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**DOCTORAL (PHD) THESIS**

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# Prevention of MSD by Assessing Psychosocial Factors in Manual Handling Tasks in the Workplace

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**DOCTORAL SCHOOL ON SAFETY AND SECURITY SCIENCES**

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## D 12) DECLARATION AGAINST PLAGIARISM AND CORRECT REFERENCING

I, Erazo Chamorro Vanessa Cristina, declare that the dissertation entitled: Prevention of MSD by Assessing Psychosocial Factors in Manual Handling Tasks in the Workplace I wrote myself, using only the sources given in the list of references. All passages that I have taken verbatim or with identical content but paraphrased from other sources are clearly indicated by citing the source.

Date: 2025 September 01

ERAZO CHAMORRO VANESSA CRISTINA

(Signature)

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# INTRODUCTION

**Personal motivation and interest**: Drawing from my personal experiences, I was motivated to conduct a study on "Prevention of MSD by Assessing Psychosocial Factors in Manual Handling Tasks in the Workplace." Additionally, my work as an instructor and researcher has reinforced my determination to tackle these significant workplace safety issues.

At a higher technological institute, I served as both a professor and a researcher. In this role, I presented industrial automation lectures, worked on the research coordination team, and developed automation projects on my own. Additionally, I provided advisory services to regional businesses and sectors. I conducted a lecture on industrial safety, which was a key experience in my career. I began considering how stress impacts the safety and comfort of industrial automation workers. I recognised this as a unique opportunity to merge my research interests, professional experience, and passion for creating safe workplaces. This context highlights the pressing need to address the psychosocial factors contributing to MSD in industrial tasks. I was inspired by these experiences to investigate how psychological variables contribute to the development of musculoskeletal disorders (MSDs) and to suggest workable solutions for enhancing ergonomics and safety results in industrial settings. My research aims to identify these factors and propose solutions tailored to them.

Security and safety are essential elements of every industrial setting. My goal is to improve workplace safety by promoting knowledge in this area and enhancing workplace design. I am driven by the desire to make a meaningful contribution to society through my work. This research aligns perfectly with my goals, offering the platform to explore and address critical occupational safety issues.

**Scientific motivation:** Throughout my career, I have been involved in industrial automation projects where workers frequently handled large crates, rolls of wire, and electronic equipment, often experiencing back discomfort and psychological fatigue. As a result, they requested a rigorous study to link stress factors to healthy working practices. This study has far-reaching implications: improving worker comfort and managing hand fatigue has the potential to increase work performance, reduce absenteeism and reduce the risk of musculoskeletal disorders.

## Actuality of the topic

To earn a living. With the emergence of occupational health, the concept of work and our perception of the workplace have evolved in recent years and are now the subject of continuous research [1], [2]. From that point, and throughout history, the concept of "work" has evolved dramatically as a result of globalisation, a unique economic trend [3]. Approximately 1848, the Industrial Revolution's focus on industrial hygiene enabled the first steps towards what is now recognised as occupational health. [4].

The next step was to start ‘Working for a suitable life’. The realisation that just producing money without considering workers' health could harm not only the workers but also the owners of these businesses was the impetus that propelled the concept of occupational safety forward [5]. Work has evolved from "simply making money" to today, when the concept of decent work is recognised as a human right. [4], [6], [7].

As the ILO (International Labour Organisation) points out in its agenda, the main difficulty in making a comprehensive environment safe is a recurring case study [8]. The analysis and assessment of safety risks are specific, but the principle must be applied to all workplaces. Continuous research into safety issues has led to the emergence of new risk elements in the workplace [9], ranging from those that are obviously visible (physical factors) to those that are hidden but deeply present, and some of which can be more harmful (psychological factors) [10], [11]. Physical and psychological risk factors are both directly linked to the development of work-related disorders.

Two categories define the conception of a safe climate or workplace. The initial category consists of individual-level analysis that describes departments or units within a firm. The second category operates at the group level and considers safety at the organisational level, referring to management attitudes and business rules [12]. In addition, the psychological safety environment is linked to employees' views of safety within the organisational structure of the company about specific policies and practices, such as employee training on safety and security measures [13], [14], [15].

In today's world, a wide variety of risk identification tools and processes are available, including record assessment, information gathering approaches, checklist analysis, assumption analysis, causal mapping and various other methods to reduce the impact of a hazardous workplace [16], [17], [18]. The importance of risk identification in the workplace is a significant issue in industrial tendencies in the current setting, and the objective of the research is to bring value to the field.

As a primary workplace hazard, poor ergonomics is the leading cause of work-related problems in industry. As shown in Figure 1, a cause-and-effect analysis is applied to prevent musculoskeletal disorders. As the primary intent, the understanding of safety science is the primary factor in the application to identify a solution [19].

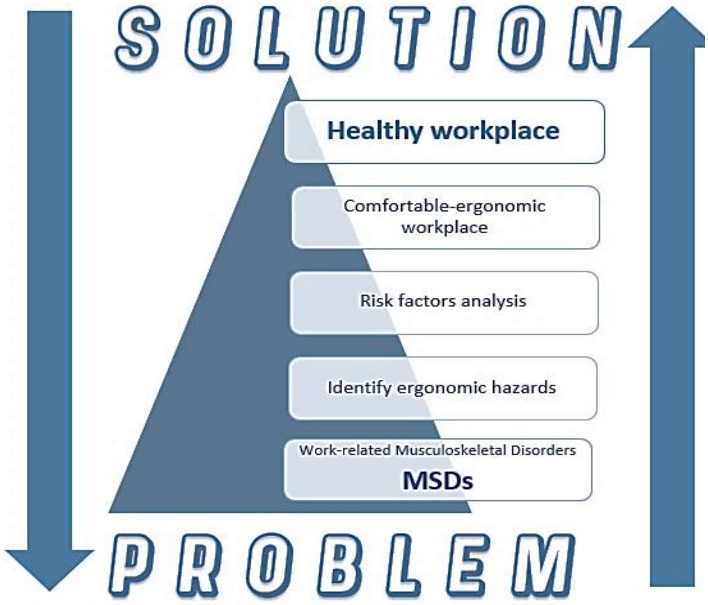


*Figure 1 Overview of cause-and-effect relationships between healthy workplaces and biomechanics.*

Since workplace safety has a direct impact on workers' well-being, corporate productivity, and the sustainability of economic activity, its importance cannot be understated. Stress is a significant psychological hazard that heavy workloads, unrealistic deadlines, a lack of control over tasks, and poor relationships at work can cause. Therefore, workplaces must reduce stress because excessive stress has a negative impact on employees' well-being and overall organisational performance.

A safe workplace must meet the parameters established to guarantee it in this definition. These specific parameters are divided into groups: i) Physical work environment. ii) Psychosocial work environment, as shown in Figure 2, which asserts that lowering biomechanical ergonomic risk factors at work is directly related to improving the physical work environment. [19]. In today's digitised workplaces, task performance relies heavily on cognitive capacity, which encompasses mental processes involved in information processing such as memory retention, attention, decision making and learning. The cognitive demands of job-related tasks often exceed the intrinsic boundaries of human cognitive capacities, but working environments can also strain these capacities. As research on disruptions and interruptions has shown, many working conditions impede cognitive performance [20], [21].


*Figure 2 Identified needs to achieve a healthy workplace*

Inadequate stress management can result in severe mental and physical health problems, such as anxiety, depression, burnout, heart disease, and musculoskeletal illnesses. This causes companies to lose a lot of money because it not only lowers production but also raises absenteeism and turnover rates [22].

The psychological demands of work are significant today and will remain so in the future. Although the cognitive load associated with work environments and work practices is widely recognised and actively debated as a substantial risk factor, little research has directly and systematically sought to develop situations that support people in performing cognitively demanding tasks [22].

The cognitive demands of today's fast-paced, heavily technological workplaces have increased, making stress management even more crucial. Employees' cognitive capacity is frequently exceeded by workplace disturbances, multitasking, and information overload, which exacerbates stress levels. Stress reduction improves decision-making, creativity, and overall productivity, while also enhancing the health of employees. Businesses can create a more sustainable and healthy work environment, ensuring long-term success and employee retention, by managing stress at both the individual and organisational levels.

## Formulation of the scientific problem

As the industry considers workplace safety and risk reduction, it is critical to assess the effects of different physical and psychological risk factors on employees' health and well-being. This demonstrates that addressing the primary risk factors in the workplace is essential.

The significant number of occupational accidents that occur each year, mainly resulting in days away from work, has become a substantial cause for concern. The main objective is to improve the organisational framework and prevent future occupational accidents.

A key professional issue is integrating ergonomic concepts with safety criteria. To promote decent work as a human right and strike a healthy balance between workplace design and new strategies, new approaches are needed. The importance of occupational health is stressed, particularly regarding safety issues in the workplace. It highlights the importance of analysing and assessing safety hazards, which can be either overt (physical) or covert (psychological).

Workstation engineering is a deliberate and scientific technique for measuring recurring and essential stresses in the workplace. The technical problem is to develop effective methods of using tools at workstations, considering individual variations in activities and applications, and satisfying the different needs of individuals while performing numerous tasks.

## Scope

Cognitive load and psychological demands in the workplace are key elements that affect worker performance, and research is needed to design environments that support people in cognitively demanding activities. This reflects the complex nature of workplace safety, which includes physical and psychological risk concerns, organisational management, and the cognitive needs associated with modern digital workplaces. Identifying key workplace risk variables and providing key insights for occupational health and safety.

The scope of this research focuses on understanding and mitigating psychosocial risk factors associated with manual handling tasks in the workplace. By examining the effects of psychosocial stressors on employees' physical tasks, including lifting and posture, the study seeks to increase workplace safety. It emphasises how crucial it is to recognise and manage psychological as well as physiological dangers to establish a safer and healthier workplace.

The research will systematically identify psychosocial stressors and distractions that influence the risk of musculoskeletal disorders (MSDs) during manual material handling. It will analyse how these factors affect workers' physical responses and susceptibility to injury. In addition, technological devices will be used to assess the impact of stressors on posture and muscle strain, integrating biofeedback to develop preventive strategies to reduce the risk of MSDs.

Another critical aspect of the study is to understand the workers' perspective on psychological risk factors. Using decision-making techniques, the research will assess how workers perceive and prioritise psychosocial stressors in manual handling tasks, providing insight into their role in workplace safety. Finally, controlled laboratory experiments will be conducted to quantify the impact of these identified stressors on manual handling performance, fatigue accumulation, and movement efficiency, contributing to a comprehensive risk prevention framework.

## Objectives

- Demonstrating that increasing workplace comfort can prevent and reduce the risk of work-related illnesses, such as musculoskeletal disorders (MSDs) in manual handling scenarios, by managing the factors related to the psychosocial aspects that directly influence cognitive ergonomics, improves security and safety in the workplace.
- To analyse the influence of psychosocial factors on the risk of developing musculoskeletal disorders in manual handling activities, by the identification of the main psychosocial factors and their impact on physical effort and susceptibility to injury in the work environment.
- To identify the cognitive ergonomic factors at the workplace that influence occupational health problems, particularly those that are directly related to the prevention of MSDs; using a systematic literature review and word cloud analysis; to define the most critical factors to consider in a manual handling task of lifting loads within the workplace.

## Hypotheses of the research

**Hypothesis 1 (H1):** Pushing comfort in the workplace by properly managing psychosocial ergonomic factors helps optimise conditions during manual handling tasks, mitigates stress-induced muscular activity reduction (SMAR), and enhances occupational safety, reducing the risk of musculoskeletal disorders (MSDs).

**Hypothesis 2 (H2):** Systematic categorisation and prioritisation of psychosocial factors based on worker perceptions can effectively identify the most impactful stressors and distractors in manual handling tasks and allow for effective targeted interventions.

**Hypothesis 3 (H3):** The integration of psychosocial risk factors into manual handling has the potential to create distractions that can increase the risk of musculoskeletal disorders (MSDs) in the workplace.

**Hypothesis 4 (H4):** The application of recognised ergonomic principles, in combination with observational analysis and advanced machine learning techniques, enables highly accurate detection of stress-related physiological responses induced by psychosocial stressors, which significantly influence muscular activity patterns and increase the risk of work-related musculoskeletal disorders (MSDs) during manual handling tasks.

## Research methods

In preparing my thesis, I have divided my research into three parts as shown in Figure 3. In the first part, I conducted a systematic review to determine the neurocognitive factors in manual handling aimed to prevent MSDs in the workplace, identifying factors related to neuro-ergonomics. In the second part, I developed a survey and data analysis to determine workers' perceptions of different neuro-ergonomic factors, as distractors can affect manual handling. In the third part, the experimental study is applied to determine the stress produced by the inclusion of these neuro-ergonomic factors during manual handling tasks.

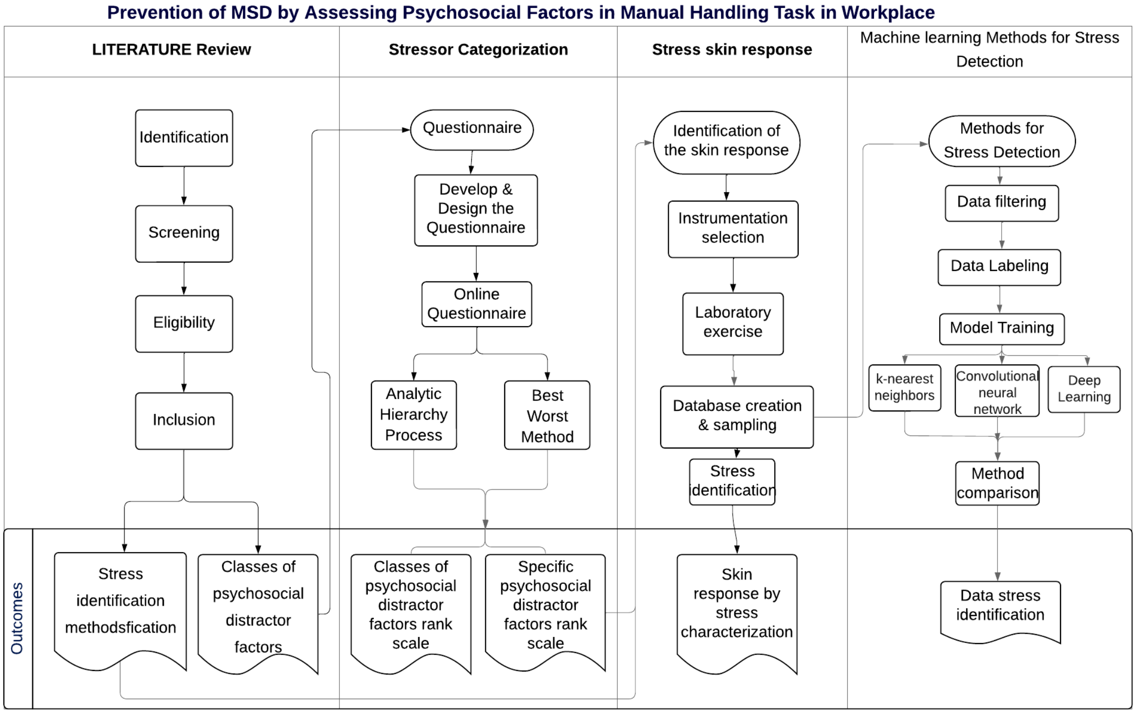


*Figure 3 Structure of the dissertation*

## Research limitations

To investigate how the risk of musculoskeletal disorders (MSDs) is related to manual handling, psychosocial ergonomics and cognitive ergonomics. This research intends to carefully navigate the complexities of measuring psychosocial and cognitive factors and addressing potential ethical concerns associated with the proposed interventions.

The practical application and measurement of psychosocial components can be challenging. Due to the complexity and interdependence of these variables, isolating the individual contribution of each factor to safety benefits in manual handling contexts can be challenging. Psychosocial and cognitive ergonomic factors are difficult to measure due to their subjective nature and difficulty in quantification. Using structured tools such as AHP and BWM to categorise worker perceptions, individual differences, and contextual variables may affect the accuracy and consistency of the results obtained in different industrial settings.

Incorporating psychosocial risk factors as stressor distractors into manual handling tasks to demonstrate the effect of recommended weight limits on reducing the risk of MSDs is challenging because most body measures are invasive laboratory tests. In this context, the number of possibilities can be a difficulty during the experimental part.

The accuracy of physiological signals used to measure stress responses, such as heart rate variability (HRV) and galvanic skin response (GSR), may be affected by external factors such as sensor location, ambient temperature and individual physiology.

The practical value of the controlled laboratory setting of the experimental phase is also limited because real-world workplaces are often dynamic and unpredictable, which can have different effects on stress and fatigue.

## Structure of the dissertation

The research was divided into three main phases, each of which employed a different methodological process to examine the effect of psychosocial factors on the risk of musculoskeletal disorders (MSDs) during manual handling tasks. The first phase involved a systematic review of the existing scientific literature on psychosocial risk factors and MSDs, conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method. A meta-analysis was then performed using Comprehensive Meta-Analysis (CMA) software to calculate effect sizes and assess the correlation between psychosocial stressors and reduction in muscular activity (SMAR). This theoretical phase established the scientific basis and identified the key psychosocial stressors to be investigated further.

