



## Original Article

# COVID 19-related burnout among healthcare workers in India and ECG based predictive machine learning model: Insights from the BRUCEE-Li study



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## ABSTRACT

**Objectives:** COVID-19 pandemic has led to unprecedented increase in rates of stress and burn out among healthcare workers (HCWs). Heart rate variability (HRV) has been shown to be reflective of stress and burnout. The present study evaluated the prevalence of burnout and attempted to develop a HRV based predictive machine learning (ML) model to detect burnout among HCWs during COVID-19 pandemic.

**Methods:** Mini-Z 1.0 survey was collected from 1615 HCWs, of whom 664, 512 and 439 were frontline, second-line and non-COVID HCWs respectively. Burnout was defined as score  $\geq 3$  on Mini-Z-burnout-item. A 12-lead digitized ECG recording was performed and ECG features of HRV were obtained using feature extraction. A ML model comprising demographic and HRV features was developed to detect burnout.

**Results:** Burnout rates were higher among second-line workers 20.5% than frontline 14.9% and non-COVID 13.2% workers. In multivariable analyses, features associated with higher likelihood of burnout were feeling stressed (OR = 6.02), feeling dissatisfied with current job (OR = 5.15), working in a chaotic, hectic environment (OR = 2.09) and feeling that COVID has significantly impacted the mental wellbeing (OR = 6.02). HCWs with burnout had a significantly lower HRV parameters like root mean square of successive RR intervals differences (RMSSD) [ $p < 0.0001$ ] and standard deviation of the time interval between successive RR intervals (SDNN) [ $p < 0.001$ ] as compared to normal subjects. Extra tree classifier was the best performing ML model (sensitivity: 84%)

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**Conclusion:** In this study of HCWs from India, burnout prevalence was lower than reports from developed nations, and was higher among second-line versus frontline workers. Incorporation of HRV based ML model predicted burnout among HCWs with a good accuracy.

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## 1. Introduction

Burnout among healthcare workers (HCWs) including physicians has reached crisis proportion with over 2 in 3 physicians in the United States experiencing a burnout sometimes in their career.<sup>1,2</sup> Longitudinal surveys suggest that physicians have about 1.4 times higher likelihood of burnout as compared to other working adults in the United States.<sup>3</sup> Though variably defined, burnout combines emotional exhaustion, depersonalization, and a sense of reduced personal accomplishment.<sup>4</sup> Overall, the prevalence of burnout has been reported in the range of 0%–80.5%, mostly due to the variations in the definition of burnout. Burnout has been found to be driven by high job stress, high time pressure and workload, and poor organizational support.<sup>5</sup>

The ongoing coronavirus disease (COVID-19) pandemic has further contributed to widespread psychological problems including burnout among medical professionals and HCWs all over the world.<sup>6</sup> Early studies of HCWs exposed to COVID-19 patients found high rates of self-perceived burnout; a study from Japan reported burnout rates of 40% among nurses and more than 30% among technical staff.<sup>7,8</sup> However, there is paucity of systematic studies reporting burnout during COVID-19 pandemic among medical professionals from low- and middle-income countries such as India. This is especially important given that India has experienced the second highest burden of cumulative cases in the world. The prior studies had either small sample sizes<sup>9–12</sup> or included only a uniform group of participants.<sup>13</sup> Hence, the generalizability of these studies is limited. Accurate estimates of burnout among HCWs in India is also important given the paucity of resources for mental well-being and increasing demand on mental health providers.<sup>14</sup> Characterizing burnout among HCWs and implementing strategies to mitigate are important given the significant association between burnout and self-perceived medical errors.<sup>15</sup>

