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Neurophysiological determinants of occupational stress and burnout

Uwarunkowania neurofizjologiczne stresu i wypalenia zawodowego

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ABSTRACT

Introduction

Research results show that one of the greatest health challenges of the 21st century, especially in developed countries, is becoming the fight against the effects of living too fast, including the fight against occupational stress and burnout. Strategies for prevention, early detection, as well as early response to threats and modern therapies are being implemented in the aforementioned area. The key to further improving the effectiveness of the aforementioned endeavors is becoming a fuller understanding of the understanding of the changes taking place in the body and their mechanisms, in order to break the chain of cause and effect - at various stages by various means.

Aim of the study

The purpose of this article is to elucidate the neurophysiological determinants of occupational stress and burnout, including ocupational, including through the path of research review and the development of computational models based on artificial intelligence.

Materials and methods

A literature search was conducted in six bibliographic databases: PubMed, EBSCO, PEDro, Web of Science, Scopus and Google Scholar. Articles were searched in English using the following keywords: occupational stress, burnout, marker, electroencephalography, EEG, magnetic resonance imaging, MRI, fMRI, computed tomography, CT, positron emission tomography, PET and similar. The search was for publications published through January 2023. Another search was for the aforementioned databases and keywords, but in conjunction with computational models – following keywords were added: computational model, machine learning, artificial

intelligence, virtual patient, digital twin and similar. Neurophysiological determinants of occupational stress and burnout as far as computational models of occupational stress and burnout were analysed and discussed.
Results
The best currently observed neurophysiological markers of occupational stress and burnout may currently be a combination of EEG analysis (alpha power (IAF, PAF), P300, ERP (VPP and EPN)), diagnostic PET imaging (ACC, insular cortex and hippocampus) and monitoring changes in cortisol, prolactin, adrenocorticotropic hormone (ACTH), corticotropin-releasing hormone (CRH) and thyroid hormones, as well as plasma BDNF levels. In addition, ERPs (LPPs) are a marker significantly differentiating burnout from depression.
Conclusions
The combination of traditional clinimetric tests, the aforementioned neurophysiological tests and AI-based big data analysis will provide new classifiers, highly accurate results and new diagnostic methods.

Keywords: occupational stress, burnout, marker, electroencephalography, EEG, magnetic resonance imaging, MRI, fMRI, computed tomography, CT, positron emission tomography, PET, computational model, machine learning, artificial intelligence, virtual patient, digital twin.

STRESZCZENIE
Wprowadzenie
Wyniki badań wskazują, że jednym z największych wyzwań zdrowotnych XXI wieku, zwłaszcza w krajach rozwiniętych, staje się walka ze skutkami zbyt szybkiego życia, w tym walka ze stresem zawodowym i wypaleniem zawodowym. W powyższym obszarze wdrażane są strategie zapobiegania, wczesnego wykrywania, a także wczesnego reagowania na zagrożenia i nowoczesne terapie. Kluczem do dalszego zwiększania skuteczności wspomnianych przedsięwzięć staje się pełniejsze zrozumienie rozumienia zmian zachodzących w organizmie i ich mechanizmów, aby przerwać łańcuch przyczyn i skutków - na różnych etapach za pomocą różnych środków.
Cel pracy
Celem niniejszego artykulu jest wyjaśnienie neurofizjologicznych uwarunkowań stresu zawodowego i wypalenia zawodowego, w tym poprzez przegląd badań oraz rozwój modeli obliczeniowych opartych na sztucznej inteligencji.
Materiał i metodyka
Przeprowadzono wyszukiwanie literatury w sześciu bibliograficznych bazach danych: PubMed, EBSCO, PEDro, Web of Science, Scopus i Google Scholar. Artykuły wyszukiwano w języku angielskim z użyciem następujących słów kluczowych: stres zawodowy, wypalenie, marker, elektroencefalografia, EEG, rezonans magnetyczny, MRI, fMRI, tomografia komputerowa, CT, pozytonowa tomografia emisyjna, PET i podobne. Wyszukiwanie dotyczyło publikacji opublikowanych do stycznia 2023 roku. Kolejne wyszukiwanie dotyczyło wyżej wymienionych baz danych i słów kluczowych, ale w połączeniu z modelami obliczeniowymi - dodano następujące słowa kluczowe: model obliczeniowy, uczenie maszynowe, sztuczna inteligencja, wirtualny pacjent, cyfrowy bliźniak i podobne. Analizie i dyskusji poddano uwarunkowania neurofizjologiczne stresu i wypalenia zawodowego oraz modele obliczeniowe stresu zawodowego i wypalenia zawodowego.
Wyniki
Najlepszymi obecnie zaobserwowanymi neurofizjologicznymi markerami stresu zawodowego i wypalenia zawodowego może być obecnie połączenie analizy EEG (moc alfa (IAF, PAF), P300, ERP (VPP i EPN)), diagnostycznego obrazowania PET (ACC, kora wyspowa i hipokamp) oraz monitorowanie zmian kortyzolu, prolaktyny, hormonu adrenokortykotropowego (ACTH), hormonu uwalniającego kortykotropinę (CRH) i hormonów tarczycy, a także poziomu BDNF w osoczu. Ponadto ERP (LPP) stanowią marker istotnie różnicujący wypalenie od depresji.
Wnioski
Połączenie tradycyjnych testów klinimetrycznych, ww. badań neurofizjologicznych i opartej na AI analizy big data, zapewni nowe klasyfikatory, wysoce trafne wyniki i nowe metody diagnostyczne.

