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A Prospective Pilot Study of the Biometrics of Critical Care Practitioners during Live Patient Care using a Wearable "Smart Shirt"

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Abstract

Objective: To measure the biometrics (heart rate, heart rate variability) of critical care physicians during live clinical patient scenarios.

Design: Participants wore the Hexoskin biometric smart shirt (Hexoskin, Carrè Technologies, Montreal, Quebec) during live clinical activities.

Setting: 24-bed tertiary care children's hospital pediatric intensive care unit

Subjects: Pediatric critical care attendings and fellows.

Interventions: Heart rate (HR), respiratory rate (RR), and heart rate variability (HRV) were recorded during clinical shifts. Activities included subject baseline (SB), patient rounds (PR), tracheal intubation (TI), and central line insertion (CL).

Measurements and main results: Mean HR for the activities SB, PR, TI, and CL were 81 ± 3.65, 85 ± 4.75, 99 ± 10.83, and 108 ± 8.97 beats per min, respectively. Mean standard deviation dispersion perpendicular and along the axis of identity (SD1/SD2) were 0.244 ± 0.038, 0.220 ± 0.022, 0.180 ± 0.050, and 0.167 ± 0.015, respectively. P values for mean HR, max HR, and HRV were significant when comparing SB with TI (0.010, 0.027, and 0.001) and CL (0.007, 0.001, and 0.012) but not when comparing with PR (0.026, 0.125, and 0.321). Comparison of SD1/SD2 for TI versus CL showed no statistical significance, P=0.578. Poincaré plots confirmed the similar patterns of physiologic activation. Subject baseline and PR plots were fan-shaped, suggesting primary parasympathetic input. TI and CL were torpedo-shaped, suggesting sympathetic activation.

Conclusion: Study of the biometrics of physicians as they deliver real-time critical patient care is feasible using wearable technology. Critical care activities requiring not only thought, focus, and planning but also the physical execution of technical skills, such as IT or CL insertion, resulted in higher levels of sympathetic activation. Further study of physicians from various specialties and different levels of experience, the use of stress mitigation techniques, and correlation with procedural success or failure is warranted.

Keywords: Children; Pediatric intensive care unit (PICU); Heart rate variability; Burnout; Stress; Biometrics

Introduction

Biometrics, the science of using measureable characteristics to describe individuals, often is grouped into physiologic or behavioural categories [1,2]. Examples include fingerprints and retinal vessel patterns, which are distinctive to an individual. There is growing interest, however, in measurement of physiologic biometrics, such as heart rate (HR), with regard to health and wellness.

Continuous measurement of patient vital signs is standard practice and has led to improvements in morbidity and mortality. In the developing world, as many as 50-80% of children with septic shock die. In developed countries with pediatric intensive care units (PICU), that figure is as low as 13.9% [3]. Most health professionals, while good at monitoring patients, are ignorant of their own biometrics while delivering care under stressful conditions.

Until recently, measurement of HR, respiration rate (RR), and heart rate variability (HRV) required cabled monitors in a physiology laboratory or the use of the bulky, portable Holter apparatus. This made study of live conditions challenging. Devices like the Fitbit (San Francisco, CA), Jawbone (San Francisco, CA), and Nike Fuelband (Beaverton, OR) are sold as a way to lose weight and improve wellness and employees are incentivized with lower insurance premiums for compliance. Roughly 3.3 million fitness bands/trackers were sold between April 2013 and March 2014 [4].

Making use of a sophisticated, reliable, and portable personal monitoring system, this study set out to quantify the biometrics (HR, HRV) of critical care doctors in live clinical patient care scenarios as a measure of physician stress. We hypothesize it is feasible to measure biometric changes in critical care physicians as they deliver care to patients.

Materials and Methods

Population

The protocols and methods for this study were approved by the Nemours/Alfred I. duPont Hospital for Children Institutional Review Board (project number 780981). In total, one critical care attending (male), two senior fellows (both male), and two junior fellows (one male, one female) participated. There were no exclusion criteria as this was a voluntary, prospective, observational study.

Study design

The Hexoskin Smart Shirt (Hexoskin, Carrè Technologies, Montreal, Quebec) is marketed as the most advanced biometric shirt available, measuring more body metrics than any other wearable technology product and with greater precision. Hexoskin contains two respiratory loops and three cardiac dry textile electrodes. Its integrated activity sensor, respiratory sensor, and heart sensor measure data in real time and record for up to 14 h via a small (40 g) "brain" contained in a pocket pouch. Data synchronize with a phone application and cloud storage and can be analyzed through a secure website.

