IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 12 September 2022, accepted 25 October 2022, date of publication 28 October 2022, date of current version 7 November 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3217770

RESEARCH ARTICLE

A Statistical Learning Approach to Evaluate Factors Associated With Post-Traumatic Stress Symptoms in Physicians: Insights From the COVID-19 Pandemic

SAYANTI MUKHERJEE[1], LANCE RINTAMAKI[2], JANET L. SHUCARD[3], ZHIYUAN WEI[1], LINDSEY E. CARLASARE[4], AND CHRISTINE A. SINSKY[5]

[1]Department of Industrial and Systems Engineering, School of Engineering and Applied Sciences, University at Buffalo, Buffalo, NY 14260, USA
[2]Department of Communication, College of Arts and Sciences, University at Buffalo, Buffalo, NY 14260, USA
[3]Department of Neurology, Jacobs School of Medicine and Biomedical Sciences, University at Buffalo, Buffalo, NY 14260, USA
[4]Health Care Research and Policy Analysis, American Medical Association, Chicago, IL 14260, USA
[5]Professional Satisfaction, American Medical Association, Chicago, IL 14260, USA

Corresponding author: Sayanti Mukherjee (sayantim@buffalo.edu)

This work was supported by the 2019-20 State University of New York (SUNY) Research Seed Grant Program RFP #20-03-COVID.

ABSTRACT Physicians facing the COVID-19 pandemic are likely to experience acute and chronic, and often unpredictable, occupational stressors that can incur post-traumatic stress symptoms (PTSS), prevention of which is of utmost importance to enhance healthcare workforce efficiency. Unlike previous studies, in this paper we developed a generalized data-driven framework to generate insights into the complex, nonlinear associations of cognitive/occupational factors with physicians' PTSS-risk. Data were collected from practicing physicians in the 18 states with the largest COVID-19 cases by deploying a cross-sectional, anonymous, web-based survey, following the second COVID-19 peak in the US. Analyses revealed that physicians directly treating COVID-19 patients (frontline) were at higher occupational risk of PTSS than those who didn't (secondline). We implemented a suite of eight statistical learning algorithms to evaluate the associations between cognitive/occupational factors and PTSS in frontline physicians. We found that random forest outperformed all other models, in particular the traditionally-used logistic regression by 6.4% (F1-score) and 9.6% (accuracy) in goodness-of-fit performance, and 4.8% (F1-score) and 4.6% (accuracy) in predictive performance, indicating existence of complex interactions and nonlinearity in associations between the cognitive/occupational factors and PTSS-risk. Our results show that depression, burnout, negative coping, fears of contracting/transmitting COVID-19, perceived stigma, and insufficient resources to treat COVID-19 patients are positively associated with PTSS-risk, while higher resilience and support from employer/friends/family/significant others are negatively associated with PTSS-risk. Insights obtained from this study will help to bring new attention to frontline physicians, allowing for more informed prioritization of their care during future pandemics/epidemics.

INDEX TERMS Post-traumatic stress symptoms (PTSS), depression and burnout, COVID-related damaging factors, resilience and social support, nonlinear relationships, predictive analytics.

I. INTRODUCTION

Identification and utilization of accurate information on factors associated with post-traumatic stress symptoms (PTSS) is instrumental for developing targeted interventions for post-traumatic stress disorder (PTSD) in physicians and other healthcare providers [1]. To this end, a number of studies have focused on the identification of risk factors for PTSD, including the type and frequency of traumatic events (e.g., combat exposure, rape/sexual assault, being female and

The associate editor coordinating the review of this manuscript and approving it for publication was Dongxiao Yu.

previously married) [2], peri-traumatic factors [3], early predictors of PTSD [4], [5], and gene expression profiles identifying emergent PTSD [6]. However, most of these studies were based on the general linear model and other statistical methods that are not optimally suited to explore the complex interactions between linear, non-linear or non-normally distributed risk indicators encountered during trauma and its early aftermath [7]. Thus, such models often underestimate the risk of developing post-traumatic stress symptoms (PTSS) and PTSD. In addition, previous studies have identified risk indicators at the group level, thereby overlooking within-group heterogeneities [8].

Compared to the US general population, for whom the lifetime risk of developing PTSD by age 75 is 8.7% and the twelve-month prevalence is 3.5% [9], the risk of PTSD in physicians is significantly higher. For instance, studies show that the prevalence of PTSD among physicians of both sexes is 14.8%, with the range varying among studies between 4.4% to 28% [10]. Physicians' work stress and its association with a higher risk of PTSD have been discussed in the extant literature [10], [11], [12], [13]; however, the recent COVID-19 pandemic has added a significant burden on the healthcare system. It has been well-documented during previous epidemics, including SARS-2003, H1N1 Influenza-2009, and MERS-2012, that frontline physicians (i.e., those treating infected patients) endure formidable social, psychological, and emotional stressors [14], [15], [16], [17]. COVID-19, however, far exceeds in scope and scale of the devastation wrought by these earlier outbreaks.

First identified in December 2019 in Wuhan China, the SARS-CoV-2 COronaVIrus Disease-19 (COVID-19) rapidly became a global pandemic by March of 2020. As of September 2022, there were over 600 million reported confirmed cases and 6.5 million people have died with COVID-19 worldwide. Thus, the consequences of COVID-19 are formidable and far-reaching, revealing fragility in our healthcare system and the risks faced by those who serve within it. Physicians have been overrun by caseloads of acutely ill patients [18], [19], insufficient resources [19], [20], and risks inherent to working with a new and highly infectious disease, culminating in the deaths of over 1,043,921 Americans (September 9, 2022) [21]. As a result, evidence is mounting that a significant psychological toll is incurred by frontline physicians [22], [23], who experience high stress, anxiety, depression, compassion fatigue and burnout sustained from working with COVID-19 patients [24], [25]. Of particular concern is the traumatic nature of COVID-19 associated stressors, which raise the likelihood of post-traumatic stress symptoms (PTSS) incurred by frontline physicians [26].

Physicians with PTSS are susceptible to self-destructive coping strategies (e.g., substance abuse) in attempt to manage their symptoms, other mental health conditions (e.g., depression), and suicidality [13], [27], [28]. Workplace-generated stressors (e.g., long working hours, time pressures) interfere with physicians' functioning, which may affect the quality of their care provision [29], [30], [31]. In addition, working for prolonged periods in such stressed environments increases their likelihood of leaving the healthcare system entirely [32], [33], [34]. Lack of established knowledge and treatment strategies, alongside changes in their work environment, may altogether critically affect the mental health and functioning of physicians treating COVID-19 patients [35].

For these above-mentioned reasons, identifying variables vital to assessing and predicting the risk for PTSS among frontline physicians is key to ameliorating mental health burdens they face. Recently, several studies have focused on assessing the COVID-19 induced risk on the development of PTSD in physicians [19], [36], [37], [38], [39], [40], [41], [42], [43], [44]. Most of these studies are based on exploratory data analysis and/or implementing simple linear regression models (e.g., logistic regression) to assess the PTSD trauma-related stressors in physicians. Linear models are predominantly used to model mental health outcomes because of their easier interpretability and lower computational cost; however, the theoretical foundations of such models employ rigid assumptions regarding the underlying distribution of data, such as linearity and normality [45]. Such assumptions, however, often do not hold, producing poor generalization performance [46]. Moreover, such conventional assessments and linear models fail to account for the potential complex, nonlinear interplay of factors associated with PTSS, leading to underestimation of risk and suboptimal decision-making around preventive and responsive interventions. In their stead, studies increasingly champion data-driven techniques to better understand complex nonlinear relationships in the contexts of mental and public health [47], [48], [49], [50], [51].

Learning algorithms are becoming popular data-driven techniques that employ pattern recognition and computational learning theory. These techniques are particularly well-suited for modeling complex and nonlinear relationships [52], making them ideal for studying PTSS risk. Such algorithms are unfettered by rigid model assumptions, producing models and data-driven predictions derived only from the input observations [53]. Recently, a growing number of studies are utilizing machine learning to predict PTSS in specific contexts, especially focusing more on patients and the general population [1], [54], [55], [56], [57], [58], [59], [60], [61], [62]. Moreover, most have focused on the prediction of trauma-related disorders or identification of individuals likely to suffer from PTSS, without specification of the underlying factors that might be instrumental in triggering PTSS. Studies have yet to focus on physicians in the context of COVID-19, and/or preclude underlying work environment factors of potential consequence to PTSS. Physicians on the frontlines of emergent infectious diseases are at higher risk of PTSS than their peers [63], [64], [65], [66]; however, most available studies focus on the entire medical community without comparing how these risks may differ between physicians treating infectious patients and those who are not. In the context of the current pandemic, recent studies demonstrate that the convergence of rapid acceleration of COVID-19 transmission rates, uncertainty about the virus, and limited treatment strategies have often exacerbated already excessive workloads among frontline physicians, exposing public health systems on the verge of collapse [35]. Yet, assessment of these phenomena is still in its infancy in the United States [36], [37], [67], [68], which leads the world in COVID-19 cases.

Therefore, although it is well-established in the literature that physicians are at a higher risk of experiencing PTSS than the general population, there are several gaps. First, most of the existing empirical literature on studying the risk factors of PTSS reveal a unilateral focus on descriptive and explanatory statistical modeling, which is not optimally suited to explore the complex interactions between linear, non-linear or non-normally distributed risk indicators encountered during trauma and its early aftermath. Second, although studies have focused on specific types of risk factors for PTSS in physicians, a holistic approach to the numerous types of risk factors associated with PTSS in physicians has not been taken. Third, despite the prevalence of using machine learning algorithms in healthcare studies to predict PTSS in specific contexts, they do not attempt to specify the underlying factors that may be instrumental triggers of PTSS in individuals. An accurate assessment of the scope and severity of mental health threats among frontline physicians is important to advance global efforts in preparing for such threats. Comparison of the prevalence of PTSS in physicians who *did* versus *did not* have a direct role in the treatment of COVID-19 patients could offer additional insights into the mental health costs incurred by frontline physicians. Of critical importance, however, is identifying variables correlated with PTSS prevalence and understanding of their complex nonlinear interactions. This information could be leveraged to evaluate factors associated with increased risks for PTSS, as well as identify and assess the protective factors.

To address the aforementioned critical issues, in this study we developed a generalized, data-driven framework to identify and assess a multitude of factors that are strongly associated with a higher likelihood of PTSS among frontline physicians. First, we examined PTSS and other measures of mental health in frontline physicians in comparison with physicians were not involved directly in the treatment of COVID-19 patients to identify the higher-risk group of physicians. Second, for the higher-risk group, we modeled the risk of PTSS as a function of various metrics characterizing mental health burden, work environment and occupational characteristics, and demographics. A suite of statistical learning models, including linear regression and non-linear ensemble tree-based models, was implemented to evaluate the PTSS risk among the high-risk group physicians. Finally, we conducted statistical inferencing using variable importance analysis and partial dependence plots to identify and evaluate the key factors most strongly associated with the risk of developing PTSS in the high-risk group.

We implemented our proposed framework following the second COVID-19 peak in the US, at approximately 6 months into the pandemic, and conducted the analysis for the 18 most-affected US states as a case study because of the following reasons:

- A dearth of information regarding the contagiousness, transmissibility and virulence of the COVID-19 virus, which created an environment of fear for frontline healthcare workers.
- The unprecedented surge of infectious patients increased the workload for frontline healthcare workers, which, when combined with lack of incentives and social exclusion/stigmatization, significantly exacerbated psychological distress among frontline healthcare workers.
- The healthcare system was inundated with a surge of infectious patients, enduring shortages of quality personal protective equipment, and experiencing poor management of its healthcare professionals, all of which worsened stress within these work environments.
- We aimed to capture the variability in physicians' PTSS risk across various geographical locations, patient demographics, political environments, and other factors, thus selecting the 18 most COVID-affected states (more than 40,000 COVID-19 cases as of June 2020) in the US.

This framework is designed to be generalized and adapted to any spatiotemporal resolution (i.e., any state or region, country or time period), provided adequate data are available. The proposed approach has the potential to assess the workplace-induced PTSS risk of physicians that would aid in designing informed intervention strategies. Not only would resulting interventions based on such modeling be of immediate use in the ongoing COVID pandemic, the management inherent both to the gathering and application of such information would likely inform intervention efforts for future pandemics our world assuredly will face.

II. OBJECTIVES

The aims of the current study were to: 1) evaluate the symptoms of PTSS among frontline physicians compared to secondline physicians and identify the higher-risk group among them; 2) predict PTSS risk in the higher-risk group using nonparametric statistical learning algorithms; 3) identify and rank the key predictors associated with the risk of experiencing PTSS by the higher-risk group; and 4) determine the linear/nonlinear patterns of these predictors. Various types of stressors were analyzed, including the novel COVID-related social, emotional, and cognitive factors as well as other known factors, influencing the development of PTSS, such as psychological resilience [69], [70], [71], exposure rate [67], [68], [72], occupational role [68], age [66], [73], sex [63], marital status [74], isolation [66], coping strategies [66], [74], [75], along with social support from family [74], [76], friends and colleagues, and organizational support [74], [75], [77].

III. MATERIALS AND METHODS

A. STUDY DESIGN

Following IRB approval, a cross-sectional, web-based survey developed by our interdisciplinary team was deployed to physicians from the American Medical Association's (AMA) Physician Masterfile database between August 7 and September 26, 2020. Surveying immediately followed the second COVID-19 US contagion peak [78]. Participation was voluntary and targeted physicians were from states reporting the greatest COVID-19 caseloads (more than 40,000 COVID-19 cases as of June 2020) [21], including New York, California, New Jersey, Illinois, Texas, Massachusetts, Florida, Pennsylvania, Michigan, Georgia, Maryland, Virginia, North Carolina, Arizona, Louisiana, Connecticut, Ohio, and Indiana. A layout of the survey design is provided in Figure 1.

B. PARTICIPANTS

Physicians from all specialties were recruited identified in the AMA Physician Masterfile, a near-complete record of all US physicians, independent of AMA membership. Canvassing e-mails (including study description and survey link) were sent on August 7 and 26, 2020. From 36,372 physicians (opening invitation), 1,478 responses were recorded, of which 1,017 responses (completing PTSD Checklist: PCL-5) were analyzed (sequential steps of data preprocessing is provided in Section III-E, Figure 2-1A).

