Digital Interventions to Reduce Distress Among Frontline Health Care Providers: Analysis of Self-Perceived Stress

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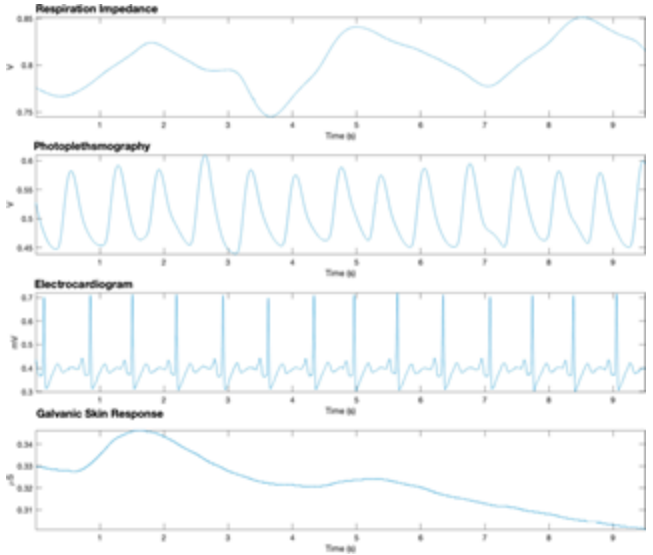
Introduction

- Healthcare workers have reported experiencing moral distress due to the constraints of COVID-19 Pandemic

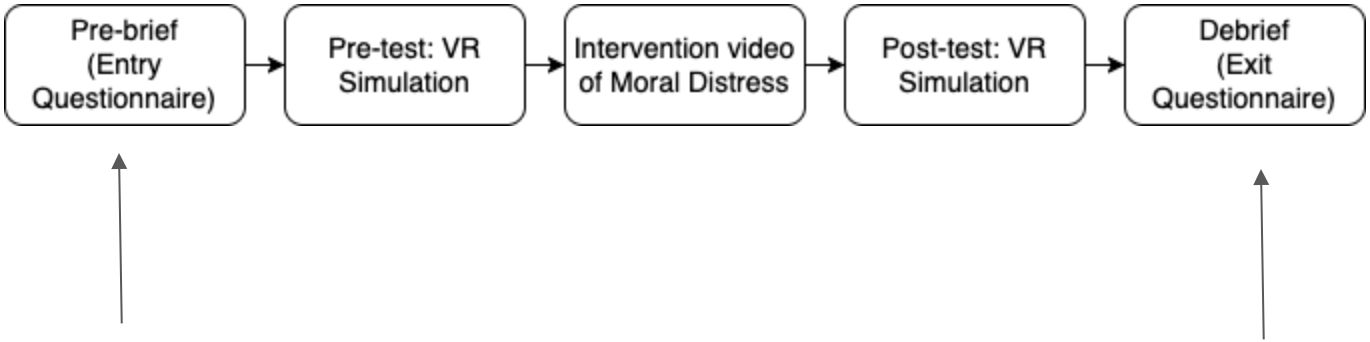
Objective

- Understand moral distress through the use VR simulation to simulate the ICU during COVID-19
- Use and evaluate potential digital interventions



Dataset

- n=15 healthcare workers
- Data collection involved
  - Passive physiological signals
  - Active mental health questionnaires



Dataset

- VR
  - Simulation
- Biopac
  - Respiration
  - Oxygen Saturation
  - Heart Rate
  - Skin conductance
- Mental health questionnaire
  - Perceived Stress Scale (PSS)-10

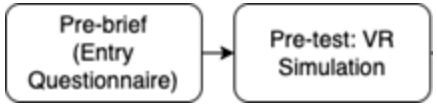
Methods

- Pre-processing
- Feature extraction
- Classification

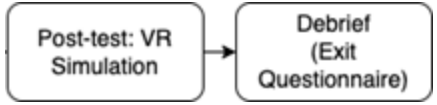
Pre-processing

- Physiological data
  - Normalization of data
  - Segmented the data
  - Windowing of 20 seconds
- PSS-10
  - Clustered to low, moderate and high severity **