The electrocardiographic sensor is a one-channel, 256 Hz detector with variability rates from 30 to 220 beats per min (bpm) making it suitable to perform HRV analysis. Acceleration and activity level, as well as step counting, are standard with each device. Energy expenditure in the form of kilocalories is calculated. Breathing rate, minute ventilation, and a calculation of oxygen consumption are also reported.

Finally, the device can also measure inactivity and sleep parameters by tracking total sleep duration, sleep position changes, time asleep in each position, and an estimation of sleep efficiency. The shirt demonstrated low variability, good agreement, and consistency of data in scientific studies [5-7].

Study subjects wore the Hexoskin Smart Shirt during PICU shifts after establishing baseline rest measurements. Heart rate, RR, and HRV were recorded as opportunities arose during shifts. The PICU activities included patient rounds (PR), tracheal intubation (TI), and central line (CI) insertion. Data were time marked via the paired Bluetooth application and then electronically encrypted, password protected, and stored on the Hexoskin website.

Heart rate variability

Heart rate variability is the beat-to-beat changes manifested through regulation of the autonomic nervous system, temporal changes, and respiratory variation. Standard deviation (SD) 1 is the dispersion of point's perpendicular to the axis of the line of identity and represents an instantaneous beat-to-beat variability. Standard deviation 2 is the dispersion of points along the axis of the line of identity and represents continuous beat-to-beat variability [8-10]. Standard deviation 1 determines the width of the ellipse (short-term variability), whereas SD2 equals the length of the ellipse (long-term variability) [11]. The SD1/SD2 ratio represents the randomness in the HRV time series [11,12].

In 1996, the European Society of Cardiology and the North American Society of Pacing Electrophysiology created the HRV standards, which VivoSense (Vivonoetics, San Diego, CA) software utilizes to obtain their values. Poincarè plots provide a graphical representation of HRV by plotting R-R interval (n+1 along Y-axis) against the previous R-R interval (n along X-axis).

A line of identity is drawn through the plot, with SD1 representing the dispersion of points perpendicular to that line and SD2 representing points along the line. A long, slender "torpedo" shape is representative of sympathetic activity; a fan or "comet" shape represents a balance between parasympathetic and sympathetic activity. Calculation of SD1/SD2 ratios provided numerical quantitation of parasympathetic/sympathetic activity.

Statistical analysis

Paired t test was performed on maximum HR, average HR, absolute and percentage change in HR, and HRV (using SD1/SD2) as markers of physiologic stress. Heart rate maximum was calculated using the Tanaka formula.

Heart rate reserve, defined as the difference between maximum possible HR and resting HR, provides insight as to the intensity of the activity. Calculations compared subject baseline (relaxed while at home) with activities recorded during PICU work. VivoSense software generated HRV calculations and analysis. Each recording was analyzed for artifact with high sensitivity and low interpolation. All sessions had greater than 95% quality based on validated software metrics. Individuals were compared with self to eliminate composition and demographic differences.

Results

Participant demographics

Table 1 presents the summary demographic data for each participant. Average age was 34.8 ± 5.03 years, weight 90 ± 15.28 kg, height 1.74 ± 0.06 m. Body mass index was similar among all males (mean 29.6), with the female fellow being substantially less (23.1).

Primary determinants

Mean, minimum, and maximum HR; SD; and absolute and percentage change in HR were calculated for participants in each activity. These data are presented in **Table 2**. Resting baseline HR average for all participants was 81 ± 3.65 bpm. Heart rates ranged from a minimum of 60 bpm to a maximum of 101 bpm. Despite differences in age, sex, and body composition, resting baseline was similar for all participants. Due to the small sample size, there was no analysis to determine if level of athletic fitness correlated to HR averages.

Table 1 Baseline characteristics of subjects (*Max HR is 208-0.7*Age (years) **HRR is max heart rate-resting heart rate (utilized baseline HR to determine resting HR)).