C. OUTCOME/RESPONSE VARIABLE: POST-TRAUMATIC STRESS SYMPTOMS (PTSS)

As defined by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), PTSD is a psychiatric disorder that follows exposure to a traumatic event (Criterion A), and is characterized by four symptom criteria: (i) Criterion B: intrusive, distressing thoughts; (ii) Criterion C: persistent avoidance of trauma-related stimuli; (iii) Criterion D: alterations in cognition and mood; and (iv) Criterion E: heightened arousal and reactivity [9]. Symptoms of PTSD can persist for decades [79]. We employed the PTSD Checklist (PCL-5), a commonly used research and clinical screening questionnaire based on the DSM-5 [80] to assess PTSD symptoms (i.e., PTSS). In the PCL-5 section of the survey, physicians were instructed the following: *"In this subsection there is a list of reactions that people may have in response to a very stressful experience. Keeping in mind your worst/most stressful event(s) related to COVID-19, how much were you bothered by the following in the PAST MONTH"*. The PCL-5 is a 20-item, 5-point scale (0=not at all to 4=extremely), and respondents rated how bothered they were by each symptom in the past month. The total score range is 0–80, with 33 or greater indicating probable PTSD according to PCL-5 scoring. A diagnosis of PTSD can only be made by a trained clinician using an in-person interview; thus, we use the term "PTSS" to indicate the symptom ratings of physicians, with the highest ratings being suggestive of the greatest risk for developing PTSD. The results of the PCL-5 data for frontline and secondline physicians are presented in Table 2, Section IV-B.

To optimize the categorization of physicians into PTSS groups from low PTSS (low risk of PTSD) to high PTSS (high risk for PTSD) for the predictive analyses, we combined the DSM-5 and PCL-5 scoring criteria, similar to methods suggested by the National Center for PTSD [81]. This procedure included using only PCL-5 items rated as 2 (moderately) or higher, which constitutes clinically significant symptom endorsement, and then applying this level of endorsement to the number of DSM-5 items required for each of the four criterion: at least one item in Criterion B (re-experiencing), one in Criterion C (avoidance), two in Criterion D (negative beliefs), and two in Criterion E (hyperarousal) [9]. In Section IV-B, Table 3 presents the frequency of frontline and secondline physicians, separately, who endorsed PCL-5 symptoms as 2 or higher. Using the scoring criteria specified above, all physicians (i.e., frontline and secondline) were categorized into four symptom groups: *High PTSS* (scores of $\geq$2 in at least 3 DSM-5 categories, PCL-5 $\geq$33), *Moderate PTSS* (score of $\geq$2 in 2 DSM-5 categories, $\geq$ 12 and $\leq$ 33 PCL-5 score), *Low PTSS* (score of $\geq$2 in none or 1 DSM-5 categories, PCL-5 score $\geq$12 and $<$33), and *Very Low PTSS* (score of $\leq$2 in none or 1 DSM-5 categories, PCL-5 score $<$12). Further, for the model implementation, the two highest and two lowest groups were combined to create a **"High PTSS Risk Group"** (High PTSS/Moderate PTSS), and a **"Low PTSS Risk Group"** (Low PTSS/Very Low PTSS).

D. PREDICTOR CANDIDATES

The survey design layout depicted in Figure 1 shows the different types of information that were collected. Besides the response variable (information on PTSS), the various categories of variables that were collected include: (i) mental health and emotional wellbeing; (ii) factors/stressors in the work environment; (iii) organizational and social support; (iv) personal characteristics; and, (v) demographics. Details of the specific types of information collected under these categories are described below.

1) MENTAL HEALTH AND EMOTIONAL WELLBEING

The Patient Health Questionnaire (PHQ-9) [9 items, 4-level Likert scale: 0-3 score range per item, total score: 0-27] [82] and the single-item, 5-point burnout scale [1 item, 5-level Likert scale: 1-5 score range] [83] were used to assess the severity of symptoms of depression and burnout, respectively. We categorized depression into five levels based on total PHQ-9 scores [82]: minimal [total score=1-4]; mild [total score=5-9]; moderate [total score=10-14]; moderately severe [total score=15-19]; and severe [total score=20-27].

2) FACTORS/STRESSORS IN THE WORK ENVIRONMENT

Occupational characteristics and COVID-19 specific experiences included living arrangement changes, workload, non-routine work, resource availability, decision-making, exposure rates (e.g., time with COVID-19 patients, intubation/aerosol-generating procedures of suspected/ confirmed COVID-19 patients), perceived stigma from treating COVID-19 patients, and turnover intent (switching units/teams, leaving current employer, or leaving healthcare entirely).

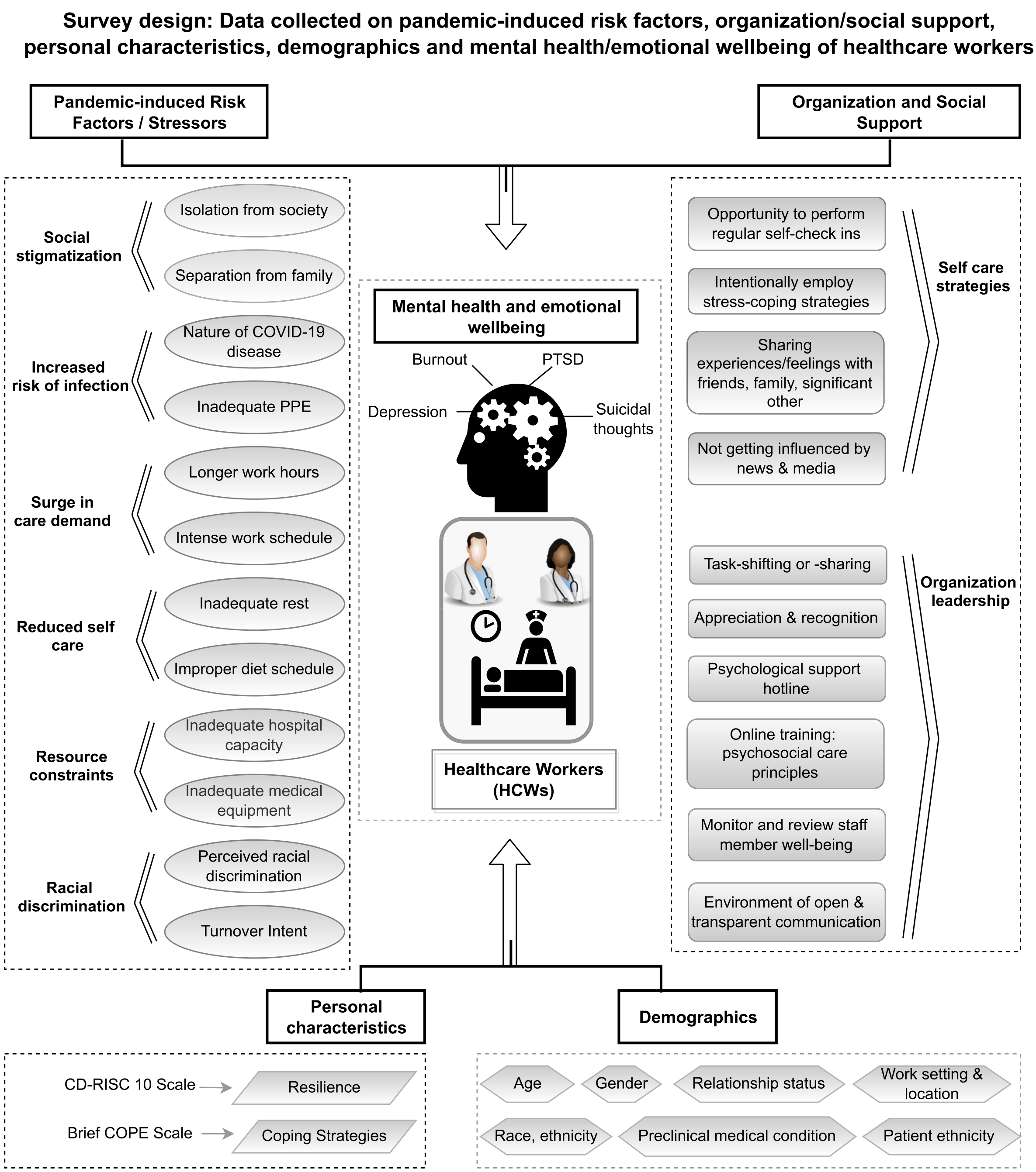

FIGURE 1. Survey design: Types of data collected.

3) ORGANIZATIONAL AND SOCIAL SUPPORT

Perceived organizational and social support was assessed using the 8-item 7-point Survey of Perceived Organizational Support scale [8 items, 7-level Likert scale: 1-7 score range per item] (SPOS; items 1, 3, 7, 9, 17, 21, 23, 27) Eisenberger et al., which was classified into positive support (item numbers: 1, 9, 21, 27) [84] and negative support (item numbers: 3, 7, 17, 23) [84] for our analysis. Perceived available support from family, friends, and significant others was measured employing the 3-item Multidimensional Scale of Perceived Social Support (MSPSS) [85].

4) PERSONAL CHARACTERISTICS

Resilience and stress coping characteristics were measured, respectively, with the Connor-Davidson Resilience Scale (CD-RISC-10) [10 items, 5-level Likert scale: 0-4 score range per item, total score: 0-40] [86] and, the Brief-COPE Scale [28-item, 4-level Likert scale: 1-4 score range per item] [87]. The Brief-COPE scores indicate individuals' negative/positive dominant coping strategies among 14 categories, each scored separately with a range of 2-8. The 14 categories include self-distraction, active coping, denial, substance abuse, use of emotional support, use of instrumental support, behavioral disengagement, venting, positive reframing, planning, humor, acceptance, religion, and self-blame [87].

5) DEMOGRAPHICS

Demographics included age, sex, ethnicity, race, immigration status, and marital status. Workplace characteristics included training/years of experience, primary work setting, hospital type, and work setting within hospital.

Before implementing the models and conducting statistical analyses, it was essential to assess multicollinearity among the variables before performing statistical analysis. The presence of multicollinearity can mask the effect of the predictor variables on the response and bias the coefficient estimates in the case of linear regression. The correlation analysis and selection of the final variables was conducted in order to remove the highly correlated variables (correlation coefficient $|\rho| \leq 0.9$). Similar strategy was used in previous research to minimize the masking effects of the variables and facilitate better statistical inferencing [88], [89], [90], [91], [92], [93], [94]. A detailed description of all the variables along with their descriptive statistics is provided in Table A1 in the Supplementary File.

E. METHODOLOGICAL FRAMEWORK

In this paper, we propose a generalized, data-driven, PTSS risk assessment framework that consists of three parts: i) **Part-1:** a survey based data collection and preprocessing (discussed above, see Figure 2-Part 1A) and classification of the various PTSS risk levels among physicians (discussed above, see Figure 2-Part 1B); ii) **Part-2:** statistical analysis and predictive models development including simple statistical analyses to compare the PTSS risk levels among both the frontline and secondline physicians (see Figure 2-Part 2A), and then implementing various predictive algorithms to evaluate the PTSS risk among the high-risk physician group (see Figure 2-Part 2B); and, iii) **Part-3:**: model interpretation and inference, including statistical inferencing that leverages variable importance analysis and evaluating partial dependence plots (see Figure 2-Part 3). This section provides supervised statistical learning and the various modeling techniques that we adopted in our research to evaluate the factors associated with a higher risk of PTSS among physicians facing a crisis situation in their workplace.

1) COMPARATIVE ASSESSMENT OF PTSS BETWEEN FRONTLINE AND SECONDLINE PHYSICIANS

Independent samples t-tests and Chi-square (χ^2 test) analyses were used to test the PCL-5 scores (Table 2) and frequency of endorsed symptoms (Table 3) between frontline and secondline physicians, respectively. Chi-square analyses (χ^2 test) and t-tests were also implemented after obtaining the key variables from the model implementation to determine if the findings were considered significant at 2-tailed $p \leq 0.05$ (see Figure 2-Part 2A).

2) STATISTICAL LEARNING

Learning algorithms have been gaining more attention in the field of public health recently [95], [96]. Compared with the conventional linear statistical models, the major advantages of applying statistical learning models include: 1) the ability to capture the underlying interdependent and nonlinear relationships of the data [96], [97]; 2) capacity to discover specific patterns and trends that could be unknown to humans, and 3) subsequent strong predictive ability [98]. Broadly speaking, supervised learning method is applied to estimate a regression function capable of predicting the response variable Y conditioned on a set of inputs X, such that the loss function for measuring errors is minimized. The generalized form can be mathematically written as $Y = f(X) + \epsilon$, where ϵ is the irreducible error follows $\epsilon \sim \mathcal{N}(0, \sigma^2)$ [45], [99]. The loss function $\mathcal{L}$ represents the deviation of observed values from the estimated values of Y. In this study, the response variable Y represents the high vs. low risk of PTSS experienced by the group of physicians who is found to be at a higher risk of experiencing PTSS, with the rest of the variables in the dataset are denoted as a vector of predictor variables X.

Statistical learning models can be broadly classified into parametric, semi-parametric and non-parametric models. Parametric models assume a functional form of f expressed in terms of coefficients and independent variables [45], [99]. Thus, in lieu of estimating an arbitrary function f, the model ends up estimating only the coefficients characterizing the function. The coefficients or parameters are independent of the training data set and depends on the model itself. On the contrary, the non-parametric methods do not make any assumption about the shape of the function. The non-parametric methods essentially fit closest to the actual shape of f. By utilizing data in novel ways to estimate the dependencies, non-parametric models often have a superior predictive power over parametric models. However, the non-parametric methods are data-intensive and highly dependent on data quality [45], [99].

