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Occupational Stress Among Healthcare Workers and the Feasibility of a Machine Learning-Based Risk Screening Approach

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Abstract

Introduction: Occupational stress among healthcare workers is a major determinant of burnout, reduced quality of care, and adverse mental health outcomes. In Poland, evidence remains fragmented across professions, limiting system-wide understanding. This study aimed to identify sociodemographic and occupational predictors of stress among healthcare workers and to evaluate the feasibility of a machine learning (ML)-based proof-of-concept screening model for detecting high-risk individuals.

Materials and methods: A cross-sectional survey of healthcare professionals in Poland (N = 178) was conducted between November 2025 and January 2026 using the Perceived Stress Questionnaire (PSQ-30). Participants were categorized into a high stress (PSQ $\geq$ 0.60) and a low-moderate stress group. Statistical analyses included reliability testing, non-parametric comparisons, MANOVA, and multivariable logistic regression. A Random Forest classifier with repeated cross-validation was developed to predict high levels of stress using demographic, occupational, and psychosocial variables.

Results: The PSQ-30 demonstrated excellent reliability (Cronbach's $\alpha \approx$ 0.96). High stress prevalence was 14.6%. Night-shift work emerged as the strongest predictor of high stress (OR $\approx$ 3.45–12.4), while greater work experience was associated with lower levels of stress. The profession was not an independent predictor after adjustment, although nurses showed a higher proportion of stress. Significant differences across professions were observed only for the Joy subscale (p = 0.026), with paramedics reporting lower scores. Department differences were not significant after accounting for sample size variability. The ML model achieved an ROC AUC value of 0.728, with 70% sensitivity and a high negative predictive value (97%), supporting its utility as a screening tool. The key predictors included age, pediatric department, and workplace conflict.

Conclusions: Occupational stress in Polish healthcare workers is driven primarily by work patterns, particularly night shifts, rather than the profession alone. ML-based screening models seem promising for early identification of high-risk individuals, enabling timely preventive interventions.

Keywords: occupational stress; healthcare workers; burnout; machine learning; screening model; PSQ-30

Streszczenie

Wstęp: Stres zawodowy wśród pracowników ochrony zdrowia jest istotnym czynnikiem wypalenia zawodowego, obniżenia jakości opieki oraz pogorszenia zdrowia psychicznego. W Polsce dane pozostają fragmentaryczne, co ogranicza całościową ocenę sytuacji. Celem badania była identyfikacja socjodemograficznych i zawodowych predyktorów stresu oraz ocena

wykonalności opartego na uczeniu maszynowym (ML) modelu przesiewowego typu proof-of-concept do wykrywania osób z grupy wysokiego ryzyka.

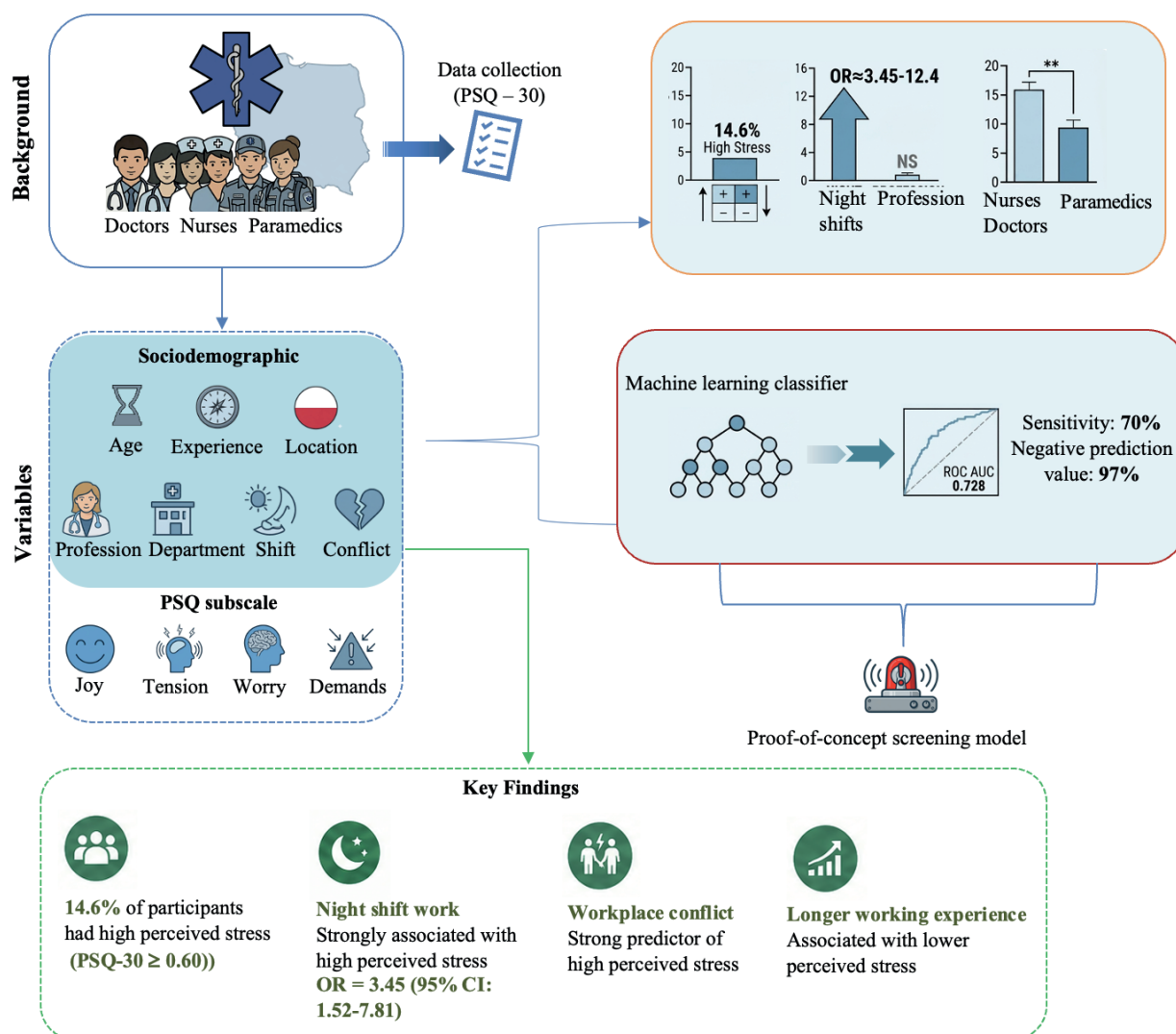
Materiały i metody: Badanie przekrojowe przeprowadzone wśród 178 polskich pracowników ochrony zdrowia (lata 2025-2026) z wykorzystaniem kwestionariusza PSQ-30. Wysoki poziom stresu ($PSQ \geq 0,60$) analizowano za pomocą regresji oraz algorytmu uczenia maszynowego typu Random Forest.

