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# Continuous physiological signal measurement over 24-hour periods to assess the impact of work-related stress and workplace violence☆

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A R T I C L E I N F O

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A B S T R A C T

Work-related stress has long been recognized as an essential factor affecting employees' health and wellbeing. Repeated exposure to acute occupational stressors puts workers at high risk for depression, obesity, hypertension, and early death. Assessment of the effects of acute stress on workers' wellbeing usually relies on subjective self-reports, questionnaires, or measuring biometric and biochemical markers in long-cycle time intervals. This study aimed to develop and validate the use of a multiparameter wearable armband for continuous non-invasive monitoring of physiological states. Two worker populations were monitored 24 h/day: six loggers for one day and six ICU nurses working 12-hr shifts for one week. Stress responses in nurses were highly correlated with changes in heart rate variability (HRV) and pulse transit time (PTT). A rise in the low-to high-frequency (LF/LH) ratio in HRV was also coincident with stress responses. HRV on workdays decreased compared to non-work days, and PTT also exhibited a persistent decrease reflecting increased blood pressure. Compared to loggers, nurses were involved in high-intensity work activities 45% more often but were less active on non-work days. The wearable technology was well accepted by all worker participants and yielded high signal quality, critical factors for long-term non-invasive occupational health monitoring.

## 1. Introduction

Occupational stress can be characterized as a state of cascading biological activation triggered by internal or environmental agents that alter a person's capacity to adapt (Lazarus, 1993). The sources of occupational stress include extended and irregular work hours, shift-work, chronic psychosocial strain affecting sleep patterns (Demerouti et al., 2000), and acute stressful events such as workplace violence. Experiencing repeated exposure to stressors may put workers at high risk for suicide, depression, obesity, hypertension, morbidity, and early death (McCraty et al., 2009). Moreover, the COVID-19 pandemic-related focus on essential workers and on health disparities has pointed to an expanded immediacy for field research and stress interventions (Willetts et al., 2018).

To date, most assessments of occupational stressors or stressful events are either anamnestic, based on self-reported questionnaires and surveys, or reliant on cumbersome and intermittent biometric and biochemical measurements (Willetts et al., 2018), (Namazi et al., 2019). However, self-report of stressors and episodes of stress via surveys is often unreliable or subject to recall bias. Most biometric and biochemical measurements often interfere with the work process or demand interruption for sensor recording. Moreover, intermittent measures are potentially inaccurate and unable to address the physiological responses to stressors in real-time.

Stress causes the human coping mechanism to produce cortisol and adrenaline, which initiates a chain of events at the molecular,

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physiological, and whole-body levels. The release of these hormones is practically impervious to real-time monitoring, but humoral factors drive physiological responses that impact the sympathetic nervous system (SNS), heart rate, heart rate variability (HRV), sleep pattern, and blood pressure (BP) (Dalmeida and Masala, 2021). Thus, monitoring BP, sleep, and cardiovascular responses in momentary epochs and over multiple 24-h periods may enable examination of acute and accumulated strain as well as interactions between work and non-work risk design factors. Recent advances in wearable sensors and mobile technologies have facilitated the continuous and non-invasive monitoring of physiological changes to external events with a number of biomarkers (Alberdi et al., 2016). Lately, researchers in occupational physiology have used wearable devices to collect physiological data in the field (Ioannou et al., 2021a), (Ioannou et al., 2021b). These studies captured heart rate, HRV, and skin/core temperature to assess workers' health, certain diseases, and productivity in the workplace.

Among the aforementioned physiological signals, heart rate variability (HRV) has been used as a quantitative marker of autonomic nervous system (ANS) activation and has been demonstrated to be correlated with emotional regulation and stress when wearable sensors are used (Kaufmann et al., 2011). HRV is often measured using RMSSD (root mean square of successive differences between R-R intervals) in time series and LF/HF ratio (low to high-frequency power ratio) of inter-beat intervals (IBI) in the frequency domain. A decrease in RMSSD due to high sympathetic or low parasympathetic activity can be interpreted as an indicator of the stress response (Kaufmann et al., 2011). Frequency-domain studies of HRV also exhibit increases in low-frequency components associated with sympathetic stimulation that is reflective of psychophysiological strain (Castaldo et al., 2015).

Ambulatory blood pressure monitoring (ABPM) is another non-invasive measurement tool for measuring stress at work. While a traditional nocturnal BP drop is recognized, there has been evidence for a non-conforming nighttime level in stressful work. Moreover, shiftwork with nocturnal hours has generally been associated with sustained periods of hypertension during sleep. ABPM monitoring has established robust associations between patterns of hypertension, nocturnal expression, and variability between high and lower measurements that have been correlated with both defined stress and cardiovascular disease (Steptoe and Kivimäki, 2012; Boggia et al., 2007; Kikuya et al., 2000). However, the principal limitations of ABPM as a measure of stress at work and diurnal stress reaction during sleep have been cumbersome. Despite the appeal of the concept of continuous monitoring, signal quality with cuff measurement has remained elusive (Sharma et al., 2017). To overcome the limitations of compression cuffs that can only be used intermittently, the measurement of pulse transit time (PTT) has been widely studied as an advantageous method for deriving continuous blood pressure (CBP) (Le et al., 2020). This method is based on changes in pulse wave velocity (PWV), the rate at which aortic pressure waves travel through the body. PWV is a classical measure of arterial stiffness and one of the most important contributing factors to BP. PWV can be estimated using pulse transit time (PTT), which refers to the travel time of a pressure wave between two arterial sites. Our working hypothesis has been that PTT can be used to accurately assess variations and trends of CBP linked to stress without extensive calibration for individuals. Thus, PTT may offer a practical means for monitoring changes in CBP indicative of acute stress responses.

Commercially available devices on the market for measuring stress mostly rely on single-modal indices (i.e., activity level, heart rate, skin temperature), have low data quality performance in field studies, and do not have continuous ABPM (Smets et al., 2018). This study developed and tested a custom armband designed to continuously capture multi-modal physiological signals for several consecutive days, including single-channel ECG, PPG, and 3-axis accelerometry. We also validated the usability of the custom armband in a demanding outdoor environment with loggers and explored its applicability in a study with nurses. In both studies, armband performance was compared with an applied standard, Empatica E4 wristband. The participant's daily activity levels, sleep patterns, HRV, and PTT were extracted from the measured signals collected in separate field studies. We are also able to report on the feasibility of linking acute physiological responses to a specific workplace stressor experienced by ICU nurses. To our knowledge, this is the first research study measuring instances of workplace stressors along with multiple health parameters, including a CBP parameter monitored continuously for 24-h periods over 7 days, without interfering with a participant's daily activities.

