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Fuzzy Approach to Computational Classification of Burnout—Preliminary Findings

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Featured Application: Potential application of the work concerns automatic or semi-automatic systems for early work-related stress or burnout detection and classification.

Abstract: There is a common belief that medical professions generate more work-related stress and earlier job burnout. We tested two groups: study group 1: medical (physical therapists, $n = 30$), and study group 2: non-medical (informaticians, $n = 30$). The purpose of this study was to find new, more reliable models for calculating work-related stress and burnout in the two aforementioned different professional groups. In the paper, we focused on a new model of algorithm based on AI methods that extends the interpretability of the scale of results obtained using the MBI test. The outcomes of the Maslach Burnout Inventory (MBI) were analysed in both study groups. These became the starting point for the development of three different fuzzy models, from which, after comparison, the one best suited to the study groups and the way they were evaluated was selected. Among the patients participating in the study, the following results were obtained: MBI values expressed as median values were significantly higher in group 2 than in group 1. The computational analysis showed that the contribution of the different parts of the MBI test to the final score was unequal in both groups. AI allowed for optimal selection of the model parameters for the study group, from which an algorithm was created to optimise the selection of tools or their parameters. A computational tool can do this faster, more accurately, and more efficiently, becoming an important supporting tool. In the medical context, the main benefit of the results presented in this paper is the definition of an evaluation model that transforms the MBI test scores into a universal percentage scale while preserving the properties of the guidelines underlying the MBI. An additional advantage of the proposed solution is the readability and flexibility resulting from the linguistic rules underlying the model.

Keywords: computational models; fuzzy logic; fuzzy systems; occupational stress; burnout

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1. Introduction

Workers' mental health, and in particular, work stress, depression, and burnout are important public health issues according to the World Health Organisation (WHO); governmental and non-governmental organisations; and professional, scientific, and clinical associations. Current efforts focus on mental health equity, with particular attention to vulnerable and at-risk groups [1]. The authors identified the levels of mental health and inequities in the impact of stress on different groups, especially vulnerable and disadvantaged groups. In particular, risk factors may include socioeconomic status or occupation (e.g., medical or irregular income), gender, sexual orientation, ethnicity, age, religion, refugee or immigrant status, and physical or mental disability. There is a common belief that medical professions generate more work-related stress and earlier job burnout [2–5]. Therefore, we tested two groups: medical (physiotherapists) and non-medical (informaticians). The consequences of stress and professional burnout can be very serious for the employees themselves, their families, and their clients, as well as the entire institutions/companies in which they work. On the basis of existing research, it is possible to identify which factors are key to, for example, subjectively perceived well-being or performance at work. These are grouped into physical, cognitive, and affective and classified at the individual level, work level, and family level [6–8]. The strength and manner of affect depends on many factors. Analysis and computational modelling help to isolate them, analyse them, and encapsulate them with mathematical and cognitive mechanisms that will help to improve experimental research in the future. Fuzzy logic helps us describe values and processes whose values are described linguistically, with some uncertainty.

A similar method has previously been successfully used for computational analysis of clinical gait analysis data [9,10] where Ordered Fuzzy Numbers were used [11,12]. This model is particularly useful in cases where the direction of change plays an important role, such as in many health problems.

Creating artificially intelligent computational models of phenomena is the traditional way to combine theoretical concepts and experimental results. This makes it possible not only to extract potential mechanisms of action, sometimes not yet fully understood, but also to make inferences and estimates on the basis of sets of incomplete, uncertain data or to predict future values. Classical machine learning (ML) based on n-dimensional feature vectors can be considered as an approximation of reality using multivariate statistics. In some cases, including biomedical analysis, the aforementioned approximation may not be sufficient to perform a differential diagnosis and to evaluate the progress of the therapy process, thus increasing the efficiency of diagnosis, therapy, rehabilitation, and care for specific cases. Traditional ML involves automating the process of finding the hypothesis (model) that best fits the observed data. In order to objectify the above-mentioned activity, it is necessary to search, in a data-driven manner, the widest possible hypothesis space in order to exclude strongly local solutions. This is due to the fact that complex systems have a complex structure of hypothesis space with many local minima, previously unknown, with large amounts of available data. The problem lies in the representation of the data. Most of the data, including the traditional information on input and output states, are described by vectors, which at the same time enforce some traditional ways of processing them, based, among others, on sets of equations. Our proposed fuzzy representation allows for a linguistic representation of the data, which better reflects the continuous rather than granular structure of the data describing our reality, most physical and chemical phenomena, and health, but for the digital computational process.

