

AN INTERPRETABLE TYPE-1 FUZZY SYSTEM FOR DATA-DRIVEN OCCUPATIONAL STRESS PREDICTION

KHALID ALMOHAMMADI¹

¹Computer Science Department, University of Tabuk, Tabuk, Saudi Arabia

E-mail: ¹kalmohammadi@ut.edu.sa

ABSTRACT

Job stress affects employee well-being, organisational performance and psychological and physical health, leading to significant organisational costs. Nevertheless, evaluating it remains a challenge because it differs according to employee characteristics and the complex and correlated nature of other workplace factors. Traditional methods for assessing occupational stress are typically based on the guidelines and opinions provided by specialists. Thus, they fail to capture differences in stress perceptions between specialists and employees and do not use accumulated data to foster learning and interpretability. This study presents a novel type-1 fuzzy logic-based system for predicting occupational stress by correlating the impact of five inputs—workload, working hours, job satisfaction, managerial support and job security—on employees' actual perceived stress levels. The proposed system incorporates self-learning capabilities from data, enabling it to predict employee stress levels. The interpretability of the extracted rules enhanced specialists' understanding of the impact of workplace environmental characteristics within a lifelong learning framework. Various preliminary experiments were conducted on 31 employees at Tabuk University. Data on employee characteristics and corresponding stress levels were collected and used as primary inputs and outputs for developing transparent and interpretable type-1 fuzzy logic models. The results indicated that the proposed system could predict employee stress levels with high accuracy, exhibiting a low average error and standard deviation. Moreover, it could effectively address the uncertainty and complexity inherent to employee characteristics and work environment stress. The proposed system enabled specialists to understand and predict work-related stress and gain insights into its contributing factors and the relationships among them.

Keywords: *Type-1 Fuzzy Logic, Fuzzy Rule-Based System, Occupational Stress Prediction, Workplace Stress Assessment, Interpretable Machine Learning*

1. INTRODUCTION

Job stress is a significant concern in occupational health because exposure to psychological and social pressures in the workplace can affect employees' mental and physical well-being [1],[2]. This scenario may lead to serious health problems such as anxiety, burnout, depression and cardiovascular disease [2],[3],[4]. It can also decrease job satisfaction and increase the likelihood of resignation or job loss, which negatively impacts organisations due to high financial cost and operational burden [5],[6]. Therefore, developing preventive and effective methods for assessing and managing job stress is essential[2],[4]. However, considering the complex and uncertain interactions among these factors, measuring job stress using fixed or precise values is difficult. This challenge becomes increasingly difficult because stress factors differ across employee experiences, employers and working environments.

Machine learning (ML) approaches have been widely used in occupational stress

research. They can be used to understand complex relationships between inputs and factors that influence work-related stress [7],[8]. Moreover, ML approaches can be used to analyse employee survey datasets to detect patterns and identify relationships between demographic, organisational, psychological, social and behavioural factors [9]. This ability allows them to learn from current employees' historical data and predict levels of stress for future employees [10]. These models are flexible because they can be updated and improved overtime whenever new data become available. This feature makes them capable of adapting to the dynamic nature of working environments and employee needs [8],[11]. In addition, these methods can transform daily organisational data and survey results into clear and useful insights. Lastly, they support early intervention and enhance employee well-being by providing organisations with practical, evidence-based strategies for reducing the negative effects of occupational stress [12].

White box approaches such as fuzzy logic are effective tools for assessing the causes and effects of occupational stress. These models are easy to read, analyse and understand because they can explain the contribution of different factors to stress outcomes among employees [13]. Although black-box models can achieve high predictive accuracy, they typically fail to provide clear explanations of relationships between input variables (e.g. workload, role conflict, organisational climate and psychosocial conditions) and outcomes (e.g. stress intensity and burnout risk) [14],[15]. For this reason, fuzzy logic is suitable for assessing occupational stress because stress-related factors are typically expressed using subjective and imprecise terms such as ‘high workload’, ‘moderate pressure’ or ‘low support’, which are difficult to represent using crisp values. In addition, fuzzy logic is easy to understand IF then rules, enabling it to capture the uncertainty and ambiguity inherent to related stress data while maintaining clarity and interpretability [16]. Therefore, explainable white-box approaches are beneficial for managers and psychologists, as they help identify major causes of stress and provide easy-to-interpret intervention strategies.

The current study proposes a type-1 fuzzy logic-based system (T1FLS) framework for predicting occupational stress. The proposed system learned and correlated the relationships between five employee inputs—workload, working hours, job satisfaction, managerial support and job security—according to employees’ actual stress levels. Data were collected via an anonymous survey. These data were combined with the membership functions used in the self-learning system to capture and learn employees’ stress behaviours through explainable white-box models. These learned models were then used to predict stress levels and provide organisations with support in proactively managing employee well-being through continuous stress monitoring and prediction within a lifelong learning environment. In addition, these models provide organisations with valuable insights into stress-related behaviours and underlying workplace factors that contribute to occupational stress. This scheme will help manage healthier employers and reduce the hidden costs associated with poor performance and low levels of job satisfaction.