In this research, the function f is constructed leveraging a library predictive models including a parametric model such as the traditionally-used logistic regression [100], [101], and non-parametric models such as the random forest (RF) [102], bootstrap-aggregating (bagging) [99], Naïve Bayes [103], gradient boosting method [104], Bayesian additive regression trees [105], [106], support vector machines [107], [108], [109], and neural networks [110]. Selection of the optimal predictive model was based on the generalization performance of the models [45], [99]. By implementing a series of experiments, RF outperformed all the models, both in terms of goodness of fit and predictive accuracy. Thus, we selected RF as our final model to assess the PTSS risk in

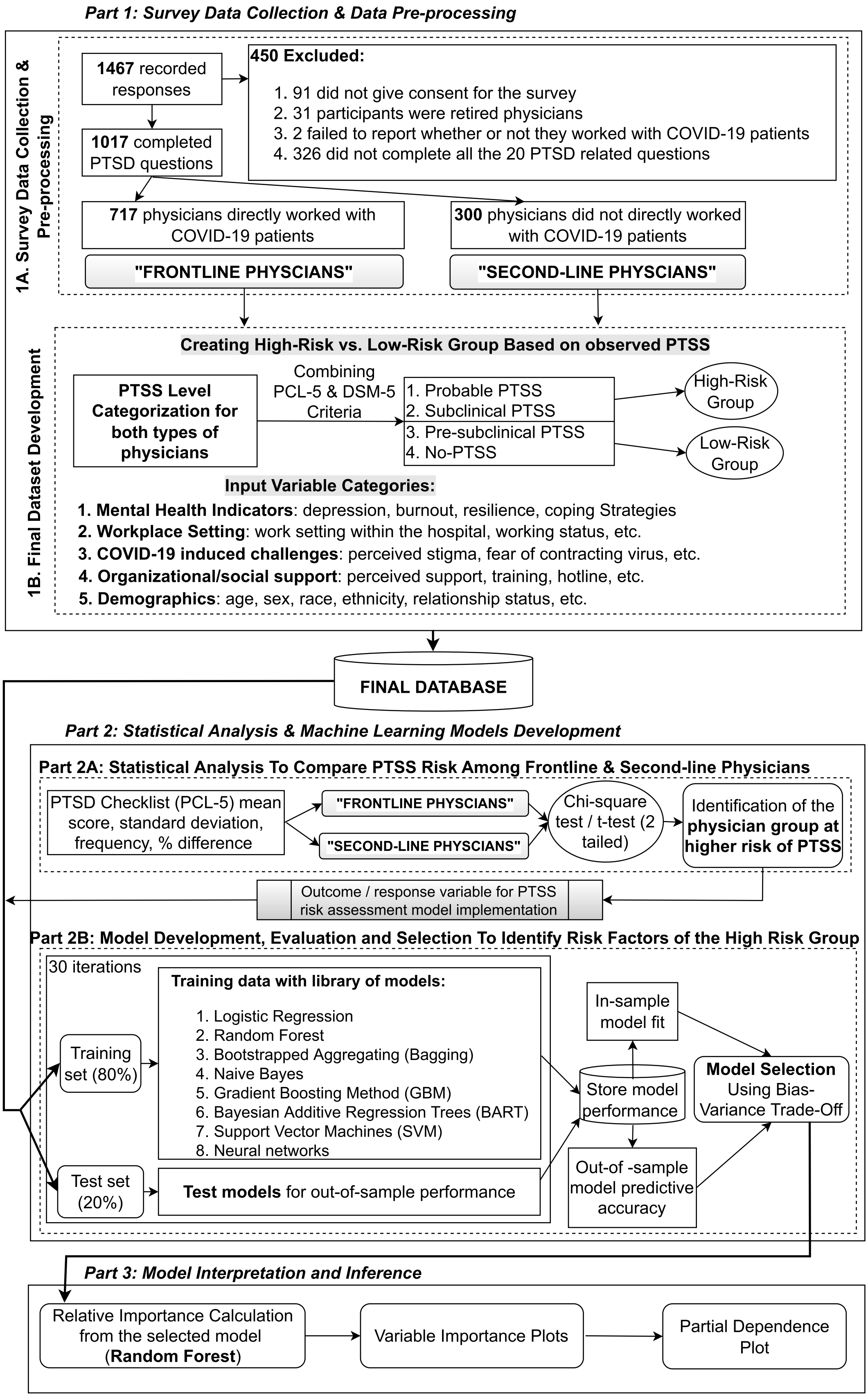

FIGURE 2. Generalized data-driven framework to evaluate the risk of Post Traumatic Stress Symptoms in Physicians.

the frontline physicians. Details of random forest algorithm and model selection techniques are provided in the following subsections. Brief overview of all the other models is provided in the Supplementary File.

a: RANDOM FOREST: ALGORITHM DESCRIPTION

Random forest technique combines a bootstrap aggregating approach combined with feature randomness when building each tree, creating a multitude of decision trees. The overall model performance is then calculated by averaging predictions from each of the single trees. Mathematically, random forest can be defined as an ensemble tree-based learning model that consists of B bootstrapped regression trees T_b. The model development process is explained in details in the Algorithm 1 [102].

Algorithm 1 Random Forest Algorithm [99], [102]

1: **Input:** Data set with dimension (N, M) where N is the number of data points & M is the number of input variables; Ensemble tree size B
2: **for** $b = 1$ to B: **do**
3: Build a bootstrap sample N_b from data set of size N by randomly sampling $|N_b|$ data points with replacement.
4: Treat N_b as the training data set, while the remaining data is used as validation set to estimate tree's prediction error.
5: Fit a decision tree model T_b on the training data set N_b by recursively repeating the following steps for each terminal node of the tree, until the minimum node size $n_{\min}$ is reached.
i) Select m variables randomly from the M variables ($m \ll M$).
ii) Pick the best variable/split-point among the m.
iii) Split the node into two daughter nodes.
6: **end for**
7: **return** $\{T_b \mid 1 \leq b \leq B\}$
8: **Output:** Ensemble tree model whose prediction is given by average of predictions across all trees:

$$\widehat{f}_{RF} = \frac{1}{B}\sum_{b=1}^{B} T_b \tag{1}$$

b: PREDICTIVE ACCURACY VS. MODEL INTERPRETABILITY

Generally speaking, flexible non-parametric methods have higher predictive power than the "rigid" parametric methods. However, this improved predictive power comes at the cost of easier interpretability. To make inferences based on non-parametric, ensemble tree-based methods, "variable importance analysis" (VI) and "partial dependence plots" (PDPs) are implemented. The VI analysis helps to identify the most important variables associated with a higher PTSS risk by calculating importance of each PTSS predictor variable, measured using the Gini index [102]. The PDPs are applied to help in understanding the effects of the predictor variable of interest x_j on the response in a "ceteris paribus" condition to control all the other predictors.

Mathematically, the estimated partial dependence can be represented as [111]:

$$\widehat{f}_j(x_j) = \frac{1}{n}\sum_{i=1}^{n}\widehat{f}_j(x_j, x_{-j,i}). \tag{2}$$

Here, $\widehat{f}$ represents the statistical model (in this case random forest); x_{-j} denotes all the variables except x_j; n denotes the number of observations in the training data set. The estimated PDP of the predictor x_j provides the average value of the function $\widehat{f}$ when x_j is fixed and x_{-j} varies over its marginal distribution. Quantified marginal effects could indicate an increase/decrease in PTSS risk with increase/decrease in magnitude of the predictor, thus helping to categorize predictors as damaging/protective factors, respectively. All analyses were performed in R (version-3.1) and RStudio (version-1.1.463).

c: BIAS VARIANCE TRADE-OFF AND MODEL SELECTION

Bias variance trade-off is the key to model selection in supervised learning theory. Optimal generalization performance of a predictive model hinges on its ability to simultaneously minimize the bias and variance, thus controlling the complexity of the model. Cross validation is the most widely used technique for balancing models' bias and variance [45], [112]. Thus, we leveraged a percentage randomized holdout technique to estimate the predictive accuracy of the resulting models. More specifically, out-of-sample predictive accuracy of each model was calculated by implementing 30 iterations where, in each iteration, 20% of the data was randomly held out to test the model, while the model was trained on the remaining 80% data [45], [112]. The optimal model can be selected in such a way that it outperforms all the other models in terms of in-sample goodness-of-fit and out-of-sample predictive accuracy.

To evaluate the performance of the classification models, we leveraged the widely-used statistical metrics based on the Confusion matrix, such as Accuracy (%), Recall (%), Precision (%), F1 score, and Area Under the Curve (AUC, or C-statistic), for both goodness-of-fit and predictive accuracy [113]. Accuracy is defined as the ratio of the total number of correct predictions to the total number of predictions made for a given dataset. Precision is the ratio of correctly predicted positive examples to the total number of positive examples that were predicted. Recall quantifies the number of correct positive predictions made out of all positive predictions that could have been made. F1-score provides a way to combine both precision and recall into a single measure that captures both properties. Mathematically, when only one class is considered, the standard F1-score is defined as the harmonic mean of P and R,

$$F1 = \frac{2PR}{P + R} \tag{3}$$

where

$$P = \frac{TP_i}{TP_i + FP_i}, \tag{4}$$

$$R = \frac{TP_i}{TP_i + FN_i}, \tag{5}$$

TP_i is the number of test instances correctly assigned to the class i (that is, the number of true positives), FP_i is the number of test instances the system predicts mistakenly to be a member of the class i (that is, the number of false positives), and FN_i is the number of test instances that belong to the class i in the real data but not in the system output (that is, the number of false negatives). F1-score is known to be more informative and useful than classification accuracy if there is a problem with class imbalance. We also leveraged AUC, which is calculated by the area under the receiver operating characteristic (ROC) curve. F1 score and AUC, which are mainly used in unbalanced datasets, were used in this study to evaluate the models' performances [113]. Finally, the model that outperformed all the other models in terms of goodness-of-fit and predictive accuracy was selected as the final predictive model for statistical inferencing. This is a well-known statistical process that ensures that the statistical learning models do not overfit the data and provide accurate predictive performance, while providing interpretability benefits [45], [112].

IV. RESULTS

In this section, we present the results from our case study. Specifically, this section includes: (i) a description of the socio-demographic characteristics of the survey participants who were included in the analysis; (ii) a comparative assessment of the post-traumatic stress symptoms (PTSS) between the frontline and the secondline physicians, and identification of the groups with higher (*High PTSS Risk Group*) and lower levels (*Low PTSS Risk Group*) of PTSS; and (iii) identifying and evaluating the key factors that are positively or negatively associated with the higher levels of PTSS in the *High PTSS Risk Group* identified in Step (ii). We also discuss the performance of the various statistical learning models that were implemented to identify and assess the key predictive factors, including the rationale for final model selection followed by statistical inferencing (i.e., identifying and evaluating the key factors as discussed above).

A. PARTICIPANTS' SOCIO-DEMOGRAPHIC CHARACTERISTICS

Table 1 presents the socio-demographic data and statistical comparisons between frontline and secondline physicians. Although largely homogenous, they were not identical, with small differences between the groups found across age, years in practice, sex, primary work setting, current work status, and underlying conditions. Frontline physicians were an average of three years younger and had three years less work experience than did secondline physicians. Sex composition of frontline physicians was similar, whereas the secondline physicians skewed female. Whereas both groups were largely concentrated in academic medical centers and group practices, a larger percentage of frontline physicians worked in hospitals than did secondline. Finally, although the vast majority of both groups worked full-time in medicine, secondline physicians were 11% more likely to be part-time than were frontline physicians. All demographic and workplace variables were controlled for in our subsequent analyses, mitigating those minor differences that were found between the groups.

B. COMPARISON OF PTSS BETWEEN THE PHYSICIAN GROUPS

Overall, 717 frontline physicians and 300 secondline physicians completed the PCL-5. Table 2 presents the PCL-5 data using the full-scale scores of 0 to 4. Section 1 lists the means (SDs) of frontline vs. secondline physicians for each of the 20 PCL-5 items. More frontline than secondline physicians had significantly higher scores for all of the items in Criterion B (re-experiencing) and C (avoidance), four of seven items in Criterion D (negative cognition/mood), and four of six items in Criterion E (heightened arousal). Section 2 of Table 2 lists PCL-5 composite criterion scores and the PCL-5 total score (calculated by summing all PCL-5 item scores) for both groups. Frontline compared to secondline physicians had significantly higher criterion scores and PCL-5 total score for both groups. Table 3 lists the number (percentage) of frontline vs. secondline physicians who endorsed each of the PCL-5 items with scores of 2 or higher (considered clinically significant). Chi-square (χ^2 test) analyses indicated that a greater number of frontline than secondline physicians endorsed four items in Criterion B, one item in Criterion C, three items in Criterion D, and two items in Criterion E. This table (Table 3) presents a non-traditional way of examining PCL-5 scores by looking at the frequency of individuals who score items in the clinically significant range ($\geq$2, moderate to severe).

Table 4 presents categorization of the physicians into four PTSS groups using the scoring method of 2 or higher as clinically significant, as described in Section III-C. The *Very Low PTSS* and the *Low PTSS* groups are considered low risk for experiencing PTSS, whereas the *Moderate PTSS* and *High PTSS* groups are considered to be at high risk for experiencing PTSS (see Table 4, *Moderate PTSS Risk Group* and *High PTSS Risk Group*). This categorization was applied to both the frontline and secondline physicians. We observed that 30.82% of the frontline physicians fell in the high-risk category compared to 21.33% of secondline physicians. Notably, 10.54% of frontline physicians reported high PTSS compared to the 5.0% of secondline physicians. Thus, frontline physicians are at a higher risk of experiencing clinically significant PTSS compared to the secondline physicians. Hence, *we considered frontline physicians as our target group for evaluating the risk of PTSS*. Frontline physicians included in the low-risk (n=309) and high-risk (n=137) groups answered all questions for each of the predictor measures. This dataset was

TABLE 1. Demographics of the sample population (^ = t-test; * = χ^2 test).

Sample Demographic Characteristics	Frontline Physicians: No. (%) (n= 717)	Secondline Physicians: No. (%) (n= 300)	p-value
Age, mean (SD)	51.35 (11.3)	54.57 (11.81)	.0283^
Missing	160	53	
Sex			
Male	317 (44.21)	98 (32.67)	
Female	323 (45.05)	181 (60.33)	
Non-conforming, non-binary, transgender	1 (0.14)	0 (0)	<.001*
Prefer not to answer	6 (0.84)	1 (0.33)	
Missing	70	20	
Ethnicity			
Hispanic / Latino	59 (8.23)	22 (7.33)	
Non-Hispanic	589 (82.15)	258 (86.0)	.623*
Missing	69	20	
Race			
American Indian or Alaskan Native	1 (0.14)	0 (0)	
Asian	91 (12.69)	26 (8.67)	
Black or African American	25 (3.49)	14 (4.67)	
Native Hawaiian or Pacific Islander	1 (0.14)	0 (0)	.166*
White	466 (64.99)	222 (74.0)	
Others	55 (7.67)	17 (5.67)	
Missing	78	21	
Immigration Status			
U.S. immigrant	109 (15.20)	40 (13.33)	
Not an U.S. immigrant	540 (75.31)	240 (80.0)	.390*
Missing	68	20	
Relationships Status			
Single	94 (13.11)	30 (10.0)	
Married	512 (71.41)	230 (76.67)	
Partnered	38 (5.3)	12 (4.0)	.096*
Widow / Widower	5 (0.7)	6 (2.0)	
Missing	68	22	
Number of years practicing, mean (SD)	21.76 (10.94)	25.49 (12.57)	.003^
Missing	81	22	
Primary Work Setting			
Academic medical center	146 (20.36)	57 (19.0)	
Group practice	150 (20.92)	82 (27.33)	
Hospital	182 (25.38)	24 (8.0)	
Solo practice	55 (7.67)	40 (13.33)	<.001*
Two-physician practice	24 (3.35)	18 (6.0)	
Outpatient center	42 (5.86)	27 (9.0)	
Others	41 (5.72)	30 (10.0)	
Missing	77	22	
Current Working Status			
Full-time	567 (79.08)	209 (69.67)	
Part-time	62 (8.65)	59 (19.67)	
Furloughed	5 (0.7)	1 (0.33)	<.001*
Laid off	1 (0.14)	3 (1.0)	
On leave	7 (0.98)	6 (2.0)	
Missing	75	22	
Having underlying health conditions			
Yes	242 (33.75)	124 (41.33)	
No	452 (63.04)	162 (54.0)	.024*
Not sure	23 (3.21)	14 (4.67)	
Pregnancy (self or partner)			
Yes, pregnant or with a newborn	50 (6.97)	14 (4.67)	.215*
No	667 (93.03)	286 (95.3)	

TABLE 2. PTSD Checklist (PCL-5) mean score and standard deviation differences between frontline and secondline physicians based on the scoring range 0 to 4.