Fuzzy boundaries between states or their variability under the influence of a set of parameters place high demands on computational models. In some cases, this makes it possible to distinguish correct behaviour (in medicine: physiological), from incorrect behaviour (in medicine: pathological), that is, to artificially capture the so-called norm from the data. It is important when the abovementioned norm fluctuates under the influence of the environment (environmental factors), but also when it can be changed on purpose as part of controlling the value of modifiable factors (e.g., increasing the immunity of society by vaccination or reducing the risk of civilization diseases by promoting a well-balanced diet, physical activity, or not smoking). The rate of occurrence or impact of the aforementioned changes can vary, depending on the factor and sometimes the direction of change. Some processes escalate very quickly but reverse slowly, and some even have non-linear dynamics (e.g., on the snowball principle), including ranges of values (e.g., due to the threshold value and saturation area of the process).

Existing computing solutions have not quite lived up to expectations. There is a lack of computational models of occupational stress or burnout, especially as these are initially relatively quick, simple, and cheap models, allowing for screening of data rather than in-depth analysis of phenomena, which will come later. There is lack of previous works as well as the models for comparison. To the authors' knowledge, this is the first study to assess and compare work stress and burnout between physical therapists and informaticians. We identified only one article concerning the application of AI in burnout assessment concerning the use of electrocardiogram data generated from people experiencing burnout to develop an AI-enabled model (convolutional neural network (CNN)) to predict the presence of stress and burnout in healthcare workers in the COVID-19 era [13]. We identified only two papers on the application of AI to stress detection and management. The first of them focussed on the rapidly growing use of conversational agent interventions (including chatbots and robots) for mental health. All 13 studies reviewed reported a reduction in psychological distress post-intervention, and five controlled studies showed significant reductions in psychological distress compared to the non-robotic control groups. Although the effectiveness and acceptability of the conversational agent intervention for mental health problems was promising, further experimental studies demonstrating its efficacy and effectiveness are needed. It is also necessary to improve the intervention itself, fully elucidate the mechanisms of action, and demonstrate equivalence with other treatments. This may increase user and clinician acceptance and maximise reach [14]. The second study examined the use of heart rate variability (HRV) as an objective measure of psychological stress in a surgical setting. HRV provides an objective method of assessing work-related stress—it was able to identify stressors and indicate differences in stress levels between participants. The use of uniform guidelines to standardise testing and to perform artifact correction will further improve crucial assessment of the long-term effects of psychological stress and recovery [15].

It is worth underlining the fact that the purpose of this study was not to be a contribution to the psychometric analysis of MBI. It aimed to find new, more reliable models for calculating work-related stress and burnout in two different professional groups (medical and non-medical). In the paper, we focused on a new model of algorithm based on AI methods that extends the interpretability of the scale of results obtained using the MBI test. The contribution of the work will enhance the possibilities of computational support of assessment and further prognosis of work-related stress and burnout.

2. Materials and Methods

2.1. Materials

The results of the MBI were analysed in study group 1 (n = 30): physical therapists, and in study group 2 (n = 30): informaticians. For the purpose of the study, it was difficult, but possible, to find a population of informaticians with a balance between the number of men and women. According to current datasets, women in Poland constitute 52% of the population, yet their share of the labour market is 44%, and in strictly engineering positions in major companies, it is only 16%, which includes the 30% (and growing) of professionals in the IT industry. Global trends are similar. A clinical summary of the subjects is presented in Table 1.

Table 1. Sample characteristics.

	Study Group 1 (*n* =30, 100%)	**Study Group 2 (*n* =30, 100%)**
Age (years)		
Mean	26.73	25.80
SD	4.03	4.15
Min	22	20
Q1	24	23
Median	25	24.5
Q3	29	27
Max	34	35
Seniority (years)		
Mean	3.03	3.30
SD	2.61	2.58
Min	1	0
Q1	1	1

Table 1. *Cont.*

	Study Group 1 (*n* =30, 100%)	Study Group 2 (*n* =30, 100%)
Median	1.50	3
Q3	4.75	4
Max	8	9
Gender:		
Females (F)	18 (60%)	16 (53.33%)
Males (M)	12 (40%)	14 (46.67%)

The results were stored in an MS Excel spreadsheet and analysed using the Statistica 13 software. The *p*-value was set at 0.05.

2.2. Methods

There is at least several clinical scores and scales used to assess work stress, burnout, and well-being, including the PSS-10, MBI, and SWLS [16–22].

Perceived Stress Scale (PSS) is a classic stress assessment instrument [16,17]. The PSS-10 has good internal consistency across scales, measuring two aspects: perceived helplessness and perceived self-efficacy with a Cronbach's alpha ranging between 0.74 and 0.91 [16–18].

Maslach Burnout Inventory (MBI) measures burnout as defined by the World Health Organization (WHO) and in the International Classifications of Diseases (ICD-11: QD85).

MBI has been in development since 1983 [19,20]. A review of 6541 studies, of which 19 were evaluated and 15 were on the MBI, showed that sufficient validity can only be achieved when combining the MBI with other scales [21].

The primary results of the Satisfaction with Life Scale (SWLS) to be considered are the described indicators of subjective well-being. It contributes to the definition of "well-being at work" and to the development of effective interventions to improve both well-being outcomes and their correlates: general health, social relationships, and quality of life. Low health and well-being in employees lead to many consequences, such as sick leave, low productivity, and absenteeism [22].

