

OBJAWY WYPALENIA ZAWODOWEGO JAKO PODSTAWA MODELU OBLICZENIOWEGO

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Streszczenie: *Obecnym wyzwaniem jest zbadanie i optymalizacja obliczeniowych miar wypalenia zawodowego w celu obiektywnego określenia najlepszego sposobu obliczania satysfakcji z pracy, wypalenia zawodowego i predyktorów zamiaru odejścia z pracy w różnych grupach zawodowych. Celem badań prezentowanych w artykule był przegląd badań w zakresie obliczeniowego określenia zależności między doświadczaniem stresu w pracy a występowaniem objawów wypalenia zawodowego.*

Słowa kluczowe: *inteligencja obliczeniowa, sztuczne sieci neuronowe, model obliczeniowy, wypalenie zawodowe, zaangażowanie w pracę, motywacja do pracy.*

Burnout symptoms as a basis for computational model

Abstract: *The current challenge is to explore and optimise computational measures of burnout to objectively determine the best way to calculate job satisfaction, job burnout and predictors of intention to quit across occupational groups. The aim of the research presented in this article was to review studies in the field of computational determination of the relationship between the experience of stress at work and the occurrence of symptoms of professional burnout.*

Keywords: *computational intelligence, artificial neural networks, computational model, professional burnout, commitment to work, motivation to work.*

1. Wprowadzenie

Data science and computational models are increasingly being used due to the increasing availability of large data sets and the ability to perform advanced analytics in a relatively short time and at low cost, including with free tools. In a situation of rapid change, this allows leaders to stay abreast of this rapidly changing situation and the key factors shaping it, not always given in

an obvious way [1]. The challenge is to explore and optimise computational measures of burnout to objectively determine the best way to calculate job satisfaction, job burnout and predictors of intention to quit across occupational groups [2]. The Maslach Burnout Inventory-Human Services Survey (MBI-HSS) was used to assess job burnout in 452 Brazilian hospital nursing staff. Adjusted logistic regression models were fitted using different calculations of job burnout to estimate the outcomes of

interest. The sum of mean scores of the burnout subscales was the best predictor of job satisfaction (Cox-Snell $R^2 = 0.312$; Nagelkerke $R^2 = 0.450$) and intention to quit (Cox-Snell $R^2 = 0.156$; Nagelkerke $R^2 = 0.300$), as was high emotional exhaustion (Cox-Snell $R^2 = 0.219$; Nagelkerke $R^2 = 0.316$). MBI-HSS calculations can be used to estimate the impact of job burnout on nurse performance [2]. The use of multiple contemporary data science methods (e.g. natural language processing - NLP, artificial neural networks - ANN) for 15 different types of outcomes relevant to nurses was identified. The largest number of studies explored readmissions issues and pressure injuries, while topics such as acceptance of artificial intelligence/machine learning, professional burnout, patient safety and ward culture were underrepresented. Such studies help to understand the breadth and depth of the use of data science capabilities to improve clinical processes and patient outcomes that are relevant to nurses, and to identify gaps in the literature that need to be explored [1]. At the behavioural level, training overload increased impulsivity in economic choice by tending to favour immediate rewards over delayed rewards in a computational model. At the neural level, training overload results in reduced activation of the lateral prefrontal cortex, a key region of the cognitive control system, during economic choice. There is therefore a functional link between endurance exercise and the exercise of cognitive control. The concept of cognitive control fatigue combines the functional consequences of excessive physical training and mental work into a single neuro-computational mechanism that may contribute to other forms of clinical burnout syndromes [3]. Many activities require persistence in decision making, i.e. that the reward is worth the effort, even when fatigue sets in. Computational modelling was used in two effort-based tasks, one behavioural and one during fMRI showing that two latent fatigue states fluctuate from moment to moment on different time scales, but both reduce willingness to exert effort for reward. The value of one state increases after effort but is recoverable by rest, whereas the other unrecoverable state gradually increases with work. These results provide a computational framework for understanding the brain mechanisms of persistent and momentary fatigue [4]. Apathy and fatigue have distinct aetiologies but can manifest in phenotypically similar ways: each can lead to impaired goal-directed behaviour. Self-descriptive (questionnaire) ratings of apathy and fatigue were strongly correlated, i.e. these questionnaires were not sensitive to fundamental differences between the two traits and greater effort discounting was strongly associated with higher scores across all questionnaires,

