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Using Explainable Supervised Machine Learning to Predict Burnout in Healthcare Professionals

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Abstract. Burnout in healthcare professionals (HCPs) is a multi-factorial problem. There are limited studies utilizing machine learning approaches to predict HCPs' burnout during the COVID-19 pandemic. A survey consisting of demographic characteristics and work system factors was administered to 450 HCPs during the pandemic (participation rate: 59.3%). The highest performing machine learning model had an area under the receiver operating curve of 0.81. The eight key features that best predicted burnout are excessive workload, inadequate staffing, administrative burden, professional relationships, organizational culture, values and expectations, intrinsic motivation, and work-life integration. These findings provide evidence for resource allocation and implementation of interventions to reduce HCPs' burnout and improve the quality of care.

Keywords. burnout, healthcare professionals, supervised machine learning

1. Introduction

Burnout is an occupational hazard characterized by emotional exhaustion, depersonalization, and diminished personal achievement. Before the COVID-19 pandemic, 20-40% of healthcare professionals (HCPs) reported severe burnout [1]. The COVID-19 pandemic has further increased HCPs' burnout to levels that pose a threat to maintaining a functioning healthcare workforce [2]. Burnout in HCPs can contribute to low quality of care, impair cognitive processes and lead to patient safety issues including patient harm [3]. Thus, there is an urgent need to examine the key factors contributing to HCPs' burnout during the COVID-19 pandemic.

HCPs' burnout is a complex multi-factorial problem that is often affected by several non-linear factors. The US National Academy of Medicine (NAM) proposed a systems-based framework and identified evidence-based work system factors that contribute to HCPs' burnout [4]. These factors are also further mediated by individual characteristics such as gender, age, and race. However, limited studies have utilized this theoretical model in

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examining the key factors contributing to HCPs' burnout during the COVID-19 pandemic.

In recent times, few studies have applied inductive data-driven methodologies such as supervised machine learning classifiers to predict HCPs' burnout [5]. However, to the best of our knowledge, no previous study has utilized this methodology to examine the role of work system factors and demographic factors in predicting HCPs' burnout during the COVID-19 pandemic. Further, we use feature selection methods to identify key factors that best predict HCPs' burnout to provide evidence for targeting interventions to reduce HCPs' burnout and improve quality of care.

2. Methods

2.1 Data collection and study measures

A composite survey was created to assess the following: demographic factors (clinical position, gender, race, and marital status), burnout using the 2-item Maslach Burnout Inventory (MBI) [6], and severity ratings of 21 evidence-based work system factors based on the NAM's system-based framework [4]. The survey was designed using Qualtrics Online Survey Software and administered to 450 HCPs in oncology, primary care, and surgery departments of a large academic medical center. The survey was administered between November 2020 and May 2021 with a participation rate of 59.3% (Table 1). The study was approved by the UNC-Chapel Hill Institutional Review Board.

The outcome variable is burnout, with emotional exhaustion (EE) (1 to 6) and depersonalization (DP) (1 to 6). An EE and DP summative score >3 correlates best with a more inclusive definition of burnout [6]. However, for this analysis, we considered a score >3 on EE and DP individually as a more restrictive definition of burnout to categorize the HCPs into two classes: with (≥ 3 EE & ≥ 3 DP) and without burnout (<3 EE & < 3 DP). The input variables were the 21 work system factors and 4 demographic characteristics.

Table 1. Number and type of survey responses

Feature		**Data type**	**No. (%)**
Burnout		Categorical	
	With burnout		105 (30.33%)
	Without burnout		162 (60.67%)
Clinical position		Categorical	
	Physician		70 (26.22%)
	Nurses		89 (33.33%)
	Residents		17 (6.37%)
	Pharmacists		3 (1.12%)
	Non-clinicians		88 (32.96%)
Gender		Categorical	
	Male		42 (15.73%)
	Female		196 (73.41%)
	Non-binary		4 (1.50%)
	Transgender male		4 (1.50%)
	Transgender female		3 (1.12%)
	Prefer to self-describe		3 (1.12%)
	Prefer not to disclose		15 (5.62%)

Race		Categorical	
	Caucasian		180 (67.42%)
	African American		29 (10.86%)
	Latino or Hispanic		5 (1.87%)
	Asian		8 (3.00%)
	Native American		3 (1.12%)
	Native Hawaiian or Pacific Islander		2 (0.75%)
	Other		14 (5.24%)
	Prefer not to disclose		25 (9.36%)
Marital status			
	Single		49 (18.35%)
	Married		161 (60.30%)
	Divorced		14 (5.24%)
	Separated		7 (2.62%)
	Widowed		6 (2.25%)
	Other		6 (2.25%)
	Prefer not to disclose		24 (8.99%)
Work system factors		Ordinal	
	Excessive workload		264 (98.88%)
	Unmanageable work schedules		261 (97.75%)
	Inadequate staffing		259 (97.00%)
	Time pressure		260 (97.38%)
	Inefficient workflows		258 (96.63%)
Job demands	Interruptions and disruptions		257 (96.25%)
	Inadequate technology		256 (95.88%)
	Moral distress		259 (97.00%)
	Patient factors		256 (95.88%)
	Administrative burden		255 (95.51%)
	Lack of recognition for QI activities		258 (96.63%)
	Lack of dedicated time		257 (96.25%)
	Lack of support for research		255 (95.51%)
	Professional relationships		254 (95.13%)
	Organizational culture		257 (96.25%)
Job resources	Physical work environment		254 (95.13%)
	Values and expectations		256 (95.88%)
	Job control		259 (97.00%)
	Intrinsic motivation		253 (94.76%)
	Extrinsic motivation		260 (97.38%)
	Work-life integration		259 (97.00%)