Segment 1 -



Segment 2 -



**The PSS-10 scale has a 0-40 range with diagnosis of low, moderate and high perceived stress for score ranges of 0-13, 14-26, and 27-40, respectively

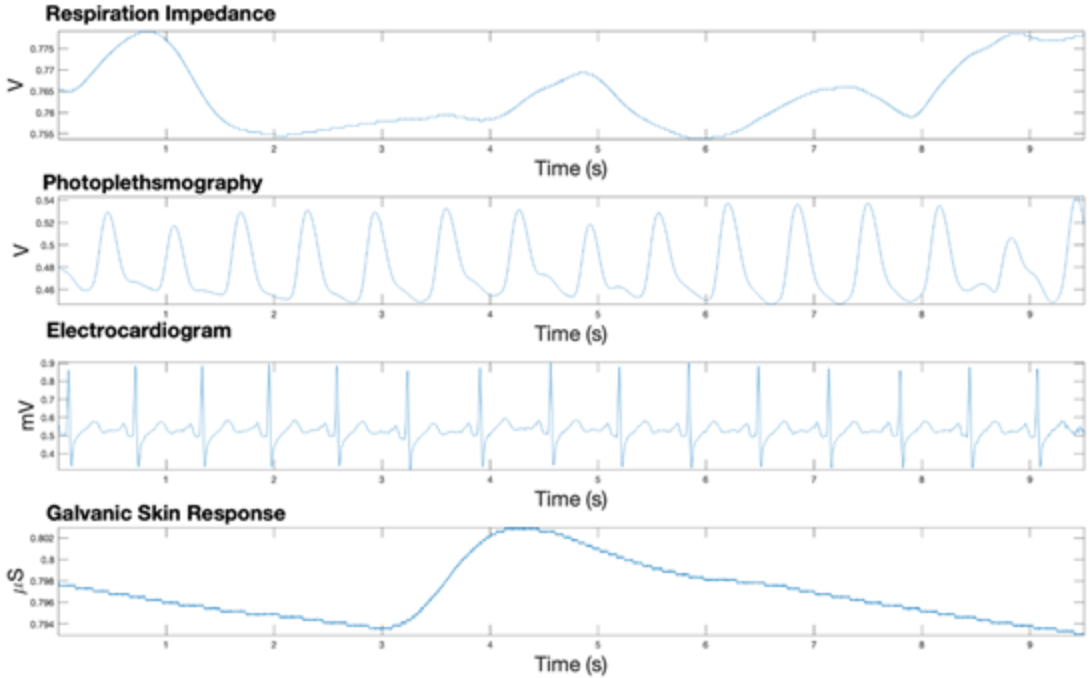
Feature Analysis

Feature	Description
Mean	Average value of the window
Variance	Variance value of the window
LF	Relative power of low frequency band of HRV (0.04–0.15 Hz)
HF	Relative power of low frequency band of HRV (0.15–0.4 Hz)
VLF	Relative power of low frequency band of HRV (0.0033–0.04 Hz)
LF/HF	Ratio of Low and High frequency
RMSSD	Root mean square of successive RR interval differences