In the second phase, a structured online survey was distributed to workers in industries involving manual handling tasks. The goal was to collect data on workers' perceptions of the impact of psychosocial stressors. The data were analysed using multicriteria decision-making tools: the Analytic Hierarchy Process (AHP) and the Best Worst Method (BWM), to prioritise the most influential stressor categories and sub-factors, providing a classification of psychosocial risks based on worker perception and complementing the theoretical findings.

The third phase consisted of controlled laboratory experiments involving the performance of standardised manual handling tasks. Wearable devices were used to collect real-time physiological signals in monitoring stress and fatigue levels. Machine learning algorithms were then used to classify the signals and recognise stress patterns for the identification of stress-induced physiological changes during the manual handling task. The rest of the research is in the structure of five chapters as follows:

In **Chapter 1**, A systematic literature review is presented to identify the neurocognitive factors in manual handling aimed at preventing MSDs in the workplace, to identify factors related to neuroergonomics, and to consider and provide a comprehensive overview of the incorporation of psychosocial factors as stressor distractors in lifting tasks.

In **Chapter 2**, the worker's perception categorises the psychosocial components found in the PRISMA literature review. The Analytic Hierarchy Process (AHP), together with the Best Worst Method (BWM), determines the influence of this classification to identify the primary distractions and the secondary psychosocial risk factors to determine the importance of their impact on the tasks.

In **Chapter 3**, Experimental observation is used to determine the influence of psychosocial factors categorised as most important in workers' perceptions (Chapter 2) and how these factors affect manual handling tasks.

In **Chapter 4**, A comparative analysis of machine learning methods for stress identification and pattern recognition using the Chapter 3 dataset to support the prevention of musculoskeletal disorders.

In **Chapter 5**, Conclusions explain the notable findings in the research and establish how psychosocial factors significantly influence manual handling performance by characterising and identifying stress patterns related to MSD risk.

Finally, the inclusion of references and supplementary materials in this research serves to substantiate and enrich the proposed comprehensive model. It also strengthens its foundation in existing scientific work.

# 1 PRISMA-BASED LITERATURE REVIEW OF MANUAL HANDLING AND STRESSOR IDENTIFICATION FOR THE PREVENTION OF MSDS

In the manual handling field, a detailed exploration of ergonomic interventions, injury prevention strategies, and biomechanical implications provides information about the involved factors. The structured approach is composed of an introductory part, PRISMA methodology, result presentation, and discussion.

## 1.1 Manual Handling

Any action involving the use of force to lift, lower, push, pull, carry, move, hold or restrain a person, animal or object is referred to as manual handling [23]. There is a risk of harm if these tasks are performed incorrectly, and research shows a clear link between manual handling and musculoskeletal problems [24].

The Recommended Weight Limit (RWL) is used in manual handling to reduce the risk of injury by determining the maximum safe weight a person should lift based on real-world conditions. It is calculated using the revised NIOSH lifting equation, which is based on a multi-factor model that assigns a weight to each of the six work factors. The weights are represented by coefficients that act to reduce the load constant, i.e. the maximum load weight that should be lifted in perfect circumstances [25]. Equation 1 defines the RWL:

$$\boldsymbol{RWL = LC * HM * VM * DM * AM * FM * CM} \tag{1}$$

Where the Recommended Weight Limit (RWL) includes the Load Constant (LC), which serves as the starting weight; the Horizontal Multiplier (HM), which takes into account the distance of the load from the body; the Vertical Multiplier (VM), which takes into account the height of the lift; the Distance Multiplier (DM), which calculates the vertical travel of the load; the Asymmetric Multiplier (AM), which determines the angle at which the torso twists; the Frequency Multiplier (FM), which takes into account the Distance Multiplier (DM), which calculates the vertical travel of the load; the Asymmetry Multiplier (AM), which determines the angle at which the torso twists; the Frequency Multiplier (FM), which examines the frequency and duration of the lift; and the Coupling Multiplier (CM), which assesses the quality of the hand-to-object grip [25].

To reduce the risk of injury, the Manual Handling Regulations provide a hierarchy of control methods. The first duty is to eliminate hazardous manual handling tasks wherever possible. Where this isn't possible, consideration should be given to task/workplace organisation and the accessibility of lifting equipment. Employers must provide health and safety training and information to their employees; where necessary, this should be supplemented by additional guidance on the hazards of manual handling errors and how to prevent them [26].

In manufacturing, distribution, mining, construction and agriculture, manual handling is often used for specialised tasks such as setting up scaffolding on building sites, laying bricks on uneven surfaces and operating power equipment above shoulder height [27].

### 1.1.1 Manual handling position

Reducing the load on the spine by improving lifting techniques can help reduce the risk of low back pain. For this reason, instruction in lifting technique is usually part of the primary and secondary prevention of back pain. However, the effectiveness of such instruction depends on whether or not it reduces spinal loading. The idea that squatting, which involves bending the knees rather than the back, reduces spinal loading has been around for some time and is still widely accepted [28]. The stoop, squat and weightlifting techniques for lifting the box established are illustrated in Figure 4 [27].

Lifting techniques, particularly for the L5/S1 joint, indicate strength requirements for low back ligament strain and L5/S1 disc compression. The techniques focus on four main factors: hand placement, back posture, knee alignment and foot placement.

*Figure 4 The stoop, squat and weightlifter techniques for lifting the box.*

There are two primary foot placement positions: The straddle position, with one foot in front and one behind the weight, provides more stability due to its larger base. An alternative is the parallel position, where the feet are placed side by side.

The recommended positions for the knees are squatting or bending the knees, which transfers the weight to the stronger leg muscles, reduces the moment arm and reduces the load on the lower back ligaments. On the other hand, if the load is too heavy to fit between the knees, you can still use a squatting position, although this is considered more dangerous. Recommendations for back posture vary; some encourage a flat back to minimise ligament strain and improve muscular control by keeping the spine in its normal shape when standing. Because it activates the ligaments to take some of the load off the muscles, a curved back can be beneficial. The hand placement technique covered is the opposite hand hold, which increases the load on the lower hand while providing stability by placing one hand on the upper outer corner of the load and the other on the lower inner corner. The parallel grip is an alternative position where the hands are placed on opposite sides of the object [29].

### 1.1.2 Improper manual handling consequences

As low back pain (LBP) is usually considered to be mechanical in nature, any mechanical stress on the supporting tissues, muscles, ligaments and bones of the spine can exacerbate symptoms. The specific nature of the disease processes or trauma that cause mechanical LBP is rarely known. Symptoms of LBP include pain, stiffness, muscle tension, weakness in the legs or feet, and a tingling or burning sensation running down the legs [30].

During their working lives, 85% of people will experience some form of LBP; 60% of these people will still report symptoms five years later. LBP has a significant social and economic impact on people of working age. LBP is the reported number three reason for surgery, number five for hospitalisations, and the number two reason for consulting a physician [31].

Stress is reported by individuals, representing 28.17% of the cases, which places it in the lower third of the causes listed. Among the listed causes are sciatica (52.11%) and nerve injury (50.70%). These causes have to do with stress and continue to be an essential contributor to back pain incidence. It highlights how both physical and psychological factors are involved [32].

In a cross-sectional and retrospective epidemiological study, one thousand nine hundred and fifty people were asked about the most severe episode of LBP they had experienced [33]. The prevalence of sciatica, especially below the knee, is higher in men who perform manual handling (9.5%) and vibration-related occupations (10.1%). The prevalence of sciatica below the knee is higher among women who perform manual handling occupations (14.7%) and tasks involving posture (13.3%). Interestingly, women experience more sciatica above the knee (20.7% in manual handling and 20.2% in the reference group) than males (7.7%–7.3%). Nerve pain radiating along the path of the sciatic nerve, which runs from the lower back through the hips and buttocks and down each leg, is common after poor manual handling. Workers in manual handling occupations have higher rates of sciatica, especially sciatica below the knee. For women, the incidence and severity of sciatica are significantly higher in manual handling jobs than in other populations [33].

### 1.1.3 Stressors and the Effects of Stress

In the industrial sector, there is ample evidence of workplace stress. Stress affects estimators' ability to do their jobs and their interpersonal relationships. Perceived stress is a state that people experience psychologically when they perceive an imbalance between the demands placed on them and the resources available to meet those demands [34].

Job (or workplace) stress is the unpleasant physical and emotional strain reactions that occur when job demands do not match the needs, resources or capabilities of the worker. Stress is caused by any situation at work that an individual perceives as dangerous and beyond their ability to cope with. Workplace stress has a significant correlation with low performance, high absenteeism and underperformance [35].

Long-term exposure to stress at work usually results in physiological and psychological effects. The Office of Health and Safety states that long-term stress is associated with adverse health effects, such as (1) injuries; (2) mental ill health, including depression; (3) musculoskeletal disorders; and (4) cardiovascular disease. Workplace stress is negatively correlated with job satisfaction and is associated with high rates of employee turnover [36]. Low job performance in manufacturing is related to the experience of job stress. In an industrial setting, job stress is associated with an increased risk of accidents at work and occupational injuries. In an industrial setting, work stress is associated with an increased risk of occupational accidents and injuries [35].

The causes of low back pain study [32], proposes a questionnaire to identify the most common causes of low back injuries; 71 participants identified the leading causes. According to the results, stress is a significant factor in developing low back pain, affecting 28.17% of cases, if compared to other common causes like walking. While disc problems (59.15%), lifting (56.34%), and sciatica (52.11%) are more prevalent, the fact that sciatica is a nerve inflammation also related to stress remains a notable contributor to muscular weakness. This indicates that mental stress plays a substantial role in exacerbating low back pain, potentially through mechanisms like increased muscle tension, a reduced pain threshold, and inflammation.

Increased muscle soreness and tension caused by perceived stress eventually lead to physical weakness. Life stressors, such as work pressure and personal relationships, cause long-term stress reactions that maintain muscle tension and worsen musculoskeletal problems. Chronic musculoskeletal pain problems are promoted by prolonged stress. The hypothalamic-pituitary-adrenal (HPA) axis is activated, resulting in the release of cortisol and other stress hormones that lead to chronic muscle tension and impaired muscle performance [37]. Table 1 summarises how different aspects of mental stress (causes) lead to various physiological and psychological changes (effects) that contribute to muscular weakness.

*Table 1 Effects of Stress on Musculoskeletal Health*

| Cause | Effect |
|---|---|
| **Perceived Stress** | Increased muscle tension and pain, leading to muscular weakness |
| **Life Stressors** | Trigger chronic stress responses, leading to sustained muscle tension and musculoskeletal issues. |
| **Chronic Exposure to Stress** | Development of chronic musculoskeletal pain disorders |
| **Activation of the HPA Axis** | Release of cortisol and stress hormones causes persistent muscle tension and impaired muscle function. |
| **Increased Production of Pro-inflammatory Cytokines** | Leads to inflammation in muscles and joints, contributing to muscular weakness and pain |
| **Changes in Muscle Metabolism** | Reduced muscle strength and endurance due to chronic stress |
| **Altered Neuromuscular Control** | Resulting in muscle fatigue and weakness |
| **Comorbid Psychosocial Factors (e.g., anxiety, depression)** | Exacerbate the perception of pain and contribute to a cycle of pain and muscle weakness |
| **Need for High-Quality Research** | More studies are required to clarify mechanisms and identify interventions for stress-induced muscular weakness. |

### 1.1.4 Sources of stressors in industry

Most companies need to improve production. This creates high expectations for workers, which in turn leads to increased demands and stress. Workers should maintain a high level of task activity to achieve the company's goals [38]. The degree to which a person experiences stress can be influenced by their ability to respond appropriately to stressful situations and events.

Compared to workers in other sectors, industrial workers operate in a very different environment. Industrial workers are under intense pressure to maintain efficiency and meet output targets. They often handle heavy machinery and materials while working in physically demanding environments that can lead to physical strain and injury. Additionally, industrial workers must adhere to strict safety protocols to prevent accidents, adding to their stress levels [39].

### 1.1.5 Stressors

Organisational pressures and personal risk factors interact to cause stress and burnout. Employees' mental and physical health suffers as a result of the interaction between organisational pressures, such as work overload, role conflict, under-promotion and participation levels, and personal factors, such as personality and family issues. An imbalance between an employee's efforts and the benefits they receive, or between the demands placed on them and their ability to cope, is often at the root of job stress. Five categories are used to conceptualise organisational stressors presented in Table 2.

*Table 2 Categories of Job-Related Stressors*

| Level | Stressor Factor Type | Meaning | Related Category | Category Description |
|---|---|---|---|---|
| Top Level | **Psychosocial Stressor Factors** | Stressors arise from organisational structures, work settings, and social interactions. Psychological, psychophysical. | **Relationships at Work** | Describes the interactions between employees and their subordinates, colleagues, and superiors. |
| | | | **Organisational Structure and Climate** | Describes how the organisation's structure affects employees. |
| Second Level | **Psychological Stressor Factors** | Internal stressors related to emotions, cognition, and mental well-being. | **Career Development** | Includes factors that affect the future of an employee within the organisation. |
| | **Psychophysical Stressor Factors** | Stressors resulting from psychological and physical demands. | **Job-Intrinsic Stressors** | Factors that increase the difficulty and complexity of tasks, making the workload too heavy. |
| | **Psychology Stressor Factors** | Mental processes and stressors that affect how an individual perceives, acts and thinks. | **Role within the Organisation** | Reflects role ambiguity and role conflict when job tasks and expectations are unclear. |

### 1.1.6 Reactions to stressors

When excessive or perceived negatively, stress can negatively impact a person's performance of tasks and their overall health. Employees often try to manage and reduce their stress levels through a variety of techniques, including avoidance, social and religious support, and positive reinforcement. Stress patterns associated with workers' personal and professional responsibilities. Depending on the type of stressor, its intensity, importance, and the worker's emotional and physical status, there are several ways in which workers react to it. Stress can cause a variety of responses, including behavioural, emotional, physiological, and cognitive [40].

Prolonged and excessive stress can hurt a person's performance and overall health. Employees who believe they are under a lot of stress can often become depressed and are vulnerable to psychiatric disturbances such as mental distress, burnout and suicidal thoughts. In addition to sadness, stress can lead to other mental health problems, such as binge drinking or reckless drug use [41].

## 1.2 Methodology

In manual handling, the primary objective is to develop practical solutions that minimise risks, reduce injuries, and enhance worker safety and productivity in manual handling tasks. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was used to conduct the Systematic reviews. Focusing on these stressor factors to provide reliable evidence of their effects, the methodology is composed of: (I) Data Sources and Search Strategy; (II) Eligibility Criteria; (III) Data Extraction; (IV) Quality Assessment; (V) Analysis Procedures.

### 1.2.1 Data Sources and Search Strategy

The following multidisciplinary electronic databases provided the scientific publications in English that were part of this investigation. Scopus, PsycINFO, PubMed, Web of Science, Cochrane Library, Excerpta Medica Database (EMBASE), NIOSH, and World Health Organisation, International Labour Office ILO database, European Agency for Safety and Health at Work EU-OSHA database and Occupational Safety and Health Administration OSHA database. Keywords were then used to identify relevant publications from the databases: (manual AND handling OR lifting AND loads ) AND ( stress OR job AND stress OR worker AND stress ) OR ( security AND factors OR work AND risk OR ergonomics AND risk ). Keywords were identified based on previous systematic reviews in the field of workplace risk factors for musculoskeletal disorders and ergonomics [26], [42] [43].

