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Original Article

Design and rationale of an intelligent algorithm to detect BuRnoUt in HeaLthcare workers in COVID era using ECG and artificiaL intelligence: The BRUCEE-LI study

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ABSTRACT

Background: There is no large contemporary data from India to see the prevalence of burnout in HCWs in covid era. Burnout and mental stress is associated with electrocardiographic changes detectable by artificial intelligence (AI).
Objective: The present study aims to estimate the prevalence of burnout in HCWs in COVID-19 era using Mini Z-scale and to develop predictive AI model to detect burnout in HCWs in COVID-19 era.
Methods: This is an observational and cross-sectional study to evaluate the presence of burnout in HCWs in academic tertiary care centres of North India in the COVID-19 era. At least 900 participants will be enrolled in this study from four leading premier government-funded/public-private centres of North India. Each study centre will be asked to recruit HCWs by approaching them through various listed ways for participation in the study. Interested participants after initial screening and meeting the eligibility criteria, will be asked to fill the questionnaire (having demographic and work related with Mini Z questionnaire) to assess burnout. The healthcare workers will include physicians at all levels of training, nursing staff and paramedical staff who are involved directly or indirectly in COVID-19 care. The analysis of the raw electrocardiogram (ECG) data and development of algorithm using convolutional neural networks (CNN) will be done by experts.
Conclusions: In Summary, we propose that ECG data generated from the people with burnout can be utilized to develop AI-enabled model to predict the presence of stress and burnout in HCWs in COVID-19 era.

1. Background

There is a growing evidence of increased prevalence of psychological problems (stress, depression, anxiety, insomnia and substance abuse) and feeling of “burnout” among medical

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professionals and health care workers (HCWs) all over the world in the COVID-19 era.[1] Burnout is defined as "a syndrome of emotional exhaustion, depersonalization, and reduced personal accomplishment that can occur among individuals who work with people in some capacity," and it is considered as an outcome of long-term exposure to occupational stress.[2] In a study of HCWs exposed to COVID-19 patients, half of them self-perceived burnout.[3] Burnout appears to be higher in young, relatively less experienced, and frontline HCWs.[4] Increased working hours, the number of COVID-19 patients cared for, and limited logistic support are some of the factors responsible for increased burnout. A recent study from Japan has reported burnout in more than 40% of nurses and more than 30% of technical staff.[5] The plausible reasons of high burnout in these categories are lower decision-making authority, lack of social support and expectation of appreciation. An analysis done during the peak of the COVID-19 pandemic in Italy has revealed that approximately 60% of HCWs experienced emotional exhaustion, more than 50% experienced depersonalization and about 45% had at least one physical symptom in the previous 4 weeks.[6] In particular, increased irritability, change in food habits, difficulty falling asleep and muscle tension were very frequently experienced by the majority of the respondents.[6]

Sparse data on psychological issues, burnout and stress among medical professionals in India is of concern. A study conducted in early days of COVID-19 pandemic in India has reported moderate level of stress in 80% of HCWs and depressive symptoms requiring treatment and anxiety symptoms requiring further evaluation in 11.4% and 17.7% of HCWs, respectively.[7] With the relaxation of lockdown measures, India has now witnessed a prolonged period of increase in new COVID-19 cases every day. Now, India is experiencing the 2nd highest burden of cumulative cases and 3rd highest case fatalities. We can therefore expect a significantly higher prevalence of stress, burnout and other mental health outcomes in HCWs during this stage of pandemic.

There are many validated scores for measuring burnout in HCWs, like Maslach Burnout Inventory (MBI) and Copenhagen Burnout Inventory (CBI).[5] The accuracy and reliability of such lengthy questionnaires depends on the quality of information provided by the subjects. Use of abbreviated scores like 10-point Mini-Z scale versus traditional 22-item MBI has concordant odds of burnout.[8] However, even with these simple measures, many times HCWs are not willing to answer and may either not realize themselves or hesitate in seeking care for burnout. Therefore, we need a more objective tool to accurately capture the rates of burnout in busy HCWs.

