Quantifying Occupational Stress in Intensive Care Unit Nurses: An Applied Naturalistic Study of Correlations Among Stress, Heart Rate, Electrodermal Activity, and Skin Temperature

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Objective: To identify physiological correlates to stress in intensive care unit nurses.

Background: Most research on stress correlates are done in laboratory environments; naturalistic investigation of stress remains a general gap.

Method: Electrodermal activity, heart rate, and skin temperatures were recorded continuously for 12 -hr nursing shifts (23 participants) using a wrist-worn wearable technology (Empatica E4).

Results: Positive correlations included stress and heart rate ($\rho = .35$, $p < .001$), stress and skin temperature ($\rho = .49$, $p < .05$), and heart rate and skin temperatures ($\rho = .54$, $p = .0008$).

Discussion: The presence and direction of some correlations found in this study differ from those anticipated from prior literature, illustrating the importance of complementing laboratory research with naturalistic studies. Further work is warranted to recognize nursing activities associated with a high level of stress and the underlying reasons associated with changes in physiological responses.

Application: Heart rate and skin temperature may be used for real-time detection of stress, but more work is needed to validate such surrogate measures.

Keywords: critical care, job stress, physiological measurement, nursing and nursing systems, naturalistic study

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INTRODUCTION

Intensive care unit (ICU) personnel including physicians, respiratory therapists, pharmacists, and case managers (Mealer et al., 2012; Pastores et al., 2019), and particularly nurses (Donchin & Seagull, 2002), experience high levels of stress. Fundamental aspects of nursing care in critical care environments include initiating and facilitating ongoing dialog with clinicians and family members related to life support interventions, palliative care, and end-of-life discussions. Furthermore, ICU nurses repeatedly carry responsibility for rapid intervention for severe physiologic deterioration events, cardiopulmonary resuscitation events, and interactions with families and others in high-stress situations (Mealer et al., 2012). Cumulative exposure to acute stress may lead to psychological distress and burnout syndrome—a state of fatigue, frustration, and diminished interest (Embriaco et al., 2007; Mealer et al., 2017). In nursing, burnout is associated with an increase in absenteeism and turnover rates (Aiken et al., 2002; Scanlan & Still, 2019; Van der Heijden et al., 2019; Wang et al., 2020). Turnover alone is costing the U.S. economy an estimated $2.1 million each year (Heinrich, 2001).

Traditionally, occupational stress has been measured using self-reported instruments (Augusto Landa et al., 2008; Farquharson et al., 2012; Rodriguez-Paras et al., 2018; Sveinsdóttir et al., 2006). However, self-reported instruments suffer from subjects' biases, retrospective memory retrieval, and study administrators' influence on responses (Johnston et al., 2016). To address these drawbacks, direct measurements of physiological responses such as heart rate (HR; or pulse rate [PR] when measured using photoplethysmography [PPG]), heart rate variability (HRV), electrodermal activity (EDA), skin temperature (ST), cortisol levels, blood pressure, and pupil diameter data have been investigated for assessment of stress (Greene et al., 2016) and other related constructs such as workload and arousal (Hancock & Matthews, 2019; Matthews et al., 2015). The recent evolution and availability of HR, EDA, and ST sensor technology has enabled continuous collection of physiological responses in real-world settings and has empowered naturalistic research (Healey & Picard, 2005; Jenks et al., 2020; Mehler et al., 2012; Rodrigues et al., 2015; Schneegass et al., 2013). While naturalistic studies of stress using wearable sensors (e.g., Chen et al., 2014; Giakoumis et al., 2012; Giannakakis et al., 2017; Gjoreski et al., 2017; McDuff et al., 2014) have shown promise in complementing participant self-report and simulated laboratory-based measurement, the correlations between several psycho-physiological responses used to assess stress have not been documented in unconstrained and naturalistic environments. Understanding correlations between stress and physiological responses in a complex dynamic work environment such as an ICU with long shift durations, as well as fluctuations in time pressure, workload, and emotional strain is necessary to assess convergence with the published evidence of such correlations, which are mostly drawn from lab studies. This knowledge is necessary and will have implications for the design and development of effective stress monitoring technologies.

Our objective is to compare and contrast correlations between EDA, HR (estimated using PPG), and ST responses with stress between a naturalistic study of ICU nurses and the lab-derived correlations. We first provide a review of documented correlations (the following subsection) before evaluating such correlations in our own exploratory study (remaining sections).