The main instruments used in the study to measure work stress and burnout were the MBI and SWLS.

2.3. Statistical Analysis

The results of MBI were subjected to statistical and computational analysis. All data were analysed using Statistica version 13. The normality of the data distribution was checked using the Shapiro–Wilk test ($\alpha = 0.05$). Values for distributions close to the normal distribution were presented using mean values and standard deviation (SD). Values for distributions different from the normal distribution were presented by median, minimum value, maximum value, and lower quartile (Q1) and upper quartile (Q3). Spearman's Rho was used to describe correlations between the results. The significance level was set at 0.05 because this value is commonly used in biomedical publications, and we would like to ensure that our results can be compared with others published within the topic of burnout analysis.

2.4. Computational Methods

The problem is very complex, and we are still searching for a mathematical solution appropriate for its description, both in terms of values and changes over time. The problem of professional burnout can be considered imprecise due to:

- dependence on the context of the occupation: there are different causes of burnout in medical professions and others (e.g., in office work) and other cause-effect relationships (including those resulting from strategies to counteract burnout, e.g., frequency of job rotations);

- occurrence of up to 12 phases of job burnout: honeymoon, onset, chronic, habitual, etc., during the course of burnout (even up to several years);
- various symptoms, often co-occurring at different levels of intensity: exhaustion, lack of energy, constant fatigue, sleep disorders, reduced performance, concentration and memory problems, inability to make decisions, etc.;
- factors differentiating patients, such as diet, sleep, physical activity, co-occurrence of movement disorders (e.g., in physiotherapists);
- about different directions of changes in values, e.g., due to obtaining temporary support from co-workers or family, vacation, therapy, etc.;
- with different susceptibility to negative trend reversal.

In addition, there is a lack of precise mathematical models, and the tool for computational analysis is fuzzy logic in the form of a fuzzy system. With our models, we want to answer the following question in the future: can this cause value fluctuations and uncertainty even when using several tests simultaneously?

One of the popular techniques for defining fuzzy systems is neuro-fuzzy techniques (an example is presented in [23]). However, the proposed fuzzy models represent linguistically described models already defined and used by medical professionals (psychologists). Therefore, the propositions presented in this paper use Mamdani-type fuzzy systems, which are effective for linguistically represented models.

Three models were proposed on the basis of general suggestions from the description of the MBI. From the characteristics of the MBI, we can point to the general numerical properties of the results. First, there are three groups of the data which together are interpreted as a final evaluation of burnout. Each of those groups has a different range of values and direction of interpretation. Those groups are as follows:

1. “Emotional exhaustion” X_{em}

- range of values $X_{em} = (0; 54)$;
- general interpretation: the higher the value, the worse the psychological condition.

2. “Depersonalisation” X_{dep}

- range of values $X_{dep} = (0; 30)$;
- general interpretation: the higher the value, the worse the psychological condition.

3. “Lack of personal achievements” X_{achiev}

- range of values $X_{achiev} = (0; 48)$;
- general interpretation: the lower the value, the worse the psychological condition—note that it is opposite to the other groups.

These three groups together make up input data X to the models (and in the general analysis):

$$X = \{X_{em}, X_{dep}, X_{achiev}\}.$$

The following common parameters of fuzzy systems were used in all of the proposed models:

- aggregation of premises in the rules: PROD;
- implication: MIN;
- aggregation of results from the rules (accumulation): MAX;
- deffuzyfication: centre of gravity (COG).

By using fuzzy systems in the model of evaluation, we obtain a flexible tool for scaling the results. We use that advantage to make the results scale as an interval [0;1]. However, in the proposed models, the output linguistic variables will vary due to the significant difference of the models.

The proposed models of evaluation are presented in the sequence of their evolution, from the first simple transition of MBI idea to the fuzzy system, to the most interesting and promising model of a hierarchical fuzzy system.

We use mainly normal trapezoidal fuzzy sets (they can also be called fuzzy intervals); therefore, to describe them, we use a similar notation as in LR fuzzy sets (see Dubois, 1980 [24]). However, we change the order of the values. For example, a trapezoidal fuzzy set T can be describedas below:

$$T = (l, k_1, k_2, r)$$

where l is the beginning of the support of T, r is end of the support, and k_1, k_2 define the kernel interval of trapezoidal fuzzy set T.

2.4.1. Basic Fuzzy Evaluation Model—Proposition 1

First, a concept of the fuzzy evaluation model was defined with three inputs each for each group of values—linguistic variables. Each variable consists of two values: "low" and "high".