This study predicts occupational stress and explores how workplace factors influence stress levels. Black-box approaches can predict stress outcomes, but they often make it difficult to understand the role of each factor in a readable way. The proposed T1FLS handles this issue using learned, interpretable membership functions and IF-

Then rules. The research contribution is a data-driven white-box framework linking employee inputs to understandable stress predictions and support early organisational intervention.

The remainder of this paper is organized as follows. Section two reviews related work. The main factors affecting occupational stress is described in Section 2.1. An overview of the ML approaches for stress prediction in Section 2.2, and an overview of type-1 fuzzy logic systems is presented in Section 2.3. Section 3 describes the proposed interpretable T1FLS for data-driven occupational stress prediction, including the system methodology, input and output variables, membership functions, and rule generation mechanism. Section 4 describes the experiments conducted and analyses the results. Section 5 concludes the study and outlines directions for future research

2. RELATED WORK

2.1 Factors Influencing Occupational Stress

Various organisational and individual factors influence occupational stress[17]. Many studies have identified factors that could increase or decrease employees’ perceived stress levels [19]. Based on this review, the study used these factors as inputs for the system proposed in T1FLS. Workload is one of the most common factors of job stress. Excessive job demands, unrealistic deadlines and extremely complex tasks can place physical and psychological pressures on employees [18],[20]. Previous studies have demonstrated a strong relationship between increased workload and occupational stress across occupational groups [21]. Moreover, the literature has demonstrated that work-related factors play a major role in occupational stress, accounting for approximately 23.1% of all contributing factors [19]. Therefore, workload is one of the major inputs that must be considered in the development of effective models for assessing and predicting occupational stress.

Another important factor that contributes to job stress is working hours. Lengthy and unorganised work tasks lead to employee fatigue and emotional exhaustion [18],[22],[23]. Numerous studies have highlighted that long working hours and overtime might have serious health consequences such as depression, anxiety and cardiovascular disease [23]. This aspect includes the total number of hours worked per week, because excessive working hours can influence stress levels among employees [21]. Another important factor is job

satisfaction. Employees who report high levels of satisfaction with salary, career status and work environment, including the way they are treated by their managers, exhibit low levels of job stress [21], [24]. However, low levels of job satisfaction can lead to frustration and disengagement from the working environment. Therefore, job satisfaction is negatively associated with work-related stress [21], supporting its importance as an input factor in the proposed predictive model.

Managerial support is a critical factor of job stress reduction. Managers who provide employers with guidance, recognition and open communication enable them to cope effectively with job demands, which decreases stress levels [25],[26]. By contrast, several studies have reported that limited managerial support could cause various job stress problems [26]. For example, nurses in hospitals who receive greater support from supervisors exhibit low levels of job stress [25]. Similarly, transformational leadership characterised by empathy, encouragement and supportive behaviour will lead to low stress levels among employees [27]. Job security is another valuable factor in stress reduction, because employees who perceive stability in their employment are less likely to experience anxiety about their future [28]. The current study employed five input variables (i.e. workload, working hours, job satisfaction, managerial support and job security) and one output variable (i.e. employees' perceived job stress) to develop the proposed T1FLS.

2.2 Machine Learning Approaches for Occupational Stress Prediction

Many ML and AI techniques have been used to predict job stress levels given their ability to learn from data, model underlying causes and assess impacts on employees [7]. These techniques help organisations identify the factors that influence job stress, classify employees according to stress severity and provide preventive interventions that can improve productivity [29], [30]. The typical predicted model outcome is stress level, commonly represented using categories such as low, medium and high to support the classification process [7],[31]. In general, ML methods for stress prediction can be classified into two major models: black and white box models. The characteristics of these two models are critical for selecting the most appropriate approaches for predicting occupational stress in terms of required levels of accuracy and readability.

Black-box models, such as artificial neural networks, deep learning and support vector machines, have shown strong predictive

performance due to their ability to identify and capture complex nonlinear patterns within data [32],[33],[34]. For example, Li and Liu [32] proposed a deep convolutional neural network based on physiological signals and achieved an accuracy of more than 99% in binary stress classification. Zhang and Qi [33] developed deep learning-based classification and regression models to predict worker stress using employment-related data. Similarly, in [34] who proposed a deep neural network to classify employees as stressed and satisfied, achieving 88.40% accuracy. In addition, the researchers in [1],[29],[35] have applied random forest and XGBoost models and achieved high accuracy rates in stress detection using surveys and workplace data. However, the interpretability of these models are typically limited, thus leading to difficulty for managers and occupational stress specialists in understanding and analysing the factors that strongly influence stress outcomes.