Dyskusja: Kwestionariusz PSQ-30 wykazał doskonałą rzetelność (α Cronbacha $\approx 0,96$), a częstość wysokiego poziomu stresu wyniosła 14,6%. Praca zmianowa nocna była najsilniejszym predyktorem wysokiego stresu ($OR \approx 3,4512,4$), natomiast dłuższy staż pracy wiązał się z niższym ryzykiem. Po uwzględnieniu czynników zakłócających zawód nie był niezależnym predyktorem, choć u pielęgniarzek częściej obserwowano wysoki stres. Istotne różnice między zawodami dotyczyły jedynie podskali Radość ($p = 0,026$), z niższymi wynikami u ratowników medycznych. Różnice między oddziałami nie utrzymały istotności po uwzględnieniu liczebności grup. Model ML osiągnął AUC ROC 0,728, czułość 70% i wysoką ujemną wartość predykcyjną (97%), potwierdzając przydatność jako narzędzia przesiewowego. Głównymi predyktorami były wiek, praca na oddziale pediatrycznym i konflikty w miejscu pracy.

Wnioski: Stres zawodowy wśród polskich pracowników ochrony zdrowia wynika przede wszystkim z trybu pracy, a zwłaszcza z dyżurów nocnych, a nie wyłącznie z samego zawodu. Modele przesiewowe oparte na uczeniu maszynowym wydają się obiecujące w zakresie wczesnej identyfikacji osób z grupy wysokiego ryzyka, umożliwiając podjęcie interwencji profilaktycznych w odpowiednim czasie.

Słowa kluczowe: stres zawodowy, pracownicy ochrony zdrowia, wypalenie zawodowe, uczenie maszynowe, model przesiewowy, PSQ-30

Graphical Abstract



1. Introduction

In the healthcare system, persistent stress is closely intertwined with burnout and has been linked to deterioration in the quality and safety of care, with lower patient satisfaction [1,2]. High stress levels can increase the risk of burnout by up to 4 times [3]. Burnout can be considered an outcome of prolonged stress [4]. Therefore, it can be described as a consequence of chronic or unsuccessfully managed workplace stress. It can be characterized by emotional exhaustion, hardened attitudes, detachment, and feelings of ineffectiveness and is a major risk factor for and a direct cause of severe mental health issues, including suicidal ideation, anxiety, depression, sleep disturbances and substance use [5–7]. Burnout can also contribute to ineffective coping mechanisms and difficulty in managing work-related stress [7–11].

Clinical work is routinely characterized by high cognitive demands, time pressure, emotional labor, and high-stakes decision-making, with excessive workloads, prolonged cognitive demand, low job control, and other psychosocial hazards being important risk factors for mental health and functioning [12–16], commonly co-occurring with symptoms of depression, anxiety and other mental health symptoms that impact quality of life [17–20]. The shortage of healthcare personnel in Poland [21] is both a driver of and a stressor upon the system and the healthcare workers themselves, creating excessive workload and prolonged cognitive demands that lead to stress. Stressors are internal or external factors that an individual perceives as causing stress, including job-related factors [22].

Research shows a significant geographical and demographic imbalance, specifically a lack of data on psychological distress and healthcare practitioners operating outside Western Europe [23]. While research extensively documents the high prevalence of burnout among Polish physicians (up to 60%) [24] and nursing staff, existing research remains largely divided by profession. Most studies focus on a single cohort, such as neurologists, nurses or physicians in general [24–33], precluding a comparative, horizontal analysis of how sociodemographic and professional predictive factors across the entire healthcare spectrum.

The aim of this study, therefore, is to identify the sociodemographic and professional predictive factors of occupational stress among medical staff in Poland and to evaluate the feasibility of using these factors to build a machine learning-based proof-of-concept screening model capable of accurately screening for high-risk individuals. Assessing occupational stress and related factors can help identify healthcare workers at higher risk of adverse outcomes, such as burnout, job dissatisfaction,

and intent to leave their positions. Machine learning (ML) models can help build a predictive model to screen high-risk individuals [34–37] based on sociodemographic, professional, and stress data [38]. Such identification and screening are important in providing timely and effective care and intervention [35]. Early detection of stress is also important in planning interventions and managing comorbid health complications [39].

2. Materials and methods

Participants and study setting

This cross-sectional study included healthcare professionals currently working in Poland. Data were collected between November 2025 and January 2026 using a self-administered online questionnaire developed in Google Forms. The questionnaire was available in both Polish and English, and participants were provided with study information before providing electronic informed consent.

Participants were recruited using a non-probability convenience sampling approach through online distribution of the survey to healthcare professionals. Eligible participants were adults (≥ 18 years) currently employed in a healthcare profession in Poland. Healthcare professionals were defined as individuals working in clinical or healthcare-related professions, including physicians, nurses, pharmacists, dentists, paramedics, physiotherapists, psychologists, laboratory scientists, and other allied healthcare professionals.

A total of 228 questionnaires were received. Following data screening, 50 responses were excluded because they were incomplete or submitted by respondents outside the study's geographical scope (outside Poland). Consequently, 178 questionnaires were included in the final analyses. The study participants represented multiple healthcare settings, including hospitals, outpatient clinics, pharmacies, primary healthcare centers, and correctional healthcare facilities. Responses were obtained from 67 unique healthcare facilities across multiple regions of Poland, including Poznań, Kraków, Gdańsk, Olsztyn, Opoczno, Toruń, and other locations, indicating broad national representation. Participants were employed within the National Health Fund (NFZ), the private sector, or both. The recruitment was conducted through open online distribution using convenience sampling, so the total number of healthcare professionals who received the survey invitation could not be determined. Therefore, a response rate could not be calculated.

All participants provided informed electronic consent before participation in the study. Participants remained anonymous because no personally identifiable information (e.g., names or contact details) was collected,

and all questionnaire data were handled in accordance with approved ethical standards for secure data management and confidentiality. The study was reviewed by the Bioethics Committee of Poznan University of Medical Sciences (reference KB-784/25), which confirmed that the project constituted a non-experimental questionnaire-based study that did not require formal consent from ethical committee approval under Polish law.

The perceived stress questionnaire (PSQ)

Stress was assessed using the 30-item Perceived Stress Questionnaire (PSQ-30), a validated instrument that measures general levels of perceived stress experienced over the preceding year, answered on a four-point Likert-type scale (1 = almost never, 2 = sometimes, 3 = often, 4 = usually). Items 1, 7, 10, 13, 17, 21, 25, 29 are reverse-coded (4=1, 3=2, 2=3, and 1=4) [40]. Higher scores represent a higher level of perceived stress. The PSQ index is calculated by subtracting 30 from the raw score and dividing the result by 90 to obtain a score between 0 and 1. Participants completed the standard PSQ-30 without modification. Therefore, the questionnaire assessed overall perceived stress rather than stress specifically attributable to occupational factors. Occupational characteristics (e.g., profession, department, shift work, workplace conflict and years of experience) were also collected and analyzed as potential factors associated with perceived stress.

Data Coding and Variable Preparation

The pre-processing data and variable coding were performed in R using the dplyr package. Participants were classified into stress groups based on their PSQ scores. Consistent with the population-based construct validation study by Kocalevent et al. [41], in a sample of 2552 participants, participants with PSQ scores ≥ 0.60 were classified as having high levels of perceived stress, whereas those with scores < 0.60 were classified as having low-to-moderate perceived stress. This threshold was derived from the normative PSQ-30 data (mean = 0.30, SD = 0.15), in which scores exceeding two standard deviations above the population mean (> 0.60) were considered indicative of a high perceived stress level, while scores between 0.45 and 0.60 represented a moderate perceived stress level. A corresponding binary variable was also created (1 = High, 0 = Low-Moderate). Gender was coded as 0 for male and 1 for female. Work experience was coded as 1 (< 1 year), 2 (1 to 5 years), or 3 (> 5 years). Conflict exposure was coded as 0 for no conflicts, 1 for conflict with patients, 2 for conflict with patients' family, 3 for conflict with co-workers, 4 for conflict with patients and patients' family, 5 for conflict with patients and co-workers, 6 for conflict with patients'

family and co-workers and 7 for conflict with patients, patients' family, and co-workers. All analyses were carried out in R version 4.3.2 (unless otherwise stated).