Słowa kluczowe: stres zawodowy, wypalenie, marker, elektroencefalografia, EEG, rezonans magnetyczny, MRI, fMRI, tomografia komputerowa, CT, pozytonowa tomografia emisyjna, PET, model obliczeniowy, uczenie maszynowe, sztuczna inteligencja, wirtualny pacjent, cyfrowy bliźniak.

I. Introduction

One of the greatest health challenges of the 21st century, especially in developed countries, is becoming the fight against the effects of living too fast, including the fight against occupational stress and burnout.

Professional burnout syndrome, manifested by emotional exhaustion, lack of a sense of personal accomplishment and depersonalization, is the result of chronic occupational stress, and was first mentioned as early as the 1970s [1-3]. It has been included in the International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10 CM) under the heading "Factor affecting health and health care contact (Z00-Z99)" as a "state of life exhaustion," and defined in the ICD-11 as "feelings of energy depletion or exhaustion," occupational burnout is still not recognized as a disorder in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM 5) [3-7].

The extent and severity of burnout syndrome symptoms depend on both work-related (exogenous) and personal (endogenous) factors. Persistent stress and burnout result in reduced quality of life and are associated with an increased risk of sleep disorders and several medical disorders, including mild cognitive impairment, diabetes and cardiovascular disease. The active coping strategies currently used to deal with stress and burnout promote improvements in psychological resilience and adaptive behavior, but primarily stress-reducing activities, improving working conditions and reducing exposure to occupational stressors. Taken together, they can mitigate burnout-related changes in the body, and hence should be introduced as early as possible in the clinical course of burnout syndrome [8].

Strategies for prevention, early detection, as well as early response to threats and modern therapies are being implemented in the aforementioned area. The key to further improving the effectiveness of the aforementioned endeavors is becoming a fuller understanding of the understanding of the changes taking place in the body and their mechanisms, in order to break the chain of cause and effect - at various stage.

A better understanding of the neurophysiological determinants of occupational stress and burnout, including through computational models, becomes the basis for developing more effective methods of prevention and therapy.s by various means. The current lack of evidence for an objective neurobiological marker of burnout syndrome makes the final stages of diagnosis difficult [3, 9-12]. The main goal of medical research therefore seems to be to provide up-to-date data for use by clinicians to improve the effectiveness of diagnosis, therapy and care of long-term stress and occupational burnout. This is sometimes difficult due to the lack of a complete picture of the mechanisms of physiology and pathology of the observed phenomenon, as well as unclear links between experimental findings and theories that attempt to explain them comprehensively. This gap is being attempted to be filled by computational models [3].

We use computational models of diseases, especially those based on artificial intelligence, when we encounter:

- a lack of complete understanding of the mechanisms of diseases and their interaction,
- the diverse etiology of diseases,
- the many different theories within the Evidence-Based Medicine paradigm,
- the "data rich and theory poor" problem - there is a lack of theories that explain the processes in question comprehensively, with sufficient predictive power,
- lack of good computational models to date that combine different levels of analysis.

Computational models of medical conditions allow:

- cheaper and faster testing of hypotheses, including those that are difficult to perform in the real world (e.g., for medical, technical, legal, ethical reasons, etc.),
- the formulation of a general vision of how things work (also within the framework of a so-called digital twin of a patient, system or organ), and the possibility of scaling toward increasingly detailed or partial solutions,
- study of isolated mechanisms,
- simplification of mechanisms too complex for direct modeling,
- modeling of damage, including isolated damage.

Limitations of computational models that we must take into account include:

- the need to scale models, as modeling without scaling is usually impossible due to the complexity of the phenomenon, while one-size-fits-all models tend to be too general, and models that are too detailed tend to be inflexible,
- the need to precisely define the purpose - models usually answer only specifically the questions posed beforehand by their designers,
- the need to provide the appropriate signals and levels of processing required for a specific function (e.g., cognitive), which can be difficult in the case of stress and burnout,
- in the absence of knowledge, there is a need to provide realistic hypotheses to fill research gaps.

Computational models have so far shown their effectiveness as support for diagnosticians and therapists in at least several areas of biomedical data analysis: gait analysis [13], building models of autism spectrum disorders [14], brain stem and subcortical systems [15]. New analytical and model computational approaches are undertaken as new data is acquired and new concepts are verified [16-19]. This applies in particular to comparative studies of models and predictive models [20,21].

II. Aim of the study

The purpose of this article is to elucidate the neurophysiological determinants of occupational stress and burnout, including ocupational, including through the path of research review and the development of computational models based on artificial intelligence.

