Data Mining Project: Correlating Physiological Signals with Perceived Stress: A Data-Driven Study on Nurses During the COVID-19 Pandemic

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***Abstract*—This study investigates the correlation between physiological signals and self-reported stress levels among nurses during the COVID-19 pandemic. Using multimodal data collected from wearable devices worn by nurses during their shifts, we analyzed physiological parameters including heart rate (HR), electrodermal activity (EDA), skin temperature (TEMP), and blood volume pulse (BVP). Through comprehensive data preprocessing, windowing techniques, and statistical correlation analysis, we identified personalized physiological patterns associated with various stress levels. Our findings demonstrate significant variability in individual responses to stress, with EDA showing the most consistent positive association with high-stress conditions across participants. Furthermore, textual analysis of self-reported stress surveys revealed that COVID-related challenges, staff shortages, and technical difficulties were prominent stressors. This research contributes to understanding how wearable sensor technology can be leveraged for real-time stress monitoring in healthcare settings, potentially improving occupational wellbeing during crisis situations.**

***Index Terms*—stress detection, physiological signals, healthcare workers, COVID-19, multimodal data, wearable sensors**

I. Introduction

Workplace stress has emerged as a significant occupational health concern, particularly within healthcare environments where high-pressure situations are commonplace. Nurses, as frontline healthcare workers, often experience elevated stress levels due to their demanding roles, which can negatively impact both their well-being and the quality of patient care they provide. The COVID-19 pandemic dramatically intensified these pressures, with healthcare workers facing unprecedented challenges including increased workload, staffing shortages, resource limitations, and heightened risk of infection.

Stress monitoring in healthcare settings has traditionally relied on retrospective self-reporting methods, which may be subject to recall bias and cannot capture real-time physiological responses to stressors. The advent of wearable sensor technology offers a promising alternative approach, enabling continuous, objective measurement of physiological signals that may correlate with stress states. Such technology could potentially provide insights into stress patterns and triggers that might otherwise go undetected through conventional assessment methods.

The significance of this research lies in its potential to advance our understanding of the relationship between objectively measured physiological signals and subjectively experienced stress in real-world healthcare settings. By analyzing these correlations, we aim to identify reliable physiological markers of stress that could inform the development of real-time stress monitoring systems for healthcare workers. Furthermore, by examining the contextual factors contributing to stress among nurses during the pandemic, our findings may offer valuable insights for designing targeted interventions to mitigate workplace stress in healthcare environments.

This study forms part of a broader effort to leverage data mining techniques for health monitoring applications, contributing to the growing field of affective computing and stress detection systems. Unlike controlled laboratory studies, our analysis is based on data collected in an authentic work environment during an extraordinary global health crisis, providing a unique opportunity to examine stress responses under genuine occupational pressure.

II. Related work

Recent research highlights the growing interest in detecting stress using physiological signals and wearable devices, especially in real-life environments such as workplaces and academic settings. Our work builds on these efforts by integrating self-reported stress data with multi-sensor physiological measurements, focusing on healthcare professionals. Below are ten relevant studies and datasets related to our methodology and objectives.

The **AffectiveRoad** dataset was designed to analyze drivers' stress levels in real-world conditions using Empatica E4 and Zephyr Bioharness 3.0, capturing multimodal physiological data during a 1-hour 26-minute driving test [1].

The **WESAD** dataset is one of the most widely used resources for stress and affect recognition using wearables. It includes data from 15 participants who underwent emotional and cognitive stress tests while wearing Empatica and RespiBAN devices [2].

The **SWELL** dataset focuses on stress in office environments, capturing physiological signals and behavioral data (e.g., posture, facial expressions) using Mobi, Kinect, and uLog tools while participants performed cognitively demanding tasks [3].

The **MDPSD** dataset provides multimodal recordings from students during stress-inducing activities, such as Trier Social Stress Test (TSST) and color-word tasks. It includes EDA and photoplethysmography (PPG) signals [4].

A study on **Real-Time Stress Assessment of Nurses** demonstrated the feasibility of monitoring stress levels using wearable biosensors in hospital settings, highlighting challenges in real-time deployment [5].

In [6], the authors analyzed heart rate variability (HRV) to assess stress among nurses, showing that wearable ECG devices can offer reliable insights into work-related stress responses.