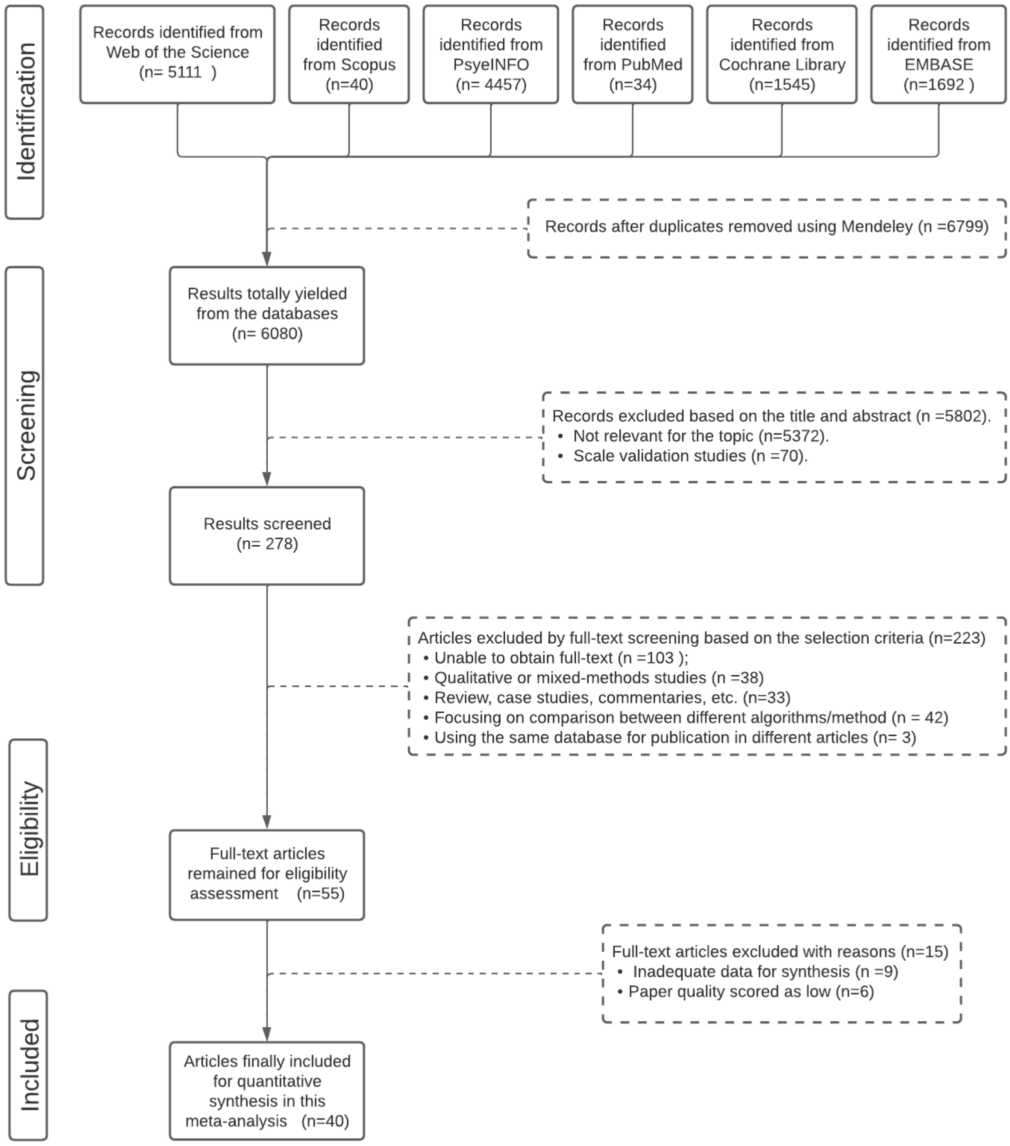


*Figure 5 Flowchart of the selection and inclusion procedure*

The occupational health and Health field has been extensively studied over the past decades; therefore, articles published after the 1980s have been included in this review. The references of the scientific papers used in the research were added manually, verified and located in the list of references of this dissertation. This systematic review was concluded around the end of 2024. The search and selection process for the current meta-analytic study is shown in Figure 5. 12879 records were initially identified through manual searches and online resources. 6080 records were retrieved from the databases after 6799 duplicates were removed using Mendeley software. After reviewing the abstract content and title, 5802 records were deemed inapplicable to the topic or primarily concerned with scale validation. After full-text screening, 223 articles were excluded according to the exclusion criteria. After the eligibility assessment, 55 full-text publications were eliminated. In the end, 40 journal articles were included in this meta-analysis for quantitative synthesis. The title and abstract of each article were independently assessed. In addition, full-text publications were obtained and examined according to the qualifying standards.

### 1.2.2 Eligibility Criteria

Studies were eligible for inclusion if they met the following criteria: (a) they were empirical studies; (b) they primarily addressed workplace risk factors associated with MSDs and ergonomics in manual handling or lifting; and (c) their sample size included at least thirty individuals. Quantitative studies with longitudinal or cross-sectional designs were included. The journals included were published in English only. Studies with a larger sample size were selected for this meta-analysis if they were published in the same database.

The following criteria were used to exclude publications from this meta-analysis: (a) the full article could not be found online, in university libraries or by emailing the researchers; (b) the papers had not been peer-reviewed; (c) the study dealt with a muscle characteristic other than stress; (d) the study analysed causes other than repetitive task movements; (e) the studies compared different hand conditions; (f) the studies examined cross-cultural issues or different geographical regions; (g) the studies were not empirical studies, such as literature reviews, commentaries, letters to the editor or case studies; or (h) the studies were of low quality.

### 1.2.3 Data Extraction

From the selected studies, the most critical elements were extracted and summarised in a single report. Fifty per cent of the 40 studies were chosen randomly for independent data extraction. (a) Author(s) and year of publication; (b) Sample size; (c) Study design (measurement technique and body location); (d) Effect size; and (i) Identify among the elements that were extracted and coded the attributes of data evaluation applied principles in studies using multiple devices to assess different aspects of the body response, using data from the device with the most favourable characteristics. The methodology outlined in a previous study was used to select the initial dataset for the study [44]. Using the Newcastle-Ottawa Scale (NOS) criteria, the quality of the selected studies was assessed [44].

### 1.2.4 Analysis Procedures

Meta-analyses were conducted with CMA software (CMA, v. 3.0). To account for the heterogeneity of the trials, we first pooled the effect size estimates using random effects models. The total effect size was determined by an overall analysis based on prior research. The majority of the studies in our review presented effect size using convertible statistics, such as Pearson's correlation coefficient (r) for correlational data, log odds ratios for binary data, or normalised mean difference for continuous data [45].

## 1.3 Results

This section presents the results of the Correlation test, which assesses the influence of publications on the collected data related to Workplace risk assessment.

### 1.3.1 Correlation test

The next step in this process was to assess publication bias in the selected studies using Egger's correlation test and Begg-Mazumdar rank correlation test.

The mental stress and muscular activity reduction (SMAR) evaluation method and the sample effect are correlated with studies that aim to avoid work-associated disorders related to body muscles ($r = 0{,}480$, $Q = 23.04$, $p < 0.001$), according to the results of this meta-analysis. The 95% confidence interval for the mean effect size is between 0,825 and 0,902. Within this range, the mean effect size of all similar studies might fall anywhere. With an I-squared statistic of 99%, it can be concluded that sampling error does not account for 99% of the variance in reported effects. Instead, it represents variance in genuine effects. The effect sizes of the chosen studies for the SMAR evaluation variables sizes varied from -0.399 to 0.751.

The mean impact size being zero is the null hypothesis that the Z-value tests. Z-value is 8,470, $p < 0.0001$. The null hypothesis is rejected using a criterion alpha of 0.050, and it is concluded that the results are significant in the universe of populations similar to those in the analysis.

### 1.3.2 Workplace risk assessment

The main risk identification models are methodical approaches used to identify and assess potential risks. These models help to proactively identify, analyse and prioritise risks to implement effective risk management strategies. These are summarised in Table 3.

*Table 3 Risk Identification*

| Risk identification | Tittle | Author | Explanation method |
|---|---|---|---|
| Cumulative risk | "Implications of applying cumulative risk assessment to the workplace" [46]. | Mary Fox, Kristen Spicer et al. | Cumulative risk assessment (CRA) applied in phases: i) Hazard identification. ii) dose-response assessment iii) exposure assessment. iv) risk characterisation |
| | "The Future of Risk Identification in a Rapidly Changing Sociotechnical Work Environment" [47]. | Joann Kirby et al. | A risk frame created using a mixed methodology of theoretical knowledge and a survey |
| | "Workplace interventions for common mental disorders: a systematic meta-review" [48]. | Joyce Sadhbh, Modini Matthew, Helen Christensen et al. | Evaluate the workplace interventions that may facilitate the prevention, treatment, or rehabilitation of a worker with a diagnosis of depression or anxiety. |
| | "Health problems and psychosocial work environment as predictors of long-term sickness absence in employees who visited the occupational physician and/or general practitioner about work: a prospective study" [49]. | Helene Andrea, Anna Beurskens et al. | Determine the relationship between the psychosocial work environment, health problems and incidence of long-term sickness. |
| | "A systematic review on workplace interventions to manage chronic musculoskeletal conditions" [50]. | Glykeria Skamagki, Andrew King et al. | Determine whether there are practical actions inside the workplace that reduce chronic musculoskeletal disorders. |
| | "How We Prevent Prevention of Musculoskeletal Disorders in the Workplace" [51] | Kim Tae. | Examine the knowledge about the prevention of work-related musculoskeletal pain and musculoskeletal disorders. |
| | "Long-Term Sickness Absence Due to Mental Disorders Is Associated with Individual Features and Psychosocial Work Conditions" [52] | João Silvestre da Silva-Junior. | Evaluating workers on sick leave for more than 15 days due to disabling psychiatric illnesses. |
| Latent risk | "Workplace hazard identification and management: The case of an underground mining operation " [53]. | Susanne Bahn. | The study utilises findings from two workshops conducted with 77 employees, applying research methodology. |
| | "Workplace Safety: A Strategy for Enterprise Risk Management" [54]. | Janet Jule. | Utilise leadership to enhance accountability and minimise injury risks. This involves planning to improve workplace safety by preventing injuries such as overexertion and contact with objects. |
| | "A Multidimensional Approach to Modelling for Workplace Risk Assessment" [55] | Antonis Targoutzidis et al. | Use tags for accident, human error and risk perception models. |

| Risk identification | Tittle | Author | Explanation method |
|---|---|---|---|
| | "Workplace hazard identification: What do people know and how is it done?" [56] | Maciej Serda et al. | Based on two hazard identification and hazard management training workshops to teach workers |
| | "A comparative outline for quantifying risk ratings in occupational health and safety risk assessment" [57] | Muhammet Gul. | PFAHP is used in weighting risk parameters of the 5 × 5 matrix method. |
| | "Determination of the risk at the workplace, assessment And its rank calculation, in mining activities" [58] | Zeqiri, Kemajl Kortnik, Joze Mijalkovski. | Evaluate the risk in the workplace caused by a particular agent through rank through empirical formulas. |
| | "Hazard Identification, Risk Assessment, and Control Measures as an Effective Tool of Occupational Health Assessment of Hazardous Process in an Iron Ore Pelletizing Industry" [59] | B. Rout and B. Sikdar. | Identify all possible hazards in the workplaces of an iron ore pelletizing industry to conduct a health risk assessment. |
| | "Investigating Wearable Technology for Fatigue Identification in the Workplace" [60]. | Griffiths, Christopher Bowen, Judy Hinze, Annika. | Compilation of psychological data collected from wearable systems to determine how an individual performs tasks in the workplace. |
| | "The Consequences Of Psychosocial Risks In The Workplace In Legal Context" [61]. | Seilerová Monika. | Determine the need for the legal regulation of mental workload and the increasing effects of its shortcomings. |
| | "Musculoskeletal health in the workplace" [62] | Joanne Crawford. | Determine the changes produced by chronic MSK conditions from 2000, and how we can help people with these conditions recover after suffering from them. |
| | "Need for a new workplace safety and health (WSH) strategy for the fourth Industrial Revolution" [63] | Gabriel Chia et al. | To promote a total Worker Health responsive approach in the face of rapid technological advancements |
| | "Exposure to Environmental and Occupational Particulate Air Pollution as a Potential Contributor to Neurodegeneration and Diabetes: A Systematic Review of Epidemiological Research" [64] | Eirini Dimakakou et al. | Identify the link and mechanisms associated with particulate exposure and disease pathogenesis. |
| | "Artificial Intelligence-enabled Wearable Medical Devices, Clinical and Diagnostic Decision Support Systems, and Internet of Things-based Healthcare Applications in COVID-19 Prevention, Screening, and Treatment" [65] | Barnes Robin, Zvarikova, Katarina. | Utilise machine learning algorithms to optimise diagnostic speed and precision, thereby identifying the most vulnerable individuals. |

Table 4 lists the primary risk factors for musculoskeletal illnesses based on the International Organisation for Safety and Health at Work and related research that takes ergonomic risks into account [66]. These groups fall into the following categories: Mechanical Risks (RM), Physical (RP), Chemical (RC), Ergonomic (RE), and Psychosocial (RPY) [67], [68].

*Table 4 Main factors contributing to musculoskeletal disorders*

| LEADING RISK FACTORS RELATED TO MUSCULOSKELETAL DISORDERS | | | |
|---|---|---|---|
| Clasification /Code | Cause | Effect | Example |
| RP1 | Application of big efforts | Critical overloading | Carrying, pushing or pulling, lifting heavy objects |
| RP2 and RE1 | Moving weighty loads during long periods. | Degenerative diseases, particularly in the lumbar spine | Manual materials manipulation |
| RM1 and RP3 | Repeated movements during the handling of objects | Fatigue and Overload in Specific Muscles | Assembly work, check-out work, and a long time typing |
| RE3 | Working in unergonomic posture | Overload of the skeletal and muscular system | Working with the trunk, or hands or arms, heavily bent or twisted |
| RE4 | Load by static muscular | Long-lasting muscular activity [keeping the static position] and possible overload in specific muscles | Working in a limited space |
| RE5 | Muscular inactivity | Decrease in the functional capacity of tendons, muscles and bones | Long-term sitting work with short muscular demands |
| RM1 RE6 | Monotonous repetitive movement | Unspecific complaints in the extremities | Repeated activity of the same muscles with pauses without relaxation |
| RM2 | Constantly vibration | Dysfunction of nerves, reduced blood flow, degenerative disorders, and psychological disorders caused by stress. | Manipulating a machine with annoying vibration or using vibrating hand tools. |
| RE7 | Physical environmental aspects: light, sounds, temperature, etc | Damage to the sensory organs of the worker, diseases in the sensory nervous system, and psychological disorders caused by stress. | Work in an environment that is improperly lit, noisy, and has an uncomfortable temperature, among other issues. |
| RCH1 | Exposure to chemical products or factors in the workplace. | Burn, injury or permanent illness. | Direct contact with a specific chemical product can produce injury or illness. |
| RPS1 | Physical and social outcomes such as work-related stress, burnout or depression. | Stress, Depression. | Poor communication between the manager and workers |

Muscle, bone and joint problems, known as musculoskeletal disorders (MSDs), are caused by a combination of physical (biomechanical) and psychological/social (biopsychosocial) factors. People are now more aware of these issues as a result of efforts by health and safety managers to improve working conditions. Table 5 presents the compilation for each risk category derived from the literature processing, as shown in Table 4.

*Table 5 Risk identification results*

| Identified Risk | Number of appearances | Cited researches |
|---|---|---|
| Mechanical risk | 7 | [49], [50], [51], [53], [56], [58], [59] |

| | | |
|---|---|---|
| Physical risk | 13 | [46], [47], [50], [51], [53], [54], [55], [57], [59], [60], [62], [64], [65] |
| Chemical risk | 3 | [53], [57], [59] |
| Ergonomic risk | 18 | [46], [47], [48], [49], [50], [51], [52], [54], [55], [57], [58], [59], [60], [61], [62], [63], [64], [65] |
| Psychosocial risk | 3 | [49], [52], [61] |

Once the risk has been identified and categorised, the next step is to determine how the risk relates to the main topic and which risk is more prevalent throughout the work activities. The result is shown in Figure 6 [66].

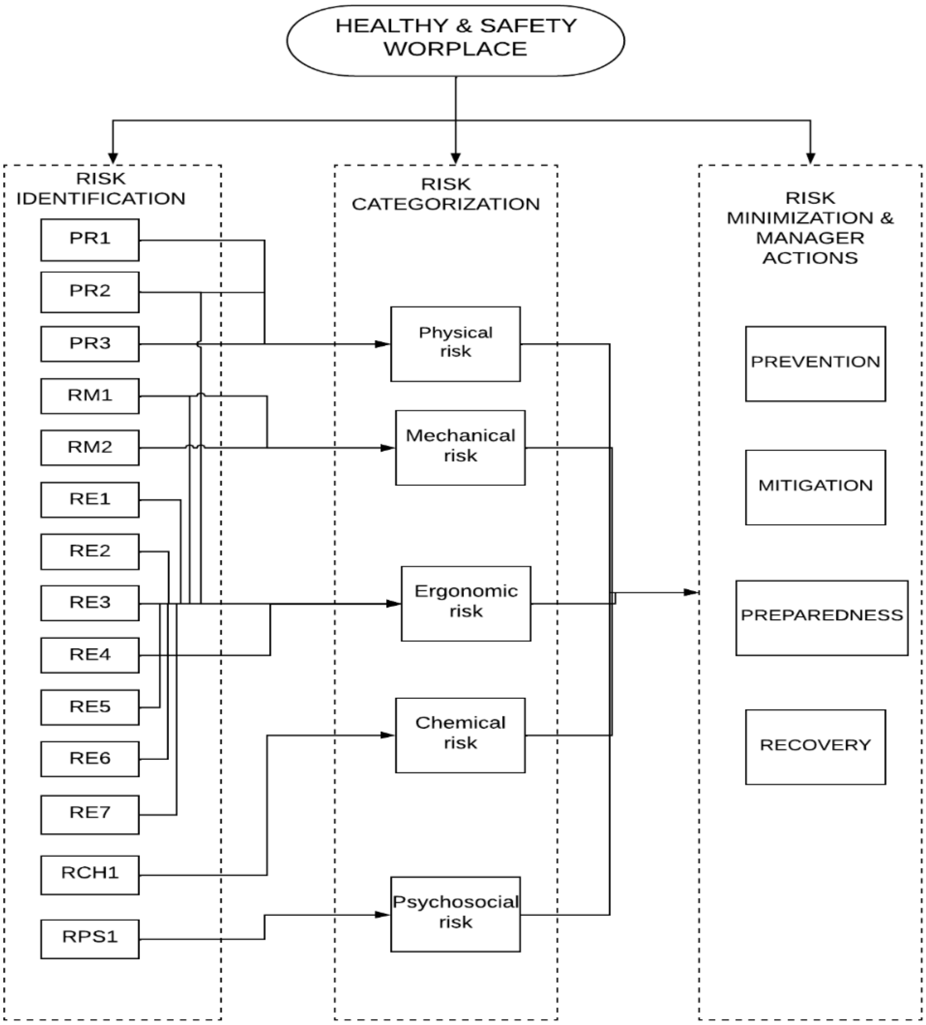


*Figure 6 Risk relation and definition*

According to risk relations, MSDs include work-related ailments like bursitis, tenosynovitis, epicondylitis, and tendon discomfort, as well as diseases like sciatica and carpal tunnel syndrome. These disorders can also cause back pain and other regional pain syndromes without a specific pathology. The discomfort and trauma that can arise from poorly constructed workplaces are one of the primary causes of MSDs. Therefore, analysing work-related MSDs involves identifying potential workplace hazards and ensuring that the environment is safe and healthy. The analysis of risk identification and the creation of a theoretical framework from Table 5, Risk Identification Results and Their Relationships, as shown in Figure 6, Risk Relationship and Definition, constitute the typology phase of this study. All potential risk types are generated and named by identifying the different combinations. Procedures are then developed to assess the workplace to reduce risk and improve working conditions. The process is shown in Figure 7 [66].

