Cardiorespiratory Adaptations to Work Volume on an Automobile Assembly Line

Dania Furk, Luís Silva[a], Mariana Dias[b], Phillip Probst[c] and Hugo Gamboa[d]

Laboratório de Instrumentação, Engenharia Biomédica e Física da Radiação (LIBPhys-UNL), Departamento de Física, Faculdade de Ciências e Tecnologia, FCT, Universidade Nova de Lisboa, 2829-516 Caparica, Portugal

Keywords: Cardiovascular, Respiratory, Workload, Occupational Health.

Abstract: Automobile assembly workers have to perform repetitive tasks with varying workload volumes, according to their assigned workstation, on a daily basis. With inadequate recovery, this type of occupational activity has been shown to cause cardiovascular problems. Despite these concerns, cardiovascular and respiratory adaptations to workload variations are often overlooked. This study aims to analyze Electrocardiogram (ECG) and Respiratory Inductance Plethysmography (RIP) data to understand the evolution of cardiorespiratory adaptations to three specific work volumes. A sample of sixteen male operators (age = 38±8 years; BMI = 25 ± 3 kg.m^2) volunteered from three workstations (H_1, H_2 and H_3) with different work cycle durations (1, 3 and 5 minutes, respectively). The results showed that activities with distinct workloads cause different responses through the data collection in cardiovascular load, heart rate variability (HRV), and respiratory frequency, variability, and coordination. The workload volume and work phase both influenced the cardiorespiratory acute response of the operators on the automobile assembly line, something that could improve individual-specific management of tasks assigned to workers.

1 INTRODUCTION

In 2021, a survey (CEDEFOP, 2023) carried out by the European Union determined that the majority of workers within the EU are employed in the manufacturing sector. On average, employees such as machine operators and assemblers, work for 39.7 hours per week (Eurostat, 2023).

For the majority of that time, operators are exposed to numerous occupational hazards such as repetitive movements, awkward postures, static positioning, and forceful exertions (Niu, 2010). These types of activities have been shown to have consequences for worker's cardiovascular health, due to the prolonged, low to moderate intensity nature of the physical activity performed (Holtermann et al., 2018). Another problem with this type of occupation is the insufficient recovery of the cardiac system, leading to continuous stimulation of the body's inflammatory response, which can lead to the development of cardiac risks and diseases or their aggravation (Geurts and Sonnentag, 2006).

Specifically, assembly-line jobs have been previously linked with high blood pressure, (Pickering et al., 1996), atherosclerosis (Krause et al., 2007), a well-known cardiovascular risk, increased mortality (Krause et al., 2017) and long-term sickness absence (Holtermann et al., 2012).

Regarding respiration, the monitoring of this biosignal's frequency is used to assess effort in sports (Nicolò et al., 2017b) and has shown its usefulness in the identification of cognitive load, environmental stress, and other relevant factors in occupational settings (Massaroni et al., 2019).

Current occupational risk quantification tools consider different body parts and key indicators of biomechanical load, where an expert fills in a pre-defined scoring sheet by watching the workers perform their tasks. Some of the most common scoring sheets are the job strain index, OCRA (Occupational Repetitive Action), the EAWS (European Assembly Worksheet), and the revised NIOSH (National Institute for Occupational Safety and Health) equation (Andreas and Johanssons, 2018). The last equation, besides establishing work practice guides for manual lifting defining limits on workload, recommends that the demands put on workers should not surpass 30% of their aerobic capacity in an 8-hour continuous shift (NIOSH, 1981).

[a] https://orcid.org/0000-0001-9811-0571
[b] https://orcid.org/0000-0002-0172-4559
[c] https://orcid.org/0000-0003-3239-9813
[d] https://orcid.org/0000-0002-4022-7424

Furk, D., Silva, L., Dias, M., Probst, P. and Gamboa, H.
Cardiorespiratory Adaptations to Work Volume on an Automobile Assembly Line.
DOI: 10.5220/0012587800003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 1*, pages 71-81
ISBN: 978-989-758-688-0; ISSN: 2184-4305

The incorporation of this risk information into workplace management has shown positive outcomes such as a reduction in work-related illnesses, workers' compensation costs, absenteeism, and increased productivity (Goggins et al., 2008; Baraldi and Kaminski, 2011). These methods present multiple shortcomings as they focus only on the biomechanical aspect of work not accounting for other factors such as individual specific differences and physiological load. Furthermore, this analysis relies mainly on observational methods, that are time-consuming and less accurate for smaller body parts (Takala et al., 2010), also giving limited knowledge about internal adaptations to the task (van der Beek and Frings-Dresen, 1998).

The use of wearables allows the direct measurement of motion and biosignals activity in real-time, providing means to more individual-specific planning and interventions in real occupational settings (Romero et al., 2016; Goggins et al., 2008)

Previous studies on real assembly lines have put their main focus on cardiovascular response. Lundberg et al. measured self-reports of work characteristics and of perceived physical load, accompanied by the evaluation of objective measures: HR (Heart Rate), blood pressure, catecholamines, and cortisol, finding that perceived stress was associated with neuroendocrine response and that during work both HR and blood pressure were significantly increased (Lundberg et al., 1989). To study the impact of minimization of non-productive time during work activities, to complement biomechanical exposure, Palmerud et al. and Kazmierczak et al. quantified job exposure based on HR monitoring by extracting the Reserve Heart Rate (RHR) of the workers, where the first one found that mean HR decreased (Palmerud et al., 2012), and the latter, when adopting this strategy, increased cardiovascular load.(Kazmierczak et al., 2005). The modeling of ideal working time based on energy expenditure of assembly-line workers was also developed, based on moderate workload tasks (Ayabar et al., 2015). The energy expenditure was computed based on HR measurements of workers, with smart watches, from three different assembly lines.