Another study explored the relationship between physiological stress indicators and academic performance. It found that higher stress signals (like HR and EDA) correlated with lower exam performance [7].

In [8], the authors proposed a multi-modal deep learning framework that combines time and frequency domain features of physiological signals (including ACC, HR, and EDA) to enhance stress classification accuracy.

A study on **Neurophysiological Correlates of Stress** integrated EEG and peripheral physiological signals to classify multi-level stress using machine learning, supporting the effectiveness of multimodal signal fusion [9].

Finally, a review by **Lazarou et al.** discussed real-time stress prediction using wearable sensors, emphasizing the potential of continuous monitoring in real-world environments [10].

III. Objectives

The primary aim of this project is to investigate the relationship between physiological signals and self-reported stress levels among nurses working during the COVID-19 pandemic, using data mining techniques to extract meaningful patterns and correlations. This research addresses two key questions: first, how physiological signals correlate with self-reported stress levels among nurses during the COVID-19 pandemic; and second, what primary contextual factors contribute to stress among nurses, and how these factors are reflected in physiological data.

For the first research question, we hypothesize that physiological signals, particularly heart rate (HR) and electrodermal activity (EDA), will show significant positive correlations with self-reported stress levels. Specifically, increased stress may manifest as elevated HR, higher EDA, and potentially changes in skin temperature and blood volume pulse patterns. These physiological indicators could serve as reliable markers for real-time stress monitoring in healthcare settings.

Regarding the second research question, we anticipate that contextual stressors such as COVID-related challenges, increased workload, staff shortages, and patient crises will likely manifest physiologically through distinct patterns in the measured signals.

The expected outcomes of this research include the identification of specific physiological signals or combinations of signals that serve as reliable indicators of stress in nurses working in hospital settings; and categorization of the most significant stressors affecting nurses during the COVID-19 pandemic.

These objectives align with the broader goal of applying data mining techniques to improve healthcare worker well-being and organizational efficiency in high-stress environments, particularly during extraordinary circumstances such as a global pandemic.

IV. Data

The dataset used in this project was collected by researchers from the University of Louisiana at Lafayette at Opelousas General Health System in the United States [11]. The data collection took place between April and December 2020, during the height of the COVID-19 pandemic. The goal was to create a dataset for studying continuous stress detection in real hospital environments, specifically among nurses.

Physiological data was collected using Empatica E4 wristbands worn by nurses during their shifts. The dataset includes electrodermal activity (EDA), heart rate (HR), blood volume pulse (BVP), inter-beat interval (IBI), skin temperature (ST), and accelerometer (ACC) signals, each recorded at different sampling frequencies. In addition to this sensor data, nurses completed end-of-shift surveys to report self-perceived stress events and their causes.

The physiological data is stored in CSV files, while the survey responses are stored in an Excel file. The survey data contains additional time-based variables like start and end times of stress events, durations, and subjective stress level ratings.

A. Data Pre-processing

1) Initial Data Structure: The raw dataset was highly fragmented and stored in a hierarchical format. It consisted of multiple compressed ZIP files, each representing a session or a batch of data collected from a nurse. Inside each ZIP file were subfolders containing CSV files corresponding to different physiological signals such as Heart Rate (HR), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Accelerometer (ACC), Inter-Beat Interval (IBI), and Skin Temperature (TEMP). Each CSV file included only signal values, with the first two rows used to describe metadata: the initial timestamp of the recording and the sampling frequency (in Hz). Additionally, the files did not explicitly contain the nurse ID or structured time columns—this information was only embedded within the filenames, following the format `NurseID_InitialTimestamp.csv`.

During this stage, we learned that the data was not directly suitable for analysis due to its fragmented organization and lack of embedded identifiers. This presented a challenge, as data across different signals and individuals could not be aligned without additional parsing and transformation. This structural inconsistency was a primary problem that we addressed in the next step.

2) Data Integration: To unify the dataset for analysis, we performed the following steps:

- Recursively extracted all ZIP files, including nested ones.
- Parsed and added Nurse ID and initial timestamp to each record, extracted from the filename.
- Calculated actual timestamps for each sample using the initial timestamp and sampling frequency metadata.
- Moved all processed CSV files to a flat root directory for easier access and removed empty directories to maintain a clean workspace.

This integration allowed us to uniquely identify each record and prepare the dataset for further signal alignment.