III. Material and methods

A literature search was conducted in six bibliographic databases: PubMed, EBSCO, PEDro, Web of Science, Scopus and Google Scholar. Articles were searched in English using the following keywords: occupational stress, burnout, marker, electroencephalography, EEG, magnetic resonance imaging, MRI, fMRI, computed tomography, CT, positron emission tomography, PET and similar. The search was for publications published 1980-2023 (fig. 1, fig. 2)
Another search was for the aforementioned databases and keywords, but in conjunction with computational models – following keywords were added: computational model, machine learning, artificial intelligence, virtual patient, digital twin and similar.

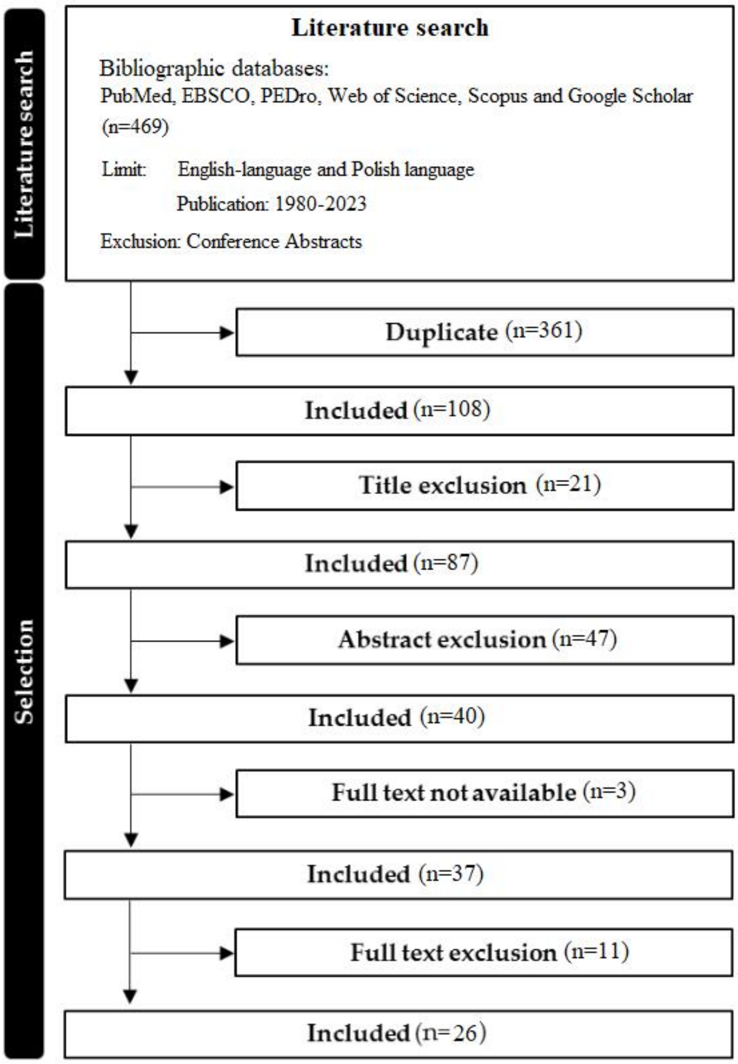


Fig. 1. Flow chart describing the selection process.

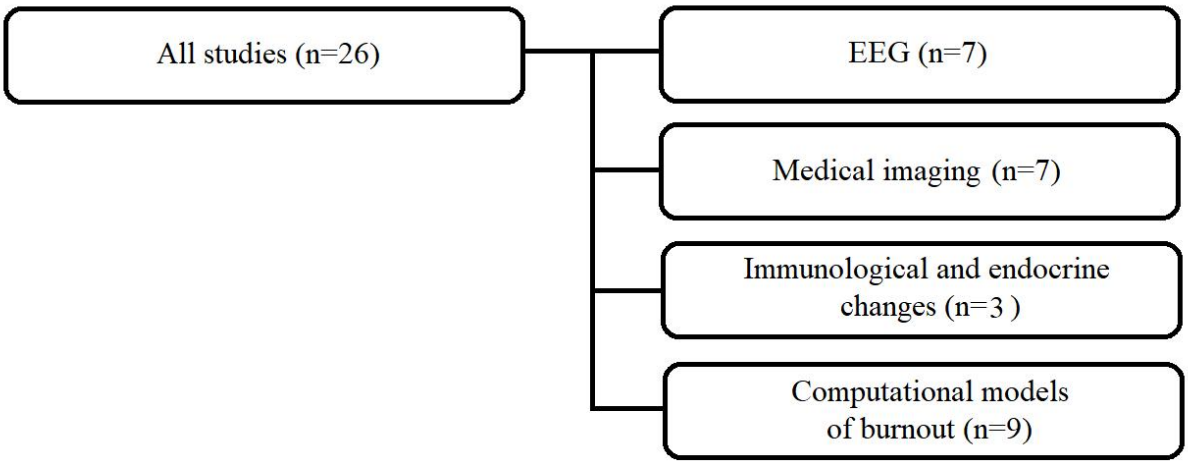


Fig. 2. Tree chart of the distribution of studies into categories.

