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BSc in Biomedical Engineering

CARDIORESPIRATORY RESPONSE TO WORK VOLUME ON AN AUTOMOBILE ASSEMBLY LINE

MASTER IN BIOMEDICAL ENGINEERING

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Abstract

Repetitive tasks can lead to long-term cardiovascular problems due to continuous strain and inadequate recovery, resulting in inflammatory processes. The automobile operators on the assembly line are exposed to these risks when workload volume varies according to the workstation type.

Despite these concerns, current ergonomic assessments focus primarily on biomechanical aspects and rely on sometimes, subjective and time-consuming metrics, overlooking cardiovascular and respiratory adaptations to workload variations.

The aim of this study was to analyse the cardiorespiratory response to different workload volumes and ergonomic risk tasks in the context of an automotive assembly line.

Sixteen male operators (age=38.38±8.33 years; BMI=25.27±2.54 kg.m^2) volunteered from three workstations (H1, H2 and H3) with different work cycle durations (1, 3 and 5 minutes respectively). Electrocardiogram (ECG), respiratory inductance plethysmography (RIP) and accelerometer (ACC) data were collected during their work shift.

The results showed significant differences in the evolution and between workstations in several key indicators of cardiovascular load ($p \in [< 0.001, 0.027]$), heart rate variability ($p \in [0.001, 0.018]$), respiratory frequency ($p \in [< 0.001, 0.035]$), its variability ($p \in [< 0.001, 0.028]$) and thoraco-abdominal coordination ($p \in [< 0.001, 0.042]$).

Some common variables to all workstations, of adaptation, were also encountered, in standard deviation of the RR intervals (p=0.032) and in abdominal respiratory rate range (p=0.026) and standard deviation (p<0.001). These indicators also showed to be useful in the discrimination of tasks that lie in distinct ergonomic risk ranks.

The workload volume and work phase both influenced the cardiorespiratory acute response of the operators on the automobile assembly line.

Keywords: Workload, Cardiorespiratory adaptations, Occupational Health, Operator,Automobile Industry, Industry 4.0, ECG, RIP

Resumo

Tarefas repetitivas podem levar a problemas cardiovasculares a longo-prazo, por meio de esforço contínuo e tempo de recuperação inadequado, instigando vias inflamatórias. Em linhas de montagem automóvel os trabalhadores estão sujeitos a este tipo de risco quando o volume de trabalho varia de acordo com o posto de trabalho.

Apesar disto, as avaliações ergonónimcas actuais centram-se na medida de parâmetros biomecânicos do trabalho, recorrendo a métodos, muitas vezes, subjetivos e demorados, que não têm em conta as adaptações fisiológicas a diferentes cargas de trabalho.

O objetivo deste estudo foi analisar a resposta cardiorrespiratória a volumes de trabalho e riscos ergonómicos distintos no contexto de uma linha de montagem na indústria automóvel.

Dezasseis trabalhadores do sexo masculino (idade=38.38±8.33 anos ; IMC=25.27±2.54 kg.m^2) de três postos da linha de montagem (H1, H2 e H3) com tempos de ciclo distintos (1, 3 e 5 minutos respetivamente) voluntariaram-se para o estudo.

A recolha de dados do Eletrocardiograma(ECG), pletismografia de indutância respiratória(RIP) e Acelerómetro(ACC), foi feita num período do seu turno.

Os resultados apresentaram diferenças significativas na evolução e entre tarefas de volume distintos nas métricas de carga cardiovascular ($p \in [< 0.001, 0.027]$), variabilidade da frequência cardíaca ($p \in [0.001, 0.018]$), frequência respiratória ($p \in [< 0.001, 0.035]$), na sua variabilidade ($p \in [< 0.001, 0.028]$) e na coordenação toracoabdominal ($p \in [< 0.001, 0.042]$).

Algumas variáveis de adaptação comum entre postos de trabalho foram encontradas, no desvio padrão dos intervalos RR (p=0.032) e na amplitude (p=0.026) e desvio padrão (p<0.001) da frequência respiratória. Estes indicadores também se mostraram úteis na distinção entre tarefas com classificação de risco ergonómico específicos.

O volume de trabalho e a fase da recolha, ambos influenciaram a resposta cardiorrespiratória aguda dos trabalhadores na linha de montagem automóvel.

Palavras-chave: Carga de trabalho, Adaptações cardiorrespiratórias, Saúde Ocupacional, Operário,Indústria automóvel, Indústria 4.0, ECG, RIP

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List of Abbreviations

ABD Abdominal *(pp. 17, 27–30, 32, 33, 35, 37, 38)*
ACC Accelerometer *(pp. 2, 5, 11–14, 17, 18, 35, 40)*

BMI Body Mass Index *(p. 21)*

CVL Cardiovascular Load *(pp. 16, 24, 25, 30, 31)*
CVS Cardiovascular Strain *(pp. 16, 24, 25, 30, 36)*

EAWS European Assembly Worksheet *(pp. 3, 22, 36)*
ECG Electrocardiogram *(pp. 2, 4, 5, 7, 8, 11–16, 27, 35, 39, 40)*
EMD Empirical Mode Decomposition *(p. 17)*
EMG Electromyography *(pp. 11–13, 18, 40)*
ER Ergonomic Risk *(pp. 2, 3, 30, 33, 35–37, 39)*

HR Heart rate *(pp. 4, 7, 8, 16, 25, 30, 31, 35–37)*
HRV Heart rate variability *(pp. 4, 5, 8, 9, 16, 20, 35–38)*

ILO International Labour Organization *(p. 6)*
IMF Intrinsic Mode Function *(p. 17)*

MVC Maximum Voluntary Contraction *(p. 13)*

NIOSH National Institute for Occupational Safety and Health *(pp. 3, 6)*

PS Phase Synchrony *(pp. 27, 28, 33, 37, 38)*

RC Rib cage *(pp. 17, 27, 28, 32, 33, 35, 37, 38)*
RHR Relative Heart Rate *(pp. 7, 9, 16, 25, 30, 31, 36)*
RIP Respiratory Inductance Plethysmography *(pp. 2, 5, 8, 11–14, 27, 35, 39, 40)*

RMS Root Mean Square *(p. 15)*

RMSSD Square root of the mean sum of the square differences between NN intervals *(p. 5)*

RPE Rate of Percieved Exertion *(p. 13)*

RR Respiratory Rate *(pp. 17, 28–30, 32, 33, 35, 37, 38)*

SD Standard Deviation *(pp. 8, 16, 19, 25, 27–33, 35–38)*

SD1 Poincaré plot standard deviation perpendicular to the line of identity *(p. 5)*

SD2 Poincaré plot standard deviation along the line of identity *(pp. 5, 25, 31, 36)*

SDRR Standard Deviation of the RR intervals *(pp. 5, 25, 27, 31, 35, 36)*

SSM Self-Similarity Matrix *(pp. 18, 19)*

1

Introduction

1.1 Context and Motivation

In the European Union the highest employment percentage was found in the Manufacturing Sector in 2021 [2], with plant and machine operators and assemblers working an average of 39.7 hours per week [3].

For the majority of that time, operators are exposed to numerous occupational hazards such as repetitive movements, awkward postures, static positioning and forceful exertions [4]. In addition, occupational physical activity performed at low intensity and for extended periods of time instigates adaptations according to the task demands, and may be detrimental to health by causing disease or aggravating preexisting conditions, such as cardiovascular disease [5], [6].

The lack of decision latitude, a characteristic of assembly-line machine paced work, has also been linked to higher blood pressure [7], a known risk-factor for cardiovascular disease.

The application of ergonomic design and interventions has shown to reduce work-related illnesses, workers' compensation costs, absenteeism and increased productivity and quality of production, with payback time generally being less than one year [8], [9].

The analysis of occupational risk focuses mostly on biomechanical loads of the performed task, not taking other factors into consideration, such as individual specific differences and physiological load. This analysis relies mainly on observational methods, that are time-consuming and less accurate for smaller body parts [10], also giving limited knowledge about internal adaptations to the task [11].

With the rise of industry 4.0, where reliable human-machine interactions are used to leverage productivity and workers well being, the use of wearables has become a trend, where direct measures of activity and biological data can be acquired in real-time, providing means to proactive prevention and continuous information of physical status to the worker and managers [12].

1.2 Objectives

To understand if there are potentially health damaging cardiorespiratory adaptations that are not currently accounted for during car manufacturing tasks, the aim of this thesis is to examine those responses to different work-volumes and Ergonomic Risks (ERs) by means of cardiovascular and respiratory load in a real automobile assembly line.

By monitoring workers' multiple biosignals (Accelerometer (ACC), Electrocardiogram (ECG) and Respiratory Inductance Plethysmography (RIP)) during a period of their normal activity, the quantification of their adaptations over time can lead to more personalized work interventions and task management.

To accomplish the described general aim four specific objectives are delineated:

- Identify variations in volume among assembly line workstations.
- Compare the cardiovascular responses corresponding to different workstation volumes.
- Compare the respiratory response in relation to different workstation volumes.
- Determine if cardiorespiratory responses vary accordingly to the biomechanical risk stratification.

Identifying relevant biomarkers that can make a distinction between different types of tasks, can give more insight and an objective measurement of the underlying physiological demand of each workstation and the hazards that workers are exposed to.

The research work described in this dissertation was carried out in accordance with the norms established in the ethics code of Universidade Nova de Lisboa. The work described and the material presented in this dissertation, with the exceptions clearly indicated, constitute original work carried out by the author.

2

Theoretical Concepts

2.1 Occupational Health

Occupational Health is a branch of public Health with three main focuses, maintaining and proactively preserving the workers' health, leveraging the workplace to incentive healthy and safe environments and develop policies and working structures that ensure positive job culture. It involves multiple sciences such as psychology, occupational medicine and ergonomics [13].

2.2 Ergonomics

Ergonomics is a multidisciplinary field that encompasses physiology, anatomy and psychology with the purpose of adjusting the occupational environment to the needs of the worker, leading to improvements in the operators health and productivity [4]. It has three main fields of study: Physical (physiology, biomechanics and anatomy), Cognitive (perception, reasoning and memory) and Organizational ergonomics (policies and organizational structure) [14]. In this thesis, only the physical aspect is studied.

2.2.1 Ergonomic Risk

The evaluation of ERs can be done in several ways: self-reporting, observational and direct measurement methods. Observational methods involve an expert that fills in a pre-defined scoring sheet by watching the operators perform their tasks.

There are multiple scoring methods that take into account different body parts and different key indicators of biomechanical load, such as intensity, duration and frequency of the observed work. Some of the most used tools are the revised National Institute for Occupational Safety and Health (NIOSH) equation, the job strain index, OCRA(Occupational Repetitive Action) and the European Assembly Worksheet (EAWS) [15].

The EAWS is the scoring worksheet used by the studied assembly production company. It encompasses whole-body and upper-limb assessment of risk factors, resulting in a traffic light like risk score estimation [16], its scheme is represented in Figure 2.1.

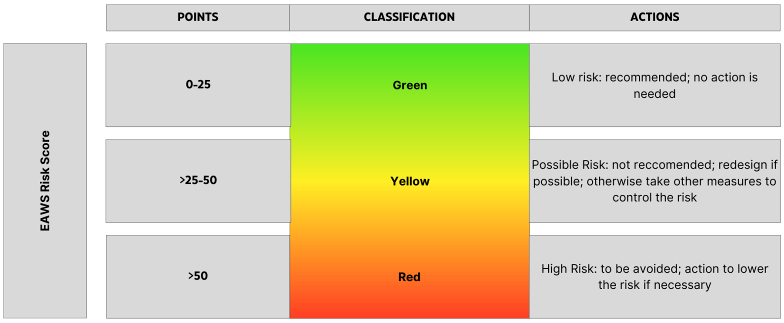


Figure 2.1: European Assembly Worksheet overall estimation scheme, adapted from [17].

2.3 Biosignals

2.3.1 Electrocardiography

The ECG is an exam that measures electrical activity of the heart, where an action potential is formed at the sinoatrial node that, in normal circumstances, is transmitted sequentially to the atria,the atrioventricular node, the bundle of His and Purkinje fibers to the Ventricles , making the heart contract periodically. In a normal ECG three shapes should be distinguishable, corresponding to different phases of polarization and depolarization of the structures of the heart: the P wave, the QRS complex and the T wave [18]. This measurement is done by placing at least 2 electrodes on opposite sides of the heart, so when electric current passes they can detect and register the potential between those points [19]. The shape of the overall graph depends on the positioning of the electrodes [18].

The ECG gives us important information to evaluate the state of the heart. Features such as the R-R interval, that corresponds to the distance in time between two QRS complexes, represents Heart rate (HR), a value that can indicate abnormalities in cardiac rhythm [20].

2.3.1.1 Heart Rate Variability

Heart rate variability (HRV) is the variation in time of the intervals between two consecutive heart beats, the RR intervals, and when ectotopic or abnormal beats are excluded are called the Normal to Normal intervals. This variability can be tied to the health condition of the heart, as HRV reflects its capacity of adaptation to different stimuli, regulated by the Autonomic Nervous System [21].

This system is made of sympathetic and parasympathetic components, where the formers' activity increases in response to stressful situations and exercise, while the latter is predominant in resting conditions, maintaining and conserving energy and regulating basic body functions. Specifically speaking of the heart, sympathetic stimulation increases HR and force of contraction, while parasympathetic stimulation does the opposite [22].

Clinically significant measurements can be derived from HRV, in the time,frequency and non-linear domains. As recommended by the Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology, the ECG recording should have a certain length, for short recordings 5 minutes and long-term recordings are of at least 24 hours.

Some examples of the parameters are Standard Deviation of the RR intervals (SDRR), Square root of the mean sum of the square differences between NN intervals (RMSSD) [21], Poincaré plot standard deviation perpendicular to the line of identity (SD1) and Poincaré plot standard deviation along the line of identity (SD2), the width and length of the ellipse that was fitted to the Poincaré plot (current RR intervals plotted against the following RR interval), respectively [23].