3) Resampling to Common Frequency: The dataset included signals recorded at different sampling frequencies, shown below:

Signal	**Frequency (Hz)**
Heart Rate (HR)	1.0
Electrodermal Activity (EDA)	4.0
Skin Temperature (TEMP)	4.0
Accelerometer (ACC)	32.0
Inter-Beat Interval (IBI)	64.0
Blood Volume Pulse (BVP)	64.0

To harmonize all signals, a common frequency of 4 Hz was chosen. Low-frequency signals (e.g., HR) were upsampled using interpolation, and high-frequency signals (e.g., BVP, ACC) were downsampled using time-based selection via `.asfreq()`.

This step helped ensure synchronized data across all physiological modalities and reduced the overall dataset size (e.g., BVP down from 7 GB). While resampling improved compatibility and performance, it also introduced new limitations. Upsampling introduced interpolated values, which may not reflect actual physiological events and can lead to oversmoothed data. Downsampling, on the other hand, may cause a loss of temporal granularity, especially for high-frequency signals that could contain subtle but important fluctuations related to stress.

After that, all individual files for each signal type were concatenated into five master CSV files. These five files were merged into a unified dataset using a composite key of timestamp and nurse ID. This resulted in a single table with aligned signals for each nurse over time, forming the foundation for subsequent analysis.

Through the entire preprocessing pipeline, we gained critical insights into the dataset's structure, limitations, and required transformations. Although we addressed key flaws such as misalignment and fragmentation, the consequences of data interpolation and reduction in frequency should be considered when interpreting correlation results and model outputs, as they may affect sensitivity and temporal accuracy.

4) Preprocessing the Survey Results: The daily self-reported stress surveys were preprocessed separately:

- **Timestamp Construction:** The dataset included separate columns for `date`, `start_time`, and `end_time`. These fields were merged to form complete datetime values and localized using the `America/Chicago` timezone. Unix timestamps (`start_timestamp`, `end_timestamp`) were also computed to enable efficient time-based operations.
- **Duration Validation:** To validate the integrity of reported durations, each `duration` string (formatted as `HH:MM:SS`) was converted into seconds and compared against the calculated difference between `start_timefull` and `end_timefull`. A mismatch flag was generated to detect inconsistencies, which were printed for manual inspection. This served as a quality control step to ensure consistency in temporal data.
- **Final Preparation:** After validation, auxiliary columns used only for internal checks were removed. The cleaned survey data was then sorted chronologically by `start_timestamp` and `id`. This finalized dataset was used as the foundation for subsequent analysis and modeling steps.

Then we have merged the resampled physiological dataset with the pre-processed stress survey results by matching the timestamp ranges with recorded physiological signal records.After this merge we encountered some missing records due to unrecorded signals for specific time periods and resampling changes of some signals. We have identified missing value percentages and their correlations between signals as in Fig. 1, to learn what imputation methods to follow. According to the analysis TEMP, EDA, BVP and HR contain around 0.5 missing correlation indicating when one variable appears there is a 50% chance the other variable to be present. Since only two participant data had extended periods of missing data, therefore their removal had less impact than imputing, which could lead to unexpected outcomes. For the short missing sequences in HR signal(occurred due to frequency mismatch) were imputed using average of adjacent values.

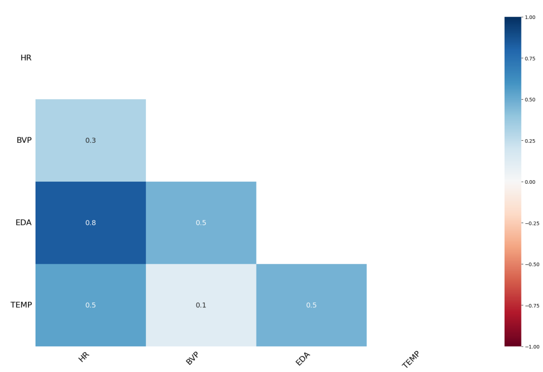

Fig. 1. Heatmap of missing correlations of data

V. METHODS

Following the data pre-processing and cleaning stages, we employed a series of analytical methods to investigate the correlations between physiological signals and self-reported stress levels among nurses during the pandemic period.