Stress and burnout involve both psychological and physiological responses to the environmental stressors. This affects the functioning of autonomic nervous system (ANS) which is the major response system for modulating body's physiological reaction to stress.<sup>16</sup> Heart rate variability (HRV) has been used to assess the overall activity of ANS and is a non-invasive marker of cardiovascular dysautonomia.<sup>17</sup> A greater HRV is considered to be more adaptive as it reflects the ability of ANS to cope with external and internal stressors while a low HRV reflects a maladaptive state.<sup>18</sup> Previous studies including a meta-analysis have reported lower HRV among subjects reporting stress and burnout.<sup>18–20</sup> However, there is limited data regarding the role of HRV as an objective indicator of stress/burnout in HCWs dealing with COVID-19 pandemic. Machine learning based on its adaptive ability can evaluate large amount of data from multiple sources (ECG, questionnaires) to identify and predict burnout in HCWs.<sup>21</sup> Results obtained from ML algorithms are far more accurate as compared to those from the traditional logistic regression.<sup>21</sup> This makes ML based on demographic and HRV features a promising tool to detect the presence of burnout in HCWs dealing with COVID-19 pandemic. The present study was designed to determine the prevalence of burnout among HCWs during the COVID-19 period in four leading

academic centers in India dealing with COVID-19 patients and to develop a HRV based predictive ML model to detect burnout.

## 2. Methods

This report presents findings from our study that was conducted between (1st August 2020 to 15th December 2020) that coincided with the peak of COVID-19 cases in India. The detailed methodology of the present study has been published previously.<sup>22</sup>

### 2.1. Participants

This observational and cross-sectional study was conducted across four academic tertiary care centers in India and enrolled physicians at all levels of training, nursing staff and paramedical staff involved directly or indirectly in the care of patients with COVID-19. The study was approved by the ethical review committee at each center and participants provided informed consent prior to completing study related procedures and assessments. Participants were recruited using in-person contact (preferred), messenger services, or via email. As reported previously,<sup>22</sup> participation in the study was permissive and only excluded individuals who had pre-existing structural heart disease which would interfere with developing an electrocardiogram-based artificial intelligence algorithm. Healthcare providers who were presently working in direct contact with COVID-19 positive patients or COVID-19 suspect patients were referred to as frontline COVID-19 HCWs. Healthcare providers who were presently not in direct contact with COVID-19 positive/suspect patients or who were working as support staff for frontline workers were referred to as second-line COVID-19 HCWs. Rest of them were grouped as non-COVID related HCWs.

### 2.2. Assessments

All the participants filled out the study proforma that included select socio-demographic (such as age, gender, religion, marital status, profession, and number of duty hours per week) and clinical features (history of diabetes and hypertension) along with the Mini Z 1.0 questionnaire as a measure of burnout.<sup>23,24</sup> Features of burnout (score  $\geq 3$  on Mini-Z burnout item),<sup>25,26</sup> feeling stressed (score  $> 3$  on Mini-Z high stress item), and being unsatisfied with current job (score  $\leq 3$  on satisfaction item) were noted down. The Mini-Z also includes assessments of the atmosphere in primary work area (ranging from calm to busy but reasonable to hectic or chaotic).

### 2.3. Data for ML model

A 12-lead ECG at 500Hz of 60 s duration was recorded for all subject using the Vesta 301i machine and the ECG data was stored in a digital raw format. Time domain HRV features were extracted from lead II of the ECG using HRV analysis python library version 1.0.4. A total of 12 HRV features were extracted which included (i) max HR (maximum heart rate), (ii) mean HR (mean heart rate), (iii) mean NNi (mean normal-to-normal intervals), (iv) pNNS0

(percentage of successive RR intervals that differ by more than 50 ms), (v) pNN20 (percentage of successive RR intervals that differ by more than 20 ms), (vi) RMSSD (root mean square of successive RR intervals differences), (vii) SDNN (standard deviation of the time interval between successive RR intervals), (viii) SDNN (RR) (standard deviation of the successive difference between RR intervals), (ix) CVSD (Coefficient of variation of successive difference equal to the RMSSD divided by mean NN interval), (x) CVNNi (Co-efficient of variation equal to the ratio of SDNN divided by mean NN interval), (xi) Range NNI (range normal-to-normal intervals), (xii) SD HR (desired heart rate standard deviation). After extracting the HRV features, entire ECG data was categorized as those belonging to the burnout/stress group or normal subjects. The patients having burnout or stress were taken together in order to develop an effective ML based model. The entire data was divided into (a) training dataset and (b) testing dataset. HRV and demographic features were used for developing a total of six ML models including Random Forest, CatBoost, Extra-tree classifier, XG Boost, K Nearest Neighbour and Gradient Boosting Classifier. These models were trained to distinguish between subjects with burnout/stress and normal ones (Fig. 1: central illustration). The model performance was compared using area under the curve (AUC), accuracy, F1 score and sensitivity (Fig. 2A). Top performing ML model was evaluated using the permutation-based feature ranking (Fig. 2B). Python sklearn library was used for developing the ML models.