Research on the effect of this kind of work on cardiorespiratory adaptations has also been made. Nardolillo et al. simulated assembly line tasks and extracted Heart Rate Variability (HRV) from HR of participants, measured with a wearable device. The participants included individuals who were either currently employed in the sector or a related field, as well as students of varying ages and genders. It was concluded that there were no significant differences in frequency domain metrics between stages of work, but there were marked differences in some of the time metrics Mean RRi (intervals between consecutive heartbeats), Standard Deviation (SD) of Normal to Normal RRi intervals, and RRi Triangular Index) between some of the trials (Nardolillo et al., 2017).

In our previous work, both Respiratory Inductance Plethysmography (RIP) and ECG were monitored in simulated repetitive tasks under a fatigue-inducing protocol, where thoraco-abdominal coordination (Silva et al., 2022) and HRV (Carvalho et al., 2023) parameters were analyzed from non-worker participants. In these studies, results showed a decrease in correlation and PS between the respiratory movements of the chest and abdominal walls, and a decrease in HRV between trials.

It was verified that current research on assembly lines focused on exploring RHR (Relative Heart Rate) as a measure of job exposure, aiming to predict or analyze the effects of interventions made on the line organization, not considering other physiological measures. The ones that do, normally were simulated tasks, not in a real work context and their participants weren't workers of the sector.

This study aimed to check for possible health issues related to heart and breathing functions caused by car manufacturing tasks. We monitored workers' heart and respiratory signals, ECG, and RIP, respectively, on a real assembly line during their regular work.

This work is part of the OPERATOR 4.0 project (Zenithwings, Fraunhofer AICOS, LIBPhys-UNL, Volkswagen Autoeuropa, NST Apparel Lda, FPCEUP, Controlconsul, Universidade do Minho, Institute for Medical Engineering and Science at MIT, 2020), which has the support of MIT Portugal.

The remaining sections of this document are organized as follows: in Section 2 the materials and methods used are described, including a brief description of the study sample, the followed data acquisition protocol, and adopted statistical analysis. In Section 4 the results are presented, in Section 5 their discussion, and in Section 6 the drawn conclusions and the proposed future work.

2 MATERIALS AND METHODS

To characterize cardiovascular and respiratory responses to cyclical work, multiple biosignals of assembly line operators were monitored on the field, during real tasks.

2.1 Participants

The collected data of 16 subjects from the assembly workstations were analyzed (age: 38 ± 8 yrs; body mass index: 25 ± 3 kg.m^2; physical activity: 220 ± 135 minutes per week).

To be able to analyze the physiological response to distinct work volumes, the included participants were part of three workstations of the assembly processes, 8 from H_3, 4 from H_2, and 4 from H_1. All were right-handed male workers on automotive assembly lines and all rotate between workstations.

2.2 Workstations

In this factory, the manufacturing of vehicles relies on multiple processes. This study focused only on the activities carried out in the final stage of production as they rely on manual handling: the assembly and alignment of the last parts to be mounted on the car. The tasks performed at the studied workstations are specified:

- The setting of tail lights and prefit alignments were recorded in H_1, these tasks had a mean cycle time of 3 minutes.
- At H_2 alignments of the side doors, rear end, and front end were analyzed, with the mean duration of the cycle being 5 minutes.
- At last, in the H_3 area the final stages of the assembly are performed: rear-view mirror, cowl top, boot panel, and the trunk symbol mounting were monitored, these activities had a cycle-time of 1 minute.

In Figure 1 the dominant positions in which workers perform each of the activities mentioned above are represented.

2.3 Data Collection

Following the reading and signing of the informed consent, personal information (age, height, physical activity habits, and dominant hand) was asked of the participants. After this, their body mass was measured with a digital scale.

Next, all devices for the biosignals monitoring were mounted (further detailed in the following subsection), and the volunteers placed the mobile phone in their uniform pockets, and their activity was monitored for about 50 minutes of normal occupational activity. Simultaneously with the beginning of the data collection, a video of the first 4-5 cycles of the performed task was recorded.

Figure 1: Dominant positions of the tasks from each workstation.

The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of the University of Porto.

2.3.1 Sensor Setup

The followed protocol comprised the measurement of ECG, RIP, and ACC signals. The sensor placing started by cleaning the skin areas on which electrodes were to be attached, to optimize skin-electrode conductivity, hair removal, abrasion, and alcohol cleaning were done on each subject.

Firstly, three disposable adhesive Ag/AgCl electrodes (Ambu®), attached to each electrode cable from the ECG sensor (PLUX WIRELESS BIOSIGNALS S.A.), were placed in a configuration to minimize arm and chest movement artifacts. On the left side of the sternum, the positive was positioned at the level of the manubrium, and the negative was put on the superior part of the sternum's body. The ground electrode was placed on the left anterior superior iliac spine.

Following this, RIP signals were monitored with two inductive sensors (PLUX WIRELESS BIOSIGNALS S.A.) attached to two elastic belts: one over the chest passing underarms and the other band at the umbilicus level (Gastinger et al., 2014; Silva et al., 2022), they were adjusted to the participant's anatomy.

A triaxial ACC (PLUX WIRELESS BIOSIGNALS S.A.) was also used and was placed on the center of the lower back, secured with an elastic belt.

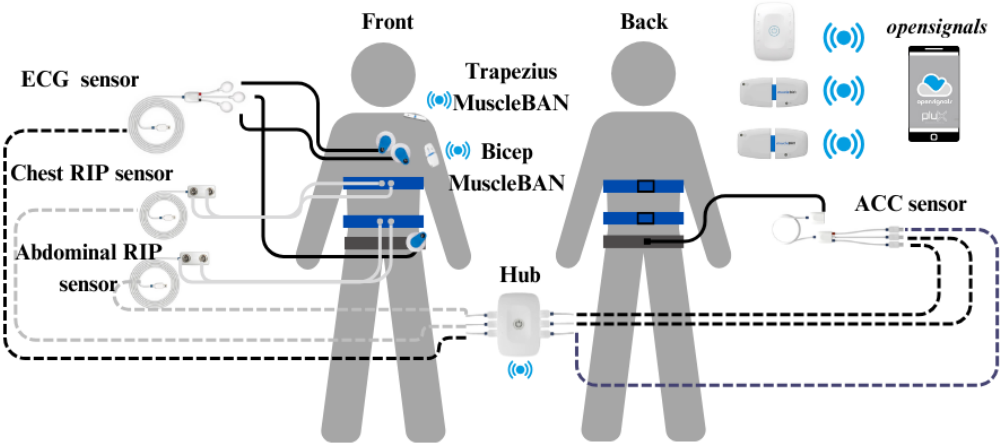

Figure 2: Sensor setup for signal acquisition.