White box models, such as decision trees, rule-based systems, linear regression and FLSs, provide transparent, interpretable and easy-to-understand decision making models [36],[37]. Study in [36], applied the C5.0 decision tree algorithm to classify perceived stress among healthcare professionals and achieved 94.1% accuracy. Fuzzy logic is a highly valuable method for predicting occupational stress, because it can address uncertainty and model subjective linguistic judgements such as low workload or high stress [16], [37],[38]. Neuro-fuzzy models developed in [16] and achieved accurate predictions while maintaining interpretability through if-then rules. In addition, in [38], proposed a hybrid fuzzy logic-deep learning framework and achieved 98.7% accuracy for stress classification. Because occupational stress is inherently subjective and difficult to measure precisely, white-box approaches, particularly fuzzy systems, are considered effective for predicting perceived stress levels while maintaining clarity and transparency in understanding occupational stress behavior.

2.3 Overview of Fuzzy Logic Systems

Fuzzy systems have been considered a major advancement in data processing and computational intelligence and gained widespread recognition in various commercial and technological domains such as digitalisation, knowledge engineering, image and signal processing and pattern recognition [39], [40]. In many of these domains, knowledge associated with environmental conditions and human factors is naturally uncertain and imprecise, limiting the effectiveness of

conventional mathematical frameworks in representing such information. FLS architecture addresses these challenges by supporting the design of robust inference mechanisms that are capable of operating within noisy and uncertain real-world environments. In addition, they allow the representation of imprecise information in a structured, flexible and interpretable manner. Type-1 FLSs are commonly used in applications in which membership functions are defined through crisp and deterministic boundaries [39].

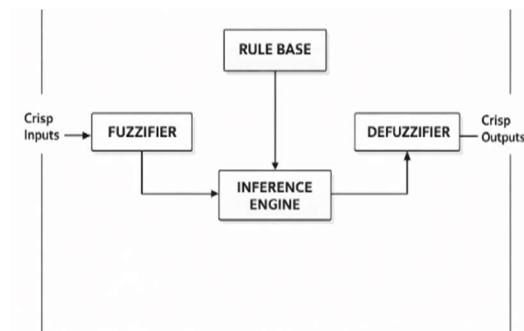


Figure 1: Overview of a Fuzzy Logic System

In 1965, Zadeh [41] proposed fuzzy logic as a mathematical framework designed to model human reasoning and decision-making processes. In contrast to classical binary logic, which limits truth values to true or false, fuzzy logic enables propositions to possess degrees of truth that continuously vary between these two values, extending the principles of conventional set theory [42]. An FLS consists of four fundamental components, namely, a fuzzifier, rule base, inference engine and defuzzifier (Figure 1) [42]. A rule base can be constructed using numerical data or knowledge of domain experts. After the rule base is established, the FLS operates as a nonlinear mapping that transforms crisp input values into crisp outputs, which can be mathematically represented as $y = f(x)$ [42]. This capability makes FLSs appropriate for modelling complex and multi criteria conditions such as level of stress, in which underlying factors cannot be represented precisely through numerical values alone. Moreover, the transparency and interpretability of the FLS architecture enhances its usability for system developers and end users.

2.4 Research Gap and Distinction from Prior Work

Previous studies have employed black- and white-box models to predict occupational stress.

However, most black-box models offer limited explanations, whereas various interpretable models focus little on practical use in the workplace. This study addresses this gap by incorporating survey-based factors, fuzzy rule generation and stress-level interpretation in a T1FLS framework. This paper clarifies the novelty of the proposed work and its practical relevance to monitoring early workplace stress.

3. THE PROPOSED INTERPRETABLE TYPE-1 FUZZY SYSTEM FOR DATA-DRIVEN OCCUPATIONAL STRESS PREDICATION

The proposed interpretable T1FLS is designed to predict job stress. It will be built using employee data that describe the effects of working environments on current stress levels. Data were collected using a designed survey completed by employees to capture five input variables—workload, working hours, job satisfaction, managerial support and job security—along with their current perceived levels of job stress. Informed consent was obtained from all participants prior to their participation in the survey. After collecting the datasets, the T1FLS processes the accumulated data using fuzzy membership functions designed for each input and output variable. Thus, the model establishes relationships between inputs and outputs through fuzzy rules instead of relying on a fixed mathematical formulation. Following data collection, the input and output variables are fuzzified using membership functions that convert raw values into linguistic categories such as ‘low stress’, ‘medium stress’, ‘high stress’ and ‘very high stress’. This scheme enables the system to address imprecise information. The learning rule methodology is based on an unsupervised one-pass approach [43],[44], in which the model collects employee data, generates learned rules and enables the T1FLS to predict job stress levels, as demonstrated in [43],[44].