2.4. Statistical analyses

Descriptive statistics were used to summarize the characteristics of participants, stratified by their exposure to COVID-19 patients (frontline, second-line, and non-COVID HCWs) as well as based on the presence vs. absence of burnout (score  $\geq 3$  on MINI-Z burnout item). The prevalence of burnout with the 95% confidence interval was estimated using the exact binomial method. The age and duty hours were categorized into three categories using tertile cut-offs. Univariate and multivariate logistic regression analyses were used to evaluate the association of these features with the

presence of burnout. Variables in univariate analyses that had *p*-value less than 0.2 were considered as possible predictors of burnout and were included in the multivariable analysis using ENTER method. Nagelkerke *r*-square value was used for goodness of fit and area under receiver operating characteristics (ROC) curve of model classification. The SPSS version-16 [ Chicago, SPSS Inc.] statistical software used to analyze the study data. *P*-value less than 0.05 was considered as significant.

3. Results

Of the 1615 participants of this study, 664 (41.1%), 512 (31.7%) and 439 (27.2%) were frontline, second-line, and non-COVID HCWs, respectively. The health workers characteristics and other details are summarized in the Table 1. The overall prevalence of burnout was 16.2% [95%CI: 14.5–18.1], see Supplementary Table 1. The percentage of frontline, second-line and non-COVID HCWs who reported experiencing burnout were 14.9% [95% CI:12.3–17.8], 20.5% [95% CI: 17.1–24.3], and 13.2% [95% CI:10.2–16.7], respectively. In the entire study cohort, 26.9% of the participants were not satisfied with their work. Percentage of frontline, second-line, and non-COVID HCWs who were not satisfied with work were 25.3%, 31.2%, and 24.1%, respectively. Most of the respondents (68.9%) reported working in a busy but reasonable work environment. A majority of frontline (65.7%) and second-line (57%) HCWs reported that COVID-19 pandemic had at least some effect on their mental wellbeing (Supplementary Table 1). In contrast, most non-COVID HCWs (74.3%) reported that COVID-19 pandemic did not have any effect on their mental wellbeing.

The health care worker's characteristics of those who experienced burnout and those who did not are summarized in the Table 2. In univariate analyses, features that were significantly associated (unadjusted *p* < 0.05) with higher likelihood of burnout were female gender, nuclear family type, presence of hypertension, feeling stressed, being a physician, feeling that COVID has affected the mental wellbeing, and working in a chaotic, hectic environment; see Table 2 for OR and 95% CI. In multivariate analyses, features that were associated with higher likelihood of burnout were