Reliability Analysis

The internal consistency of the Perceived Stress Questionnaire (PSQ-30) was assessed using Cronbach's alpha in R (package psych). All PSQ items (Q1–Q30) were identified, ordered numerically, and converted to numeric format prior to analysis. The overall scale reliability was estimated with Cronbach's alpha using automatic key checking to account for reverse-scored items, and item-total statistics were examined to evaluate individual item contributions. Subscale reliability was then computed for the four established PSQ-30 dimensions (Worry, Tension, Joy and Demands) based on standard item groupings. Subscale scores were calculated for each participant as the mean of the items in the corresponding subscale.

Profession and stress subscales

In order to examine whether stress profiles differed across professions (doctor, nurse, paramedic), a multivariate analysis of variance (MANOVA) was performed with the four PSQ subscales as dependent variables and profession as the independent variable. Pillai's trace was used as the test statistic due to its robustness to violations of multivariate assumptions [42–44]. Significant multivariate effects were followed by post hoc pairs of subscales comparisons of subscales were conducted using estimated marginal means with FDR-adjusted p-values ($p < 0.05$).

Sample size estimation for the department

The sample size requirement for between-department comparisons of PSQ scores was estimated using one-way analysis of variance ANOVA. Departments with fewer than five participants were excluded to ensure stable effect-size estimation. Cohen's f was derived from the ANOVA eta-squared values. Power analyses ($\alpha = 0.05$, power = 0.80) were performed assuming both a standard medium effect ($f = 0.2$) and the observed effect size, yielding the required sample size per department.

Effect Size Analysis for high versus low-moderate stress group

Differences in PSQ scores between High and Low-Moderate stress groups were quantified using both parametric and non-parametric effect size measures. The primary emphasis was placed on the Wilcoxon rank-biserial correlation, with additional estimates including Cohen's d , Glass's Δ , Hedges' g , and eta-squared derived from one-way ANOVA. The non-parametric epsilon-squared was also calculated. Group differences

were visualized using boxplots with jittered individual observations overlaid.

Analysis of profession versus high stress

Associations between profession and stress group were first examined using Pearson's chi-square test. Group differences were visualized using proportional bar plots. Multivariable logistic regression was then used to assess whether profession independently predicted high stress after adjusting for age, gender, work experience, and shift type. Results are reported as odds ratios with 95% confidence intervals.

Analysis of departments versus high stress

Differences in PSQ scores across departments were assessed using the Kruskal-Wallis test due to non-normality. Associations between department and stress group were examined using chi-square tests and visualized with proportional bar plots. In order to avoid biased inference from sparse data and quasi-separation, analyses were restricted to departments with ≥ 5 respondents. The multivariable logistic regression adjusted for age, gender, work experience, and shift type was used to identify independent predictors of high stress.

A funnel plot was applied to distinguish true departmental effects from random variation due to sample size.

Machine learning analysis

Non-clinical demographic, occupational and psychosocial variables were used to train a Random Forest classifier to predict high stress status. Departments and professions with fewer than five observations were excluded to ensure model stability and avoid sparse-category bias during cross-validation. Models were trained using repeated 5-fold cross-validation with up-sampling to address class imbalance. Performance was evaluated using cross-validated predictions, with ROC AUC as the primary metric and sensitivity prioritized to optimize early detection of high-risk individuals. Variable importance analysis was used to identify key early-warning predictors.

3. Results

A total of 178 respondents were included in the final study after excluding 50 responses with incomplete answers or from regions other than Poland. Table 1 shows the characteristics of the study population.

Table 1. Descriptive statistics of the study population

	Level	Overall (SD)	Low-Moderate (SD)	High (SD)
n		178	152	26
PSQ (mean (SD))		0.37 (0.19)	0.31 (0.14)	0.71 (0.09)
Age (mean (SD))		37.38 (11.30)	36.91 (11.27)	40.12 (11.27)
Gender (%)	Male	53 (29.8)	50 (32.9)	3 (11.5)
	Female	125 (70.2)	102 (67.1)	23 (88.5)
Marital status (%)	Civil Union	53 (29.8)	47 (30.9)	6 (23.1)
	Cohabiting (significant other)	23 (12.9)	21 (13.8)	2 (7.7)
	Divorced	11 (6.2)	7 (4.6)	4 (15.4)
	Married	51 (28.7)	47 (30.9)	4 (15.4)
	Separated	2 (1.1)	1 (0.7)	1 (3.8)
	Single	27 (15.2)	21 (13.8)	6 (23.1)
	Widowed	11 (6.2)	8 (5.3)	3 (11.5)
Children (mean (SD))		0.43 (0.50)	0.43 (0.50)	0.42 (0.50)
Education (%)	Associates	1 (0.6)	1 (0.7)	0 (0.0)
	Bachelor	12 (6.7)	8 (5.3)	4 (15.4)
	Doctorate	8 (4.5)	6 (3.9)	2 (7.7)
	Masters	43 (24.2)	35 (23.0)	8 (30.8)
	MD	72 (40.4)	61 (40.1)	11 (42.3)
	Paramedic (2 years training)	10 (5.6)	10 (6.6)	0 (0.0)
	Paramedic (3 years training)	31 (17.4)	30 (19.7)	1 (3.8)
	Postdoc	1 (0.6)	1 (0.7)	0 (0.0)