Subject	Age (years)	Weight (kg)	Height (m)	Sex	Position	Predicted Max HR	Heart Rate Reserve
A	44	100	1.78	M	Senior Attending	177	111
B	32	85	1.68	M	Third Year Fellow	186	99
C	34	107	1.8	M	Second Year Fellow	184	113
D	35	95	1.78	M	First Year Fellow	184	103
E	29	63	1.65	F	First Year Fellow	188	112

Table 2 Summary of measured activities (Mean HR; shown in bold type followed by range and standard deviation in parentheses. Percentage change in mean HR from resting state shown in parentheses after absolute change in heart rate).

Subject	Resting HR	Rounds HR	D in HR	Intubation HR	D in HR	CVL HR	D in HR
			(% D)		(% D)		(% D)
Subject A	87; 79-92 (2.29)	85; 69-101 (4.67)	-2 (-2.3%)	116; 95-147 (13.32)	29 (33.33%)	110; 100-120 (4.49)	23 (26.44%)
Subject B	87; 81-99 (2.56)	102; 90-118 (4.23)	15 (17.24%)	99; 87-116 (5.21)	12 (13.79%)	101; 90-115 (4.07)	14 (16.09%)
Subject C	72; 60-101 (6.33)	71; 57-92 (5.58)	-1 (-1.39%)	86; 77-107 (6.31)	14 (19.44%)	117; 98-138 (7.34)	45 (62.5%)
Subject D	77; 73-85 (2.06)	80; 68-99 (4.86)	3 (3.9%)	102; 84-126 (9.72)	25 (32.47%)	98; 86-119 (5.69)	21 (27.27%)
Subject E	82; 75-95 (4.99)	89; 76-109 (4.43)	7 (8.54%)	101; 83-123 (6.97)	19 (23.17%)	114; 98-127 (4.59)	32 (39.02%)

During PRs, participants obtained recordings ranging in duration from 49 min, 51 s to 3 h, 23 min, 56 s. Average HR during rounds was 85 ± 4.75 bpm. Heart rate ranged from 57 to 118 bpm. There was no statistically significant difference when comparing mean baseline HR with PR (P=0.259). On average, the HR of participants increased 4.4 bpm (5.2%). There was also no statistically significant difference when comparing resting baseline HR maximum with PR HR maximum (P=0.126). Of note, the average and maximum HR for the third-year fellow was greater than for the remainder of the group.

For the TI activity, participants obtained recordings ranging in duration from 9 min, 2 s to 27 min, 47 s. Average HR during intubation was 99 ± 10.83 bpm. Heart rate ranged from 77 to 147 bpm. There was a statistically significant difference when comparing mean baseline HR to TI (P=0.001). On average, the HR of participants increased 19.8 bpm (24.4%). There was also a statistically significant difference when comparing baseline HR maximum to TI HR maximum (Ps=0.027).

During CL placement, participants obtained recordings ranging in duration from 14 min, 9 s to 40 min, 53 s. Average HR during CL placement was 108 ± 8.97 bpm. Heart rate ranged from 86 to 138 bpm. There was statistically significant difference when comparing mean baseline HR to CL placement HR (P=0.007). On average, the HR of participants increased 27 bpm (34.3%). There was also statistically significant difference when comparing baseline HR maximum to CL placement HR maximum (P=0.001).

When comparing TI to CL placement, mean HR was 101 and 108, respectively. The greatest rise in HR among all tasks performed was seen during CL insertion (34.4%). However, statistically, there was no significance between these two activities, with a P-value of 0.277 for the mean HR and 1.0 for the maximum HR. Although the CL placement activity produced higher mean, maximum, and change in HR, statistically, these activities could not be differentiated.

Heart rate variability

Data reporting HRV parameters are summarized in **Table 3**. When comparing SD1/SD2 ratios, the baseline mean was 0.244 ± 0.038. Patient rounds mean was 0.220 ± 0.022. There was no statistically significant difference between these activities (P=0.321). The SD1/SD2 mean for intubation was 0.180 ± 0.050 (P=0.001). The SD1/SD2 for CL placement was 0.167 ± 0.015 (P=0.012). When comparing SD1/SD2 TI with CL placement, there was also no statistical significance, (P=0.578). The SD1/SD2 data followed the same pattern as the HR mean and maximum. **Table 4** provides a summary of p values for comparison of the mean HR, maximum HR and SD1/SD2 ratios during the measured activities to baseline readings. **Supplemental Figure 1** depicts the Poincaré plots for each participant and each activity; this is the graphical representation of SD1 and SD2. As stated previously, the wider the data points, the more parasympathetic activity; the narrower the plot, the greater the sympathovagal activity. For each participant, baseline and PR plots were fan- or comet-like, suggesting a greater degree of parasympathetic input and less overall stress on the participant. This agrees with the SD1/SD2 values for each activity. Endotracheal intubation and CL placement were much more torpedo-shaped, suggesting a greater degree of sympathetic input **(Figure 1)**.