These three sensors with an acquisition rate of 350 Hz, were all connected to the 8-channel wireless Hub, PLUX Biosignals (PLUX WIRELESS BIOSIGNALS S.A.), that streamed the data from each of the sensors to the *opensignals*, (PLUX WIRELESS BIOSIGNALS S.A.) software, to a smartphone (Xiaomi Redmi Note 9, running Android 10).

The right trapezius' and biceps' motion data was also captured with two MuscleBAN, (PLUX WIRELESS BIOSIGNALS S.A.) devices, at a rate of 1000 Hz and also transmitted to *opensignals*, (PLUX WIRELESS BIOSIGNALS S.A.).

The ACC data from the lower back, bicep, and trapezius were acquired for purposes of device synchronization and signal segmentation since the tasks involve a lot of repetitive arm movements.

A scheme of the sensor configuration is shown in Figure 2.

2.4 Signal Processing

2.4.1 Electrocardiography

Most of the features that were extracted from the ECG signal are based on the detection of the R peaks, so other wave shapes were suppressed to highlight them. To do that, a Maximum Overlap Discrete Wavelet Transform (MODWT) was used to filter ECG, given the non-stationary nature of this signal (Hess-nielsen and Wickerhauser, 1996; Chen and Tsui, 2020), where the chosen wavelet for each subject was based on the maximization of the signal energy to signal Shannon entropy ratio (He et al., 2015), resulting in the db2 wavelet being the best one. These time series were decomposed into 6 wavelet levels, and the signal was reconstructed with the level 4 coefficients by performing the inverse wavelet transform. These coefficients corresponded to a frequency band of 10.94-21.88 Hz. Next, an R-peak detection algorithm based on the Shannon Energy Envelope (Xu and Du, 2022) was applied to the filtered signals. The first step was the normalization of the signal's amplitude, followed by the computation of its Shannon Energy, and envelope using a moving root mean square with a window of 70 samples. Like this, the R-peaks were enhanced and were detected with the scipy's *findpeaks* function (Virtanen et al., 2020), applying a minimum distance of 120 samples and a minimum height of 0.15.

From the detected R-peaks several features were extracted quantifying both HRV and Cardiovascular Load as they have been previously used in multiple studies to evaluate cardiovascular load in occupational context (Dias et al., 2023). The specific metrics are indicated in Table 1.

Table 1: ECG extracted features.

HRV (ms)	Cardiovascular Load (%)
SDRRi	RHR
RMSSD	CVL
SD1	CVS
SD2	

SDRRi- Standard deviation of consecutive RR peak intervals; RMSSD - Root Mean Square of the consecutive RR peak intervals; RHR- Reserve Heart Rate; CVS- Cardiovascular Strain; CVL- Cardiovascular Load; SD2- Poincaré plot standard deviation along the line of identity.

2.4.2 Respiratory Inductance Plethysmography

Initial filtering was made by a finite impulse response bandpass with cut-off frequencies of 0.15 and 0.45Hz (Silva et al., 2022). Next, the signal was decomposed in Intrinsic Mode Functions (IMFs) with a filter based on Masked Sift Empirical Mode Decomposition (EMD) (Liu et al., 2013). IMF-4 was chosen to reconstruct the respiratory signal as it was the one that presented the most clear respiratory pattern. Both signals from the chest and abdominal belt were subjected to this procedure.

From the filtered signal, respiratory rate (RR) in breaths per minute was determined for both thoracic and abdominal walls, with a zero-crossing detection algorithm (Rétory et al., 2016). The rib-cage percentage (RC%) defined as the Rib Cage's (RC) contribution to tidal volume as a percentage of the sum of both RC and Abdominal (ABD) volume variation (Ryan et al., 2020) was also computed. Full Cross-correlation between RC and ABD signals was extracted, using a moving window of 400 samples (Makowski et al., 2021). At last, PS between the two signals from each belt was determined, by applying the Hilbert Transform to both signals and the subtraction of their extracted imaginary parts (phase) (Silva et al., 2022).

2.4.3 Accelerometer

To denoise the ACC data obtained from the triaxial ACC mounted on the center of the lower back and from the ACCs in the MuscleBAN devices, a bandpass-filter with cut-off frequencies of 0.1Hz and 10Hz was used (Silva et al., 2022; Lester et al., 2004). Next, the signals were smoothed with a window of 0.2 seconds.

2.5 Signal Segmentation

2.5.1 Signal Synchronization

To be able to identify cycles, the first step was to synchronize the signals acquired from the multiple devices. This was accomplished by first matching the sampling frequencies of the signals, followed by their alignment, by computing the full cross-correlation between the ACC signals of the three devices, as each volunteer before data recordings was asked to perform 10 jumps, a marked movement to match these signals in time, leaving all of them in the same initial condition.

2.5.2 Self-Similarity Matrix

As this study was done in a real automobile assembly line, there were unexpected events, such as line stops, bathroom breaks, and tasks performed with additional movements or in a different way. Despite that, the monitored activities should have a repeating pattern, as they are performed with specific movements in a certain order. As no timestamps or videos were available for the full acquisition the identification of anomalies and cyclic patterns and the segmentation of these signals was accomplished by a Self-Similarity Matrix (SSM) method. This method has already been used successfully to segment time series, in human activity recognition, biosignals segmentation (Rodrigues et al., 2022), and in work-cycle anomaly and pattern detection (Santos et al., 2021).