IV. Results

Burnout is associated with cognitive and emotional dysfunction. For this reason, the growing number of neurophysiological and neuroimaging studies translates into expanding knowledge and clinical practice in the area of neural mechanisms related to individual components of burnout (emotional exhaustion and depersonalization).

IV.1. EEG

Burnout develops as a result of prolonged stress, which is associated with dysfunction of the hippocampus, one of the neuronal generators of the P300 [22,23]. Reduced P300 amplitude, reduced beta power and lower peak alpha frequency have been observed in patients with burnout in EEG studies [3,24]. These values are associated with both burnout and gender as predictive factors [3,24]. At the same time, the hippocampus is part of the limbic system and plays an important role in the expression of emotions and visceral and endocrine functioning [25] (table 1).

Table 1. Selected studies regarding neurophysiological determinants of occupational stress and burnout studied by EEG [1].

Study	Desing	Sample	Outcomes
Luijtelaar et al. (2010) [3]	Brain function in burnout patients by analyzing EEG and neuropsychological outcomes	13 burnout subjects 13 healthy controls	Reduced P300 potency, peak alpha and beta in burnout patients
Tement et al. (2016) [26]	Relationship between potential biomarkers in the alpha frequency band and self-reports of burnout and the role of gender	117 subjects	IAF is associated with depression and power is associated with burnout, males had significantly higher score in burnout questionnaire
Golonka et al. (2019) [10]	Differences in brain activity by analyzing EEG power versus resting frequency in burnout and control patients	131 burnout employees, 143 healthy controls	Observed increase in dysfunction of the brain's regulatory systems correlating with increase in the severity of clinical symptoms

P300 is associated with memory updating and attentional allocation, hence a reduced P300 amplitude can be seen as a physiological confirmation of attention and memory problems in patients with burnout [27-29]. The individual alpha frequency (IAF) is considered a more accurate measure of spectral distribution than the peak

alpha frequency (PAF). At the same time, IAF is associated with the features of the white matter structure (fiber density, axon diameter, myelination), and also reflects various other neuronal processes [30]. In turn, PAF is associated with reduced cerebral blood flow and reduced brain oxygenation and correlates negatively with subjective assessments of fatigue, including total fatigue [31] and cognitive readiness [32], including worse results in memory tasks [33] (fig. 3).
Daytime fatigue and mild cognitive changes in patients may be explained by the influence of sleep [34]. For these reasons, the literature suggests the use of at least two biomarkers of burnout: alpha power (IAF, PAF) and P300, which together constitute a non-invasive, reliable, reflective and hereditary solution, distinguishing burnout from other diseases [26].

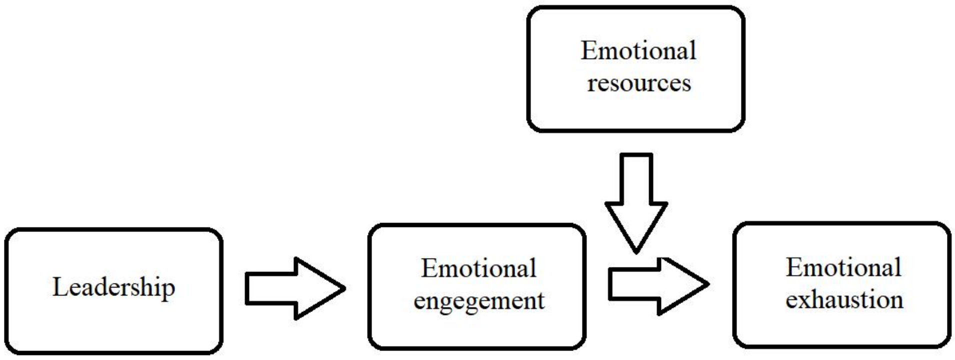


Figure 3. Emotional exhaustion model [3].

EEG activity during the Iowa gambling task used to study decision-making processes showed overactivity of the amygdala, association cortex, dorsolateral prefrontal cortex and primary visual cortex. The results of the aforementioned analyses form the basis for the development of machine learning classifiers, but the search for the most effective classifier for biomarkers of cortical decision-making activity in healthy individuals as well as those with burnout is still ongoing [35].
In another study, a 256-channel EEG instrument (EGI System 300) was used to collect psychophysiological data, and the Maslach Burnout Inventory General Survey (MBI-GS) and Areas of Worklife Survey (AWS) were used to measure burnout symptoms and working conditions. A statistically significant lower alpha power in the open-eye condition was observed in patients (cortical hyperactivity, greater mental effort, activated compensatory mechanisms) with burnout compared to the control group. Furthermore, gender may be important for the correlation between burnout symptoms and EEG spectral features [36].
A study using event-related potentials (ERP) components (N170, vertex positive potential (VPP), early posterior negativity (EPN) and late positive potential (LPP)) as indicators of emotional information processing and Maslach Burnout Inventory - General Survey (MBI-GS) and Areas of Worklife Survey (AWS) scores showed an association between neurophysiological activity and burnout syndrome in the context of emotional processing. This is also indicated by the fact that VPP and EPN are correlated with two symptoms of burnout: emotional exhaustion and cynicism. Thus, VPP and EPN may represent further neurophysiological markers of burnout, more specifically: emotional exhaustion and cynicism. Additionally, the observed lack of decline in LPP may be used as a marker to significantly differentiate burnout from depression [9].
Usage experimental procedures of potentials related to the ERP event (Go/NoGo Task and Doors Task) showed that in the absence of the observed difference in performance between burnout and the control group, there are significant differences at the neuronal level in all analyzed aspects of information processing: stimulus and reaction [12,37,38].