Table 1. Descriptive statistics of the study population

	Level	Overall (SD)	Low-Moderate (SD)	High (SD)
Employment (%)	Freelance	2 (1.1)	1 (0.7)	1 (3.8)
	Fulltime	152 (85.4)	134 (88.2)	18 (69.2)
	Internship	1 (0.6)	1 (0.7)	0 (0.0)
	Parttime	9 (5.1)	3 (2.0)	6 (23.1)
	Seasonal	1 (0.6)	1 (0.7)	0 (0.0)
	Temporary	13 (7.3)	12 (7.9)	1 (3.8)
Employer (%)	Both	68 (38.4)	59 (39.1)	9 (34.6)
	NFZ (National Health Fund)	98 (55.4)	82 (54.3)	16 (61.5)
	Private	11 (6.2)	10 (6.6)	1 (3.8)
Profession (%)	Dentist	4 (2.2)	4 (2.6)	0 (0.0)
	Doctor	75 (42.1)	62 (40.8)	13 (50.0)
	Midwife	2 (1.1)	2 (1.3)	0 (0.0)
	Nurse	49 (27.5)	37 (24.3)	12 (46.2)
	Paramedic	45 (25.3)	44 (28.9)	1 (3.8)
	Pharmacist	1 (0.6)	1 (0.7)	0 (0.0)
	Scientist	2 (1.1)	2 (1.3)	0 (0.0)
Work experience (%)	<1 year	3 (1.7)	2 (1.3)	1 (3.8)
	1–5 years	65 (36.5)	55 (36.2)	10 (38.5)
	5+ years	110 (61.8)	95 (62.5)	15 (57.7)
Shift (%)	Day	151 (84.8)	133 (87.5)	18 (69.2)
	Night	27 (15.2)	19 (12.5)	8 (30.8)
Conflict (%)	None	7 (3.9)	5 (3.3)	2 (7.7)
	Patient	11 (6.2)	9 (5.9)	2 (7.7)
	Patient family	35 (19.7)	26 (17.1)	9 (34.6)
	Coworker	14 (7.9)	10 (6.6)	4 (15.4)
	Patient + Patient family	33 (18.5)	32 (21.1)	1 (3.8)
	Patient + Coworker	13 (7.3)	11 (7.2)	2 (7.7)
	Patient family + Coworker	18 (10.1)	17 (11.2)	1 (3.8)
	Patient + Patient family + Coworker	47 (26.4)	42 (27.6)	5 (19.2)
Department (%)	Aesthetics	1 (0.6)	1 (0.7)	0 (0.0)
	Allergy & Pulmonology	1 (0.6)	0 (0.0)	1 (3.8)
	Cardiology	3 (1.7)	1 (0.7)	2 (7.7)
	Dentistry	4 (2.2)	4 (2.6)	0 (0.0)
	Dermatology	1 (0.6)	0 (0.0)	1 (3.8)
	Diabetology	1 (0.6)	0 (0.0)	1 (3.8)
	Pharmacy	1 (0.6)	1 (0.7)	0 (0.0)
	Emergency Medicine	72 (40.4)	71 (46.7)	1 (3.8)
	Endocrinology	3 (1.7)	2 (1.3)	1 (3.8)
	Family Medicine	4 (2.2)	3 (2.0)	1 (3.8)
	Gastroenterology	1 (0.6)	1 (0.7)	0 (0.0)
	Intensive Care Unit (ICU)	6 (3.4)	5 (3.3)	1 (3.8)

Table 1. Descriptive statistics of the study population

	Level	Overall (SD)	Low-Moderate (SD)	High (SD)
Department (%)	Internal Medicine (IM)	27 (15.2)	24 (15.8)	3 (11.5)
	Laboratory	1 (0.6)	1 (0.7)	0 (0.0)
	Neurology	2 (1.1)	1 (0.7)	1 (3.8)
	Obstetrics and gynecology (OBGYN)	7 (3.9)	6 (3.9)	1 (3.8)
	Oncology	4 (2.2)	2 (1.3)	2 (7.7)
	Ophthalmology	1 (0.6)	1 (0.7)	0 (0.0)
	Orthopedics	7 (3.9)	7 (4.6)	0 (0.0)
	Primary Care (PC)	4 (2.2)	2 (1.3)	2 (7.7)
	Pediatrics	11 (6.2)	7 (4.6)	4 (15.4)
	Pediatric Immunology, Allergy & Pulmonology	1 (0.6)	1 (0.7)	0 (0.0)
	Pediatric Oncology	1 (0.6)	1 (0.7)	0 (0.0)
	Pediatric Orthopedics	1 (0.6)	1 (0.7)	0 (0.0)
	Pharmacy	1 (0.6)	1 (0.7)	0 (0.0)
	Prison	1 (0.6)	1 (0.7)	0 (0.0)
	Psychiatry	1 (0.6)	1 (0.7)	0 (0.0)
	Pulmonology	1 (0.6)	1 (0.7)	0 (0.0)
	Radiology	1 (0.6)	0 (0.0)	1 (3.8)
	Simulation	1 (0.6)	1 (0.7)	0 (0.0)
	Surgery	4 (2.2)	3 (2.0)	1 (3.8)
	Tropical Disease	3 (1.7)	3 (2.0)	0 (0.0)
	Urology	1 (0.6)	0 (0.0)	1 (3.8)

SD – Standard Deviation

Reliability result

The PSQ-30 questionnaire shows excellent reliability (Cronbach's $\alpha \approx 0.96$), indicating that the items are highly consistent and measure a common underlying construct. The near-identical alpha coefficients for raw and standardized scores suggest that item variances and correlations are well balanced. Item-total correlations are moderate to high (≈ 0.45 – 0.79), meaning that each item contributes meaningfully to the total score. No item appears poorly aligned with the scale. The subscale reliability results were as follows: Worry: $\alpha = 0.74$ (acceptable), Tension: $\alpha = 0.82$ (good), Joy: $\alpha = 0.88$ (very good), Demands: $\alpha = 0.93$ (excellent). This pattern supports the reliable measurement at both the total scale and subscale levels. The PSQ-30 and its derived subscale scores (computed as row means) are psychometrically sound for subsequent analyses in this sample.

Sample Size and Power Analysis

A one-way analysis of variance ANOVA was conducted to estimate the effect size of differences in PSQ scores across departments, restricting analyses to departments with at least five participants to ensure

stability. The observed effect size was Cohen's $f = 0.239$, corresponding to a medium effect. Power analysis ($\alpha = 0.05$, power = 0.80) indicated that approximately 35–38 participants per department are required to reliably detect both a conventional medium effect ($f = 0.2$) and the observed effect size across the five departments. Although only the emergency department reached and exceeded the required 40 participants, the effect size suggests that the current effect size is adequate for planning sufficiently powered group comparisons.

Effect size interpretation for high stress group versus low-moderate stress group

The difference in PSQ scores between the High and Low-Moderate stress groups was quantified primarily using the Wilcoxon rank-biserial correlation (r_{rbj}), a robust non-parametric effect size. The analysis yielded $r_{rbj} = 0.61$, which represents a large effect. This indicates a high probability that a randomly selected individual from the High stress group has a higher PSQ score than a randomly selected individual from the Low-Moderate group, reflecting substantial separation between the groups in rank distributions.

Supporting metrics were concordant with this finding. The non-parametric epsilon-squared ($\epsilon^2 = 0.37$) also indicated a large group effect, suggesting that over one-third of the variability in PSQ ranks is attributable to stress group membership. Parametric indices (Cohen's $d \approx 2.95$; $\eta^2 \approx 0.52$) similarly pointed to very large differences. However, given the unequal group sizes and potential non-normality, the rank-biserial correlation provides the most appropriate and conservative estimate of effect magnitude.

Stress Group Characteristics and Associations

The distribution of the stress groups is shown in **Figure 1A**. Shapiro–Wilk tests indicated non-normality in

PSQ scores for both the High ($W = 0.897$, $p = 0.013$) and Low-Moderate groups ($W = 0.972$, $p = 0.003$), supporting the use of nonparametric tests. The analysis of categorical associations revealed that stress group membership was related to Gender ($\chi^2 = 3.88$, $p = 0.049$) and Shift type ($\chi^2 = 4.43$, $p = 0.035$), but not with department conflict exposure ($\chi^2 = 12.19$, $p = 0.095$). Corresponding proportional plots are shown in **Figure 1B** (Shift type by stress group) and **Figure 1C** (Conflict exposure by stress group).

Wilcoxon rank-sum tests confirmed that the High-stress group had significantly higher PSQ scores than the Low-Moderate-stress group ($W = 0$, $p < 0.001$), whereas age did not differ between groups ($W = 1576.5$, $p = 0.10$).