Classification and validation

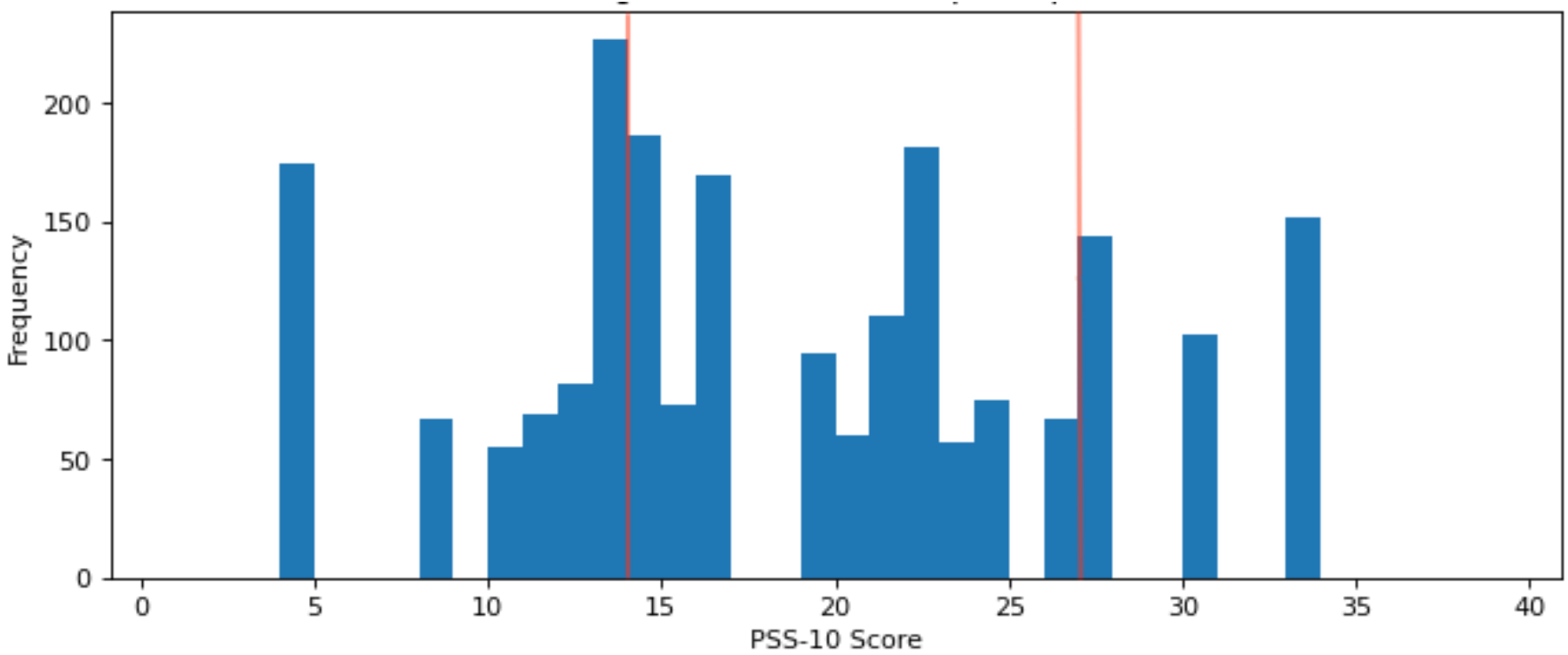
- Classification evaluated the separability between the PSS-10 severities among the users
- SVM and DT
  - Synthetic Minority Oversampling Technique (SMOTE)
  - Weighted classification
  - Downsampling