Mental stress is associated with prolonged QT interval, T wave alternans, decreased Atrioventricular (AV) nodal refractoriness and heterogeneity of repolarization.[9] Prior studies suggest that acute mental stress promotes adverse changes in left atrial electrophysiology, as measured by p terminal force in V1 (PTFV1) (duration in milliseconds times the value of the depth (μV) of the downward deflection (terminal portion) of the median P-wave in lead V1) on the 12-lead ECG.[10] Recently, a study has suggested that psychological stress can lead to adverse transient electrical changes like abnormal P-wave axis, which may predispose to atrial fibrillation.[11] Moreover, heart rate variability which is a reliable marker of stress can also be used for objective assessment of psychosocial health.[12] **Therefore, we propose that ECG data generated from the people with burnout can be utilized to develop AI-enabled ECG models to predict the presence of stress and burnout in HCWs.[13]**

The present study is designed to determine the prevalence of burnout in HCWs in COVID-19 era in leading academic centres in India, and develop an AI-enabled ECG algorithm. This AI-based model may help in early detection and more objective assessment of burnout in HCWs compared to the existing questionnaire-based approaches.

2. Methodology

2.1. Design, sampling, criteria and participating centres (Fig. 1)

This is an observational and cross-sectional study to evaluate the presence of burnout in HCWs in academic tertiary care centres of North India in the COVID-19 era. We identified four leading premier government-funded/public-private centres of North India (Supplementary material A) for participation in this study. Each study centre will be asked to recruit HCWs by approaching them through in-person contact (preferred), messenger services and email for participation in the study. Interested participants will be screened by the study team for the eligibility criteria and enrolled. They will be asked to fill the Mini Z questionnaire to assess burnout. The analysis of the raw ECG data and the development of algorithm using convolutional neural networks (CNN) will be done by experts at Indraprastha Institute of Information Technology, Delhi (IIIT-D), India. The ethical clearance has been obtained from the participating centres. The consent from all the subjects will be obtained.

2.1.1. Inclusion and exclusion criteria

Healthcare providers will be assessed for the willingness to provide informed consent for the study. The study will include.

- $\geq$18 years of age at the time of enrolment who understand and agree to comply with planned study procedures.
- Recovered COVID-19 positive HCWs

The study will exclude.

- Subjects with pre-existing structural heart disease

2.1.2. Definitions

The Healthcare workers will include physicians at all levels of training, nursing staff and paramedical staff who are involved directly or indirectly in Covid-19 care. Healthcare providers who are working in direct contact with covid positive patients or covid suspect patients will be referred to as Frontline Covid-19 health care workers.

Healthcare providers who are not in direct contact with covid-19 positive/suspect patients or who are working as support staff for frontline workers will be referred to as Second Line covid-19 health care workers.

Rest All workers will be third line Healthcare workers.

2.2. Objectives of study

2.2.1. The objectives of the study are

2.2.1.1. Primary objectives

a. To estimate the prevalence of burnout in HCWs in COVID-19 era using Mini Z-scale.

b. To develop predictive AI-enabled ECG model to detect burnout and/or stress in HCWs healthcare providers in COVID-19 era

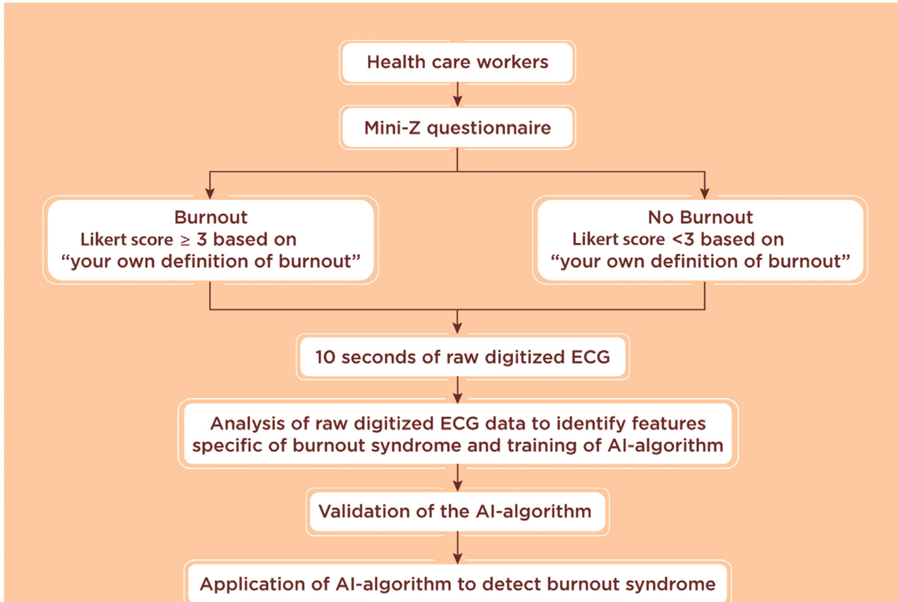

Fig. 1. Schematic representation of study protocol.