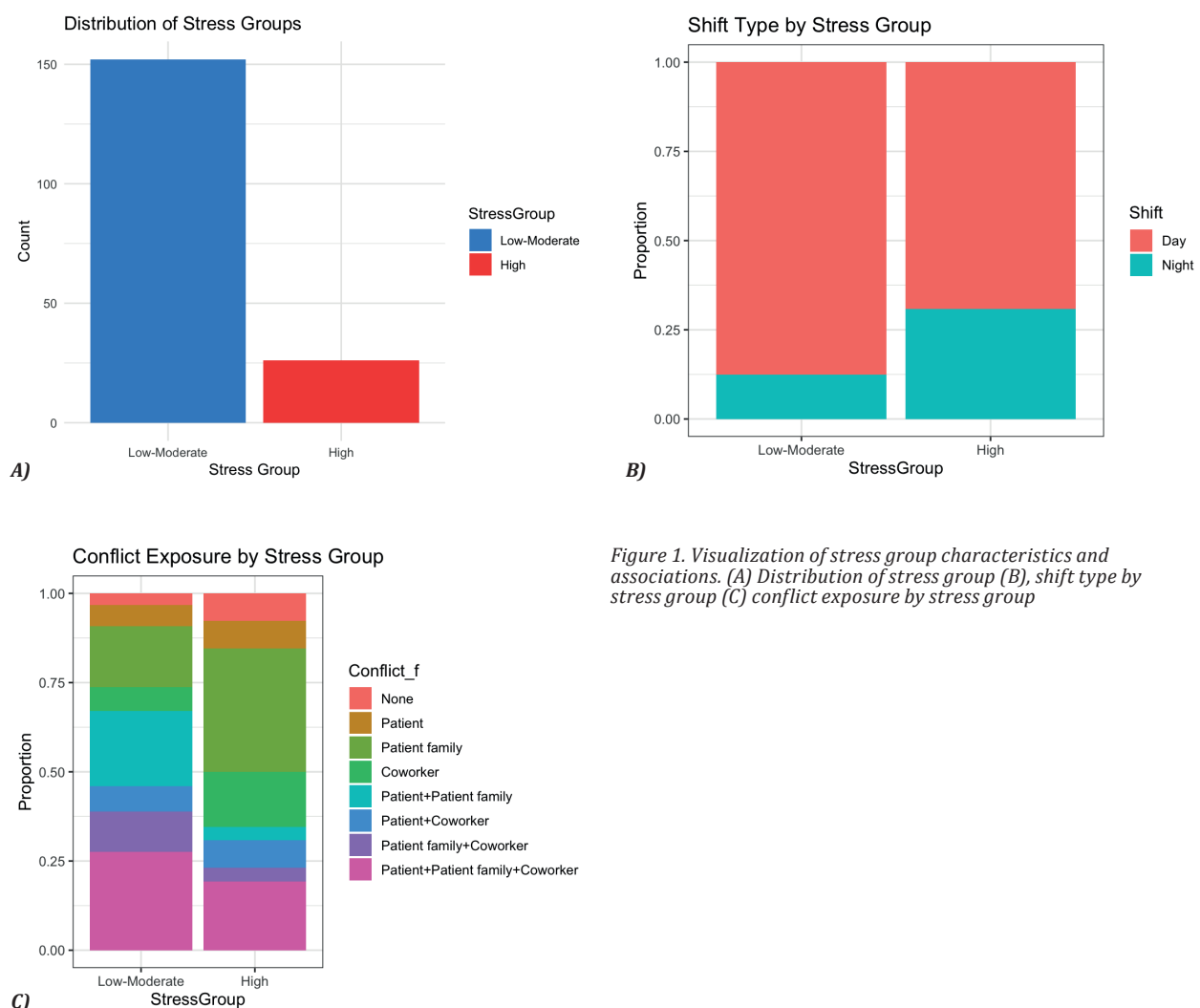


Figure 1. Visualization of stress group characteristics and associations. (A) Distribution of stress group (B), shift type by stress group (C) conflict exposure by stress group

Multivariable logistic regression identified independent predictors of high levels of stress: night shift (OR = 11.5, 95% CI: 1.54–124, $p = 0.02$) and long work experience (>5 years) (OR = 0.0009, 95% CI: 0.000001–0.6, $p = 0.03$). These findings are exploratory and not intended for precision or generalization, given the large CIs resulting from the small sample size of our dataset. A small sample

size often leads to a wide CI [45]. Other demographic and departmental factors were not statistically significant. Model diagnostics indicated acceptable multicollinearity (VIF < 5 for all key predictors) and excellent fit (Hosmer–Lemeshow $p = 0.985$). Influence diagnostics did not reveal any problematic points.

Profession and high stress result

At the univariate level, stress group distribution did not differ significantly by profession ($\chi^2 = 11.36$, $df = 6$, $p = 0.078$), although the pattern suggested variability across professional categories. The proportional distribution of High versus Low-Moderate stress across professions is illustrated in **Figure 2A**. However, some professions exhibited higher proportions of high stress (>20%), despite the overall non-significant chi-square result, with nursing showing the highest proportion (**Figure 2B**).

The multivariable logistic regression, adjusting for

age, gender, work experience and shift type, profession was not independently associated with high stress. In contrast, night shift work remained a significant predictor of high stress (OR = 3.45, 95% CI: 1.02–11.8, $p = 0.045$). Age, gender and work experience were not statistically significant in the adjusted model.

These findings suggest that apparent differences in the stress prevalence across professions are largely explained by work-related factors, particularly night-shift exposure, rather than by the profession itself.

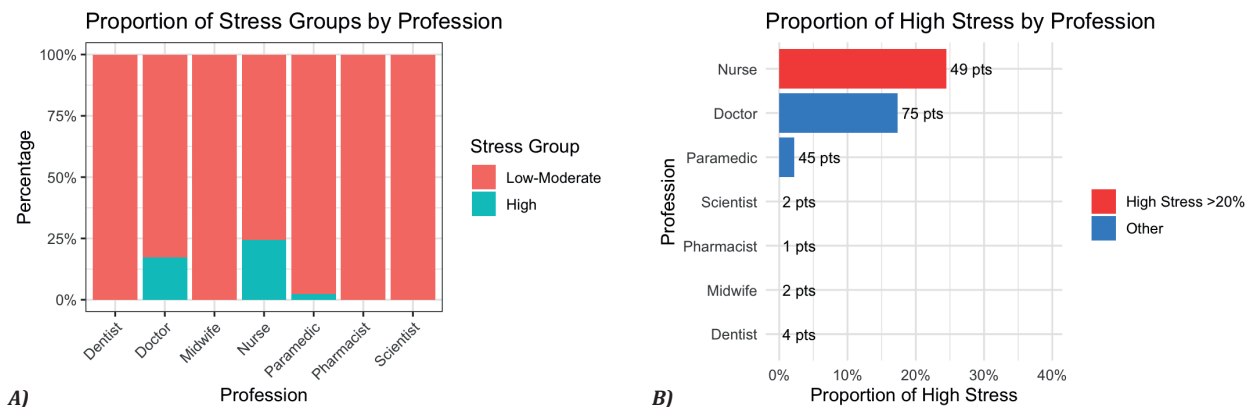


Figure 2. Proportion of (A) stress groups by profession and (B) high stress by profession. Pts – participants.