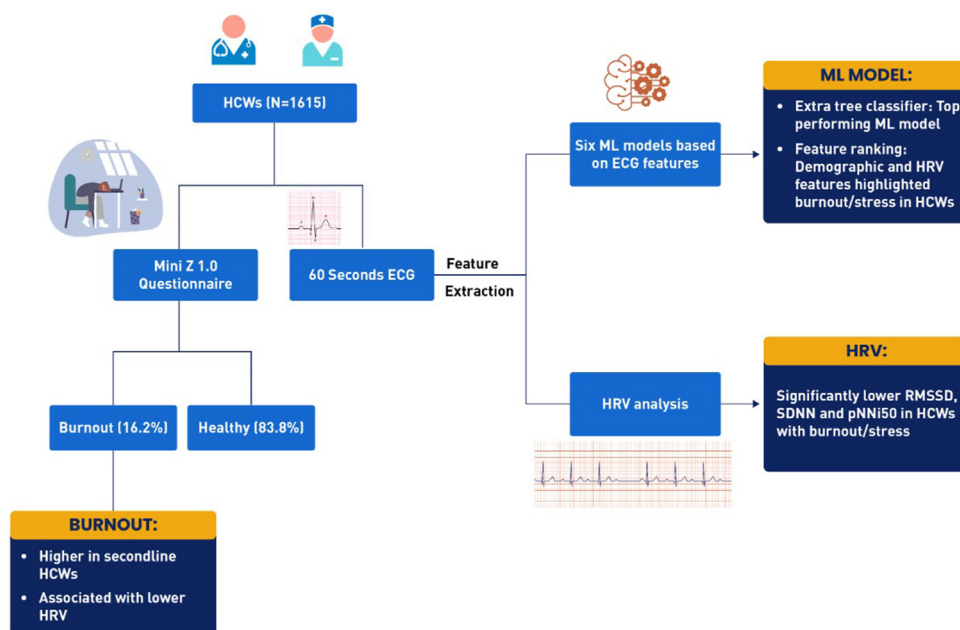


Fig. 1. Central illustration of the burnout assessment and heart rate variability (HRV) analysis of HCWs dealing with COVID-19 infection.

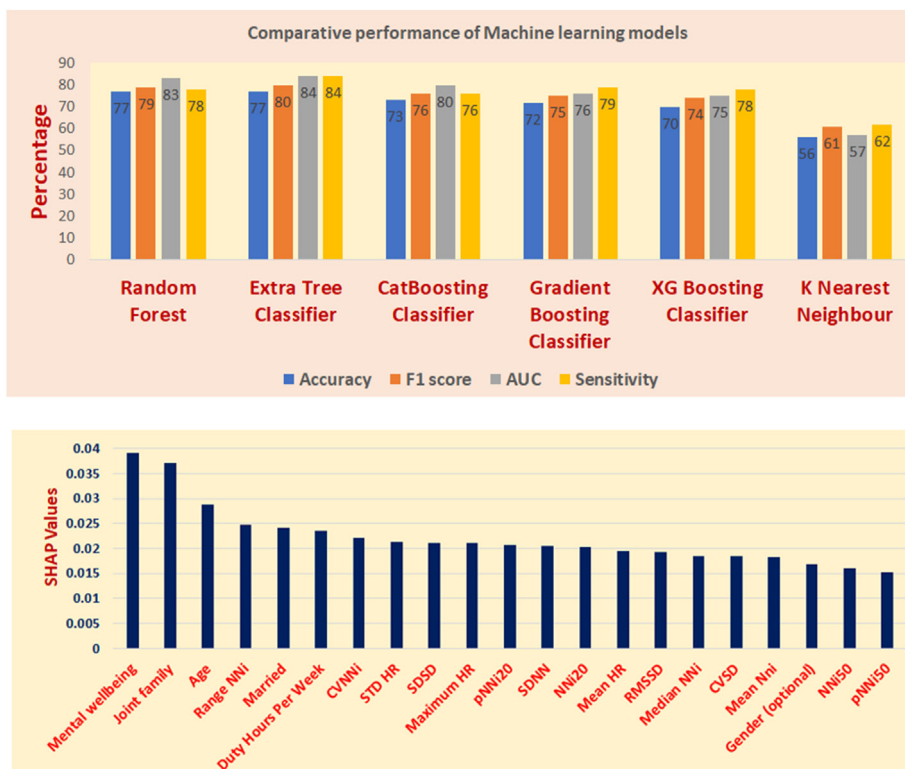


Fig. 2. A: Comparative performance of the HRV based various ML models Overall classification 85% with specificity = 94% and sensitivity = 38.5%; Negelkerke = 0.418; Area under Receiver Operating Characteristic curve = 87.9 [95% CI: 85.9–89.8]; B: Bar diagram showing the extra tree classifier-based permutation importance feature ranking.

Table 1 Sociodemographic and clinical features of participants included in the study.