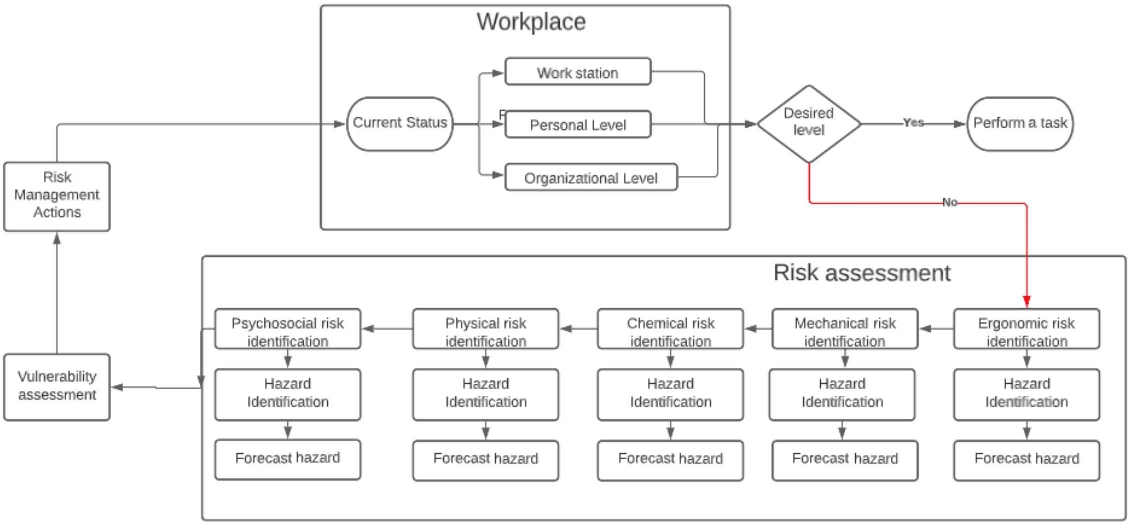


*Figure 7 Workplace evaluation method.*

Stress is also significantly increased by unfavourable organisational traits, subpar management techniques, and interpersonal disputes. Every day, various stressors, including multiple times and sectors, are presented in Table 6. High workplace demands, unclear roles, an overwhelming workload, insufficient resources, a lack of task management, and the effects of irregular work schedules and non-traditional work hours are some of the main stressors.

*Table 6 Occupational Stress Factors Across Various Studies and Reports*

**LIST OF GROUPS OF FACTORS**

| PAPERS TITLE | GROUP OF FACTORS | REFERENCE |
|---|---|---|
| **Quality of Employment Survey** | task complexity/job demand/stressful job/hazardous job<br>role ambiguity<br>underutilization<br>quantitative workload/overload<br>resource inadequacy<br>insecurity<br>non-participation | Public Law 91-596 (1970) [69]<br>Margolis, Kroes and Quinn (1974) [70]. |
| **Job Demands and Worker Health Study** | quantitative workload/overload<br>inadequate social support<br>role ambiguity<br>conflict resolution/bad interpersonal interaction<br>worker control/control over tasks/supervision | Cobb and Kasl (1980) [71] |
| **Control/demand research** | worker control/control over tasks/supervision<br>machine-paced/pacing<br>scheduling/shiftwork<br>physical environment<br>decision making<br>conflict/bad interpersonal interaction | Colligan, Smith and Hurrell (1977) [72]<br>Tasto, Colligan, Skjei and Polly (1978)<br>Smith, M.J., Colligan, Fro&t and Tasto (1979)<br>Chadwick, Chesney, Black, Rosenman, and Sevelius (1979) [73]<br>Colligan and Murphy (1979) [74];<br>Colligan, Pemtebaker and Murphy (1982) [75]<br>Cobb and Kasl (1977) [75]<br>Hurrell (1985) [76] |
| **Work in America** | Scheduling/shiftwork/night working<br>Machine-paced/pacing<br>Worker control/ over control tasks/supervision | Work in America (1973) [77] |
| **Work Schedules and Fatigue** | scheduling/shiftwork/night working | Work Schedules and Fatigue (Rosa & Colligan, 1988) [78] |
| **Stress perspective 1990s** | task complexity/job demand/stressful job/hazardous job<br>scheduling/shiftwork/night working<br>insecurities concerning career<br>Bad management style | HIV/AIDS from a stress perspective (1993) [79]<br>Agriculture Initiative 1996[80]<br>National Occupational Research Agenda (NORA) 1996 [81] |

| | | |
|---|---|---|
| **Healthy Work Organisations** | inadequate management style/inadequate management practices | Lim & Murphy,( 1997) [82] |
| | Perceived stress was continuous improvement at work/pressure to improve your skills. | |
| | conflict resolution/bad interpersonal interaction | |
| | diversity | |
| | no sense of belonging | |
| | negative values (technology, employee growth) | |

The factors that lead to occupational stress are highlighted, along with the frequency with which these factors are mentioned in studies. Table 7 shows how these stressors have a significant impact on employees' stress levels and highlights the importance of addressing these stressors through improved communication, better management practices and a supportive work environment to reduce stress and promote employee well-being.

*Table 7 Stressors and their impact on employees' stress levels*

| TOTAL OF DIFFERENT GROUPS OF FACTORS FOUNDED | | |
|---|---|---|
| No | GROUP OF FACTORS | TOTAL MENTIONS |
| 1 | inadequate social support | 1 |
| 2 | Bad management style | 1 |
| 3 | bad organisational characteristics (such as climate, culture, and communication | 1 |
| 4 | conflict resolution/bad interpersonal interaction | 3 |
| 5 | decision making | 1 |
| 6 | diversity | 1 |
| 7 | inadequate management style/inadequate management practices | 1 |
| 8 | insecurities concerning career | 1 |
| 9 | insecurity | 1 |
| 10 | job mobility | 1 |
| 11 | machine-paced/pacing | 2 |
| 12 | negative values (technology, employee growth/development, and valuing the individual | 1 |
| 13 | no sense of belonging | 1 |
| 14 | non-participation | 1 |
| 15 | organizational effectiveness | 1 |
| 16 | Perceived stress was continuous improvement at work/pressure to improve your skills. | 1 |
| 17 | physical environment | 1 |
| 18 | quantitative workload/overload | 2 |
| 19 | resource inadequacy | 1 |
| 20 | role ambiguity | 2 |
| 21 | scheduling/shiftwork/night working | 4 |
| 22 | task complexity/job demand/stressful job/hazardous job/concentration demand | 2 |
| 23 | underutilization | 1 |
| 24 | worker control/control over tasks/supervision | 3 |

In addition, it presents factors that contribute to stress and dissatisfaction at work, organised into groups such as management practices, physical work environment, and interpersonal interactions. These factors include intrinsic characteristics such as inadequate social support, poor management style, physical demands and job insecurity. It classifies and categorises the problems faced by employees in the workplace, focusing primarily on management practices, the physical work environment and interpersonal interactions. Three critical factors that affect stress in the workplace are "worker control", "conflict resolution" and "scheduling". "Worker control describes how much authority workers have over their tasks, procedures and environment. "Conflict resolution is essential to maintaining a good working environment, as unresolved conflicts can cause tense relationships. Finally, "scheduling" hurts workers' wellbeing by determining working hours, shifts and deadlines [83], [84], [85].

### 1.3.3 Classes of psychosocial stressors factors

Workers today face a variety of psychosocial stresses at work that have a significant influence on their general job satisfaction, well-being, and productivity.

*Worker control* refers to the degree of autonomy employees have over their tasks, work pace, and decision-making processes. High levels of stress, resentment and burnout can result from a lack of control over one's workplace. Employees often feel helpless and demotivated when they are micromanaged or have little control over their work, which can have a detrimental effect on their emotional and physical well-being. Worker control is considered a stressor in the workplace. It affects millions of workers every year and is a significant cause of a range of health problems across Europe [85].

*Conflict resolution* in the workplace can be caused by differing viewpoints, different ways of working, poor communication or conflicting interests. Poorly managed conflict creates a toxic work environment that leads to stress, reduced performance and emotional exhaustion. Good conflict resolution techniques, such as systematic problem solving, mediation and open communication, are crucial to creating a productive workplace [81].

*Scheduling* plays a fundamental role in managing workplace stress, as poorly structured work schedules can lead to burnout, fatigue, and work-life imbalance. 64% of employees who had their shifts modified reported experiencing moderate psychological discomfort, 75% of employees said their sleep was terrible, and 82% of those whose shifts were changed said the same [81], [86].

Work-related stress is directly responsible for around 16% of depression cases in the EU. In addition to its impact on mental health, work-related stress is a major contributor to the development of cardiovascular disease, with estimates suggesting that work-related stress accounts for 16% of cases among men and 22% among women in Spain [61].

### 1.3.4 Stress identification methods

Stressful situations activate the hypothalamic-pituitary-adrenal (HPA) axis. This causes neurons in the hypothalamus, a part of the brain known as the 'master gland', to release a hormone called corticotropin-releasing hormone (CRH). Another hormone called adrenocorticotropin (ACTH) is secreted and released by the pituitary gland, also located in the brain, in response to the production of CRH. Once released from the pituitary gland, ACTH travels through the bloodstream to the adrenal glands, located above the kidneys, where it causes the release of so-called stress hormones. The glucocorticoids, known as cortisol in humans, and the catecholamine norepinephrine are the two primary stress hormones [87].

When a scenario is perceived as stressful, the hypothalamic-pituitary-adrenal (HPA) axis is activated, ultimately leading to the release of catecholamines and cortisol in humans. Human physiological indicators of stress that have been proven to work include cortisol and proxy indicators of sympathetic activity.

Saliva can be used to measure cortisol, which is a non-invasive method. In addition, when collecting saliva, there is no need for trained professionals to insert catheters, as is the case with blood samples. In that context, other human biological markers of stress hormones are currently being evaluated [79], [88].

Blood pressure is an essential indicator of stress. The force that pressure applies to the walls of blood vessels is measured by blood pressure. Direct neuronal conduction and the neuroendocrine effects of adrenaline and noradrenaline are the causes of the increase in heart rate activity as a result of the stress response. When epinephrine is in the bloodstream, the ventricles of the heart respond by contracting faster and harder. Heart rate variability, or HRV, has become a practical and affordable way to measure cardiovascular stress. HRV is the variance in beat-to-beat heart rate interval, or the measured interval between heartbeats. Due to the presence of catecholamine cascades, a decrease in variability is typically a sign of increased stress. When faced with physical or psychological problems, these cascades often overwhelm regular variability [88] .

Eccrine sweat is the physiological basis for the electrodermal assessment of the stress response. These sweat glands, most commonly found in the palms and soles of the hands, are derived from the terminal efferent ends of sympathetic neurons and respond to psychological stimuli rather than heat. Although Ach, rather than NE, is the neurotransmitter at the sweat gland itself, measuring this activity provides valuable information about the activity of the sympathetic nervous system. Passive methods, such as skin potential (SP) or active GSR techniques, can be used to measure electrodermal activity [88].

There has been evidence that skin conductance can be an indicator of the level or intensity of emotional arousal. This signal applies to various aspects of health, as well as being a robust and reliable indicator of emotional state. The activity of the skin's sweat glands determines skin conductance, which is not affected in the slightest by sweaty hands. A minimal current flows through the skin when the two electrodes of the Skin Response apply a very small, completely safe and undetectable electrical voltage [88].

## 1.4 Discussions

Manual handling is any activity that involves the use of physical force to lift, lower, push, pull, carry, move, hold or confine a person, animal or object. Although many organisations rely on these activities, there is a significant risk of musculoskeletal problems if they are not carried out correctly. The research shows the link between manual handling and these types of injuries, highlighting the importance of using the proper procedures and taking preventative measures. This is consistent with studies on back injuries.

The association between mental stress, muscle activity reduction (SMAR) and work-related musculoskeletal disorders was found to be significantly influenced by the results of the Egger correlation test and the Begg-Mazumdar rank correlation test. A strong correlation was found ($r = 0.480$, $Q = 23.04$, $p < 0.001$), with a 95% confidence interval ranging from -0.399 to 0.751 and a mean effect size of 0.834.

This suggests a strong correlation between SMAR assessment techniques and a reduction in work-related muscular complaints.

This research encompasses risk identification, which covers several areas, including chronic musculoskeletal disorders, the psychosocial work environment and cumulative risk. Mechanical, physical, chemical, ergonomic and psychosocial hazards are the main risk factors for MSDs. The meta-analysis showed that ergonomic risks are more common than physical risks. Mechanical, chemical and psychological risks were also reported, although to a lesser extent. When these risk factors are analysed, it is clear that poor management techniques and poorly designed workplaces are major contributors to occupational stress and MSDs. Integrating information from different studies emphasises the need for a comprehensive workplace safety plan that addresses both psychological and physical factors.

Ergonomic workplace design can significantly reduce the repetitive movements and physical strain that lead to musculoskeletal disorders (MSDs). This can be achieved by providing adjustable workstations and chairs and encouraging frequent breaks to reduce physical stress. Improving management procedures is a priority. Appropriate workload distribution, clear role descriptions and effective communication can reduce the risk of psychosocial problems. It's also essential to have support systems in place and to promote a happy.

In addition, potential hazards can be easily identified and addressed through routine monitoring and evaluation using risk assessments. Wearable technology can be used to track stress and fatigue in real time, providing data for informed treatment. Finally, education and training are essential. By educating employees about mental health and safe working practices, they can take proactive steps to reduce risks. Offering workshops on stress management and hazard identification can further improve worker safety.

This research, in line with previous studies, classifies a wide range of conditions as musculoskeletal disorders (MSDs), including sciatica, carpal tunnel syndrome, bursitis, tenosynovitis, epicondylitis and tendon disorders. These conditions can lead to back pain and other regional pain syndromes, often without a specific disease. One of the main causes of the discomfort and suffering that leads to MSDs is poorly designed workplaces. Identifying potential workplace hazards and ensuring a safe and healthy environment are therefore essential to research into work-related MSDs.

By examining a variety of workplace conditions, this study established a theoretical framework of risk relationships and definitions to classify all possible types of risk. As a result of this analysis, protocols are developed to assess and reduce risks and improve working conditions. In addition, unfavourable organisational characteristics, inadequate management techniques and interpersonal disputes exacerbate stress in the workplace. Everyday stressors include excessive demands, unclear responsibilities, excessive workloads, lack of resources and erratic work schedules. The significant impact of stressors on employee stress levels highlights the need for improved management techniques, supportive workplaces and communication.

The study findings show that increasing employee happiness, decreasing turnover, and creating a healthy work environment are all critical to lowering the percentage of employees who quit their jobs. In line with research showing that 35% of employees between the ages of 18 and 25 leave their jobs due to chaotic schedules reported by previous studies [89].

## 1.5 Literature Review Conclusions

Physical stress reduces a worker's ability to lift the maximum allowable weight properly. This includes fatigue, muscle strain and prolonged discomfort. Fatigue caused by stress reduces muscle strength, posture and stability.

The study identified stressors from organisational structures that contribute to creating an uncomfortable psychosocial workplace. Within this category, worker control plays a significant role, as it determines the level of autonomy of employees. Additionally, conflict resolution is essential to maintaining a positive work atmosphere. Another critical factor is scheduling, which affects employees' well-being by regulating work hours, shifts, and deadlines. In addition, psychosocial stress has been found to reduce RWL by weakening muscle control, increasing risk-taking behaviour and decreasing concentration, which increases the likelihood of using the wrong lifting technique and exposure to stress-related environmental factors. For this reason, workplace lifting assessments must include a thorough evaluation of the worker's susceptibility to stress and stress reduction protocols.