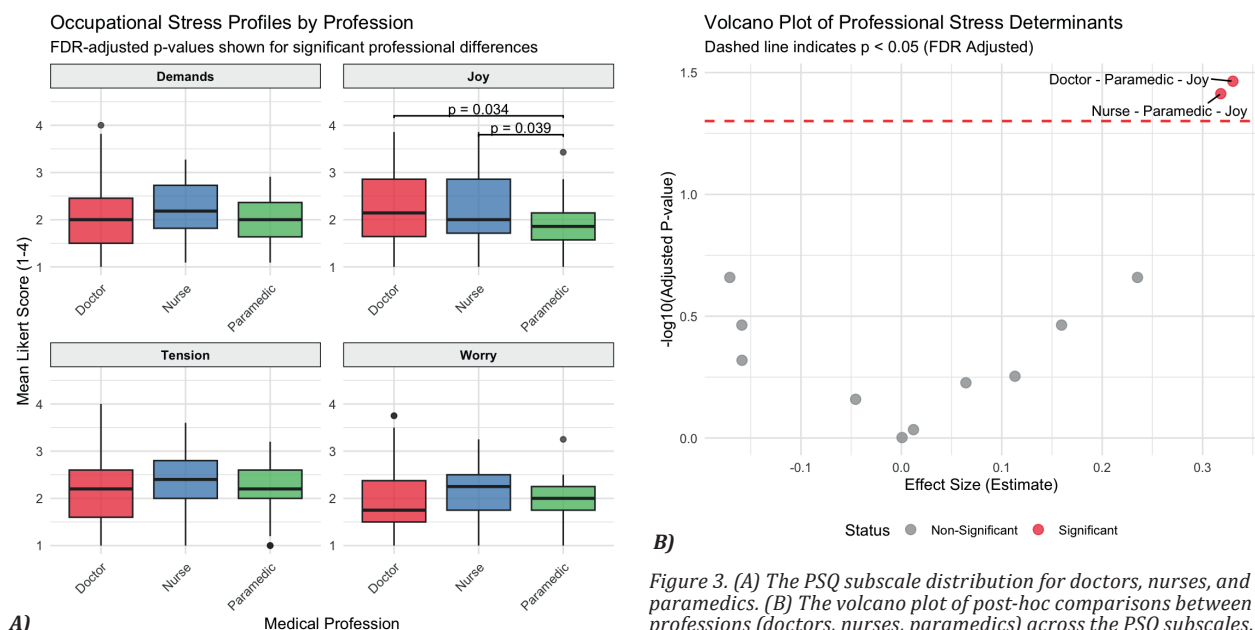
Occupational stress subscale profiles by profession

Visual analysis of subscale distributions suggested differences in stress profiles across professions (**Figure 3A**). Nurses tended to have higher median scores for Demands, Tension, and Worry, while paramedics had lower Joy scores than doctors and nurses.

A significant multivariate effect of profession on the PSQ subscale scores was observed (Pillai's trace = 0.142, $F(8,328) = 3.12$, $p = 0.002$). Univariate analyses indicated that this effect was associated with differences

in the Joy subscale ($F(2,166) = 3.73$, $p = 0.026$), whereas no significant differences were observed for Worry ($p = 0.367$), Tension ($p = 0.344$), or Demands ($p = 0.173$).

Post-hoc comparisons on the Joy subscale showed that paramedics reported a significantly lower Joy than both doctors (estimate = 0.33, $p = 0.034$) and nurses (estimate = 0.32, $p = 0.039$), while no other pairwise differences reached statistical significance. **Figure 3B** visually summarizes both the effect size and the statistical significance of the post-hoc result.



B)

Figure 3. (A) The PSQ subscale distribution for doctors, nurses, and paramedics. (B) The volcano plot of post-hoc comparisons between professions (doctors, nurses, paramedics) across the PSQ subscales. The red dashed lines indicate statistically significant differences (FDR-adjusted $p < 0.05$).

Results of departmental differences and high stress

Overall PSQ scores differed significantly across departments (Kruskal-Wallis $\chi^2 = 49.10$, $df = 30$, $p = 0.015$), indicating heterogeneity in stress burden at the departmental level. Consistently, a univariate chi-square test showed a strong association between department and stress group ($\chi^2 = 72.00$, $df = 30$, $p = 0.00003$). However, the chi-square approximation is not valid due to sparse cell counts across several departments, which are influenced by their small sample sizes ($n \leq 3$). Several departments appeared to exceed a pragmatic threshold of >20% high stress (Figure 4A), but these patterns were

largely associated with the departments with very small sample sizes (often $n \leq 3$).

After restricting the analyses to departments with at least five respondents, only six departments met the inclusion criteria. The funnel plot analysis (Figure 4B) demonstrated that, after accounting for sampling variability, none of the departments with $n \geq 5$ lay clearly outside the 95% control limits, indicating no statistically robust departmental outliers. Within this subgroup, the Pediatric department showed the highest proportions of high stress, whereas OBGYN, Emergency and Orthopedics were at or below the institutional average (Table 2).