We applied a time-windowing technique to transform the resampled 4Hz frequency physiological signals into structured segments suitable for analysis. We have divided the physiological data into fixed 1-minute windows, each comprising of 240 samples. This windowing length was chosen to balance the temporal status and physiological interpretation, providing a fine-grained resolution to detect transient stress responses while reading the signals with minimized noise. We have selected only complete windows with full set of 240 samples(including all 250ms/4Hz intervals) to ensure consistency and avoid introducing bias from uneven sampling. Afterwards grouping the data by NurseID, minute window and stress level was performed with aggregated functions with key statistical features-mean and standard deviation across each window, for all considered signals, capturing the central tendency and variability in the data.

Since all the stress levels recorded from wearable devices are personalized signals which are identified to be unique and vary by the user according to [12], we explored individual differences and assessed the signal behaviors across participants and stress levels. Boxplots were used to identify participant specific trends and variability, and to possibly identify a value range for each signal that can be categorized as a high stress triggering indicator. Pair-plots allowed for multidimensional view of relationships between different physiological variables, further stratified by stress levels.

In order to quantify the strength and relationships of these signals with stress levels, we performed correlation analysis with both Pearson and Spearman correlation coefficients. The ability of these methods to detect linear relationships and non-linear monotonic trends. This dual approach ensures more detailed and nuanced assessment of signal relevance, particularly given the possibility that physiological responses to stress may not always contain linear relationships in nature.

Beyond numerical correlations, we also conducted a textual analysis of the self-reported stress surveys using descriptive details provided by nurses over daily stressful incidents. These content were categorized into broader stress event types as in Table I, where we processed them using natural language tools to extract key terms.

To visualize the insights from these, we generated word clouds for each stress category to qualitatively identify common contextual triggers to understand how these factors affect the stress levels.

Overall the combination of temporal feature extraction, statistical correlation, visual analytics and qualitative survey analysis enabled a multi-factor investigation of the data with the objective of finding correlations as the research question address. By integrating both qualitative and quantitative perspectives, we aimed to produce insights that are not only statistically explained but also contextually meaningful.

TABLE I
CATEGORIES AND RECORDED SURVEY DESCRIPTIONS

Category	**Mapped survey content**
Staff Crisis	lack of supplies, increased workload
COVID-Related	covid related, treating a covid patient
Patient Care	patient in crisis, documentation, competency stress
Family Matters	patient or patient's family
Workload	increased workload, documentation
Technical Issues	technology related stress, work environment issues
Emotional Stress	safety physical or physiological threats
Communication	doctors or colleagues, administration lab

VI. RESULTS

Here we present the findings of our data-driven analysis, exploring the relationships between physiological signals and recorded stress among nurses during covid-19 pandemic. Through a combination of visualizations, statistical analysis and survey text interpretations, we measures valuable insights on how stress correlates with wearable device signal patterns and contextual events.

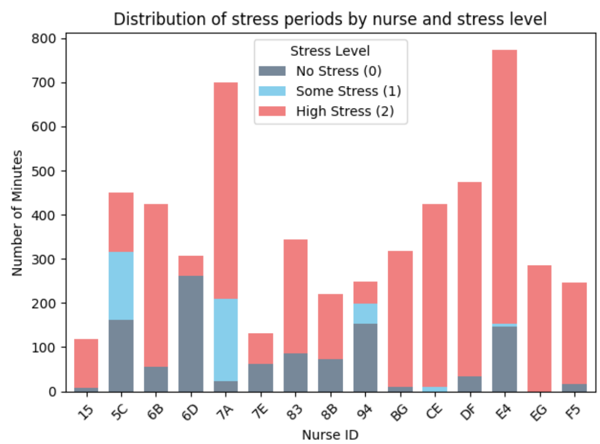

Fig. 2. Distribution of stress time across NurseID and Stress level

To gain an initial overview of stress prevalence, a stacked bar plot (Fig. 2) is generated NurseID wise and number of minutes recorded during the session under each stress category. The findings indicate high stress periods are dominant in the dataset across most participants and some stress periods are relatively less with minimal durations. These findings indicate predominant state of high stress during both study periods, reflecting intense physiological burden experience by nurses during the pandemic.