Physiological Responses to Stress

Most HR and skin-based physiological measures are controlled through the activation of sympathetic nervous system (SNS) and/or the parasympathetic nervous system (PNS), which make up the autonomic nervous system (ANS). SNS activates in stressful situations to prepare the body for fight-or-flight responses, and the PNS triggers to restore body homeostasis via relaxation responses (Andreassi, 2013).

Electrodermal activity and stress. EDA is a measure of the subject's electrical skin conductance (Greene et al., 2016) and is solely controlled by the SNS (Boucsein, 2012; Cacioppo et al., 2007). Skin conductivity is influenced by surface sweat and sweat glands triggered by stress as well as positive and negative emotions (Kreibig, 2010). Time series of skin conductance has two main features: tonic and phasic responses. Tonic response, or skin conductance level (SCL), is the overall long-term trend of the electrodermal time series, and phasic, skin conductance responses (SCRs), are the acute spikes in the SCL (Benedek & Kaernbach, 2010). In addition to SCR amplitude, other well-known temporal features of SCR are latency and rise and recovery time (Dawson et al., 2017). An SCR is called a specific response once it is triggered by a stimulus. A nonspecific response, conversely, is spontaneous (Benedek & Kaernbach, 2010).

Electrodermal activities, as a prime indicator of stress and mental workload, have been measured in different domains such as healthcare (Ritz et al., 2000), transportation (Mehler et al., 2012; Ruscio et al., 2017; Schneegass et al., 2013), psychology (Blechert et al., 2006; Nomikos et al., 1968), and engineering (Acerbi et al., 2017). Most of the previous research establishes that phasic EDA increases significantly in a stressful or demanding situation (Giannakakis et al., 2019). Schneegass et al. (2013) collected subjective and objective data from drivers to assess the potential of physiological responses to detect automotive drivers' workload in different road types (e.g., freeway and highway), finding that SCR and ST were sensitive to different road types. Ruscio et al. (2017) studied the drivers' mental workload in normal driving versus assisted-driving tasks and associated the elevated SCR of assisted-driving tasks with the higher mental workload of drivers. Hernandez et al. (2011) trained a machine learning model on SCR data collected from a call center's employees and predicted stressful calls with an accuracy of 73.4%.

Heart rate and stress. Unlike EDA, HR is controlled by either SNS, PNS, or both (Berntson et al., 1994). In an acute crisis, HR increases and the pattern of blood distribution changes (Schneiderman et al., 2005). When the stressful situation is alleviated, PNS triggers to slow down the HR (Choi & Gutierrez-Osuna, 2009; Greene et al., 2016) and restores the body to normal condition. de Looff et al. (2018) reviewed 38 articles related to occupational stress and reported a positive correlation between HR and stress; however, it was recommended that results across studies be compared with caution, as both HR (Bexton et al., 1986) and EDA (Hot et al., 1999, 2005) display diurnal variation. A recent study on emergency medicine residents' HR data using wearable technology revealed that most participants experienced at least one episode of very high level of stress in their shifts, which was associated with maximum HR data (Jenks et al., 2020). HR has also been studied in the context of low arousal (Borghini et al., 2014). For example, a study of prolonged night driving has shown the HR decline due to fatigue and drowsiness (Riemersma et al., 1977).

Electrodermal activity, heart rate, and stress. Early stress studies were conducted to assess the effect of stress on individuals using a combination of EDA and HR (Boucsein, 2012; Folkins, 1970; Gatchel et al., 1977; Niemelä, 1975; Nomikos et al., 1968). In addition to stress, heightened EDA and HR have been used as indices for mental workload (Hart & Hauser, 1987; Ruscio et al., 2017; Schneegass et al., 2013); arousal (Boucsein, 2012); and anxiety, anger, and fear (Kreibig, 2010). One study (Nomikos et al., 1968) investigated the effect of the anticipatory stress on the viewer of scenes of industrial accidents and noticed that SCL increased significantly but not HR. Folkins (1970) studied the responses of individuals who received electric shocks delivered in different time intervals from 5 s to 20 min; the SCL and HR were increased significantly in time intervals up to 1 min.