1. "Emotional exhaustion" X_{em}-trapezoidal fuzzy sets; $X^L{}_{em}$ represents "low" and $X^H{}_{em}$ represents "high":

$$X_{em} = \{X^L{}_{em}, X^H{}_{em}\}, X^L{}_{em} = (0, 0, 16, 27), X^H{}_{em} = (16, 27, 54, 54)$$

2. "Depersonalisation" X_{dep}-fuzzy sets:

$$X_{dep} = \{X^L{}_{dep}, X^H{}_{dep}\}, X^L{}_{dep} = (0, 0, 8, 14), X^H{}_{dep} = (8, 14, 30, 30)$$

3. "Lack of personal achievements" X_{achiev}-fuzzy sets:

$$X_{achiev} = \{X^L{}_{achiev}, X^H{}_{achiev}\}, X^L{}_{achiev} = (0, 0, 31, 39), X^H{}_{achiev} = (31, 39, 49, 49)$$

The values of the proposed sets are taken from the general interpretation of the MBI method [16,17]. The used fuzzy sets are presented in Figure 1.

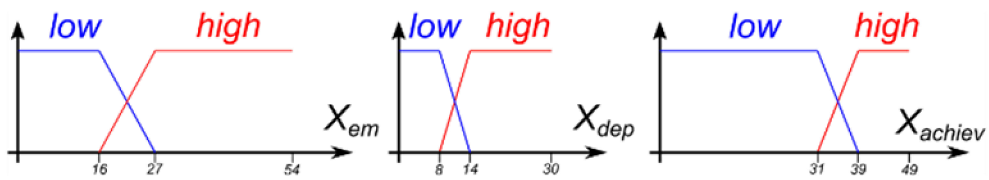

Figure 1. Used fuzzy sets.

As we have three inputs with separate values to maintain the flexibility of the expression in the rule base of the fuzzy system, we need four output values. As was mentioned before, for the evaluation, we use the [0;100] interval. Therefore, output variable E is described as below:

$$E = \{Y_1, Y_2, Y_3, Y_4\},$$

$$Y_1 = (0, 0, 0, 0.333), Y_2 = (0, 0.333, 0.333, 0.667), Y_3 = (0.333, 0.667, 0.667, 1),$$
$$Y_4 = (0.667, 1, 1, 1).$$

We can notice that these are triangular fuzzy sets; however, for the consistency of the description, we kept the four-value notation.

The centre of gravity (COG) method is used to perform the defuzzification. It should therefore also be mentioned that for practical reasons, to avoid extra scaling in the computer processing, we use some extended fuzzy sets (see Figure 2), $Y_1 = (-0.333, 0, 0, 0.333)$ and $Y_4 = (0.667, 1, 1, 1.333)$, to make it possible to obtain exactly 0 and exactly 1 as defuzzified values (Figure 1).

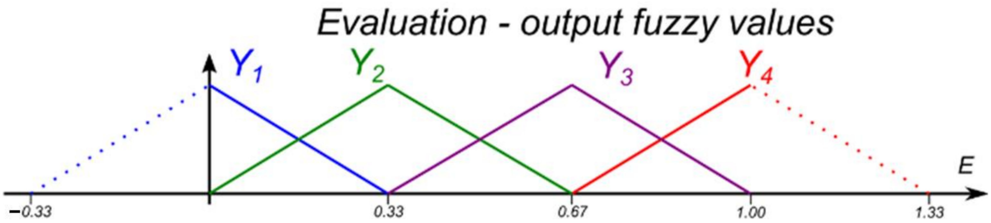

Figure 2. Output fuzzy values.

The rule base consists of eight rules which represent the basic assumptions of the MBI method. The more aspects of burnout return a higher state, the worse the person's psychological condition.

The specific rules are as follows:

$$R_1\text{: IF } x_{em} \text{ is } X^L{}_{em} \text{ AND } x_{dep} \text{ is } X^L{}_{dep} \text{ AND } x_{achiev} \text{ is } X^L{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_2\text{: IF } x_{em} \text{ is } X^H{}_{em} \text{ AND } x_{dep} \text{ is } X^L{}_{dep} \text{ AND } x_{achiev} \text{ is } X^L{}_{achiev} \text{ THEN } e = Y_3,$$
$$R_3\text{: IF } x_{em} \text{ is } X^L{}_{em} \text{ AND } x_{dep} \text{ is } X^H{}_{dep} \text{ AND } x_{achiev} \text{ is } X^L{}_{achiev} \text{ THEN } e = Y_3,$$
$$R_4\text{: IF } x_{em} \text{ is } X^L{}_{em} \text{ AND } x_{dep} \text{ is } X^L{}_{dep} \text{ AND } x_{achiev} \text{ is } X^H{}_{achiev} \text{ THEN } e = Y_1,$$
$$R_5\text{: IF } x_{em} \text{ is } X^H{}_{em} \text{ AND } x_{dep} \text{ is } X^H{}_{dep} \text{ AND } x_{achiev} \text{ is } X^L{}_{achiev} \text{ THEN } e = Y_4,$$
$$R_6\text{: IF } x_{em} \text{ is } X^L{}_{em} \text{ AND } x_{dep} \text{ is } X^H{}_{dep} \text{ AND } x_{achiev} \text{ is } X^H{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_7\text{: IF } x_{em} \text{ is } X^H{}_{em} \text{ AND } x_{dep} \text{ is } X^L{}_{dep} \text{ AND } x_{achiev} \text{ is } X^H{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_8\text{: IF } x_{em} \text{ is } X^H{}_{em} \text{ AND } x_{dep} \text{ is } X^H{}_{dep} \text{ AND } x_{achiev} \text{ is } X^H{}_{achiev} \text{ THEN } e = Y_3,$$

where R_i is consequent rules; x_{em}, x_{dep}, x_{achiev} are input values from the MBI questionnaire for certain groups of questions, respectively: "emotional exhaustion", "depersonalisation", and "lack of personal achievements"; and e is evaluation partial value as the result of the rule.