The box plots grouped by NurseID and stress level with mean aggregated results for HR, EDA, TEMP and BVP show how the signals span its values for each stress incidents in Fig 3. HR measurement doesn't show difference with stress levels and the variations of HR can in reality increase due to non-stress physical activities limiting its reliability as a stress indicator. Skin temperature also does not show clear trends across stress levels as it can also be influenced by external factors as room temperature. EDA shows more consistent positive association with stress as many participants showed

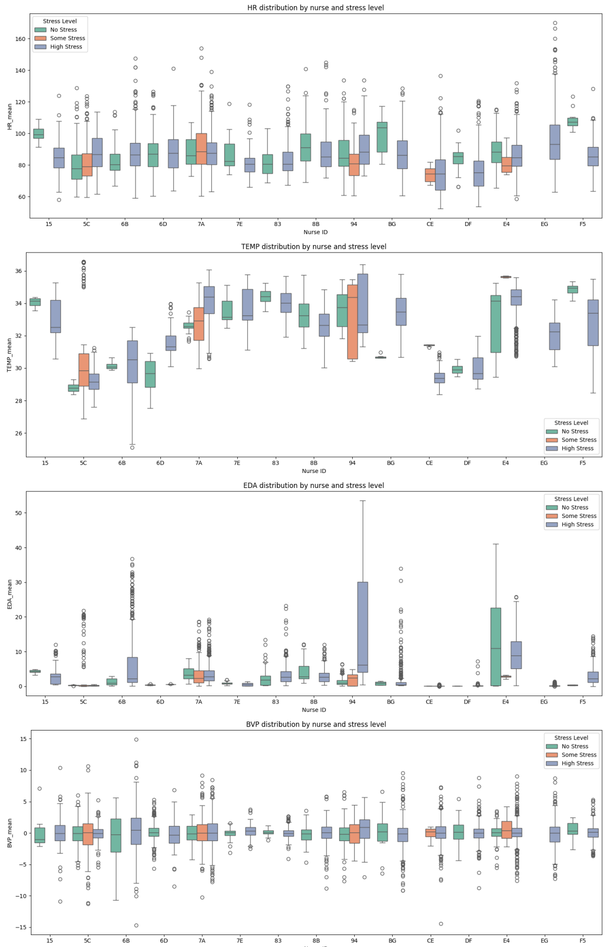

Fig. 3. Boxplots for mean of signals across NurseID and Stress level

higher average values during high-stress conditions. Although BVP shows a relatively stable value range with mean values, when plotting with standard deviation as in Fig 4 it shows increased variability during high-stress periods for several nurses.

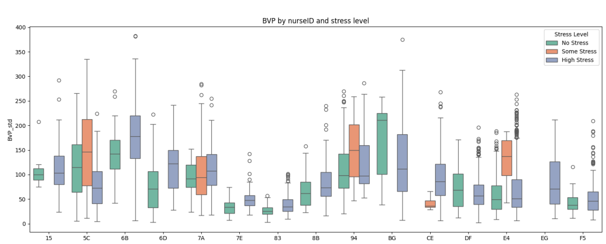

Fig. 4. Boxplot for bvp signal variation across NurseID and Stress level

We have further explored the multivariate relationships using pairplots as in Fig 5. Here we can observe skewed distributions in signals EDA and TEMP with non-linear patterns between stress levels. The visible increase in EDA during stress events reinforce the boxplot observations.

Building upon this to quantify the relationships we have used Pearson and Spearman correlations for a sub-group of NurseIDs as in Fig 6. The findings are positive correlations with stress on EDA in a subset of nurses. Skin temperature also correlates with a subset of participants but not consistent through out the dataset. The P-values of below 0.05 values in the Tables II and III indicate strong significance with stress levels. EDA and TEMP shows strong relation for some subjects while HR and BVP high variability and weaker relationship to stress levels.