2.5.3 Data Cleaning

In the followed protocol, multiple sensors were used simultaneously, which led some of them to fail to acquire or to disconnect during the acquisition. Also, in some cases, there were unexpected assembly line stops, which led us to exclude those recordings from the analysis, to guarantee that only comparable data were used. All the signals were cut from the first to the last detected work cycles. This way, the recordings were left with 40 minutes to be analyzed.

3 STATISTICAL ANALYSIS

To evaluate how workload affects cardiorespiratory response throughout the acquisition, the signals were studied at two-time points: the first and last 10 minutes, extracting the cardiac and respiratory indicators at each of those times.

The employed statistical test was a Mixed ANOVA, as there were two factors: the workstation and the phase (first and last 10 minutes) at which the metric was extracted. To be able to perform a more robust test, the sample size was increased to balance the minority workstations, by cluster-based oversampling, i.e., generating artificial samples with the SMOTE (Synthetic Minority Over-sampling TEchnique) algorithm (Chawla et al., 2002).

To guarantee that the results obtained were reliable, 500 simulations changing the random seed of the over-sampler were performed and the determination of the p-value was computed with the harmonic mean combined p-value method, as it is used for dependent tests (Wilson, 2019).

The obtained p-values were corrected for violation of normality and equality of variance principles, by using the Yeo-Johnson power transform (Yeo and Johnson, 2000) and the Welch correction, respectively. The considered level of significance was 5% and when indicators were under it, they were further analysed by the Tukey post-hoc.

4 RESULTS

4.1 Cardiovascular Response

The most notable results of the mixed test were that H_3 had an evident decrease in SDRRi, SD of RHR, coefficient of variation of HR, and SD2. The H_2 workstation had a meaningful change in HR that decreased with time. The values of the extracted ECG metrics of station H_1 were generally smaller and remained constant through the recording.

The results from the Mixed ANOVA simulation statistics of the cardiac indicators are presented in Table 2 where the p-value of each interaction is shown, and significant results are presented with an *.

Table 2: Mixed ANOVA results for the cardiovascular metrics.

Variables	p_g	p_{ph}	p_{int}
HR	0.432	0.006*	0.043*
Max HR	0.486	0.097	0.038*
SDRRi	0.530	0.018*	0.009*
CV HR	0.273	0.001*	0.017*
RHR	0.229	<0.001*	0.021*
SD RHR	0.274	<0.001*	0.030*
CV RHR	0.071	0.563	0.007*
CVS	0.051	0.008*	0.094
CVL	0.027*	0.006*	0.058
CVL range	0.075	0.198	0.040*
SD2	0.502	0.015*	0.008*

HR- Heart Rate; SDRRi- Standard deviation of consecutive RR intervals; RHR- Reserve Heart Rate; CVS- Cardiovascular Strain; CVL- Cardiovascular Load; SD2- Poincaré plot standard deviation along the line of identity; Max- Maximum; Min-Minimum; SD Standard Deviation; CV- Coefficient of Variation; p_g- harmonic mean combined p-value for the between factor; p_{ph}- harmonic mean combined p-value for the within factor; p_{int}- harmonic mean combined p-value for the interaction; * significant result at a confidence level of 5%.

The post-hoc tests are presented in Figure 3.

4.2 Respiratory Response

The statistical analysis revealed that the mean and maximal ABD RR was greater, and so was its SD for the H_2 workstation. Substantial reduction in respiratory correlation and PS was seen for H_2 and H_1 stations, respectively. In contrast, H_3 subjects maintained the relationship between both wall motions through the analyzed time, having the highest mean values of this metric within the assembly line.

The results from the Mixed ANOVA simulation tests of the respiratory indicators are presented in Table 3.

Table 3: Mixed ANOVA results for the respiratory metrics.

Variables	p_g	p_{ph}	p_{int}
Max RC	0.534	0.033*	<0.001*
Min RC	0.891	0.533	<0.001*
SD RC	0.391	0.491	0.013*
ABD	0.190	0.468	<0.001*
Max ABD	0.697	<0.001*	<0.001*
SD ABD	0.539	0.008*	0.077
Correlation	0.022*	<0.001*	0.013*
PS	0.022*	<0.001*	0.015*

RC- Ribcage; ABD- Abdominal; PS- Phase synchrony; p_g- harmonic mean combined p-value for the between factor; p_{ph}- harmonic mean combined p-value for the within factor; p_{int}- harmonic mean combined p-value for the interaction; * significant result at a confidence level of 5%.

The post-hoc results are presented in Figure 4.

5 DISCUSSION

This research aimed to better understand cardiorespiratory adaptations to cyclical work of tasks with specific work volumes, and determine if there were acute changes in the explored indicators extracted from ECG and RIP signals throughout the data collection. It was expected that the physiological response would change according to the different workload volumes that are associated with the workstation. To do so, data was analyzed considering two factors: phase and workstation.

In terms of the cardiovascular indicators, HR is used as an indicator of the load put on the cardiovascular system (Samani et al., 2012; Umer, 2020), whereas HRV provides relevant information on autonomic regulation to different stimuli (Mccraty and Shaffer, 2015). The influence of the parasympathetic nervous system on HR prevails over sympathetic activity during resting and moderate effort conditions, with increased variability in inter-beat intervals (Sammito et al., 2015). A decrease in HRV parameters has been previously linked to fatigue and work stress, but it is also observed as a reaction to physical activity, intensity, and duration (Tsai, 2017; Tonello et al., 2014; Brockmann and Hunt, 2023).