It is worth remembering here that for the "lack of personal achievements" group, the meaning is reversed, so high values mean a worse psychological state, not better. Thus, R_8 is all high states not concluding with the higher (worse) evaluation, which would be Y_4.

2.4.2. Hierarchical Fuzzy Evaluation Model—Proposition 2

The next evaluation model was extended to the hierarchical fuzzy construction. It simplified the evaluation of certain groups—some effects of burnout according to the MBI method. At the lower level, we have three mini fuzzy systems with two rules each. Their role is to evaluate each parameter separately, then its result is transferred as input to the next level fuzzy system, whose role is to aggregate the partial evaluations into one global evaluation of psychological state of the given person. A general structure of the proposed fuzzy system is presented in Figure 3. The first level is two very simplified SISO fuzzy systems, with two fuzzy input values—the same as in the previous solution. As for the output variable, we use two values: $Y_1 = (0, 0, 0, 1)$, and $Y_2 = (0, 1, 1, 1)$. Moreover, as before, they are extended for the purposes of simplifying the calculations, to make defuzzification by centre of gravity fit into interval [0;1].

Rules for "emotional exhaustion" are as follows:

$$R_1\text{: IF } x_{em} \text{ is } X^L{}_{em} \text{ THEN } e_{em}{=}Y_1,$$

$$R_2\text{: IF } x_{em} \text{ is } X^H{}_{em} \text{ THEN } e_{em}{=}Y_2.$$

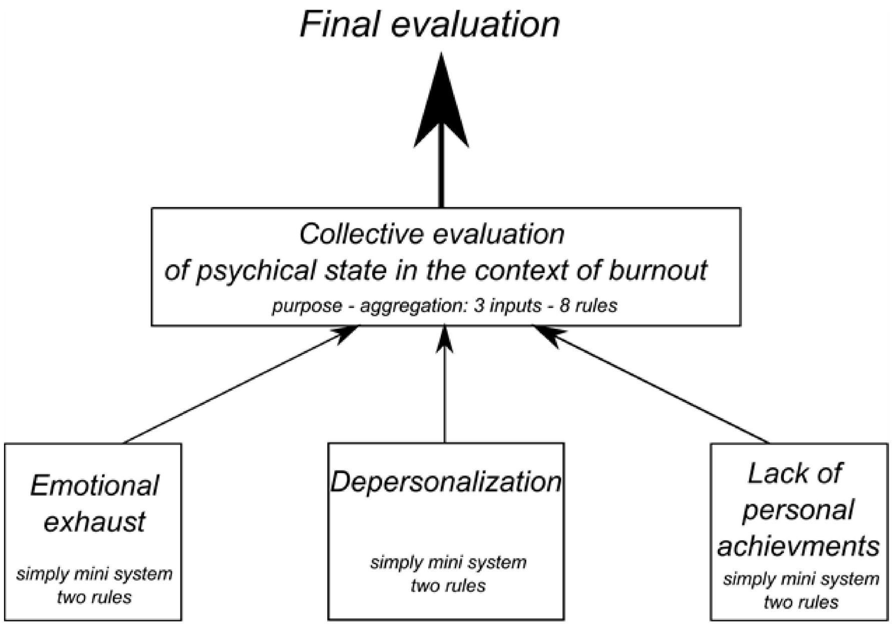

Figure 3. General structure of the proposed fuzzy system.

For "depersonalisation", the rules are adequate; however, we have an inverted evaluation for "lack of personal achievements", so

$$R_1\text{: IF } x_{achieve} \text{ is } X^{L}{}_{achieve} \text{ THEN } e_{achiev} = Y_2,$$
$$R_2\text{: IF } x_{achieve} \text{ is } X^{H}{}_{achieve} \text{ THEN } e_{achiev} = Y_1.$$