2.3.2 Respiratory Inductance Plethysmography

RIP is a non-invasive method of monitoring pulmonary function by placing two elastic bands with embedded coils around the chest and abdominal walls. The output is proportional to the variation of the cross-sectional area of the surfaces surrounded by those bands [24], [25].

The resulting breathing pattern allows us to retrieve information about the respiratory rate, the contribution of the chest movement to breathing, as well as the synchrony and phase angle between the breathing patterns resultant from both walls [24], [26], [27].

2.3.3 Accelerometer

An ACC is a sensor capable of measuring the rate of change in velocity (acceleration) along one or more axis, normally measured in gravitational units (g) [28]. Like this it is possible to obtain information of acceleration along the x, y and z axes enabling its use in activity monitoring, recognition of postures and movements [29]. In this work it was essential for signal synchronization acquired with multiple devices and to automatically segment signals.

3

Literature Review

Occupational health plays a vital role in preventing occupational health risks by matching job requirements to the physical and psychological capabilities of employees, in line with guidelines jointly developed by the International Labour Organization (ILO) and the World Health Organization (WHO). This ensures the holistic well-being of employees, encompassing their physical, mental and social aspects [30].

The area of Ergonomics is a key part of occupational health application [4], as it prioritizes and designs work settings with the optimal relationship of operators well-being and productivity [14].

Organizations such as ILO and the NIOSH have established recommendations and guidelines with the purpose of improving workers conditions and standardizing policy, on these topics. Specifically the NIOSH has established work practices guides for manual lifting where they defined limits on workload (frequency, handled load, distances of the material handling) and physiological demands of work, specifically they state that in an 8 hour continuous shift, it should not surpass 30% of aerobic capacity [31].

These serve as guides for states and countries to legislate on occupational requirements to ensure safety and good conditions at workplaces. Some examples are the International Organization for Standardization (ISO) standards on Manual Handling [32] and the European Community Directive 89/391/EEC [33]. As noted by [4] there are some shortcomings of these ergonomic legal criterion, reporting that they have precarious consideration of the time and dose effects of physical problems faced at the workplace, limiting their attention to biomechanical exposure, that is known not to be the sole contributor to work-related disease.

Concern for productivity with the reduction of workload of the operators was dated back to the early 1900's with the introduction to time-motion studies [34]. In the 1950's [35] performed a physiological assessment in an iron factory, for tasks of different intensity and proposed a classification of heaviness of work based on pulse frequency and oxygen consumption.

From the 1970's to the early 2000's, multiple studies were carried out to understand cardiorespiratory load of work, both in laboratory settings and in-field studies, looking to develop stratification of work demands by means of oxygen consumption, energy expenditure, HR measures and self-reporting scales. The goals were to uncover if different types of work and tasks had more pronounced relative aerobic strain on workers, with consideration of time and evaluate the impact of certain ergonomic interventions in acute physiological adaptations [36]–[40]. Some of the most relevant findings were that occupational stress and strain are dependent upon the performed task, and its physiological evaluation is crucial to understand certain aspects of work so they can be adjusted [37]. Also an upper limit of aerobic intensity of a job with a certain workload was established for different work shift durations, expressed as a percentage of Relative Heart Rate (RHR), for an 8 hour-shift it was found to be of 24.5% [39].

Some of these techniques were deemed unpractical and time consuming due to limitations in the equipment that was available at the time [40], but in recent years, the development of wearable technology and the appearance of Industry 4.0 has facilitated the ubiquitous monitoring of workers during their shifts. With the data recovered from these devices, a more individual-specific and evolution of physical variables can be used for planning and interventions in real occupational settings [12], [41].

Specifically speaking of previous studies on assembly-lines, Lundeberg et al. measured self-reports of work characteristics and of perceived physical load, and objective measures were also evaluated, HR, blood pressure, catecholamines and cortisol. A nurse was required to measure blood pressure with a sphygmomanometer and a stethoscope, and HR was determined by 60 second palpitations [42]. The main findings of this study were the association of perceived stress with neuroendocrine response and that during work both physiological types of measurement were significantly increased during work at a car manufacturing assembly line.

In the works of Palmerud et al. and Kazmierczak et al. the impact of introducing a different strategy to the assembly line, called rationalization (minimization of non-productive time during work activities) was evaluated. In both, job exposure was measured with RHR based on heart rate measures from telemetry ECG. In the first study, with the adoption of a different work strategy, mean HR decreased [43]. For the second study it was noted that the type of task performed had a high load on the cardiovascular system[44]. Even tough these studies measured cardiac metrics, their sole focus wasn't on this parameter, and movement aspects are detailed much more in depth.

The modeling of ideal working time based on energy expenditure of assembly-line workers was also developed, based on moderate workload tasks [45]. The energy expenditure was computed based on HR measurements from a wearable watch, of workers from three different assembly lines. The chosen model was based on two computed variables, total kcal per pieces and total kcal per operating time (cycle duration), and had a determination coefficient of 94.1 with an estimated standard error of 45.1. They also collected information that further characterised subjects, but did not choose the models that included these variables.

By simulating assembly line tasks Nardolillo et al. extracted HRV from HR of participants, measured with a wearable HR monitor. The participants encompassed 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 (specifically Mean RR, Standard Deviation (SD) of Normal to Normal RR intervals, and RR Triangular Index) for some of the comparisons.

The evaluation of cardiorespiratory responses in research scenarios can be accomplished with multiple methods. Oxygen consumption (VO_2), measured in L/min, is the most reliable measurement of workers physical capacity [39], but this involves the use of invasive equipment that is not practical in real work scenarios. As VO_2 is the product of arteriovenous oxygen difference, stroke volume, and HR, and considering the ease of measuring HR, it has become a popular alternative for assessing cardiovascular load.

HR can be measured by Photoplethysmography (changes of blood flow in vessels) [46] or ECG (Electrical activity of the heart), both methods are non-invasive and have portable devices.

Another method of quantifying this type of physiological response is blood pressure monitoring, where cuff-base measurements are the gold standard, but for ambulatory applications are not practical, since the devices aren't easily transported and subjects have to be still and relaxed when measuring this parameter [47]. Also it does not allow a continuous monitoring [48].

Self-reporting of perceived physical exertion is also a common method to be used as it is easily applied and is less costly than other methods [49]. Even tough this is an easy to use and useful tool, its relationship with direct measures is ambiguous, in some studies it overestimates [50], underestimates [51] and agrees with direct measurements of physical intensity [38], [42].

In recent studies, it has been shown that respiratory frequency is important to assess physical effort in sports [52] and is useful for the identification of cognitive load, environmental stress and other relevant factors in occupational settings [53]. Multiple devices can be used to monitor respiration, and RIP has shown to be suitable in both laboratory settings and in less controlled environments [53]. It has already been used in a previous study to measure fatigability in simulated repetitive work [54].

Cardiovascular diseases are an identified possible consequence of low-intensity work physical activity, leading to concepts such as the physical activity paradox and cardiovascular reactivity. The first states that physical activity at work is not beneficial as it is in leisure-time activities [5], the other one affirms that without sufficient recovery, stimulation of the body's inflammatory responses will take a toll on the worker's health [55].

Monitoring cardiorespiratory activity becomes worrisome as high levels of occupational physical activity have been associated with degrading effects to health. Multiple cardiovascular risks, mortality and long-term sickness absence in workers with low leisure physical activity have been identified[6], [56], [57].

This is a difficult task as numerous factors on the assembly-line can influence the reaction of the cardiorespiratory system. Environmental factors such as temperature and noise, job characteristics, such as working hours, shifts, break times and task demands (repetitiveness and posture) [58]–[64].

Operators individual traits also affect these physiological measurements, their body mass, age, gender, physical fitness, exercise habits and work related stress [42], [65]–[68].

Encountered studies on assembly-line mainly focused on exploring RHR as a measure of job exposure, not considering other physiological measures. The ones that do, normally were simulated tasks, and not in real scenario work. Also, most of these studies aimed to predict or analyze effects of interventions made on the line organization.

The objectives of this Thesis are to explore multiple physiological variables related to respiration and cardiac response to different workloads, including HRV, as they can bring useful information [69], and characterize each studied assembly line station. The dependence of these variables on workload, moment of measurement, total time of acquisition and biomechanical exposure were studied.

4

Methods

With the purpose of characterizing physiological response to cyclical working, biosignals of multiple assembly line operators were monitored on the field, during real tasks performed on a daily basis.

This section begins with the description of this study, of its participants, the protocol used to collect data and a general description of the activities performed during acquisitions. Following this, the methods used to process the signals and the extracted parameters are described. At last the statistical approach to analyze this data is explained.

4.1 Study Design

4.1.1 Study type

This dissertation's study was transversal, as measurements from each subject were collected only once, and exploratory, as the physiological adaptations of stations with distinct work volumes and frequency was sought to be understood and thus a potential biomarker that could be useful for ergonomic planning and occupational health monitoring.

4.1.2 Study Research Questions

The objective of this dissertation was to answer specific questions concerning physiological workload of the assembly line workers, more specifically:

1. Are there differences in physiological response between H1, H2 and H3 workstations?

2. Are there any differences in the physiological responses between the start of an assembly line task and 40 minutes after the end of the task in terms of its volume?

3. Are there any common adaptations to all workstations?

4. Are cardiorespiratory monitored variables related to biomechanical scores of the performed task?

4.2 Data Collection and Protocol

4.2.1 Participants

The data collection was performed on a total of 46 voluntary participants. In this study, 16 subjects from the assembly workstations were included (age: 38.38 ± 8.33 yrs; body mass index: 25.27 ± 2.54 kg.m^2; physical activity: 220.35 ± 135.78 min.week^{-1}, 8 from H_3, 4 from H_2 and 4 from H_1. All were right handed male workers from Volkswagen Autoeuropa automotive assembly lines. This was considered a representative sample of the factory as the majority of workers are male. Each subject had the purpose and protocol of the study clearly explained to them, also they read and signed informed consents to be included.

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

4.2.2 Tasks

In the assembly line, the tasks performed at the studied workstations are specified:

- The setting of tail lights (SBBR's) and prefit alignments were recorded in H_1.
- At H_2 alignments of the side doors, rear end and front end were analyzed.
- At last, in the H_3 area the final stages of the assembly are performed: rear-view mirror, cowltop, boot panel and the trunk symbol mounting were monitored.

In Figure 4.1 the parts of the car involved in each of the activities mentioned above are represented:

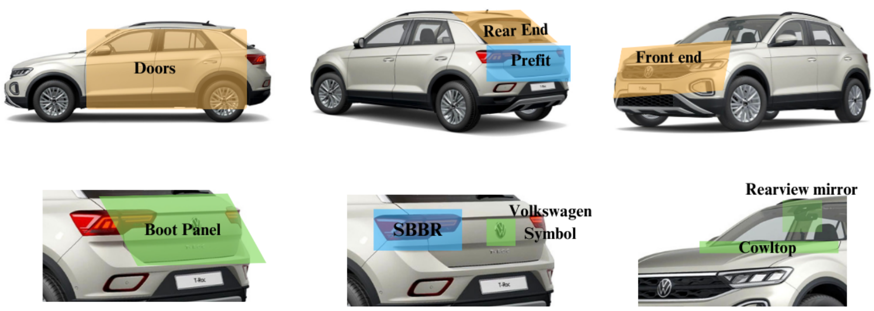


Figure 4.1: Parts of the vehicle involved in the analyzed tasks of each workstation. **Blue**: H_1; **Orange**: H_2; **Green**: H_3.

4.2.3 Materials

To analyze physiological response to repetitive work, multiple signals were acquired including ECG, RIP, Electromyography (EMG) and ACC data.

For the ECG measurement, three disposable adhesive Ag/AgCl electrodes were attached to each electrode cable from the ECG sensor. RIP signals were obtained with two elastic belts and two inductive sensors attached to each one of them. A triaxial ACC was also used. These last three sensors were all connected to the 8-channel wireless Hub, that streams the data from each of the sensors to the *opensignals* software.

In order to monitor EMG two MuscleBAN devices were used, they include an EMG sensor, triaxial ACC and magnetometer, streaming as well to *opensignals*. Also four disposable adhesive Ag/AgCl electrodes were used in each data recording.

All of these devices are part of the *biosignalsplux* Kit [70].

In addition, a camera was used to record the first work-cycles of each subject.

4.2.4 Protocol

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

4.2.4.1 Sensor setup

The sensor placing started by cleaning of 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, the three ECG electrodes were placed in a configuration to minimize arm and chest movement artifacts, something previously determined by investigators in the laboratory. On the left side of the sternum, the positive was positioned at the level of the manubrium, the negative on the superior part of the sternum's body. The ground electrode was placed on the left anterior superior iliac spine.

Afterwards, the subjcet was asked to contract the muscles where the MuscleBAN devices were to be positioned: the biceps brachii and the upper trapezius, to ensure they were on their belly. Only the dominant limb was monitored.

The RIP rib cage band was strapped over the chest passing underarms and the abdominal band at the umbillicus level [25], [54], and was adjusted to the participant's anatomy.

At last the ACC was placed on the center of the lower back, secured with an elastic belt.

The ECG, RIP and ACC sensors were all connected to the Hub, and this data was set to be acquired at 350 Hz and sent to the software. The MuscleBANs were set to be recorded at a sampling rate of 1000 Hz and also streamed to *opensignals*.