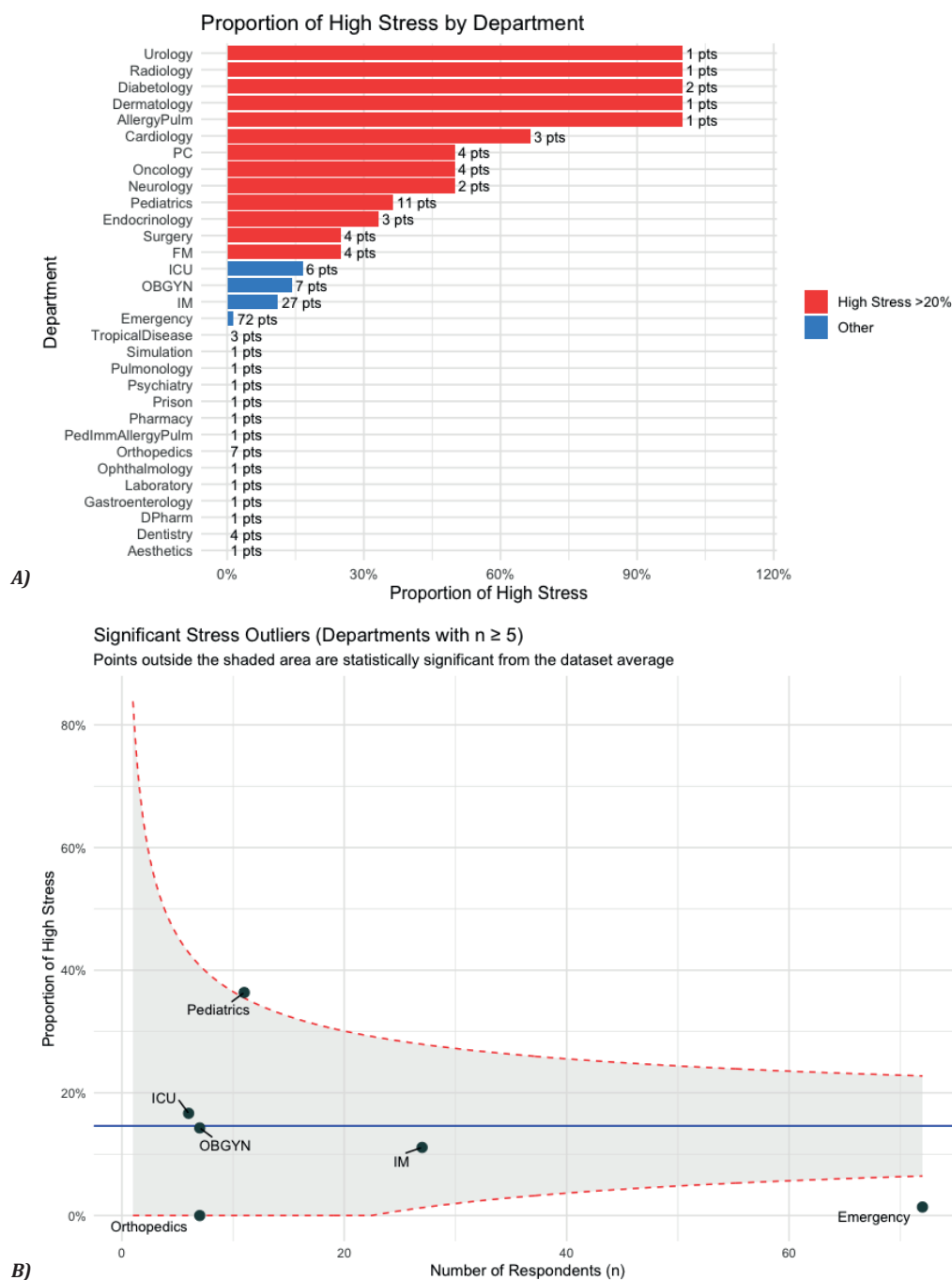


Table 2. Departments with ≥ 5 Respondents: Proportion of High Stress

Department	Total (n)	High Stress	Proportion of High Stress	95% CI
Pediatrics	11	4	36.4%	[0.15,0.65]
Intensive Care Unit	6	1	16.7%	[0.03,0.56]
Obstetrics & gynecology	7	1	14.3%	[0.03,0.51]
Internal Medicine	27	3	11.1%	[0.04,0.28]
Emergency	72	1	1.4%	[0.00,0.07]
Orthopedics	7	0	0.0%	[0.00,0.35]

Night-shift work was independently associated with substantially higher odds of high stress (OR = 12.4, 95% CI: 1.63–94.6), whereas increasing length of work experience was associated with lower odds of high stress. Compared with staff with <1 year of experience, those with 1–5 years (OR = 0.014, 95% CI: 0.0002–0.95) and >5 years (OR = 0.002, 95% CI: 0.00002–0.23) had a markedly lower odds of high stress. Although confidence intervals were wide, reflecting sparse data in some categories, the consistency of effect direction and statistical significance supports the robustness of these findings. This instability supports the conclusion that the observed departmental differences are largely attributable to work-pattern characteristics, particularly night shifts, rather than to department membership itself.

Machine learning-based screening model for high stress detection

The machine learning model was designed to evaluate whether non-clinical factors can function as a reliable proof-of-concept screening model for identifying healthcare workers at risk of high levels of stress before progression to burnout. Given the public-health objective of prevention, model sensitivity was prioritized to maximize early detection of the 26 high-stress individual

in the dataset.

After repeated cross-validated predictions, the Random Forest classifier achieved an ROC AUC value of 0.728 (**Figure 5A**), indicating good discriminative ability between high stress and low-moderate-stress individuals. Using a probability threshold of 0.20 to prioritize sensitivity, the model achieved 70% sensitivity, 76.7% specificity, 76.2% accuracy, and 73.4% balanced accuracy. This indicates that the model successfully identifies 3/4 of high-stress levels, supporting its utility as a rule-out and early-warning screening tool. Although the positive predictive value was modest (21%), the negative predictive value remained high (97%), reflecting the expected trade-off when prioritizing early detection in an imbalanced dataset, and is acceptable in a screening context where false positives are preferable to missed cases. The model is intended to flag individuals for further assessment, rather than definitive diagnosis.

Variable importance analysis (**Figure 5B**) revealed that psychosocial and occupational context variables contributed more to predictive performance than demographic factors alone. The top 3 most influential predictors are age, pediatric department and workplace conflict.

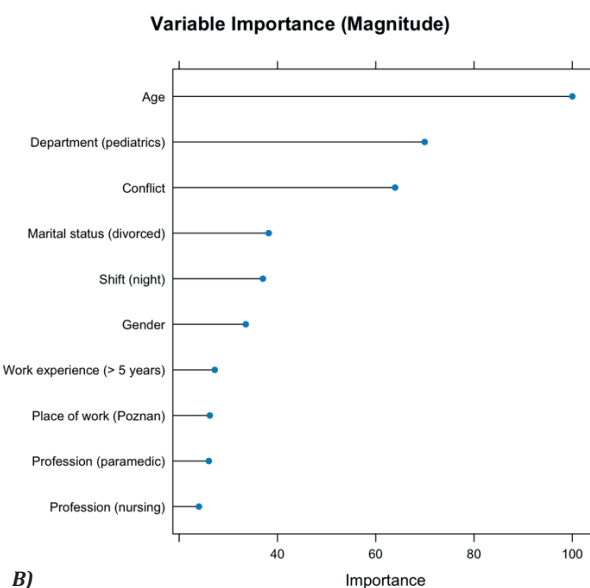
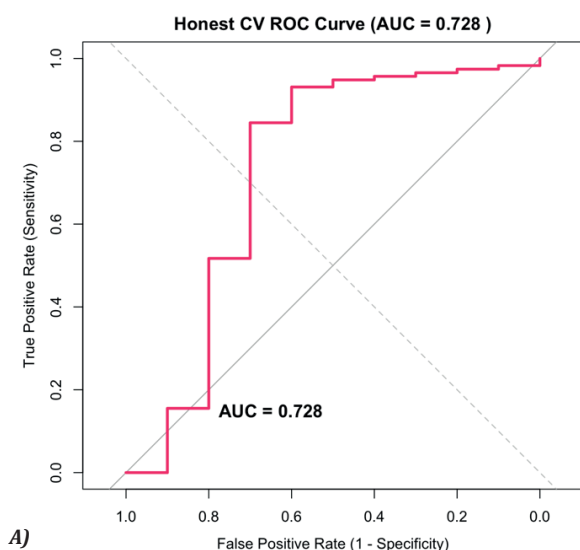


Figure 5. Machine learning plot of (A) ROC curve and (B) variable importance

4. Discussion

The study findings demonstrated the prevalence of stress among healthcare workers, highlighting occupational stress as a significant concern in clinical environments. Stress group categories showed a statistically significant association with gender, suggesting potential differences in stress exposure or coping mechanisms. Female healthcare workers often experience higher levels of occupational stress and burnout compared to their male colleagues, associated with factors such as the double burden of balancing demanding shifts with household responsibilities, along with workplace gender inequality, gender-based harassment, pay gaps, and lower autonomy [46–51]. Female physicians had reported up to 60% higher risk of burnout, even after adjusting for age and other factors [52]. Gender disparities may reflect differing workplace expectations, variations in work-life balance pressures, or sociocultural roles influencing perceived stress.

The most significant findings from our study are that night shift work and work experience of more than five years are independent predictors of high stress, with night shift work remaining a key predictor when controlled for profession. Night shift workers had a higher odds ratio of reported high stress. This is consistent with other studies that found that for every additional night or weekend call shift, physicians had a higher odds ratio for burnout [52]. This finding is important as night shift work is known to be associated with increased stress, anxiety, and depression among healthcare workers [53].