When analyzing the values for cardiovascular load features in Table 2 and looking at the evolution of HRV in Figure 3, it seems that the H_3 workstation tasks place a higher demand on the cardiovascular

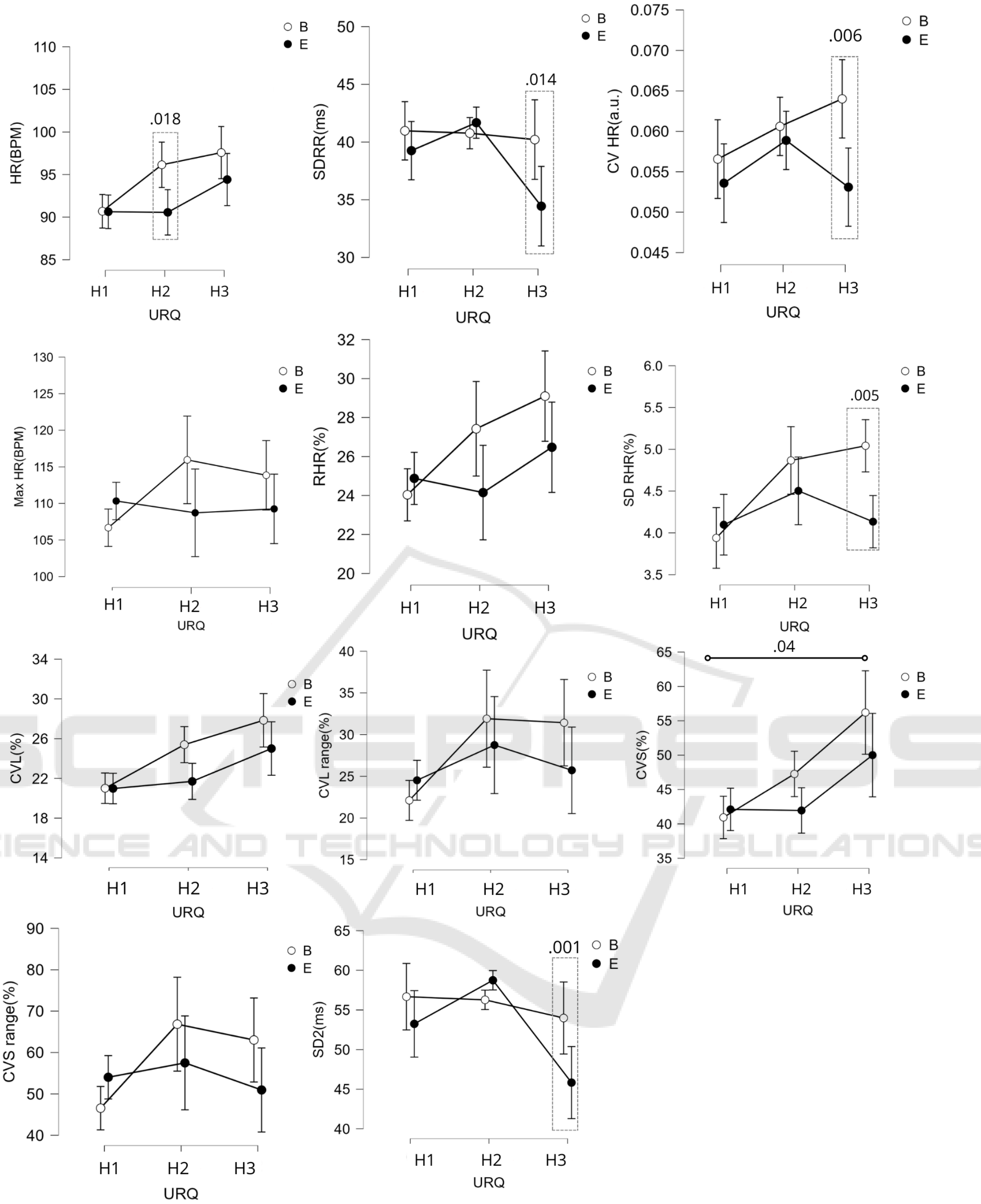

Figure 3: Descriptive plots with Tukey test results for the significant cardiac variables. URQ: Workstation; B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

system in terms of both load and cardiovascular regulation mechanisms. Indeed in these groups, the repetition of movements is more frequent, something that has been associated with increased metabolic, cardiac and perceived stress (Mang et al., 2022), additionally a lot of movements are performed above-head in the mentioned workstation, that in similar activities have shown to increase HR and blood pressure (Astrand et al., 1968). A significant decrease in HRV parameters has also been found in simulated assembly line tasks (Carvalho et al., 2023), but here a fatigue-inducing protocol was applied.

Regarding respiratory adaptations, respiratory frequency is an indicator of physical workload (Nicolò