suggesting that a common feature of both traits is lower motivation to engage in effortful behaviour. These findings have important implications for the assessment of both apathy and fatigue, particularly in clinical groups where these traits often co-occur [5]. Based on a social information processing approach and resource behaviour theory, collective burnout emerged as an organisational-level construct (employees shared perceptions of how burned out their colleagues are) and to predict individual burnout beyond indicators of demands and resources. Results from computational modelling showed that perceived collective burnout at time 1 was a significant predictor of burnout at time 2, after accounting for prior levels of burnout, demands (workload, teacher-student ratio, absenteeism rate) and resources (quality of school facilities). Perceived collective burnout is an important feature of the work environment that may be a significant factor in the development of burnout [6]. Current issues of particular relevance to psychiatry include the relationship between burnout and mental illness, attempts to redefine burnout as simply exhaustion, and the relative lack of evaluative research into potential interventions for treating and/or preventing burnout. The goal of treating burnout is usually to enable people to return to and be successful in their work, psychiatry should make an important contribution by identifying treatment strategies that would be most effective in achieving this goal [7]. Higher levels of autonomy, competence and relatedness predicted job burnout, even after accounting for job demands. Job resources such as basic psychological needs outlined by self-determination theory, along with perceived respect, buffer the negative impact of secondary trauma on job burnout. The occupational resource of perceived esteem also buffers the negative impact of physical job demands on burnout. These findings suggest that although job demands may be difficult to change, increasing the satisfaction of job resources may help mitigate burnout in physiotherapists. The current findings highlight the need for workplace interventions that cultivate the satisfaction of basic psychological needs, such as autonomy, competence and connectedness, to address job burnout among physiotherapists [8]. The COVID-19 coronavirus stress and burnout were positively related to depression, anxiety and stress, and negatively related to resilience. Coronavirus stress and COVID-19 burnout were correlated with increased levels of depression, anxiety and stress more than resilience, age and gender. The results also showed that coronavirus stress and COVID-19 burnout experienced in the later phases of the pandemic may be persistent risk factors for mental health problems [9].

Little is known about the variation in responses to work-related stress among new medical professionals (e.g., nurses) and the influence of demographic and organizational characteristics. Occupational stress levels in 343 newly recruited nurses were measured using the Occupational Stress Scale for Newly Graduated Nurses, and results were compared using latent growth modelling and group subgroup modelling of occupational stress development trajectories. The study found a significant decrease in occupational stress over the first three years of employment, with three distinctive trajectories observed: low occupational stress (19.1% of the sample); medium occupational stress (67.1%) and high occupational stress (13.8%). Subgroups with different demographic characteristics differed significantly in their perception of occupational stress during the first three years of practice, hence the need to develop models, observe and detail the developmental trajectories of occupational stress, establish alerts and tailor future intervention programmes (peer support programmes, standardised preceptor systems) [10]. Comprehensive Meta-Analysis analysis of the data, including meta-regression analysis, showed that as the sample size increases, the prevalence of depression and anxiety among frontline healthcare workers caring for patients with COVID-19 decreases [11].

There are many different research approaches related to occupational stress resulting from human-computer interaction (laboratory studies, cross-sectional studies, longitudinal case studies and intervention studies). Physiological, biochemical, somatic and psychological indicators of stress associated with occupational activities involving human-computer interaction have been identified. Many similar stressors have historically been observed in other automated occupations. Primary among these are:

- high workload,
- high work pressure,
- reduced control over work,
- inadequate training of workers in the use of new technologies,
- monotonous tasks,
- relations with superiors,
- fear of job security.

New stressors include:

- technology failures,
- technological slowdowns,
- electronic performance monitoring.

The effects of stress related to human-computer interaction in the workplace are:

- increased physiological arousal,

- somatic complaints (including musculoskeletal);
- mood disorders (anxiety, fear and anger),
- reduced quality of working life (reduced job satisfaction).

Interventions to reduce the stress associated with this:

- more effective approaches to technology implementation,
- increased employee participation in technology implementation,
- appropriate ergonomic conditions,
- increased organisational support,
- improved work content,
- appropriate workload,
- increased opportunities for social support,
- focus on system sustainability [12].