PCL-5 items for each DSM-5 Symptom cluster (Criterion B, C, D, E)	Frontline physicians (n= 717)	Secondline physicians (n= 300)	t-test (p-value)
	Mean (SD)	Mean (SD)	
Section 1			
Criterion B: Re-experiencing Symptoms			
1. Disturbing memories	0.82 (0.98)	0.49 (0.82)	<.001
2. Disturbing dreams	0.59 (0.91)	0.35 (0.75)	<.001
3. Flashbacks	0.35 (0.80)	0.17 (0.53)	<.001
4. Feeling upset when reminded of event	0.72 (0.97)	0.50 (0.86)	<.001
5. Physical reactions when reminded of event	0.47 (0.86)	0.33 (0.75)	.009
Criterion C: Avoidance Symptoms			
6. Avoiding memories related to event	0.64 (0.95)	0.44 (0.85)	.001
7. Avoiding external reminders of event	0.53 (0.90)	0.37 (0.78)	.003
Criterion D: Negative alterations in cognitions, mood			
8. Trouble remembering part of event	0.35 (0.77)	0.16 (0.59)	<.001
9. Negative beliefs about self, other, world	0.60 (1.03)	0.49 (0.87)	.1
10. Blaming yourself	0.57 (0.94)	0.40 (0.83)	.005
11. Feeling fear, horror, anger, guilt, shame	0.66 (1.00)	0.55 (0.88)	.07
12. Loss of interest in activities	0.78 (1.06)	0.60 (0.86)	.006
13. Feeling distant from others	1.23 (1.21)	1.09 (1.16)	.086
14. Trouble feeling positive feelings	0.76 (1.05)	0.58 (0.91)	.005
Criterion E: Heightened arousal and reactivity			
15. Irritable behavior	0.89 (1.01)	0.69 (0.88)	.002
16. Taking risks	0.25 (0.65)	0.12 (0.39)	<.001
17. Hyper-vigilance: super alert, on guard	0.88 (1.11)	0.69 (0.97)	.006
18. Feeling jumpy, or easily startled	0.53 (0.94)	0.41 (0.77)	.028
19. Difficulty concentrating	0.83 (1.04)	0.74 (0.91)	.195
20. Trouble falling or staying asleep	1.16 (1.19)	1.03 (1.12)	.1
Section 2			
PCL-5 Criterion and Total Scores (range)			
Criterion B: Total score (0-20)	2.95 (3.87)	1.83 (3.11)	<.001
Criterion C: Total score (0-8)	1.17 (1.76)	0.81 (1.56)	.001
Criterion D: Total score (0-28)	4.94 (5.67)	3.88 (4.69)	.002
Criterion E: Total score (0-24)	4.54 (4.53)	3.68 (3.7)	.002
Total PCL-5 Score (0-80)	13.61 (14.39)	10.2 (11.39)	<.001

then used to train and test the statistical learning algorithms to predict and evaluate the factors associated with higher risk of experiencing PTSS.

C. MODEL SELECTION

As discussed in Section III-E2.c, selection of an optimal predictive model was based on generalization performance of the models [45], [99].This included assessment of goodness-of-fit (results shown in Table 5) and predictive accuracy (results shown in Table 6). We conducted significance tests of F1 scores and Area Under the Curve (AUC) measures (refer to Tables A2 and Table A3 in the Supplementary File) across every pairing of predictive models. Based on the prediction performance, the tree-based models such as random forest (F1=0.88; 95% CI, 0.87-0.89), bagging (F1 = 0.86; 95% CI, 0.85-0.87), gradient boosting method (F1=0.86; 95% CI, 0.85-0.88) and Bayesian additive regression trees (F1=0.87; 95% CI, 0.86-0.88), outperformed the black-box algorithms such as Naïve Bayes (F1=0.85; 95% CI, 0.84-0.87) and neural network (F1=0.85; 95% CI, 0.84-0.86). On the other hand, the traditionally used logistic regression performed worst with the least F1 score (F1=0.84; 95% CI, 0.83-0.86). Note, although the support vector machine algorithm demonstrated a superior predictive performance to the random forest in terms of F1 score (F1=0.88; 95% CI, 0.86-0.89), it was not selected because the superior performance was obtained at the cost of reduced interpretability. Moreover, in terms of AUC measure, random forest also exhibited a higher predictive power (AUC=0.76; 95% CI, 0.75-0.78) than the other models, although they were not statistically different based on the paired t-test (Table A3). Therefore, ultimately we selected random forest, given it offered: 1) best goodness-of-fit performance among all the models (refer to Table 5); 2) highest overall predictive accuracy (accuracy=82.52%, 95% CI, 81.16-83.89; recall=93.11%, 95% CI, 91.92-94.31) (refer to Table 6); 3) best prediction performance determined by F1 score (refer to Table 6); and, 4) more interpretability than its competitors such as the support vector machine and other black-box algorithms [114]. Note that, compared to the traditionally used logistic regression model, random forest

TABLE 3. PTSD Checklist (PCL-5) frequency and percentage differences between frontline and secondline physicians based on the scoring range 0 to 4.

PCL-5 items for each DSM-5 Symptom cluster (Criterion B, C, D, E)	Frontline physicians No. (%) who endorsed score ≥ 2	Secondline physicians No. (%) who endorsed score ≥ 2	χ^2 (p-value)
Section 1			
Criterion B: Re-experiencing Symptoms			
1. Disturbing memories	144 (20.08)	30 (10.0)	<.001
2. Disturbing dreams	100 (13.95)	23 (7.67)	.007
3. Flashbacks	59 (8.23)	9 (3.0)	.004
4. Feeling upset when reminded of event	124 (17.29)	32 (10.67)	.01
5. Physical reactions when reminded of event	79 (11.02)	25 (8.33)	.24
Criterion C: Avoidance Symptoms			
6. Avoiding memories related to event	110 (15.34)	27 (9.0)	.009
7. Avoiding external reminders of event	85 (11.85)	28 (9.33)	.29
Criterion D: Negative alterations in cognitions, mood			
8. Trouble remembering part of event	59 (8.23)	10 (3.33)	.007
9. Negative beliefs about self, other, world	117 (16.32)	35 (11.67)	.072
10. Blaming yourself	98 (13.67)	30 (10.0)	.132
11. Feeling fear, horror, anger, guilt, shame	105 (14.64)	35 (11.67)	.247
12. Loss of interest in activities	147 (20.5)	41 (13.67)	.013
13. Feeling distant from others	265 (36.96)	95 (31.67)	.124
14. Trouble feeling positive feelings	150 (20.92)	41 (13.67)	.009
Criterion E: Heightened arousal and reactivity			
15. Irritable behavior	154 (21.48)	50 (16.67)	.097
16. Taking risks	34 (4.74)	3 (1.0)	.006
17. Hypervigilance: super alert, on guard	168 (23.43)	52 (17.33)	.038
18. Feeling jumpy, or easily startled	94 (13.11)	29 (9.67)	.153
19. Difficulty concentrating	142 (19.8)	53 (17.67)	.482
20. Trouble falling or staying asleep	239 (33.33)	83 (27.67)	.09

TABLE 4. PTSD symptom severity groups: Frequency (percent) of PCL-5 scores for physicians in each PTSS group.

PTSS Symptom Severity Groups	Frontline physicians (n= 717)	Secondline physicians (n= 300)	p-value χ^2
Very Low PTSS	413 (57.6)	202 (67.33)	.005
Low PTSS	83 (11.58)	34 (11.33)	.998
Moderate PTSS	144 (20.08)	49 (16.33)	.192
High PTSS	77 (10.74)	15 (5.0)	.005
Low PTSS Risk Group	496 (69.18)	236 (78.66)	
High PTSS Risk Group	221 (30.82)	64 (21.33)	

offered an improvement of goodness-of-fit by 6.4% in F1 score and 9.6% in accuracy, while it's out-of-sample predictive performance improved by 4.8% and 4.6% in terms of F1 score and accuracy, respectively. A comparative assessment of all the models in terms of their out-of-sample predictive accuracy in terms of F1-score is provided in Figure 3.

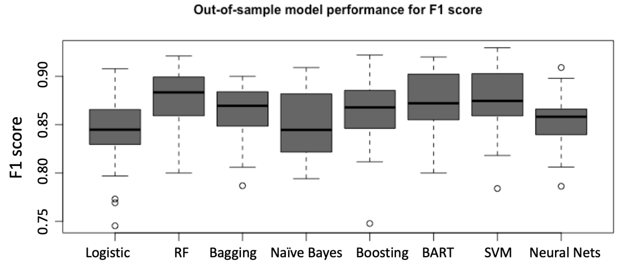

FIGURE 3. Comparative assessment of out-of-sample predictive performance of the different models in terms of F1 scores.

D. IDENTIFYING THE KEY PREDICTORS ASSOCIATED WITH THE RISK OF EXPERIENCING PTSS IN FRONTLINE PHYSICIANS

The central aim of this study was to determine which variables best predict PTSS risk among frontline physicians and how these variables relate to higher risk of PTSS, or possible protection from PTSS. Fig. 4 depicts the variable rankings (rank no.1—most important predictor) (see Section III-E2.b for details). In the figure, the various types of predictor variables are coded in different colors. From the figure we

TABLE 5. Comparison of Goodness-of-fit among a library of statistical learning models.

	Logistic	Random Forest	Bagging	Naive Bayes	GBM	BART	SVM	NN
F1 Score	0.94	1.00	1.00	0.87	1.00	0.93	0.94	0.98
AUC	0.89	1.00	1.00	0.81	1.00	0.85	0.86	0.96
Accuracy, %	91.27	100.00	99.80	82.62	100.00	89.21	90.65	97.03
Recall, %	95.17	100.00	99.97	85.92	100.00	95.96	98.24	98.37
Precision, %	92.48	100.00	99.75	88.71	100.00	89.31	89.35	97.41

TABLE 6. Comparison of Prediction Performance among a library of statistical learning models.

	Logistic	Random Forest	Bagging	Naive Bayes	GBM	BART	SVM	NN
F1 Score	0.84	0.88	0.86	0.85	0.86	0.87	0.88	0.85
AUC	0.76	0.76	0.76	0.78	0.78	0.77	0.76	0.77
Accuracy, %	78.87	82.52	80.65	80.16	81.27	81.48	81.97	79.95
Recall, %	84.18	93.11	88.78	84.17	87.26	89.58	92.79	85.64
Precision, %	84.81	83.40	84.06	86.53	85.75	84.46	82.98	85.26

observed that out of the top 20 variables, nine variables characterize the work environment (green), five variables describe the personal characteristics (blue), three variables depict organizational and social support (yellow), two variables describe mental health of the physicians (red), and one variable depicts demographics (grey). Therefore, considering both the ranking and the number of variables depicting each of the predictor categories, it can be concluded that work environment is the most important factor associated with the PTSS severity levels in physicians.

Table 7 illustrates statistical significance of the top 20 variables indicated in Fig. 4. For the continuous variables, we used t-test for the continuous variables and χ^2 test for the ordered variables to determine if the factors differed significantly between the low-risk and the high-risk groups of frontline physicians.

E. EVALUATING THE ASSOCIATIONS OF KEY PREDICTORS AND THE RISK OF PTSS IN FRONTLINE PHYSICIANS

This section presents the various associations of the identified key factors with the risk of experiencing PTSS in frontline physicians. The associations are obtained using partial dependence plots (PDPs) (see III-E2.b for details). The PDPs of the top 20 most important variables are illustrated in Fig. 5. Our findings are organized into two categories: 1) damaging factors (higher scores associated with higher PTSS risk); and, 2) protective factors (higher scores associated with lower PTSS risk). *Note, these observed relationships are associations/correlations, and not causal relationships*. However, understanding such relationships can help the healthcare policymakers to make informed decisions in designing and implementing strategies to help minimize the risk of experiencing PTSS among physicians while working in a stressed work environment.

1) DAMAGING FACTORS

A cohort of cognitive/psychological variables—depression, burnout, fear—top the list of variables associated with higher risk of experiencing PTSS (Fig. 4). PTSS risk increased dramatically even when mild–moderate depressive symptoms were present (Fig. 5-1). PTSS risk became significantly prevalent with moderate–high burnout levels (burnout score $\geq$ 3) (Fig. 5-2). Also, two types of fear—fear of contracting COVID-19 (Fig. 5-4), fear of transmitting it to loved ones (Fig. 5-5)—coincided with higher PTSS risk, presenting a ''V-shaped,'' nonlinear relationship. Additionally, three coping strategies that were associated with increased PTSS risk include self-blame, venting, and behavioral disengagement had a ''V-shaped,'' nonlinear relationships. Self-blame (Fig. 5-3) and behavioral disengagement (Fig. 5-12) demonstrated a strong linear correlation with PTSS risk, whereas venting presented a ''V-shaped'' curvilinear relationship with PTSS risk (Fig. 5-14). Three occupational characteristics—increases in job difficulty (Fig. 5-7), lack of resources (Fig. 5-16), and perceived stigma for working with COVID-19 patients (Fig. 5-10)—were also associated with increases in PTSS risk. Physicians demonstrated resilience to encounter challenges until they reached their highest levels. Among demographics, only age influenced PTSS risk, where service beyond 30 years demonstrated a positive association with higher risk of PTSS (Fig. 5-13). Finally, attrition variables, represented by physician's intention to switch medical units (Fig. 5-9), leave their employer (Fig. 5-20), or leave healthcare entirely (Fig. 5-6), were positively associated with increased risk of PTSS. Our data show that frontline physicians with higher risk of PTSS have higher intentions to switch medical units (1 in 2.5[1]), leave their current employer (1 in 2.2), or even leave the healthcare industry altogether (1 in 3.2) compared to their peers with lower risk of PTSS (switch teams=1 in 6.5; leave current employer=1 in 4.75; leave healthcare industry=1 in 10).

[1] ''1 in X'' can be interpreted as 1 out of X US physicians, who are working at the frontlines treating COVID-19 patients and have displayed higher levels of PTSS, have moderate to high likelihood of switching the teams or leaving their current employer or leaving the healthcare industry altogether in the next 2 years.