The setup of the sensors is represented in the next Figure:

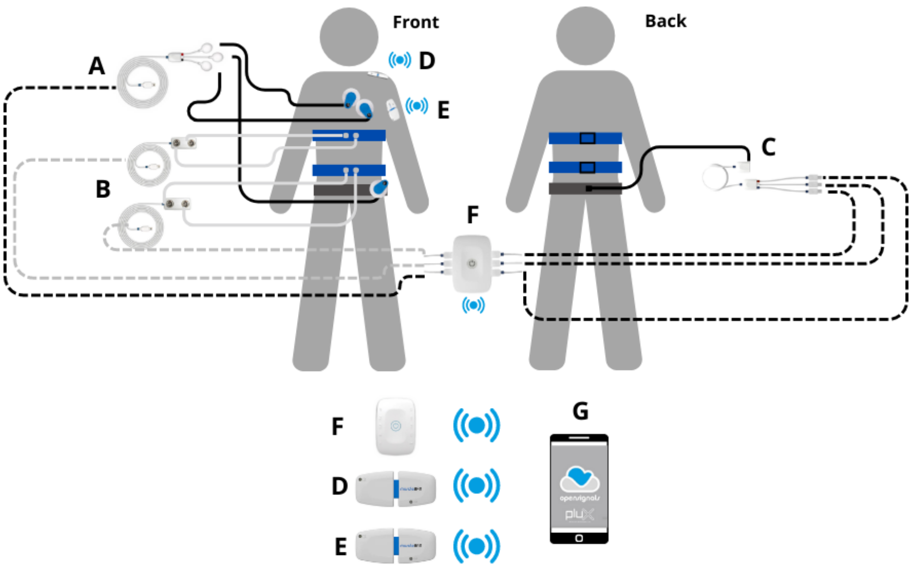


Figure 4.2: Sensor setup for signal acquisition. A: Electrocardiogram sensor, B: Chest (top) and Abdominal (bottom) Respiratory Inductance Plethysmography sensors, C: Accelerometer, D: Trapezius MuscleBAN, E: Bicep MuscleBAN, F: Hub, G: Mobile phone with *opensignals*.

4.2.4.2 Signal acquisition

When sensor placement and verification of connection with the mobile phone was concluded, the participant was asked to jump 10 times, for synchronization purposes, followed by the Maximum Voluntary Contraction (MVC) test of each muscle for EMG normalization, this last step was done 2 times for each muscle, to ensure that the maximum was reached. This was the first recording.

Next the subjects were asked to place the phone in their pockets, again they were asked to jump 10 times and carry out about 50 minutes of normal occupational activity, this was the second recording.

4.2.4.3 Scale of Perceived exertion

At the end of each acquisition the participants were inquired about the subjective score of difficulty (Rate of Percieved Exertion (RPE)) of the monitored task, at the beginning (between 1 minute and 2 minutes after starting the acquisition), in the middle (after 30 minutes had passed) and at completion.

4.3 Signal Processing

For this study, only the ECG, RIP and ACC data from the sensors were studied, from the Muscle BANs only the ACC data was used.

4.3.1 Units Conversion

Each one of the sensors outputted raw values that had to be converted into physical units. For this, each sensor's data-sheet provides a transfer-function. For the ECG, RIP and MuscleBANs the number of bits per channel is the same, and is equal to $n = 16$ [71]–[73]. For ECG and ACC the operating voltage is equal to $VCC = 3V$. First, the transfer functions for the devices connected to the hub are represented by the following Equations.

$$ECG(mV) = \frac{(\frac{ADC}{2^n} - 0.5).VCC}{G_{ECG}}.1000 \quad (4.1)$$

$$RIP(\%) = (\frac{ADC}{2^n} - 0.5).100\% \quad (4.2)$$

Where G_{ECG} is equal to 1019.

For the ACC sensor a prior calibration of the sensor had to be done to obtain C_{max} and C_{min}, the calibration values. To do so, a very slow rotation of 360º had to be made around each one of the axis. The calibration values are extracted from the raw values obtained from this calibration protocol by finding the maximum and minimum values. The following Equation shows its transfer function.

$$ACC(g) = \frac{ADC - C_{min}}{C_{max} - C_{min}}.2 - 1 \quad (4.3)$$

At last we needed to transform the raw values from the ACC from the MuscleBANs, that have an operating voltage of $VCC = 2.5V$ and gain G_{EMG} is 1100.

$$ACC_{MB}(g) = (ADC - \frac{2^n}{2}).(\frac{8}{2^n}) \quad (4.4)$$

4.3.2 ECG signal processing

4.3.2.1 ECG filtering

The removal of artifacts and frequencies that are not representative of heart activity and that hinder its analysis is essential for a correct interpretation of the ECG .

Most of the features that were extracted from this signal are based on the detection of the QRS complex, so other wave shapes were suppressed to highlight the R peaks.

Multiple frequency ranges have been proposed as the intervals of interest to get the optimal R-peak and Elgendi et al. had the maximal accuracy for 8-20 Hz [74].

Wavelet based methods are used to filter ECG given the non-stationary nature of this signal, this is, it is a signal that changes in time and in frequency [75], [76].

There are multiple wavelets that can be used to decompose the signals [77]. The tested wavelets were of the Debauchies(db2, db3, db4, db10) and Symlet families(sym2, sym3, sym4, sym5).

To choose the best wavelet with which signals could be decomposed, a quantification of how much the R-peaks are enhanced had to be made. The used method was proposed by [78], where the most suitable base wavelet is the one that maximizes energy-to-Shannon entropy ratio:

$$Er = \frac{E_{Energy(c)}}{E_{Entropy(c)}} \tag{4.5}$$

Where $C(n) = [c_0, c_1, .., c_n]$, is the wavelet coefficient sequence, derived from the discrete wavelet decomposition at scale j of the noisy ECG signal ($S(n) = [s_1, s_2, ..., s_n]$).

$$E_{Energy}(c) = \sum_{i=1}^{N} (|c(j,i)|)^2 \tag{4.6}$$

and $c(j,i)$ is the ith coefficient of the jth level of decomposition of S(n). $E_{Entropy}(c)$, is the Shannon Entropy of the wavelet coefficients computed as:

$$E_{Entropy}(c) = -\sum_{i=1}^{N} pi.log_2(pi) \tag{4.7}$$

$$Pi = \frac{|c(i)|^2}{E_{Energy}(c)} \tag{4.8}$$

This criteria resulted in the db2 wavelet, for all signals.

Using the modwtpy package [79], this time-series was decomposed into 6 wavelet levels, using the *modwt* function. Level 4 decomposition coefficients were stored and used to perform the inverse wavelet transform to reconstruct the signal and thus give us the filtered result, in traditional wavelet filtering this corresponds to a frequency band of 10.94-21.88 Hz.

4.3.2.2 R-peak detection

The following steps are based on [80], that had a very similar experimental setup as the one used in this study. Initially baseline shift was removed and normalization of the signal amplitude was performed, in order to compare signals from different subjects, and to make the R-peak detection algorithm more efficient, using the following Equation (4.9):

$$a[n] = \frac{s[n]}{max_{n=1}^{N}(|s[n]|)} \tag{4.9}$$

Here s[n] is the filtered signal and a[n] the normalized signal, N is the number of samples.

Next the Shannon Energy was computed, followed by the Envelope, as done in [81]–[83]. The envelope was computed using a moving Root Mean Square (RMS).

$$se(n) = -a[n]^2.log_2(a[n]^2) \tag{4.10}$$

$$r[n] = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} se(n-1)^2} \tag{4.11}$$

The window should be of approximately the size of the duration of a QRS complex [81], a normal duration of the QRS complex for individuals over 16 years old should not exceed 110 ms [84], given that the sampling rate is of 350Hz this equates to 38.5 samples. The chosen length for the window in this algorithm is of 70 samples.

After this, normalization of the envelope was performed, once again using 4.9, so its values lied between -1 and 1. The envelope was transformed into a square signal by applying a threshold (th) equal to -0.1 , as shown in the following inequality:

$$sq[n] = \begin{cases} 1, & \text{if } \mathrm{r[n]} > \mathrm{th} \\ 0, & \text{if } \mathrm{r[n]} <= \mathrm{th} \end{cases} \tag{4.12}$$

At last a half-correction is done on the filtered signal, and this last transformed time-series is multiplied by the square signal that results from 4.12.

With the signal from the last operation, the R-peaks were detected using scipys's [85] *findpeaks* function, using a minimum distance of 120 samples, and a minimum height of 0.15.

4.3.2.3 R-peak correction

Incorrect and ectotopic beats have to be corrected in the HRV time-series, as it can result in misleading results in the HRV metrics [21].

Even though this algorithm detects most R-peaks, some outliers where encountered, so a correction was performed by a sliding window on the HRV time-series.

Given the interval: $[\bar{x}-1.3\sigma, \bar{x}+1.3\sigma]$, $\bar{x}$ is the mean and σ is the SD of the RR intervals in the corresponding window.

When RR intervals were above this range it meant that the algorithm must have missed a R-peak, so it was replaced by the mean value of the window's RR intervals. When a point was under this range it was eliminated, because it was considered an extra detection.

4.3.3 ECG metrics

With the computation of the HRV time-series, other indicators were extracted from the ECG, such as: RHR, Cardiovascular Strain (CVS) and Cardiovascular Load (CVL), as they have been previously used in multiple studies to evaluate cardiovascular load in occupational context [69].

Some of these metrics rely on the calculation of age-adjusted HR Maximum: $HR_{max} = 208 - 0.7 \times age$ [86].

$$RHR = \frac{HR_{work} - HR_{rest}}{HR_{max} - HR_{rest}} \times 100\% \tag{4.13}$$

$$CVS(\%) = \frac{HR_{work} - HR_{rest}}{HR_{rest}} \times 100\% \tag{4.14}$$

$$CVL = \frac{HR_{work} - HR_{rest}}{HR_{max(8hr)}} \times 100\% \tag{4.15}$$

Here $HR_{max(8hr)}$ refers to the maximum acceptable heart rate for an 8 hour shift, $\frac{1}{3}(220 - age) + HR_{rest}$ [87].

4.3.4 RIP

4.3.4.1 RIP filtering

Initial filtering was done to remove noise out of the frequency range of this physiological signal.

According to literature, respiratory cycles in rest can range from 12-20 [88] breaths per minute and in exercise can go up to 59 [89] breaths per minute.

The filtering method was based on the one used by [54], first a 5th order finite impulse response band-pass filter with cut-off frequencies of 0.15 and 0.45 Hz was applied to the signal.

Next, the signal is decomposed with Masked Sift Empirical Mode Decomposition (EMD) to obtain it´s Intrinsic Mode Functions (IMFs), this means that we are able to separate the actual signal in the low frequency band, the tissue artifacts in the high-frequency band and ambient noises in all of the bands. By choosing the appropriate IMFs to reconstruct the signal, we get a clear respiratory pattern [90]. Both signals from the chest and abdominal belt were subjected to this procedure.

4.3.4.2 RIP metrics

Finally, the respiration measures were derived from this signal. Rib cage (RC)% that is defined as the rib cage's contribution to tidal volume as a percentage of the sum of both RC and Abdominal (ABD) volume variation [27].

$$RC\% = \frac{|RC|}{|RC| + |ABD|} \times 100\% \tag{4.16}$$

Also Respiratory Rate (RR) in breaths per minute, was determined for each one of the walls, by using a similar peak detection method as [91].

Correlation between RC and ABD signals was determined using a rolling window [92].

At last phase synchrony between the two signals from each belt was determined, by applying the Hilbert Transform to both signals, extraction of the imaginary part (phase) from each of them, and finally the subtraction of the imaginary parts.

4.3.5 Accelerometer

To denoise the ACC data both from the triaxial accelerometer mounted on the center of the lower back and from the ACCs in the MuscleBAN devices, a band-pass filter of the 3rd order with cut-off frequencies of 0.1 Hz and 10 Hz was used [54], [93].

Next, the signals were smoothed with a window of 0.2 seconds and converted from g-force to ms^{-2}, $ACC_{ms^{-2}} = 9.8 \times ACC_g$.

4.4 Signal synchronization

Since the EMG signals were obtained with a separate device and a different sampling frequency from the ones collected with the hub, synchronization of all signals was accomplished. First a downsampling of the EMG and of the three axis of the ACC data of the muscleBAN's from 1000Hz to 350 Hz was done. After this, the signals were aligned by using the *synchronise_signals* function from *biosignalsnotebook* package, where the dephasing between two signals is determined by computing the full cross-correlation between them [94].

This was accomplished by first synchronizing the z-axis of the lower-back accelerometer with the y-axis of the trapezius MuscleBAN and at last alignment of the z-axis of the Hub accelerometer (already synched with the trapezius), with the x-axis of the bicep's MuscleBAN. These axes were chosen based on where the jumping movements were most evident. The following Figure(4.3) represents each sensor's orientation axes.

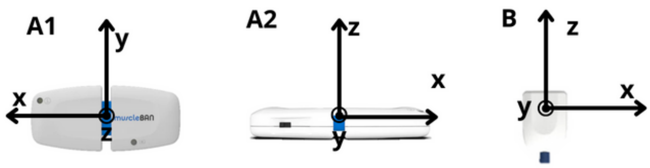


Figure 4.3: Axes orientation of each device-A1: Muscle BAN's Top view, A2: Muscle BAN's Side view, B: Lower back Accelerometer.

4.5 Signal Segmentation

4.5.1 Self-similarity Matrix

The recording of these biosignals as mentioned before, was done in a real automobile assembly line, so there were unexpected events that happened, such as line stops, bathroom breaks, a task that was 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.

In this study it was only possible to video record the first 4 to 5 cycles of the subjects work, so the identification of anomalies and cyclic patterns, and segmentation of the full length of these signals, was accomplished by a Self-Similarity Matrix (SSM) based method.

This method that had its origin in music structure analysis, can also be used to segment other time-series, and has been used successfully for human activity recognition and other biosignals segmentation [95] and in work-cycle anomaly and pattern detection [96].

It consists of transforming the signal into a feature vector, using a sliding window of size w with an overlap of o. The resulting matrix will have a shape of n features by m sub-sequences of the signal ($m = (N - w)/o$), N is the length of the time-series) [97].