The prevalence of visual field abnormalities appears to be increased among Japanese workers who are intensive computer users, especially if they have refractive defects [13].

Compatible surfaces result in higher levels of muscle activation in the lower limbs facilitating increased caloric expenditure. Trends towards a sedentary lifestyle at work and increased obesity mean that active sitting facilitates increased caloric expenditure and muscle activation [14].

Increasing use of information and communication technology (ICT) devices is causing increasing exposure to visual display devices and important workplace health problems. The association between axial length of eye (AL) extension and ICT use was significantly higher in the >8 hour/day group compared with the <1 hour/day group. The association was particularly strong in the older groups, and higher-risk activities included word processing, emailing, preparing presentation materials and web browsing. In contrast, no such relationship was observed for the use of ICT for private purposes such as playing games. It is not known whether the effects of these two activities (ICT use at work and at home) add up [15].

The aim of the research presented in this article was to review studies in the field of computational determination of the relationship between the experience of stress at work and the occurrence of symptoms of professional burnout.

2. Concepts

Computational models of burnout are rare. Lack of complete knowledge on the neural correlates of burnout focuses studies mainly on the hypothalamus-pituitary-adrenal axis [16], but attempts to construct them are found mainly in modelling factors of sports training and related burnout [17-20]. The classical model of burnout is based on the following paradigm: adaptation to job stress may be influenced by risk factors:

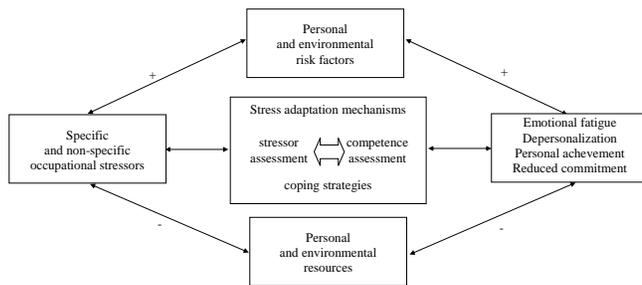
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 Objawy wypalenia zawodowego jako podstawa modelu obliczeniowego

- personal: inappropriate professional motivation, skill deficiencies, feelings of helplessness, developmental deficits in autonomy,
 - environmental: lack of support, social transformation and disorganization, material shortages,
- increasing the likelihood of professional burnout.

The above mentioned risk factors during adaptation to chronic stress can be counteracted by:

- subjective resources: professional competences and coping skills, sense of empowerment,
- environmental resources: social support, favourable organisational climate, anti-burnout counselling, recreational environment in the workplace (figure 1).

Fig. 1. Classical model of burnout [21].



The key to correct model operation is the proper selection of weights (forces of interactions between individual elements of the model) and their influence (inhibitory, excitatory) on the final effect of input signal processing. The aforementioned selection of combinations and weights is still a subject of research, selection and testing, as models should be personalised to a specific situation/person (figure 3, figure 4).

Fig. 2. Idea of model based on Brief Burnout Questionnaire Revised [22].

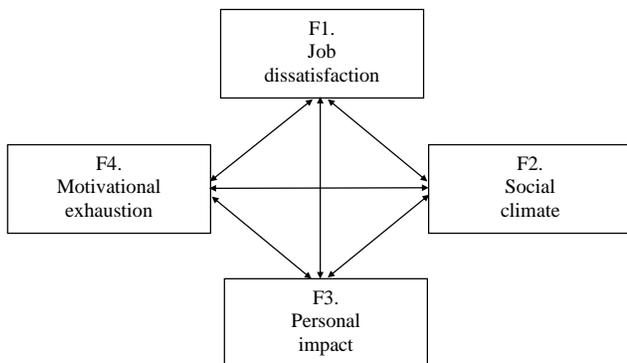


Fig. 3. Realization of model based on Brief Burnout Questionnaire Revised [22]