In contrast, work experience of more than five years was associated with a lower probability of high stress levels. More experience reduces stress vulnerability [54]. This suggests that in healthcare, more experience contributes to improved clinical confidence, enhanced coping strategies, and better emotional regulation. This increased experience leads to lower levels of burnout [52,55,56]. Healthcare workers with lower professional experience are at higher risk of developing mental illness [57,58]. The study by Abdulghani et al. reported an inverse relationship between the year of physician residency training and reported levels of stress, with year-one residents reporting the highest percentage of overall stress compared to year-four residents [59]. Another study found that nurses and physicians who had worked for more than 7 years reported lower levels of tendency to experience negative emotions such as anxiety, depression, anger and self-doubt than those who had worked for shorter periods [60].

Although not statistically significant, conflicts with patients' family was the highest conflict associated with high stress. Conflicts with patients' families are one of the highest work-related stressors [61]. These conflicts

are common in Polish healthcare settings [58]. In one study, conflict between healthcare workers and patients' families occurred in almost half of cases (48%) [62], with conflicts involving adolescents and pediatric patients being more difficult to manage [63,64]. Causes of these conflicts include poor communication, distrust, lack of confidence, differences in treatment plans and care, power dynamics, sociocultural differences, family health literacy, and strong negative opinions [63,64].

Despite a low overall proportion of respondents by profession, nurses reported the highest level of stress compared with doctors, paramedics, and all other professions, although the difference was not statistically significant. Compared to other healthcare workers, nurses report lower job satisfaction and higher burnout levels, particularly among clinical nurses [65–68]. While providing care, nurses are directly responsible for ensuring patients' safety [69], which may contribute to their higher levels of stress. The higher prevalence of high stress among nurses in our study might also be due to differences in the rating of stress and stressors among healthcare workers. Research has shown that doctors and nurses grade stress and stressors differently [70].

On the stress subscale, paramedics reported lower joy levels, indicating lower job satisfaction than doctors and nurses. The lack of job satisfaction in paramedics is related to the increased workload for paramedics [71]. As paramedics are often first responders, especially in ambulatory care settings, they are exposed to higher levels of stress, burnout, and workload [72–74]. Paramedics who work in ambulatory settings witness trauma while working long hours with possibly less support than healthcare workers in hospitals [75].

Pediatrics and ICU departments exhibited the highest proportions of high stress. These departments are characterized by patients who require advanced clinical management, high emotional intensity, rapid, high-stakes decision-making, and exposure to critical or life-threatening situations [76–84]. The prevalence of stress and burnout in ICU workers is high, at around 70% [82,83]. Pediatric nurses have been reported to have high stress, burnout, fatigue, anxiety, panic attacks, fear, and being overworked [85,86]. In comparison with doctors in the ICU, nurses are reported to experience greater stress, higher burnout and lower job satisfaction than doctors [82,87]. In a study on the mental health of pediatric nurses, participants cited increased workload and inadequate time for various tasks as contributing factors towards anxiety and depression [88]. Departmental environments may therefore play a central role in the development of stress.

The random forest model successfully identified over 75% of high stress cases (specificity) with an accuracy

of 76.2%, demonstrating a good predictive performance. Machine learning models are being used to predict stress [39,89], with models such as random forests achieving up to 79% accuracy for burnout in healthcare workers [90], 90% for stress in nurses [91], and 75.3% for burnout in nurses [92]. The most influential predictors were age, department (pediatrics), and workplace conflicts. Younger healthcare workers often report higher stress due to limited experience and professional adjustment, especially in demanding departments such as the ICU and in first-responder roles [87,93]. Burnout is also associated with younger age and less work experience in ICU nurses [94]. Future research should therefore explore the relationship between age, experience, and resilience. These findings suggest that stress arises from a combination of organizational, interpersonal, and demographic factors. Machine learning approaches may therefore complement traditional statistical methods in identifying at-risk healthcare workers. The present model should be interpreted as an exploratory screening model rather than an operational early warning system. Its use would require external validation, calibration assessment, and evaluation in larger, multicenter samples before any implementation.

This study is strengthened by the use of a psychometrically robust instrument, the Perceived Stress Questionnaire (PSQ-30), which demonstrated excellent internal consistency and supports reliable assessment of perceived stress across both total and subscale scores. The combination of descriptive, nonparametric, and multivariable regression analyses with a machine learning approach enhances analytical rigor. The inclusion effect size metrics alongside statistical significance further improves the interpretability of the results. Importantly, integrating a random forest model underscores the study's translational potential, positioning machine learning as a feasible early-warning tool for identifying at-risk healthcare workers.

However, several limitations should be acknowledged. The relatively small sample size, particularly the limited number of high-stress cases, reduces statistical power and contributes to wide confidence intervals, limiting the precision of effect estimates. Subgroup analyses are further constrained by sparse data across professions and departments, restricting the reliability and generalizability of these comparisons. The cross-sectional design precludes causal inference and limits understanding of temporal relationships between occupational exposures and stress outcomes. Additionally, reliance on self-reported measures introduces potential reporting and recall biases. The absence of key variables, such as workload intensity, staffing levels, and institutional support, is an unmeasured

factor that may have influenced the results. Stress was assessed using the PSQ-30 questionnaire, which measures general perceived stress rather than occupational stress specifically. Although occupational characteristics were examined as predictors of stress among healthcare workers, the study did not include validated instruments specifically designed to assess occupational stress or related constructs such as burnout, job demands, job control, organizational support, workload, or work-home conflict. Consequently, the observed associations should be interpreted as relationships between occupational exposures and perceived stress rather than direct measures of occupational stress. Finally, although the machine learning model showed promising performance, it was developed on a single dataset without external validation, and its relatively low positive predictive value suggests it should be used as a screening rather than a diagnostic tool and requires validation in larger, more diverse healthcare populations.

5. Conclusion

The present study confirms that occupational stress is prevalent among healthcare workers in Poland and is shaped by an interplay of demographic factors (e.g., age), organizational factors (e.g., department, night shifts), and interpersonal factors (e.g., workplace conflict). Night shift work and early career status emerged as key predictive factors, while longer professional experience was associated with lower risks, underscoring the role of adaptive coping and clinical maturity. The observed department-specific burdens, particularly in ICU and pediatric settings, highlight structural and contextual factors that contribute to stress within healthcare systems. Complementing these findings, the random forest model demonstrated potential predictive capability, supporting the integration of machine learning as a practical tool for early identification of high-risk individuals.

Future research should prioritize longitudinal and multi-center designs to establish causal pathways between occupational exposures and stress outcomes, while incorporating biological and psychological markers of resilience. Further validation and external generalizability of machine learning models across diverse healthcare systems are also essential. In terms of policy, institutional frameworks should mandate routine stress surveillance, regulate shift patterns, and implement gender-sensitive workplace policies that address inequities, harassment and work-life balance. Intervention strategies should include structured mentorship for early-career professionals, targeted support in high-intensity departments, conflict management training, and organizational reforms to reduce workload and improve staffing levels. The combination of a data-driven proof-of-

concept screening model with systemic and individualized interventions offers a scalable pathway to mitigate stress and improve workforce wellbeing and patient care outcomes in Poland.

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Data availability statement

The data are presented in the manuscript.

Ethics approval

In accordance with institutional and national regulations, this non-experimental, questionnaire-based study did not require formal approval from a bioethics committee. A written exemption was provided by the appropriate institutional body. All participants provided informed consent, and the data were collected anonymously and handled in compliance with ethical standards.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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