According to the study, job dissatisfaction is primarily caused by inconsistent work schedules. Reducing stress and preventing over-control can be achieved by giving employees more authority over their work and allowing them to participate in decision-making. In addition, effective conflict resolution techniques can reduce workplace tensions and create a more cooperative and encouraging atmosphere.

The study also found a strong correlation between work-related MSDs, mental stress and muscle activity reduction (SMAR), highlighting the importance of SMAR assessment methods in reducing muscle complaints. Chronic MSDs, the psychosocial work environment and cumulative risk were all included in the risk identification process, with ergonomic risks being more common than physical risks.

The meta-analysis revealed a significant correlation between psychosocial stress and SMAR, indicating that inadequate workplace design, poor management practices, and unfavourable organisational environments have a negative impact. However, it did not establish a clear hierarchy of the most critical factors in manual handling contexts. This limitation underlines the necessity of moving from a broad identification of risks toward a more systematic categorisation.

- **Thesis (T1):** With a systematic PRISMA literature review and using a correlation analysis of the studies (which presented an index $r = 0.480$ and $p < 0.001$), I proved that psychosocial distractor factors, mainly worker control, conflict resolution, and scheduling, induce mental stress causing muscular activity reduction (SMAR), which has a direct impact on the risk of musculoskeletal disorders (MSDs) in manual handling.

Own publications related to this chapter: [66], [90], [91]

# 2 CATEGORISATION OF STRESS FACTORS IN MANUAL HANDLING TASKS

In the field of manual handling, a multicriteria categorisation of stressors is essential for understanding the risk in the workplace. A structured methodology for categorising stressors is presented, including an introduction, a detailed explanation of the methods, a presentation of the results and a discussion of their implications.

## 2.1 Introduction

Psychosocial stressors have often been shown to be associated with psychological dysfunction, depressive symptoms and health-related behaviours such as medication use, doctor visits and sickness absenteeism. Workplace psychosocial stressors have been linked to immunological disorders, cardiovascular disease and musculoskeletal problems [92]. Psychosocial stressors have the potential to alter pain perception or cause physiological alterations that could lead to musculoskeletal issues. These factors are most closely associated with musculoskeletal problems, whether acute or chronic, and are the cause of back pain or other musculoskeletal problems [93].

Instances of psychosomatic complaints and musculoskeletal issues, such as back pain, joint and muscle disorders, and more persistent back problems, have been linked to intense work speed. A sense of generalised poor health, as well as many indications of (ill-)health behaviour, were related to poor intellectual judgment, particularly monotony in the workplace [92].

Linking psychosocial stressors to a range of other health outcomes, including psychosomatic symptoms and health-related behaviours, is significant and similar in strength to those between psychosocial stressors and musculoskeletal problems [92]. Workplace psychosocial stressors have been linked to a higher likelihood of going off sick with a confirmed mental health condition. The risk was up to 76% higher for workers who were exposed to these work-related stressors than for those who were not.

One of the additional risk factors for WRMSDs has been identified as workplace psychosocial stressors. For example, job dissatisfaction, lack of autonomy and social support, and high workload are factors that have been associated with an increased risk of WRMSD. Similarly, the risk of WRMSD has been increased by high levels of mental demand or pressure, particularly when combined with low levels of reward. Perceived safety and the perceived danger of WRMSD have also been shown to be negatively affected by a lack of social support [94]. While these findings establish the critical role of psychosocial factors, they also demonstrate how complicated their interactions are, as not all stressors contribute equally to the development of MSDs. It evidences a need for a multi-criteria approach to classify and prioritise stressors, focusing on how workers and experts perceive their influence on manual handling tasks. By applying the theoretical framework developed in Chapter 1 to a decision-making model, practical classifications can be ensured, which serve as the basis for developing targeted preventive strategies.

**Multicriteria methods**

To identify ergonomic elements that can lead to MSDs and enhance individuals' quality of life through prevention initiatives, professionals in ergonomics have started utilising multicriteria decision-making (MCDM) methods. These models have helped address numerous issues related to work illness prevention, and the models that have been created have also helped resolve a significant number of issues with job scheduling in the sector. By connecting the mobility components with the MCDM models, researchers from all over the world have begun to examine this model in depth [95].

The Analytic Hierarchy Process (AHP) technique is an applicable multi-criteria model that depends on the judgment and experience of a manager to determine the best course of action for solving a complex problem according to predetermined criteria. In other words, it helps decision-makers determine which course of action best meets their needs and evaluates the situation.

The respondent's decision criteria, however, are one of the weaknesses of the AHP method, as the answer can be seen as a personal argument at some point. The preference of the decision maker, which has a strong influence on the results, determines the criteria of perception, evaluation, correction and selection, which makes the AHP process somewhat blurred. Besides, the dependencies between the AHP variables frequently cause inconsistent weighting of the criteria and results that do not reflect reality [96]. To overcome these limitations, AHP weight vectors were subjected to Pareto optimisation. By using pairwise comparison matrices in an actual case study, the authors were able to change the weighting of the AHP vectors [97].

The AHP provides an organised, methodical and quantitative approach to decision-making, making it an essential tool for risk classification in the workplace. Workplace hazards often involve numerous factors, each with varying degrees of severity and frequency, including safety hazards, ergonomic risks, chemical exposures and psychological stressors. By organising complex issues into hierarchical levels, assigning weights to each criterion through paired comparisons, and ensuring consistency of judgments, AHP enables decision-makers to prioritise risks [98], [99].

The Best-Worst Method (BWM) is a professional multi-criteria decision-making (MCDM) technique that is particularly useful for classifying risks in the workplace because it can improve the accuracy and consistency of decisions. Workplace risks include a variety of elements, each with a different degree of impact and probability, such as mechanical failure, chemical exposure, ergonomic hazards and psychological stress. By asking experts to identify the most important (best) and least important (worst) criteria, BWM helps decision-makers prioritise these risks and minimise the discrepancies that often occur in paired comparisons. For workplace risk assessment, BWM is more effective than more conventional techniques, such as AHP, because it requires fewer comparisons while maintaining a higher degree of consistency [100], [101].

## 2.2 Methodology

This section describes the tools and materials used in the research, including an explanation of the survey methodology. Microsoft Excel algorithms developed in Office 365 were used to solve the Best Worst Method (BWM) and Analytic Hierarchy Process (AHP) models. The methodology used in this study follows the approach presented by previous researchers [102], providing a structured, Excel-based algorithmic tool framework for solving multi-criteria decision problems. A cross-check analysis was carried out by two researchers (V.C.E-C and R.P.A-R) from Obuda University individually, and the results were finally verified.

This is followed by a detailed presentation of the study and an explanation of the approach taken.

### 2.2.1 Survey

Meetings and discussions were conducted with safety and health professionals to identify the key factors influencing manual handling stress. An initial criteria sample was presented at the Engineering Symposium at Bánki 2022 and was used to determine, condense, and validate the survey instrument. This pilot involved ergonomics experts drawn from multiple related disciplines, including occupational health, psychology, rehabilitation, medicine, and academia [103]. In October 2024, the survey was carried out using the snowball sampling method with the help of Google Forms (ANNEX C). The participants were selected from industries where manual handling activities and material storage take place and included 185 men and 98 women of different age groups, which represents a sample with a 95% confidence level and less than 6% margin of error. The survey was completed online in 15 to 20 minutes per person. Based on the criteria or groups identified in section 1.3.2 and shown in Table 5, each worker identified the degree of influence of the stressors during the activity.

### 2.2.2 Criteria for the design and description of the Saaty scale

One of the most critical aspects of the study is the organisation and selection of the criteria to be applied or considered to find out how psychosocial factors affect manual handling tasks. This is necessary so that the criteria can be arranged according to the requirements of the multi-criteria approach used. Developing criteria and sub-criteria enables the examination of the hierarchy of importance chosen by the study participants, both separately and together. Based on the literature review on the impact of stressors on lifting, our project study identified three primary criteria and nine supporting criteria. An explanation of each criterion relating to the first level is also given in Table 8, together with the coding for each main criterion. The criteria are coded from C1 to C3. As a result, these criteria are easy to identify in Figure 8. Conversely, Table 9 provides an explanation of the nine sub-criteria selected that relate to the second level. To help the reader identify them with the main criteria (C1-C3), they have been coded.

*Table 8 Main criteria and description of the criteria*

| *Code* | *Criteria* | *Description* |
|---|---|---|
| *C1* | *Worker Control / Control Over Tasks / Supervision* | *The level of managerial control and the degree of autonomy employees have over their work. Productivity, job satisfaction and decision making are all affected.* |
| *C2* | *Conflict resolution / bad interpersonal interaction* | *Managing disputes and addressing negative interactions between workers reduces tension and improves collaboration, productivity, and team dynamics.* |
| *C3* | *Scheduling/shiftwork/night working* | *Organisation of working hours, rotating shifts and night work.* |

Thus, C 1.2 indicates the second criterion falling under the first main criterion (C1) (shown in Figure 8).

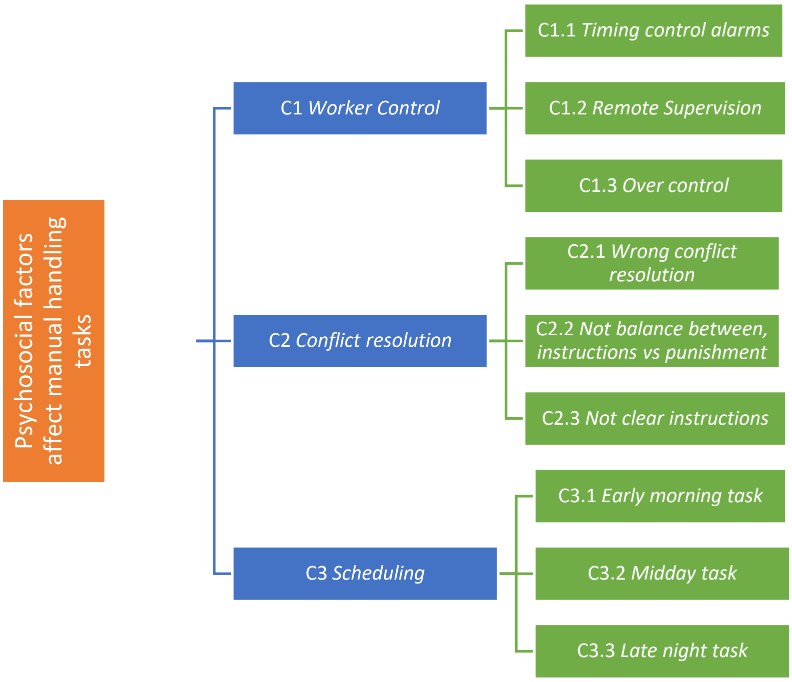


*Figure 8 The hierarchical structure*

Comprising 9 sub-criteria from the first level, the second level is the focus of the second section of the Saaty scale. For example, the first sub-criterion relating to Criterion 1 is labelled C1.1. Table 9 lists each criterion along with a code indicating which primary criterion it falls under. This means that the second level of Figure 8 is the place where you can find them.

*Table 9 Sub-criteria and description*

| *Code* | *Explanation* | *Description* |
|---|---|---|
| *C1.1* | *Timing control alarms* | *Used a tool to monitor and manage the time spent on tasks to maintain focus, improve productivity, and ensure deadlines are met.* |
| *C1.2* | *Remote Supervision* | *Managing and overseeing employees from a distance, typically through digital tools. It enables monitoring, feedback, and guidance without in-person interaction.* |
| *C1.3* | *Over control* | *The supervisor gives excessively bossy or micromanaging instructions during tasks, limiting employee autonomy at all times.* |
| *C2.1* | *Wrong conflict resolution way* | *Ineffective methods of addressing disputes can escalate tensions, harm relationships, and negatively impact the workplace.* |
| *C2.2* | *Not a balance between instructions vs punishment* | *Excessive punishment compared to guidance leads to a negative work environment and decreased motivation.* |
| *C2.3* | *Not clear instructions* | *Poorly communicated directions for tasks, leading to confusion, mistakes,* |

| Code | Explanation | Description |
|---|---|---|
| | | *reduced productivity, and employee frustration.* |
| *C3.1* | *Early morning task* | *Work is scheduled during the early hours of the day, which can impact employee alertness, productivity, and work-life balance.* |
| *C3.2* | *Midday task* | *Work is scheduled around midday, often when employees are most alert and productive.* |
| *C3.3* | *Late-night task* | *Work scheduled during nighttime hours, which can disrupt sleep patterns and affect focus, health* |

### 2.2.3 Analytic hierarchy process (AHP)

A methodical multi-criteria decision-making technique is the Analytical Hierarchy Process (AHP). The main advantage of AHP is its ability to verify and minimise discrepancies in expert opinions. This approach streamlines group decision-making and reduces bias in the process by using the geometric mean of individual scores to reach a consensus. Using a variety of options, AHP can be applied to multi-objective, multi-criteria and multi-actor decisions. It generates scores by combining ranks and paired comparisons. Analytic Hierarchy Process (AHP) can be used to model situations where there are no precisely measurable variables, such as risk and uncertainty, because it assesses scales rather than measures. AHP is based on three fundamental ideas: comparing values, deconstructing structure, and creating hierarchical priorities. By breaking down a decision problem into its component parts, it is possible to create hierarchies of criteria to determine the relative importance of each criterion [104].

The Occupational Health and Safety Department used AHP to create a decision support tool that ranked the risk variables associated with the development of musculoskeletal problems in the shoulder and neck [105], [106].

In AHP, the decision problem is usually divided into a hierarchy of distinct subproblems that can be studied separately. Each component in the hierarchy can be related to any aspect of the decision problem. Once the hierarchy has been constructed, respondents assign a numerical scale to each pair of alternatives $(A_i, A_j)$, as shown in Table 10 [95]. By contrasting the pairs of choices according to how they affect a higher-ranking element in the hierarchy, numerical scales are assigned.

Table 10 AHP scale for combinations.

| Numerical Scale | Definition | Verbal Explanation |
|---|---|---|
| **1** | Both elements hold equal importance | The two elements contribute equally to the given characteristic |
| **3** | One element has slightly less importance than the other | Experience and judgment slightly favour one element over the other |
| **5** | One element is significantly more important than the other | Assessments and experience strongly favour one aspect over the other |
| **7** | One element is clearly dominant over the other | Practical evidence confirms the strong preference for one element |
| **9** | One element is overwhelmingly dominant | Irrefutable evidence supports the superiority of one element |
| **2, 4, 6, 8** | Intermediate values between adjacent levels | The assessment lies between two defined levels |
| **Reciprocals (1/x)** | Assigned value when comparing activity i to activity j | When comparing j to i, the reciprocal value is used |

In 1990, Saaty suggested determining the consistency of judgments using the following equation[104]:

$$\text{Consistency ratio} = CR = \frac{CI}{RC} \tag{2}$$

And,

$$\text{Consistency index} = CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

Where $\lambda_{max}$ denotes the largest eigenvalue, it's crucial to remember that for a comparison to be deemed credible, the comparison must be consistent, meaning that fewer than 10% of the values are different. Saaty (1990) illustrates how the following equation can also be used to assess the consistency of judgments. In addition to measuring the degree of inconsistency observed in the pairwise comparisons, the Consistency Ratio (CR) predicts the degree of inconsistency for random judgments of the same size. It shows how consistent the decisions made in the pairwise comparisons are.

### 2.2.4 Best Worst Method

The weights of the criteria and sub-criteria have been generated using the Best Worst Method (BWM), which increases the reliability of the comparison process and decreases the quantity of pairwise comparisons. The largest or most significant criterion or alternative is the one that is most crucial when making decisions. In contrast, the least important or poorest criterion or option has the opposite effect.

Using a simple optimisation model, the goal is to ascertain the optimal weights and consistency ratio. The model is built using the comparison system. The BWM involves five steps. Step 1: Choose a set of standards by which to judge decisions. Identifying criteria is necessary before making a decision (C1, C2,..., Cn). The alternatives' performance is evaluated using these standards.

Step 2: Identify which criteria are most and least suitable for the decision setting. The best criterion could be the most desirable, and the worst the least desirable or least essential. In this case, only the criteria are considered, not the values of the criteria.

Step 3: Decide which of the criteria is most crucial. The representation of this value will be a number between 1 and 9. The resulting Best criterion denotes the preference of the criterion selected over all other criteria.

Step 4: Find out which of the other criteria is preferable to the least favourable. The worst criterion would be compared with the preference of the above criteria.

Step 5: Determine the ideal weights. To determine the optimal criterion weights, the most significant absolute discrepancies are considered.

Following the calculation of the optimal weight scores, the consistency is examined by calculating the consistency ratio using the following formula:

$$CR = \frac{\xi^*}{\text{Consistency index}} \tag{4}$$

## 2.3 Results

The first part of the research presents the demographic data of the participants, which gives an insight into the categorisation of psychosocial stressors in the workplace. Analysis of the age distribution of the 285 respondents, shown in Figure 9, shows that the largest group consists of employees aged 46-54 (39.3%), followed by those aged 19-26 (26.3%), 36-46 (12.6%), 27-35 (11.9%), 15-18 (7%) and over 55 (7%). These findings provide the basis to assess how different workplace stressors affect the well-being and job stability of employees across various age groups.