$$x^{(t)}; y^{(t)} \quad (t = 1, 2, \dots, N), \quad (1)$$

To build a rule base that captures behavioural patterns underlying employee stress, predefined membership functions are applied to the input and output data. In the current study, the rule extraction method adopted is based on an improved and extended version of the Mendel–Wang method [43],[44], which is commonly considered a one-pass approach for deriving fuzzy rules from datasets. The antecedent and consequent fuzzy rule sets partition

the input and output domains into separate fuzzy regions. Based on multiple input-output data instances, the system then generates rules that capture the underlying functional relationship between $x = (x_1, \dots, x_n)^T$ and $y = (y_1, \dots, y_k)^T$. The representation is formulated as follows [43],[44]:

$$\begin{aligned} & \text{If } x_1 \text{ is } A_1^{(l)} \text{ and } \dots x_n \text{ is } A_n^{(l)} \text{ Then} \\ & y_1 \text{ is } B_1^{(l)} \text{ and } \dots y_k \text{ is } B_k^{(l)} \end{aligned} \quad (2)$$

where $l = 1, 2, \dots, M$, where M indicates the total number of rules, and l represents the rule index. For each input variable x_s , V fuzzy sets A_s^q , $q = 1, \dots, V$, are defined. Similarly, W fuzzy sets B_c^h , $h = 1, \dots, W$, are defined for each output variable y_c . The single-output rule method is adopted to simplify the subsequent notation because the concept can be easily extended to rules with multiple outputs [43],[44]. The stages involved in the rule extraction process are outlined as follows:

Step 1:

For a fixed input-output pair $(x^{(t)}, y^{(t)})$ from dataset (1), where $t = 1, 2, \dots, N$, the membership values $\mu_{A_s^q}(x_s^{(t)})$ are evaluated for each membership function $q = 1, \dots, V$ and for every input variable $s = 1, \dots, n$. The index $q^* \in \{1, \dots, V\}$ is then identified according to the following equation.

$$\mu_{A_s^{q^*}}(x_s^{(t)}) \geq \mu_{A_s^q}(x_s^{(t)}) \quad (3)$$

Based on the input-output pair $(x^{(t)}, y^{(t)})$, the following rule is derived [43],[44]:

$$\begin{aligned} & \text{If } x_1^t \text{ is } A_1^{q^*}, \dots, \text{ and } x_n^t \text{ is } A_n^{q^*}, \\ & \text{then } y \text{ is centered at } y^{(t)} \end{aligned} \quad (4)$$

Each input variable x_s is associated with a corresponding fuzzy set A_s^q , $q = 1, \dots, V$, which defines its linguistic characterization. In principle, this configuration allows the generation of up to V^n possible rules, where n represents the number of input variables. However, considering the dataset, only rules whose regions contain at least one data point are generated from the V^n possible combinations. Consequently, in Step 1, a single rule is derived from each input-output data pair. For every input variable, the fuzzy set with the highest membership value is selected in the IF part of the rule. This process is illustrated in Equations (3) and (4).

However, this does not represent the final rule established in the next step. In addition, the rule weight is calculated using the following equation [43],[44]:

$$w^{(t)} = \prod_{s=1}^n \mu_{A_s^q}(x_s^{(t)}) \quad (5)$$

The rule weight $w^{(t)}$ represents the degree to which the data point $x^{(t)}$ belongs to the fuzzy regions that define the rule.

Step 2:

To derive rules from the N data samples using Equation (3), Step 1 is repeatedly applied to each data point $t = 1, \dots, N$. A large number of data points result in the generation of numerous rules through the execution of Step 1. Among these rules, some share identical IF sections and are therefore identified as conflicting rules; i.e., rules with the same antecedent membership functions but different consequent values. In this step, rules with identical IF components were combined to produce a single rule.

Consequently, the N rules were organized into groups, with each group containing rules with identical IF sections. If M such groups are assumed to exist, group l consists of N_l rules, as presented below [43],[44]:

$$\begin{aligned} & \text{if } x_1 \text{ is } A_1^{(q^l)}, \dots, \text{ and } x_n \text{ is } A_n^{(q^l)}, \\ & \text{then } y \text{ is centered at } y^{(t_u^l)} \end{aligned} \quad (6)$$

where N_l and t_u^l denote the index of data points associated with the group. The weighted average of the rules within the conflicting group is computed as follows [43],[44]:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} w^{(t_u^l)}}{\sum_{u=1}^{N_l} w^{(t_u^l)}} \quad (7)$$

In this context, the N_l rules are combined into a single rule with the following formulation [43],[44]:

$$\text{If } x_1 \text{ is } A_1^{(l)}, \dots, \text{ and } x_n \text{ is } A_n^{(l)}, \text{ then } y \text{ is } B^{(l)} \quad (8)$$

where the output fuzzy set $B^{(l)}$ is selected based on the following criterion: among the W possible output fuzzy sets B^1, \dots, B^W , the fuzzy set B^{h^*} is determined as follows [43],[44].

$$\mu_{B^{h^*}}(av^{(l)}) \geq \mu_{B^h}(av^{(l)}) \quad (9)$$

For $h = 1, 2, \dots, W$, fuzzy set B is selected as B^{h^*} . As indicated above, the proposed system processes pairs of input-output variables and

produces multiple outputs. Step 1 is unique in terms of the number of outputs associated with each rule, whereas Step 2 provides a simple extension that enables rules to include multiple outputs. Accordingly, the computations described in Equations (7) and (9) were repeated for each output.