IV.2. Medical imaging studies

The mechanisms of occupational burnout are still poorly understood, especially in neuroimaging studies. This indicates that the relationship between the neural components of burnout and cognitive changes may be more complex than previously thought (table 2).

Table 2. Selected studies regarding neurophysiological determinants of occupational stress and burnout studied by medical imaging [1,2].

Study	Desing	Sample	Outcomes
Jovanovic et al. (2011) [39]	Limbic function test with PET on chronic stress subjects	16 stress subjects, 16 healthy controls	Functional disconnection between amygdala and ACC/MPFC in chronically stressed subjects
Durning et al. (2013) [40]	Burnout modulates brain activity during clinical reasoning in physicians	17 internal medicine residents, 17 board-certified internists	Depersonalization was related to less BOLD in DLPFC and MFG Exhaustion of emotions was related with more BOLD in MFG and CC
Savic (2013) [41]	Structural changes in the brain in connection with occupational stress in the MRI study	40 burnout subjects, 40 healthy controls	Reduced volume of the amygdala, caudate nucleus, and impaired motor function in burnout patients
Blix et al. (2013) [42]	Gray matter and white matter volume were compared between patients with chronic work-related stress and healthy subjects in MRI study	30 burnout subjects, 68 healthy controls	Reduced volumes of GM, ACC, and DLPFC in burnout patients
Tei et al. (2014) [43]	Relationship between self-reported burnout severity scores and psychological measures of empathic disposition	25 nurses in active service	The severity of burnout decreased brain activity related to empathy, AI/IFG and TPJ activity negatively correlated with emotional exhaustion
Gavelin et al. (2017) [44]	Relationship between burnout and neuron activation in working memory processing in patients with stress-induced exhaustion	55 patients with a clinical diagnosis of exhaustion syndrome,	Lack of correlation between level of burnout and working memory performance, striatal frontal nerve responses related to working memory modulated by severity of burnout
Savic et al. (2018) [45]	Cerebral effects of chronic occupational stress and their possible reversibility	48 patients with occupational exhaustion syndrome, 80 healthy controls**,** After 1–2 years: 25 patients with occupational exhaustion syndrome. 19 healthy controls	Chronic work-related stress associated with partially reversible structural abnormalities, sustained attention and verbal memory impaired only among females

The brain structures of patients with burnout that are related to emotions, motivation and empathy differ significantly from the same structures in healthy people. To the above brain structures include thalamus, hippocampus, amygdala, coccyx, striatum, dorsolateral prefrontal cortex (DLPFC), anterior cingulate cortex (ACC), anterior cingulate cortex (ACC), posterior cingulate cortex (PCC), anterior hemisphere brain (AI), inferior frontal gyrus (IFG), middle frontal gyrus (IFG), middle frontal gyrus (MFG), temporoparietal junction (TPJ), and gray matter (GM). In addition, the ACC, insular cortex, and hippocampus show changes on PET imaging in patients with burnout [46]. AI and ACC are involved in empathy [47,48], moreover, behavioral studies indicate a strong relationship between occupational burnout and empathy [49-53], and lack of empathy is one of the sub-elements of burnout syndrome.

Brain structures (amygdala, hippocampus, caudate and putamen) they differ in burnt-out people due to their specific neurophysiological functions. The amygdala and hippocampus are part of the limbic system playing an important role in memory, emotions, emotional learning and behavior, motivation and rewarding. There is a theory about burnout syndrome in relation to the limbic system and its structures, according to which the limbic system has a direct impact on all three main dimensions of burnout syndrome, i.e. emotional exhaustion, depersonalization and lack of personal achievement. In turn, the striatum, the input nucleus to the basal ganglia, provides the reception of excitatory signals from cortical and subcortical structures. From the above reasons it allows the basal ganglia to integrate information from various cortical and subcortical areas, initiate the movements of our body and motor expression of emotions [25]. This is the basis for further research in the search for correlations between the caudate ganglion, putamen, and professional burnout.

IV.3 Immunological and endocrine changes

Immunological and endocrine changes observed in patients with burnout indicate dysfunction of the hypothalamic-pituitary-adrenal (HPA) axis (fig. 4). Measurements of hormonal reactivity, i.e. cortisol, prolactin, adrenocorticotropic hormone (ACTH), corticotropin-releasing hormone (CRH) and thyroid hormones, are considered markers of HPA disruption by chronic stress [54,55]. This applies to both their pulsatile and diurnal fluctuations [54,55].
In addition, plasma levels of brain-derived neurotrophic factor (BDNF) are higher in people with chronic stress. Its role in the mechanisms of stress-related disorders may be crucial; moreover, perhaps the increase in peripheral BDNF levels may represent a neuronal protection mechanism operating under chronic stress [56].

