Modeling Workplace Predictors of Depression and PTSD in Healthcare Professionals Using Machine Learning

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Abstract. Mental health is a critical concern for healthcare professionals(HCPs), with stressors like long hours, heavy workloads, and traumatic events increasing the risk of depression and PTSD, further exacerbated by the COVID-19 pandemic. This study examines workplace factors predicting depression and PTSD among HCPs in 4 hospitals in south-east United States using a cross-sectional survey and validated tools. We compare four classifiers with four selection methods to predict depression and PTSD. Feature importance methods (SHapley Additive exPlanations(SHAP) and permutation importance) revealed key predictors such as the availability of health programs, workplace injuries, life satisfaction, and workplace harassment. Logistic Regression and SVM consistently achieved high accuracies (78.57% for depression and 96.43% for PTSD). Findings highlight the need for targeted interventions and improved workplace conditions to promote HCPs' mental health.

Keywords. Workplace factors, depression, PTSD, healthcare professionals, machine learning

1. Introduction

Mental health remains a critical concern for healthcare professionals (HCPs), including nurses and physicians, who are routinely exposed to stressors such as long working hours, heavy workloads, and traumatic events[1,2]. These stressors often manifest differently across roles; for instance, nurses frequently face high patient loads and exposure to trauma, while physicians may encounter decision-making pressures and legal liabilities. These challenges substantially increase the risk of depression and post-traumatic stress disorder (PTSD), negatively impacting job satisfaction, productivity, and patient safety[3,4]. The COVID-19 pandemic further exacerbated these risks with added stressors like resource shortages and prolonged shifts[4,5].

Workplace factors, including workload management, psychological safety, and access to resources, are pivotal in shaping mental health outcomes[1,7]. Adverse conditions such as workplace violence, resource constraints, and heavy patient loads are linked to increased risks of depression and PTSD[1,3]. This study utilizes the National Institute of Occupational and Safety Health (NIOSH) framework to highlight the role of workplace factors in affecting HCPs' mental health. To the best of our knowledge, no previous study has utilized machine learning (ML) methods to assess the interaction of workplace factors with demographic factors to predict the mental health of HCPs[1,8]. Thus, this study aims to utilize traditional ML methods to identify workplace factors across five domains that predict depression and PTSD among HCPs. This research could offer data-driven actionable insights for improving HCPs' mental health.

2. Methods

2.1 Data Collection and Study Measures

A composite survey was created to investigate the following: demographic factors (age, gender, marital status, job role, and years of experience), workplace factors based on the NIOSH Worker Well-Being Questionnaire, chosen for its comprehensive assessment of workplace domains, depression as measured by Patient Health Questionnaire-9 (PHQ-9) (0–27 scale), chosen for its reliability and relevance in evaluating depression in HCPs, and PTSD using PTSD Checklist for DSM-5 (PCL-5) (0–80 scale, cutoff ≥33), selected for its alignment with DSM-5 criteria and nuanced symptom evaluation. The survey was designed using Qualtrics Online Survey Software and administered between September to December 2022 to physicians and nurses in 4 hospitals (one academic medical center and three rural hospitals) of a large healthcare system in South-East United States in this IRB-approved study. (Table1)

Table 1. Number and type of survey responses

Feature	Data type	No. (%)