## 2. Method

### 2.1. Study design and participants

To demonstrate the feasibility and reliability of assessing physiological responses using the custom-developed armband, we tested the armband in two different workplace environments. In the first study, we recruited six loggers in Maine, USA. Mechanized logging requires outdoor work but the operators' activity levels are relatively low because they spend the most time in logging vehicles. The main objective of the Logger Group study is to validate the form factor, field usability, and applicability in demanding outdoor environments. In the second study, we recruited six nurses working within the intensive care unit (ICU) at the University of Connecticut John Dempsey Hospital. Nurses usually work indoors with less environmental interference, and their activity levels during work are quite high. In addition, the nurses had a very different type of work week with 12-h shifts and work-leisure intermittency. The main objective of the Nurse Group study is to test reliability of the custom armband over a 7-day period and to capture physiological responses to instances of workplace violence.

All participants wore a custom armband sensor on the left upper arm. All participants also were asked to wear an Empatica wristband (E4) on the left arm throughout the study period as a comparative source to our design. In the case of nurse participants, the E4 was also used for logging incidents of workplace violence. All participants filled out a demographic survey at the beginning of their study period and a usability survey at the end of their study period. They were also asked to take a short daily diary survey to record sleep time and aspects of their daily routines.

Participants signed and dated written informed consent documents for the respective study protocols and were able to understand and comply with the protocol requirements, instructions, and protocol-stated restrictions. Criteria were applied to exclude cases with systolic and diastolic BP higher than 180 mmHg and 100 mmHg, respectively. The study protocols were reviewed and approved by Basset Healthcare and UConn Health Institutional Review Boards.

**Loggers Group:** Six loggers working between 8 and 12 h shifts (mean age = 35.3; SD = 19.72; ages 18–66) were recruited from two different logging sites. The loggers operate inside motorized logging equipment, such as feller bunchers, processors, and harvesters, to cut and drag trees, albeit performing little physical activity. The group was monitored continuously for 24-h, including work, sleep, and leisure time. Eligible participants were recruited by study staff in the morning at their worksite (around 9:00 a.m.) and consented during a brief break from their shift. On the morning of the next day, participants met with study staff (around 9:00 a.m.) to return the devices and take a usability survey before being discharged. Participants received $100 for the completion of the one-day study.

**Nurses Group:** Six nurses (mean age = 31.0, SD = 5.48, ages 22–38; four female) working 12-h shifts (four day shifts and two night shifts) were recruited for this study. Participants were monitored continuously (24 h per day) over a 7 day period that included at least 3 workdays. Participants were recruited by study staff at staff meetings and through colleagues. Interested participants contacted study staff and set up an introductory meeting where participants were introduced to the study, signed consent forms, and completed a demographic survey. On workdays, participants had brief meetings daily with study staff in order for their armband and Empatica wristband to be swapped with ones that were fully charged and to verify monitoring integrity. On days off, nurses received an extra set of wearable devices and were instructed on how to replace them when the batteries ran low. Participants received $250 for the completion of the week-long study. Fig. 1 summarizes the protocol of Nurse Group study.

Because of the very different natures of logging and ICU nursing and due to our interests in nursing stresses during COVID-19, the Nurse Group was also asked to log incidents of workplace violence involving patients and other staff. Participants used the push-button event marker on the E4 to record the time of incidents. They were also asked to complete a brief survey soon after these incidents to rate incident severity using a survey app (PIEL) installed on their smartphone. The incident survey was composed of a series of eight questions designed to capture incident characteristics. Only incident time and incident stress severity (1 = Not at all stressful, 2 = Somewhat stressful, amd 3 = Very stressful) are reported here.

### 2.2. Custom armband design

**The Armband.** We designed and developed custom electronic circuits mounted on printed circuit boards (PCBs) that integrated one-channel ECG, a multi-LED PPG sensor, and a 3-axis accelerometer (Fig. 2). A 3D-printed enclosure protects the electronics with a dimension of $30 \times 30 \times 5mm$, which was embedded in a stretchable fabric to be worn on the upper arm. The armband's PPG sensor was positioned within the armband to target the brachial artery. The armband was secured with Velcro, allowing the user to adjust the armband for a snug fit regardless of arm circumference. The ground electrode and the negative-input electrodes of the ECG were designed to attach to the arm, and the positive input electrode of the ECG was designed to attach to the chest. The PPG sensor was placed targeting the brachial artery. A 3.7 V rechargeable Li-Polymer battery was suited to the armband to provide power to the electronics for more than 96 h continuously.

**Analog Front-End (AFE) and Microcontroller.** An ADS1191 (Texas Instruments, Inc., Dallas TX, USA) was used for the single-channel ECG. The sampling rate of the ECG was set to 125 Hz. The ECG board is configured with several external discrete components for the right leg driver and input bandpass filter to increase common-mode rejection. For PPG measurement, a fully integrated multi-LED pulse oximeter sensor was used (MAX30101, Maxim Integrated, San Jose, CA). The PPG sensor is configured to use the built-in green LED (537 nm), and the sampling rate was set to 100 Hz. A 3axis MEMS accelerometer (LIS2DH12, STMicroelectronics, Switzerland) was used to measure activity level. Bandpass filters (0.1–20 Hz.) were used prior to sampling at 25 Hz.

A 32-bit microcontroller (STM32L433, STMicroelectronics, Geneva, Switzerland) was used for synchronous data recording. Recorded data are stored in a micro-SD (secure digital) memory card. The MCU and the micro-SD card are mounted on a 25 × 25 mm PCB. The ECG and PPG AFEs are also mounted on a 25 × 25 mm PCB, allowing the microcontroller PCB to be stacked with the AFE PCB to reduce the overall size of the electronics. The wearable sensor module operates on a 1.8 VDC power supply and a separate 3.3 VDC power supply. The battery could be charged via a micro-USB connector on the board.

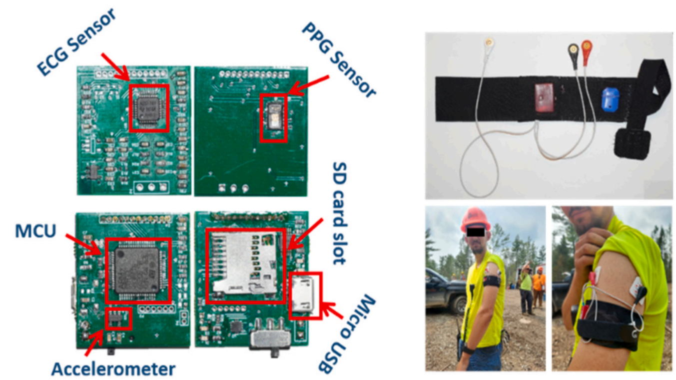


**Fig. 2.** The assembled armband sensor with enclosure and the photograph of the participant (right), front and rear view of AFE and MCU board (left).