Category		Number (%)	Frontline (n = 664)	Second-line (n = 512)	Non-COVID (n = 439)
Profession	Doctor	263 (16.3)	156 (24.2)	81 (15.8)	26 (5.9)
	Nurse	509 (31.5)	284 (44.1)	182 (35.5)	43 (9.8)
	Nursing orderly	182 (11.3)	77 (12.0)	56 (10.9)	49 (11.2)
	Lab/OT	130 (6.8)	26 (4.0)	70 (13.7)	34 (7.75)
	Other supporting staff	531 (32.9)	120 (18.6)	123 (24.0)	288 (65.6)
Age [Mean (SD)]	Minimum: 18 yrs; Maximum: 66 yrs	37.74 (10.73)	35.05 (10.16)	39.35 (10.81)	39.93 (10.94)
Gender	Female	631 (39.1)	289 (43.5)	252 (49.2)	90 (20.5)
	Male	984 (60.9)	375 (56.5)	260 (50.8)	349 (79.5)
Marital Status	Single	404 (25.0)	215 (32.4)	106 (20.7)	83 (18.9)
	Married	1211 (75.0)	449 (67.6)	406 (79.3)	356 (81.1)
Family type	Joint family	799 (49.5)	292 (44.0)	255 (49.8)	252 (57.4)
	Nuclear Family	816 (50.5)	372 (56.0)	257 (50.2)	187 (42.6)
Duty hours*	≤42 h	555 (34.4)	207 (31.2)	208 (40.6)	140 (31.9)
	>42–≤48 h	880 (54.5)	351 (52.9)	251 (49.0)	278 (63.3)
	>48 h	180 (11.1)	106 (16.0)	53 (10.4)	21 (4.8)
Religion	Christian	168 (10.4)	90 (13.6)	61 (11.9)	17 (3.9)
	Hindu	1302 (80.6)	516 (77.7)	398 (77.7)	388 (88.4)
	Muslim	122 (7.6)	50 (7.5)	42 (8.2)	30 (6.8)
	Other	16 (1.0)	4 (0.6)	8 (1.6)	4 (0.9)
Diabetes	Sikh	7 (0.4)	4 (0.6)	3 (0.6)	0 (0.0)
	Present	106 (6.6)	42 (6.3)	37 (7.2)	27 (6.2)
HTN	Absent	1509 (93.4)	622 (93.7)	475 (92.8)	412 (93.8)
	Present	176 (10.9)	70 (10.5)	63 (12.3)	43 (9.8)
Smoking	Absent	1439 (89.1)	594 (89.5)	449 (87.7)	396 (90.2)
	Smoker	147 (9.1)	53 (8.0)	47 (9.2)	47 (10.7)
	Non-smoker	1468 (90.9)	611 (92.0)	465 (90.8)	392 (89.3)

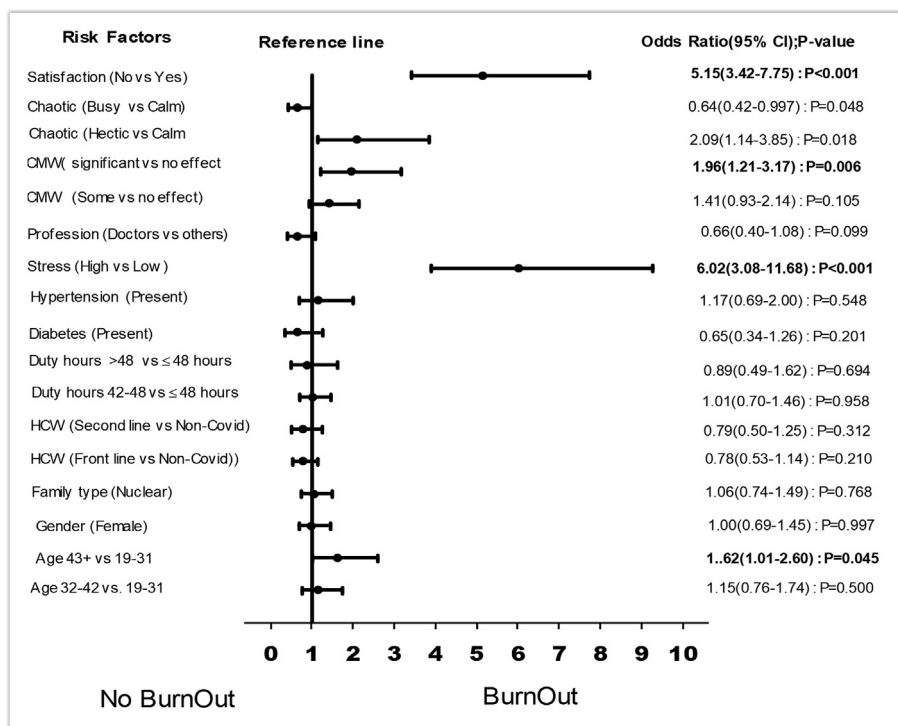
feeling stressed (OR = 6.02, 95% CI: 3.90–9.29), feeling dissatisfied with current job (OR = 5.15, 95% CI: 3.42–7.75), working in a chaotic, hectic environment (OR = 2.09, 95% CI: 1.14–3.85) and feeling that COVID has significantly impacted their mental well-being (OR = 6.02, 95% CI: 3.90–9.29), see Fig. 3.

