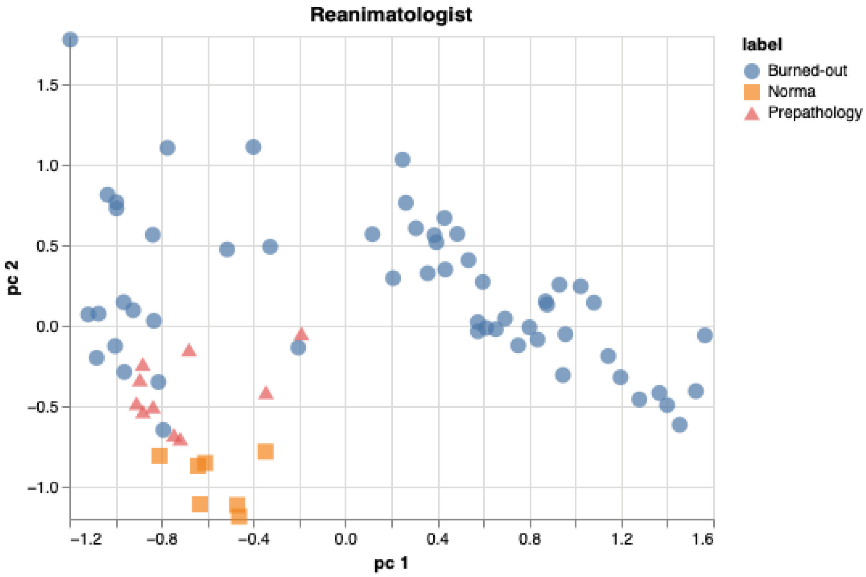

Fig. 6. Principal component (pc1, pc2) visualization of different groups among anesthesiologists

Table 5. Results of the Eli5 explanation regarding the informativeness of questions from the MBI-GS among anesthesiologists

Weight	Feature
+0.462	MBI_16_ef
+0.413	MBI_11_ef
+0.378	MBI_12_ef
+0.359	MBI_05_ef
+0.336	MBI_03_ee
+0.219	MBI_13_zy
+0.199	MBI_01_ee
+0.194	MBI_07_ef
+0.126	MBI_15_zy
+0.017	MBI_02_ee
+0.009	MBI_06_ee
-0.175	MBI_08_zy
-0.258	MBI_09_zy
-0.275	MBI_10_ef
-0.287	MBI_04_ee
-0.575	MBI_14_zy
-1.366	BIAS

The informative questions of the questionnaire were set as follows:

– 11ef – I feel exhilarated when I accomplish something at work;
– 12ef – I have accomplished many worthwhile things in this job;
– 14zy – I have become more cynical about whether my work contributes anything;
– 16ef – At my work, I feel confident that I am getting things done.

3.3 Group of Oncologists

A medical and psychological study of oncology doctors revealed a high level of emotional exhaustion in 8 (21.6%) respondents, a high level of cynicism in 9 (24.3%) specialists (see Table 4). The group of prepathology in this sample consisted of 9 oncologists (see Fig. 7).

The working conditions of oncologists, in some aspects, bear similarities to those of anesthesiologists (caring for critically ill patients). However, research findings indicate that oncologists exhibit a lower susceptibility to emotional exhaustion and cynicism, resulting in a lesser reduction in personal achievements compared to their counterparts in the field of intensive care.

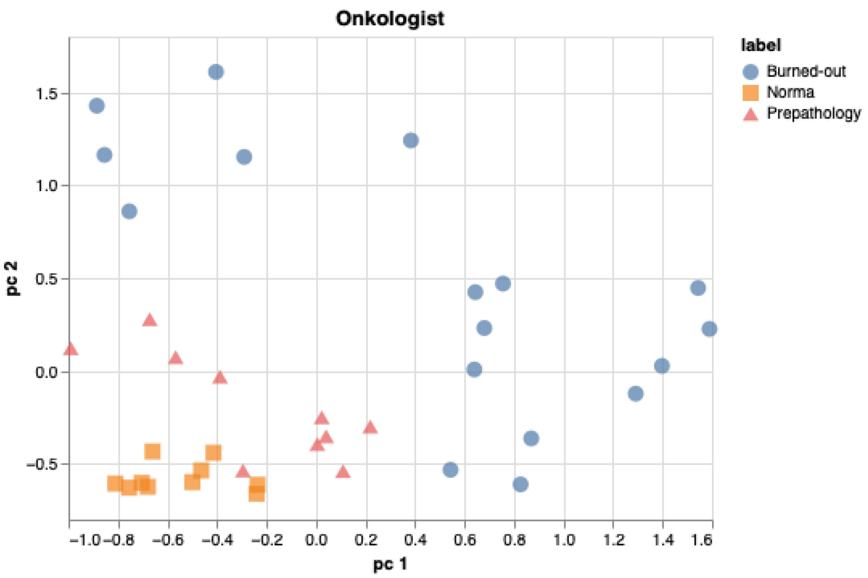

Fig. 7. Principal component (pc1, pc2) visualization of different groups among oncology doctors.