It is worth noting that the proposed wearable electronics were designed based on the wearable sensors platform that our group previously developed and used for other studies in a laboratory environment (Hossain et al., 2019), (Heo et al., 2021).

### 2.3. Signal processing methods

Physiological signals collected in field studies include more severe motion artifacts than signals collected in controlled laboratory studies; thus, we performed signal conditioning to remove instances when the signals were corrupted due to motion artifacts. The signals could then be processed to obtain activity levels, the HRV measures, and PTT within 1-min epochs.

**Signal Conditioning.** Visual scans of the time series data were performed to remove sections of data whenever environmental noise or motion artifacts were dominant. Following that, spikes or peaks unrelated to physiological signals were removed using a median filter, and an EMG noise detection algorithm (Sharma et al., 2017) was applied to all data to remove EMG artifacts and extract clean ECG signals (Fig. 3 (a)). Then, fifth-order bandpass filters (2–30 Hz) were applied to remove noise due to DC drift and local muscle activity (Fig. 3(b)). Additionally, a median filter with adaptive windows was utilized to inhibit low-frequency noise, such as baseline drift, and to remove impulse noise

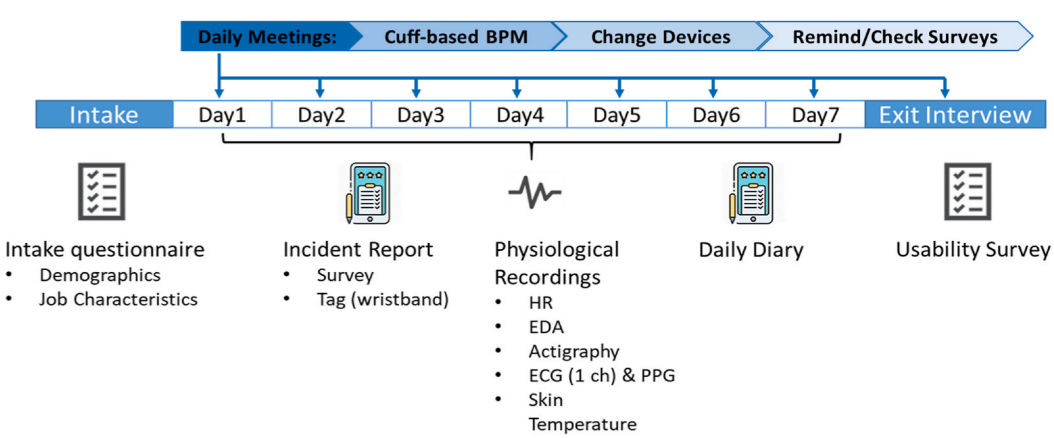


**Fig. 1.** Summary of the study protocol for the Nurse Group study.

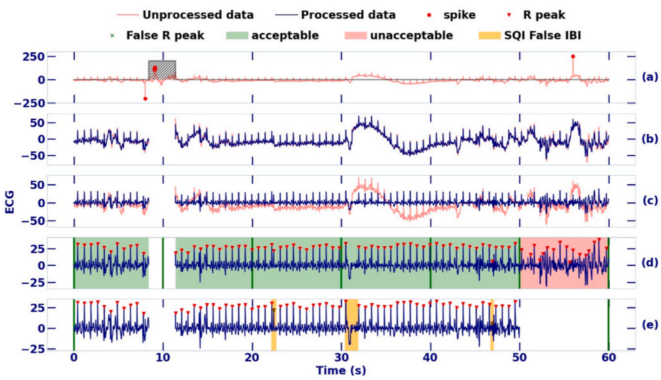


**Fig. 3.** Steps in the denoising of the ECG signal: (a) a median filter removes spikes and detects corrupted parts of data using EMG algorithm; (b) a bandpass filter removes muscular noise; (c) an adaptive median filter suppresses baseline drift; (d) SQI on 10sec windows is applied to remove unqualified segments; and (e) unphysiologic R-R peaks are marked for exclusion in the further analyses.

from the ECG signal while protecting the edge features (Raphisak et al., 2004) (Fig. 3(c)). We used Pan and Tompkins's algorithm (Wang et al., 2010), (Álvarez et al., 2013) to detect R peaks and calculate inter-beat-intervals (IBIs) before windowing. Next, the signal quality index (SQI) (Friesen et al., 1990) was employed to remove unphysiological IBIs (Fig. 3(d)). The data were segmented into 10-s windows and classified as either 'physiologic' or 'unphysiologic' based on the following rules: (1) the HR range for an adult must be between 40 and 180 beats per minute (bpm); (2) confining the maximum acceptable gap between successive R-peaks to 3 s allowing no more than one beat missed detection; and (3) allowing no more than 15 percent change of the IBI in a 10-s segment. If the SQI identifies an IBI segment as' unphysiologic', the IBIs in that segment were removed from further analysis. Lastly, preceding and following R-R peaks with close range or longer IBI (ventricular ectopic) were identified and marked as abnormal and removed (Fig. 3(e)). In order to maintain the length and structural characteristics of the IBI series, spurious IBIs are substituted through cubic spline interpolation of neighboring intervals (Kaufmann et al., 2011).

PPG signal conditioning was similar to what was done for ECG. The PPG signal was first filtered using a sixth-order Butterworth lowpass filter with a 15 Hz cutoff frequency. However, unlike the approach used for ECG data, peak detection was only allowed in a defined time window between two consecutive ECG R-peaks. The adaptive threshold method (Orphanidou, 2018) was then used to detect a PPG systolic peak (Psystolic) within each defined window to represent a peak followed after an ECG R-peak.

Accelerometer signals were filtered using a first-order Butterworth infinite impulse response (IIR) high-pass filter with a cutoff frequency of 0.25 to remove acceleration due to gravity. Then, a fourth-order Butterworth low pass filter with a cutoff frequency of 20 Hz was applied. To reduce dependence on device orientation, the vector magnitude (VM) of the XYZ axis was computed. The variability of vector magnitude with a 60-s window was calculated to classify the activity levels.

**Epoch-based Feature Extraction.** HR, HRV, and PTT were calculated with non-overlapping 1-min windows. Quantified signals with 1-min epochs have exhibited the same discriminatory power as 5-min and 10-min epochs (Shin et al., 2009). The beat-to-beat analysis is sensitive to artifacts and prone to false spikes. However, an epoch-based method has the advantage of being less dependent on the accurate classification of individual beats.