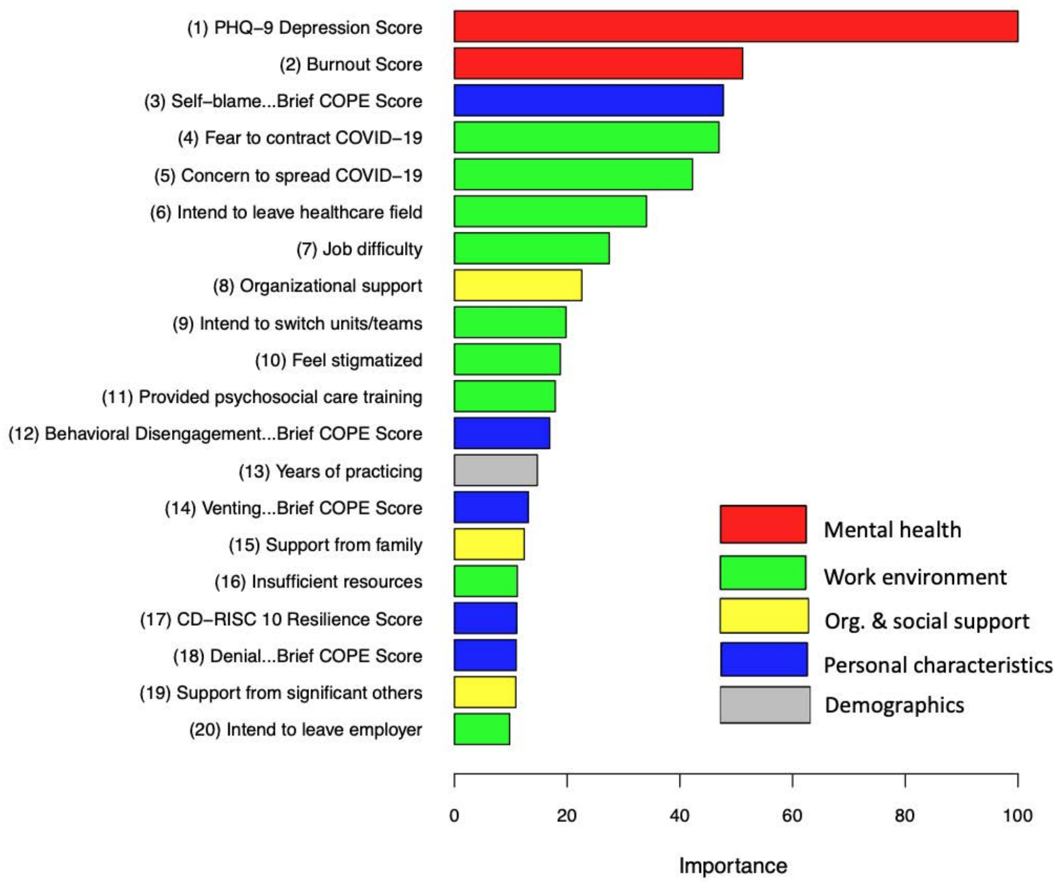

FIGURE 4. Key predictors associated with PTSD risk in practicing physicians during COVID-19 pandemic.

TABLE 7. Top 20 predictors of PTSS risk in frontline US physicians treating COVID-19 patients (^ = t-test; * = χ^2 test).

Rank	Variable names	Scale Range Min-Max	Low risk group (N=309) Mean (SD)	High risk group (N=137) Mean (SD)	VIP	Statistical analysis	p-value
1	PHQ-9 Depression score	0 – 27	3.7 (3.5)	11.4 (5.6)	100	t = -14.77	< .001^
2	Burnout score	1 – 5	2.3 (0.8)	3.4 (1.0)	51	t = -11.50	< .001^
3	Self-blame—Brief COPE Score	2 – 8	2.8 (1.2)	4.3 (1.7)	48	t = -8.88	< .001^
4	Fear to contract COVID-19	0 – 4	1.9 (1.2)	2.9 (0.9)	47	t = -9.47	< .001^
5	Concern to spread COVID-19	0 – 4	2.4 (1.2)	3.4 (0.9)	42	t = -9.77	< .001^
6	Intend to leave healthcare field	0 – 4	0.4 (0.8)	1.2 (1.2)	34	t = -7.15	< .001^
7	Job difficulty	0 – 4	2.1 (1.0)	2.9 (1.0)	27	t = -7.92	< .001^
8	Organizational support	0 – 24	16.1 (6.9)	10.8 (8.1)	23	t = 6.58	< .001^
9	Intend to switch units / teams	0 – 4	0.5 (1.0)	1.4 (1.4)	20	t = -5.98	< .001^
10	Feel stigmatized	0 – 4	0.9 (1.0)	1.5 (1.4)	19	t = -5.14	< .001^
		Yes	120 (38.8)	30 (21.9)			
11	Provided psychosocial care training (employer)	No	90 (29.1)	61 (44.5)	18	χ^2= 14.81	< .001*
		Not sure	99 (32.0)	46 (33.6)			
12	Behavioral disengagement—Brief COPE Score	2 – 8	2.5 (0.9)	3.4 (1.6)	17	t = -6.30	< .001^
13	Years of practicing	-	20.8 (10.7)	20.4 (10.6)	15	t = 0.33	.74
14	Venting—Brief COPE Score	2 – 8	4.2 (1.6)	5.0 (1.4)	13	t = -5.57	< .001^
15	Support from family	1 – 7	6.0 (1.3)	5.4 (1.6)	12	t = 3.74	< .001^
16	Insufficient resources	5-Jan	2.3 (1.1)	2.8 (1.2)	11	t = -4.80	< .001^
17	CD-RISC 10 Resilience score	0 – 40	32.2 (5.0)	30.0 (5.6)	11	t = 3.83	< .001^
18	Denial—Brief COPE score	2 – 8	2.4 (0.8)	2.9 (1.4)	11	t = -4.18	< .001^
19	Support from significant others	1 – 7	6.2 (1.4)	5.8 (1.6)	11	t = 2.13	< .001^
20	Intend to leave employer	0 – 4	0.8 (1.1)	1.4 (1.4)	10	t = -4.89	< .001^

2) PROTECTIVE VARIABLES

Numerous variables appeared to be protective in nature. The degree to which people felt supported by loved ones, such as friends/family (Fig. 5-15), significant others (Fig. 5-19) and their organization (Fig. 5-8) coincided with lower risk of experiencing PTSS [36]. PTSS risk spiked slightly as participants reported higher degrees of organizational support (Fig. 5-8). Participants who received training from employers

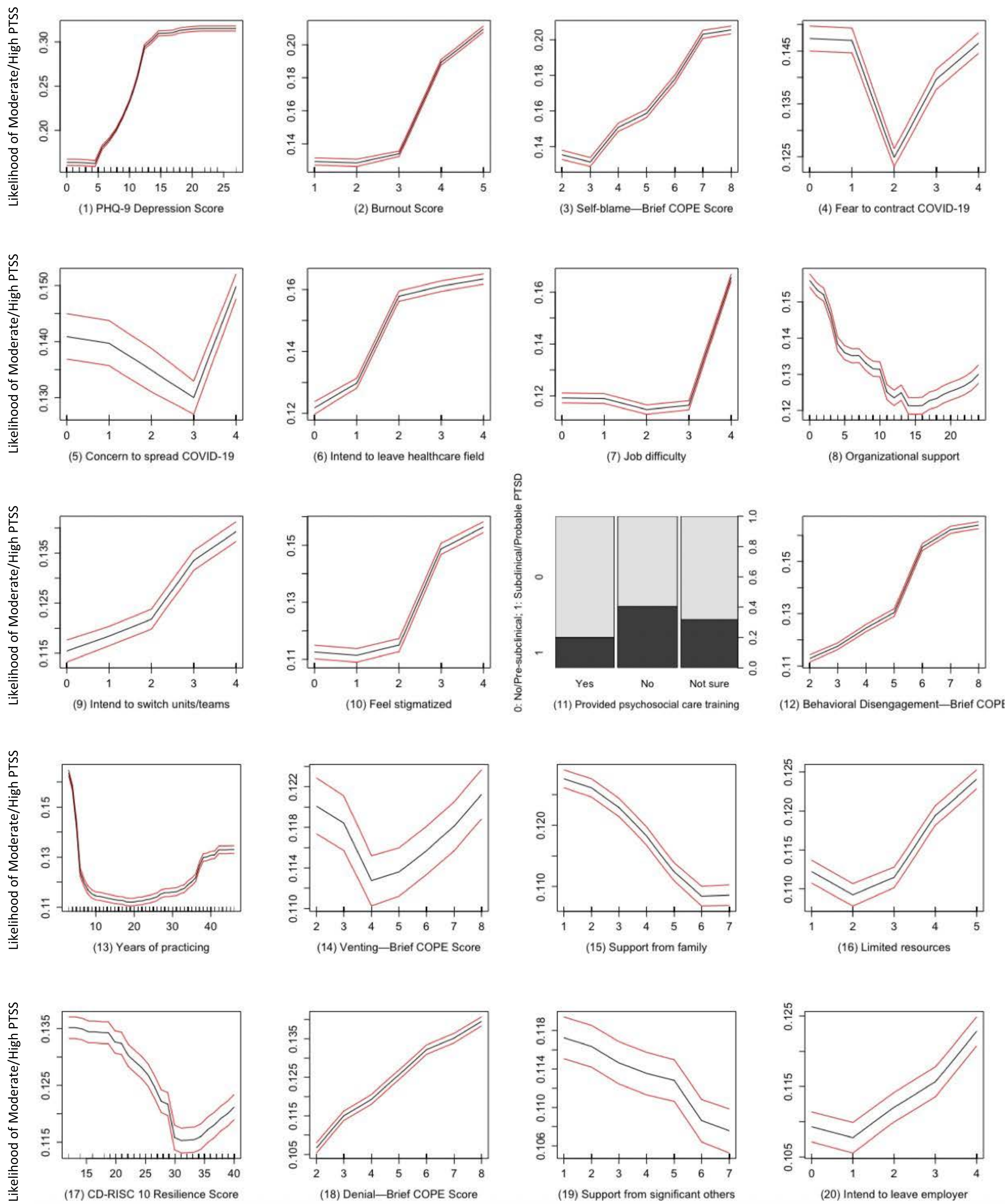

FIGURE 5. Relationships of top 20 predictors to increase the likelihood of developing moderate and high PTSS (black curve is the average marginal effect of the predictor variable; red lines indicate the 95% confidence intervals).

in psychosocial care reported lower risk of PTSS (Fig. 5-11) compared to their peers who received no such care or were unsure of receiving such care. Increases in resiliency were associated with decline in PTSS risk (Fig. 5-17); however, PTSS risk begins to climb at the highest resilience levels. Lastly, Fig. 5-18 suggests that as participants relied more on denial, PTSS risk was higher.

V. DISCUSSION

Physicians on the frontlines of COVID-19 are in crisis. Among physicians in our study working directly with COVID-19 patients across multiple specialties and states, 10.74% had high PTSS and 20.08% had moderately high PTSS, for a combined total of 30.82% at the risk of developing PTSD. By comparison, in the US general population the lifetime risk of developing PTSD by age 75 in the US general population is 8.7% and the twelve-month prevalence is 3.5% [9].

In Table 2 (see Section IV), we observed that frontline physicians had a number of significantly higher PCL-5 item scores and total scores than secondline physicians. These results reveal symptoms that are associated with increased risk of PTSS for frontline physicians, as well as the need to identify currently at-risk physicians for interventions. Our results also support the assumption that working directly with COVID-19 patients can meet PTSD Criterion A of the DSM-5 (having experienced a traumatic event).

The findings reported in Table 2 underscore not only how overall rates of PTSD differ between frontline and secondline physicians, but also how symptoms vary between these groups. The International Classification of Diseases, 11th Edition [115], in aiming to create an abbreviated symptom assessment for PTSD, selected six items (among the 20 symptoms of PTSD included in DSM-5 and PCL-5) that are the most specific to PTSD [116]. These include flashbacks and nightmares (Criterion B, Re-experiencing), avoiding memories and external reminders (Criterion C, Avoidance), and hypervigilance and exaggerated startle response (Criterion D, Hyperarousal). Our analysis from the case study indicated that all six of these items differed significantly between frontline and secondline physicians (Table 2). Interestingly, three items on which both the physician groups endorsed similar and considerable rates (negative beliefs, difficulty concentrating, and trouble sleeping), are highly correlated with other dysphoric conditions [117]. Rather than being specific to PTSD, these three items may instead indicate concurrent stress-related symptoms among physicians, which warrants further examination.

Our analysis also presented a unique way of examining PCL-5 scores by looking at the number of physicians who scored in the clinically significant range ($\geq$2, moderate to severe) (see Table 3). While PCL-5 mean score comparisons are traditionally used to analyze differences between groups using the full range of scoring (0 to 4), they do not reveal the number of participants who endorse a particular score or range of scores. The use of frequency data provides additional information about the number of physicians who experience clinically significant PTSS. For example, Table 3 shows that a similar number of frontline and secondline physicians experienced problematic sleep (33.3% and 27.67%, respectively) (PCL-5; item 20), whereas, more frontline than secondline physicians experienced disturbing memories (20.08% and 10.0%, respectively) (PCL-5; item 1). Further exploration of frequency data could allow for the identification of the most relevant clinical symptoms associated with PTSS-related disturbances in frontline physicians and other healthcare workers.

Unique to our study, statistical inferencing from the predictive models indicated that cognitive outcomes such as depression and burnout were the greatest predictors of increased risk for experiencing PTSS among frontline physicians. Previous studies have also shown that PTSD risk among physicians is positively associated with depression and burnout [19], [118]. Although burnout often coincides with depression among physicians [119], they have been shown to have different mental health outcomes [120]. For example, while depression is directly associated with suicidal ideation among physicians, burnout was associated with more self-reported medical errors than depression [120]. Consistent with this, burnout and depression were independent predictors of PTSS risk in our analyses. In fact, depression, which has long been found to co-occur with PTSD in the aftermath of traumatic events [13], [121], [122], was the greatest predictor of higher risk for experiencing clinically significant PTSS in physicians treating COVID-19 patients in the aftermath of the pandemic. Its significance underscores the need for physicians and healthcare administration to remain vigilant for indicators of depression, potentially engaging in active monitoring of its prevalence among frontline physicians. Statistical inferencing from the learning models revealed that, unlike the linear relationship between PTSS risk and depression, PTSS risk was positively associated with only the high burnout levels. In addition, PTSS risk levels were observed to be high when fears of contracting or transmitting COVID-19 were minimal, dipped when these fears were moderate, then dramatically spiked when fears were great (see Figure 5-4). Although moderate fear appears protective, low and high levels of fear may follow patterns similar to those discussed earlier, with high fear triggering trauma and low fear serving as a proxy for negative coping strategies such as denial. Out of the 57 predictor variables used in this study, it is noteworthy that nine of the top twenty predictors of PTSS fall in the category of work environment, with six falling in the top ten. Burnout is also known to result directly from workplace stressors, and tends to resolve when individuals take a break from the workplace. The significance of work environment and burnout as top predictors is that many of these are externally driven and can be modified through organizational implementation of changes in the workplace, as opposed to personal traits and factors outside the workplace which are less open to organizational change.

Further our analysis also revealed that physicians who vented (i.e., complained or processed trauma experiences with others) *the least* and *the most* were at higher risk for PTSS, while those who vented a moderate amount presented lower PTSS risk. We speculate that minimal venting may forego the benefits of externally processing the traumatizing events and provoke trauma-induced symptoms [123], [124], whereas high levels of venting are a proxy for turmoil, a phenomenon found in other high stress-contexts [124], [125]. Similarly, increased institutional support largely decreased the risk of PTSS; however, our modeling reveals a spike in the PTSS risk at the highest degrees of organizational support. As with venting, the highest levels of organizational support may be provided for those who are in the greatest need. Lastly, the spike in PTSS risk at the highest levels of resilience may come from physicians coping via a form of denial—another factor within the top 20 PTSS risk predictors. Understanding and exploring such nuances will further inform both theory and practice, helping support frontline physicians through such crises.