The followed steps to accomplish signal segmentation were:

- Signal selection and downsampling: for each subject the signal that presented the most cyclic pattern was selected to be used for SSM calculation, the size of the window and overlap were also manually chosen. Subsequent downsampling of the signals to the frame rate of the camera was achieved.
- Feature extraction: next the features were extracted from the signals, peak to peak distance, absolute energy, mean, SD, autocorrelation, traveled distance, kurtosis and skewness of the signal, computed with TSFEL [98].
- SSM computation: a z-normalization of the features (row-wise normalization) and a futher (colum-wise) normalization was done. The SSM was computed by applying the dot product between the feature matrix's transpose by itself (cosine distance between each segment of the feature matrix) [95].
- Self-similarity function: column-wise sum of features, that enhance parts of the signal with similar structure [95], was made.
- Anomaly and cycles detection: thresholding the self-similarity function, and detecting its fiducial points. [96]
- Confirmation: synchronization of the signals and video by last detected jump. Comparison of the positions from the last step with annotations on the video.

A scheme of these steps is shown in Figure 4.4.

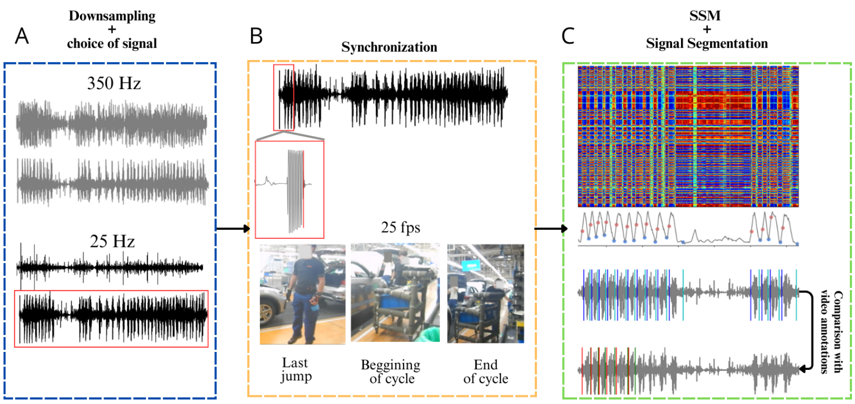


Figure 4.4: Steps followed to segment data.**A**- Visualization of multiple signals, and choice of the most cyclic patterned one with its subsequent downsampling to the camera's frame rate. **B**- Signals and video synchronization, by identifying last jump in both signal and video. **C**- Computation of the Self-Similarity Matrix and of the self-similarity function, thresholding and finding fiducial points to segment the signal, at last comparing with the video annotations.

4.5.2 Data cleaning

Not all subjects were included for further analysis in this specific study based on some key factors that affected the quality and applicability of the collected data.

For instance, in this study some of the variables to be extracted and studied require minimum data lengths, like the measurement of HRV, that weren't accomplished in some of the recordings. So, the decided value for the duration of the recording was of at least 50 minutes, to ensure it had enough information even after subsequent stages of data cleaning and processing.

Another reason for subject exclusion was lack of representativity of certain workstations in the attained database. Mainly due to unforeseen staff shortages and unavailability, which affected the distribution of data collection efforts.

As this protocol included multiple sensors some of them failed or were disconnected during the acquisition, also unexpected assembly line stops of big length happened. As a result, even the selected recordings that initially met the time criterion when further reduced by the removal of irrelevant segments and other imperfections and had to be excluded.

For the above reasons, 16 subjects were screened for analysis.

Subsequent to subject selection, all the signals were cut from the first detected work-cycle, to the last, like this, jumps and ending of acquisition information that were not relevant for the study were deleted for the signals analysis. This left the recordings with 40 minutes.

4.5.3 Work cycle metrics

As the onsets and offsets of working-cycles were obtained in the last step, time-metrics were computed.

The positions of the onsets are $S[n] = s_1, s_2, ..., s_N$ and of the offsets $E[n] = e_1, e_2, ..., e_N$, where N is the number of cycles.

The work-cycle duration time was defined as the difference between the ending and respective beginning of that cycle.

The effective working time was determined by summing all work-cycle times in the recording as $\sum_{i=0}^{N} e(n) - s(n)$.

The percentage of effective working time is the effective working time divided by the time of monitored work. Finally, cycle percentage of "transition time" was also computed for each cycle, as can be seen in Equations 4.17 and 4.18, respectively.

$$EWT\% = \frac{\sum_{i=0}^{N} e(n) - s(n)}{TT} \times 100\% \quad (4.17)$$

$$CTT(\%) = \frac{s(n+1) - e(n)}{e(n) - s(n)} \times 100\% \quad (4.18)$$

Here EWT is the Effective Working Time, CTT is Cycle Transition Time and TT Total Time of acquisition.

This type of indicator was computed in order to characterize the studied task in terms of work volume and density, and find how physiological response changes when presented with different types of these stimuli.

The time passed between identified cycles was all considered "transition time" to the next cycle, and was not discriminated into further classification.

4.6 Statistical Analysis

The different stations' tasks have specific work-volumes associated to them, so their biosignals were investigated. To guarantee the groups homogeneity a Kruskal-Wallis test was conducted, by studying body mass index, age and physical activity data. The used post-hoc was the Dunn test.

Between each group there wasn't a significant difference at the level of Physical Activity, (p-valuePA $\approx$ 0.105) and at the level of Body Mass Index (BMI) (p-valueBMI $\approx$ 0.687). For Age there was a statistically meaningful result (p-valueAge $\approx$ 0.047), when performing the Dunn test, it was found that the age of the subjects from H_2 and H_3 stations pose a statistical difference(p-value = 0.041) admitting a significance level of 5%. When looking at the physiological meaning of this difference, the age gap does not have significance (H_3 = 34.38 ± 6.93, H_2 = 46.75 ± 6.70), something concluded by [99], where physical workload did not differ between young (33 years) and ageing (52 years) workers.

To answer each research question, different types of statistical analysis were used and are explained below.

4.6.1 General physiological response to distinct work-volumes

The first research question that was addressed was if there were particular physiological responses from subjects performing tasks with different work-volumes. To accomplish this the Kruskal-Wallis test was utilized on the different physiological indicators between the H_1, H_2 and H_3 workstations' subjects for the whole 40 minutes of the recording. If any significant difference was found the Dunn post-hoc was applied, considering the Holm's p-value adjustment.

4.6.2 Evolution of physiological response between workstations

To evaluate how workload affects cardiorespiratory response over the course of time, the 40 minute signals were studied at two time points: first 10 minutes and last 10 minutes, computing the indicators proposed in 4.3.3, 4.3.4.2 at each of those times for all subjects.

Then, to analyze if there was any statistical meaningful interactions a factorial design (group vs phase) was used, performing a parametric test: Mixed ANOVA.

To be able to perform a more robust test and avoid effect-size limitations, 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 [100].

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 [101].

To test for normality the Shapiro-Wilk was performed for all levels of the experiment, if there were non-normal variables, these were further tested with the criterion based on Skewness and Kurtosis, where the absolute Z-score of those two metrics should be less than 1.96 to be normal in small sample sizes (N<30) ($Z_{skewness} = \frac{Skewness}{SE_{Skewness}}$ and $Z_{kurtosis} = \frac{Kurtosis}{SE_{Kurtosis}}$) [102], and if there was still any variable that violated this principle the Yeo-Johnson power transform was applied to make the data more normally distributed [103].

If the assumption of equality of variances between groups was not respected, the Welch correction of the p-value was made. The metrics that presented significant values were further investigated with the Tukey post-hoc test, by choosing the set of values that came from the seed with the closest p-value for the interaction effect.

4.6.3 Common physiological adaptations

To understand if the total time of acquisition was not enough to uncover certain physical adaptations, the subjects that had valid recordings of at least 60 minutes were analysed using a paired samples t-test, testing the hypothesis that independently of work-volume, there is a change in the studied physiological variables.

The first and last 10 minutes of each signal were analysed in terms of cardiac and respiratory variables. The assumption of normality was checked with the Shapiro-Wilk test, and when this assumption was violated, the Wilcoxon signed-rank test was used.

4.6.4 Evolution of physiological response according to ergonomic risk score

Finally, an analysis of the response from cardiac and respiratory systems was done between low, moderate and moderate-high biomechanical risk score tasks, with the same procedure as in 4.6.2 .

In this research low risk (EAWS <= 25, green), moderate risk (25 < EAWS <48, yellow) and high-moderate risk (EAWS >= 48,orange), were considered since the boundaries between the threshold values are not well defined. The mentioned colors can be verified in Figure 2.1.

All of the statistical tests were accomplished by using the pingouin python package [104] and the JASP computer software [105].

5 Results

This chapter depicts this thesis research results, beginning with a description of the monitored tasks. Next the results of the statistical tests are presented for each research question along with the description of the multiple metrics proposed in the previous chapter4, that were the dependent variables in this analysis.

5.1 Work-volume metrics

The analysis of the work-volume proposed metrics showed that there is a proportional growth in cycle-time duration and total number of cycles for the studied workstation. Table 5.1 summarizes the total mean cycle-time and cycles accomplished by each group.

Table 5.1: Approximate values of cycle duration in minutes and of the total number of cycles for each workstation.

Variable	H1	H2	H3
Cycle Time(min)	3	5	1
Number of cycles	13	8	30

The results of the statistical test are conferred in Table 5.2, resulting from the calculations performed over the whole signal, with the group as independent variable and work-volume metrics as dependent.

Table 5.2: Results from the Kruskal-Wallis Test of the work-volume metrics

Variable	Group			p	ϵ^2
	H1	H2	H3		
EWT(%)	80.9 ± 4.6	80.0 ± 8.8	77.8 ± 2.9	0.325	0.563
CTT(%)	19.7 ± 4.1	21.1 ± 9.1	22.8 ± 2.9	0.282	0.633
Cp10	3.4 ± 0.7	2.2 ± 0.2	7.5 ± 0.4	**0.002**	3.214
Cycle Time(min)	2.8 ± 0.5	4.5 ± 0.8	1.1 ± 0.1	**0.002**	3.195

Legend: **EWT**- Effective Working Time; **CTT**- Cycle Transition Time; **Cp10**- Cycles per 10 minutes; **H1**- medium cycle station; **H2**- long cycle station; **H3**- short cycle station. ϵ^2- epsilon squared. The values in bold are significant results.

The results of the post-hoc tests for the significant variables uncovered that there was a significant difference only between the H_2 and H_3 groups, for both cycles per 10 minutes (pdunn < 0.01) and cycle time (pdunn < 0.01). Between H_3 and H_1 the cycles per 10 minutes and cycle-time resulted in pdunn = 0.115, pdunn = 0.117 and between H_1 and H_2 pdunn = 0.695, pdunn = 0.700, respectively.

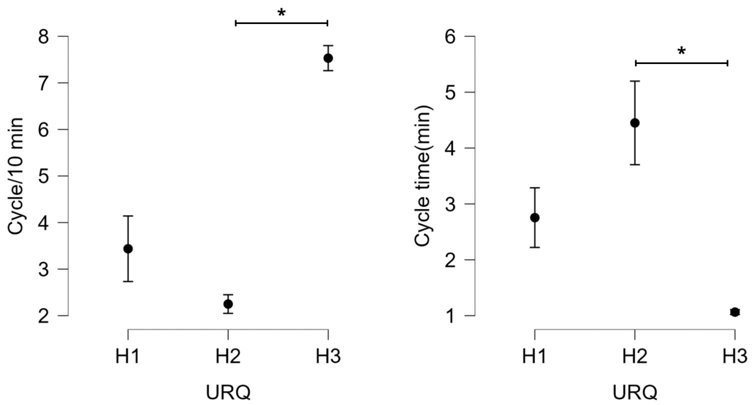


Figure 5.1: Results from the Dunn post-hoc comparisons for the volume metrics. The * indicates a statistical meaningful result. URQ: Workstation.

5.2 Cardiovascular Metrics

5.2.1 Cardiac response differences between workstations

The results for the cardiac metrics over the whole recording time, divided by workstations did not present any significant results, they can be seen in I, Table I.1.

5.2.2 Cardiac response evolution to different workloads

The results from the Mixed ANOVA simulation statistics of the cardiac indicators are presented in Table 5.3. These suggest that there were differences between workstations for CVL (p=0.027) and were tendentious for CVS (p=0.051), when ignoring the effect of phase.

The phase at which the metrics were measured also culminated into multiple main effects, for HR, SDRR, coefficient of variation of HR, RHR, SD of RHR, CVS, CVL and SD2 ($p \in [< 0.001, 0.018]$).

The effect of interaction between workstations and phases was also meaningful for some indicators (HR, Maximum HR, SDRR, Coefficient of variation of HR, RHR, SD of RHR, Coefficient of variation of RHR, CVS range, CVL range and SD2) with $p \in [0.007, 0.043]$.