**Heart Rate and Heart Rate Variability.** For RMSSD calculations, successive IBIs in ms is squared within non-overlapping time windows of 60 s and then averaged before obtaining the square root of the sum. For LF/HF ratio, IBIs were analyzed in the frequency domain using a Fourier transform to quantify spectral power (Govindan et al., 2019). Total power in the frequency domain is typically scored separately in two prominent frequency bands: LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz). LF power is proportional to cardiac sympathetic and parasympathetic nerve activity; HF power decreases from baseline during acute stress experiences, and additive stress is reflected by proportional changes. Thus, LF/HF ratio has been widely used as an indicator of stress responses (Heathers, 2014).

**Pulse Transit Time (PTT).** The PTT was calculated from the time delay between the R-wave peak of ECG to the maximum point of the second derivative of the PPG signal ($dt^2\ PPG/dt^2$) during the ascent of the waveform that follows each heartbeat because of an increase in local blood flow. To calculate PTT, we defined a segment window between successive R peaks, then found the peak of the second derivative of the PPG signals within this segment. Calculated PTTs for all heartbeats were averaged over non-overlapping 60-s time windows. BP is a function of PTT for an artery with a known length of L (Gosling and Budge, 2003), (Mahadevan et al., 2021) and can be estimated with the following equation.

$$BP = -\frac{2}{\alpha}\ln(PTT) + \frac{ln\frac{2r\rho L^2}{hE_0}}{\alpha} \quad (1)$$

where $E_0$ is the arterial elastic modulus at zero pressure, ρ is the density of the blood, γ, h, and α are coefficients that must be calibrated by an individual. As seen in this equation, BP cannot be estimated by PTT alone without calibration. However, PTT can be considered a surrogate of BP changes as a decrease in PTT may indicate an increase in BP and vice-versa.

**Total Sleep Time (TST).** We utilized a classification model provided by the python packages SleepPy and biobank accelerometer to detect activity levels based on the accelerometer sensor on the armband (Mahadevan et al., 2021), (Doherty et al., 2017). Cole's function (Cole et al., 1992) determined whether the subject was awake or asleep using preceding, actual, and succeeding time points. This function calculates a moving average, which considers the activity levels four and two epochs before and after the current epoch to label the time point as sleep or awake. Using Cole's function, total sleep time (TST) was calculated as the total duration of 60-s epochs scored as sleep during in-bed sleep intervals. For activity mode recognition, a model based on the random forest is trained to identify four predefined classes of behavior from accelerometer data (Willetts et al., 2018). Two criteria were used for each class: in movement posture, the number of steps in 60-s epochs with 50% overlap (i.e., number of steps of sleep ≅ 0, sedentary <10, low-intensity activity<30, and high-intensity activity>30), and in still posture, the threshold of magnitude vector (i.e., threshold of sleep ≅ 0, sedentary <10%, low-intensity activity<30%, and high-intensity activity>30%).

## 3. Experimental results

### 3.1. Heart rates

The measured signals were processed by the aforementioned signal conditioning and analysis methods to extract HRs, activity levels, and TSTs from the armband data and the E4. We compared the qualities of the measured physiological signals and their relationship with motion artifacts. As expected, ECG signals obtained from the armband were less sensitive to motion artifacts compared to PPG sensors – one is co-located with the ECG sensor on the armband (aPPG), and the other is integrated on E4 (wPPG). Fig. 4 shows the Bland-Altman plots comparing the mean of two measurements against the difference ($Mean_{AB}$) for all 12 participants (in Logger Group and Nurse Group studies combined) and 48 days of the experiment, where performance is separated by activity level and device type.

Limits of agreement (LOA) are determined based on $Mean_{AB}$ and

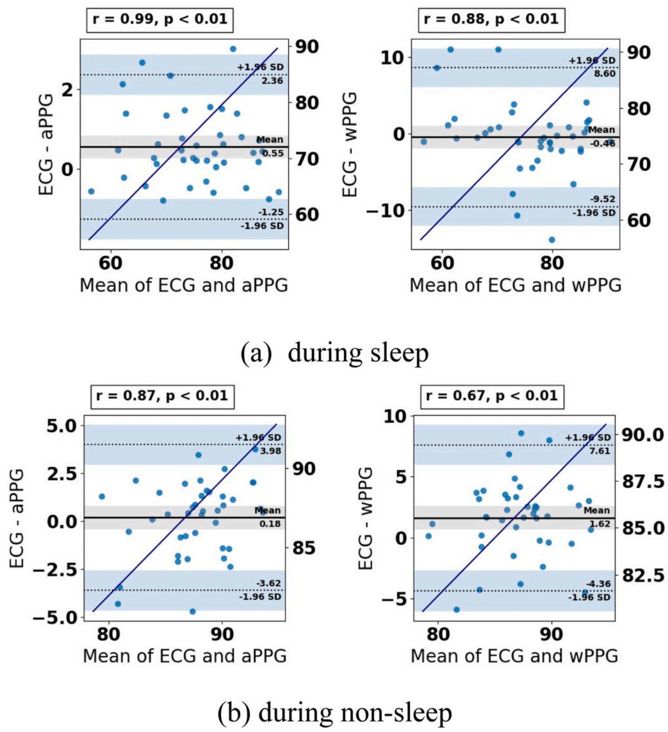


**Fig. 4.** Bland–Altman plots of differences between ECG (reference) and PPG sensors on E4 (wPPG) and the armband (aPPG).

standard deviation of differences ($SD_{AB}$) and settled at [$Mean_{AB} \pm 2SD_{AB}$]. The upper and lower dashed lines in the figure indicate the 95% CI, which is a limit of agreement for the two recording procedures. During sleep (Fig. 4(a)), when we assumed the motion artifacts were negligible, the correlation between ECG and PPG sensors were high (99% and 88% for aPPG and wPPG, respectively), and the most data points were located near the mean for both PPG sensors. During the non-sleep time (Fig. 4(b)), however, the 95% confidence interval and mean value increased, and the correlation with reference decreased with intensified activity level. While the correlation factor between wPPG and ECG decreases to 0.67, aPPG still show high correlation with the ECG (r = 0.87, *p-value* < 0.01). Also, we found that wPPG consistently overestimated HRs during the non-sleep time. As an example, Fig. 5 compares HRs results of the ECG, aPPG, and wPPG sensors obtained from a participant for 24 h. This figure reveals that the HRs obtained from the three sensors are similar to each other during sleep, but HRs measured by wPPG were regularly overestimated compared to the ECG. This is because wPPG signals are more influenced by wrist motion artifacts and ambient noise.