At the same time, according to the results of the "professional effectiveness" scale, it is proven that despite the rather high levels of emotional exhaustion and cynicism among doctors, a low reduction of personal achievements in 9 (24.3%) specialists is noted.

Informative questions in the group of oncology doctors (see Table 6).

Table 6. Results of the Eli5 explanation regarding the informativeness of questions from the MBI-GS among oncology doctors

Weight	Feature
+0.466	MBI_12_ef
+0.458	MBI_11_ef
+0.327	MBI_14_zy
+0.132	MBI_16_ef
+0.092	MBI_01_ee
+0.077	MBI_02_ee
-0.006	MBI_09_zy
-0.021	MBI_10_ef
-0.025	MBI_04_ee
-0.033	MBI_13_zy
-0.127	BIAS
-0.213	MBI_03_ee
-0.214	MBI_08_zy
-0.268	MBI_07_ef
-0.280	MBI_15_zy
-0.317	MBI_05_ef
-0.581	MBI_06_ee

As you can see from the Table 6 informative questions were determined by all scales of the questionnaire with a model accuracy of 0.78 ± 0.23:

- 06 ee – I feel burnt out from my work;
- 11 ef – I feel exhilarated when I accomplish something at work;
- 12 ef – I have accomplished many worthwhile things in this job;
- 14 zy – I have become more cynical about whether my work contributes anything.

3.4 Group of Emergency Care Workers

Among emergency medical specialists, the highest level of emotional exhaustion is noted. However, a distinctive feature of this cohort is that, concurrently, there is a high self-assessment of professional effectiveness. Additionally, this indicator is the highest among all the investigated specialties.

According to the results of the survey of emergency medical care specialists, high levels of emotional exhaustion were noted in 33 (37.5%) respondents, a high level of cynicism in 34 (38.6%), and a high level of reduction of personal achievements was revealed only in 11 (12.5%) survey participants, which, as with oncologists, also confirms positive assessments of the effectiveness of their work among employees (see Table 4).

The prepathology group in this cohort consisted of 23 workers (see Fig. 8).

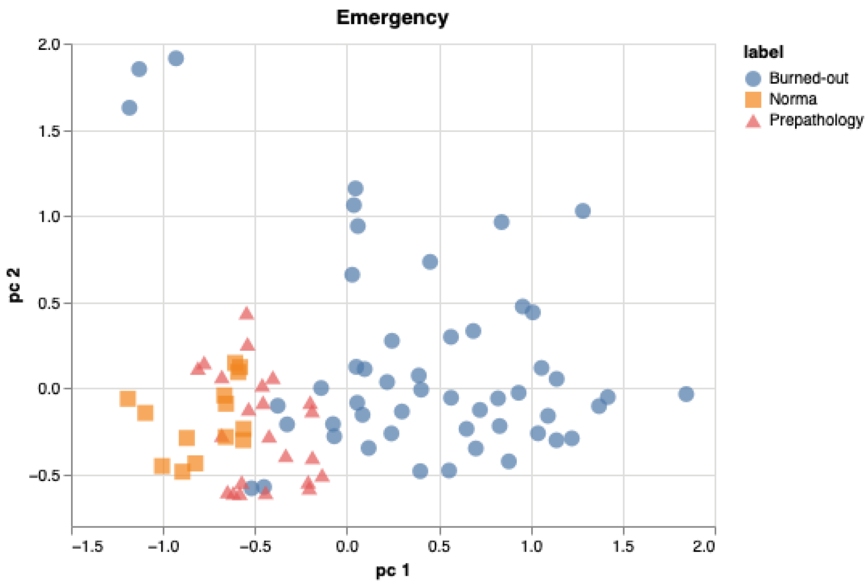

Fig. 8. Principal component (pc1, pc2) visualization of different groups among emergency care workers.

A regression model trained on MBI-GS data has an accuracy of 0.78 ± 0.23. Informative questions of the questionnaire on the "depersonalization/cynicism" and "emotional exhaustion" scales for this group of employees were the following (see Table 7):

- 01 ee – I feel emotionally drained by my work;
- 08 zy – I have become less interested in my work since I started this job;
- 13 zy – I just want to do my job and not be bothered;
- 14 zy – I have become more cynical about whether my work contributes anything.

4 Discussion

There are many reasons why medical professions are among the most psychologically demanding professions. This classification stems from the fact that medical workers regularly interact with different groups of patients, which requires a high level of responsibility in patient care, professionalism in conducting procedures, resistance to various levels of stress and other aspects of psychological stress during diagnosis and therapy. In addition, empathy is a professional necessity for healthcare professionals. However, when patients' problems are perceived as a personal burden, compounded by the many challenges of modern life, this can lead to excessive fatigue and eventually manifest in negative mental states.