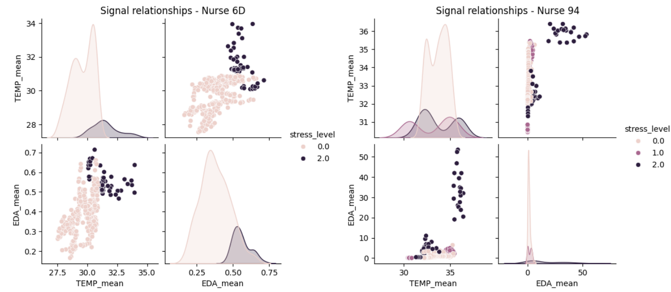

Fig. 5. Pairplots for TEMP and EDA signals correlation with Stress level

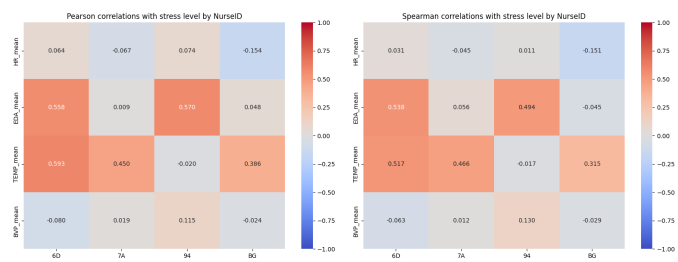

Fig. 6. Pearson and Spearman correlation heatmaps for several NurseIDs against Stress level

TABLE II
PEARSON CORRELATION P-VALUES FOR PHYSIOLOGICAL SIGNALS AND NURSES' STRESS LEVELS

Measure	6D	7A	94	BG
HR_mean	0.2664137068	0.0784311527	0.2442524341	0.0058606782
EDA_mean	0.0000000000	0.8209544365	0.0000000000	0.3899706516
TEMP_mean	0.0000000000	0.0000000000	0.7545586160	0.0000000000
BVP_mean	0.1606684511	0.6222456485	0.0710523405	0.6695527977

TABLE III
SPEARMAN CORRELATION P-VALUES FOR PHYSIOLOGICAL SIGNALS AND NURSES' STRESS LEVELS

Measure	6D	7A	94	BG
HR_mean	0.5824047549	0.2346371189	0.8586305579	0.0069088346
EDA_mean	0.0000000000	0.1372057593	0.0000000000	0.4244411368
TEMP_mean	0.0000000000	0.0000000000	0.7887241352	0.0000000097
BVP_mean	0.2718670106	0.7574426800	0.0408909315	0.6022265719

The survey response analysis is performed to quantitatively analyze the daily stress events submitted by nurses. Since the content varies and lengthy, we have used categorization methods and cluster incidents. According to the wordcloud details in Fig 7 no stress events include emotional stress and patient handling scenarios which nurses are practiced to perform in their job scope. The some stress incidents are recorded by them mostly due to communication and technology related difficulties. High stress events are due to covid related matters, staff crisis which pressures with increased workload during the pandemic peaks. These wordclouds helps to identify major stress triggering events.

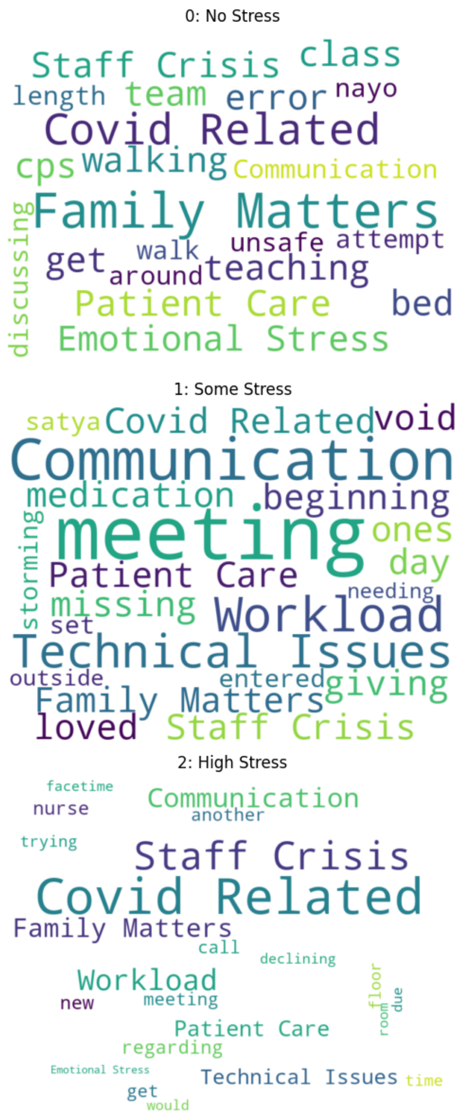

Fig. 7. Self-reported survey description categories distribution word cloud

VII. Discussion

Our analysis demonstrated statistically significant correlations between certain physiological signals, particularly EDA, TEMP and nurses' self-reported stress levels, as illustrated in Fig 6. HR also played a role indicating stress level for some nurses. These confirmed our hypothesis that EDA and HR will be the primary factor in stress level. But on the higher level, the result is inconsistent and cannot be apply for all participants. The P-value from Table II and III showed notable associations with stress events for specific individuals, but completely no correlation with other participants, suggesting that the data can be influenced by other factors, such as environment. So these signals alone provide limited predictive capability for stress indication. This result confirmed the finding of the previous studies. Our findings reinforce the view that while physiological measures might hold promise, reliance on one single physiological signal without recalibration or contextual information will impact predictive accuracy.