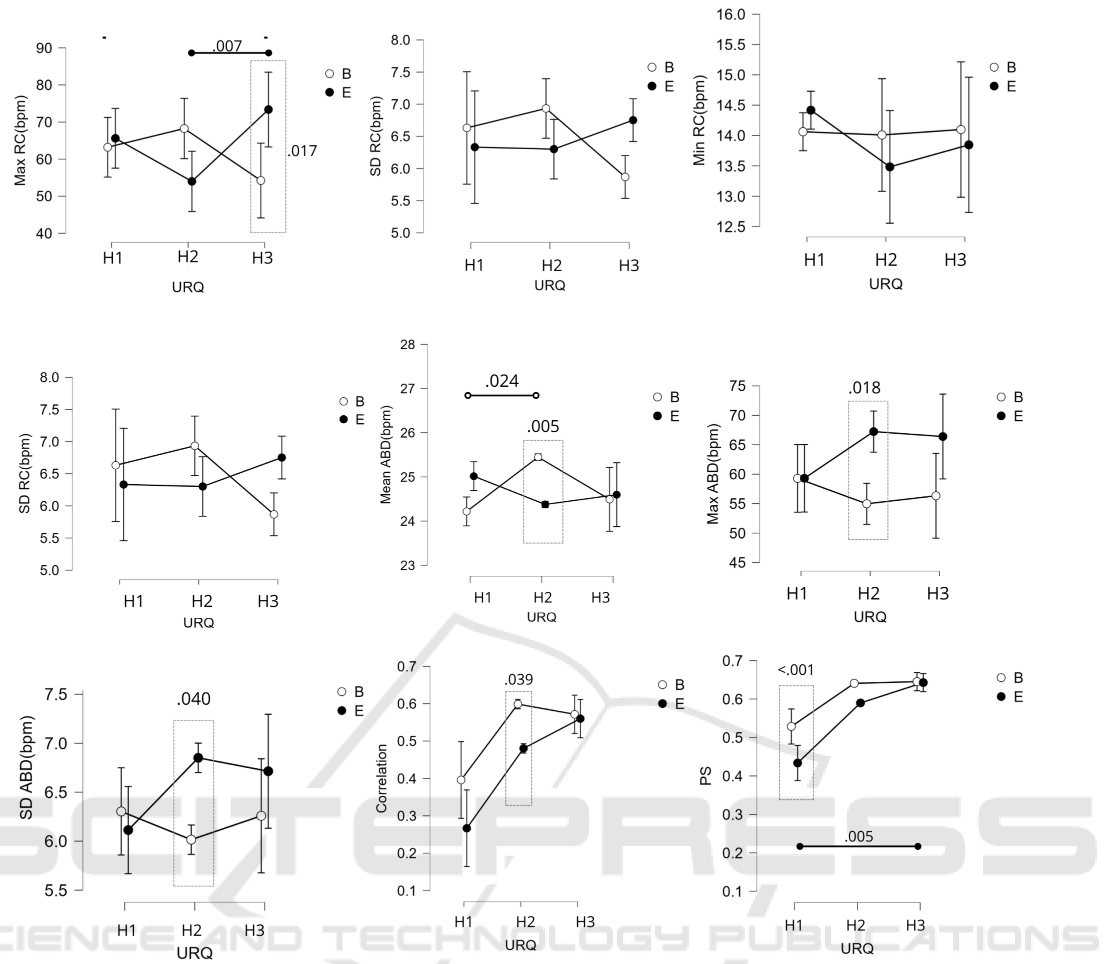

Figure 4: Descriptive plots with Tukey test results for the significant respiratory variables. URQ: Workstation; H1- medium cycle station; H2- long cycle station; H3- short cycle station; B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

et al., 2017a). Thoraco-abdominal asynchrony is used as a measure of respiratory muscle load, defined as the unmatching movements of the RC and ABD walls, expressed in phase angle (Hammer and Newth, 2009).

From the observed workstations, the H_2's ABD respiratory variables present the most distinct evolution from the initial and final 10 minutes, as shown in Figure 4. This suggests a chaotic movement of the abdominal muscles, meanwhile, RC parameters did not change, reflected in the diminished correlation between their motion as confirmed by 3. The tasks performed on the line involve arm movements, a possible explanation for these results is the fact that the inspiratory thoracic muscles are exerting less force for breathing, leaving ABD expiration muscles and the diaphragm to compensate (Celli et al., 1988).

The asynchronous motion between walls through the data collection period was evident in H_1 and H_2 workstations and is consistent with the results in Silva et al., where phase and correlation decreased between baseline and fatigue trials in a simulated repetitive task (Silva et al., 2022). The H_3 subjects maintained the relationship between both wall motions through the analyzed time, which suggests different adaption mechanisms inherent to this station when compared to the others.

These parameters are easily monitored with different wearable applications, such as smartwatches, being that this information could be used to leverage task rotation, by identifying which tasks are harder for each employee. This type of approach has already been used in the construction sector to quantify task demands (Sadat-Mohammadi et al., 2021). Another possible application is the monitoring and prevention of health problems of the operators. For instance, the identification of a parameter that is above or under recommended limits, where an alert could be sent to the worker and supervisor that they need a break. This has already been applied in Tsai, but in the construction industry (Tsai, 2017).

6 CONCLUSIONS AND FUTURE WORK

The cardiorespiratory adaptations to different work volumes were studied using ECG and RIP signals monitoring during a period of the shift of multiple operators.

The analysis of the evolution of the chosen cardiac and respiratory indicators showed contrasts among tasks with distinct work volumes, where cardiac load was higher in the H_3 workstation and respiratory difficulty appeared to be higher in the H_1 and H_2 workstations, revealing distinct strategies of adaptation depending on work-volume.

These findings are enthusiastic as they corroborate the usefulness of the integration of respiratory monitoring in assembly-line occupational settings and reinforce the importance of measuring operators' cardiac activity. The found variables could be further used in task management and interventions at the workplace.

The time of acquisition in future research should be longer to obtain a broader vision of the operators' response to their daily shift and further understanding of internal compensation mechanisms. Moreover, an increase in sample size to amplify the representativity of the studied factory and effect size of statistical analysis.

This research underscores the potential and significance of cardiorespiratory monitoring in enhancing both task management and worker well-being on assembly lines. By doing so, it paves the way for a more human-centered workplace environment. This should be considered to identify possible degradation of worker's long-term well-being.

ACKNOWLEDGEMENTS

This work was supported by Project OPERATOR (NORTE01-0247-FEDER-045910), co-financed by the European Regional Development Fund through the North Portugal Regional Operational Program and Lisbon Regional Operational Program and by the Portuguese Foundation for Science and Technology, under the MIT Portugal Program. M. Dias and P. Probst were supported by the doctoral Grants SFRH/BD/151375/2021 and RT/BD/152843/2021, respectively, financed by the Portuguese Foundation for Science and Technology (FCT), and with funds from the State Budget, under the MIT Portugal Program.

REFERENCES

Andreas, G.-W. J. and Johanssons, E. (2018). Observational Methods for Assessing Ergonomic Risks for Work-Related Musculoskeletal Disorders. A Scoping Review. *Revista Ciencias de la Salud*, 16:8–38.

Astrand, I., Guharay, A., and Wahren, J. (1968). Circulatory Responses to Arm Exercise with Different Arm Positions. *Journal of Applied Physiology*, 25(5):528–532.

Ayabar, A., De la Riva, J., Sanchez, J., and Balderrama, C. (2015). Regression model to estimate standard time through energy consumption of workers in manual assembly lines under moderate workload. *Journal of Industrial Engineering*, 2015.