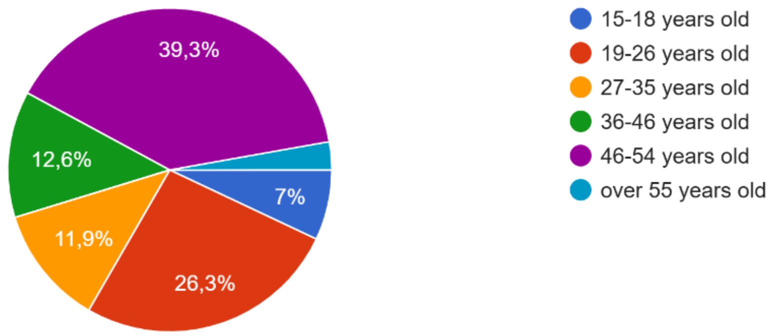


*Figure 9 Analysis of the age distribution of the 285 respondents*

The distribution of the continents from which the respondents came provides a valuable context for analysing perceptions of workplace-related psychosocial stressors, as shown in Figure 10. The majority of the 285 participants were from the Americas (56.1%), followed by Europe (33.7%), Asia (6%) and Africa (4.2%).

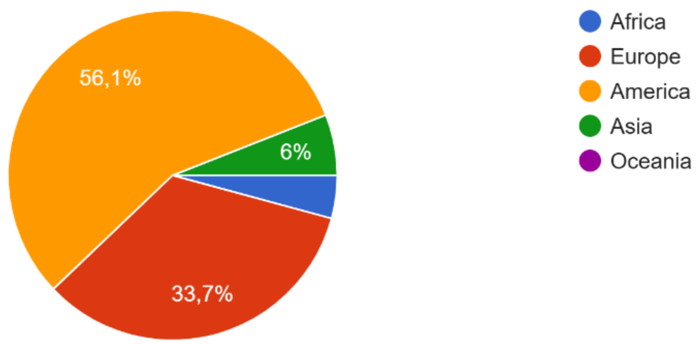


*Figure 10 Distribution of respondents' birth continents*

The gender distribution of respondents shown in Figure 11 provides an insight into how psychosocial stressors are perceived. Most respondents are male (65.4%), while 34.6% are female. The data shows how psychosocial stressors affect employees differently depending on the gender dynamics in the workplace.

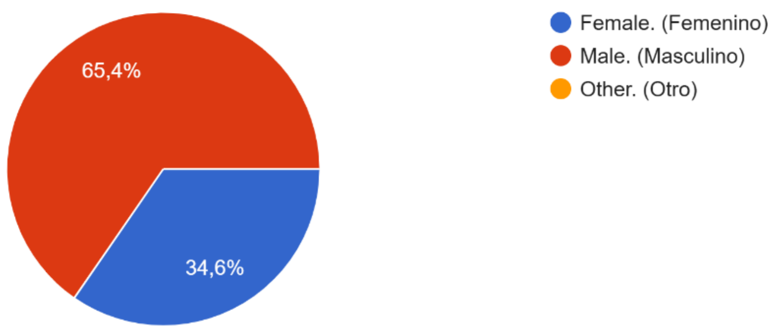


*Figure 11 Gender distribution of respondents*

The educational background of the 285 respondents shown in Figure 12 provides essential information about how psychosocial stressors affect workers based on their academic and technical training, particularly in industrial roles. The largest group, 'Other' (46%), represents individuals with technical training and training in industrial tasks, followed by those with a BSc. holders (41.1%), MSc. holders (10.5%) and a small percentage of Ph.D. holders.

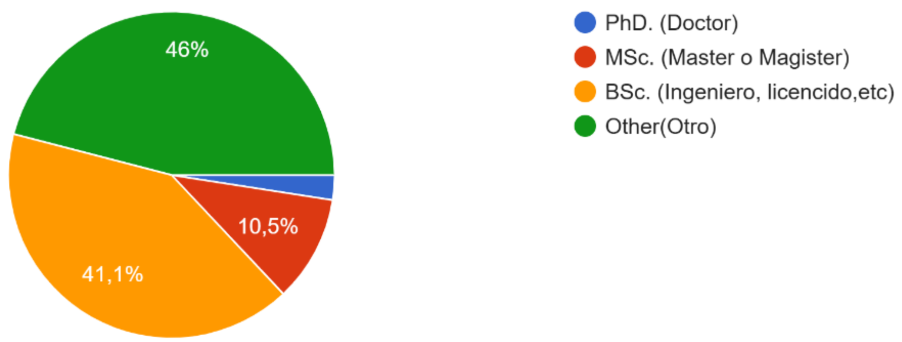


*Figure 12 Educational background*

Statistics from a survey with 285 respondents who classified various psychosocial pressures using 18 different questions (Q1–Q18) are displayed in ANNEX D. According to the mean scores, Q12 (5.88), Q16 (5.88), Q15 (5.77), Q17 (5.76) and Q9 (5.72) have the highest scores. From the opposite direction, Q10 (3.58), Q5 (3.78), Q3 (4.40) and Q8 (4.41) have the lowest values. The standard deviation and range are used to examine the variability in perception, and Q5, Q10, Q3 and Q8 show considerable variability (SD > 1.2). The distribution of responses is also demonstrated by skewness and kurtosis values; Q9, Q12, Q15 and Q16 have negative skewness. Positive skewness was observed for Q3, Q5, Q8 and Q13. The reliability of the responses is confirmed by the confidence interval (CI ~0.11 to 0.17), which reinforces the consistency of stressor identification.

After analysing the demographics of the participants, the AHP technique and the Best-Worst method are the two multi-criteria methods used to split the results, as described in the methodology.

**Best-Worst method**

The respondents were asked to compare the primary requirements for Workplace Dynamics and Task Management at level one, such as "Worker control / Control Over Tasks / Supervision" (C1) and "Conflict resolution / bad interpersonal interaction" (C2).

Table 11 Determine the benchmarks used to initiate the BWM comparison by following the steps outlined in the methodology.

*Table 11 benchmarks criteria*

| Criteria Number = 3 | Criterion 1 | Criterion 2 | Criterion 3 |
|---|---|---|---|
| Names of Criteria | Worker Control | Conflict resolution | Scheduling |

The benchmarks for the best and worst criteria in this analysis were found by analysing the data provided by the experts. The best and worst selected criteria must be entered in the following step, and the identified criteria are shown in Table 12.

*Table 12 The best and worst criteria identified*

| | |
|---|---|
| Select the Best | Worker Control |
| Select the Worst | Scheduling |

Pairwise comparisons (PCs) for each branch of the decision system must be constructed after obtaining all of the aggregated weights of the 285 evaluators, as indicated below, in accordance with the BWM approach. The process compares the best criteria, as shown in Table 13, against the other criteria with weighted values.

*Table 13 Best criteria comparison*

| Best to Others | Worker Control | Conflict resolution | Scheduling |
|---|---|---|---|
| Worker Control | 1 | 4 | 5 |

Continuing with the comparison, Table 14 demonstrates the worst criteria comparison against the other criteria using the provided scale from evaluators.

*Table 14 Worst criteria comparison*

| Others to the Worst | Worker Control | Conflict resolution | Scheduling |
|---|---|---|---|
| Scheduling | 5 | 3 | 1 |

Step 5 of the methodology provides the resulting weighting of the criteria according to the BWM. Table 15 shows this data.

*Table 15 resulting weight*

| | Worker Control | Conflict resolution | Scheduling |
|---|---|---|---|
| Weights | 0.685 | 0.203 | 0.111 |

The $ks_i^*$ shows to what extent the results are reliable. The reliability of the results is further determined, and the $ks_i^*$=0.13 indicates the degree of dependability. The resulting numbers show proper consistency, usually falling between 0 and 0.2.

The criteria are significantly different as seen in Figure 13, where "Worker Control" accounts for over 68% of the entire value. At the same time, the other two categories are less, making up nearly 20% and 11% of the total, respectively. This is an illustration of how risks are distributed when employees develop their activities.

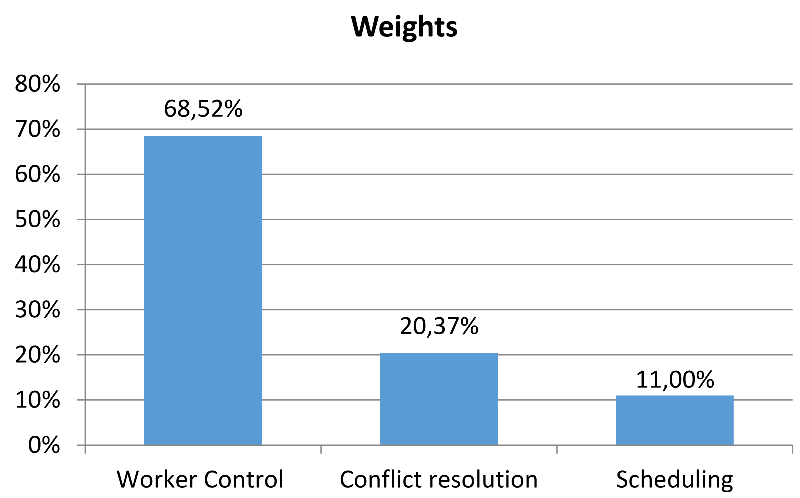


*Figure 13 Criteria Weights*

### 2.3.1 Worker control sub-criteria

The identified man criterion "Worker control" has intrinsic divisions of sub-criteria. The respondents were asked to compare these divisions at the secondary level, such as "Timing control alarms" (C1.1) and "Remote control" (C1.2). Table 16 Determine the benchmarks used to initiate the BWM comparison by following the steps outlined in the methodology.

*Table 16 Benchmark criteria*

| Criteria Number = 3 | Criterion 1 | Criterion 2 | Criterion 3 |
|---|---|---|---|
| Names of Criteria | Timing control alarms | Remote Supervision | Over control |

By examining the data that the respondents submitted, the benchmarks for the best and worst sub-criteria in this study were discovered. The best and worst selected criteria must be entered in the following step, and the identified criteria are shown in Table 17.

*Table 17 The best and worst sub-criteria identified*

| | |
|---|---|
| Select the Best | Over control |
| Select the Worst | Remote Supervision |

According to the BWM technique, pairwise comparisons (PCs) for every branch of the decision system must be created for every sub-criteria assessment. The process is comparing the best sub-criteria, as indicated in Table 18, with all the others.

*Table 18 Best sub-criteria comparison*

| Best to Others | Timing control alarms | Remote Supervision | Over control |
|---|---|---|---|
| Over control | 5 | 6 | 1 |

Using the scale provided by the evaluators, Table 19 presents the comparison of the worst sub-criterion against the other sub-criteria.

*Table 19 Worst sub-criteria comparison*

| Others to the Worst | Timing control alarms | Remote Supervision | Over control |
|---|---|---|---|
| Remote Supervision | 3 | 1 | 5 |

The methodology's fifth step gives the sub-criteria's final weighting in accordance with the BWM. This data is displayed in Table 20.

*Table 20 resulting sub-criteria weight*

| Weights | Timing control alarms | Remote Supervision | Over control |
|---|---|---|---|
| | 0.1746 | 0.1111 | 0.7143 |

The degree of reliability of the results is indicated by the $ks_i{}^* = 0.159$, and the reliability of the results is demonstrated by the ksi with a result lower than 0.2.

Figure 14 illustrates how the sub-criteria differ significantly from one another. Specifically, over control accounts for over 71% of the overall value, whilst the other two categories contribute less, accounting for around 17% and 11% of the total, respectively. This serves as an example of how risks are allocated as workers expand their scope of work.

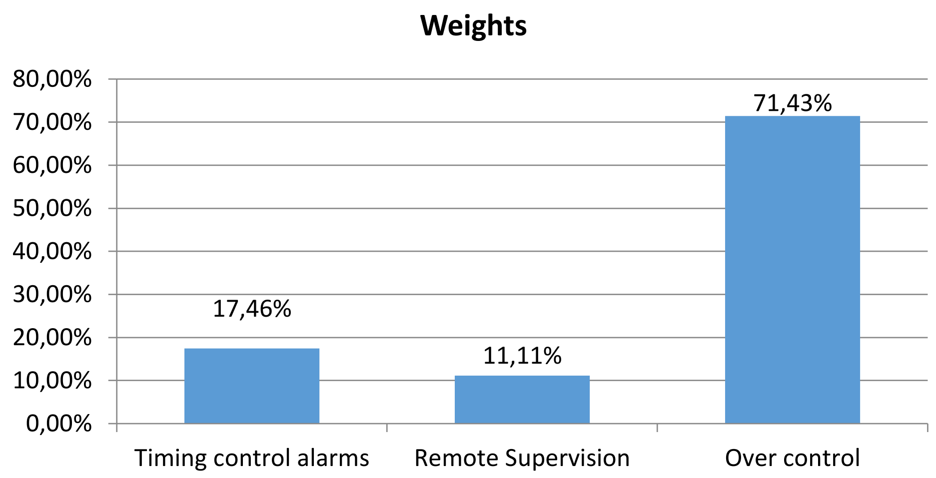


*Figure 14 Sub-criteria Weights*

### 2.3.2 AHP Method analysis

Using the method's guided scale, the experts graded the risk, including its immediate impact on the worker's health as well as the possibility of future sickness. The method created by Thomas L. Saaty (AHP) is used in paired comparison to determine the degree of risk importance when evaluating the stressors' importance. This approach makes it possible to assess and classify risk thoroughly [107], [108].

*Table 21 Matrix A= Risk evaluation ratio*

| **Matrix** | | Worker Control | Conflict resolution | Scheduling | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 5 | Wi | Ci | LAMDAi |
| Worker Control | 1 | 1.00 | 4.00 | 5.00 | 2.71 | 0.67 | 0.98 |
| Conflict resolution | 2 | 0.25 | 1.00 | 3.00 | 0.91 | 0.23 | 1.19 |
| Scheduling | 3 | 0.20 | 0.33 | 1.00 | 0.41 | 0.10 | 0.89 |

To compare and determine the next steps required to complete the computation, Table 21 displays matrix A, which illustrates the relationship between each stressor and the scale. To ensure that the priority values (weights) allocated to criteria or alternatives are on a comparable scale, the reported data are normalised after the matrix comparison has been established. Table 22 shows the normalisation for matrix A.

*Table 22 Normalized matrix*

$$A^N = \begin{bmatrix} 0.74 & 0.79 & 0.64 \\ 0.15 & 0.16 & 0.27 \\ 0.11 & 0.05 & 0.09 \end{bmatrix}$$

The Consistency Index (CI) and Random Consistency Index (RCI) are calculated using equations 2 and 3, respectively. Therefore, if the value is less than 0.1, it determines the consistency of the expert opinion. Table 23 shows the results. The RCI indicates how inconsistent random judgments of the same size should be, the consistency ratio (CR) indicates how consistent the judgments were, and the CI measures how inconsistent the paired comparisons were.

*Table 23 Consistency ratio*

| | | |
|---|---|---|
| *Ci=* | *0.04288335* | |
| *Rci=* | *0.66* | |
| *CR=* | *0.0650* | *Consistent* |

The stressors level S* was finally determined with the consensus indicator and measures the overall level of agreement between the decision criteria. The average group judgements are compared with the individual judgements to assess the presence of each criterion. The primary stressors in the workplace, highlight that 67.42% of Worker Control. Following this, 22.60% identify Conflict Resolution as a source of stress. Finally, Scheduling is the least reported stressor, with 10.10%. Figure 15 shows the critical impact of control over work on stress levels, with conflict management and scheduling being less prominent but still relevant.