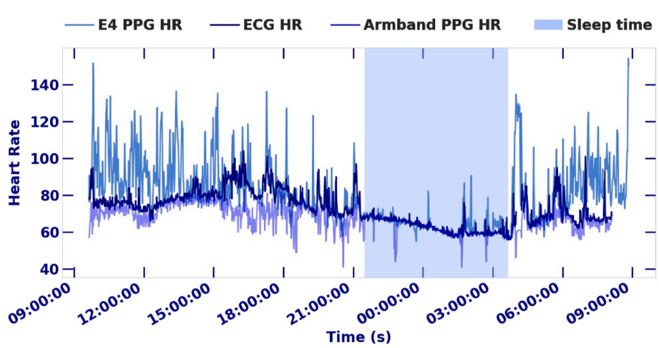


**Fig. 5.** Comparing HR changes during 24-h using three different modalities.

### 3.2. Activity levels

Accelerometer signal on the wrist recorded greater acceleration peaks and motions than the armband accelerometer (aACC). Thus, we relied on the aACC data to score participants' activity levels. Vector magnitudes from aACC were classified into four categories - sleep, sedentary, low-intensity motion, and high-intensity motion based on metabolic equivalents (Lynch et al., 2019).

Analysis of actigraphy data presented in (Fig. 6) shows a mean percentage 28.3 (SD = 4.5), 45.1 (SD = 7.87), and 36.52 (SD = 6.47) of sedentary, 20.47 (SD = 3.83), 25.47 (SD = 3.01), and 28.07 (SD = 6.5) of low-intensity, and 51.2 (SD = 7.57), 29.45 (SD = 5.47), 35.41 (SD = 6.83) of high-intensity for nurses' workday (W), nurses' leisure day (L), and loggers, respectively. Compared to the Logger Group, the Nurse group had 22.51% less sedentary time on average during their workdays (95% CI = −15.54 to −0.9, *p-value* < 0.05) and 27% less low-intensity activity (95% CI = −14.46 to −0.73, *p-value* < 0.05), and 30.84% more high-intensity activity during their shift. Also, nurses had 42.48% less high-intensity activity during their non-work daily routines (95% CI = −30.25 to −13.25, *p-value* < 0.001), while 37.25% and 19.6% were more sedentary and busy with low-intensity activities during their leisure time, respectively (95% CI = 0.56 to 9.43, *p-value* < 0.05). We also observed that, compared to day shift nurses, night-shift nurses were (14.21%) less involved in high-intensity activities (95% CI = 5.82 to 22.6, *p-value* < 0.01) and were more (7.45%) sedentary (*p-value* < 0.05) or (7%) doing low-intensity work. This is mostly because nurses were busier on the day shift but had a more sedentary role on the night shift in our study.

### 3.3. Total sleep time

Total sleep time (TST) was measured using the aACC. The average TST for the Nurse Group was 403 min (SD = 45.4) on a workday and 494.42 min (SD = 105.15) on a leisure day. Also, the average TST for the Logger Group was calculated at 445.83 min (SD = 44.57), which showed a 10.4% longer TST compared to the Nurse Group on a workday. However, there was no statistically significant difference between the two groups (95% CI = −99.74 to 15.7, *p-value* = 0.14).

Interestingly, TSTs during leisure days in the Nurse Group was 22.68% longer than on workdays (95% CI = −227.65 to −19.68, *p-value* < 0.05). A more detailed look revealed that night-shift nurses had more

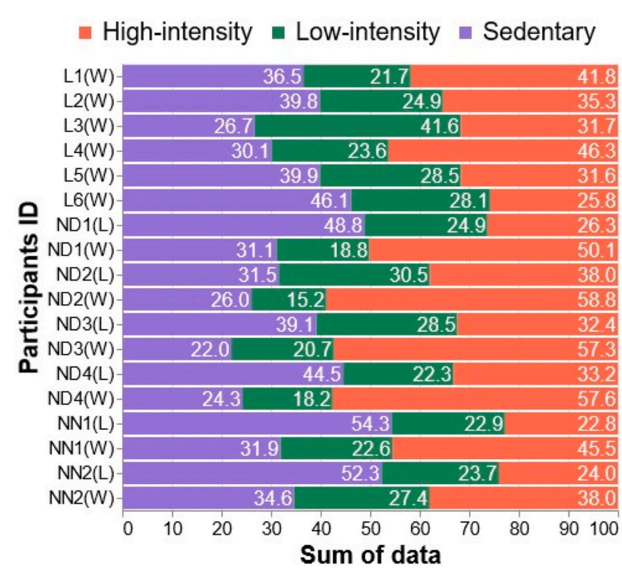


**Fig. 6.** Activity level in percentage for all participants averaged across workdays and leisure days (NDx: Nurse dayshift, NNx: nurse night shift, L: Leisure days, W: workdays, and Lx: Loggers).

sleep (30.5%) on leisure days ($p$-$value < 0.005$) and less sleep (17.76%) on workdays ($p$-$value < 0.02$). Fig. 7 compares TST on self-reported surveys versus analysis of data from the aACC. The average error between the two approaches showed an insignificant ±32.72 min error over all 48 days of data collection ($p$-$value = 1.53$), which is negligible considering memory recall and algorithm error.

### 3.4. Usability of the custom armband

Fig. 8 summarizes the evaluation of the armband useability survey. The vast majority of participants found the armband and E4 easy and comfortable to wear. However, 33% percent of participants reported that the E4 interfered with their work, compared to 17% for the armband. Also, 33% of participants encountered unexpected problems with the E4, while only 17% reported a problem with the armband. The problems reported were: devices turn off unexpectedly, electrode wires break during high-intensity exercise, and skin irritation occurs from electrode use. However, none of the reported problems caused serious usability concerns or prevented device use.

### 3.5. Heart rate variability

We plotted the values of RMSSD of study participants on an age-HRV chart in Fig. 9 to be able to compare this indicator of cardiovascular health to healthy individuals. The blue shaded area in Fig. 9 represents the middle 50% of RMSSDs plotted by age for healthy individuals (WHOOP). This figure shows an age-related change in cardiac autonomic nervous function reflected by a decline in HRV (Porges, 1992), (Zulfiqar et al., 2010). For nurses, we also separately indicated RMSSDs obtained from workdays and non-work days. As shown in the figure, significantly low RMSSDs during workdays were observed from two dayshift nurses, while their RMSSDs during leisure days were within the middle 50% range. There were 17 days when at least one workplace violence incident was reported during a shift, but even on days without a reported incident, average HRV on these 10 days was below the healthy range, implying carryover effects of stress that was overwhelming. In regard to the Logger Group, it is also worth noting that four loggers aged 18 to 31 have low RMSSDs compared to healthy individuals of their age, while the RMSSDs of older participants (age of 58 and 67) are within the normal range of healthy individuals at the same age. This suggests that the cardiovascular health of the younger loggers may be at high risk due to the low activity levels in this work, something that would be compounded by poor eating habits that are known to be common in this population of workers (Arza et al., 2019).