The membership functions and fuzzy rules derived from the input and output data collectively enabled the system to identify behavioral patterns and predict employee stress levels. The system adopted singleton fuzzification, product inference, and center-of-set defuzzification [43],[44]. The mapping from a precise input vector x to a precise output vector $y = f(x)$ is obtained using the following equation:

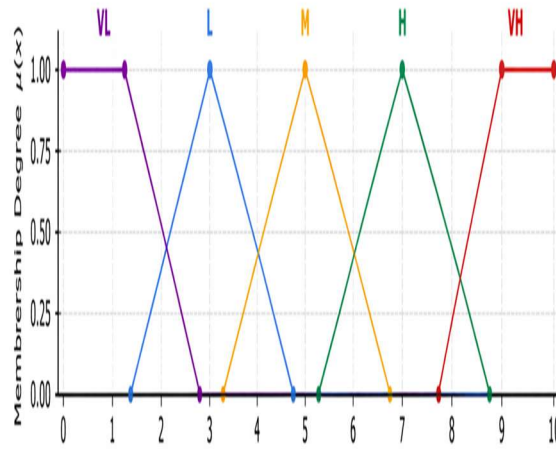
$$y(x) = f_s(x) = \frac{\sum_{l=1}^M y^l \prod_{i=1}^n \mu_{F_i^l}(x_i)}{\sum_{l=1}^M \prod_{i=1}^n \mu_{F_i^l}(x_i)} \quad (10)$$

where M indicates the total number of rules in the rule base, and y^l corresponds to the centroid of the l th fuzzy output.

4. EXPERIMENTS AND RESULTS

A pilot evaluation was conducted to examine the performance of the proposed interpretable T1FLS predictive model using survey data collected from 31 employees working in Tabuk University. Data were obtained in advance using a questionnaire; the participants provided self-reported assessments of workplace conditions and perceived current stress levels. Each input and output was rated using a 10-point Likert-type scale, where 1 and 10 represented the lowest and highest levels, respectively, of the measured variable. The five workplace factors were used as input variables, while employees' current job stress levels were assessed using the same scale and used in the T1FLS as the output variable. All inputs and outputs were categorised as predefined linguistic variables generated from the designed membership functions. A type-1 FLS is implemented using the designed membership functions combined with the inputs and outputs to generate the learned rules described in Section 3 (Figure 2 shows an example of the designed membership functions). These membership functions were designed to represent the uncertainty inherent to subjective self-reported assessments and variations in employee perceptions. As occupational stress is not directly measurable and is commonly inferred through multiple correlated workplace factors, fuzzy representation provides an appropriate modelling framework.

Figure 2: The designed T1FLS membership functions for



the working hours input.

Following data collection, the dataset was processed according to the rule extraction methodology described in Section 3. Type-1 fuzzy sets and the corresponding rule bases were generated automatically using the one-pass learning algorithm reported in [43],[44], enabling the direct derivation of interpretable if-then rules from the data. An example of the extracted rules is as follows:

R23: If the workload is medium, and the actual working hours are high, and the job satisfaction is high, and the managerial support is high, and the job security is high, then the level of stress is low.

System performance was assessed using the average prediction error and standard deviation of the prediction errors. This proposed system achieved an average prediction error of 0.778 and a standard deviation of 0.646 (see Figure 3 for comparisons between actual versus predicted stress levels). The average prediction error of 0.778 shows that the predicted and reported stress scores differed by less than 1 point on a 10-point scale. Thus, the proposed T1FLS provides a close estimation of stress while maintaining interpretable prediction via the developed system. Importantly, the results demonstrate that the proposed T1FLS can serve as an interpretable decision support tool for monitoring occupational stress by converting workplace conditions into predicted stress scores using a transparent rule-based fuzzy logic methodology. These findings support the usefulness of fuzzy logic in occupational assessment compared with traditional numerical and black-box approaches. This result suggests that the proposed T1FLS system may help organisations predict possible workplace stress cases at early stages.

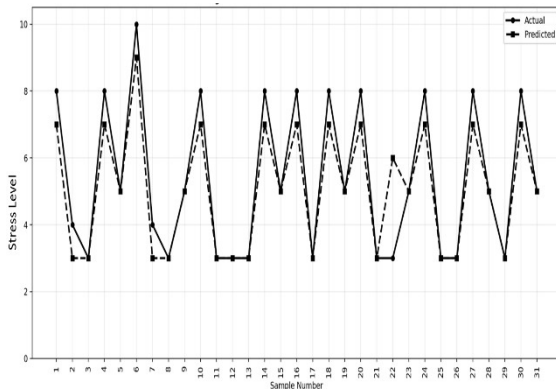


Figure 3: Actual vs. predicted stress levels using the proposed T1FLS

4. CONCLUSIONS

This paper proposed a T1FLS for predicting occupational stress using an interpretable, self-learning and white-box approach. This work supports the objective of converting subjective workplace factors into explainable stress-level predictions. The system modelled nonlinear relationships among five workplace inputs—workload, working hours, job satisfaction, managerial support and job security—to predict employees' job stress levels. The framework addressed the uncertainty and subjectivity inherent to occupational stress assessment while maintaining full transparency of its decision rules. Experimental validation using data from 31 employees demonstrated that the system achieved lower average prediction error and standard deviation, which indicates its ability to deliver accurate and interpretable predictions of stress levels. Therefore, this system can be a valuable decision support tool for organisations that intend to proactively monitor employee well-being and use data-driven approaches to address stress among employees.