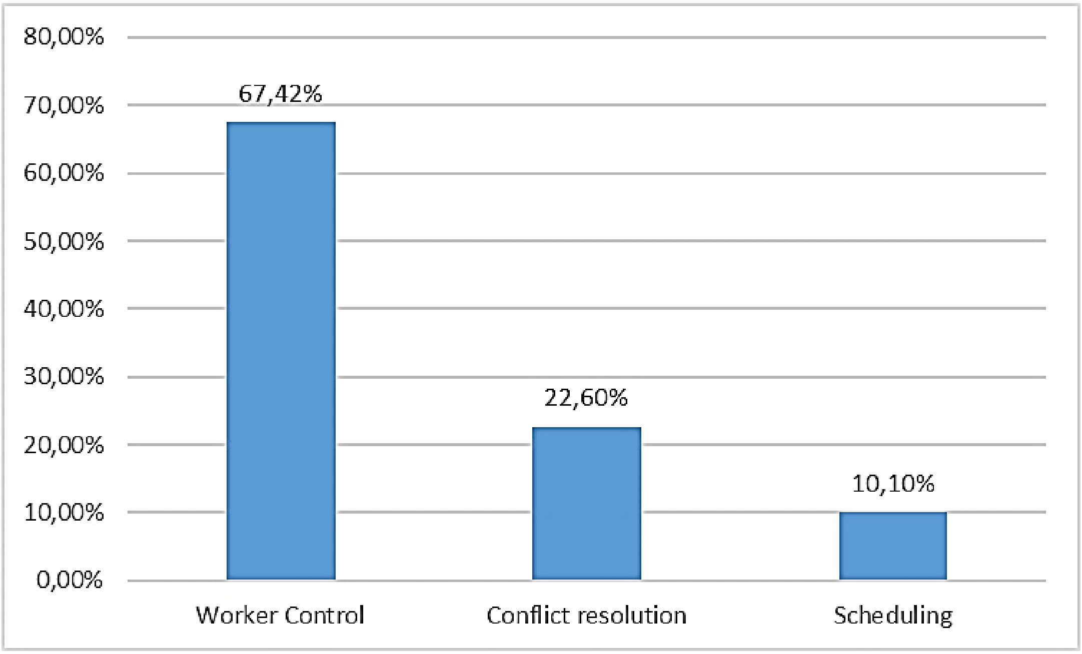


*Figure 15 Risk evaluation results*

### 2.3.3 Worker control sub-criteria AHP analysis

The identified main criterion, "Worker control", has intrinsic divisions of sub-criteria. These divisions were compared using AHP at a secondary level, such as "Timing control alarms" (C1.1) and "Remote control" (C1.2). Table 24 Determine the benchmarks used to initiate the AHP comparison by following the steps outlined in the methodology.

*Table 24 Sub-criteria Matrix A= Risk evaluation ratio*

| Matrix | | Over control | Timing control alarms | Remote Supervision | Wi | Ci | LAMDAi |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | | |
| Over control | 1 | 1 | 5 | 6 | 3.11 | 0.72 | 0.98 |
| Timing control alarms | 2 | 1/5 | 1 | 3 | 0.84 | 0.19 | 1.23 |
| Remote Supervision | 3 | 1/6 | 1/3 | 1 | 0.38 | 0.09 | 0.88 |

Equation 5, which calculates the validity consistency ratio (CI) and random consistency ratio (RCI), indicates the consistency of the specialist evaluation if the value is less than 0.1. Table 25 presents the findings. The consistency ratio (CR) shows the level of consistency in the assessments.

*Table 25 Sub-criteria Consistency Ratio*

| | | |
|---|---|---|
| *Ci=* | *0.04700755* | |
| *Rci=* | *0.66* | |
| *CR=* | *0.0712* | *Consistent* |

The results of the Row Geometric Mean Method (RGMM) using Shannon A and B are used to calculate the AHP consensus. The highest value shown is associated with overcontrol. Managers must therefore take these considerations into account when assessing the stresses associated with lifting loads. Figure 16 shows that a significant factor related to workplace stress is Over Control, with 71.72%, identified as the primary source of stress, implying that excessive oversight or micromanagement is a significant issue. Timing Control Alarms are a stressor measured as 19.47%. Lastly, Remote Supervision causes stress for 8.81%.

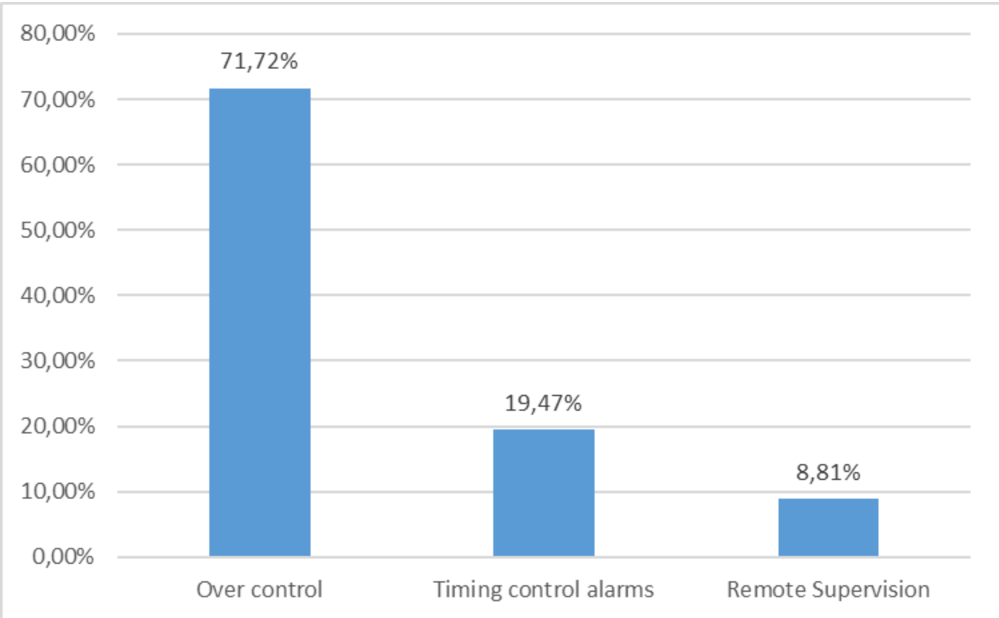


*Figure 16 Sub-criteria Risk evaluation results*

## 2.4 Discussions

The process of classifying stressors in the context of occupational health examines how different elements, particularly psychosocial stressors, affect an individual's physical and mental health. This highlights the value of ergonomics and decision-making models such as Best Worst Method (BWM) and Analytic Hierarchy Process (AHP) in identifying risks and improving worker safety [109].

Psychosocial stressors are strongly associated with a range of adverse health effects, including depressive symptoms, psychological dysfunction and physical illnesses such as musculoskeletal disorders (MSDs). In the workplace, psychosocial stressors like intense workloads, lack of autonomy, and insufficient social support are particularly significant in the development of WRMSDs [110].

A methodology was used in this study to investigate into the leading causes of manual handling stress in different sectors. The methodology was created with two primary objectives in mind: first, determining the psychosocial elements that impact manual handling activities, and second, evaluating the impact of these factors using multi-criteria decision-making procedures like the Best-Worst Method (BWM) and Analytic Hierarchy Process (AHP). This approach is in line with previous researchers ' analysis of the influence of the risk on the workplace [109], [111], [112].

Identifying the ergonomic elements that lead to WRMSDs is a significant management concern. Multi-criteria decision-making (MCDM) models have become popular among ergonomists as a means of addressing these issues. These models help to assess different stressors and their effects on workers' health, enabling companies to take more effective preventive measures. The Analytic Hierarchy Process (AHP) is one such method that rates ergonomic elements based on variables, including the dangers to workers' health and safety.

The survey was conducted in targeted industries that engage in manual handling and material storage, allowing participants to rank stressors they encountered using criteria established in a prior chapter's research to determine the primary and secondary criteria that are central to the study’s analysis.

The snowball sampling approach used for the survey could have introduced bias, as respondents may have recommended individuals within their professional networks. To mitigate this, the initial participants were selected from a range of industries and occupations to increase diversity, and demographic data was examined to track participation. The overall ranking of psychosocial stressors was also less affected by sampling bias due to the application of established, validated criteria and decision-making techniques (AHP and BWM), which also helped to ensure consistent responses.

The integration of the BWM and AHP approaches yielded a thorough and multifaceted comprehension of the psychosocial stressors associated with manual handling jobs. In all approaches, "Worker Control" emerged as the most critical component, while "Over Control" was identified as a significant stressor within this criterion. These results are helpful for sectors looking to optimise work environments through the modification of management techniques to lower stress levels, increase autonomy, and increase job efficiency. A repeatable foundation for future research on the manual handling of stress and psychosocial risk factors is also provided by the study's methodology. The criteria were derived from a systematic, PRISMA-based literature review to ensure scientific relevance. Using structured, multicriteria decision-making methods (AHP and BWM) added analytical rigour by quantifying subjective inputs within a consistent framework. The sample size was sufficiently large and demographically diverse to enhance the reliability of the results and support a more comprehensive interpretation.

## 2.5 Main contributions

The study provided an in-depth analysis of the stress factors affecting manual handling, particularly the psychosocial elements. By using a survey and multi-criteria decision-making techniques such as the Best Worst Method (BWM) and the Analytic Hierarchy Process (AHP), key criteria affecting manual handling stress were identified. "Worker control was recognised as the most critical factor in level 1. "Scheduling was recognised as the least significant factor.

AHP, applied to the overall criteria, emphasised the importance of "Worker Control" in manual handling stress, assigning it a weight of 67.42%, closely aligning with the BWM result of 68.52%. "Timing Control Alarms" and "Remote Supervision" were ranked significantly lower at 21% and 10%, respectively.

In line with Worker Control, the BWM technique identified Over Control as the dominant sub-criterion with a weight of 71.43%. This suggests that the two most stressful aspects for workers performing manual handling tasks are having excessive control over their work and insufficient autonomy. AHP revealed that "Over Control" by supervisors was the most prominent sub-criterion, accounting for nearly 71% of the stress.

The robustness and reliability of the results were demonstrated by the consistency ratios obtained using the two approaches. With a Consistency Ratio (CR) of 0.065, the experts' conclusions in the AHP analysis were reliable and consistent. Similarly, BWM shows a consistency ratio ($ks_i^*$= 0.159), indicating that the results are trustworthy.

The application of both BWM and AHP enabled cross-validation of the findings. Although they took different approaches, BWM focused on best and worst comparisons, while AHP relied on pairwise comparisons; both techniques yielded nearly identical results, which strengthened the findings.

- **Thesis (T2):** By applying MCDM to categorize the psychosocial factors in a sample of 283 participants (185 men and 98 women), with a 95% confidence level and 5.83% margin of error, I proved that 'Worker control' is the main psychosocial category affecting manual handling tasks, when compared to the other two categories (conflict resolution and scheduling), since its weight of importance is 67.42% in the AHP method (CI: 0.065), and cross-validated by the BWM at 68.52% (${ks_i}^*$: 0.13). And inside the 'Worker control' class, 'Overcontrol' is the most important factor, when compared to the other two (Timing control alarms and Remote Supervision), with 71.72% in the AHP method (CI: 0.071), cross-validated by 71.43% in the BWM method (${ks_i}^*$: 0.159).

Own publications related to this chapter:[90], [103]

# 3 STRESS SKIN RESPONSE IN MANUAL HANDLING ANALYSIS FOR THE PREVENTION OF MSD

In the field of manual handling, a detailed study of galvanic skin response provides information about the stress level during this task. The structured approach to biofeedback-based skin response detection consists of an introduction, methodology, presentation of results, and discussion.

## 3.1 Introduction

Galvanic skin response (GSR) or electrodermal activity (EDA) is the physiological perspective used to understand how the body reacts to stimuli. A phasic or low-frequency response [electrodermal response (EDR)] and a tonic or extremely low-frequency response [electrodermal level (EDL)] make up the GSR. It has an obvious connection to an external stimulus. This makes the EDA signal highly useful for a variety of study domains, including emotion identification and computing [113].

Skin conductance has been shown to convey information about the arousal or intensity of an emotional state. As well as being established as a strong and reliable indicator of emotional state, this signal has also been shown to apply to other areas of health [114], [115], [116].

Sweaty hands are not the slightest change that affects skin conductance, which depends on the activity of the skin's sweat glands. The two electrodes of the Skin Response apply a very small, completely safe and undetectable electrical voltage to the skin, through which a tiny current passes. The skin becomes wetter and the current conducts better when the sweat glands are more active. As a result, the skin's conductivity increases [117].

In micro-Siemens (μS, where μ stands for 'millionth' and 'Siemens' is the unit of conductivity), the Skin Response measures the conductance of the skin. Skin resistance, which is the reciprocal of skin conductance ($1S = 1/\Omega$), is another term often used to refer to the same phenomenon [117].

The autonomic nervous system regulates the sweat glands of the skin. Both the parasympathetic and sympathetic nervous systems are part of the autonomic nervous system. Sweat glands on the skin are a good way of detecting 'internal tension' as they are only innervated by the sympathetic nervous system, meaning that the parasympathetic nervous system has no effect. When stressors are encountered, the sympathetic nervous system triggers all of the body's emergency responses, putting it in a more alert state of readiness for action: blood pressure and pulse increase, blood glucose levels rise to access a readily available source of energy, and alertness increases. Under the influence of a stressful stimulus, the sweat glands become more active, which in turn causes an increase in skin conductance. Mental activity, emotional arousal, deep breathing, or even being startled - for example, by an unexpected clap of the hand or a loud drop of an object on the floor - can all be considered stimuli [117], [118].

**Electrode Recording Sites**

Two electrodes are often used for electrodermal recording. Endosomatic recording requires one active and one inactive site, but exosomatic methods often use two active sites. To eliminate the possibility of an electrode making direct electrical contact with the other, the two electrodes can be placed on the thenar or hypothenar eminence. Figure 17 illustrates the preferred location for electrode placement [117], [118].

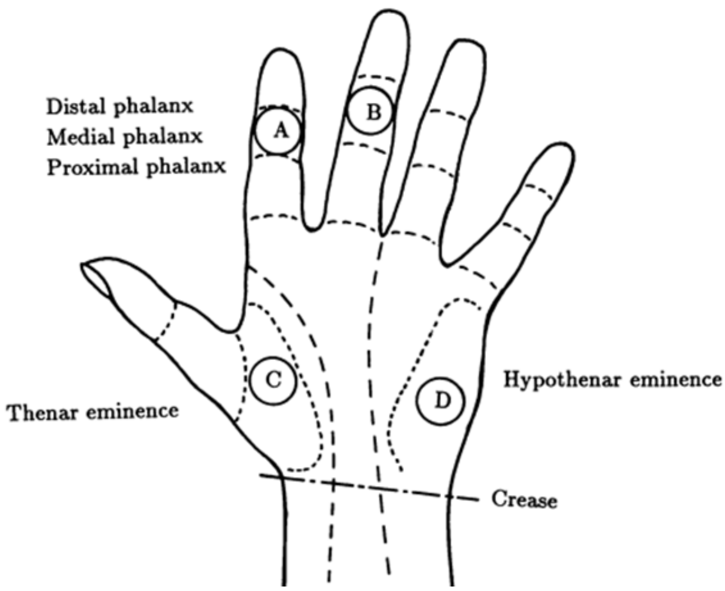


*Figure 17. Preferred palmar or volar electrode sites.*

The disc electrodes used in EDA have their electrode surface on the underside of a cylindrical plastic chamber. The electrolyte-containing electrode cream is poured into the gap between the electrode surface and the bottom of the ring. The electrode in cross-section is shown in Figure 18. A sintered silver/silver chloride (Ag/AgCl) layer has been applied to a spherical silver plate approximately 6 mm in diameter. The electrodes are typically attached to the skin using double-sided adhesive sleeves of the appropriate size [117], [118]..

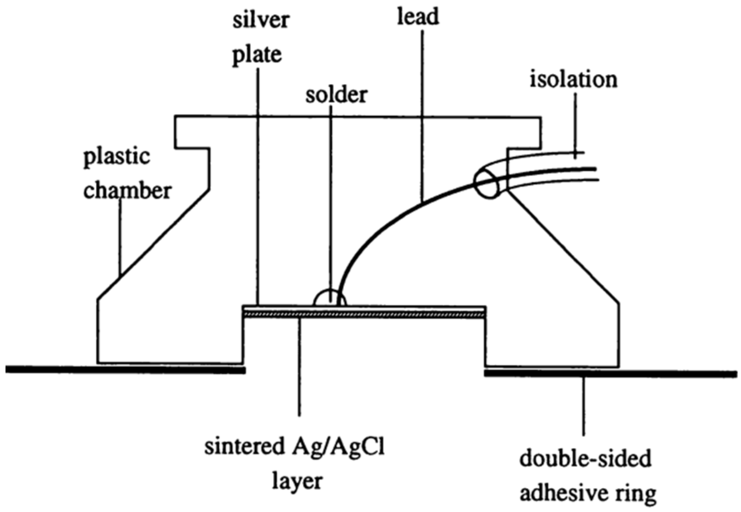


*Figure 18. Electrode*

## 3.2 Methodology

This section describes the tools and materials used in the research, including an explanation of the experiment methodology. This is followed by a detailed presentation of the study and an explanation of the approach taken.

### 3.2.1 Sample

For this study, a total of 13 people (12 men and 1 woman) who had no prior history of MSDs affecting the upper extremities volunteered. Each participant received an informed permission form and a synopsis of the experiment's objectives and methods at the start of the study, as shown in ANNEX E. Conventional methods such as K-Nearest Neighbours (KNN) and Convolutional Neural Network (CNN) typically achieve accurate identification and classification with several thousand samples per class, according to established criteria [119]. To guarantee model stability and generalisation in deep learning, it is frequently advised to include at least 10,000–50,000 labelled samples, particularly in architectures with several layers [120].

. The reference measurement was the signal that was recorded at the hand. For every subject, the palm of the hand serves as the measurement location. Attached to the Thenar and Hypothenar eminences were the electrodes. Figure 19 shows the sensors and locations used during the research. The data collected from the electrodes is used by the eSense Skin Response / Skin Conductance Sensor Biofeedback, a compact and highly effective sensor designed to measure your skin conductance through the microphone input of a smartphone. A smartwatch is also used to track HRM in real time.