Table 5.3: Mixed ANOVA results from the 500 simulations on the cardiovascular metrics

Variables	Group						p_g	η_p^2	p_{ph}	η_p^2	p_{int}	η_p^2
	H1		H2		H3							
	B	E	B	E	B	E						
HR(BPM)	90.7 ± 15.5	90.6 ± 16.6	96.2 ± 10.4	90.6 ± 5.9	97.6 ± 13.4	94.4 ± 15.0	0.432	0.040	**0.006**	0.261	**0.043**	0.225
Max HR(BPM)	106.7 ± 18.4	110.3 ± 16.1	116.0 ± 19.4	108.7 ± 9.7	113.9 ± 15.5	109.3 ± 20.8	0.486	0.001	0.097	0.071	**0.038**	0.224
Min HR(BPM)	71.2 ± 14.8	71.7 ± 12.6	73.1 ± 3.5	71.7 ± 5.7	74.6 ± 11.3	76.5 ± 11.7	0.613	0.020	0.793	< 0.001	0.406	0.073
HR range(BPM)	29.7 ± 6.8	34.2 ± 8.5	41.4 ± 8.5	35.9 ± 6.2	39.3 ± 11.5	32.7 ± 10.6	0.155	0.094	0.179	0.001	0.053	0.219
SDRR(ms)	41.0 ± 14.0	39.0 ± 11.0	41.0 ± 8.0	42.0 ± 8.0	40.0 ± 12.0	34.0 ± 7.0	0.530	0.025	**0.018**	0.192	**0.009**	0.349
RMSSD(ms)	19.0 ± 5.0	17.0 ± 8.0	24.0 ± 7.0	25.0 ± 7.0	24.0 ± 15.0	22.0 ± 12.0	0.123	0.129	0.424	< 0.001	0.445	0.054
CV HR	6.0 ± 2.0	5.0 ± 1.0	6.0 ± 1.0	6.0 ± 1.0	6.0 ± 2.0	5.0 ± 1.0	0.273	0.043	**0.001**	0.318	**0.017**	0.282
RHR(%)	24.0 ± 6.0	24.9 ± 6.5	27.4 ± 6.4	24.2 ± 2.7	29.1 ± 6.6	26.5 ± 6.8	0.229	0.075	**<0.001**	0.268	**0.021**	0.269
Max RHR(%)	32.5 ± 11.1	35.3 ± 0.0	51.8 ± 19.0	42.5 ± 8.2	42.4 ± 9.2	39.0 ± 12.5	0.309	0.027	0.090	< 0.001	0.055	0.179
Min RHR(%)	9.9 ± 3.9	9.3 ± 1.4	9.4 ± 0.3	8.5 ± 2.5	9.4 ± 3.4	11.1 ± 4.9	0.474	0.041	0.777	< 0.001	0.345	0.083
RHR range(%)	28.8 ± 9.9	31.4 ± 8.5	35.2 ± 14.5	31.9 ± 5.0	33.0 ± 10.2	27.9 ± 10.6	0.196	0.001	0.175	< 0.001	0.074	0.184
SD RHR(%)	3.9 ± 1.3	4.1 ± 1.0	4.9 ± 1.4	4.5 ± 0.8	5.0 ± 1.4	4.1 ± 1.2	0.274	0.001	**<0.001**	0.387	**0.030**	0.241
CV RHR	5.7 ± 1.0	5.9 ± 0.6	5.5 ± 0.7	5.1 ± 0.4	6.0 ± 1.3	6.5 ± 0.7	0.071	0.211	0.563	< 0.001	**0.007**	0.361
CVS(%)	40.9 ± 9.9	42.1 ± 6.4	47.3 ± 9.0	41.9 ± 6.6	56.2 ± 14.2	50.0 ± 9.8	0.051	0.213	**0.008**	0.253	0.094	0.174
CVS range(%)	46.6 ± 11.9	54.0 ± 19.1	66.8 ± 26.1	57.5 ± 9.8	63.0 ± 19.6	51.0 ± 11.3	0.133	0.076	0.162	< 0.001	**0.040**	0.242
CVL(%)	21.0 ± 4.4	21.0 ± 2.9	25.4 ± 5.3	21.7 ± 3.1	27.9 ± 5.7	25.0 ± 4.8	**0.027**	0.258	**0.006**	0.265	0.058	0.207
CVL range(%)	22.1 ± 5.2	24.5 ± 8.0	31.9 ± 13.9	28.8 ± 5.0	31.4 ± 9.3	25.7 ± 6.5	0.075	0.136	0.198	< 0.001	**0.040**	0.241
SD1(ms)	14.0 ± 6.0	14.0 ± 6.0	18.0 ± 5.0	18.0 ± 5.0	17.0 ± 10.0	15.0 ± 8.0	0.123	0.129	0.424	< 0.001	0.445	0.054
SD2(ms)	57.0 ± 21.0	53.0 ± 16.0	56.0 ± 11.0	59.0 ± 12.0	54.0 ± 15.0	46.0 ± 9.0	0.502	0.035	**0.015**	0.202	**0.008**	0.360

Legend: **HR**- Heart Rate; **SDRR**- Standard deviation of RR intervals; **RMSSD**- Root mean square of successive RR interval differences; **RHR**- Reserve Heart Rate; **CVS**- Cardiovascular Strain; **CVL**- Cardiovascular Load; **SD1**- Poincaré plot standard deviation perpendicular to the line of identity ; **SD2**- Poincaré plot standard deviation along the line of identity; **Max**-Maximum; **Min**-Minimum; **SD Standard Deviation**; **CV**- Coefficient of Variation; **H1**- medium cycle station;**H2**- long cycle station; **H3**- short cycle station; **pg**- harmonic mean combined p-value for the between factor; **pph**- harmonic mean combined p-value for the within factor; **pint**- harmonic mean combined p-value for the interaction. η_p^2- partial eta squared. The significant results are in bold.

The Tukey test determined that H_2 had a significant decrease in HR between phases, the H_3 workstation had a relevant decrease in SDRR, Coefficient of Variation of HR, SD of RHR and of SD2. Between workstations only CVS for H_1 was distinctively smaller when compared with H_3's values, at the beginning.

It is also evident that the subjects from the H_1 station have very low variation of these metrics across time.

In Figure 5.2 the evolution in time of these variables, from the three workstations are represented, where the dashed line box represents a within significant result and its value is beside it. Interactions between the variables are also noticeable by crossing of lines.

The between-factor significant results are presented with a line between the corresponding groups, with distinct marker tips, whether differences are found at the beginning phase (B-circle marker) or at the end (E-solid circle marker).

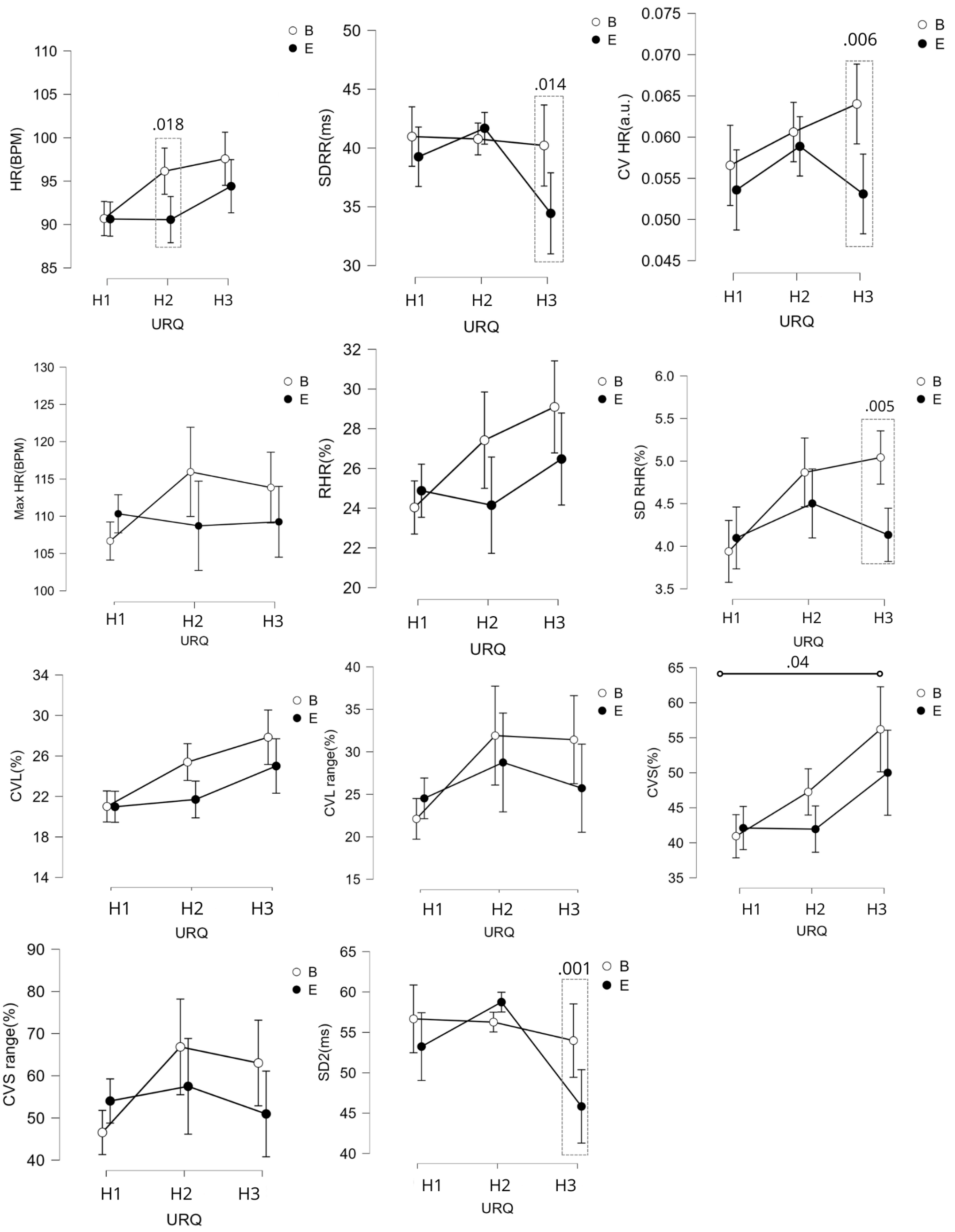


Figure 5.2: Descriptive plots with Tukey test results for the significant cardiac variables. URQ: Workstation; **H1**- medium cycle station;**H2**- long cycle station; **H3**- short cycle station;B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

5.2.3 Common cardiac adaptations

When computing the ECG derived metrics for the subjects with 60 minute valid recordings, independently of the workload, SDRR (p=0.03) presented a significant decline from the beginning to the end of the recording. In the following table are the results from the paired t-test analysis on the cardiac measurements for this analysis.

Table 5.4: Results from the paired samples t-test of the 60 minute ECG indicators.

Variable	Phase		Test	p-value	Effect size
	B	E			
HR(BPM)	93.2 ± 10.4	91.3 ± 6.0	Student	0.480	0.311
CV HR(BPM)	6.0 ± 1.0	5.0 ± 1.0	Student	0.096	0.837
SDRR(ms)	37.0 ± 7.0	35.0 ± 7.0	Student	**0.032**	1.202
RMSSD(ms)	21.0 ± 7.0	18.0 ± 5.0	Student	0.099	0.837
RHR(BPM)	22.5 ± 8.1	20.5 ± 3.6	Wilcoxon	0.844	0.143
CV RHR(%)	4.5 ± 0.7	4.7 ± 0.8	Student	0.369	-0.403
CVL(%)	18.9 ± 5.8	17.4 ± 2.9	Student	0.484	0.308
CVS(%)	35.1 ± 10.0	32.4 ± 5.5	Student	0.489	0.305
SD1(ms)	15.0 ± 5.0	12.0 ± 4.0	Student	0.099	0.825
SD2(ms)	50.0 ± 10.0	48.0 ± 9.0	Student	0.071	0.934

Legend: **HR**- Heart Rate; **SDRR**- Standard deviation of RR intervals; **RMSSD**- Root mean square of successive RR interval differences; **RHR**- Reserve Heart Rate; **CVS**- Cardiovascular Strain; **CVL**- Cardiovascular Load; **SD1**- Poincaré plot standard deviation perpendicular to the line of identity; **CV**- Coefficient of Variation; **SD2**- Poincaré plot standard deviation along the line of identity. The significant values are in bold. Effect-size for the Student t-test is Cohen's d and for Wilcoxon the matched rank biserial correlation.

5.3 Respiratory Metrics

5.3.1 Respiratory response differences between workstations

The Kruskall-Wallis test results for the RIP derived metrics, for the whole 40 minutes, did not reveal any significant differences in their means regarding the workstation. The results and description of each metric can be found in I in table I.2.

5.3.2 Respiratory response evolution to different workloads

The following Table(5.5) presents the results for the Mixed ANOVA test on the 500 simulations of oversampled data from the RIP measurements.

The main effect of stations was significant on correlation and Phase Synchrony (PS) (pcorrelation=0.0022, and pPS=0.044), when ignoring the effect of the phase of measurement. When looking at the main effect of phase on these indicators, it was significant for maximum RC, maximum ABD, SD of abdominal frequency, correlation and PS ($p \in [< .001, 0.033]$).

In terms of interaction of the between-within factors, maximum RC,minimum RC, SD of the RC RR, ABD mean RR, maximum ABD RR, correlation and PS all showed relevant values ($p \in [< 0.001, 0.015]$).

Table 5.5: Mixed ANOVA results from the 500 simulations on the respiratory metrics.