Table 3 Summary of heart rate variability.

Subject	SD1/SD2 Resting	SD1/SD2 Rounds	SD1/SD2 Intubation	SD1/SD2 CVL
Subject A	0.178	0.2	0.096	0.144
Subject B	0.239	0.221	0.187	0.187
Subject C	0.247	0.261	0.192	0.17
Subject D	0.26	0.214	0.176	0.173
Subject E	0.296	0.202	0.251	0.159

Table 4 Summary of p-values for each activity when compared to baseline resting state.

Parameter	Rounds	Intubation	CVL
Mean HR	0.259	0.01	0.007
Max HR	0.125	0.027	0.001
SD1/SD2 Ratio	0.32	0.001	0.012

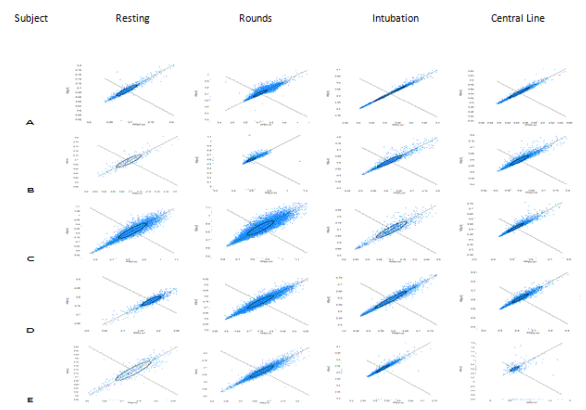

Figure 1 Poincaré plots. (CL: Central Line; RR: Respiratory Rate; Y axis: R-R interval (n+1) in seconds (s); X axis: R-R interval (n) in seconds (s)).

Discussion

In this project, using a "smart shirt," the authors captured the biometric parameters of pediatric critical care physicians while caring for live patients. Although there have been a handful of studies in a simulated environment, this is the first to quantify the biometrics of the physicians in real time while caring for PICU patients [13-16]. The mobile technology associated with this smart shirt allowed the physicians to accurately record their own vital signs while they delivered care.

It is stressful to care for critically ill patients in the PICU. By comparison, studies of police work have shown that officers suffer both physical and psychological job stress. Chronic stress and over-production of cortisol has been linked to the reduction of lymphocytes and is suggested as a culprit for the high rate of hospital admissions found in the police population [17,18]. A meta-analysis of over 300 articles by Segerstrom and Miller cited that stressors with short temporal parameters elicit potentially beneficial changes in the immune system (fight or flight response); however, as stressors become more chronic, more components of the immune system are affected in a detrimental way [19].

Job stress is also associated with physician burn out. A survey of 6,880 physicians by the American Medical Association and Mayo Clinic evaluated the prevalence of burnout between 2011 and 2014 [20]. Burnout rates were higher for all specialties in 2014 with nearly a dozen specialties experiencing more than a 10% increase. Reasons cited included poor h, low pay, stressful conditions, work-life balance inequity, excessive paperwork, and regulatory mandates. Self-analysis of biometrics cannot remedy all of these factors but could improve the effects of stress on practitioners.

In the mid-1950s, Selye described general adaption syndrome as a physiologic explanation of the body's reaction to stress within a three-phase model: alarm phase, resistance phase, and exhaustion phase [21]. This cascade of events activates the hypothalamic-pituitary-adrenal axis, increasing cortisol and subsequently causing release of norepinephrine and epinephrine, leading to a reflexive increase in HR and RR [22,23].

During insertion of a central venous catheter or breathing tube in an ill pediatric patient, there were statistically significant increases in both mean HR and maximum HR. This phenomenon was expected, as the procedural skills seen in pediatric critical care carry with them certain expectations. The patients are ill and often unstable with smaller target blood vessels than adults. Peripheral access in children is often difficult to achieve and maintain. The trachea of an infant or child is anatomically different from that of adults; it is smaller, more anteriorly located, and cone-shaped. Children have a larger tongue, relative to mouth size, and an omega-shaped epiglottis that are difficult to control [24,25]. Additionally, time to desaturation in children due to a smaller functional residual capacity makes TI a time-sensitive procedure. Patient rounding by comparison is a more cerebral exercise that often affords time to make and change decisions.