The small sample size and the data collected from participants' responses from a single institution limit the study. In future work, the proposed system will be validated using larger and more diverse datasets, and considering additional inputs associated with job roles and culturally specific contexts. An interval type-2 fuzzy logic system will be implemented to capture the linguistic and numerical uncertainties and compared with the proposed T1FLS.

REFERENCES:

- [1] S. Matheswaran, M. S. Kalpana, U. Allimuthu, and C. Singh, "Workplace stress detection and mental health prediction using machine learning," in *Proc. 11th Int. Conf. Communication and Signal Processing (ICCSP)*, IEEE, 2025, pp. 660–665, doi: [10.1109/ICCSP64183.2025.11088739](https://doi.org/10.1109/ICCSP64183.2025.11088739).
- [2] D. C. Ganster and C. C. Rosen, "Work Stress and Employee Health: A Multidisciplinary Review," *J. Management*, vol. 39, no. 5, pp. 1085–1122, 2013, <https://doi.org/10.1177/0149206313475815>
- [3] M. Kivimäki and I. Kawachi, "Work stress as a risk factor for cardiovascular disease," *Current Cardiology Reports*, vol. 17, no. 9, p. 74, 2015, doi: [10.1007/s11886-015-0630-8](https://doi.org/10.1007/s11886-015-0630-8)
- [4] K. Bhui, S. Dinos, S. Stansfeld, and P. White, "A synthesis of the evidence for managing stress at work: A review of the reviews reporting on anxiety, depression, and absenteeism," *J. Environmental and Public Health*, vol. 2012, p. 515874, 2012, doi: [10.1155/2012/515874](https://doi.org/10.1155/2012/515874)
- [5] J. Hassard, K. Teoh, G. Visockaite, P. Dewe, and T. Cox, "The cost of work-related stress to society: A systematic review," *J. Occupational Health Psychology*, vol. 23, no. 1, pp. 1–17, 2018, doi: [10.1037/ocp0000069](https://doi.org/10.1037/ocp0000069).
- [6] D. Shaholli, G. Mantione, and G. La Torre, "Work-related stress costs assessment: a narrative review," *Clinica Terapeutica*, 2023, doi: [10.7417/CT.2023.2464](https://doi.org/10.7417/CT.2023.2464).
- [7] M. J. Hasan, J. Sultana, S. Ahmed, and S. Momen, "Early detection of occupational stress: Enhancing workplace safety with machine learning and large language models," *PLoS ONE*, 2025, doi: [10.1371/journal.pone.0323265](https://doi.org/10.1371/journal.pone.0323265).
- [8] M. Razavi, S. Ziyadidegan, A. Mahmoudzadeh, *et al.*, "Machine learning, deep learning, and data preprocessing techniques for detecting, predicting, and monitoring stress and stress-related mental disorders: Scoping review," *JMIR Mental Health*, vol. 11, e53714, 2023, doi: [10.2196/53714](https://doi.org/10.2196/53714).
- [9] U. S. Reddy, A. V. Thota, and A. Dharun, "Machine learning techniques for stress prediction in working employees," in *Proc. IEEE Int. Conf. on Computational Intelligence and Computing Research (ICCIC)*, Madurai, India, 2018, <https://doi.org/10.1109/ICCIC.2018.8782395>