Variables	Group						p_g	η_p^2	p_ph	η_p^2	p_int	η_p^2
	H1		H2		H3							
	B	E	B	E	B	E						
RC(bpm)	24.7 ± 1.4	24.4 ± 1.2	26.0 ± 1.0	25.4 ± 0.5	24.5 ± 1.6	24.8 ± 1.2	0.113	0.181	0.504	0.001	0.131	0.136
Max RC(bpm)	63.2 ± 11.5	65.6 ± 9.8	68.2 ± 11.3	54.0 ± 3.2	54.2 ± 5.3	73.4 ± 15.8	0.534	0.031	0.033	0.110	**<0.001**	0.457
Min RC(bpm)	15.2 ± 0.8	13.7 ± 1.3	14.1 ± 0.8	14.9 ± 0.6	14.4 ± 1.9	14.4 ± 0.9	0.891	0.001	0.533	0.001	**<0.001**	0.385
SD RC(bpm)	6.6 ± 1.1	6.3 ± 1.1	6.9 ± 0.7	6.3 ± 0.6	5.9 ± 0.7	6.8 ± 0.9	0.391	0.050	0.491	0.001	**0.013**	0.315
ABD(bpm)	24.2 ± 0.2	25.0 ± 0.6	25.5 ± 0.3	24.4 ± 0.4	24.5 ± 1.3	24.6 ± 0.9	0.190	0.126	0.468	0.001	**<0.001**	0.458
Max ABD(bpm)	59.3 ± 5.9	59.3 ± 5.5	55.0 ± 3.5	67.2 ± 2.7	56.3 ± 10.8	66.4 ± 11.5	0.697	0.020	**<0.001**	0.365	**<0.001**	0.352
Min ABD(bpm)	14.1 ± 0.4	14.4 ± 0.5	14.0 ± 0.8	13.5 ± 1.4	14.1 ± 0.8	13.8 ± 1.4	0.282	0.056	0.621	0.001	0.694	0.019
SD ABD(bpm)	6.3 ± 0.5	6.1 ± 0.6	6.0 ± 0.5	6.9 ± 0.3	6.3 ± 0.8	6.7 ± 1.1	0.539	0.018	**0.008**	0.260	0.077	0.174
RC(%)	53.3 ± 13.3	54.3 ± 14.3	59.1 ± 1.9	59.1 ± 2.5	55.2 ± 9.7	55.9 ± 8.8	0.423	0.038	0.105	0.079	0.265	0.088
Correlation(%)	40.0 ± 28.0	27.0 ± 38.0	60.0 ± 6.0	48.0 ± 8.0	57.0 ± 17.0	56.0 ± 18.0	**0.022**	0.174	**<0.001**	0.477	**0.013**	0.279
PS(%)	53.0 ± 13.0	43.0 ± 15.0	64.0 ± 3.0	59.0 ± 4.0	64.0 ± 10.0	64.0 ± 10.0	**0.044**	0.158	**<0.001**	0.420	**0.015**	0.263

Legend: **RC**- Rib cage respiratory frequency; **ABD**- Abdominal respiratory frequency; **RC(%)**- Percentage of Rib cage contribution to respiration; **Correlation**- Correlation between Rib cage and Abdominal breathing; **PS**- Phase Synchrony between Rib cage and Abdominal breathing; **Max**- Maximum; **Min**- Minimum; **SD**- Standard Deviation; **H1**- medium cycle station; **H2**- long cycle station; **H3**- short cycle station; **pg**-harmonic mean combined p-value for the between factor; **pph**- harmonic mean combined p-value for the within factor; **pint**- harmonic mean combined p-value for the interaction. η_p^2- partial eta squared. The significant results are in bold.

The post-hoc results are presented in the descriptive Figure 5.3. The symbols used to highlight relevant results are the same as the ones used in cardiac variable post-hoc analysis(5.2.2). Here significant differences were revealed within the maximum RC in the H_3 station, and a meaningful difference between the values of this metric for H_3 and H_1 at the last 10 minutes of recording.

The H_2 station's workers presented strong indications of differences between the measured phase for mean ABD RR, maximum ABD RR, SD of ABD frequency and correlation between the respiratory walls.

The maximum ABD RR also showed a evident contrast between H_1 and H_2 values measured in the end of acquisition.

Regarding phase synchrony, the H_1 group suffered a meaningful decrease from the start to the end of the monitored task. When comparing the H_3 to the H_1 operators' end measurements of this indicator, there was a noteworthy discrepancy.

It was observed that the H_1 station has a less pronounced variation of its RR variables than the other two workstations, but in terms of correlation and synchrony, along with the H_2 workstation, it was identified a reduction as time passed, contrary to The H_3 workstation that maintained its values.

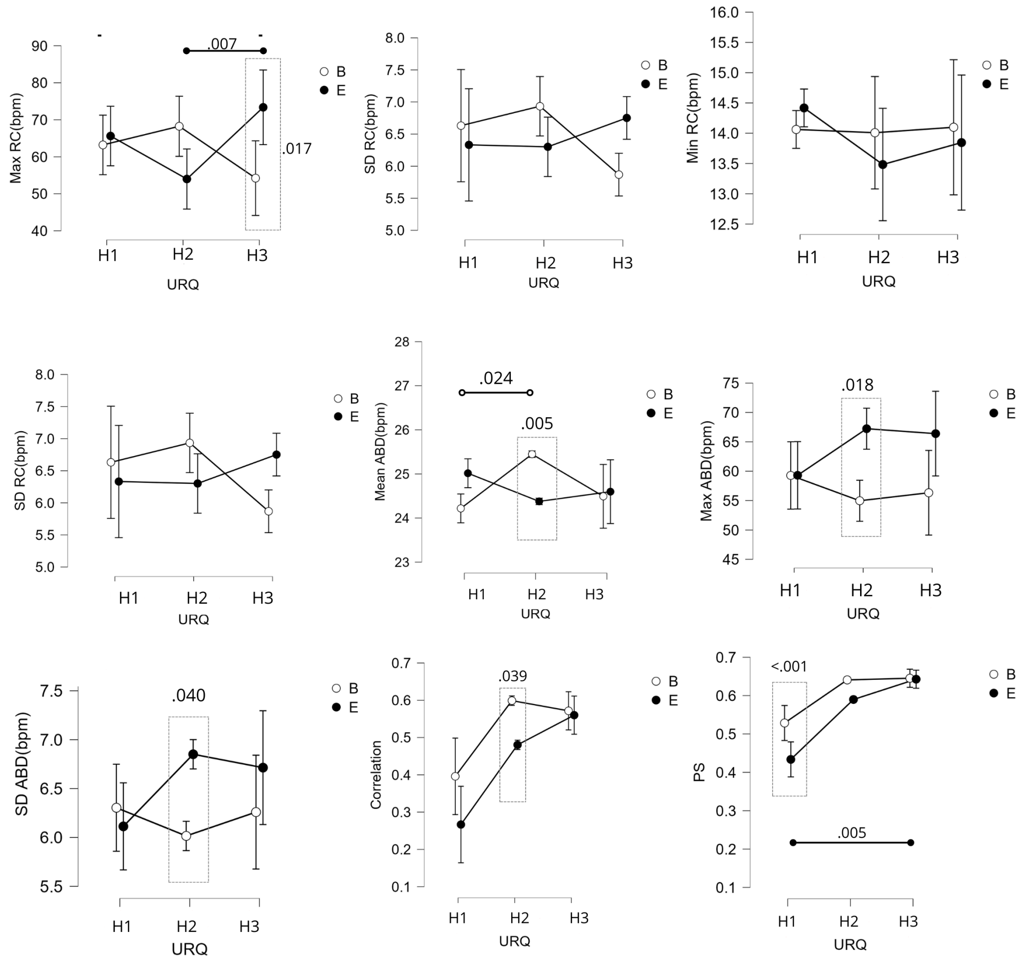


Figure 5.3: Descriptive plots with the Tukey test results for the significant respiratory variables. URQ: Workstation; **H1**- medium cycle station; **H2**- long cycle station; **H3**- short cycle station; B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

5.3.3 Common respiratory adaptations

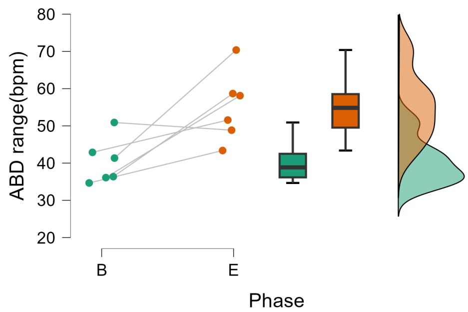
For the valid 60 minute recordings it was ascertained that the SD of the ABD RR and its range revealed a remarkable distinction from beginning to end regardless of work volume ($p<0.001$ and $p=0.003$, respectively), shown in the Table 5.6. There was tendency of both of these variables to increase, something that can be verified by the raincloud plots in Figure 5.4.

Table 5.6: Results from the paired samples t-test for the 60 minutes respiratory indicators.

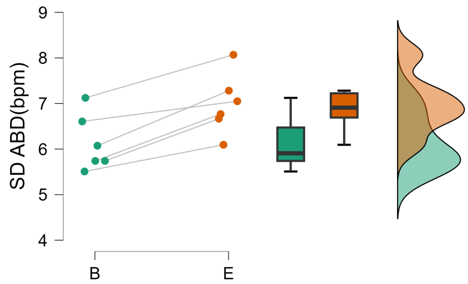
Variable	Phase		Test	p-value	Effect size
	B	E			
RC(bpm)	24.2 ± 1.0	24.2 ± 1.0	Student	0.954	0.025
SD RC(bpm)	6.5 ± 1.0	6.0 ± 0.8	Student	0.464	0.324
RC range(bpm)	55.7 ± 15.9	44.9 ± 10.1	Student	0.314	0.456
ABD(bpm)	24.7 ± 0.9	24.5 ± 0.6	Student	0.571	0.247
SD ABD(bpm)	6.1 ± 0.6	7.0 ± 0.7	Student	**<0.001**	-2.991
ABD range(bpm)	40.4 ± 6.1	55.2 ± 9.4	Student	**0.026**	-1.277
RC(%)	64.7 ± 11.3	63.7 ± 10.2	Student	0.289	0.484
Correlation(%)	56.0 ± 14.0	51.0 ± 18.0	Student	0.321	0.449
PS(%)	64.0 ± 7.0	62.0 ± 9.0	Student	0.289	0.484

Legend: **RC**- Rib cage respiratory frequency; **ABD**- Abdominal respiratory frequency; **RC(%)**- Percentage of Rib cage contribution to respiration; **Correlation**- Correlation between Rib cage and Abdominal breathing; **PS**- Phase Synchrony between Rib cage and Abdominal breathing; **SD**- Standard Deviation; Effect-size for the Student t-test is Cohen's d and for Wilcoxon the matched rank biserial correlation. The significant results are in bold.

In the following Figure it is shown the raincloud plots for ABD RR range and SD.



(a) Raincloud plot of the beginning and end of the 60 minute recording of Abdominal respiratory frequency range.



(b) Raincloud plot of the beginning and end of the 60 minute recording of Abdominal respiratory frequency standard deviation.

Figure 5.4: Significant results of the Respiratory measurements from the 60 minute recordings.B: beginning (Green); E: ending (Orange).

5.4 Ergonomic risk Analysis

5.4.1 Cardiac response

The results of the 500 simulations mixed ANOVA on the cardiac metrics of tasks with different ERs showed that there were meaningful discrepancies in HR, its maximum, minimum, range and coefficient of variation, RHR and its maximum, range, SD and coefficient of variation, CVS range and CVL range ($p \in [< 0.001, 0.010]$).

In terms of phase's main effect, it was significant for HR and its coefficient of variation, SDRR, RHR and its SD, CVL and SD2 ($p \in [0.001, 0.031]$).

The only relevant interaction was found in SD RHR (p=0.038).

Table 5.7: Mixed ANOVA results from the 500 simulations on the cardiovascular metrics for the Ergonomic Risk Stratification.

Variables	Risk Stratification						p_g	η_p^2	p_{ph}	η_p^2	p_{int}	η_p^2
	Low		Moderate		Moderate-High							
	B	E	B	E	B	E						
HR	78.7 ± 9.5	76.7 ± 11.2	92.5 ± 13.8	89.0 ± 14.2	99.8 ± 11.5	97.7 ± 10.8	**0.001**	0.429	**0.008**	0.230	0.626	0.008
Max HR	86.1 ± 9.5	85.3 ± 13.8	116.5 ± 23.0	112.1 ± 13.7	116.2 ± 13.5	113.2 ± 16.1	**<0.001**	0.481	0.088	0.075	0.588	0.005
Min HR	66.5 ± 8.5	63.8 ± 8.7	73.3 ± 12.0	71.1 ± 12.4	76.1 ± 10.4	79.4 ± 8.6	**0.006**	0.303	0.631	0.001	0.065	0.213
HR range	22.3 ± 2.4	23.7 ± 7.4	38.8 ± 13.3	37.2 ± 4.5	40.1 ± 12.2	33.8 ± 9.2	**<0.001**	0.592	0.188	0.001	0.365	0.070
SDRR	39.0 ± 5.0	39.0 ± 3.0	42.0 ± 11.0	41.0 ± 12.0	38.0 ± 13.0	33.0 ± 7.0	0.115	0.136	**0.031**	0.177	0.071	0.210
RMSSD	20.0 ± 3.0	22.0 ± 6.0	24.0 ± 7.0	27.0 ± 9.0	22.0 ± 15.0	19.0 ± 11.0	0.429	0.054	0.525	0.001	0.082	0.176
CV HR	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	**0.008**	0.335	**0.003**	0.299	0.098	0.154
RHR	20.3 ± 5.0	18.7 ± 5.4	30.8 ± 7.6	26.3 ± 5.4	29.5 ± 6.9	27.6 ± 6.1	**0.003**	0.373	**0.009**	0.222	0.580	0.008
Max RHR	28.7 ± 6.0	28.2 ± 7.5	43.5 ± 14.6	40.9 ± 6.8	43.3 ± 9.5	41.0 ± 10.6	**0.001**	0.432	0.097	0.050	0.438	0.004
Min RHR	9.3 ± 4.1	9.2 ± 1.5	9.7 ± 1.6	8.2 ± 2.0	8.8 ± 3.0	11.6 ± 4.9	0.553	0.023	0.766	0.001	0.078	0.208
RHR range	17.3 ± 2.1	16.3 ± 5.9	35.5 ± 14.1	33.9 ± 5.0	34.5 ± 9.8	29.4 ± 8.9	**<0.001**	0.615	0.211	0.014	0.347	0.072
SD RHR	3.0 ± 0.5	2.9 ± 0.7	5.4 ± 0.9	4.9 ± 0.6	5.2 ± 1.4	4.4 ± 0.9	**<0.001**	0.618	**0.001**	0.361	**0.038**	0.194
CV RHR	6.3 ± 0.9	6.2 ± 0.6	5.2 ± 0.4	5.3 ± 0.6	5.9 ± 1.2	6.4 ± 0.7	**0.001**	0.447	0.534	0.001	0.065	0.210
CVS	58.9 ± 14.6	46.0 ± 4.6	54.0 ± 10.1	46.7 ± 5.1	52.3 ± 13.9	48.8 ± 11.8	0.690	0.002	**0.005**	0.241	0.584	0.014
CVS range	42.9 ± 6.5	44.1 ± 6.8	63.9 ± 18.6	65.6 ± 14.0	62.1 ± 22.4	51.0 ± 11.3	**0.010**	0.328	0.156	0.001	0.405	0.061
CVL	21.3 ± 6.5	20.3 ± 2.7	25.0 ± 4.8	23.0 ± 1.3	26.9 ± 6.3	25.1 ± 5.4	0.103	0.143	**0.006**	0.240	0.631	0.011
CVL range	18.7 ± 2.1	20.5 ± 4.9	34.6 ± 10.6	32.9 ± 5.3	31.8 ± 10.3	26.4 ± 5.8	**<0.001**	0.531	0.187	0.001	0.399	0.058
SD1	14.0 ± 2.0	15.0 ± 4.0	18.0 ± 5.0	16.0 ± 6.0	16.0 ± 11.0	13.0 ± 8.0	0.429	0.054	0.526	0.001	0.082	0.176
SD2	56.0 ± 9.0	54.0 ± 5.0	61.0 ± 19.0	58.0 ± 18.0	51.0 ± 15.0	44.0 ± 8.0	0.086	0.156	**0.024**	0.187	0.113	0.169