	None-minimal		96 (69.06%)
	Mild		28 (20.14%)
Depression	Moderate	Categorical	7 (5.03%)
	Moderately Severe		1 (0.72%)
	Severe		2 (1.43%)
PTSD	Without PTSD	Categorical	129 (92.80%)
	With PTSD		5 (3.60%)
	Attending Physician		22 (15.82%)
	Fellow physician		1 (0.72%)
	Physician Assistant		3 (2.16%)
Clinician Position	Registered Nurse	Categorical	93 (66.90%)
	Licensed Practical Nurse		6 (4.32%)
	Nurse Practitioner		3 (2.16%)
	Other		6 (4.31%)
	Male		23 (16.54%)
Gender	Female	Categorical	105 (75.54%)
	Non-binary		1 (0.72%)
	Prefer not to disclose		5 (3.60%)
	White		119 (85.61%)
	Black/African-American		3 (2.16%)
Race	Latino/Hispanic	Categorical	6 (4.32%)
	Other		2 (1.44%)
	Prefer not to disclose		5 (3.60%)
	Single		16 (11.51%)
	Married		95 (68.34%)
	Divorced		11 (7.91%)
Marital Status	Separated	Categorical	2 (1.44%)
	Widowed		5 (3.60%)
	Other		1 (0.72%)
	Prefer not to disclose		4 (2.90%)
	Job Satisfaction		134 (96.40%)
	Wage Satisfaction		133 (95.68%)
	Benefits Satisfaction		132 (94.96%)
	Advancement Satisfaction		133 (95.68%)
	Supervisor Support		132 (94.96%)
	Coworker Support		134 (96.40%)
	Job Security		131 (94.24%)
	Job Autonomy		134 (96.40%)
	Time Paucity/Work Overload		134 (96.40%)
	Meaningful Work		134 (96.40%)
	Work-related Positive Affect		134 (96.40%)
	Work-related Negative Affect		134 (96.40%)
	Work-related Fatigue		134 (96.40%)
	Job Engagement		134 (96.40%)
	Supportive Work Culture		133 (95.68%)
	Management Trust		132 (94.96%)
	Health Culture at Work		134 (96.40%)
	Availability of Job Benefits		132 (94.96%)
	Availability of Health Programs at work		131 (94.24%)
	Work to Non-work Conflict		130 (93.52%)
Work system factors	Non-work to Work Conflict	Ordinal	131 (94.24%)
	Workplace/schedule flexibility		130 (93.52%)
	Overall workplace safety		130 (93.52%)
	Workplace safety climate		130 (93.52%)
	Physical Work Environment Satisfaction		131 (94.24%)
	Discrimination		129 (92.80%)
	Work-related Sexual Harassment		130 (93.52%)
	Work-related Physical Violence		129 (92.80%)
	Work-related Bullying		130 (93.52%)
	Overall Health		131 (94.24%)
	Days of Poor Physical health		134 (96.40%)
	Chronic Health Conditions		134 (96.40%)
	Insomnia		129 (92.80%)
	Days of Poor Mental Health		134 (96.40%)
	Overall Stress		129 (92.80%)
	Poor Mental Health		127 (91.36%)
	Physical Activity		122 (87.77%)
	Tobacco Use		128 (92.08%)
	Alcohol Consumption		134 (96.40%)
	Risky Drinking		134 (96.40%)

Healthy Diet	133 (95.68%)
Sleep Hours	128 (92.08%)
Sleepy at Work	128 (92.08%)
Cognitive Functioning Limitations	125 (89.92%)
Work Limitations	127 (91.36%)
Productivity	127 (91.36%)
Work-related Injury	128 (92.08%)
Injury Consequence	125 (89.92%)
Life Satisfaction	126 (90.64%)
Financial Insecurity	126 (90.64%)
Activities Outside of Work	126 (90.64%)

2.2 Dataset Preparation and Data Analysis

The dataset comprised 131 samples, with input variables encompassing workplace constructs derived from the NIOSH WellBQ and demographic factors. Depression and PTSD severity scores were measured using the PHQ-9 and PCL-5 scales, as output variables. The analysis revealed a significant class imbalance in both outcomes, which influenced the selection of modeling and evaluation strategies. To maintain dataset integrity, an 80-20 train-test split was employed, yielding 107 training samples and 27 testing samples. An additional subdivision of the training set was deliberately avoided to ensure adequate representation of minority classes within the training data.

Feature selection methods—Mutual Information (MI), Chi-Square (χ^2), and Recursive Feature Elimination (RFE)—were used to identify key predictors of depression and PTSD. MI ranked features based on dependency scores; χ^2 retained those with statistically significant associations ($p < 0.01$); and RFE iteratively removed less relevant features to optimize model performance. To address class imbalance, a cost-sensitive learning approach was applied using scikit-learn's "class_weight='balanced'", which adjusts weights inversely to class frequency. Common classifiers, including Logistic Regression, Random Forest, Linear SVM, and Decision Trees, were used to predict severity levels. Feature contributions were assessed using SHapley Additive Explanations (SHAP) for model interpretability and Permutation Importance (PI) for a model-agnostic ranking of predictor relevance.