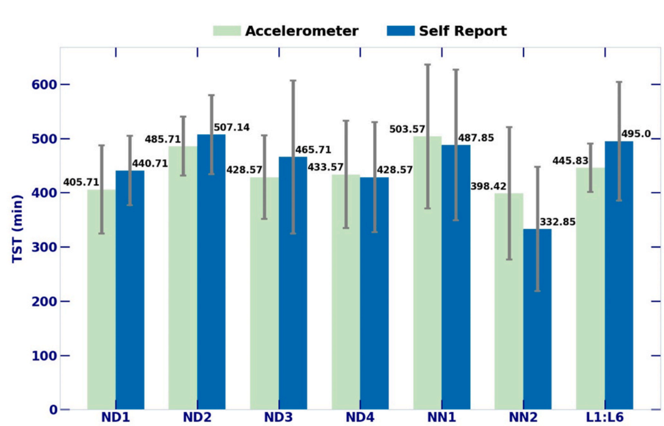


**Fig. 7.** Comparison of self-reported TSTs with measured TSTs using aACC. TST for the Nurse Group was averaged over 7 days for each participant and for the Logger Group was averaged over all participants.

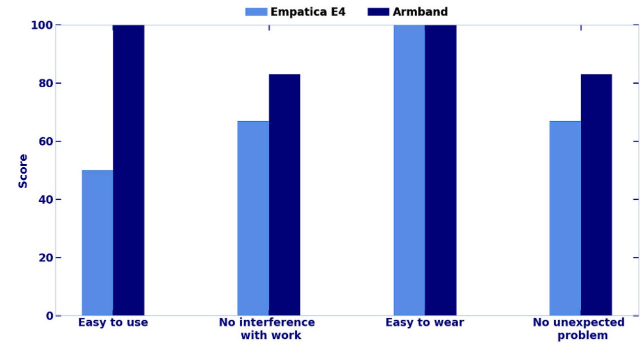


**Fig. 8.** Usability survey results.

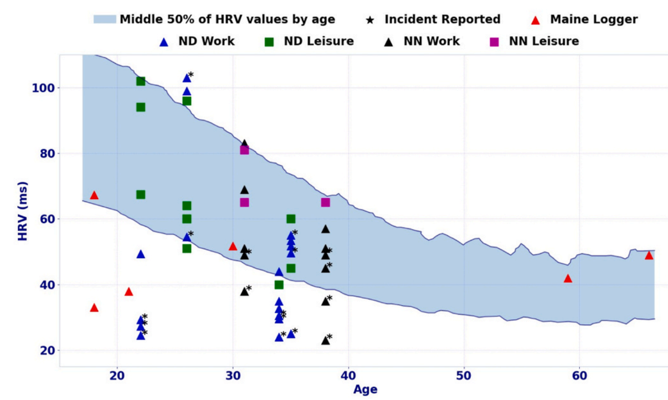


**Fig. 9.** Relationship between age, HRV, and incident in the study populations.

### 3.6. Physiological responses to workplace stressors

ICU nurses reported a total of 22 violent incidents during this study. Incident reports were excluded from analysis if the time of the incident reported in an incident survey differed by more than 30 min from the time that the E4 event button was pushed by the participant to log the event. The characteristics of reported incidents are summarized in Table 1.

To examine physiological changes linked to these incidents, PTT and LF/HF ratios were extracted from the recorded ECG and PPG signals using non-overlapping 60-s time windows, and their changes were observed during work hours. Among 22 incidents, four are discarded from physiological signal analysis due to the severe motion artifacts and reported time mismatches. Fig. 10 shows the PTT and LF/HF ratio along with activity levels of a participant in the Nurse Group on day one as an example. The baseline values were calculated by averaging over the entire work shift (solid horizontal red line). The vertical dashed line indicates the time of the incident based on when the participant pushed the E4 event button. Since we asked participants to report incidents at their earliest convenience, considering the busy nature of work in the ICU (consistent with the high activity levels throughout all work hours, as shown in Fig. 10), it cannot be known precisely when incidents occurred based on participants' use of the E4 event button. As shown in Fig. 10, PTT begins to decrease approximately 80 min prior to the button push, reflecting increasing BP, and the LF/HF ratio begins to increase

**Table 1**
Summary of self-reported incident using survey.

| Participants | ND1 | ND2 | ND3 | ND4 | NN1 | NN2 |
|---|---|---|---|---|---|---|
| Stress Scale | 1 2 3 | 1 2 3 | 1 2 3 | 1 2 3 | 1 2 3 | 1 2 3 |
| Number of Incidents | 2 4 0 | 0 2 0 | 0 2 0 | 0 6 1 | 0 1 1 | 0 3 0 |

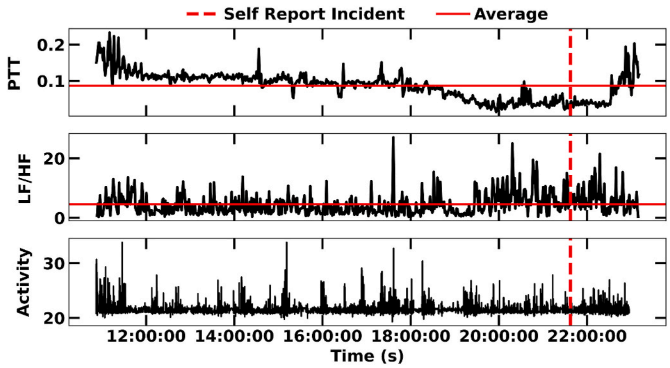


**Fig. 10.** 12-hour changes in PTT, LF/HF ratio and activity levels of a participants in the Nurse Group during work shift.

around 90 min prior to the button push. Based on this timing information, our study scored physiological signal changes 60 min before and after E4 button pushes in order to examine the acute physiological changes linked to incidents of workplace violence. In particular, physical activities are associated with physiological changes. Hence, we conjecture that increased HRV and decreased PTT along with low activity level would be a better indicator of high stress levels. For this purpose, it is required that we combine HRV and PTT data with activity and motion level for stress monitoring (Wu et al., 2015).

Figs. 11 and 12 show the averaged changes in LF/HF ratio and PTT, respectively, for 60 min before and after the reported time of the incidents (2 h in total) for all participants in the Nurse Group. Each point represents a 5min average of LF/HF and PTT. The percentage change from baseline was utilized to plot each point. Time zero was set to the incident time of E4 button pushes. Each line of a different color represents a different incident. For example, as NN2 reported 3 incidents shown in Table 1, three lines of different colors are plotted for NN2.