2.1.2.2. *Secondary objectives*

a. To evaluate demographic features and practice patterns that are associated with a higher risk of burnout in healthcare providers.

b. To assess the Stress and Satisfaction in HCW according to the scale.

c. To measure the heart rate variability in HCWs in COVID-19 era and to see the relationship of heart rate variability with burnout and stress.

2.3. *Data collection, study tool, study structure and data management*

A detailed study proforma (Supplementary material B) has been designed to include all the questions of the well-validated Mini- Z Questionnaire to detect burnout. This survey tool was developed by Dr. Mark Linzer based on work in the Physician Work Life Survey[14] and the Minimizing Error, Maximizing Outcomes (MEMO) Study.[15] Reliability of the Mini Z has been established previously (with a Cronbach's alpha of 0.8), as well as use among the targeted population of healthcare clinicians. The Mini Z offered both a short survey which could be easily administered and has actionable survey items that could yield insight to guide state and organizational responses to burnout. Each participant will be given the patient information sheet (available in two languages Hindi and English) after which they will be asked to sign the consent form (also available in two languages). All participating HCWs will then have to complete a self-administered questionnaire: Mini Z Questionnaire. The study questionnaire will be filled by the respondents in a print (paper) format. A trained facilitator well versed in both languages will be available, in case, the respondents need to understand or have clarification on anything. Additionally, an online link to fill the form will also be made available through messenger or email to the respondents, who wish to submit their forms online. All the electronic and print forms will be checked for completeness, and any deficiency or discrepancies will be resolved from the respondents via email, short message service (SMS), social media texting or telephonic communication.

After filling of the forms, the digital ECG data of 10 s duration will be collected and for each subject. ECG in all the centres will be collected using Vesta 301i machine (Recorders and Medicare Systems (P) Ltd). Data will be exported in the raw format for processing.

All the subject forms in electronic and paper will be given a unique ID during collection. The data analysis will be started after checking the data set for quality issues and missing variables. The responses of Mini Z scale will be analysed on the basis of work done by Linzer et al[14]:

i. Burnout will be defined as Mini-Z's single question number 3: metric score ≥ 3 based on "your own definition of burnout".
ii. Satisfaction will be defined as Mini-Z's single-item metric response of question 1.
iii. Stress will be defined as Mini-Z's single-item metric response of question 2.

The scoring key is attached in appendix B.

The single item burnout has been well described in literature and has comparable results to longer instruments such as MBI.[8]

A database lock will be employed to finalise the data set for final statistical analysis when target sample is achieved. No interim analysis will be conducted before the database lock and no modification of data will be done thereafter.

2.4. *Sample size and statistical analysis plan*

Prevalence of burnout in healthcare workers varies in literature from 40 to 60%.[5,6] Considering 50% burnout in HCWs and 15% relative margin of error (margin of error (d) = 1·96*standard error of proportion i.e. 7·5%) with the goal of a 99% confidence level, we require a sample of at least 296 healthcare workers for each rank. The formula used to determine the sample size is