3.1. HRV and ML model

Of the 1615 participants enrolled, interpretable data for HRV was available for 1373 subjects. Among the various HRV features, subjects with burnout/stress (n = 758) had a significantly lower RMSSD, SDNN and pNNi 50 as compared to normal subjects

**Table 2**  
Burnout and related features based on exposure to COVID-19 at workplace.

	Category	Number (%)	Frontline (n = 664)	Second-line (n = 512)	Non-COVID (n = 439)
Burnout	Present	262 (16.2)	99 (14.9)	105 (20.5)	58 (13.2)
	Absent	1353 (83.8)	565 (85.1)	407 (79.5)	381 (86.8)
Satisfaction	Dissatisfied	434 (26.9)	168 (25.3)	160 (31.2)	106 (24.1)
	Satisfied	1181 (73.1)	496 (74.7)	352 (68.8)	333 (75.9)
Stress	Present	539 (33.5)	254 (38.5)	177 (34.6)	108 (24.6)
	Absent	1071 (66.5)	406 (61.5)	334 (65.4)	331 (75.4)
Work environment	Calm	381 (23.6)	101 (15.2)	102 (19.9)	178 (40.5)
	Busy but Reasonable	1113 (68.9)	494 (74.4)	374 (73.0)	245 (55.8)
	Hectic, Chaotic	121 (7.5)	69 (10.4)	36 (7.0)	16 (3.6)
Impact of COVID on mental wellbeing	No Effect	774 (47.9)	228 (34.3)	220 (43.0)	326 (74.3)
	Some Effect	601 (37.2)	325 (48.9)	194 (37.9)	82 (18.7)
	Significant effect + Disastrous Effect	240 (14.9)	111 (16.7)	98 (19.1)	31 (7.1)



**Fig. 3.** Forest plot of multivariable logistic regression showing the factors associated with burnout. CMW=COVID Mental Wellbeing; HCW= Healthcare Workers; Total N = 1615; Burnout = 262.

( $p < 0.0001$ ,  $p < 0.001$  and  $p < 0.001$  respectively) [Table 3]. Of the six ML models trained and tested, the tree based extra tree classifier had the highest sensitivity of 84%, AUC Score of 84% and an accuracy of 77% (Fig. 2A). Feature ranking reported that mental well-being, higher joint family type, higher age, marital status and duty hours per week to be the top demographic features distinguishing between subjects reporting burnout/stress and those without. Among the HRV parameters CVNNi, SDSD, pNNi20, SDNN and RMSSD were the top features (Fig. 2B).

#### 4. Discussion

In this large multicentric survey of HCWs in India, the overall prevalence of burnout was 16.2%. The burnout was higher among second-line workers as compared to frontline workers. However, proportion of frontline and second-line HCWs who reported feeling stressed or being unsatisfied was similar. Furthermore, similar proportion of frontline and second-line HCWs felt that COVID-19

pandemic had a significant or disastrous effect on the mental wellbeing. Among these HCWs reporting burnout, a lower HRV was reported which reflected impaired adaptation of the autonomic system to cope with the stress. ML models based on HRV features were able to distinguish between HCWs reporting burnout and those without with a reasonable accuracy.