- [10] A. Garlapati, D. Radha Krishna, K. Garlapati, and G. Narayanan, "Predicting employees under stress for pre-emptive remediation using machine learning algorithm," in *Proc. IEEE Int. Conf. Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, Bangalore, India, Nov. 2020, . DOI: [10.1109/RTEICT49044.2020.9315726](https://doi.org/10.1109/RTEICT49044.2020.9315726)
- [11] O. Oyeboode, J. Fowles, D. Steeves, and R. Orji, "Machine learning techniques in adaptive and personalized systems for health and wellness," *Int. J. Human-Computer Interaction*, vol. 39, no. 12, pp. 2439–2476, 2022, doi: [10.1080/10447318.2022.2089085](https://doi.org/10.1080/10447318.2022.2089085).
- [12] R. Vij and H. Nazir, "Leveraging AI & MI for predictive analytics in stress level of private insurance employees: Comprehensive review," in *Proc. Int. Conf. Artificial Intelligence for Innovations in Healthcare Industries (ICAIHI)*, IEEE, 2023, doi: [10.1109/ICAIHI57871.2023.10489524](https://doi.org/10.1109/ICAIHI57871.2023.10489524).
- [13] S. Barbounaki and V. Vivilaki, "A fuzzy intelligent system to assess midwives' burnout conditions," *European J. Midwifery*, vol. 5, p. 53, 2022, doi: [10.18332/ejm/143363](https://doi.org/10.18332/ejm/143363).
- [14] A. L. Schneider, J. S. Do Carmo, É. O. Rodrigues, and S. L. R. Pessa, "Occupational mental health: An investigation of risk indicators using interpretable machine learning techniques," *J. Occupational and Environmental Medicine*, 2025, doi: [10.1097/JOM.0000000000003468](https://doi.org/10.1097/JOM.0000000000003468).
- [15] T. Mokheleli, T. Bokaba, and E. Mbunge, "Explainable artificial intelligence for workplace mental health prediction," *Informatics*, vol. 12, no. 4, p. 130, 2025, doi: [10.3390/informatics12040130](https://doi.org/10.3390/informatics12040130).
- [16] G. Casalino, G. Castellano, and G. Zaza, "Interpretable neuro-fuzzy models for stress prediction," in *Proc. European Society for Fuzzy Logic and Technology (EUSFLAT)*, Springer, 2023, pp. 625–636, doi: [10.1007/978-3-031-39965-7_52](https://doi.org/10.1007/978-3-031-39965-7_52).
- [17] N. Zakaria and H. Yusof, "Impact of stress: A systematic review," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Bandung, Indonesia, Mar. 6–8, 2018. [Online]. Available: <http://www.icomsociety.org/ieom2018/papers/588.pdf>
- [18] A. C. Fagerlind Ståhl, C. Ståhl, and P. M. Smith, "Longitudinal association between psychological demands and burnout for employees experiencing a high versus a low degree of job resources," *BMC Public Health*, vol. 18, no. 1, p. 915, 2018. doi: [10.1186/s12889-018-5778-x](https://doi.org/10.1186/s12889-018-5778-x).
- [19] M. Gholipour, S. Mousavi, A. Naghshbandi, and O. Ahmadi, "Factors affecting occupational stress: Identification, classification and determination of importance," *WORK: A Journal of Prevention, Assessment & Rehabilitation*, 2025, doi: [10.1177/10519815251367230](https://doi.org/10.1177/10519815251367230).
- [20] S. G. Herrero, M. Á. Mariscal Saldaña, J. G. Rodriguez, and D. O. Ritzel, "Influence of task demands on occupational stress: gender differences," *Journal of Safety Research*, vol. 43, no. 1, pp. 1–8, 2012, doi: [10.1016/j.jsr.2012.10.005](https://doi.org/10.1016/j.jsr.2012.10.005).
- [21] Z. Kavosi, H. Ranai Kordshouli, M. Zare Saadabadi, and A. Ghorbanian, "The factors related to the employees' job stress: A meta-analysis," *J. Health Manag. Informatics*, vol. 5, no. 4, pp. 145–151, 2018. [Online]. Available: https://jhmi.sums.ac.ir/article_42722_7ee173bede87b87fec58727178d71b36.pdf
- [22] W. D. T. Marianggodo, I. Noviekayati, and Suhadianto, "Determinants of employee mental health in contemporary work environments: A systematic literature review," *Int. J. Current Science Research and Review*, vol. 8, no. 12, 2025, doi: [10.47191/ijcsrr/v8-i12-14](https://doi.org/10.47191/ijcsrr/v8-i12-14).
- [23] A. Bannai and A. Tamakoshi, "The association between long working hours and health: a systematic review of epidemiological evidence," *Scandinavian Journal of Work, Environment and Health*, vol. 40, no. 1, pp. 5–18, Jan. 2014, doi: [10.5271/sjweh.3388](https://doi.org/10.5271/sjweh.3388).
- [24] E. B. Faragher, M. Cass, and C. L. Cooper, "The relationship between job satisfaction and health: a meta-analysis," *Occupational and Environmental Medicine*, vol. 62, no. 2, pp. 105–112, 2005. <https://doi.org/10.1136/oem.2002.006734>
- [25] D. S. Hall, "The relationship between supervisor support and registered nurse outcomes in nursing care units," *Nursing Administration Quarterly*, vol. 31, no. 1, pp. 68–80, 2007, doi: [10.1097/00006216-200701000-00015](https://doi.org/10.1097/00006216-200701000-00015).
- [26] K. Nieuwenhuijsen, D. Bruinvels, and M. Frings-Dresen, "Psychosocial work environment and stress-related disorders, a systematic review," *Occupational Medicine*, vol. 60, no. 4, pp. 277–286, 2010, <https://doi.org/10.1093/occmed/kqq081>