Legend: **HR**- Heart Rate; **SDRR**- Standard deviation of RR intervals; **RMSSD**- Root mean square of successive RR interval differences; **RHR**- Reserve Heart Rate; **CVS**- Cardiovascular Strain; **CVL**- Cardiovascular Load; **SD1**- Poincaré plot standard deviation perpendicular to the line of identity ; **SD2**- Poincaré plot standard deviation along the line of identity; **Max**- Maximum; **Min**- Minimum; **SD**- Standard Deviation; **pg**- harmonic mean combined p-value for the between factor; **pph**- harmonic mean combined p-value for the within factor; **pint**- harmonic mean combined p-value for the interaction. η_p^2- partial eta squared. The significant results are in bold.

The Tuckey post-hoc determined that the moderate-high risk activities had substantially smaller SDRR and coefficient of variation of HR. That there were meaningful differences between the low and moderate-high risk tasks in HR, its maximum, range, RHR range and CVL range. Differences among low risk and moderate risk was found in maximum HR, HR range and coefficient of variation, RHR range and CVL range.

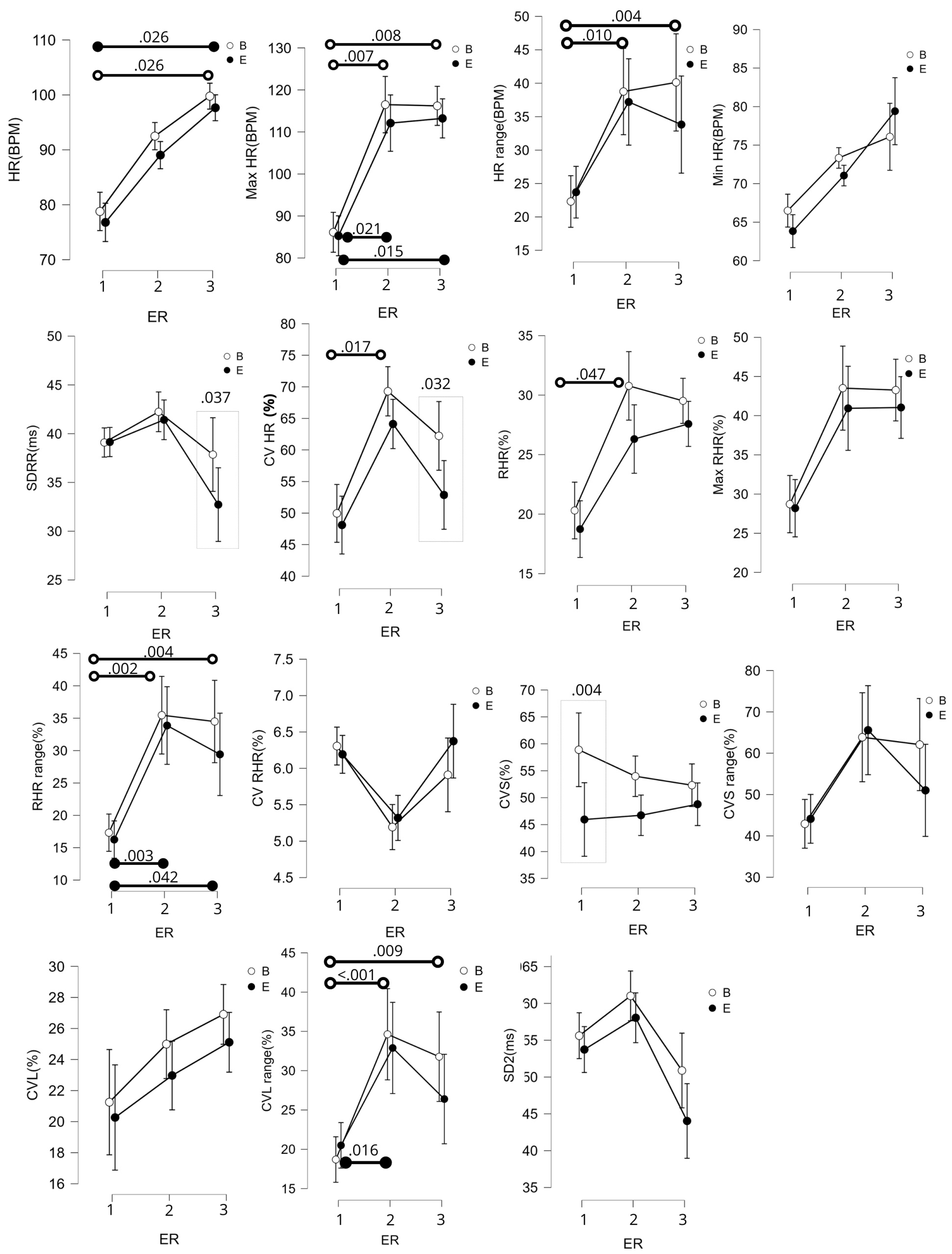


Figure 5.5: Descriptive plots with the Tukey test results for the significant cardiovascular variables. ER: Ergonomic Risk Stratification; 1: Low; 2: Moderate; 3: Moderate-High; B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

5.4.2 Respiratory response

In this analysis, it was revealed that the main effect of groups was influential on mean RR of the RC and its SD, minimum ABD RR and its SD and at last for correlation and phase synchrony ($p \in [< 0.001, 0.040]$).

When looking at the effect of phase, disregarding the group factor, it had the most impact on maximum RC and ABD RRs,SD of ABDRR, mean RC percentage, correlation and PS ($p \in [< 0.001, 0.042]$).

Multiple significant interactions were found in this analysis, RC RR, its maximum and SD, maximum ABD RR, SD of ABD respiratory frequency, correlation and PS ($p \in [< 0.001, 0.025]$)

The following table(5.8) contains the results from the Mixed ANOVA analysis of the respiratory measurements from the ER stratification.

Figure 5.6 represents the post-hoc results of the variables with meaningful significant main effects and interactions, revealing between which and within which factors they were found and respective p-value.

Distinctions between the moderate and low risk tasks were encountered in the mean RC RR in its SD and in PS. Between the moderate and high risk tasks, there was only a discrepancy in minimum ABD frequency. Between the low and moderate-high risks, SD of RC RR, minimum ABD RR and its SD differed significantly.

Table 5.8: Mixed ANOVA results from the 500 simulations on the respiratory metrics for the Ergonomic Risk Stratification.

Variables	ER						p_g	η_p^2	p_{ph}	η_p^2	p_{int}	η_p^2
	Low		Moderate		Moderate-High							
	B	E	B	E	B	E						
RC(bpm)	23.8 ± 0.4	24.3 ± 0.9	25.8 ± 1.5	25.0 ± 1.0	24.5 ± 1.6	24.9 ± 1.2	**0.008**	0.340	0.725	0.001	**<0.001**	0.529
Max RC(bpm)	57.9 ± 13.8	60.6 ± 3.3	66.3 ± 11.6	61.6 ± 10.9	54.1 ± 5.4	72.1 ± 17.0	0.407	0.001	**0.035**	0.100	**0.010**	0.325
Min RC(bpm)	15.2 ± 0.3	14.9 ± 0.3	13.8 ± 0.9	14.3 ± 1.4	14.4 ± 1.8	14.4 ± 0.9	0.052	0.227	0.683	0.001	0.465	0.025
SD RC(bpm)	6.3 ± 1.4	5.4 ± 0.1	6.9 ± 0.6	6.5 ± 0.8	6.0 ± 0.6	6.9 ± 0.7	**<0.001**	0.354	0.547	0.001	**<0.001**	0.431
ABD(bpm)	24.3 ± 0.2	24.8 ± 0.7	25.2 ± 0.8	24.9 ± 0.3	24.6 ± 1.3	24.4 ± 0.9	0.147	0.155	0.714	0.001	0.103	0.146
Max ABD(bpm)	62.7 ± 8.6	58.2 ± 5.7	56.3 ± 5.8	66.5 ± 5.5	54.5 ± 8.3	67.0 ± 11.6	0.885	0.001	**<0.001**	0.265	**<0.001**	0.417
Min ABD(bpm)	13.7 ± 0.3	14.6 ± 0.7	14.1 ± 0.7	14.5 ± 0.4	14.1 ± 0.8	13.3 ± 1.4	**0.028**	0.263	0.166	0.054	**0.009**	0.349
SD ABD(bpm)	5.9 ± 0.4	5.6 ± 0.0	5.9 ± 0.5	6.7 ± 0.2	6.4 ± 0.8	6.9 ± 1.0	**0.006**	0.375	**0.021**	0.203	**0.008**	0.338
RC(%)	60.2 ± 13.3	61.5 ± 13.8	57.1 ± 7.8	58.6 ± 8.1	55.9 ± 9.4	56.2 ± 8.8	0.487	0.043	**0.042**	0.151	0.458	0.061
Correlation(%)	63.0 ± 15.0	61.0 ± 24.0	53.0 ± 22.0	34.0 ± 31.0	54.0 ± 15.0	50.0 ± 16.0	**0.040**	0.153	**<0.001**	0.301	**<0.001**	0.326
Phase Synchrony(%)	72.0 ± 7.0	73.0 ± 11.0	59.0 ± 14.0	53.0 ± 16.0	62.0 ± 8.0	61.0 ± 9.0	**0.025**	0.195	**0.016**	0.198	**0.025**	0.223

Legend: **RC**- Rib cage respiratory frequency; **ABD**- Abdominal respiratory frequency; **RC(%)**- Percentage of Rib cage contribution to respiration; **Correlation**- Correlation between Rib cage and Abdominal breathing; **PS**- Phase Synchrony between Rib cage and Abdominal breathing; **pg**-harmonic mean combined p-value for the between factor; **pph**- harmonic mean combined p-value for the within factor; **pint**- harmonic mean combined p-value for the interaction. η_p^2- partial eta squared. The significant results are in bold.

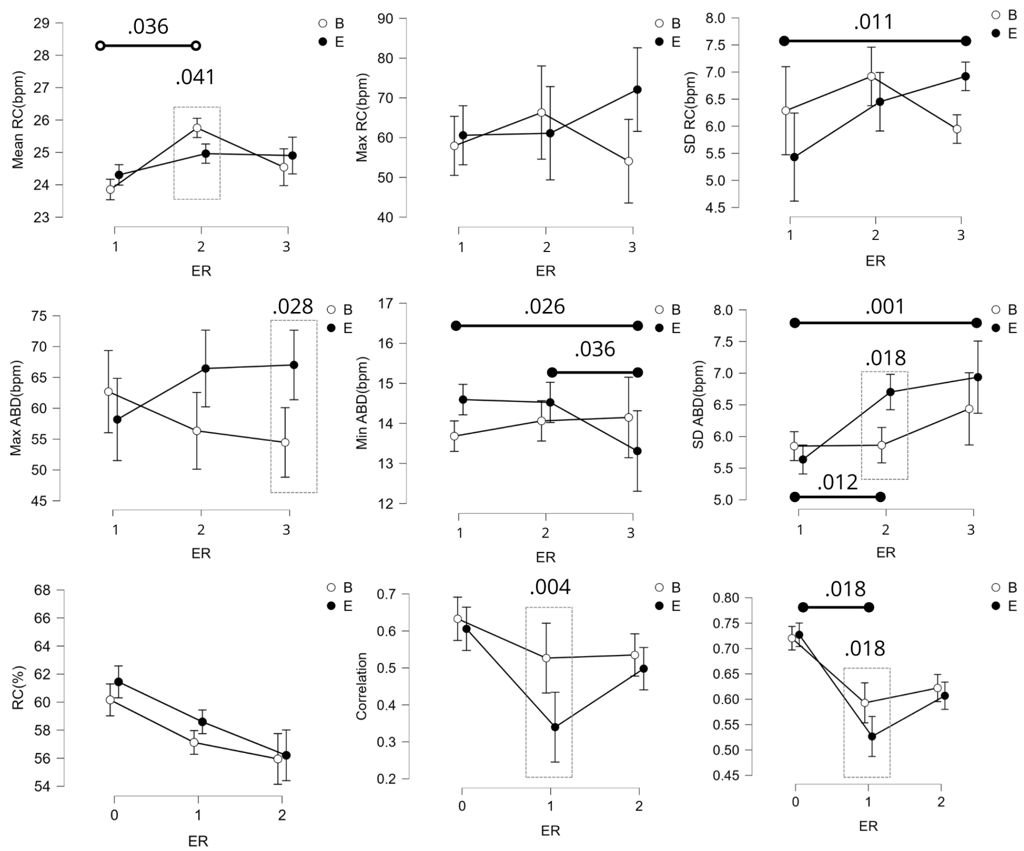


Figure 5.6: Descriptive plots with the Tukey test results for the significant respiratory variables.ER: Ergonomic Risk Stratification; 1:Low; 2:Moderate; 3:Moderate-High; B: Beginning; E: Ending. The dashed line box represents a significant result in the within factor. The solid line represents significant differences in the between factors, with markers on its tips: B-circle; E-solid circle.