Findings of this report are consistent with those in prior reports. Higher burnout rates among females in univariate analyses is similar to the recent report by Linzer et al which found that female internal medicine physician and trainees have 1.56 times higher likelihood of burnout as compared to their male counterparts.<sup>24</sup> Association between chaotic work environment and higher likelihood of burnout is also consistent with a previous report.<sup>23</sup> Several findings of this report are notable. First, the rates of burnout in the present study are much lower than what has been reported previously among HCWs.<sup>6,7,27–29</sup> These rates are also lower than the previously reported rates of depression and anxiety among HCWs.<sup>30,31</sup> The reported prevalence of burnout and psychological



**Table 3**  
Comparison of HRV parameters among HCWs reporting stress and burnout and healthy ones.

Parameters	Burn-out/stress		P-value
	Present <i>n</i> = 758 Mean ± SD	Absent <i>n</i> = 615 Mean ± SD	
Maximum HR (bpm)	83.9 ± 13.4	83.6 ± 14.8	0.73
Mean HR (bpm)	78.9 ± 11.2	78.3 ± 13.0	0.40
Mean NNI (ms)	778.7 ± 107.9	789.4 ± 126.4	0.09
Median NNI (ms)	778.6 ± 108.8	789.4 ± 126.5	0.09
NNi20	3.9 ± 2.7	4.3 ± 2.7	0.013
NNi50	1.2 ± 1.7	1.5 ± 1.8	<0.0001
pNNi20 (%)	38.6 ± 28.0	43.0 ± 28.6	<0.001
pNNi50 (%)	11.8 ± 18.2	15.5 ± 20.9	<0.001
RMSSD (ms)	27.4 ± 16.9	30.8 ± 19.2	<0.0001
SDNN (ms)	24.8 ± 14.4	27.0 ± 16.2	<0.001
SDSD (ms)	27.0 ± 16.8	30.4 ± 19.0	<0.0001
CVNNi	0.03 ± 0.02	0.03 ± 0.02	0.025
CVSD (ms)	0.03 ± 0.02	0.04 ± 0.02	<0.001
Range-NNi (ms)	95.8 ± 77.3	99.9 ± 71.4	0.30
SD HR	2.3 ± 1.2	2.4 ± 1.2	0.108

**Abbreviation:** HRV: heart rate variability; HR: heart rate; ms: millisecond; SD: standard deviation.

problems among HCW in Indian studies ranges from more than a third to a half of all studied.<sup>9–13</sup> Survey being done in the later phase of pandemic as compared to published reports, use of a more validated instrument for burnout with clearer definitions and inclusion of a larger diverse sample size are the likely explanations for the lower rates of burnout. Possibly, the burnout and anxiety were much more in the early phase of pandemic even though the COVID-19 cases were far less in India.

Secondly, greater attention needs to be paid on the burnout among second-line HCWs given that we observed higher rates of burnout among them as compared to first line HCWs. This differs from reports in the first few months of pandemic where the prevalence of mental health problems was similar among first and second-line HCWs.<sup>30</sup> However, published literature has contrasting evidences regarding the same.<sup>32,33</sup> Whereas Liang et al<sup>32</sup> showed a lack of difference in the depression and anxiety scores among first-line and second line HCW, Lai et al<sup>33</sup> showed that the psychological stress was higher among frontline workers. Though the exact reasons for this remain unclear, well defined working protocols, fixed working hours, adequate availability of personal protective equipment (PPE) and better organizational support for frontline workers could have been protective in case of frontline HCWs. Additionally, increased work load among second-line HCWs since they were dealing with both COVID-19 and non-COVID-19 patients, lack of organized effort to address mental health (anxiety and fear) of all healthcare workers and limited availability of PPE could have also contributed to higher burnout rates. The earlier studies have reported work hours, workload, infection among staff and shortage of PPE to be associated with higher burnout.<sup>34,35</sup> In one of the studies, the major reason for psychological issues among HCW included personal fears and worries regarding several factors.<sup>36</sup> Increase in manpower and better support and awareness may help in reducing these problems.<sup>30,36</sup> Third, the association between potential COVID exposure at work and burnout was no longer significant after accounting for factors such as satisfaction with work, work environment, feeling stressed, and how COVID has affected mental wellbeing. Therefore, these may serve as potentially modifiable factors that can be targeted to reduce burnout.