As we have two possible output values from the three first-level systems, the final system has 2^3 rules. Thus, the top-level fuzzy system uses the same evaluation output variable as in the Proposition 1—$E = \{Y_1, Y_2, Y_3, Y_4\}$. The rules are as follows:

$$R_1\text{: IF } e_{em} \text{ is } X^{L}{}_{em} \text{ AND } e_{dep} \text{ is } X^{L}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{L}{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_2\text{: IF } e_{em} \text{ is } X^{H}{}_{em} \text{ AND } e_{dep} \text{ is } X^{L}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{L}{}_{achiev} \text{ THEN } e = Y_3,$$
$$R_3\text{: IF } e_{em} \text{ is } X^{L}{}_{em} \text{ AND } e_{dep} \text{ is } X^{H}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{L}{}_{achiev} \text{ THEN } e = Y_3,$$
$$R_4\text{: IF } e_{em} \text{ is } X^{L}{}_{em} \text{ AND } e_{dep} \text{ is } X^{L}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{H}{}_{achiev} \text{ THEN } e = Y_1,$$
$$R_5\text{: IF } e_{em} \text{ is } X^{H}{}_{em} \text{ AND } e_{dep} \text{ is } X^{H}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{L}{}_{achiev} \text{ THEN } e = Y_4,$$
$$R_6\text{: IF } e_{em} \text{ is } X^{L}{}_{em} \text{ AND } e_{dep} \text{ is } X^{H}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{H}{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_7\text{: IF } e_{em} \text{ is } X^{H}{}_{em} \text{ AND } e_{dep} \text{ is } X^{L}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{H}{}_{achiev} \text{ THEN } e = Y_2,$$
$$R_8\text{: IF } e_{em} \text{ is } X^{H}{}_{em} \text{ AND } e_{dep} \text{ is } X^{H}{}_{dep} \text{ AND } e_{achiev} \text{ is } X^{H}{}_{achiev} \text{ THEN } e = Y_3,$$

where e_{em}, e_{dep}, and e_{achiev} are input values that are evaluations (outputs) from the first-level fuzzy systems; these values belong to the [0;1] interval.

2.4.3. Extended Hierarchical Fuzzy Evaluation Model—Proposition 3

The third proposition is an extended hierarchical model. The structure is the same as in the previous proposition. However, in the first-level systems, the information analysis is more granular. We use three fuzzy sets in the input variables: "low", "medium", and "high".

$$X_{em} = \{X^{L}{}_{em}, X^{M}{}_{em}, X^{H}{}_{em}\}, X^{L}{}_{em} = (0, 0, 0, 16), X^{M}{}_{em} = (0, 16, 27, 54),$$
$$X^{H}{}_{em} = (27, 54, 54, 54).$$
$$X_{dep} = \{X^{L}{}_{dep}, X^{M}{}_{dep}, X^{H}{}_{dep}\}, X^{L}{}_{dep} = (0, 0, 0, 8), X^{M}{}_{dep} = (0, 8, 14, 30),$$
$$X^{H}{}_{dep} = (14, 30, 30, 30).$$

$$X_{achiev} = \{X^{L}{}_{achiev}, X^{M}{}_{achiev}, X^{H}{}_{achiev}\}, X^{L}{}_{achiev} = (0, 0, 0, 31), X^{M}{}_{achiev} = (0, 31, 39, 49),$$
$$X^{H}{}_{achiev} = (39, 49, 49, 49).$$

Such a solution provides an evaluation concentrated more on the medium values. This leads to flexibility in the middle of the scale, which is appropriate and useful in the case of assessing the state of burnout.

For the output, we also use a variable with three fuzzy values:

$$E = \{Y_1, Y_2, Y_3\},$$
$$Y_1 = (0, 0, 0, 0.5), Y_2 = (0, 0.5, 0.5, 1), Y_3 = (0.5, 1, 1, 1).$$

The rules are similar to those from Proposition 2. There are only added medium value rules such as

$$\text{IF } x_i \text{ is } X^{M}{}_{i} \text{ THEN } e_i = Y_2,$$

where *i* points to one component ("emotional exhaustion", etc.) of the burnout according to the MBI method.

In the top-level hierarchy, we have the same fuzzy system as in Proposition 2.

The change between the last two propositions may be found to be cosmetic. However, for the results of the working system, it is a significant change, much more than between the first and second model.

To present the calculation procedure in more detail, we follow the individual steps on one of the analysed datasets (for the 30th set in Table 2—results for informaticians, the third model). As the input data, we have three values gathered from the questionnaires: emotions:15, depersonalisation: 7, lack of personal achievements: 17. These input data generate the outputs from the first-level systems—0.458, 4.218, and 0.730, respectively. Next, these values are used as input data for the final system. This fires all eight rules where the result after defuzzification is 0.532.

Table 2. Results for group 1.

	MBI
Mean	16.47
SD	4.19
Min	10
Q1	14
Median	15
Q3	17.75
Max	25
Distribution	data are not normally distributed

3. Results

3.1. General Results

The results of the study are presented in the tables below (Tables 2 and 3). The MBI values expressed as median values were significantly higher in group 2 than in group 1.

Table 3. Results for group 2.

	MBI
Mean	17.43
SD	2.8
Min	14
Q1	15
Median	17
Q3	18.75
Max	24
Distribution	data are not normally distributed

The computational analysis showed that the contribution of the different parts of the MBI test to the final score is unequal in both groups (Table 4).