Recent studies (Acerbi et al., 2017; Hernandez et al., 2011; Mehler et al., 2012; Ruscio et al., 2017; Schneegass et al., 2013) were particularly interested in evaluating the potential of monitoring stress using physiological responses. Acerbi et al. (2017) analyzed physiological responses collected by wearable technology and self-reported instruments to detect stress status in a laboratory experiment. The developed classifier was able to identify stress status; elevated levels of HR and SCR were reported in the stress period. Mehler et al. (2012) assessed the potential of physiological responses to develop workload detection systems for drivers. HR and SCL were collected in a naturalistic driving experiment with (imposed by secondary verbal tasks) and without mental workload. Both HR and SCL were indicative of different levels of mental workload. In healthcare, Ritz et al. (2000) examined a claim that stress and emotion cause respiratory resistance in asthmatic patients. Emotions and stress were induced by watching short video clips and stress tasks. Changes in HR and SCL caused by the stress-induced task were consistent with previous research.

Skin temperature and stress. Body temperature, as a coping mechanism, fluctuates in response to stress (Kleitman & Jackson, 1950; Marazziti et al., 1992; Vinkers et al., 2010, 2013) and anxiety (McFarland, 1985). When SNS activates, blood distribution in the body changes such that venous blood flow is reduced, and arterial blood flow is increased to support fight-or-flight responses. These blood flow changes raise the core temperature—a phenomenon referred to as stress hyperthermia (Marks et al., 2009). However, this reallocation of arterial blood flow to stress response organs is balanced with a corresponding restrictions of arterial blood flow in the extremities including the wrists and hands—a phenomenon referred to as peripheral vasoconstriction (Herborn et al., 2015). The decrease in blood flow in wrists and hands results in cooling of skin, a change that can be detected using peripheral electrodermal wrist sensors (Gjoreski et al., 2017).

ST in the wrist and hand has been evaluated to assess changes due to stress. In a relaxation instruction and a therapy procedure to treat headache, an increase in finger temperature in the relaxation period and decrease in the stress period was observed (Boudewyns, 1976). Lin et al. (2011) studied the effect of stress and depression on physiological responses and reported lower finger temperature in depressed individuals. One study reported a nonsignificant reduction in fingertip ST in female undergraduates when they watched fearful movie scenes and performed cognitive tasks (Rimm-Kaufman & Kagan, 1996). Vinkers et al. (2013) investigated the effect of stress on different regions of ST in a laboratory experiment in which participants were given a stressful task or nonstressful control. They found significant reduction in temperature at the fingertip, finger base, and hand palm, and nonsignificant reduction at the wrist during stressful tasks. Engert et al. (2014) investigated the application of thermal infrared imaging in stress detection using a standardized stress test. A decrement in temperature was noted at forehead, finger, and chin.

METHODS

A naturalistic study of ICU nurses was conducted to evaluate correlations between stress and its previously known correlates: HR, EDA, and ST.

Participants

A total of 28 participants were recruited, via email or during morning rounds, from Registered Nurses working in a 40-bed Cardiovascular ICU (CVICU) of a 900-bed tertiary care facility in the Southwestern United States. All CVICU nurses were eligible for inclusion in the study except those who wore eyeglasses, due to a study component involving eye-tracking equipment (to be detailed in a later report) conducted in parallel with the work reported here. Due to data loss associated with broken EDA and ST sensors, physiological data of 23 participants were analyzed. The majority of CVICU nurses were female (78.3%), and the average age of nurses was 35.5 (±8.5) years (Table 1).

Tools

The Empatica E4 (Empatica Inc., Cambridge, MA; Garbarino et al., 2014), a lightweight and unobtrusive watch-like technology, was used to log physiological data including HR estimation, EDA, and ST (measured from dorsal wrist) continuously. The battery life of Empatica E4 (more than 36 hr in the recording mode) as well as the wrist-watch form (with no display) makes Empatica a suitable apparatus for continuous measurement of bio-signals in nursing work environments. The E4 device has been used in various published work, and its HR and EDA sensors have been validated for accuracy (Ollander et al., 2016; Schuurmans et al., 2020; van Lier et al., 2020). For each physiological response, this device generated time-series data in the .csv format. The HR, EDA, and ST were sampled at 1, 4, and 4 Hz, respectively.