6 Discussion

This study was conducted to investigate the acute response of operators' cardiovascular and respiratory systems to tasks with different workload volumes, and also ERs, on a real automobile assembly line. It was expected that the physiological response would change according to different workload volumes that are associated to the work station. Further analysis was conducted to understand if tasks with distinct ER ranks also yielded divergent cardiorespiratory adapatations. To achieve this ECG and RIP signals of volunteer workers were tracked for a period of their shift and with ACC data, work-cycles were determined, to perform this analysis. The workloads from each station were characterized in relation to cycle length and total number of cycles, that stemmed marked contrast, with H_3 showing to have the smallest work-cycle duration (1 minute), following H_1 (3 minutes) and the longest cycle-times for H_2 (5 minutes).

The mixed design of this study included 40 minutes of the collected signals that were compared among workstations from the beginning to end of recording. Results showed significant evolution of HRV parameters and of HR. The respiratory response presented meaningful results in ABD RR parameters and in thoraco-abdominal synchrony.

To find if there were any common responses between workstations, 60 minute recordings were investigated, considering the differences found in the previous design. Significant difference in SDRR, ABD range and SD were observed irrespective of workload.

At last when looking into ER stratification and each of the tasks' evolution, HR parameters were very dissimilar from low risk to the higher ranked ERs, and HRV had interesting evolution only found in moderate-high ranks. Respiratory variables in both RC and ABD walls had notable variation and the coordination between these two also showed remarkable disparities in both of the study's factors.

6.1 Work-volume of monitored tasks

The workload of the three workstations, as expected presented significant differences in cycle-time and frequency of activity per 10 minutes between the H_2 and H_3 workstations. As for the other suggested metrics, cycle transition time and effective working time, no evident disparities were found, as workers have to keep up with the line pace and recordings with major pauses were removed, it was expected that there wouldn't be major variations in these measurements. These variables allowed us to minimize the effect of work unrelated motor tasks on the analysis.

6.2 Cardiovascular response

From the mixed study design, H_3 had evident decrease in SDRR, SD of RHR, coefficient of variation of HR and SD2, all indicators of HRV. The H_2 workstation had a meaningful change in HR that in fact decreased with time.

The CVS for H_1 was smaller than the values encountered for the H_3 station. This suggests that the tasks performed at the H_1 station are less strenuous than the ones at the H_3 workstation. It is also noticeable that the H_1's cardiac measurements suffered very little change within the recording.

Regardless of workload, the measure of total variability of RR intervals (SDRR) was decreased in the 60 minute recordings, which hints that more time could uncover destabilization of autonomic balance in the other workstations activities.

In terms of ER stratification, the moderate-high rank had a clear reduction in SDRR and in HR coefficient of variation and low ER activities showed a drop in CVS, through the acquisition.

The ER score seems to in general agree with physiological response, were in terms of HR low risk has smaller cardiac load than both moderate and moderate-high tasks, but in terms of HRV, moderate-high risk tasks are distinguished from the moderate rank, since the first one presents reduction in SDRR through the collection. By these results it may be possible to better quantify the intermediate zones of the EAWS score.

HR is used as an indicator of the load put on the cardiovascular system [106], [107], whereas HRV give us relevant information about autonomic regulation to different stimuli (environmental and psychological) [108]. In short-term recordings (<24 hours), HRV reflects the balance between the parasympathetic and sympathetic branches of the autonomic nervous system, regulatory function of the respiratory sinus arrhythmia on HR and baroreceptor sensitivity (regulation of blood pressure) [23].

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, being that this variation still exists in constant physical exertion [109].

SDRR specifically reflects overall variability, while SD2 reflects short and long-term variability and is correlated with the low-frequency band and baroreflex sensitivity [23].

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 [110]–[112].

This implies that the H_3 workstation and tasks involving moderate to high levels of ER place a higher demand on the cardiovascular system in terms of both cardiovascular load and sympatho-vagal balance. Indeed in these groups, the repetition of movements is more frequent, something that has been associated with increased metabolic, cardiac and perceived stress [113], additionally a lot of movements over-head are performed in this workstation, that in similar activities have shown to increase HR and blood-pressure [114]. The significant decrease in HRV parameters has also been found in simulated assembly line tasks [115], but here a fatigue inducing protocol was applied.

The mean HR of H1 and H3 workstations was maintained during the monitored period, while H2's was reduced from the beginning to final minutes, and when analysing their values lie in the moderate work interval (90-110 BPM) according to Astrand et al. stratification [114]. In terms of ER, the same metrics lies in the light work rank (<90 BPM) for the low and moderate ER and moderate intensity for the moderate-high ER.

6.3 Respiratory response

Respiratory frequency is an indicator of physical workload, that increases with higher metabolic demands [116] .Thoraco-abdominal asynchrony is used as a measure of respiratory muscle load, definied as the unmatching movements of the RC and ABD walls, expressed in phase angle [117].

The movements of both these walls are mediated by the respiratory muscles: the diaphragm (at contraction expands rib-cage allowing inspiration), the intercostal muscles (inspiration and expiration), abdominal muscles (mainly expiration) and accessory muscles of respiration [118].

From the observed workstations, the H_2's ABD respiratory variables present the most distinct evolution from initial and final 10 minutes, mean ABD RR dropped, the observed maximal ABD RR was greater, and so was its SD. This suggests a chaotic movement of the abdominal muscles, meanwhile RC parameters did not change, something reflected in the diminished correlation between their motion.

A substantial reduction in respiratory correlation and of PS was seen for H_2 and H_1 stations, respectively. This asynchronous motion between walls is consistent with [54], where phase and correlation decreases between baseline and fatigue trials in a simulated repetitive task. Interestingly, the 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, which suggests different adaption mechanisms inherent to this station when compared to the others.

For the 60 minute recordings ABD respiratory range and SD was increased, so ABD RR was less constant by the end of the recording. This may imply that ABDmuscles were not able to keep up with physical stress.

The moderate risk rank found its mean RC reduced, SD of ABD RR increased, a drop in correlation and in PS. The contrary growth in RC and ABD may point to more effort of ABD muscles with the decrease in RC contribution, the last two metrics suggest increase in breathing effort as both reflect the thoraco-abdominal coordination. The moderate-high group had its maximal ABD increased. The low risk activities had higher mean

RC RR and PS than the moderate tasks, lower SD of RC and ABD breathing, and higher minimum ABD RR, which suggests a lower effort of breathing for these tasks.

As 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 [119].

6.4 Limitations

In this study some limitations are pointed out. First, work experience of the volunteers was only verbally confirmed to be of at least one year, but the knowledge of how long each worker had been on the assembly-line can influence physiological measurements. In addition, the moment and conditions of data acquisition were not totally controlled by researchers, where some were taken in the morning and others in the afternoon, without supervision of stimulant substances consumption.

In terms of the employed statistical analysis for the mixed-design, it is essential to note that the results are based on an artificially balanced dataset. This balancing process was undertaken to ensure group equality in the mixed ANOVA. However, it assumes that the original sample was representative of male workers on the assembly line. Also, when the assumption of normality was not met, the test was performed on transformed data. In the analysis of recordings with a duration of 60 minutes, results may be biased by the fact that there are much more workers from the shorter cycle station than of the others, and a larger sample size should be considered in further studies.

6.5 Chapter Conclusions

Trough the analysis of the different stations on this assembly-line, some distinctive characteristics of cardiorespiratory response were revealed. These have the potential to better characterize operators physiological strain and could lead to correct predictions of activity difficulty for each worker using non-invasive continuous monitoring, leading to optimized interventions.

Some of the studied physiological parameters have been successful in the construction sector in identifying task demands (respiratory frequency and depth) [120], and have been used to detect workers fatigue and alert for the necessity of breaks (HRV) [110].

The use of breathing measurements showed to give insight into other mechanisms of physiological response to repetitive movement and should also be used in assembly-line monitoring, since it is not widely used in this sector and is also easily employed.

We also highlight that if these results are shown in such short-term recordings, we raise the possibility that longer recording times could reveal further adaptations, and should be studied in future work.

7

Conclusions and Future Work

In this Thesis, multiple research questions were sought to be answered, regarding the cardiorespiratory system adaptations in an automobile assembly line, as this sector presents high physical demands and environmental stressors that are hazardous to its workers overall health.

The cardiorespiratory adaptations to different workloads and ERs were captured by the recording of ECG and RIP signals during a period of the shift of multiple operators and a thorough description of the extracted variables was made.

With respect to general cardiorespiratory response, among different workstations, results did not present any relevant differences. However, when analyzing evolution of the chosen cardiac and respiratory measurements, contrasts were found among tasks with distinct work-volumes. Furthermore, the outcome of assessing longer recordings, suggested that the adaptations were also dependent on task duration, and different workstations presented some identical adaptations.

When analyzing different ER tasks responses through the acquisition, it was noted that there were marked differences in cardiac variables between the risk ranks, mainly some that could be used to better discriminate in the transition zone of moderate to high risk activities, and also respiratory measurements weren't always coincidental with the ER. So these variables could leverage risk scores to be more comprehensive and better quantify operators exposure.

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 operator's cardiac activity.

Multiple challenges had to be overcome along this investigation, as it was a field study, where conditions in which the data was collected weren't totally dependent on researchers. From this, confounding variables such as years of experience, part of the day and consumption of stimulant substances was not controlled. In addition to this, the unexpected events that occurred in recordings such as line stops and failure of sensors reduced the data that could be used.

This research focused on exploring ECG and RIP extracted measures of the assembly line workstations, but ACC and EMG data was also acquired and could complement the results found in this particular analysis. The recordings that were excluded because of breaks could also be useful in assessing the influence of pauses through out workers activity and the influence of other variables, such as time of day could be looked into.

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 representativity of the studied factory and effect-size of statistical analysis. It would also be interesting to get baseline values of the measured variables to compare with the ones obtained during the job.

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 isn't just about addressing immediate health concerns, it's about recognizing the enduring impact that everyday occupational activities can have on the quality of life of workers.

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Statistical Results

Table I.1: Description and results of the Kruskal-Wallis Test on the Cardiovascular indicators,for the whole 40 minutes.

Variable	Group			p	ϵ^2
	H1	H2	H3		
HR(BPM)	89.8 ± 23.7	90.3 ± 8.3	96.0 ± 15.4	0.700	0.178
SDRR(ms)	41.0 ± 15.0	45.0 ± 10.0	42.0 ± 17.0	0.871	0.069
RMSSD(ms)	18.0 ± 8.0	25.0 ± 8.0	23.0 ± 15.0	0.419	0.435
RHR(%)	23.8 ± 10.1	25.3 ± 5.4	27.9 ± 7.2	0.718	0.166
CVS(%)	42.5 ± 10.0	46.2 ± 9.0	53.2 ± 12.1	0.256	0.681
CVL(%)	21.2 ± 4.7	23.8 ± 4.4	26.5 ± 5.2	0.152	0.943
SD1(ms)	13.0 ± 6.0	18.0 ± 6.0	16.0 ± 10.0	0.419	0.435
SD2(ms)	56.0 ± 20.0	61.0 ± 13.0	57.0 ± 22.0	0.803	0.110

Legend: **HR**- Heart Rate; **SDRR**- Standard deviation of RR intervals; **RMSSD**- Root mean square of successive RR interval differences; **RHR**- Reserve Heart Rate; **CVS**- Cardiovascular Strain; **CVL**- Cardiovascular Load; **SD1**- Poincaré plot standard deviation perpendicular to the line of identity; **SD2**- Poincaré plot standard deviation along the line of identity; **H1**- medium cycle station;**H2**- long cycle station; **H3**- short cycle station. ϵ^2- epsilon squared

Table I.2: Description and results of the Kruskal-Wallis Test on the Respiratory indicators,for the whole 40 minutes.

Variable	Group			p	ϵ^2
	H1	H2	H3		
RC(bpm)	24.8 ± 1.8	25.5 ± 1.2	24.7 ± 1.3	0.551	0.298
Std RC(bpm)	6.6 ± 0.4	6.8 ± 0.4	6.2 ± 0.7	0.086	1.229
ABD(bpm)	24.5 ± 0.7	24.8 ± 0.5	24.7 ± 1.0	0.759	0.138
Std ABD(bpm)	6.4 ± 0.4	6.5 ± 0.5	6.6 ± 0.9	0.876	0.066
RC(%)	58.8 ± 18.8	58.4 ± 2.6	54.9 ± 8.8	0.367	0.501
Correlation(%)	28.0 ± 34.0	46.0 ± 8.0	58.0 ± 17.0	0.145	0.965
PS(%)	50.0 ± 17.0	58.0 ± 5.0	65.0 ± 10.0	0.231	0.733

Legend: **RC**- Rib cage respiratory frequency; **Std RC**- Standard deviation of RC respiratory frequency; **ABD**- Abdominal respiratory frequency; **Std ABD**- Standard deviation of ABD respiratory frequency ; **RC(%)**- Percentage of Rib cage contribution to respiration; **Correlation**- Correlation between Rib cage and Abdominal breathing; **PS**- Phase Synchrony between Rib cage and Abdominal breathing; **H1**- medium cycle station;**H2**- long cycle station; **H3**- short cycle station. ϵ^2- epsilon squared.

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