Table 4. Fuzzy models: MBI, and group 1 and 2.

		Physical Therapists			Informaticians		
		Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
testing	test—min values	0.000	0.000	0.000	0.000	0.000	0.000
	test—max values	1.000	1.000	1.000	1.000	1.000	1.000
	test—average values	0.410	0.423	0.500	0.410	0.423	0.500
	test—all zeroes	0.333	0.333	0.333	0.333	0.333	0.333
results	1	0.403	0.417	0.483	0.879	0.871	0.668
	2	1.000	1.000	0.632	0.333	0.333	0.285
	3	0.411	0.429	0.619	1.000	1.000	0.720
	4	0.333	0.333	0.414	0.333	0.333	0.387
	5	0.403	0.417	0.474	0.833	0.833	0.670
	6	1.000	1.000	0.660	0.333	0.333	0.290
	7	0.333	0.333	0.610	1.000	1.000	0.720
	8	0.333	0.333	0.470	0.333	0.333	0.400
	9	0.333	0.333	0.422	0.833	0.833	0.676
	10	1.000	1.000	0.687	0.333	0.333	0.278
	11	0.469	0.485	0.621	1.000	1.000	0.695
	12	0.333	0.333	0.434	0.333	0.333	0.389
	13	0.333	0.333	0.487	0.879	0.871	0.668
	14	1.000	1.000	0.676	0.333	0.333	0.278
	15	0.422	0.445	0.613	1.000	1.000	0.727
	16	0.333	0.333	0.434	0.333	0.333	0.400
	17	0.407	0.420	0.471	0.462	0.470	0.470
	18	0.333	0.333	0.397	1.000	1.000	0.558
	19	0.713	0.706	0.546	0.546	0.538	0.568
	20	0.597	0.601	0.619	1.000	1.000	0.635
	21	0.670	0.670	0.577	0.422	0.445	0.562
	22	0.333	0.333	0.389	1.000	1.000	0.608
	23	0.926	0.913	0.652	0.333	0.333	0.350
	24	0.534	0.557	0.604	1.000	1.000	0.706
	25	0.407	0.420	0.492	0.462	0.470	0.554
	26	0.596	0.583	0.620	0.666	0.666	0.622
	27	0.929	0.916	0.607	0.469	0.485	0.577
	28	0.593	0.579	0.570	1.000	1.000	0.637
	29	0.333	0.333	0.486	0.403	0.417	0.529
	30	0.407	0.420	0.484	0.333	0.333	0.532
statistical analysis	min	0.333	0.333	0.389	0.333	0.333	0.278
	max	1.000	1.000	0.687	1.000	1.000	0.727
	mean	0.541	0.544	0.542	0.639	0.641	0.539
	SD	0.246	0.242	0.092	0.294	0.292	0.149
	median	0.409	0.425	0.558	0.507	0.511	0.565
	Q1	0.333	0.333	0.471	0.333	0.333	0.389
	Q3	0.652	0.653	0.619	1.000	1.000	0.668

3.2. Fuzzy Evaluation Models Summary

Three fuzzy models were formulated. The first model represents a global attempt (in the context of the MBI questionnaire) to measure the psychological state of the people. The next two models represent another algorithm. Here, first partial evaluations were calculated. Next, a kind of aggregation was performed.

However, all of the models introduced inference on the basis of input values. New features were extracted as measurable properties of the observed phenomenon. The aforementioned datasets became the starting point for the development of three different fuzzy models, from which, after comparison, the one that was best suited to the study groups and the way they were evaluated was selected. The third model clearly has an advantage.

In summary, three fuzzy systems for the evaluation of certain psychological factors were defined in this paper. In general, the main added value of the presented proposals is the translation of existing medical procedures into evaluative algorithms while preserving the assumptions of the linguistically described model.

Computational analysis was performed using author's software. It is part of a library created for Ordered Fuzzy Numbers processing and calculations [25] over the last decade. Its results have been confirmed many times by individual calculations with spreadsheet applications such as Excel and Libre Office Calc. Further, the classic fuzzy sets processing results were compared with reference values from Matlab's Fuzzy Logic Toolbox. Additionally, the first four rows represent the testing values. This testing dataset was based on the assumptions of the MBI questionnaire. In consists in an input dataset representing hypothetical answers where the values were the minimums, maximums, and medians (rows 1 to 3). As a technical test of the fuzzy systems' behaviour, a dataset was used where all input values were zeroes (row 4).

We can see that model 3 provides the expected results for the testing data. This means that if the hypothetical answers in the MBI questionnaire point to the worst possible psychological state, then the result of the evaluation is zero—the lowest value. Similarly, for the hypothetically best psychological state, model 3 generates a result equal to one—the highest value, and for all median input values, the result is 0.5, which is the median value of the output interval.