Comparing the two plots, we can detect consistent abrupt decreases and increases in PTT and the LF/HF ratio, respectively, associated with incidents. This pattern was identified in all cases, showing a slight delay in the PTT response. For PTT, these abrupt changes caused the value to drop below the work shift baseline reference in 11 events; 6 incidents were already below baseline before the report; in 1 case PTT dropped but remained above baseline. In contrast, the LF/HF ratio for 7 cases increased above the baseline; 9 cases were already above baseline before the incident; the remaining 2 cases were below the baseline and later increased but did not return to the baseline.

Although LF/HF ratio and PTT variations were in agreement, it was not possible to determine this pattern by relying only on HRV analysis.

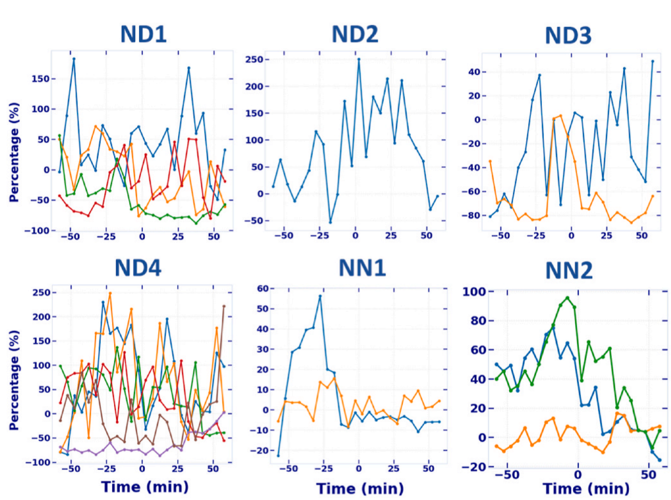


**Fig. 11.** LF/HF ratio fluctuations during the occurrence of stress.

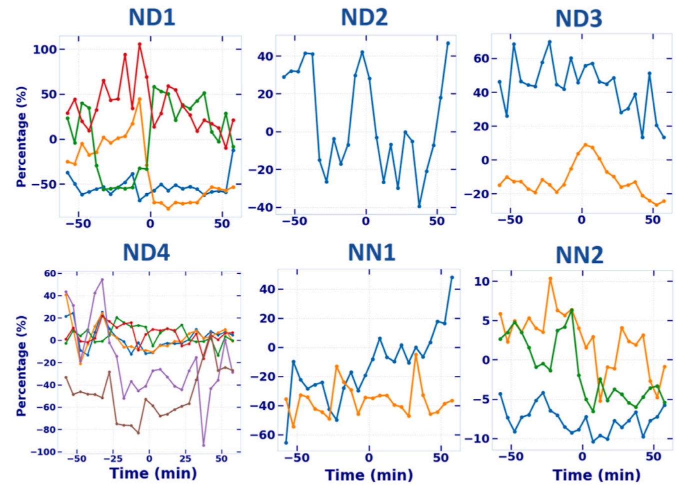


**Fig. 12.** PTT fluctuations during the occurrence of stress.

Further analysis showed LF/HF ratio increased slightly in 8 cases and for less than 20 percent before a decline, which was very similar to non-stress segments of the data. On the other hand, in most cases (8 cases), PTT showed dramatic changes of more than a 20 percent decrease, and the pattern stayed longer, less similar to other times of the workday (non-stress time).

Although the participant was asked to log the time of each incident in two ways, through use of the E4 push button and by recording the incident time in the incident survey, the exact time of incidents cannot be determined from these data. Participants may have delayed using the push button until the incident was under control, it is possible that a series of incidents occurred together and these escalated after a button push, and the self-reported time of the incident logged in the incident survey was always subject to recall error. Therefore in order to better characterize changes in PTT and the LF/HF ratio in response to the incidents, we estimated stress occurrence time (SOT) based on the patterns of PTTs and the LF/HF ratios themselves. Fig. 13 shows the averaged PTTs and LF/HF ratios aligned by estimated SOT for all incidents. The vertical line at zero shows the estimated SOT. We averaged signals across all incidents after aligning PTT and LF/HF ratios based on sudden changes and distinctive patterns that occurred in the vicinity of when

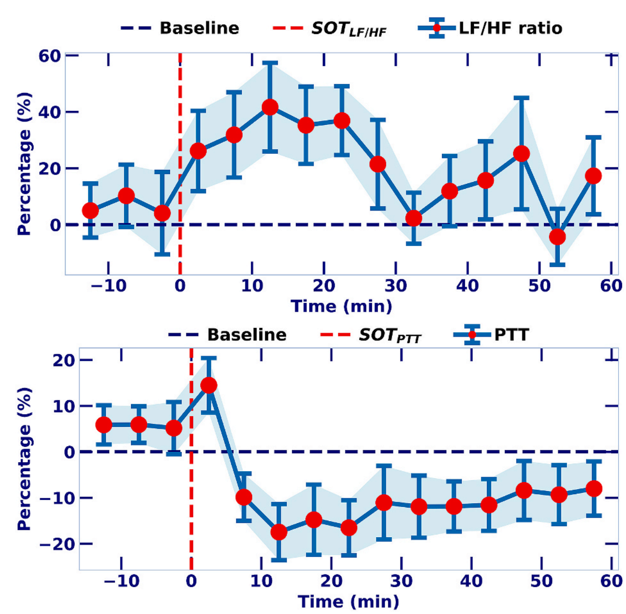


**Fig. 13.** Averaged changes in LF/HF ratio (top) and PTT (bottom).

the E4 push button was activated by the participant. Based on an examination of estimated SOT, in most cases the results showed that the LF/HF ratio was above baseline before and after the occurrence of incidents, as mentioned in the previous section. The LF/HF ratio steadily grows until it asymptotes, and then declines and reaches a local baseline in less than 30 min. There was a 49.57 percent difference between the maximum and minimum points, with an increase of 27.7% in the first 10 min following the estimated SOT.

We also observed a second peak followed by the first one with less amplitude that could be related to work activity after the incident. Fig. 13 shows that the averaged PTT peak was delayed about 5 min compared to the beginning point of LF/HF ratio increase. The PTT value for most cases was above baseline before the incident happened, and then it rapidly dropped from its starting value in less than 10 min and showed signs of sluggishly recovering after 60 min but still had not fully returned to its starting level. There was a 31.94 percent difference between the maximum and minimum points during the incident, which happened during the first 10 min of the incident. Comparing error bars on the two averaged plots also revealed that LF/HF ratio was quite variable among subjects during recovery from incidents. In contrast, PTT exhibited more generic patterns with consistent changes in relation to incidents across subjects.