3. Results

3.1 Feature Selection

Key features for predicting depression severity varied across feature selection methods (Table 2). MI identified 10 features as most relevant, while the Chi² test emphasized two critical predictors with high statistical significance ($p < 0.01$). RFE optimized feature subsets, achieving the highest accuracy of 75 % using Logistic Regression. For PTSD, MI highlighted several relevant features, whereas Chi² identified "Days of Poor Physical Health" as the most significant predictor, enabling accuracy rates as high as 96%. RFE also performed competitively, achieving accuracies ranging from 93% to 96%. To address class imbalance, a 5-fold cross-validation strategy was employed. This approach ensured representative class distributions, mitigated overfitting, and provided robust, unbiased estimates of model performance.

Table 2. *5-fold cross-validation accuracy scores of features selected by MI, Chi2, and RFE methods in predicting Depression and PTSD*

	Depression			**PTSD**		
Models	MI	Chi2	RFE	MI	Chi2	RFE
Logistic Regression	<u>0.73</u>	<u>0.70</u>	<u>0.75</u>	<u>0.97</u>	<u>0.96</u>	<u>0.96</u>
Random Forest	<u>0.75</u>	0.64	0.71	<u>0.97</u>	0.96	0.96
SVM	0.72	<u>0.70</u>	<u>0.71</u>	0.95	<u>0.96</u>	<u>0.96</u>
Decision Tree	0.70	0.60	0.71	0.96	0.96	0.96

3.2 Classification

For depression severity, Logistic Regression and SVM demonstrated the highest test accuracy (Table 3) of 79% when using Chi²-selected features. This performance was closely matched by MI-selected features (75%) but declined to 71% with RFE-selected features. The Decision Tree consistently exhibited lower accuracy, ranging from 60% to 64. Overall, *Logistic Regression* and *SVM* emerged as the most effective classifiers for predicting depression severity, particularly when Chi² or MI-selected features were employed. For PTSD severity, *SVM* achieved the highest accuracy of 96 % using Chi²-and RFE selected features while Logistic Regression achieved this accuracy only with Chi²-selected features.

Table 3. *Summary of model test accuracies*

	Depression			PTSD		
Models	MI	Chi2	RFE	MI	Chi2	RFE
Logistic Regression	0.75	0.79	0.71	0.93	0.96	0.89
Random Forest	0.68	0.68	0.67	0.93	0.93	0.89
SVM	0.75	0.79	0.71	0.93	0.96	0.96
Decision Tree	0.64	0.64	0.60	0.89	0.93	0.89

3.3 Feature Importance

SHAP analysis identified critical predictors of depression, including the *availability of health programs, feeling sleepy at work, work-related injuries, and work roles*. Workplace injuries and the unavailability of health programs were primarily associated with mild to moderate depression, whereas sexual harassment emerged as a significant predictor of severe depression. SHAP analysis also revealed substantial variability in the impact of work roles, with nursing roles exhibiting a stronger association with severe depression. Furthermore, logistic regression offered superior interpretability than PI, particularly in identifying features such as *cognitive functioning limitations and work roles*.

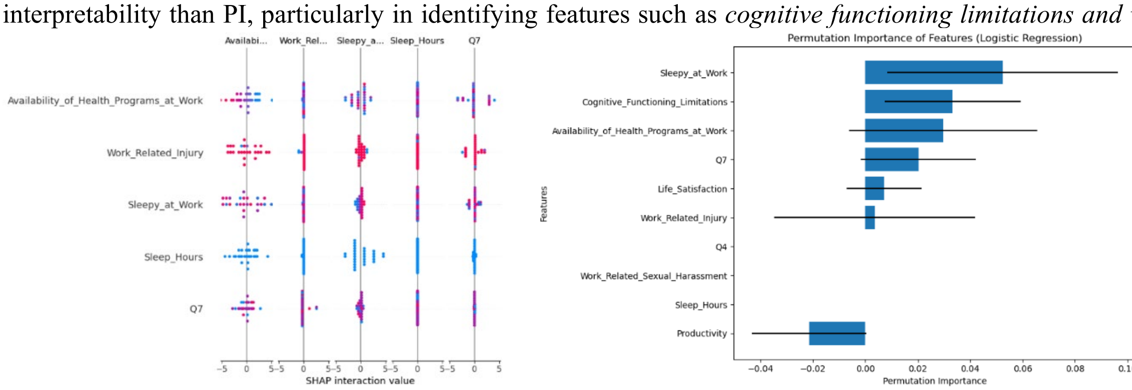

Figure 1. SHAP Summary plot (left) and Permutation Importance plot (right) highlighting features predicting depression