4. Discussion

The presented models are not so much a fragment of the research, but rather a part of the whole system of artificially intelligent analysis of biomedical research results, which will be built on their basis and tested on subsequent research results. In this way, we discover not only new tools, but also new knowledge, perhaps not extractable by other methods. This forms the core of research into the use of novel artificialintelligence methods, techniques, and tools in the broader eHealth paradigm, which is currently the mainstream of AI research, and whose utility has been demonstrated by analyses related to the COVID-19 pandemic. The research and development of such tools is beneficial both scientifically, clinically, and economically and socially, and its impact on modern healthcare can hardly be overstated.

AI-based frameworks are now increasingly being used within computer-aided diagnosis (CADx) and computer-aided detection (CADe) systems to facilitate the work of diagnosticians. This is especially true for those applications that combine group/object/pattern detection and segmentation with criteria that are complex or difficult to precisely define [26,27].

Significant limitations of the self-report study are the small sample size and the relatively young age of the participants. Data were collected in the pre-pandemic period, so research development is needed to investigate and address the group of factors and phenomena resulting from the pandemic.

Currently, both research and clinical applications lack a comparable solution. The presented results and the proposed fuzzy logic approach provide an important starting point for the development of new computational markers of burnout in different occupational groups, ages, job tenures, and genders. Our study is much broader, on larger groups and using five different tools, not only MBI or SWLS, and we consider the present results promising and preliminary. The aforementioned approach can be extended to inference and prediction using artificial neural networks, as well as to study the unevenness (degree of rapidity of change) of individual burnout indicators using multifractal analysis. Moreover, trend analysis can show the potential direction of development of the healthy patient's condition (e.g., approaching illness) or the stage of their illness and the reversibility of symptoms. Our solution allows not only for comparative studies between patient groups, but also between tools, as we will show in the next publication.

Directions for further research also include comparative studies of the computational models presented on larger samples of participants and analyses of models tailored to specific groups that were not included in this study. In an effort to advance research on stress at work, models should be more thoroughly tested on different sets of tools, perhaps other than the MBI, as well as on other groups of patients, since the two groups may experience stress differently. This will allow for the optimal selection of model parameters for the study group, creating a future algorithm to optimise the selection of tools or their parameters. A computational tool can do this faster, more accurately, and more efficiently, becoming an important supporting tool in a therapist's practice. Fuzzy logic, and in particular the presented models of fuzzy systems, make it possible to highlight phenomena and features insufficiently undertaken with traditional statistical analysis, and in some cases, also with classical computational analysis using classification or inference tools. However, this requires further research, as it may be desirable to synergise methods and techniques in this area in order to optimise the tools for characterising the results. We have previously demonstrated such synergy of computational analysis methods using clinical gait analysis as an example [6]. Future research must focus not only on acute perceived stress but also on more dangerous chronic forms of stress, hence the need to isolate features and indicators for which exceeding a certain threshold is an alarm signal for urgent therapeutic response. In our analysis, we not only performed analyses of the total score but also analysed the subscales and individual scores of each scale separately, which adds value to our study. Thus, the aggregate fuzzy model score is not a simple addition result, but a composite of the internal synergies of the tools used.

The usefulness and accuracy of artificially intelligent solutions in medicine, including in mobile applications, has already been proven many times [28–30]. In further research, we will also follow the path of developing relatively simple and cheap screening devices to enable early detection of cases requiring further, more accurate measurements.

5. Conclusions

These new models are a promising tool in the field of computational analysis of work stress and burnout, which is useful for screening. Computational analysis of occupational stress and burnout may help to identify new, more sensitive markers than the existing ones, allowing for earlier detection of very early stages of the abovementioned conditions, in order to refer them for further, more advanced measurement and, if necessary, specialised therapy. New computational tools supporting diagnosticians will improve efficiency in the area of prevention and enable early prediction of development of the risk and disease states. This will allow for better targeting and monitoring of the aforementioned phenomena and faster responses to harmful changes in the health status of employees, as well as—in the future—trend analysis and prediction of values in the medium and long term, allowing for timely implementation of strategies to prevent harmful changes and losses for companies. This becomes particularly important in the light of post-pandemic changes, which could exacerbate the described group of phenomena.

Additionally, as there are different methods (other than MBI) for the measuring of burnout and stress, it seems to be interesting to create one tool which aggregates the results from multiple of these methods. As, in general, other methods are based on the different assumptions, this makes it possible to take into consideration more aspects of burnout, which will make the evaluation even more accurate and complete. This paper shows that the hierarchical structure of the fuzzy system grants flexibility of aggregation of many sources of ideas and data, which makes this tool very useful in the future in expanding the research presented here.

In the medical context, the main benefit of the results presented in this paper is the definition of an evaluation model that transforms the MBI test scores into a universal percentage scale while preserving the properties of the guidelines underlying the MBI. An additional advantage of the proposed solution is the readability and flexibility resulting from the linguistic rules underlying the model. This approach makes it easy to account for specific characteristics of the study population when implemented and facilitates more sophisticated analysis.

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