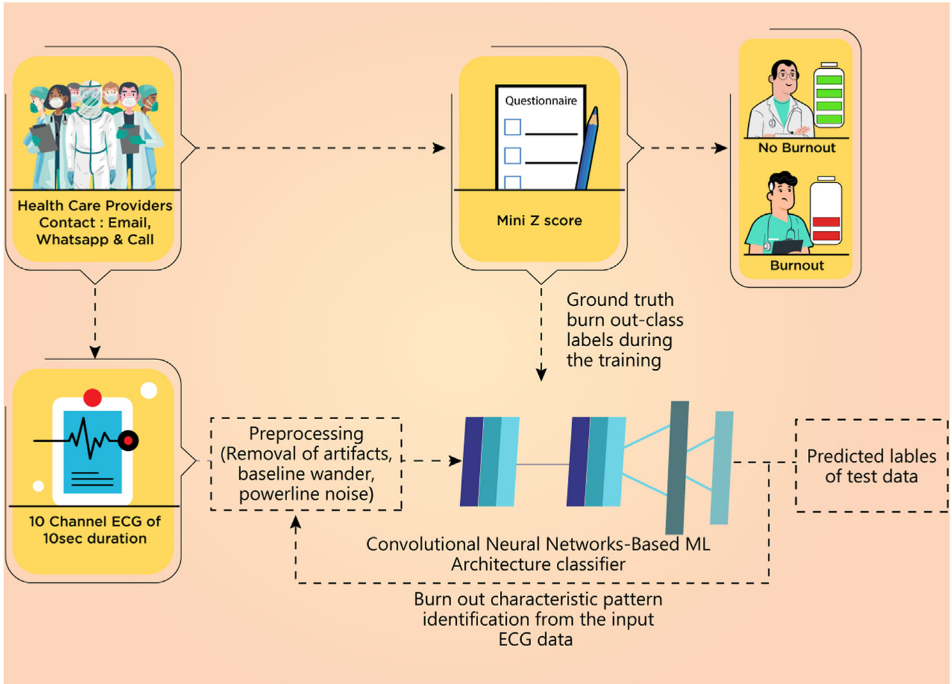

Fig. 2. Development of Intelligent algorithm to detect burnout in Health Care workers using Electrocardiogram.

$$\textit{Sample size in each rank} = \frac{Z^2_{1-\alpha/2} \times P(1-P)}{d^2} = \frac{2.58^2 \times 0.5 \times 0.5}{0.075^2} = 296,$$

where d (0.075) is relative precision (margin of error), P = expected prevalence of burnout (0.5), 1-α/2 = level of confidence (99%) = 2.58.

Since our objective is to assess the burnout in HCWs as well as according to ranking (frontline vs second line vs. third line), the total sample size required will be 3x300 = 900. Based on a conservative response rate including incomplete response as 50%, we plan to contact 1800 HCWs to get the adequate participation of at least 300 subjects per group.

Data will be analysed using standard software. Demographical characteristics will be summarised using descriptive statistics. The 95% confidence interval of burnout will be determined using the Wald method. Associations between burnout and healthcare providers characteristics will be evaluated using the chi-square test/Fisher's exact test and unpaired Student's *t*-test/Mann Whitney *U* test for continuous variables depending upon the distribution of data. Secondary analyses will incorporate additional data from Mini Z (such as overall score, satisfaction, and stress scale) as well as data from ECG (such as heart rate variability). Exploratory analysis will also evaluate the differences among first, second, and third line HCWs. Multivariate analyses will be conducted using significant features identified from univariate analyses.

2.5. ECG data preparation and development of AI model (Fig. 2)

ECG data generated from the HCWs, will be divided into burnout-ECG data and no burnout-ECG data, as per the Mini-Z's single item burnout question (Question No. 3 "your own definition of burnout") score $\geq$3 or <3 respectively. All the features of ECG including individual/combination of ECG time duration, power spectral density, time-frequency analysis features, wavelet features along with the raw ECG data will be collected. Machine Learning predictive model will be built using the training and the validation data. ECGs from 60% of the HCWs cohort will be used train the network; ECGs from 20% of the cohort will be used for internal validation and optimization of the network and the remaining 20% ECGs of HCWs, will be used to assess the AI-enabled ECGs' ability to detect burnout and stress. Different machine learning models such as support vector machine (SVM), neural network, shallow CNN, etc. will be employed. Performance of the AI models will be analysed via quantitative metrics such as area under curve (AUC), precision, recall, sensitivity, specificity, and F1-score. The model with best performance will be utilized to extract the characteristic features or the wave patterns that are used to discriminate between healthy and stress-ECG data. The findings will be analysed and intuitive understanding would be built by drawing analogy with the physiology of the stress-induced changes in the human cardiovascular system.

3. What this study is going to add to the literature

There is very limited data on burnout in healthcare providers in COVID-19 era and there is no large study that has analysed the prevalence of burnout in all categories of healthcare providers. The present study would show the contemporary pattern of burnout in all HCWs. Various demographic patterns associated with a higher risk of burnout in HCWs will be identified. Further, AI based predictive burnout model will be developed to identify the HCW with burnout by analysing the ECG. This will help to neutralise the bias associated with the use of questionnaires. In addition, the typical patterns of ECG in HCWs suffering from burnout will be identified.

Source of funding

None.

Declaration of competing interest

None declared for all authors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ihj.2020.11.145.

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