Baraldi, E. C. and Kaminski, P. C. (2011). Ergonomic planned supply in an automotive assembly line. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 21(1):104–119.

Brockmann, L. and Hunt, K. J. (2023). Heart Rate Variability Changes with Respect to Time and Exercise Intensity During Heart-rate-controlled Steady-state Treadmill Running. *Scientific Reports*, 13:8515.

Carvalho, D., Silva, L., Carvalho, M., Dias, M., Costa, N., Folgado, D., Nunes, M., Gamboa, H., Andza, K., and Edelman, E. (2023). Cardiovascular Reactivity (CVR) During Repetitive Work in the Presence of Fatigue. In Ahram, T., Karwowski, W., Bucchianico, P. D., Taiar, R., Casarotto, L., and Costa, P., editors, *Intelligent Human Systems Integration (IHSI 2023): Integrating People and Intelligent Systems*, volume 69. AHFE Open Access, AHFE International.

CEDEFOP (2023). Employed Population.

Celli, B. R., Criner, G., and Rassulo, J. (1988). Ventilatory Muscle Recruitment During Unsupported Arm Exercise in Normal Subjects. *Journal of Applied Physiology*, 64(5):1936–1941.

Chawla, N., Bowyer, K., Hall, L., and Kegelmeyer, W. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *J. Artif. Intell. Res. (JAIR)*, 16:321–357.

Chen, C.-C. and Tsui, F. R. (2020). Comparing different wavelet transforms on removing electrocardiogram baseline wanders and special trends. *BMC Medical Informatics and Decision Making*, 20.

Dias, M., Silva, L., Folgado, D., Nunes, M. L., Cepeda, C., Cheetham, M., and Gamboa, H. (2023). Cardiovascular load assessment in the workplace: A systematic review. *International Journal of Industrial Ergonomics*, 96:103476.

Eurostat (2023). Hours of work - Annual Statistics.

Gastinger, S., Donnelly, A., Dumond, R., and Prioux, J. (2014). A Review of the Evidence for the Use of Ventilation as a Surrogate Measure of Energy Expenditure. *JPEN. Journal of parenteral and enteral nutrition*, 38.

Geurts, S. A. and Sonnentag, S. (2006). Recovery as an explanatory mechanism in the relation between acute stress reactions and chronic health impairment. *Scandinavian journal of work, environment & health*, pages 482–492.

Goggins, R. W., Spielholz, P., and Nothstein, G. L. (2008). Estimating the effectiveness of ergonomics interventions through case studies: Implications for predictive cost-benefit analysis. *Journal of Safety Research*, 39(3):339–344.

Hammer, J. and Newth, C. (2009). Assessment of thoraco-abdominal asynchrony. *Paediatric Respiratory Reviews*, 10(2):75 –80.

He, H., Tan, Y., and Wang, Y. (2015). Optimal base wavelet selection for ECG noise reduction using a comprehensive entropy criterion. *Entropy*, 17(9):6093–6109.

Hess-nielsen, N. and Wickerhauser, M. (1996). Wavelets and time-frequency analysis. *Proceedings of the IEEE*, 84:523–540.

Holtermann, A., Hansen, J. V., Burr, H., Søgaard, K., and Sjøgaard, G. (2012). The health paradox of occupational and leisure-time physical activity. *British Journal of Sports Medicine*, 46(4):291–295.

Holtermann, A., Krause, N., van der Beek, A. J., and Straker, L. (2018). The physical activity paradox: six reasons why occupational physical activity (OPA) does not confer the cardiovascular health benefits that leisure time physical activity does. *British Journal of Sports Medicine*, 52(3):149–150.

Kazmierczak, K., Mathiassen, S. E., Forsman, M., and Winkel, J. (2005). An integrated analysis of ergonomics and time consumption in Swedish 'craft-type' car disassembly. *Applied Ergonomics*, 36(3):263–273.

Krause, N., Arah, O. A., and Kauhanen, J. (2017). Physical activity and 22-year all-cause and coronary heart disease mortality. *American Journal of Industrial Medicine*, 60(11):976–990.

Krause, N., Brand, R. J., Kaplan, G. A., Kauhanen, J., Malla, S., Tuomainen, T.-P., and Salonen, J. T. (2007). Occupational physical activity, energy expenditure and 11-year progression of carotid atherosclerosis. *Scandinavian Journal of Work, Environment & Health*, (6):405–424.

Lester, J., Hannaford, B., and Borriello, G. (2004). "Are You with Me?" – Using Accelerometers to Determine If Two Devices Are Carried by the Same Person. volume 3001, pages 33–50.

Liu, S., Gao, R. X., John, D., Staudenmayer, J., and Freedson, P. (2013). Tissue Artifact Removal from Respiratory Signals Based on Empirical Mode Decomposition. *Annals of biomedical engineering*, 41:1003–1015.

Lundberg, U., Granqvist, M., Hanssonand, T., Magnusson, M., and Wallin, L. (1989). Psychological and physiological stress responses during repetitive work at an assembly line. *Work & Stress*, 3(2):143–153.

Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., and Chen, S. H. A. (2021). NeuroKit2: A python toolbox for neurophysiological signal processing. *Behavior Research Methods*, 53(4):1689–1696.

Mang, Z. A., Realzola, R. A., Ducharme, J., Bellissimo, G. F., Beam, J. R., Mermier, C., de Castro Magalhaes, F., Kravitz, L., and Amorim, F. T. (2022). The Effect of Repetition Tempo on Cardiovascular and Metabolic Stress When Time Under Tension is Matched During Lower Body Exercise. *European Journal of Applied Physiology*, 122(6):1485–1495.

Massaroni, C., Nicolò, A., Lo Presti, D., Sacchetti, M., Silvestri, S., and Schena, E. (2019). Contact-Based Methods for Measuring Respiratory Rate. *Sensors*, 19(4):908.