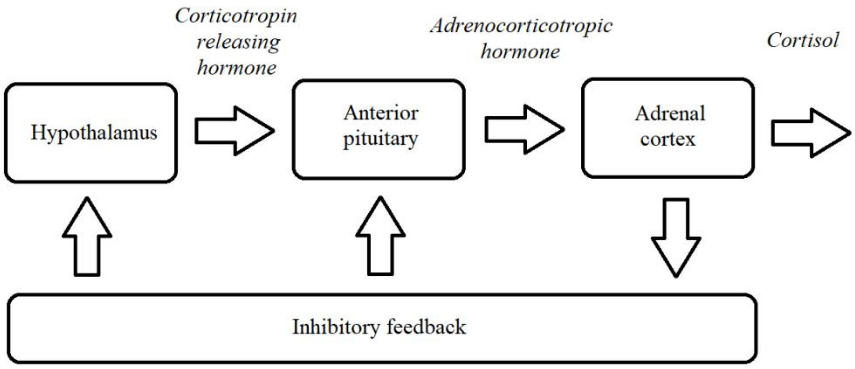


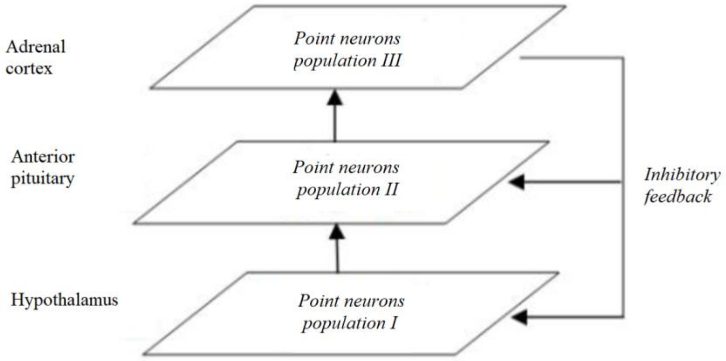
Figure 4. HPA axis.

V. Computational models of prolonged stress and burnout

There is no doubt that research on computational models of the central nervous system of the nervous system is an important element of current challenges in both computer science and biomedical engineering in medical science and clinical practice. This applies to models of physiological states as well as congenital defects, diseases and injuries, resulting in functional deficits of various types and severity [3,4].

Despite the topicality of the problem of burnout and the availability of computational tools, computational approaches to the analysis and classification of burnout began to be developed relatively recently. The results of previous studies are not satisfactory, and additionally, it is difficult to fully explain all the physiological and pathological mechanisms underlying burnout. So far, it has not been possible to develop computational models of occupational burnout with satisfactory efficiency and accuracy as well as predictive power. Hence, every new concept in this area, even quite general, is worth giving a chance, because the attempts to construct such computational models so far have not been ultimately successful [8,9].
It is known that occupational burnout has a statistically significant negative structural relationship with work efficiency. It is possible to model labor resources using structural equations and least squares estimation, mean-weighted estimation and variance-weighted estimation, but such models do not explain the entire mechanisms of the aforementioned phenomena [57]. For the more detailed models we develop, there is not enough accurate data (fig. 5) [1,2, 58-62]. So far, in our own work [1,2, 58-62], we have presented a number of original approaches to the computational analysis of burnout, both using multi-criteria analysis, analysis using artificial neural networks and fuzzy analysis. Such a wide range of computational approaches allows us not only to select the best one, but also to develop a hybrid approach best suited to the specifics of a computational problem such as the modelling of burnout.

a)



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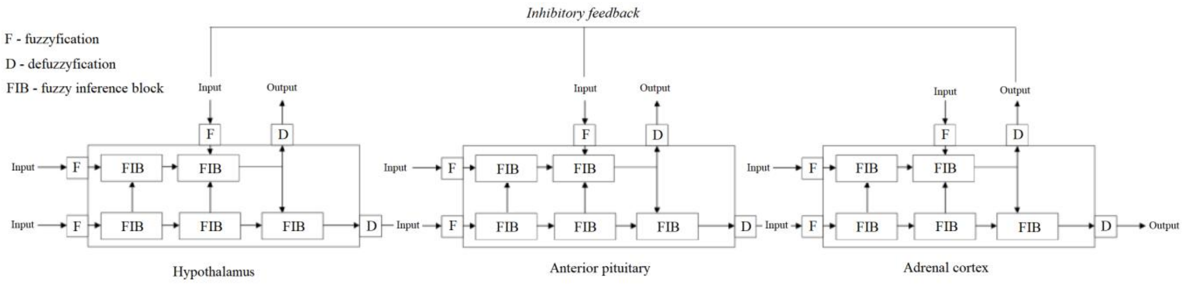

Figure 5. Computational models of prolonged stress and burnout: a) based on artificial neural networks (Emergent software model based on HPA axis structure and point Hodgkin-Huxley neurons), b) based on fuzzy logic (Matlab software) [1].