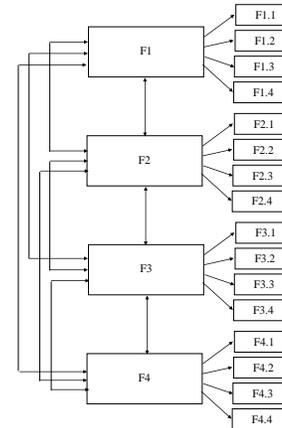
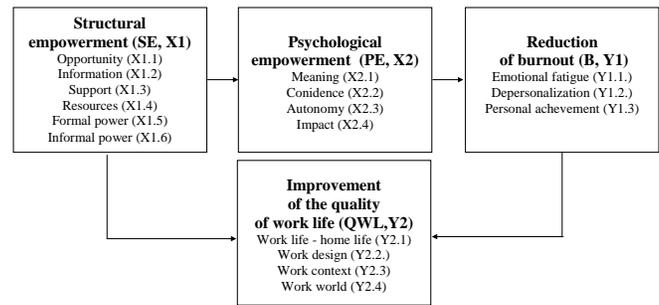


Fig. 4. Idea of empowerment model for burnout syndrome and quality of work life [23]



An accurate model can provide not only an accurate representation of a specific situation, but also allow predictions to be made. To ensure rapid convergence of models and to avoid situations that are impossible to implement in practice, models are run with a certain set of default starting parameters, usually based on the common sense experience of the researchers (figures 4-6).

Fig. 5. Realization (simplified) Idea of empowerment model for burnout syndrome and quality of work life [23]

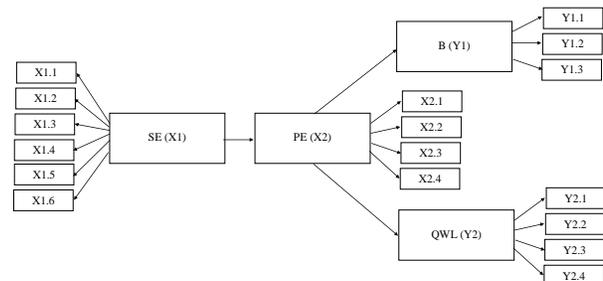
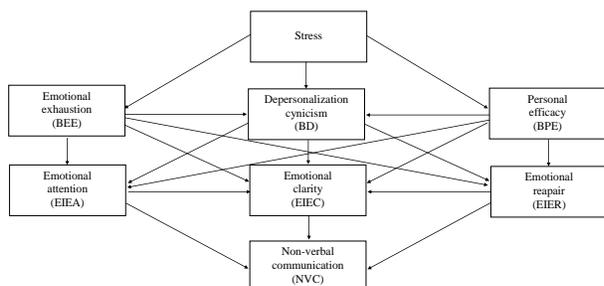


Fig. 6. Idea of explanatory model of perception of stress based on Maslach Burnout Inventory (MBI) [24]



The own models are mainly based on own research on work-related stress and burnout in a group of physiotherapists and computer scientists. Both traditional neural networks and deep learning, but also fuzzy and fractal analysis were used to develop them. This allows us to go beyond traditional paradigms and perhaps develop new, as yet undiscovered mechanisms underlying the build-up of work-related stress towards burnout. It is important to remember that the burnout model is only a special case derived from the model of a healthy body's normal response to work-related stress, and the trajectories leading to burnout may be different.

3. Discussion

Previous research on computational models of burnout has produced interesting solutions, based mainly on surveys. The development of methods of computational data analysis brings new opportunities related to deep learning, fuzzy analysis (in the area of uncertainty mapping, the impact of the direction of change or the nature of the standard: point, interval) or multifractal analysis (in the area of trend susceptibility analysis). There is a need for objectivisation of burnout surveys, their automation and personalisation. An important element of future research is predictive models, allowing digital simulation of scenarios of possible developments based on the current state and the experience base of other cases (both healthy and pathologically developing). A limitation of the research to date has been the focus on traditional surveys. The introduction of screening would allow faster identification and monitoring of both the norm and the deviations from it that occur, often specific to a population or a moment in time (e.g. a post-pandemic situation). High availability of data would enable the use of big data

analysis tools. This would enable the application of the so-called dynamic norm, i.e. the projection by means of multidimensional scaling into 3D space of trajectories of physiological and pathological changes from a large set of parameters/characteristics and their changes describing as accurately as possible the state of the patient. In this way it would be possible to image the so-called distance from the norm.

5. Wnioski

Computational models of the correct response to work-related stress and models presenting various deficiencies, deformations and overloads of the above models, including those leading to burnout, may be useful in understanding the detailed mechanisms of the above processes. The current stage of development of the aforementioned models indicates the need for further research, including towards the individualisation of computational models of burnout.

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