Mccraty, R. and Shaffer, F. (2015). Heart Rate Variability: New Perspectives on Physiological Mechanisms, Assessment of Self-regulatory Capacity, and Health Risk. *Global Advances in Health and Medicine*, 4(1):46–61. PMID: 25694852.

Nardolillo, A. M., Baghdadi, A., and Cavuoto, L. A. (2017). Heart Rate Variability During a Simulated Assembly Task; Influence of Age and Gender. volume 61, pages 1853–1857.

Nicolò, A., Marcora, S. M., Bazzucchi, I., and Sacchetti, M. (2017a). Differential control of respiratory frequency and tidal volume during high-intensity interval training. *Experimental physiology*, 102(8):934–949.

Nicolò, A., Massaroni, C., and Passfield, L. (2017b). Respiratory Frequency During Exercise: The Neglected Physiological Measure. *Frontiers in Physiology*, 8:922.

NIOSH (1981). *Work Practices Guide for Manual Lifting*. Number 81-122 in DHHS (NIOSH) publication. U.S. Department of Health and Human Services, Public Health Service, Centers for Disease Control, National Institute for Occupational Safety and Health, Division of Biomedical and Behavioral Science.

Niu, S. (2010). Ergonomics and occupational safety and health: An ILO perspective. *Applied Ergonomics*, 41(6):744–753.

Palmerud, G., Forsman, M., Neumann, W. P., and Winkel, J. (2012). Mechanical exposure implications of rationalization: A comparison of two flow strategies in a Swedish manufacturing plant. *Applied Ergonomics*, 43(6):1110–1121.

Pickering, T. G., Devereux, R. B., James, G. D., Gerin, W., Landsbergis, P., Schnall, P. L., and Schwartz, J. E. (1996). Environmental influences on blood pressure and the role of job strain. *Journal of hypertension. Supplement : official journal of the International Society of Hypertension*, 14(5):S179–85.

Rétory, Y., Niedzialkowski, P., de Picciotto, C., Bonay, M., and Petitjean, M. (2016). New Respiratory Inductive Plethysmography (RIP) Method for Evaluating Ventilatory Adaptation during Mild Physical Activities. *PLoS ONE*, 11.

Rodrigues, J., Liu, H., Folgado, D., Belo, D., Schultz, T., and Gamboa, H. (2022). Feature-Based Information Retrieval of Multimodal Biosignals with a Self-Similarity Matrix: Focus on Automatic Segmentation. *Biosensors*, 12(12).

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fasth, Fast-Berglund, Å., and Gorecky, D. (2016). Towards an Operator 4.0 Typology: A Human-Centric Perspective on the Fourth Industrial Revolution Technologies. pages 29–31.

Ryan, L., Rahman, T., Strang, A., Heinle, R., and Shaffer, T. H. (2020). Diagnostic differences in respiratory breathing patterns and work of breathing indices in children with Duchenne muscular dystrophy. *PLoS ONE*, 15.

Sadat-Mohammadi, M., Shakerian, S., Liu, Y., Asadi, S., and Jebelli, H. (2021). Non-invasive physical demand assessment using wearable respiration sensor and random forest classifier. *Journal of Building Engineering*, 44:103–279.

Samani, A., Holtermann, A., Søgaard, K., Holtermann, A., and Madeleine, P. (2012). Following ergonomics guidelines decreases physical and cardiovascular workload during cleaning tasks. *Ergonomics*, 55(3):295–307. PMID: 22409167.

Sammito, S., Thielmann, B., Seibt, R., Klussmann, A., Weippert, M., and Böckelmann, I. (2015). Guideline for the application of heart rate and heart rate variability in occupational medicine and occupational science. *ASU Int*, 2015(06):1–29.

Santos, A., Rodrigues, J., Folgado, D., Santos, S., Fujão, C., and Gamboa, H. (2021). Self-Similarity Matrix of Morphological Features for Motion Data Analysis in Manufacturing Scenarios. pages 80–90.

Silva, L., Dias, M., Folgado, D., Nunes, M., Namburi, P., Anthony, B., Carvalho, D., Carvalho, M., Edelman, E., and Gamboa, H. (2022). Respiratory Inductance Plethysmography to Assess Fatigability during Repetitive Work. *Sensors*, 22.

Takala, E.-P., Pehkonen, I., Forsman, M., Hansson, G.-Å., Mathiassen, S. E., Neumann, W. P., Sjøgaard, G., Veiersted, K. B., Westgaard, R. H., and Winkel, J. (2010). Systematic evaluation of observational methods assessing biomechanical exposures at work. *Scandinavian Journal of Work, Environment & Health*, (1):3–24.

Tonello, L., Rodrigues, F., Souza, J., Campbell, C., Leicht, A., and Boullosa, D. (2014). The role of physical activity and heart rate variability for the control of work related stress. *Frontiers in Physiology*, 5.

Tsai, M.-K. (2017). Applying Physiological Status Monitoring in Improving Construction Safety Management. *KSCE Journal of Civil Engineering*, 21:2061–2066.

Umer, W. (2020). Sensors based physical exertion monitoring for construction tasks: Comparison between traditional physiological and heart rate variability based metrics. In *Proc., Joint CIB WO99 & TG59 Conf.*

van der Beek, A. J. and Frings-Dresen, M. H. (1998). Assessment of mechanical exposure in ergonomic epidemiology. *Occupational and Environmental Medicine*, 55(5):291–299.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, İ., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., and SciPy 1.0 Contributors (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17:261–272.

Wilson, D. J. (2019). The harmonic mean p-value for combining dependent tests. *Proceedings of the National Academy of Sciences*, 116(4):1195–1200.

Xu, W. and Du, F. (2022). A Robust Qrs Complex Detection Method Based On Shannon Energy Envelope And Hilbert Transform. *Journal of Mechanics in Medicine and Biology*, 22(03):2240013.

Yeo, I.-K. and Johnson, R. A. (2000). A New Family of Power Transformations to Improve Normality or Symmetry. *Biometrika*, 87(4):954–959.