V. Discussion

The research and clinical problem lies in the early diagnosis of burnout, as more complex tests may be more sensitive in detecting cognitive dysfunction in non-clinical settings. In addition, a relationship was found between the performance of two tasks a performance of work, and insomnia was associated with subjective cognitive functioning, but not labor productivity [63].

From a scientific and clinical perspective, the concept of burnout brings with it the need to deepen the study of occupational stress. Burnout is considered from theoretical and experimental psychological perspectives. This article adds a computational perspective to help develop models that combine theories (one or more) with experimental findings. Previous models of burnout have been based on the results of their empirical studies (Maslach's multidimensional perspective, Golembiewski's phase model, Leiter's model, and Cox's transactional model of job stress) [64-67]. It is also rare to combine neurophysiological findings with the traditional questionnaire-based approach. Of the latter, the most commonly used include burnout scales (MBI-GS and Link Burnout Questionnaire (LBQ)) and organisational and individual factor surveys (Areas of Worklife Survey, State-Trait Anxiety Inventory, NEO Five-Factor Inventory, Beck's Depression Inventory). Based on their results, a structural equation path model was developed. This model examined the relationship between job burnout and organisational factors, as well as individual factors (anxiety, neuroticism and depression). So far, based on such a model, significant concordance between the MBI-GS and the LBQ has been shown for the diagnosis of burnout. In addition, the MBI-GS revealed stronger associations with organisational context and the LBQ with individual characteristics. Moreover, depression explains the impact of exhaustion (MBI-GS, LBQ), disappointment (LBQ), neuroticism (MBI-GS), and anxiety explains feelings of professional ineffectiveness (LBQ) [68].

The current identified research gap lies in the lack of integration of results from multiple sources (neurophysiological studies, surveys, etc.) at the level of multivariate computational analysis (including data-based - ML). In addition, the currently existing systems of reasoning, supporting clinical decisions and predicting health condition mainly concern sick people. Perhaps it is worth examining whether it would be faster, cheaper and more effective to develop the basics of a system intended for healthy people, people from risk groups (e.g. medical staff), as well as patients in the early stages of occupational stress and burnout. The above-mentioned approach allows for the earliest possible detection of the risk of the disease itself (and not just its occurrence) and mitigation of this risk, including by changing modifiable factors (diet, lifestyle) and keeping pharmacotherapy as a last resort. This approach shifts the focus of the health care system from treatment (medicine of sick people) to prophylaxis (preventive medicine of healthy people). This may be possible thanks to an innovative combination of existing methods of diagnostics and monitoring of occupational stress and burnout, methods and techniques of artificial intelligence into a predictive system. It would include both basic screening tests (in occupational medicine) and further, more detailed specialist diagnostics in cases that require it. By covering both healthy and sick people, susceptibility to personalization, scaling and extending to other clinical conditions or groups of patients (e.g. retirees, people just entering the labor market or still learning), the collected data would be easily transformed into clinical knowledge at the level of a single patient, groups risk or the entire population.

V.1. Directions for further studies

Further research should be conducted in order to verify and develop the hypotheses of this hypothesis presented in the article, and their ultimate goal is to develop a biomarker for diagnosing occupational burnout. Research on burnout often focuses on deficits in cognitive functioning (memory problems, impaired voluntary attention control) using behavioral and self-report measures of the consequences of burnout, but there is little research on the consequences of burnout at the neural level.

Computational analysis, inference and prediction from stress and burnout data can be part of larger eHealth systems, not only those dedicated to employees, but also to athletes, school children or the elderly, i.e. people who are in broad risk groups for general stress resulting from the pace of life or changing factors affecting well-being [67,68].

Further targeted development of dedicated hardware and software may lead to changes in the diagnosis of occupational stress and burnout, especially in the areas of:

- quick risk assessment (including against the background of the group),
- increased probability of detecting and classifying even small changes,
- a combination of traditional, neurophysiological and computational assessment in one method, which was not possible before.

The automated objective assessment of wellbeing-focused quality of life within eHealth systems can be conducted on a cyclical or continuous basis, facilitating the decision-making approach of primary care physicians, psychologists and psychiatrists, and providing the first alarm and prevention tool installed on our smartphones. This would perhaps reduce queues to specialists and secure a better classification of patients with severe occupational stress and burnout into urgent and others, ensuring a timely response (fig. 6, fig. 7). However, this requires the continuation of many interdisciplinary studies, in which the role of medical staff is crucial.