2.2 Feature selection and classification

We selected random forest to predict burnout after weighing the trade-offs between accuracy and interpretability of an array of machine learning methods. The data was split into training (80%) and testing (20%) sets. To avoid overfitting, 5-fold cross-validation (CV) was performed on the training set, where the performance of the model was iteratively evaluated on 20% of the training set. The area under the receiver operating characteristic curve (AUC) was used to evaluate the model. Initially, the RF classifier was trained with factors based on the NAM framework: work system factors & demographic characteristics, and work system factors only. Subsequently, we used chi-square, mutual information, and recursive feature elimination (RFE) to identify attributes that were most important in predicting HCPs' burnout. Features with a mutual information score >0 and chi-square p-value <0.05 were included in the analysis. RFE was done with cross-validation, where features were selected iteratively while optimizing for AUC performance. After each iteration, the less relevant features were removed, and the key factors that best predicted HCPs' burnout were identified.

3. Results

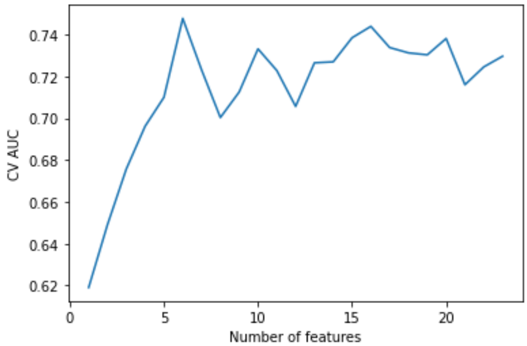

Figure 1. Optimal feature selection using recursive feature elimination

Chi-square showed that only work system factors and race were significantly ($p<0.05$) associated with burnout. RFE with eight features (Figure 1) showed the highest mean CV AUC of 0.755 in comparison to RF models with work system factors & demographic characteristics, work system factors & race, work system factors only and mutual information. In the model testing phase, RFE and work system factors & race showed the highest AUC of 0.811 (Table 1). The eight key features that best predict HCPs' burnout are *inadequate staffing, time pressure, administrative burden, professional relationships, organizational culture, values and expectations, intrinsic motivation, and work-life integration*.

Table 2. Model CV AUC (5-fold and average) and test AUC

Feature selection	**Cross-validation**						**Test**
	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average	
Work system factors & demographics (all features)	0.642	0.700	0.790	0.714	0.748	0.719	0.798
Work system factors & race	0.632	0.761	0.790	0.717	0.729	0.726	0.811
Work system factors only	0.669	0.787	0.741	0.718	0.746	0.732	0.798
Recursive feature elimination	0.661	0.842	0.805	0.762	0.704	0.755	0.811
Mutual information	0.651	0.822	0.795	0.761	0.714	0.745	0.791

4. Discussion

This study suggests that supervised machine learning methods can be used to examine the role of work system factors and demographic characteristics in predicting HCPs' burnout during the COVID-19 pandemic. Further, this study provides insights into key factors that best predicted HCPs' burnout based on feature relevance and in comparison to manually curated features from the NAM framework. HCPs are overworked and exhausted after more than a year into the pandemic. Accordingly, job demand factors such as excessive workload, inadequate staffing, and administrative burden seem to better predict HCPs' burnout. Among job resource factors, previous studies [7] have highlighted that deteriorating work-life integration has important consequences on HCPs' well-being. We did not find any demographic characteristics among the eight key predictors of burnout. However, work system factors & race had similar test accuracy as the RFE model and requires further investigation. Thus, preliminary findings from this study could provide evidence to healthcare systems on interventions that can be targeted to reduce HCPs' burnout. In future work, we plan to conduct a sensitivity analysis of the key predictors to strengthen the evidence and improve explainability.

Overall, our study findings are consistent with Nishi et al.'s study [5] that used physician survey data to develop an ensemble of machine learning models with the highest mean AUC of 0.72. Important differences between our study and their study are that they did not use a theoretical model to determine the factors contributing to HCPs burnout, assessed key factors predicting burnout using permutation importance, and did not evaluate performance on a test set. This study has several limitations. First, our results are based on a small sample of HCPs at a single academic medical center. Second, the HCPs who responded to this survey do not represent all medical specialties, groups, and subsets of the healthcare workforce. Thus, our study findings, although promising, cannot be generalized without further investigation.

5. Conclusion

Our study demonstrated that explainable supervised machine learning can be used to predict HCPs' burnout. Among 25 work system and demographic factors, eight factors were identified as the key predictors of HCPs' burnout during the COVID-19 pandemic. Further studies are needed to better understand how machine learning can be used to implement targeted interventions to reduce HCPs' burnout and improve the quality of care.

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