Design

This was a prospective naturalistic study in which physiological measures were collected during the entire 12 -hr shift of CVICU nurse participants. Data collection was part of a broader research project that collected eye-tracking data (ETD) as well as two additional shifts for longitudinal analysis. However, this paper only documents the data from the first shift for present purposes of correlational analysis. All aspects of this study were approved by the Houston Methodist IRB (Pro00019025), and participants provided written informed consent.

Procedures

The research team met with participants before the start of working shifts to explain the study objectives, procedures, and apparatus, and to collect informed consent. Following device training on the Empatica E4, participants placed the device on the wrist of the self-reported non-dominant hand. Data collection began at the start of each shift. A member of the research team was present in the central nursing station during the entire shift to address any potential issues. At the end of the 12 -h shift, the research team met the nurses at the nursing station, collected the recording device, and downloaded the data.

TABLE 1: Demographic Information of Cardiovascular Intensive Care Unit Nurses

Demographic Information	*N* (%)	National Average* *N* (%)
Sex		
Male	5 (21.7%)	1,148 (15.9%)
Female	18 (78.3%)	6,071 (84.4%)
Race/Ethnicity		
American Indian or Alaska Native	1(4.3%)	21 (0.3%)
Asian	5 (21.7%)	742 (10.3%)
Black	1 (4.3%)	400 (5.6%)
Native Hawaiian or Other Pacific Islander	3 (13.0%)	43 (0.6%)
White (non-Hispanic)		
Hispanic or Latino	1 (4.3%)	457 (6.6%)
Marital Status		
Single, Never Married	7 (30.4%)	*n*/a
Married or Domestic Partnership	15 (65.2%)	*n*/a
Widowed	0 (0.0%)	*n*/a
Divorced	1 (4.3%)	*n*/a
Separated	0 (0.0%)	*n*/a
Age, years (mean ± Std. Dev.)	35.5 ± 8.5	44
ICU experience (mean ± Std. Dev.)	8.4 ± 6.7	*n*/a

Note. *Acute Care/Critical Care and Emergency/Trauma (National Nursing Workforce Study, personal communication, August 10, 2020)

Data Analysis

Artifacts were removed from the collected data at four different phases. First, we defined cut-off values for each physiological response. The HR data over 200 bpm, ST more than 44 ° Celsius, and SCR amplitude greater than 10 micro-Siemens (μS) were removed from the dataset. Second, Empatica E4 calculated and output HR and the inter-beat interval (IBI) from blood volume pulse (BVP) signals (captured by PPG sensor) and employed an algorithm to remove the incorrect peaks due to noise in the BVP signal (Empatica, 2020). Third, a visual inspection of IBI time series data was conducted based on recommendations provided by Empatica (2020). Finally, to derive stress index (SI) from IBI signal, the Kubios V3.3.1 was employed for two reasons: first, to apply an artifact correction algorithm (Tarvainen et al., 2009) on IBI time-series as a measure to deal with missing data; and second, to measure the SI (Tarvainen et al., 2009). Since the sampling rates (4 Hz) of EDA and ST were different from the number of derived HR per second (1 Hz), physiological data were synchronized using a Python script and stored in a database for further analysis.

The SI characterizes the activity of the sympathetic part of an autonomic nervous system based on HRV; this measure was calculated for each 1 -min interval using Kubios, which is equal to the square root of Baevsky's SI (conventional unit), which utilizes the distribution of IBI as:

$$\frac{AMo}{(2Mo)\times(MxDMn)} \tag{1}$$

where Mo and AMo, respectively, are mode and amplitude of the most frequent of the IBI, and MxDMn is the range of IBI values that is indicative of variability of IBI (Baevsky & Berseneva, 2009). Baevsky's SI between 50 and

150 c.u. is considered normal; the square root of this range was used to define the intensity of sympathetic cardiac activation—stress zone; SI ≤ 12.2 c.u. represents reduced activation or normal stress zone, and SI > 12.2 c.u. indicates high activation or high-stress zone. SI—which was measured based on HRV parameters—and HR reflect activation of SNS and sympathetic arousal is expected to result in both increased mean HR and high SI. However, this positive correlation has not been documented in a naturalistic environment.