For PTSD, SHAP and PI identified the a*vailability of health programs, productivity, life Satisfaction, and work-related Sexual Harassment* as key predictors. Positive workplace conditions reduced PTSD risk, while poor life satisfaction and harassment were linked to adverse outcomes. Logistic Regression and SVM consistently highlighted these features, with SHAP providing more stable insights than PI.

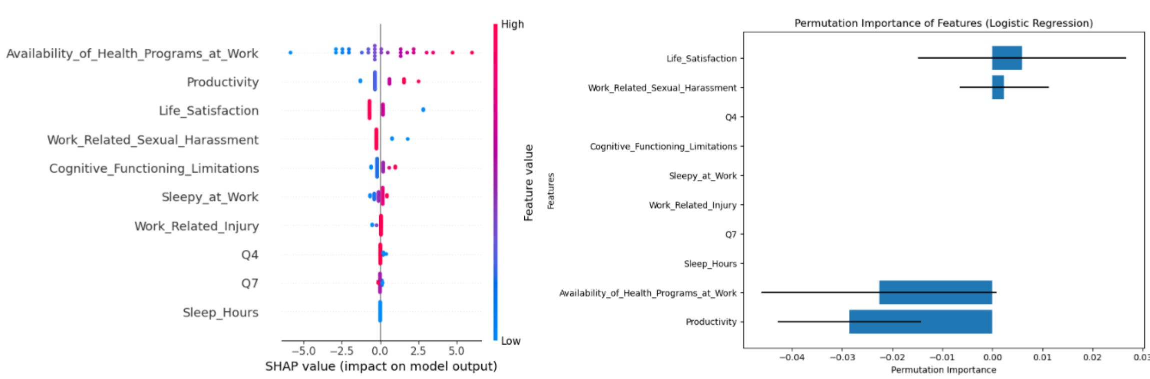

Figure 2. SHAP Summary plot (left) and Permutation Importance plot (right) highlighting features predicting PTSD

4. Discussion

This study builds upon our previous work[10–12] by predicting work system factors contributing to HCPs' depression and PTSD. Leveraging machine learning methods, we identified key workplace predictors and provided actionable insights to support HCP mental well-being. Our findings align with prior research by d'Ettorre et al.[13], which identified workplace harassment and pre-trauma factors such as years of service, exposure to violence, and mental health history as significant predictors of PTSD. Similarly, stressors including job dissatisfaction, extended working hours, and sleep disturbances have been linked to depression in healthcare settings[14]. In line with these studies, our model highlights workplace injuries, sleepiness at work, and specific job roles as key contributors to depression risk. Future research could further explore the unique occupational stressors associated with different job roles. Given the limited geographic scope of the dataset, which was confined to four hospitals in the Southeastern U.S., there is a potential for regional bias. Additional studies across diverse healthcare settings are warranted to validate these findings and to further examine the influence of workplace policies and physical environments on mental health outcomes. Additionally, the dataset exhibited significant class imbalance, with only 3.6% of participants identified as having PTSD. To address this, a cost-sensitive learning approach was applied to mitigate bias toward the majority class while preserving the real-world distribution of PTSD cases. The predictive models developed here could be integrated into clinical settings via electronic health records (EHRs) or automated alert systems to flag at-risk staff. Similar implementations demonstrate the feasibility of deploying such tools in practice[15]. Considerations for real-world adoption include data privacy, model interpretability, and alignment with clinical workflows. Despite these limitations, our findings offer valuable evidence to inform targeted interventions aimed at alleviating the mental health burden of HCPs.

5. Conclusion

Our study demonstrated that traditional ML methods can be used to predict work system factors that contribute to HCPs' depression and PTSD. Among 51 work system factors and demographic factors, seven factors were identified as key predictors of HCPs' depression and PTSD. Further studies are needed to better understand how advanced ML can be used to implement targeted interventions to improve HCPs' mental health.

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