Among demographics, only age was found to be a key predictor of PTSS risk. Previous research suggests younger physicians are less resilient to COVID-related trauma [63], [66], [68], [73], [76], [77]; however, the extant literature argues trauma is additive, suggesting older physicians would be more vulnerable following COVID-related trauma exposure [126]. Our findings offer support for both bodies of work, with the younger suffering the most, but PTSS risk markedly increasing among the older physicians.

Although the cross-sectional nature of the data prevents inferring causality, the higher intentions among frontline physicians to switch units, leave their employer, or leave healthcare completely has important implications for the future of the physician workforce [127]. With up to 50% of physicians already suffering from chronic stress and burnout entering the pandemic [36], [128], [129], [130], these new, trauma-related burdens for frontline physicians may herald an exodus from the already strained US healthcare system.

VI. LIMITATIONS

Several factors should be considered when interpreting these findings. The cross-sectional nature of these analyses prevents us from drawing conclusions about the causal relationship between predictor variables and the PTSS risk. In the future, longitudinal studies that bolster participant uptake are needed to confirm and expound upon these findings. Additionally, the study produced a relatively low response rate, which is common for non-incentivized, voluntary surveys. It is also possible that physicians experiencing emotional complications when treating COVID-19 patients were more likely to participate in the survey. However, the main contribution of our proposed study is developing a novel, data-driven framework to assess the risk of experiencing PTSS among the physicians working in a stressed healthcare environment. This framework is generalized enough that it can be applied in similar studies.

VII. CONCLUSION

Despite their considerable predictive power and increasing popularity in public health [47], [49], [50], [51], [95], [131], to the best of our knowledge, this is the first study to leverage state-of-the-art, statistical learning algorithms to predict and evaluate the factors associated with risks for experiencing PTSS in frontline physicians. Our results demonstrate the value of nonparametric, nonlinear statistical learning algorithms to reveal complex relationships between predictor variables and PTSS risk, outperforming more conventional linear logistic regression in sophistication and precision [59], [132]. Our modeling approach not only revealed interplay between damaging and protective factors for PTSS risk, but also invites speculation on the nature of curvilinear relationships between the key factors and PTSS risk.

In summary, our study identified how frontline physicians directly treating COVID-19 patients are at higher risk of experiencing PTSS than physicians who do not directly treat the COVID-19 patients in the US. Specifically, we identified key factors associated with either a higher and lower PTSS risk. The identification of such key intervention variables can help stakeholders develop the means to proactively support individuals at higher PTSS risk. Thus, either by mitigating damaging variables and/or bolstering protective variables, this research provides both physicians and their institutions useful information with which to defend against the trauma-related threats to physicians resulting from the current and possible future epidemics/pandemics. The stability and future of the US healthcare system may depend on it.

REFERENCES

[1] K.-I. Karstoft, I. R. Galatzer-Levy, A. Statnikov, Z. Li, and A. Y. Shalev, "Bridging a translational gap: Using machine learning to improve the prediction of PTSD," *BMC Psychiatry*, vol. 15, no. 1, pp. 1–7, Dec. 2015.

[2] K. C. Koenen, J. M. Stellman, S. D. Stellman, and J. F. Sommer, Jr., "Risk factors for course of posttraumatic stress disorder among Vietnam veterans: A 14-year follow-up of American Legionnaires," *J. Consulting Clin. Psychol.*, vol. 71, no. 6, p. 980, 2003.

[3] C. R. Marmar, D. S. Weiss, W. E. Schlenger, J. A. Fairbank, B. K. Jordan, R. A. Kulka, and R. L. Hough, "Peritraumatic dissociation and posttraumatic stress in male Vietnam theater veterans," *Amer. J. Psychiatry*, vol. 151, pp. 902–907, Jun. 1994.

[4] R. A. Bryant, A. G. Harvey, R. M. Guthrie, and M. L. Moulds, "A prospective study of psychophysiological arousal, acute stress disorder, and posttraumatic stress disorder," *J. Abnormal Psychol.*, vol. 109, no. 2, p. 341, 2000.

[5] B. Kleim, A. Ehlers, and E. Glucksman, "Early predictors of chronic posttraumatic stress disorder in assault survivors," *Psychol. Med.*, vol. 37, no. 10, pp. 1457–1467, Oct. 2007.

[6] R. H. Segman, N. Shefi, T. Goltser-Dubner, N. Friedman, N. Kaminski, and A. Y. Shalev, "Peripheral blood mononuclear cell gene expression profiles identify emergent post-traumatic stress disorder among trauma survivors," *Mol. Psychiatry*, vol. 10, no. 5, pp. 500–513, May 2005.

[7] G. Orrù, W. Pettersson-Yeo, A. F. Marquand, G. Sartori, and A. Mechelli, "Using support vector machine to identify imaging biomarkers of neurological and psychiatric disease: A critical review," *Neurosci. Biobehav. Rev.*, vol. 36, pp. 1140–1152, Apr. 2012.

[8] A. Y. Shalev and R. H. Segman, ''Commentary: Biological findings in PTSD—Too much or too little?'' *Prog. Brain Res.*, vol. 167, pp. 187–199, Jan. 2007.

[9] APA. *Diagnostic and Statistical Manual of Mental Disorders*. Accessed: Oct. 29, 2022. [Online]. Available: https://www.psychiatry.org/psychiatrists/practice/dsm/educational-resources/dsm-5-fact-sheets

[10] D. Jacob Sendler, A. Rutkowska, and M. Makara-Studzinska, ''How the exposure to trauma has hindered physicians' capacity to heal: Prevalence of PTSD among healthcare workers,'' *Eur. J. Psychiatry*, vol. 30, no. 4, pp. 321–334, 2016.

[11] J. A. DeLucia, C. Bitter, J. Fitzgerald, M. Greenberg, P. Dalwari, and P. Buchanan, ''Prevalence of post-traumatic stress disorder in emergency physicians in the united states,'' *Western J. Emergency Med.*, vol. 20, no. 5, p. 740, 2019.

[12] A. Lazarus, ''Traumatized by practice: PTSD in physicians,'' *J. Med. Pract. Manag.*, vol. 30, no. 2, pp. 131–134, 2014.

[13] J. Liebschutz, R. Saitz, V. Brower, T. M. Keane, C. Lloyd-Travaglini, T. Averbuch, and J. H. Samet, ''PTSD in urban primary care: High prevalence and low physician recognition,'' *J. Gen. Internal Med.*, vol. 22, no. 6, pp. 719–726, May 2007.

[14] N. De Brier, S. Stroobants, P. Vandekerckhove, and E. De Buck, ''Factors affecting mental health of health care workers during coronavirus disease outbreaks (SARS, MERS & COVID-19): A rapid systematic review,'' *PLoS ONE*, vol. 15, no. 12, Dec. 2020, Art. no. e0244052.

[15] P. Goulia, C. Mantas, D. Dimitroula, D. Mantis, and T. Hyphantis, ''General hospital staff worries, perceived sufficiency of information and associated psychological distress during the A/H1N1 influenza pandemic,'' *BMC Infectious Diseases*, vol. 10, no. 1, pp. 1–11, Dec. 2010.

[16] H. Imai, K. Matsuishi, A. Ito, K. Mouri, N. Kitamura, K. Akimoto, K. Mino, A. Kawazoe, M. Isobe, S. Takamiya, and T. Mita, ''Factors associated with motivation and hesitation to work among health professionals during a public crisis: A cross sectional study of hospital workers in Japan during the pandemic (H1N1) 2009,'' *BMC Public Health*, vol. 10, no. 1, pp. 1–8, Dec. 2010.

[17] I. Khalid, T. J. Khalid, M. R. Qabajah, A. G. Barnard, and I. A. Qushmaq, ''Healthcare workers emotions, perceived stressors and coping strategies during a MERS-CoV outbreak,'' *Clin. Med. Res.*, vol. 14, no. 1, pp. 7–14, Mar. 2016.

[18] B. M. Baumann, R. J. Cooper, A. J. Medak, S. Lim, B. Chinnock, R. Frazier, B. W. Roberts, E. S. Epel, and R. M. Rodriguez, ''Emergency physician stressors, concerns, and behavioral changes during COVID-19: A longitudinal study,'' *Acad. Emergency Med.*, vol. 28, no. 3, pp. 314–324, Mar. 2021.

[19] N. Restauri and A. D. Sheridan, ''Burnout and posttraumatic stress disorder in the coronavirus disease 2019 (COVID-19) pandemic: Intersection, impact, and interventions,'' *J. Amer. College Radiol.*, vol. 17, no. 7, pp. 921–926, Jul. 2020.

[20] C. A. Marco, G. L. Larkin, V. R. Feeser, J. E. Monti, and L. Vearrier, ''Post-traumatic stress and stress disorders during the COVID-19 pandemic: Survey of emergency physicians,'' *J. Amer. College Emergency Physicians Open*, vol. 1, no. 6, pp. 1594–1601, Dec. 2020.

[21] CDC. *Covid Data Tracker*. Accessed: Sep. 9, 2022. [Online]. Available: https://covid.cdc.gov/covid-data-tracker/#datatracker-home

[22] D. T. Myran, N. Cantor, E. Rhodes, M. Pugliese, J. Hensel, M. Taljaard, R. Talarico, A. X. Garg, E. McArthur, C.-W. Liu, N. Jeyakumar, C. Simon, T. McFadden, C. Gerin-Lajoie, M. M. Sood, and P. Tanuseputro, ''Physician health care visits for mental health and substance use during the COVID-19 pandemic in ontario, Canada,'' *JAMA Netw. Open*, vol. 5, no. 1, Jan. 2022, Art. no. e2143160.

[23] A. A. Sandford and J. A. F. Zupancic, ''Physician wellbeing during the COVID-19 pandemic: An acute on chronic condition,'' *Pediatric Res.*, vol. 91, no. 1, pp. 19–20, Jan. 2022.

[24] M. Linzer, M. Stillman, R. Brown, S. Taylor, N. Nankivil, S. Poplau, E. Goelz, C. Sinsky, M. Barbouche, C. Buhr, and F. Byrne, ''Preliminary report: U.S. Physician stress during the early days of the COVID-19 pandemic,'' *Mayo Clinic Proc., Innov., Quality Outcomes*, vol. 5, no. 1, pp. 127–136, Feb. 2021.

[25] C. Lluch, L. Galiana, P. Doménech, and N. Sansó, ''The impact of the covid-19 pandemic on burnout, compassion fatigue, and compassion satisfaction in healthcare personnel: A systematic review of the literature published during the first year of the pandemic,'' *Healthcare*, vol. 10, no. 2, p. 364, 2022.

[26] J. M. Pujo, D. Y. Fitriani, N. P. Adi, P. Portecop, D. Resiere, M. Mansyur, and H. Kallel, ''COVID-19 outbreak: Burnout and post-traumatic stress disorder, a harmful chronology for health caregivers in emergency departments and intensive care units,'' *Disaster Med. Public Health Preparedness*, pp. 1–6, 2022.

[27] J. L. Gradus, P. Qin, A. K. Lincoln, M. Miller, E. Lawler, H. T. Sorensen, and T. L. Lash, ''Posttraumatic stress disorder and completed suicide,'' *Amer. J. Epidemiol.*, vol. 171, no. 6, pp. 721–727, Mar. 2010.

[28] J. Gregory, J. de Lepinau, A. de Buyer, N. Delanoy, O. Mir, and R. Gaillard, ''The impact of the Paris terrorist attacks on the mental health of resident physicians,'' *BMC Psychiatry*, vol. 19, no. 1, pp. 1–8, Dec. 2019.

[29] M. Panagioti, K. Geraghty, J. Johnson, A. Zhou, E. Panagopoulou, C. Chew-Graham, D. Peters, A. Hodkinson, R. Riley, and A. Esmail, ''Association between physician burnout and patient safety, professionalism, and patient satisfaction: A systematic review and meta-analysis,'' *JAMA internal Med.*, vol. 178, no. 10, pp. 1317–1331, 2018.

[30] C. P. Landrigan, J. M. Rothschild, J. W. Cronin, R. Kaushal, E. Burdick, J. T. Katz, C. M. Lilly, P. H. Stone, S. W. Lockley, D. W. Bates, and C. A. Czeisler, ''Effect of reducing Interns' work hours on serious medical errors in intensive care units,'' *New England J. Med.*, vol. 351, no. 18, pp. 1838–1848, Oct. 2004.

[31] S. W. Lockley, J. W. Cronin, E. E. Evans, B. E. Cade, C. J. Lee, C. P. Landrigan, J. M. Rothschild, J. T. Katz, C. M. Lilly, P. H. Stone, D. Aeschbach, and C. A. Czeisler, ''Effect of reducing interns' weekly work hours on sleep and attentional failures,'' *New England J. Med.*, vol. 351, no. 18, pp. 1829–1837, Oct. 2004.

[32] A. F. Arnsten and T. Shanafelt, ''Physician distress and burnout: The neurobiological perspective,'' in *Mayo Clinic Proceedings*, vol. 96, no. 3. Amsterdam, The Netherlands: Elsevier, 2021, pp. 763–769.

[33] P. K. L. Merlo, B. K. M. Conen, M. B. Scott, M. K. Jones, C. E. A. Dunn, and P. J. Marshall, ''Burnout in the disaster response workforce: The impact of work roles and the COVID-19 pandemic,'' *J. Emergency Manage.*, vol. 19, no. 9, pp. 81–90, Jul. 2021.

[34] E. C. Dillon, M. Tai-Seale, A. Meehan, V. Martin, R. Nordgren, T. Lee, T. Nauenberg, and D. L. Frosch, ''Frontline perspectives on physician burnout and strategies to improve well-being: Interviews with physicians and health system leaders,'' *J. Gen. Internal Med.*, vol. 35, no. 1, pp. 261–267, Jan. 2020.

[35] T. Dolev, S. Zubedat, Z. Brand, B. Bloch, E. Mader, O. Blondheim, and A. Avital, ''Physiological parameters of mental health predict the emergence of post-traumatic stress symptoms in physicians treating COVID-19 patients,'' *Translational Psychiatry*, vol. 11, no. 1, pp. 1–9, Jun. 2021.

[36] A. Blekas, P. Voitsidis, M. Athanasiadou, E. Parlapani, A. F. Chatzigeorgiou, M. Skoupra, M. Syngelakis, V. Holeva, and I. Diakogiannis, ''COVID-19: PTSD symptoms in Greek health care professionals,'' *Psychol. Trauma, Theory, Res., Pract., Policy*, vol. 12, no. 7, p. 812, 2020.

[37] X. Li, S. Li, M. Xiang, Y. Fang, K. Qian, J. Xu, J. Li, Z. Zhang, and B. Wang, ''The prevalence and risk factors of PTSD symptoms among medical assistance workers during the COVID-19 pandemic,'' *J. Psychosomatic Res.*, vol. 139, Dec. 2020, Art. no. 110270.