Raw EDA data were processed and analyzed using LEDALAB V3.4.9 (Benedek & Kaernbach, 2010; Ledalab, n.d.). The continuous decomposition analysis approach was used to extract phasic responses and their amplitude; the amplitude threshold was set 0.1 μS. Next, averages per minute of SCR amplitude, HR, and ST were computed.

Statistical analyses were performed using R V3.6.3 (R foundation, Project for statistical computation and graphics). Continuous variables are presented as means and standard deviations. Histograms were plotted to understand the distribution of the continuous variables, and Shapiro-Wilk and Anderson Darling tests were used to determine the normality of the variables. Repeated measurement correlation by using the "rmcorr" package in R was used to establish the correlation between normally distributed physiological parameters (Bakdash & Marusich, 2017). Spearman correlation was used to establish correlation for nonnormalized physiological parameters. We report the correlation coefficient (ρ), *p* value (*p*), and 95% confidence intervals (CIs) of the physiological measures. Associations between normal and high stress were examined using bivariable and multivariable logistic regression models with generalized estimating equation (GEE) accounting for repeated measurements. Multivariable logistic regression included variables that were statistically significant in the bivariable logistic regressions. The statistical models were adjusted for age, marital status, and ICU work experience of participants. A sided α of 0.05 was used to determine statistical significance. We report odds ratio (OR) and 95% CI.

RESULTS

In addition to the expected positive correlation between the SI and HR (ρ = .35; 95% CI [0.34, 0.36]; $p < .001$), our results showed a significant positive correlation between SI with ST (ρ = .49, $p < .05$), and HR with ST (ρ = .54, $p < .05$). However, phasic EDA (SCR amplitude) was not correlated with SI, HR, or ST. Figure 1 illustrates the resulting correlations between various parameters.

Multiple logistic regression models after adjusting for demographics, marital status, number of children, and years of nursing experience in the ICU, showed that the ratio of the probability of experiencing high stress to the probability of not experiencing high stress is 1.10 times higher with an increase of one unit in HR (OR = 1.10; 95% CI [1.08, 1.11]; $p < .001$; degrees of freedom [DF] = 12274). Additionally, with every one-unit increase in ST, the ratio of the probability of being in a high-stress zone to the probability of not being in that zone are 1.20 times higher (OR = 1.20; 95% CI [1.09, 1.31] ; $p < .001$; DF = 14784). However, we did not find any significant association between phasic EDA (OR = 1.05; 95% CI [0.90 – 1.23]; $p = .53$; DF = 8001) and stress zones.

DISCUSSION

Given the increasing trend in utilization of wearable sensors and tools in naturalistic stress monitoring research, the gap in knowledge regarding the correlation between stress and various biomarkers needs further investigation. In this study, we reviewed correlations between increased stress and its biomarkers including HR, phasic EDA, and ST in a naturalistic study involving ICU nurses. Prior results indicate that EDA (Acerbi et al., 2017; McDuff et al., 2014; Ruscio et al., 2017; Schneegass et al., 2013) and HR (Finsen et al., 2001; Lackner et al., 2011; Lundberg et al., 1994; Reinhardt et al., 2012; Ritz et al., 2000; Steptoe et al., 2001) increase in healthy individuals and ST slightly but not significantly reduce at the wrist (Vinkers et al., 2013). The discriminative power of physiological responses has been studied as well: a higher level of HR and SCR amplitude (Ruscio et al., 2017; Schneegass et al., 2013) was observed in demanding tasks, and ST was