Practically, our results suggest that wearable devices could indeed be integrated into healthcare settings for real-time stress monitoring, but only if employed in personalized multi-modal systems. Relying on generalized thresholds or single-signal indicators might result in inaccuracies or misinterpretations of stress levels. This suggests that the system will always require a system to analyze the data, so that it can be suited to each individual.

There are also several limitations influenced our findings. Most significantly, the stress responses varied widely among individuals, with some reporting stress on a binary level (no stress / high stress) and others reporting more gradual variations, as demonstrated in Fig 2 . This suggests that self-reported stress levels are highly biased for each individuals, showing that for many people, they do not notice stress until a certain threshold is reached. This variability reduced the effectiveness of linear statistical approaches. Furthermore, the dataset lacked a physiological baseline ("reference point") similar to the Trier Social Stress Test [13] to establish a consistence baseline between individuals. However, we believe that the original study was constrained by ethical and practical limitations of data collection during an active pandemic, restricting the frequency and timing of measurements. The original study has circumvented this limitation by collecting the data in two sessions separated by approximately 6 months. From this point, we can clearly see that a straight-forward statistical analysis will not provide stable result unless we "reverse engineer" the data and survey to re-establish the baseline.

The dataset also fail to distinguish between adaptive (helpful) and maladaptive (toxic) stress, overlooking the multi-dimentional nature of stress. Inclusion of this dimension could have enhanced physiological data correlations and provided more nuanced understanding of stress response. We could have leveraged natural language processing (NLP) or large language models (LLM) on survey responses to differentiate stress level by type. However, current NLP techniques face significant challenges in interpreting human emotion, thus limiting the practical reliability of such methods at this stage.

VIII. Reflection on Group Work

Conducting this data mining project provided a valuable learning experience for our group, particularly in the detailed exploration and understanding of the dataset. The most interesting aspect was mining as much information as possible from the data which relying on machine learning approaches, since those are covered in another course, and in the related works. Our approach is to enhance the understanding of the data characteristics, common pitfalls in data handling, and the importance of thoroughly understanding a dataset before applying more computationally expensive methods.

The most challenging and time-consuming part of the project was data pre-processing and integration. Typically, a real life big data project will have much more size, however, our dataset still resembles some characteristics from big data that require us to employ advanced data processing and data handling techniques such as sharding, partitioning, and strategic data joins. This strengthens our skills in future projects where we have to handle a huge amount of data, as our AI systems become more and more resource and data hungry.

Overall, the project unfolded largely as planned, though we encountered unanticipated complexities related to data handling and the need for more creativity on data analysis without using Machine Learning. However, working through these challenges became a core learning outcome, reinforcing the critical need for thorough data exploration before employing advanced modeling methods. Consequently, we feel highly satisfied with our collective effort, having deepened our practical understanding of data mining beyond mere application, and appreciating the value of meticulous data comprehension as a foundation for effective machine learning.

Contributions:

Fatemeh Soufian acts as the team leader, prepares presentations, works on data integration, data re-sampling implementation, re-evaluate data for inconsistencies. Fatemeh also contributed to research quality assurance by re-evaluate the result.

Hans Madalagama works mainly as research & development, check & evaluate dataset and related works, data re-sampling R&D, data reduction implementation, data handling and processing integration, coauthor preparing presentations. Hans contributed significantly on data processing and word cloud analysis.

Ata Jodeiri Seyedian works mainly with research and team leader assistant, researched extensively on related works, data integration, windowing method R&D.

Chau Nguyen focused on implementation and operations, helped with underlying infrastructure such as project code storage (Github) and data storage, contributed to primitive dataset research & primitive data pre-processing. Chau also helped with dataset visualization, preprocessing the survey results, and helped quality assurance on the correlation analysis as well as the team presentation.

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