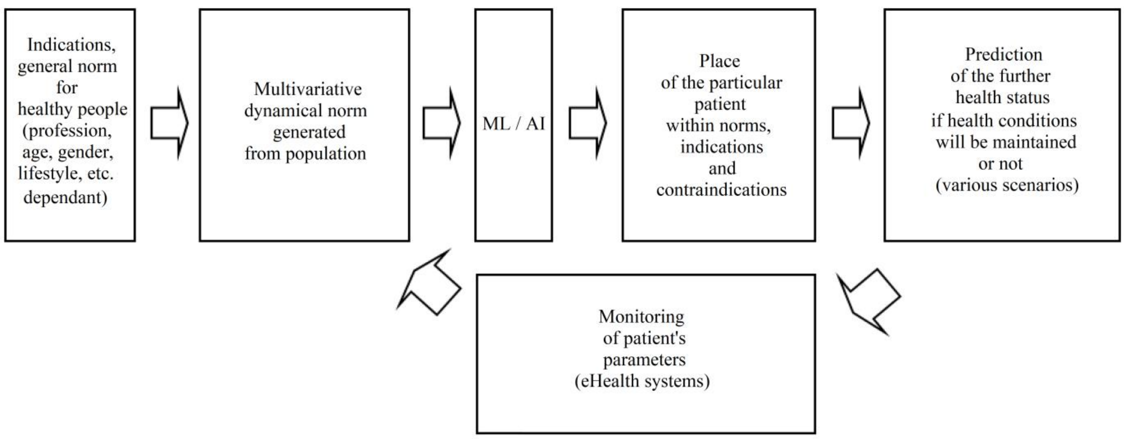

Figure 6. AI-based system of psychical preventive medicine (own version based on [69,70]).

Strengths	Weaknesses
Low cost per patient Relatively easy to introduce Intuitive use eHealth support 24/7 patient monitoring Automatization of data collection Standardization of early diagnosis AI-based analysis, reasoning and prediction Personalized medicine	Rare digitized long-term health records Need for medical staff education Need for common social awareness building AI-based fears Medicine of healthy people is not popular
Opportunities	**Threats**
Reduced workload of the medical specialists Early diagnosis Preventive alerts and interventions Early prevention of complications Bigger datasets for research, novel therapeutic methods and drugs development Novel factors for treatment scenarios	Non-acceptance Misuse of private data concerning mental health, activity, lifestyle, etc.

Figure 7. SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis for AI-based system of psychical preventive medicine (own version based on [69,70]).

Previous research indicates that, from a technological point of view, even relatively simple AI-based tools can be effective [69,70]. However, there is a need to detail which of a wide range of patient characteristics increase the likelihood of occurrence (are predictors) of occupational stress and burnout, and what is, from a computational point of view, the minimum set of such characteristics that need to be monitored in order to achieve the assumed prediction accuracy.

VI. Conclusions

Computational intelligence methods have often proven useful in the analysis of biomedical data, including in the modeling of cognitive diseases. There are already discussions about the future of research in the area of occupational stress and burnout, including defining and overlapping symptoms with other conditions [64-66]. Therefore, it can be expected that emphasis will be placed on neurophysiological research and computational models allowing for the clarification of the definition of the above-mentioned factors. diseases and the development of clear criteria and diagnostic markers.

The results of the research so far indicate that further research is still needed to understand the mechanisms observed in the neural correlates of the burnout syndrome, also with the help of artificial intelligence. So far, it has been shown that burnout syndrome is strongly associated with changes in the structures of brain, especially in regions responsible for emotions, motivation and stress, such as the HPA axis. Neuroimaging techniques give us an advantage over traditional subjective methods (interview) because they allow for a standardized, objective measurement of brain structures. Thanks to this approach, it is possible to identify specific brain structures involved in the pathogenesis of burnout and isolate those that give the earliest symptoms. Occupational stress and burnout should be treated as multi-stage processes whose growth dynamics and parameters can be objectively described in the form of a computational model. The generation of a dynamic norm from the population (as part of the process of cultural adaptation of the diagnostic process) will allow for the diversification of professions or susceptibility of the subjects. This will increase the subject of occupational burnout, facilitate understanding of the manner and pace of changes taking place, allowing for a more effective approach to prevention, diagnosis and treatment.

The computational models of burnout analyzed in this article support the development of the foundations of computational psychiatry and computational psychology. It also has a clinical effect: supporting specialists in the field of psychiatry and psychology, but also occupational medicine, in their daily efforts to reduce occupational burnout in inferring and predicting burnout, as well as identifying mechanisms and clinical indicators of chronic fatigue syndrome, work-related stress , professional burnout and natural cognitive changes.

The problem of defining burnout concerns in particular its overlap with other syndromes and disorders such as depression and anxiety. In addition, some individual characteristics affect susceptibility to burnout (e.g. neuroticism). Hence the need to link burnout measures with organizational and individual variables, and to assess the type and strength of these relationships [64-66].

In conclusion: the best currently observed neurophysiological markers of occupational stress and burnout may currently be a combination of EEG analysis (alpha power (IAF, PAF), P300, ERP (VPP and EPN)), diagnostic PET imaging (ACC, insular cortex and hippocampus) and monitoring changes in cortisol, prolactin, adrenocorticotropic hormone (ACTH), corticotropin-releasing hormone (CRH) and thyroid hormones, as well as plasma BDNF levels. In addition, ERPs (LPPs) are a marker significantly differentiating burnout from depression. The combination of traditional clinimetric tests, the aforementioned neurophysiological tests and AI-based big data analysis will provide new classifiers, highly accurate results and new diagnostic methods.

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