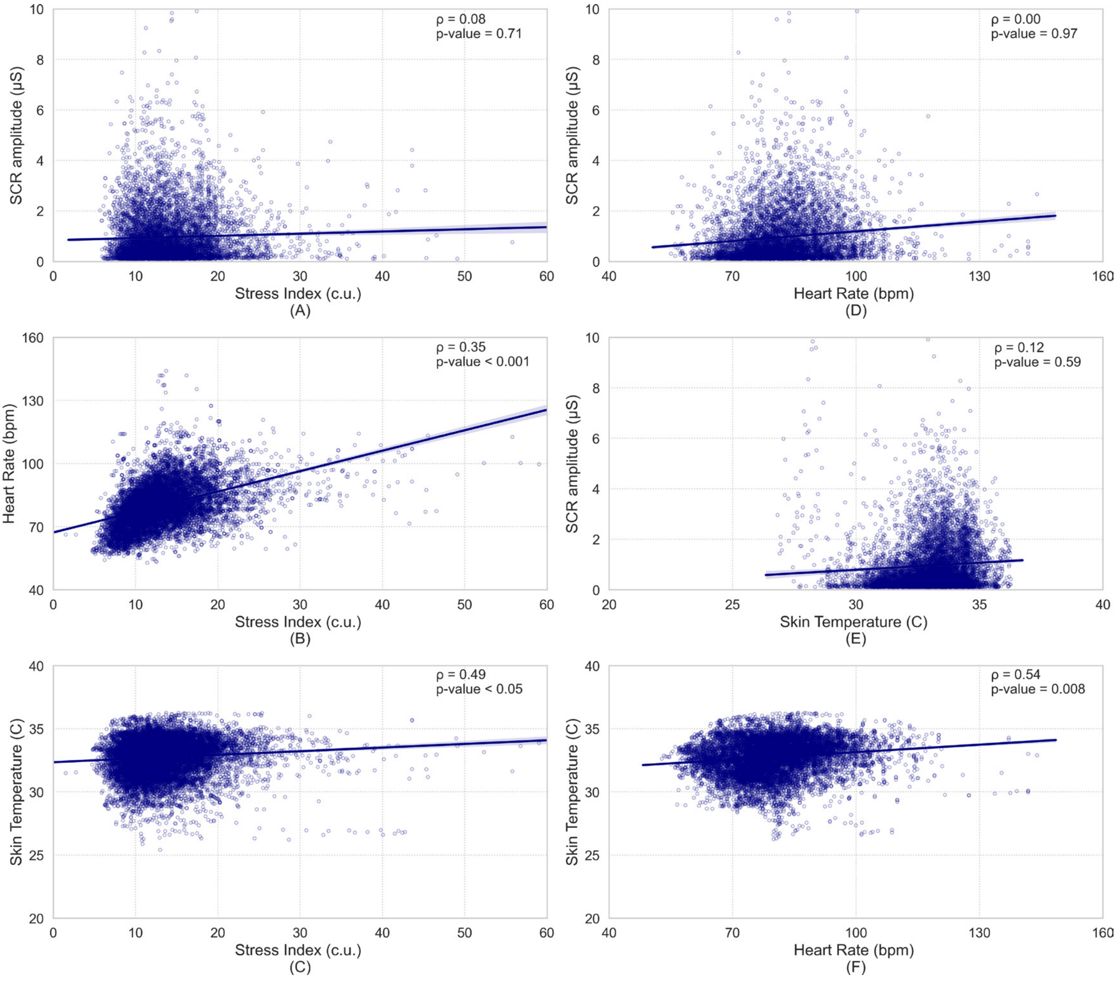

Figure 1. Correlations between stress index, heart rate, electrodermal activity, and skin temperature; stress and SCR amplitude (a), stress and heart rate (b), stress and skin temperature (c), heart rate and SCR Amplitude (d), skin temperature and SCR amplitude (e), and heart rate and skin temperature (f).

indicative of workload (Schneegass et al., 2013). Correlations between stress, HR, EDA, and SCR were therefore expected to be positive. In our findings, however, only HR was indicative of stress intensity, not EDA. Our findings also showed that the correlation between stress and ST is positive (Table 2).

Although the literature has found a positive association between phasic EDA and HR (Kettunen et al., 1998), we found no such correlation. Correlation between phasic EDA and ST (dorsal wrist) was previously reported as positive (Khan et al., 2019; Lobstein & Cort, 1978); however, this study found no correlation between SCR and ST. While the correlation between HR and ST in stressful events remains a research gap (Neves et al., 2016), given the known positive correlation between stress and HR (e.g., Acerbi et al., 2017; Folkins, 1970; Mehler et al., 2012; Ritz et al., 2000) and evidence of no correlations between stress and ST (at wrist; Vinkers et al., 2013), weak negative or no correlation between HR and ST was expected. However, our results show a significant positive correlation between these parameters. To our knowledge, this is the first empirically derived documentation of correlations between HR and ST.

TABLE 2: Comparison of Correlations Documented in the Literature Versus Those Observed in This Study's Findings

Feature	Known Correlations	Observed Correlations
Stress and SCR amplitude	+	No correlation
Stress and HR	+	+
Stress and skin temperature (dorsal wrist)	No correlation	+
SCR amplitude and HR	+	No correlation
SCR amplitude and skin temperature (dorsal wrist)	+	No correlation
HR and skin temperature	Not studied	+

Note. HR = heart rate; SCR = skin conductance response.