In an attempt to quantify which of these two procedures was more stressful, a comparison was made based on HR variables alone. We expected that TI would be more stressful than CL, but we did not find a statistically significant difference. However, CL insertion did show a 34% increase in baseline HR compared with only 24% for intubation. Perhaps because CL placement is a longer, multi-step sterile process requiring hand-eye coordination and ultrasound guidance and because it comes with the risk of vessel injury and arrhythmia, some find it more stressful.

This study also employed HRV as a more accurate method of stress analysis in human subjects. In the 1960s, Hon and Lee [26] and Wolf [27] described HRV as paramount in our understanding of the interplay between stress and physiology. Decreased variability is used as an outcome marker after myocardial infarction, in diabetic neuropathy, and in quantifying the degree of mental stress. Exercise physiologists have used HRV to optimize training and recovery for athletes [28].

Standard techniques of HRV include linear methods, time or frequency domain analysis, and geometric methods. Time domain methods are based on the beat-to-beat intervals and the subsequent SD of those intervals. Frequency domain methods (power spectral density) assign bands of frequency and count the number of intervals that match or fall into each segment. Time and frequency analysis is limited by assumptions made about the data, such as ectopic beats leading to skewed data, and must be standardized without using recordings of differing durations. Recent data suggest that linear HRV calculations fail to capture upwards of 85% of a subject's HRV, calling into question its validity [29].

Exercise science suggests that geometric or non-linear Poincaré plots are surrogates of time- and frequency-domain analysis to assess HRV. They provide better repeatability and reliability with smaller random error. They may be more suitable for diagnostic purposes and for assessing individual treatment effect. Also, despite computational challenges, the geometric analysis of Poincaré plots and SD1/SD2 ratios were more accurate [28,30].

Baseline and PR activities by Poincaré plot were fan-shaped with lower sympathetic tone when compared with torpedo-shaped TI and CL plots. Comparison of SD1/SD2 ratios between subject baseline and the individual activities confirmed the findings shown in the simplistic HR analysis. Rounding activities were comparable to resting readings. However, both TI and CL insertion SD ratios indicated statistically significant differences with a high degree of sympathetic activation. Again, this may reflect what is at stake, or at least the perceived stakes, for a physician performing a challenging procedure.

Questions not answered in this study are the focus of a planned multicenter collaboration. Comparison of HRV measurements between various levels of training within critical care and amongst different specialties with similar scope of practice is planned (emergency medicine and anesthesia).

At this time, it is unclear if there is a reduction in stress levels associated with training and experience. Some postulate that being unaware of potential consequences in a stressful situation allows the subject to work more freely and unencumbered by anxiety. An interesting survey of medical students found that dealing with the subject of death was particularly stressful. Students reported sometimes coping with alcohol. However, as they progressed in school (one would assume resulting in more experience), they reported a 50% increase in their alcohol intake [31]. Perhaps, knowing potential consequences results in more, not less, sympathetic activation explaining the higher attending response seen during intubation in this study.

The small number of subjects and inability to compare between training levels limits this study. Other limitations of the study involve the Hexoskin Smart Shirt itself. Reliable readings for HR require the shirt to be tight fitting to the skin. In addition, elastic straps designed to adhere the chest and abdominal sensors directly to the skin should be worn to reduce motion artifact. Finally, since it was difficult to predict exactly when a procedure would occur, ultrasonic gel was applied to the leads to increase conductivity.

A limitation that enhanced the study involved the Hexoskin's 14 h battery life. Rather than record for an entire 15 to 24 h shift, the project focused on shorter discreet activities. This prevented sifting through many h of data, much of which was non-stressful.

While this study demonstrates it is possible to quantitate physician biometrics, the true practice implications are unclear. Studies of physician stress are evolving, but impact on burnout, career longevity, and physician general health is unknown. Comparison between chronic and acute stressors, call shift variation, patient complexity, and census volume all need to be considered.

Conclusion

Critical care activities requiring not only thought, focus, and planning, but also the physical execution of technical skills such as TI or CL insertion, resulted in higher levels of sympathetic activation and were more stressful. Further study of real-time critical care activities in practitioners with various levels of experience, the use of stress mitigation techniques, and correlation with procedural success or failure is warranted.

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None.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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