[38] C. Carmassi, C. Foghi, V. Dell'Oste, A. Cordone, C. A. Bertelloni, E. Bui, and L. Dell'Osso, ''PTSD symptoms in healthcare workers facing the three coronavirus outbreaks: What can we expect after the COVID-19 pandemic,'' *Psychiatry Res.*, vol. 292, Oct. 2020, Art. no. 113312.

[39] W. Wu, Y. Zhang, P. Wang, L. Zhang, G. Wang, G. Lei, Q. Xiao, X. Cao, Y. Bian, S. Xie, F. Huang, N. Luo, J. Zhang, and M. Luo, ''Psychological stress of medical staffs during outbreak of COVID-19 and adjustment strategy,'' *J. Med. Virol.*, vol. 92, no. 10, pp. 1962–1970, Oct. 2020.

[40] R. M. Rodriguez, J. C. C. Montoy, K. F. Hoth, D. A. Talan, K. K. Harland, P. Ten Eyck, and W. Mower, ''Symptoms of anxiety, burnout, and PTSD and the mitigation effect of serologic testing in emergency department personnel during the COVID-19 pandemic,'' *Ann. Emergency Med.*, vol. 78, no. 1, pp. 35–43, 2021.

[41] J. Sonis, D. E. Pathman, S. Read, B. N. Gaynes, C. Canter, P. Curran, and T. Miller, ''Generalized anxiety, depression and posttraumatic stress disorder in a national sample of U.S. Internal medicine physicians during the COVID-19 pandemic,'' *Gen. Hospital Psychiatry*, vol. 71, pp. 142–144, Jul. 2021.

[42] T. Greene, J. Harju-Seppänen, M. Adeniji, C. Steel, N. Grey, C. R. Brewin, M. A. Bloomfield, and J. Billings, ''Predictors and rates of PTSD, depression and anxiety in U.K. Frontline health and social care workers during COVID-19,'' *Eur. J. Psychotraumatol.*, vol. 12, no. 1, Jan. 2021, Art. no. 1882781.

[43] T. Roberts, J. Daniels, W. Hulme, R. Hirst, D. Horner, M. D. Lyttle, K. Samuel, B. Graham, C. Reynard, M. Barrett, J. Foley, J. Cronin, E. Umana, J. Vinagre, and E. Carlton, ''Psychological distress and trauma in doctors providing frontline care during the COVID-19 pandemic in the united kingdom and Ireland: A prospective longitudinal survey cohort study,'' *BMJ Open*, vol. 11, no. 7, Jul. 2021, Art. no. e049680.

[44] C. M. Lee, M. Juarez, G. Rae, L. Jones, R. M. Rodriguez, J. A. Davis, M. Boysen-Osborn, K. J. Kashima, N. K. Krane, N. Kman, J. M. Langsfeld, and A. J. Harries, ''Anxiety, PTSD, and stressors in medical students during the initial peak of the COVID-19 pandemic,'' *PLoS ONE*, vol. 16, no. 7, Jul. 2021, Art. no. e0255013.

[45] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, vol. 2. Cham, Switzerland: Springer, 2009.

[46] E. J. Schmitt and H. Jula, ''On the limitations of linear models in predicting travel times,'' in *Proc. IEEE Intell. Transp. Syst. Conf.*, Sep. 2007, pp. 830–835.

[47] Z. Wei and S. Mukherjee, ''Health-behaviors associated with the growing risk of adolescent suicide attempts: A data-driven cross-sectional study,'' *Amer. J. Health Promotion*, vol. 35, no. 5, pp. 688–693, Jun. 2021.

[48] Z. Wei, A. B. Narin, and S. Mukherjee, ''Multidimensional population health modeling: A data-driven multivariate statistical learning approach,'' *IEEE Access*, vol. 10, pp. 22737–22755, 2022.

[49] S. Mukherjee and Z. Wei, ''Suicide disparities across metropolitan areas in the U.S.: A comparative assessment of socio-environmental factors using a data-driven predictive approach,'' *PLoS ONE*, vol. 16, no. 11, Nov. 2021, Art. no. e0258824.

[50] S. Mukherjee, E. F Boamah, P. Ganguly, and N. Botchwey, ''A multilevel scenario based predictive analytics framework to model the community mental health and built environment Nexus,'' *Sci. Rep.*, vol. 11, no. 1, pp. 1–15, Dec. 2021.

[51] S. Mukherjee, N. Botchwey, and E. F. Boamah, ''Towards mental wellbeing in cities: A data-driven learning from mental health—Environment Nexus,'' in *Proc. 30th Eur. Saf. Rel. Conf. 15th Probabilistic Saf. Assessment Manage. Conf.*, 2020, pp. 1–8.

[52] D. J. MacKay and D. J. C. M. Kay, *Information Theory, Inference and Learning Algorithms*. Cambridge, U.K.: Cambridge Univ. Press, 2003.

[53] P. Domingos, *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World*. New York, NY, USA: Basic Books, 2015.

[54] I. R. Galatzer-Levy, K.-I. Karstoft, A. Statnikov, and A. Y. Shalev, ''Quantitative forecasting of PTSD from early trauma responses: A machine learning application,'' *J. Psychiatric Res.*, vol. 59, pp. 68–76, Dec. 2014.

[55] I. R. Galatzer-Levy, S. Ma, A. Statnikov, R. Yehuda, and A. Y. Shalev, ''Utilization of machine learning for prediction of post-traumatic stress: A re-examination of cortisol in the prediction and pathways to nonremitting PTSD,'' *Translational Psychiatry*, vol. 7, no. 3, p. e1070, Mar. 2017.

[56] K. Schultebraucks and I. R. Galatzer-Levy, ''Machine learning for prediction of posttraumatic stress and resilience following trauma: An overview of basic concepts and recent advances,'' *J. Traumatic Stress*, vol. 32, no. 2, pp. 215–225, Apr. 2019.

[57] L. F. Ramos-Lima, V. Waikamp, T. Antonelli-Salgado, I. C. Passos, and L. H. M. Freitas, ''The use of machine learning techniques in trauma-related disorders: A systematic review,'' *J. Psychiatric Res.*, vol. 121, pp. 159–172, Feb. 2020.

[58] A. Bourla, S. Mouchabac, W. El Hage, and F. Ferreri, ''E-PTSD: An overview on how new technologies can improve prediction and assessment of posttraumatic stress disorder (PTSD),'' *Eur. J. Psychotraumatol.*, vol. 9, no. 1, Nov. 2018, Art. no. 1424448.

[59] S. Wshah, C. Skalka, and M. Price, ''Predicting posttraumatic stress disorder risk: A machine learning approach,'' *JMIR Mental Health*, vol. 6, no. 7, Jul. 2019, Art. no. e13946.

[60] M. A. Worthington, A. Mandavia, and R. Richardson-Vejlgaard, ''Prospective prediction of PTSD diagnosis in a nationally representative sample using machine learning,'' *BMC Psychiatry*, vol. 20, no. 1, pp. 1–10, Dec. 2020.

[61] R. D. V. Nixon, M. W. King, B. N. Smith, J. L. Gradus, P. A. Resick, and T. E. Galovski, ''Predicting response to cognitive processing therapy for PTSD: A machine-learning approach,'' *Behav. Res. Therapy*, vol. 144, Sep. 2021, Art. no. 103920.

[62] S. I. Omurca and E. Ekinci, ''An alternative evaluation of post traumatic stress disorder with machine learning methods,'' in *Proc. Int. Symp. Innov. Intell. Syst. Appl. (INISTA)*, Sep. 2015, pp. 1–7.

[63] M.-Y. Chong, W.-C. Wang, W.-C. Hsieh, C.-Y. Lee, N.-M. Chiu, W.-C. Yeh, T.-L. Huang, J.-K. Wen, and C.-L. Chen, ''Psychological impact of severe acute respiratory syndrome on health workers in a tertiary hospital,'' *Brit. J. Psychiatry*, vol. 185, no. 2, pp. 127–133, Aug. 2004.

[64] R. Maunder, J. Hunter, L. Vincent, J. Bennett, N. Peladeau, M. Leszcz, J. Sadavoy, L. M. Verhaeghe, R. Steinberg, and T. Mazzulli, ''The immediate psychological and occupational impact of the 2003 SARS outbreak in a teaching hospital,'' *Cmaj*, vol. 168, no. 10, pp. 1245–1251, 2003.

[65] L. A. Nickell, E. J. Crighton, C. S. Tracy, H. Al-Enazy, Y. Bolaji, S. Hanjrah, A. Hussain, S. Makhlouf, and R. E. Upshur, ''Psychosocial effects of SARS on hospital staff: Survey of a large tertiary care institution,'' *Cmaj*, vol. 170, no. 5, pp. 793–798, 2004.

[66] P. Wu, Y. Fang, Z. Guan, B. Fan, J. Kong, Z. Yao, X. Liu, C. J. Fuller, E. Susser, J. Lu, and C. W. Hoven, ''The psychological impact of the SARS epidemic on hospital employees in China: Exposure, risk perception, and altruistic acceptance of risk,'' *Can. J. Psychiatry*, vol. 54, no. 5, pp. 302–311, May 2009.

[67] L. Kang, S. Ma, M. Chen, J. Yang, Y. Wang, R. Li, L. Yao, H. Bai, Z. Cai, B. X. Yang, S. Hu, K. Zhang, G. Wang, C. Ma, and Z. Liu, ''Impact on mental health and perceptions of psychological care among medical and nursing staff in Wuhan during the 2019 novel coronavirus disease outbreak: A cross-sectional study,'' *Brain, Behav., Immunity*, vol. 87, pp. 11–17, Jul. 2020.

[68] J. Lai, S. Ma, Y. Wang, Z. Cai, J. Hu, N. Wei, J. Wu, H. Du, T. Chen, R. Li, H. Tan, L. Kang, L. Yao, M. Huang, H. Wang, G. Wang, Z. Liu, and S. Hu, ''Factors associated with mental health outcomes among health care workers exposed to coronavirus disease 2019,'' *JAMA Netw. Open*, vol. 3, no. 3, Mar. 2020, Art. no. e203976.

[69] G. A. Colville, J. G. Smith, J. Brierley, K. Citron, N. M. Nguru, P. D. Shaunak, O. Tam, and L. Perkins-Porras, ''Coping with staff burnout and work-related posttraumatic stress in intensive care,'' *Pediatric Crit. Care Med.*, vol. 18, no. 7, pp. e267–e273, 2017.

[70] A. A. R. M. Hamid and S. A. Musa, ''The mediating effects of coping strategies on the relationship between secondary traumatic stress and burnout in professional caregivers in the UAE,'' *J. Mental Health*, vol. 26, no. 1, pp. 28–35, Jan. 2017.

[71] A. F. Winkel, A. Robinson, A.-A. Jones, and A. P. Squires, ''Physician resilience: A grounded theory study of obstetrics and gynaecology residents,'' *Med. Educ.*, vol. 53, no. 2, pp. 184–194, Feb. 2019.

[72] H. Jung, S. Y. Jung, M. H. Lee, and M. S. Kim, ''Assessing the presence of post-traumatic stress and turnover intention among nurses post–middle east respiratory syndrome outbreak: The importance of supervisor support,'' *Workplace Health Saf.*, vol. 68, no. 7, pp. 337–345, Jul. 2020.

[73] K. Sim, P. N. Chong, Y. H. Chan, and W. S. W. Soon, ''Severe acute respiratory syndrome-related psychiatric and posttraumatic morbidities and coping responses in medical staff within a primary health care setting in Singapore,'' *J. Clin. Psychiatry*, vol. 65, no. 8, p. 19366, 2004.

[74] A. O. M. Chan, ''Psychological impact of the 2003 severe acute respiratory syndrome outbreak on health care workers in a medium size regional general hospital in Singapore,'' *Occupational Med.*, vol. 54, no. 3, pp. 190–196, May 2004.

[75] R. G. Maunder, W. J. Lancee, K. E. Balderson, J. P. Bennett, B. Borgundvaag, S. Evans, C. M. Fernandes, D. S. Goldbloom, M. Gupta, J. J. Hunter, ''Long-term psychological and occupational effects of providing hospital healthcare during SARS outbreak,'' *Emerg. Infectious Diseases*, vol. 12, no. 12, p. 1924, 2006.

[76] T. Su, T. Lien, C. Yang, Y. Su, J. Wang, S. Tsai, and J. Yin, ''Prevalence of psychiatric morbidity and psychological adaptation of the nurses in a structured SARS caring unit during outbreak: A prospective and periodic assessment study in Taiwan,'' *J. Psychiatric Res.*, vol. 41, nos. 1–2, pp. 119–130, Jan. 2007.

[77] W. J. Lancee, R. G. Maunder, and D. S. Goldbloom, ''Prevalence of psychiatric disorders among Toronto hospital workers one to two years after the SARS outbreak,'' *Psychiatric Services*, vol. 59, no. 1, pp. 91–95, Jan. 2008.