## 4. Discussion

This study introduced and evaluated the use of a wearable device to examine physiological changes in HRVs and PTT throughout work and non-work days in two different workforces, nurses and loggers. This approach provides continuous, non-invasive, objective and long-term monitoring capabilities as an alternative to cumbersome subjective self-reports at workplaces that might be biased by organizational issues, memory recall, and workers normalizing stressful events. In the Nurse Group, participants were able to record incidents of workplace violence using a wearable wristband and a smartphone app, which made it possible to analyze acute physiological changes linked to these incidents.

Our present work can be distinguished from related work in the field in several important ways. Although recent advances in wearable sensors and mobile technologies have supported continuous and non-invasive monitoring of physiological changes with a number of biomarkers, researchers in occupational physiology have not used wearable devices to collect measures of CBP along with heart rate, HRV, and skin/core temperature (Ioannou et al., 2021a), (Ioannou et al., 2021b), (Jacobs et al., 2019). Although BP is one of the established measures in the field of occupational health used to assess a worker's health status, the previous studies depended on intermittent measurements which are limited in their ability to reflect physiological stress responses and patterns of recovery linked to specific events in the workplace, such as instances of workplace violence (Juster et al., 2012). Furthermore, to our best knowledge, the continuous and non-invasive monitoring of multiple physiological signals including PTT, a biomarker of BP, both at work and outside of work on a 24-h basis for seven days is a first in the field of ergonomics and human factors studies.

Although the assessment of cardiovascular health based on BP is beyond the scope of this study, the CBP monitoring over 24-h periods is another advance in this study. While mean BPs are important, there are two additional components - diurnal and day long variations that are more essential, but difficult to assess (Steptoe and Kivimäki, 2012). To further elucidate, the type of CBP monitoring used in this study has important differences from traditional oscillometric ABPM by reducing sporadic measurement and the problem of dissociation of BP and the heart beat sequence (Kadish et al., 2004).

The main new finding of the present study is that PTT shows promise as a reliable biomarker of acute stress response and stress recovery in field studies. Incidents of workplace violence were shown to induce acute cardiovascular changes, including BP increases as indicated by changes in PTT as well as changes in the LF/HF ratio of HRV. However, changes in the LF/HF ratio of HRV due to changes in vagal tone are a more nuanced indicator. The complex and nonlinear nature of sympathetic and parasympathetic nervous activity is confounded by many factors, such as ventilatory activity, mean HR, and behavioral activity, making it difficult to pin down the physiological basis for LF/HF ratio changes with any degree of specificity. Although PTT changes were marginally larger (5 percent more) than HRV in the first 10 min from the incident, the response pattern of PTT was more distinctive in relation to its baseline versus periods without reported stressful incidents. What all this means is that it was not possible to isolate stress episodes exclusively by analyzing changes in the LF/HF ratio. Moreover, HRV recovered rather quickly whereas BP changes indicated by changes in PTT recovered gradually. We think that HRV recovery mainly coincided with vagal tone restoration (Graham et al., 2022), while PTT is regulated more peripherally and affected by local conditions in the working muscles, something that would explain why recovery to a baseline state would occur more slowly following incidents (Flouris et al., 2014).

Most incidents (82%) in the present study were reported as a stress intensity of 2 based on the self-report stress scale (0–3). Only 9.1% of the 3-intensity stress incidents are reported. Recent studies (Arza et al., 2019), (Hjortskov et al., 2004) demonstrated that PTT has a high correlation with stress scales and can be used in the quantitative assessment of stress up to five levels in a laboratory environment. Thus, assessing physiological responses to the level of stress in workplace settings still remains a challenge.

We have shown that the usability of the armband sensor was acceptable in both populations of workers inside and outside of the workplace, demonstrating high potential for use in future field studies that adopt a more holistic approach to the study of occupational health and wellness, consistent with the current Total Worker Health® initiative in the USA led by the National Institute for Occupational Safety and Health (NIOSH) (Punnett et al., 2009). In particular, the armband sensor was found to be more reliable than the wristband in both work settings. This can be explained by the form factor of the armband electronics, which were enclosed in a lightweight 3D-printed enclosure that kept the PPG and ECG sensors firmly in place and that was covered by thick fabric so as not to impose undue pressure on the brachial artery. Conversely, wrist-worn PPG was found to be adversely affected by frequent changes in sensor position due to intensive hand motions and also due to periodic exposure to intense ambient light, especially in outdoor workers. It is also worth discussing the usability of the wearable armband sensor system because it was designed for non-invasive use alongside daily activities over seven consecutive days. The usability survey confirmed the acceptability and convenience of using this technology both in and outside of the workplace, both by naïve users (loggers) and medical professionals (nurses).

There are several limitations in the presented work. First, in addition to physical activity, stress can be confounded by pharmacological factors such as caffeine, smoking, drugs, and prescribed medicines. Second, environmental factors including ambient temperature, background sound level, and code blue emergency events in ICU, must be considered as these factors affect individuals' baseline levels. Third, our study also relied on self-reported incidents that were subject to recall bias and lacked time specificity. An objective assessment of the timing and nature of acute stressors would improve upon our current methods. Fourth, another limitation is that BP changes estimated by changes in PTT were not calibrated for each person using a clinical BP device. Lastly, our wearable armband device needs to be evaluated in other occupational settings, different health conditions and a larger population group to optimize its form factor usability in the workplace. We should point out that neither of the two study populations was segmented or dichotomized. Their work in uniform and controlled environments obviates a range of environmental exposures that would characterize a more diverse workforce. Similarly, while there would be considerable interest in a larger future study that incorporates and segments concurrent morbidities, we could not incorporate a range of predictive variables given the small samples and the open inclusion.

## 5. Conclusion

This study proposed the use of a multimodal wearable armband for continuous non-invasive monitoring of physiological states both at the workplace and outside the workplace. Studies with two worker populations featuring 24 h/day demonstrated the feasibility and reliability of using a wearable armband with multiple features that included continuous monitoring of participants' physiological signals including HRs, HRVs, TST, activity levels, and PTT without interfering with their personal or work life. In addition, the study results show that the armband was more accepted by all worker participants than an E4 wristband. Given the diversity of tasks and personal movements, the high signal quality was particularly notable.

PTT was found to reflect a relatively longer period of recovery following incidents of workplace violence than variations in the LF/HF ratio of HRV. Moreover, in contrast to previous laboratory studies, we found variations between LF and HF measures were not reciprocal as has been reported previously. This study findings will be of interest not only to organizational and occupational health researchers, but also health and safety professionals.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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