- [27] J. Skakon, K. Nielsen, V. Borg, and J. Guzmán, "Are leaders' well-being, behaviours and style associated with the affective well-being of their employees? A systematic review of three decades of research," *Work & Stress*, vol. 24, no. 2, pp. 107–139, 2010. doi: [10.1080/02678373.2010.495262](https://doi.org/10.1080/02678373.2010.495262)
- [28] M. Sverke, J. Hellgren, and K. Näswall, "No security: A meta-analysis and review of job insecurity and its consequences," *J. Occupational Health Psychology*, vol. 7, no. 3, pp. 242–264, 2002, doi: [10.1037/1076-8998.7.3.242](https://doi.org/10.1037/1076-8998.7.3.242).
- [29] P. P. Shanmugapriya, P. Balasubramanie, C. R. Dhivyaa, D. S. Raia, and P. Dhivya, "Stress Prediction of Working Employees in Different Environments Using Machine Learning Techniques," in *Proc. 6th Int. Conf. Mobile Computing and Sustainable Informatics (ICMCSI)*, Goathgaun, Nepal, Jan. 7–8, 2025, pp. 1409–1414, doi: [10.1109/ICMCSI64620.2025.10883523](https://doi.org/10.1109/ICMCSI64620.2025.10883523).
- [30] A. Alberdi, A. Aztiria, A. Basarab, and D. Cook, "Using smart offices to predict occupational stress," *Int. J. Industrial Ergonomics*, vol. 67, pp. 1–14, 2018, doi: [10.1016/J.ERGON.2018.04.005](https://doi.org/10.1016/J.ERGON.2018.04.005).
- [31] A. Priya, S. Garg, and N. P. Tigga, "Predicting anxiety, depression and stress in modern life using machine learning algorithms," *Procedia Computer Science*, vol. 167, pp. 1258–1267, 2020, doi: [10.1016/j.procs.2020.03.442](https://doi.org/10.1016/j.procs.2020.03.442).
- [32] R. A. Li and Z. Liu, "Stress detection using deep neural networks," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, p. 285, 2020, doi: [10.1186/s12911-020-01299-4](https://doi.org/10.1186/s12911-020-01299-4).
- [33] Y. Zhang and E. Qi, "Happy work: Improving enterprise human resource management by predicting workers' stress using deep learning," *PLoS ONE*, vol. 17, no. 4, e0266373, 2022, doi: [10.1371/journal.pone.0266373](https://doi.org/10.1371/journal.pone.0266373).
- [34] N. Patel, S. Trivedi, and N. Faruqi, "An innovative deep neural network for stress classification in workplace," in *Proc. Int. Conf. Software and Computer Applications (ICSCA)*, IEEE, 2023, doi: [10.1109/ICSCA57840.2023.10087794](https://doi.org/10.1109/ICSCA57840.2023.10087794).
- [35] Logesh Kumar KL, L Kavisankar, RK Pongiannan,, "Leveraging hybrid machine learning to detect workplace stress in human resource systems," in *Proc. 6th Int. Conf. Inventive Research in Computing Applications (ICIRCA)*, IEEE, 2025, doi: [10.1109/ICIRCA65293.2025.11089874](https://doi.org/10.1109/ICIRCA65293.2025.11089874).
- [36] J. L. Delgado-Gallegos *et al.*, "Application of C5.0 algorithm for the assessment of perceived stress in healthcare professionals attending COVID-19," *Brain Sciences*, vol. 13, no. 3, p. 513, 2023, doi: [10.3390/brainsci13030513](https://doi.org/10.3390/brainsci13030513).
- [37] W. W. Putro, "Evaluation of physiological response to stress using fuzzy logic," *J. Engineering and Management in Industrial System*, vol. 4, no. 1, pp. 48–57, 2016, doi: [10.21776/UB.JEMIS.2016.004.01.6](https://doi.org/10.21776/UB.JEMIS.2016.004.01.6).
- [38] J. Deepakraj *et al.*, "Fuzzy logic and deep learning hybrid model for physiological stress detection in higher education," in *Proc. 5th Int. Conf. Intelligent Technologies (CONIT)*, IEEE, 2025, doi: [10.1109/CONIT65521.2025.11167821](https://doi.org/10.1109/CONIT65521.2025.11167821).
- [39] J. M. Mendel, *Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions*. Upper Saddle River, NJ, USA: Prentice Hall, 2001.
- [40] J. M. Mendel, "Fuzzy logic systems for engineering: A tutorial," *Proc. IEEE*, vol. 83, no. 3, pp. 345–377, Mar. 1995, doi: [10.1109/5.364485](https://doi.org/10.1109/5.364485).
- [41] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965, doi: [10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X).
- [42] J. Bih, "Paradigm shift—An introduction to fuzzy logic," *IEEE Potentials*, vol. 25, no. 1, pp. 6–21, Jan.–Feb. 2006, doi: [10.1109/MP.2006.1635021](https://doi.org/10.1109/MP.2006.1635021).
- [43] L. X. Wang, "The MW method completed: A flexible system approach to data mining," *IEEE Trans. Fuzzy Syst.*, vol. 11, no. 6, pp. 768–782, Dec. 2003, doi: [10.1109/TFUZZ.2003.819835](https://doi.org/10.1109/TFUZZ.2003.819835).
- [44] L. X. Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," *IEEE Trans. Syst., Man, Cybern.*, vol. 22, no. 6, pp. 1414–1427, Nov./Dec. 1992, doi: [10.1109/21.19946](https://doi.org/10.1109/21.19946).