Discrepancies between the current and previous results could be due to the differences between the research designs, environments, tasks, and type of stressors in these studies. While most of the previous research was conducted in a laboratory setting utilizing induced stress, the current research was a naturalistic study performed in a complex work environment. In addition, the previously documented correlations are in response to a wide range of mental, psychological, and physical stressors and include both healthy and nonhealthy individuals. Finally, to our knowledge this is the first study of stress correlates conducted in the ICU setting covering the entire shift of the nurse population. These factors are discussed in more details below.

Duration of stressed states. In laboratory-induced stress research, typically stress tasks do not last more than 30 min. For example, the widely used Trier Social Stress Test takes about 15 min per participant (Vinkers et al., 2013). In a real-world setting where data are captured across an extended period (e.g., 12 -hr ICU shifts), participants may be exposed to longer periods of stress due to the workload, time pressure, and demanding tasks. If that is the case, the inhibitive coping mechanism and habituation to resist prolonged activation of repeated stress (Grissom & Bhatnagar, 2009) might have affected the physiological responses. Furthermore, in long working shifts, nurses must deal with fatigue and drowsiness, which could also change the intensity of physiological responses. For instance, drowsiness has been associated with a reduction in HR (Riemersma et al., 1977).

Type of stress. In a laboratory setting study, participants receive given stress tasks one at a time. This procedure allows researchers to examine the effect of a specific stress task on physiological responses. For instance, Vinkers et al. (2013) used Trier Social Stress Test (Chen et al., 2014) to emulate mental and psychological stress. In the current study, CVICU nurses carried out several tasks including medication-related activities, administrative and clinical documentation tasks, and patient care with various complexity levels and cognitive loads which might have affected physiological variables differently.

Physical activity. In a laboratory-induced experiment, participants are asked to remain idle (often seated) while performing stress tasks. In contrast, in a naturalistic study nurses may experience different levels of physical activity throughout a working shift. Physical activity is a known source of noise in physiological data and may affect responses in unexpected ways (Martinez-Nicolas et al., 2013; Sun et al., 2012; Van Steenis & Tulen, 1997; Wilhelm et al., 2006).

Unconstrained environmental factors. Lack of control over the research environment in the current study may have resulted in several environmental factors with impacts on physiological variables of interest. For instance, in ICUs, nurses wear gloves and perform frequent hand hygiene (i.e., hand washing with soap and water, hand sanitizer). These practices could affect the measurement of physiological responses. For instance, evaporation of water or alcohol reduces ST, while wearing disposable hospital gloves could act as insulation and disrupt heat dissipation, thereby increasing ST. Hence, while blood circulation reduces, peripheral body temperature may rise by wearing gloves inside ICU rooms and decline by taking off gloves and washing hands with alcohol-based solutions.

Electrodermal lability. Individual trait differences in EDA or EDA lability have been shown to impact the rate of nonspecific response and habituation. Evidence suggests that stable or labile individuals demonstrate different electrodermal behavior (Sarchiapone et al., 2018). Future work can examine individual traits to further evaluate EDA responses to stress. In the laboratory environment, nonspecific responses could be detected as the onset of stimuli is known, while in the current naturalistic stress assessment, it is not possible to distinguish specific responses from nonspecific responses.

Limitations

This study offers data from more than 300 hr of physiological monitoring of ICU nurses in 12 -hour day and night shifts. Several technical and methodological limitations are noteworthy:

Hardware reliability. In our study, we suffered from data loss, which was associated with the Empatica E4 hardware malfunctions. For example, in some cases, data were captured with brief periods of disruption, and some devices had defective or broken EDA and ST sensors. Additionally, we noticed that the EDA sensor was sensitive to water, and nursing tasks require frequent hand hygiene. Data validation and quality checks for these events were performed through the review of eye-tracking videos, and incorrect peak EDA values due to hand hygiene were removed from the dataset. However, it is possible that some instances were not captured by the eye-tracker's forward-facing video recorder (i.e., if nurses performed hand washing without looking at the sink or dispenser).