Table 7. Results of the Eli5 explanation regarding the informativeness of questions from the MBI-GS among emergency care workers

Weight	Feature
+0.890	MBI_13_zy
+0.421	MBI_04_ee
+0.215	MBI_16_ef
+0.148	MBI_03_ee
+0.094	MBI_12_ef
+0.084	MBI_07_ef
+0.081	MBI_11_ef
+0.047	MBI_10_ef
+0.031	BIAS
-0.197	MBI_02_ee
-0.263	MBI_05_ef
-0.303	MBI_06_ee
-0.504	MBI_09_zy
-0.521	MBI_15_zy
-0.609	MBI_01_ee
-0.750	MBI_14_zy
-0.898	MBI_08_zy

A study conducted through an anonymous questionnaire administered to oncologists, anesthesiologists, and emergency medical personnel unveiled significant levels of emotional exhaustion. This included instances of diminished self-esteem, a pessimistic outlook toward work, and a decline in empathy and compassion for others. Notably, this manifestation is not indicative of a loss of creativity nor a response to monotony; rather, it represents a reaction to exhaustion stemming from stress induced by interpersonal interactions. This aligns closely with the burnout syndrome model proposed by K. Maslach and S. Jackson [24].

A modern mathematical approach allows you to quickly determine informative criteria that can be the cause of professional burnout. Taking into account the peculiarities of work organization in various medical specialties, job duties, qualification requirements and the nature of patients with whom medical workers work, it can be assumed that for anesthesiologists, the main factors leading to professional burnout are low self-esteem of their professional competence. This profession requires immediate decision-making in extremely difficult conditions that are significantly different from the standard ones. The work of an anesthesiologist often includes performing resuscitation measures and trying to save a patient's life. Unfortunately, this specialty is also often faced with fatal cases of patients, which can lead to a decrease in the confidence of doctors in their professional achievements [8]. Doctors specializing in oncology are similar to anesthesiologists in some ways because they also work with critically ill patients. However, the difference is that communication with patients usually takes more time for oncologists, and the success of their work, such as prolonging the life or recovery of the patient, becomes a motivation and a source of confidence. Nevertheless, it is important to note that the duration of this communication and a high level of empathy for patients can cause emotional exhaustion, and the specifics of work organization can cause cynicism [14].

The criteria for cynicism among emergency medical care workers may be the result of shortcomings in the organization of the work process. In particular, long working hours and shift work, which often requires additional efforts to solve organizational tasks and re-registration, etc. In addition, employees experience psycho-emotional stress due to high responsibility for the lives of patients, their own safety due to pos-sible inappropriate behavior of the patient (mental illness, alcohol or drug intoxication), false calls and low wages [5].

Therefore, the proposed machine learning method for early detection of factors leading to professional burnout among medical workers allowed to determine informative criteria based on the Maslach Burnout Inventory - General Survey. The determined indicators will become the foundation for the development of general and specific measures to prevent professional burnout among medical workers.

The next stage of research will include the development of preventive measures, including psychocorrection and targeted work with groups of medical professionals who are most at risk of professional burnout. It is also planned to recollect data and analyze it to assess the effectiveness of implemented measures.

5 Conclusions

The present study employed a machine learning approach integrated with a visual framework to identify predictors for the potential development of professional burnout syndrome (PBS) among practicing doctors based on survey data from the Maslach Burnout Inventory – General Survey (MBI-GS). The proposed model enabled early detection and prevention of PBS by providing valuable insights into the complex factors contributing to its development. Our findings revealed that the total group of prepathology consisted of 43 medical workers exhibiting a pronounced phenomenon of cynicism. By analyzing the distribution of the total sample by specialties, we identified specific assessment criteria for each group and determined the unique characteristics of PBS among intensive care physicians, oncologists, and emergency medical care workers.

The proposed mathematical approach to early detection and prevention of PBS has the potential to revolutionize its diagnosis, enabling more targeted and effective preventive measures. By taking into account the determined indices, we can work purposefully with the prepathology group, tailoring psychocorrection and preventive measures to their specific needs and peculiarities of work.

Our findings underscore the importance of addressing the unique challenges faced by different specialties in order to develop effective strategies for preventing PBS. The proposed approach has significant implications for improving healthcare quality and patient safety while promoting resilience and well-being among medical personnel. The present study demonstrates the potential of machine learning approaches integrated with visual frameworks for early detection and prevention of PBS among practicing doctors. By leveraging these methods, we can provide valuable insights into the complex factors contributing to PBS development and develop targeted interventions to promote resilience and well-being among medical professionals.

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