HRV as a measure of variations in heart rate is a promising marker of cardiovascular dysautonomia. Studies done previously have reported that exposure to both acute<sup>37</sup> as well as chronic stress<sup>38</sup> leads to a reduction in HRV. The plausible mechanism

responsible for cardiovascular diseases in those reporting burnout/stress has been imbalance between sympathetic and parasympathetic components of ANS.<sup>16</sup> Individuals suffering from burnout tend to have a lower HRV thereby implying sustained and heightened sympathetic activity with reduction in parasympathetic response.<sup>18,19</sup> Initial studies have shown that HRV measures such as RMSSD, AVNN and SDNN are one of the reliable metrics in distinguishing between stressful and non-stressful states.<sup>18</sup> However, there is a lack of data regarding the utility of objective physiological metrics such as HRV in predicting burnout in HCWs amidst COVID-19 pandemic. Present study is amongst the earliest studies to show significantly lower HRV as compared to healthy ones in HCWs dealing with COVID-19 pandemic and reporting burnout/stress. Incorporation of HRV features into ML algorithms further increase the ability to detect burnout in large population groups. ML algorithms based on artificial intelligence can process a significant amount data with good predictive abilities.<sup>21</sup> These ECG-derived HRV features as markers for stress detection have been previously used in ML algorithms such as K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Multilayer Perceptron (MLP), Random Forest (RF) and Gradient Boosting (GB).<sup>39</sup> In a study aimed to detect stress based on HRV features derived from Apple watch, MLP was the best ML model with 75% AUC, 80% Recall and 72% F1 score. Feature selection showed that time domain HRV metrics such as RMSSD and AVNN were important features in stress classification.<sup>39</sup> In our study, tree-based extra-tree classifier had highest sensitivity of 84% and an AUC Score of 84% and an accuracy of 77%. Feature ranking in our study showed that both demographic features such as mental well-being, higher marriage age, joint family type and HRV features including pNNi20, SDNN and RMSSD were the top classifiers that distinguished between subjects reporting burnout/stress and healthy ones.

There are several limitations of this report. It was cross-sectional in nature and therefore, associational in nature. Further, to minimize the burden and to facilitate study participation, the amount of information collected from respondent was limited. Therefore, it remains unclear about whether workplace environment changed due to COVID. Possibly with surge in COVID cases, most elective treatment in India was deferred and frontline hospitals were converted to COVID facilities. This may have resulted in shortened work hours for several frontline HCWs. Further, because no diagnostic criteria for burnout have been developed, the methods for identifying cases of burnout have proliferated, resulting in dramatic variations in prevalence estimates. While consistent with extant literature and supported by psychometric studies,<sup>19,40,41</sup> the assessment of burnout in the present study in the COVID-19 pandemic was based on individual's self-report on a single-item. This may miss out on certain aspects of burnout such as depersonalization that are captured with more detailed assessments.

Despite these limitations, our multicentric study has given reasonably accurate real world estimate of burnout among HCW in India using validated questionnaires. It has also identified HRV using ML model to be predictive of burnout/stress in these individuals. This would help to identify strategies to reduce or reverse HCW burnout using effective institutional and organizational strategies. Adequate staffing and training to avoid chaotic work environment may reduce the risk of burnout. Engaging HCWs to improve their satisfaction with work will build their resilience against burnout. Similarly, reducing stress at work may also mitigate the risk of burnout. Finally, systematic effort to engage HCWs in how COVID is affecting their mental wellbeing may help to identify factors that can be targeted to reduce impact of COVID-19 on mental wellbeing.

In conclusion, this is the first systematic multicentric survey of HCWs in India during Covid 19 pandemic, that found relatively low overall prevalence of burnout. HRV was significantly lower in subjects reporting burnout suggesting marked autonomic imbalance in them. Additionally, use of ML algorithms and feature ranking revealed HRV to be an important feature distinguishing burnout from healthy individuals. This calls for screening of HCWs based on HRV analysis and dedicated questionnaires for detection of burnout/stress and need for targeted strategies to improve work atmosphere and reduce burnout in HCW's.

### Declaration of competing interest

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ihj.2021.10.002>.

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