Sample size and generalizability. The sample size in this study was relatively small, and the single-site sample limits generalizability. Future work should aim to replicate the study with a larger and heterogeneous sample size from multiple ICUs by considering related covariates (e.g., sleep hours, nursing scheduling pattern, patient acuity, and ICU workload) on nurses' stress to increase the power of statistical analysis.

Identification of nursing activities and ICU stressors. In prior studies, the dissociation of multiple physiological responses and weak correlations among them were reported, and several factors were attributed to divergent results (Hancock & Matthews, 2019; Matthews et al., 2015). It was implied that not only could a task under time pressure or dual-tasking provoke different physiological responses (in terms of sensitivity and diagnostics; Matthews et al., 2015), but also such responses could differ among individuals. This indicates the necessity of ICU tasks' evaluation and context-dependent evaluation of psychophysiological responses (Baldwin & Penaranda, 2012; Matthews et al., 2015). While it was not possible to code nursing tasks in real-time due to the resource-intensive nature of longitudinal eye-tracking and physiological monitoring, work is in progress to code tasks retrospectively using the eye-tracker videos. For example, workload may have an important impact on physiological responses to stress. ICU nurses were reported to perform 23.4 tasks per hour back-to-back (Koch et al., 2012). In such a stressful environment, the interactive (Matthews et al., 2015) and hysteretic effect (impact of a precedent task's intensity on a succeeding task' workload) of nursing tasks on the physiological responses should also be considered (Hancock & Matthews, 2019). This effect suggests the order of nursing activities with different levels of stress could change the intensity of elicited responses.

Assessment of stress by other means. Due to valid patient safety concerns related to interruption of nursing activities, administering self-reported stress assessment instruments at regular intervals was not possible. While these methods suffer from various response biases (Johnston et al., 2016; Smets et al., 2019), future work should investigate the convergence between perceived stress and objective methods such as Baeversky's SI used in this work. Other objective stress measurement methods such as cortisol extraction (Greene et al., 2016) were considered but rejected due to their intrusiveness. While implementing intrusive methods remains a challenge in naturalistic studies, future work may utilize such methods in quasi-experimental designs, when possible.

Finally, it has been shown that psychophysiological responses such as HR, EDA, and ST may be associated with several intertwined constructs such as stress, workload, and arousal (Choi & Gutierrez-Osuna, 2009; Giannakakis et al., 2019; Hancock & Matthews, 2019; Kreibig, 2010). More work is warranted to use contextual information in investigating the correlations between these measures. For instance, to eliminate the undesirable effect of the physical activities on HR stress responses, accelerometer data could be analyzed to distinguish nurses' physical activity from stressors' response (Smets et al., 2019).

Conclusion

The recent growth and availability of ambulatory physiologic recording systems provide an opportunity for monitoring HR, EDA, and ST in real-time. Successful identification of stressful activities can be used to quantify and subsequently design effective interventions to reduce stress and burnout among healthcare professionals with implications for patient safety. However, there remains a gap in understanding how psychophysiological variables such as HR, EDA, and ST change due to stress in complex work environments such as nursing. This study provided empirical evidence suggesting a strong three-way positive correlation between increased stress, HR, and ST, which may suggest the efficacy of using ST for stress-monitoring applications in ICU nursing. The marked divergence between our results and the laboratory-based literature may be related to differences in variables used to measure outcomes and controlled activities but warrants further investigation. These findings illustrate the importance of diversity of methodologies to account for the limitations of different research methods and specifically generalization of findings from lab experiments to complex work environments.

While this study documented key correlations (or lack thereof) between stress and several physiological variables in a naturalistic study, more work is needed to shed light on the nursing activities associated with high levels of stress as well as the context-specific reasons associated with changes in the physiological responses. Work is in progress to investigate the context in which high stress is experienced in ICU by synchronizing data eye-tracking video, audio, and attentional resource allocation data with physiological variables. The findings may inform the development of a continuous stress monitoring tool to prevent chronic stress and burnout among ICU nurses.

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KEY POINTS

- Stress during ICU nursing tasks is correlated with heart rate and skin temperature.
- Phasic electrodermal activity was not correlated with stress despite previous evidence suggesting otherwise.
- More work is needed to validate surrogate measures of stress, and this study illustrates that naturalistic prospective data collection can reveal contrary results when compared to laboratory data.

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