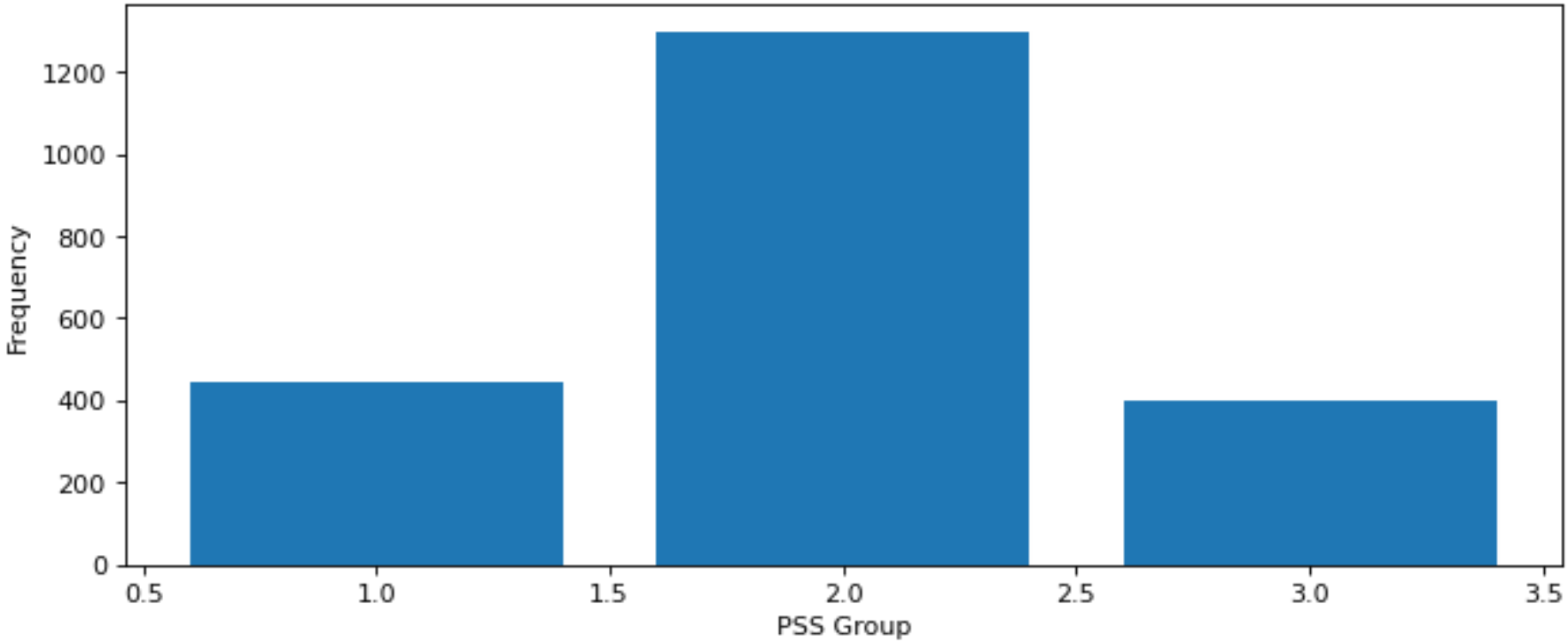
Results


Respiration Impedance
V
Time (s)
Photoplethsmography
V
Time (s)
Electrocardiogram
mV
Time (s)
Galvanic Skin Response
μS
Time (s)

Results

- Collected n=15
- Experimental length were an **average** of 47.12 with a **variation** of 6.41 minutes
- The average length of **Segment 1 and 2** were 22.16 and 24.96 minutes, respectively
- A total of **2144 windows** were created from 20-second windows


Frequency
200
150
100
50
0
0
5
10
15
20
25
30
35
40
PSS-10 Score


1200
1000
800
600
400
200
0
Frequency
0.5
1.0
1.5
2.0
2.5
3.0
3.5
PSS Group

DT	Weighted Classification	Downsampling	SMOTE
Accuracy (%)	82.23	78.55	**93.50**
Precision (%)	79.79	78.11	**93.41**
Recall (%)	79.94	78.36	**93.31**
F1 (%)	79.82	78.14	**93.35**
SVM			
Accuracy (%)	87.42	70.75	77.69
Precision (%)	84.67	72.76	78.08
Recall (%)	85.65	70.48	77.03
F1 (%)	85.11	70.11	76.92

The weighted classification weights for class 1, 2, and 3 were 1.56, 0.55, and 1.79, respectively

Discussion and Conclusion

- Our findings support literature to evaluate mental health through the use of physiological data
- Advantages of using a low-complexity algorithm are that it allows for potential deployment on edge computing devices
- Important to consider the potential limitations and ethical concerns such as data storage and analysis
- Further research is needed to evaluate the performance of the algorithm in real-world settings

Contact us!

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