[78] JHU. *Outbreak Evolution for the Current Most Affected Countries, Maps Trends New COVID-19 Cases*. Accessed: Oct. 29, 2022. [Online]. Available: https://coronavirus.jhu.edu/data/new-cases
[79] L. S. Rintamaki, F. M. Weaver, P. L. Elbaum, E. N. Klama, and S. A. Miskevics, "Persistence of traumatic memories in world war II prisoners of war: (See editorial comments by Dr. Jules Rosen, on pp 2346–2347)," *J. Amer. Geriatrics Soc.*, vol. 57, no. 12, pp. 2257–2262, Dec. 2009.
[80] F. W. Weathers, B. T. Litz, T. M. Keane, P. A. Palmieri, B. P. Marx, and P. P. Schnurr, "The ptsd checklist for DSM-5 (PCL-5)," *Scale Nat. Center PTSD PTSD Gov*, vol. 10, no. 4, pp. 1–8, 2013.
[81] Y.-C. Lu, B.-C. Shu, Y.-Y. Chang, and F.-W. Lung, "The mental health of hospital workers dealing with severe acute respiratory syndrome," *Psychotherapy Psychosomatics*, vol. 75, no. 6, pp. 370–375, 2006.
[82] K. S. Kroenke and R. Williams, "The PHQ-9: Validity of a brief depression severity measure," *J. General Internal Med.*, vol. 16, no. 9, pp. 606–613, 2001.
[83] E. D. Dolan, D. Mohr, M. Lempa, S. Joos, S. D. Fihn, K. M. Nelson, and C. D. Helfrich, "Using a single item to measure burnout in primary care staff: A psychometric evaluation," *J. Gen. Internal Med.*, vol. 30, no. 5, pp. 582–587, 2015.
[84] R. Eisenberger, R. Huntington, S. Hutchison, and D. Sowa, "Perceived organizational support," *J. Appl. Psychol.*, vol. 71, no. 3, p. 500, 1986.
[85] G. D. Zimet, N. W. Dahlem, S. G. Zimet, and G. K. Farley, "The multidimensional scale of perceived social support," *J. Personality Assessment*, vol. 52, no. 1, pp. 30–41, 1988.
[86] K. M. Connor and J. R. Davidson, "Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC)," *Depression Anxiety*, vol. 18, no. 2, pp. 76–82, 2003.
[87] C. S. Carver, "You want to measure coping but your protocol' too long: Consider the brief cope," *Int. J. Behav. Med.*, vol. 4, no. 1, pp. 92–100, Mar. 1997.
[88] S. Mukherjee and R. Nateghi, "Climate sensitivity of end-use electricity consumption in the built environment: An application to the state of Florida, United States," *Energy*, vol. 128, pp. 688–700, Jun. 2017.
[89] S. Mukhopadhyay and R. Nateghi, "Estimating climate—Demand Nexus to support longterm adequacy planning in the energy sector," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5.
[90] S. Mukherjee, C. R. Vineeth, and R. Nateghi, "Evaluating regional climate-electricity demand nexus: A composite Bayesian predictive framework," *Appl. Energy*, vol. 235, pp. 1561–1582, Feb. 2019.
[91] S. Mukherjee and R. Nateghi, "A data-driven approach to assessing supply inadequacy risks due to climate-induced shifts in electricity demand," *Risk Anal.*, vol. 39, no. 3, pp. 673–694, Mar. 2019. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/risa.13192
[92] R. Nateghi and S. Mukherjee, "A multi-paradigm framework to assess the impacts of climate change on end-use energy demand," *PLoS ONE*, vol. 12, no. 11, Nov. 2017, Art. no. e0188033.
[93] R. Obringer, S. Mukherjee, and R. Nateghi, "Evaluating the climate sensitivity of coupled electricity-natural gas demand using a multivariate framework," *Appl. Energy*, vol. 262, Mar. 2020, Art. no. 114419.
[94] P. Alipour, S. Mukherjee, and R. Nateghi, "Assessing climate sensitivity of peak electricity load for resilient power systems planning and operation: A study applied to the Texas region," *Energy*, vol. 185, pp. 1143–1153, Oct. 2019.
[95] W.-H. Lo-Ciganic, J. L. Huang, H. H. Zhang, J. C. Weiss, Y. Wu, C. K. Kwoh, J. M. Donohue, G. Cochran, A. J. Gordon, and D. C. Malone, "Evaluation of machine-learning algorithms for predicting opioid overdose risk among medicare beneficiaries with opioid prescriptions," *JAMA Netw. Open*, vol. 2, no. 3, 2019, Art. no. e190968.
[96] S. J. Mooney and V. Pejaver, "Big data in public health: Terminology, machine learning, and privacy," *Annu. Rev. Public Health*, vol. 39, no. 1, pp. 95–112, Apr. 2018.
[97] A. L. Beam and I. S. Kohane, "Big data and machine learning in health care," *Jama*, vol. 319, no. 13, pp. 1317–1318, Apr. 2018.
[98] D. S. Char, N. H. Shah, and D. Magnus, "Implementing machine learning in health care-addressing ethical challenges," *New England J. Med.*, vol. 378, no. 11, p. 981, 2018.
[99] J. Gareth, W. Daniela, H. Trevor, and T. Robert, *An Introduction to Statistical Learning: With Applications in R*. Cham, Switzerland: Springer, 2013.
[100] G. F. Glonek and P. McCullagh, "Multivariate logistic models," *J. Roy. Stat. Soc. B, Methodol.*, vol. 57, no. 3, pp. 533–546, 1995.
[101] D. W. Hosmer, Jr., S. Lemeshow, and R. X. Sturdivant, *Applied Logistic Regression*, vol. 398. Hoboken, NJ, USA: Wiley, 2013.
[102] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
[103] I. Rish, "An empirical study of the naive Bayes classifier," in *Proc. Workshop Empirical Methods Artif. Intell.*, 2001, vol. 3, no. 22, pp. 41–46.
[104] J. H. Friedman, "Stochastic gradient boosting," *Comput. Statist. Data Anal.*, vol. 38, no. 4, pp. 367–378, 2002.
[105] H. A. Chipman, E. I. George, and R. E. McCulloch, "BART: Bayesian additive regression trees," *Appl. Statist.*, vol. 4, no. 1, pp. 266–298, 2010.
[106] A. Kapelner and J. Bleich, "BartMachine: Machine learning with Bayesian additive regression trees," 2013, *arXiv:1312.2171*.
[107] M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, "Support vector machines," *IEEE Intell. Syst. Appl.*, vol. 13, no. 4, pp. 18–28, Jul. 1998.
[108] S. R. Gunn, "Support vector machines for classification and regression," *ISIS Tech. Rep.*, vol. 14, no. 1, pp. 5–16, 1998.
[109] I. Steinwart and A. Christmann, *Support Vector Machines*. Cham, Switzerland: Springer, 2008.
[110] M. A. Nielsen, *Neural Networks and Deep Learning*, vol. 25. San Francisco, CA, USA: Determination Press, 2015.
[111] B. Greenwell, "pdp: An R package for constructing partial dependence plots," *R J.*, vol. 9, no. 1, p. 421, 2017.
[112] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning*, vol. 112. Cham, Switzerland: Springer, 2013.
[113] G. Forman and M. Scholz, "Apples-to-apples in cross-validation studies: Pitfalls in classifier performance measurement," *ACM SIGKDD Explor. Newslett.*, vol. 12, no. 1, pp. 49–57, 2010.
[114] Z. Rustam, E. Sudarsono, and D. Sarwinda, "Random-forest (RF) and support vector machine (SVM) implementation for analysis of gene expression data in chronic kidney disease (CKD)," in *Proc. IOP Conf., Mater. Sci. Eng.*, 2019, vol. 546, no. 5, Art. no. 052066.
[115] WHO. *International Classification of Diseases for Mortality and Morbidity Statistics (11th Revision)*. Accessed: Oct. 29, 2022. [Online]. Available: https://www.who.int/standards/classifications/classification-of-diseases
[116] D. J. Stein, K. A. McLaughlin, K. C. Koenen, L. Atwoli, M. J. Friedman, E. D. Hill, A. Maercker, M. Petukhova, V. Shahly, M. Van Ommeren, "DSM-5 and ICD-11 definitions of posttraumatic stress disorder: Investigating 'narrow' and 'broad' approaches," *Depression Anxiety*, vol. 31, no. 6, pp. 494–505, 2014.
[117] M. W. Silverstein, J. M. Petri, L. B. Kramer, and F. W. Weathers, "An item response theory analysis of the PTSD checklist for DSM-5: Implications for DSM-5 and ICD-11," *J. Anxiety Disorders*, vol. 70, Mar. 2020, Art. no. 102190.
[118] D. M. Gainer, R. W. Nahhas, N. V. Bhatt, A. Merrill, and J. McCormack, "Association between proportion of workday treating COVID-19 and depression, anxiety, and PTSD outcomes in U.S. physicians," *J. Occupational Environ. Med.*, vol. 63, no. 2, p. 89, 2021.
[119] T. N. Jackson, J. P. Morgan, D. L. Jackson, T. R. Cook, K. McLean, V. Agrawal, K. E. Taubman, and M. S. Truitt, "The crossroads of posttraumatic stress disorder and physician burnout: A national review of united states trauma and nontrauma surgeons," *Amer. Surgeon*, vol. 85, no. 2, pp. 127–135, Feb. 2019.
[120] N. K. Menon, T. D. Shanafelt, C. A. Sinsky, M. Linzer, L. Carlasare, K. J. S. Brady, M. J. Stillman, and M. T. Trockel, "Association of physician burnout with suicidal ideation and medical errors," *JAMA Netw. Open*, vol. 3, no. 12, Dec. 2020, Art. no. e2028780.
[121] F. Pajonk, P. Cransac, V. Müller, A. Teichmann, and W. Meyer, "Trauma and stress-related disorders in German emergency physicians: The predictive role of personality factors," *Int. J. Emergency Mental Health*, vol. 14, no. 4, pp. 257–268, 2012.
[122] R. A. Shih, T. L. Schell, K. Hambarsoomian, G. N. Marshall, and H. Belzberg, "Prevalence of ptsd and major depression following trauma-center hospitalization," *J. Trauma*, vol. 69, no. 6, p. 1560, 2010.
[123] G. D. Bodie and B. R. Burleson, "Explaining variations in the effects of supportive messages a dual-process framework," *Ann. Int. Commun. Assoc.*, vol. 32, no. 1, pp. 355–398, Jan. 2008.
[124] B. Mallinckrodt, J. M. Armer, and P. P. Heppner, "A threshold model of social support, adjustment, and distress after breast cancer treatment," *J. Counseling Psychol.*, vol. 59, no. 1, p. 150, 2012.
[125] J. C. Coyne and A. DeLongis, "Going beyond social support: The role of social relationships in adaptation," *J. Consulting Clin. Psychol.*, vol. 54, no. 4, p. 454, 1986.
[126] C. M. Ogle, D. C. Rubin, and I. C. Siegler, "Cumulative exposure to traumatic events in older adults," *Aging Mental Health*, vol. 18, no. 3, pp. 316–325, Apr. 2014.

[127] C. A. Sinsky, L. N. Dyrbye, C. P. West, D. Satele, M. Tutty, and T. D. Shanafelt, ''Professional satisfaction and the career plans of U.S. Physicians,'' in *Mayo Clinic Proceedings*, vol. 92, no. 11. Amsterdam, The Netherlands: Elsevier, 2017, pp. 1625–1635.
[128] R. Y. Elbay, A. Kurtulmuş, S. Arpacıoğlu, and E. Karadere, ''Depression, anxiety, stress levels of physicians and associated factors in COVID-19 pandemics,'' *Psychiatry Res.*, vol. 290, Aug. 2020, Art. no. 113130.
[129] M. Mosheva, N. Hertz-Palmor, S. Dorman Ilan, N. Matalon, I. M. Pessach, A. Afek, A. Ziv, Y. Kreiss, R. Gross, and D. Gothelf, ''Anxiety, pandemic-related stress and resilience among physicians during the COVID-19 pandemic,'' *Depression Anxiety*, vol. 37, no. 10, pp. 965–971, Oct. 2020.
[130] S. W. Yates, ''Physician stress and burnout,'' *Amer. J. Med.*, vol. 133, no. 2, pp. 160–164, Feb. 2020.
[131] R. B. Parikh, C. Manz, C. Chivers, S. H. Regli, J. Braun, M. E. Draugelis, L. M. Schuchter, L. N. Shulman, A. S. Navathe, M. S. Patel, and N. R. O'Connor, ''Machine learning approaches to predict 6-month mortality among patients with cancer,'' *JAMA Netw. Open*, vol. 2, no. 10, Oct. 2019, Art. no. e1915997.
[132] N. T. Liu and J. Salinas, ''Machine learning for predicting outcomes in trauma,'' *Shock*, vol. 48, no. 5, pp. 504–510, 2017.

SAYANTI MUKHERJEE received the M.S. degree in economics and the Ph.D. degree in civil engineering from Purdue University, USA, and the M.S. degree in civil engineering from Iowa State University, USA. She is currently an Assistant Professor in industrial and systems engineering at University at Buffalo—The State University of New York, USA. She conducts cutting-edge interdisciplinary research to address the resiliency and sustainability challenges related to the vulnerable communities and socio-technical systems leveraging advanced learning algorithms and robust optimization techniques. More specifically, she develops quantitative models to examine systemic/stochastic impacts of various chronic/acute shocks on the interdependent socio-technical systems, develop risk-informed decision models, and investigate cost-effective adaptation measures to advance resilience and sustainability of our communities and critical infrastructure systems.

LANCE RINTAMAKI received the Ph.D. degree from the University of Illinois at Urbana-Champaign, in 2003, and the M.A. degree from Ball State University, in 1998. He is currently an Associate Professor with the Department of Communications, University at Buffalo, The State University of New York. His research interests include the intersection of communication theory and health behavior outcomes. He has a background in communication and risky behaviors, with an emphasis on stigma management as antecedent to health behavior outcomes and stress and coping in chronic illness, with an emphasis on the forms, functions, provision, and effects of social support among both patients and care providers.

JANET L. SHUCARD received the Ph.D. degree in clinical psychology from University at Buffalo—State University of New York. She is currently an Associate Professor in neurology and the Associate Director of the Division of Cognitive and Behavioral Neurosciences, Jacobs School of Medicine and Biomedical Sciences, University at Buffalo—State University of New York. As a Licensed Clinical Psychologist and a Cognitive Neuroscientist, she combines these areas of expertise to study the neurophysiological, cognitive, and psychological consequences of posttraumatic stress disorder (PTSD), multiple sclerosis, and systemic lupus erythematosus. She has been the PI on numerous federal and foundation grants, including a grant from the NIH to study the effects of PTSD on brain function in Vietnam veterans, and a recent grant from the National Institute of Justice to study of the effects of work-related traumatic stressors and symptoms of PTSD on brain electrophysiological measures of inhibition, attention, and rapid decision-making in active-duty police officers. Her studies incorporate clinical interviews, neuropsychological assessments, EEG, and MRI imaging to relate brain structure and function to measures of cognition and behavior.

ZHIYUAN WEI received the M.S. degree in industrial economics from the University of International Business and Economics (UIBE), Beijing, China, and the M.S. degree in industrial engineering from University at Buffalo—The State University of New York, Buffalo, NY, USA. He is currently pursuing the Ph.D. degree in industrial engineering with University at Buffalo. His research interests include data analytics and operations research with a focus on public health.

LINDSEY E. CARLASARE received the bachelor's degree from the University of Wisconsin—Green Bay and the master's degree from Cardinal Stritch University. She is currently the Research and Policy Manager of American Medical Association. She manages multiple research studies, partnerships, and grant programs within the professional satisfaction and practice sustainability business unit within the AMA and has been with the AMA for more than ten years. Her research interests include physician practice dynamics and the factors that contribute to professional burnout, degradation of joy in practice, work-life integration, and other impacts on physician mental and professional well-being and the sustainability of clinical practice in today's healthcare environment. She has authored or coauthored more than 20 publications in peer-reviewed journals and has contributed to and presented multiple presentations about AMA-led and AMA-sponsored research.

CHRISTINE A. SINSKY received the bachelor's and Medical degrees from the University of Wisconsin. She is currently the Vice President of Professional Satisfaction, American Medical Association. A board-certified internist, she practiced at Medical Associates Clinic and Health Plans in Dubuque, IA, for 32 years. She is also a Past Chair of the Board of Trustees of the ABIM Foundation. She has worked to improve opportunities for joy, purpose and meaning in work. Her publications on ''The Quadruple Aim,'' ''Joy in Practice,'' ''Texting while Doctoring'' and ''Creating a Manageable Cockpit for Clinicians'' have contributed to the national conversation. She has also contributed to research regarding the prevalence, drivers, and solutions to burnout among physicians. A frequent invited lecturer on practice innovation, redesign and physician satisfaction, she has presented widely, both nationally and internationally. She completed her postgraduate residency at Gundersen Medical Foundation/La Crosse Lutheran Hospital, La Crosse, WI, USA, where she worked as a Chief Medical Resident.