*Figure 19. Sensor devices for tracking biodata in the stress detection experiment*

### 3.2.2 Procedure

Before the experiments, participants completed a questionnaire about upper extremity MSDs. All participants were then given a brief explanation of the experimental protocol and given a practice test to acquaint them with the gripping task before the trials began. For this study, participants were asked to lift a load from the floor to a height of 75 cm 4 times per minute for 5 minutes. The activity is repeated twice, as shown in Figure 20. Stage 1 consists of the activity without stressors, avoiding disturbance for the worker (Figure 20A). This stage requires the participant to complete four kettlebell squats in one minute. At this stage, the participant is allowed to look at the timer and divide the activity into 4 similar periods (e.g. one repetition every 15 seconds). To begin, place your feet shoulder-width apart and stand straight. Then, bend your legs into a squat. Using both hands, pick up the kettlebell and hold it near your body. Place the kettlebell on the floor and raise your body to a standing posture before bending your legs into a squat. Return to the starting position.

In the second stage (Figure 20B), the more ranked stressor selected in Chapter 3 is included to record the data. This stage requires the participant to perform four kettlebell squats in one minute. At this stage, in contrast to the previous stage, the participant is not allowed to look at the timer and must wait for the instruction to squat to collect the kettlebell. As a second difference, the psychosocial factors are incorporated by a second participant, called the activity boss, who consistently gives different guidelines and instructions.


*Figure 20. Experimental Methodology for Detecting the Influence of Psychosocial Stressors.*

For the purpose of reaching and maintaining the same signal level from the start point, each participant was instructed to exert a consistent effort by keeping a steady pace throughout the squats (same pace during the squats). They were asked to unwind after taking part. Skin conductance was measured during all activities and constantly monitored, recording the time of each squat repetition. Participants were allowed five minutes of rest between each trial to minimise muscle fatigue. The lifting task was repeated twice for each participant, who completed 5 trials. After completing the task, each participant was asked to provide a subjective rating of discomfort and stress level using the modified Borg CR10 scale presented in Table 26 [121].

*Table 26. Modified Borg CR10 scale*

| Level | Description of Perceived Stress | Interpretation |
|---|---|---|
| *0* | No stress | Completely relaxed |
| *0.5* | Barely noticeable stress | Mild mental or emotional discomfort |
| *1* | Very low stress | Slightly uneasy |

| Level | Description of Perceived Stress | Interpretation |
|---|---|---|
| *2* | Low stress | Moderate tension, but manageable |
| *3* | Moderate stress | Feeling pressure, but still under control |
| *4* | Somewhat intense stress | High tension, affecting concentration |
| *5* | Intense stress | Significant worry, noticeable discomfort |
| *7* | Very intense stress | Emotional overload, hard to ignore |
| *9* | Extreme stress | At the limit, almost unbearable |
| *10* | Maximum stress | Overwhelming stress cannot be sustained for long |

### 3.2.3 Data classification Labelling

Stress detection using physiological indicators like heart rate monitoring and galvanic skin conductance (GSC) has become an effective means to evaluate stress conditions. GSC measures the electrical conductivity of the skin, and it rises with sweat gland activity, which is usually brought on by stress.

The instrument uses µS to express stress level data. It provides time stamps to determine the exact times at which measurements were taken. The stress variable indicates the presence of stress when its value is 2, and the absence of stress when it is 1. Analysis of cases where stress = 2 is used to track variations in µS levels during these periods to identify when stress occurs.

## 3.3 Results

The autonomic nervous system's reaction to stress, as reflected in GSC, is frequently associated with varying degrees of stress. This section presents the data from a non-invasive way to detect stress.

### 3.3.1 Galvanic Skin response

The mean conductivity value during stress is 6.98 µS. Values range from a low of 0.96 µS to a high of 13.11 µS. The 50% of the measurements during stress are between 4.01 µS and 9.98 µS. There is considerable variability in the measurements (standard deviation of 2.77). The trend lines for the stress and no-stress data are identified, and the index of the filtered Data Frames is reset to ensure proper alignment, allowing valid indices to be used to identify points.

In the next step, to evaluate the statistical significance of the trends, descriptive statistics for both stress and no-stress data were performed, and a linear regression analysis was performed to determine the p-value for the trends. These data results are presented in Table 27.

*Table 27. Descriptive statistics for the trends in both stress and no-stress data*

| Condition | Count | Mean | SD | Variance | Min | Median | Max | Skewness | Kurtosis | Slope |
|---|---|---|---|---|---|---|---|---|---|---|
| **All Data** | 35350 | 6.49 | 2.52 | 6.36 | 0.75 | 7.10 | 13.11 | -0.03 | -0.85 | |
| **Non-Stress** | 18230 | 6.02 | 2.16 | 4.68 | 0.75 | 6.18 | 9.76 | -0.34 | -1.08 | 6.43e-05 |
| **Stress** | 17120 | 6.98 | 2.77 | 7.67 | 0.96 | 7.65 | 13.11 | -0.08 | -1.08 | 2.4 e-04 |

Table 27 provides descriptive statistics and trend analysis for both stress and no-stress data. The p-value of less than 0.05 confirms that the observed increase is statistically significant, meaning it is unlikely to be due to chance.

In the first 60 seconds shown in Figure 21, the differences in skin conductance between the stress and non-stress conditions are reflected in the initial difference in body activity time. The mean skin conductance under stress is 7.28 µS, and in the non-stressed state, it is a lower mean of 5.63 µS.

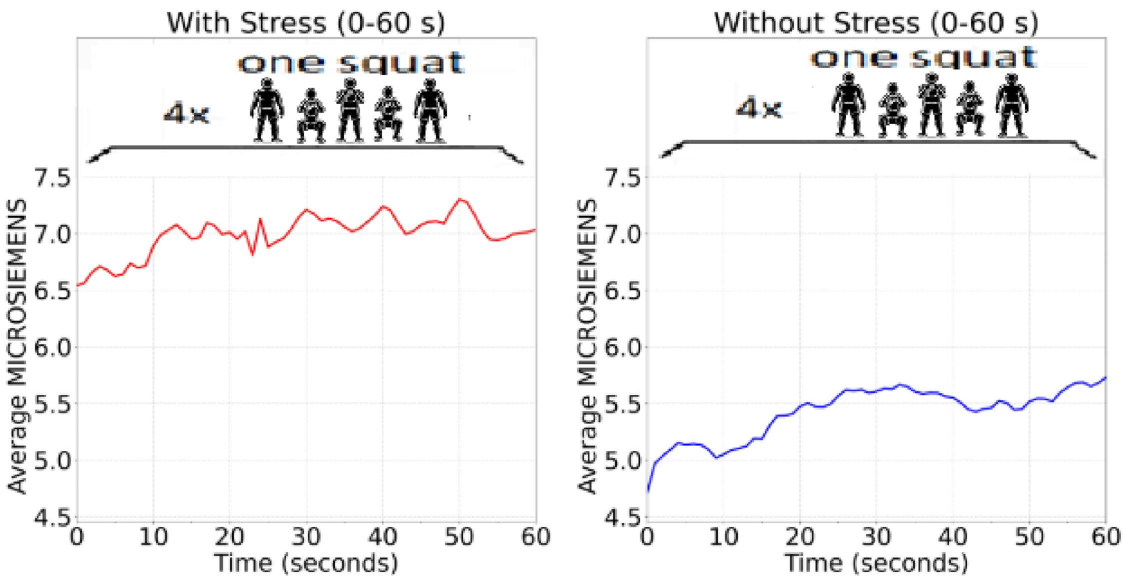


*Figure 21. Stress and Non-stress conditions in the initial periods*

Figure 22 shows the parasympathetic response during the last 60 seconds of the experiment; the differences between the stress and no-stress conditions became much more pronounced. The mean skin conductance in the stress condition increased significantly to 7.25 µS, with a standard deviation of 0.17, maximum peak 7.44 and minimum peak 6.5µS. In contrast, the no-stress condition showed a smaller increase with a mean of 6.24 µS, a standard deviation of 0.48 Max maximum peak 6.42 and minimum peak 6 µS.

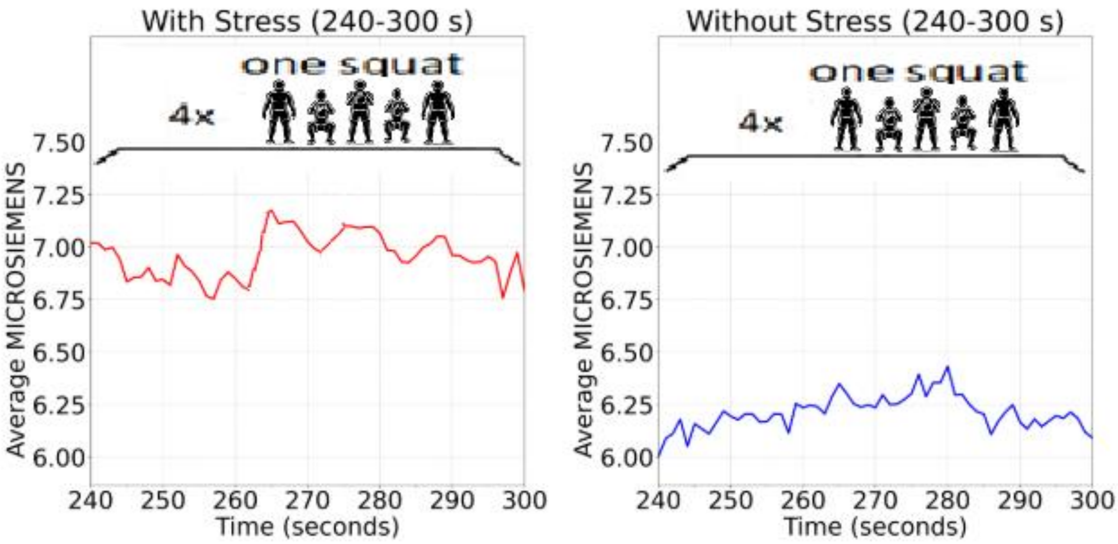


*Figure 22. Stress and Non-stress conditions in the final periods*

The p-values show highly significant differences between the stress and no stress conditions. In the first 60 seconds, the p-value was $p<0.005$, indicating that these differences did not occur by coincidence. In the last 60 seconds, the p-value was even smaller, meaning that there is virtually no chance that these differences are due to coincidence.

The patterns of the data for all participants' skin responses under stress are represented in Figure 23.

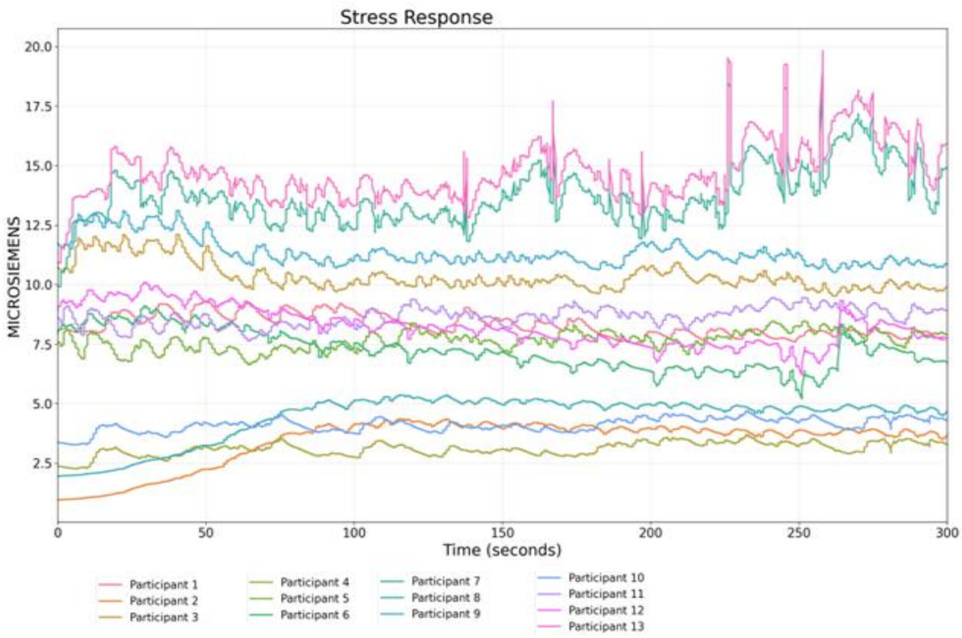


*Figure 23 Raw data stress response for all participants*

The detection zone of the patterns of the data for all participants' skin responses in non-stress is represented in Figure 24.

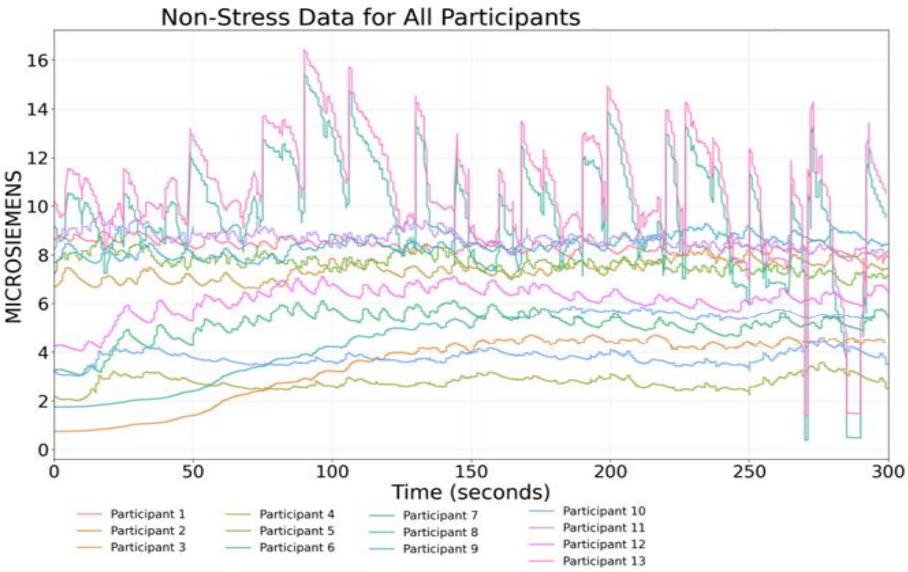


*Figure 24 Raw data non-stress skin response for all participants*

Figure 25. The slope for the no stress condition is 0.000026 µS/second (slightly positive trend), showing a slow increase. From an initial value of 5.69 µS, there is a total increase of 1.45 µS over 300 seconds. A lower linear relationship is shown by the R-squared value of 0.004983. In the stress situation, the slope is 0.001156 µS/second (positive trend), indicating a higher increase; there is a total increase of 5.67% over 300 seconds. Compared to the no-stress scenario, the R-squared value of 0.000792 indicates a stronger linear relationship.

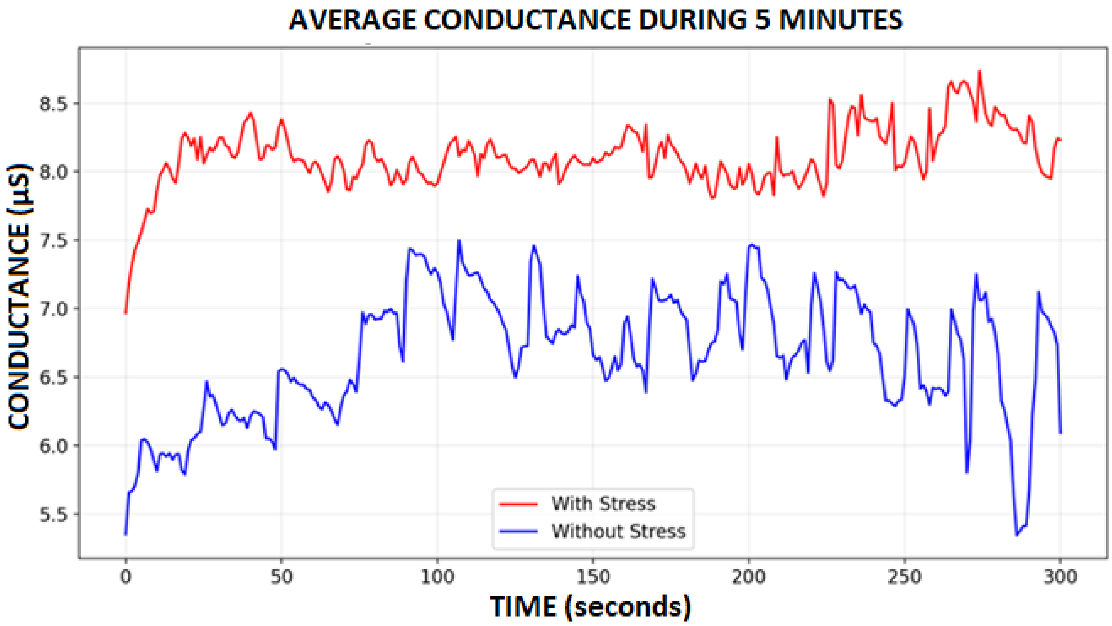


*Figure 25. Trend detection of mean stress over 5 minutes*

During the test, an external problem was detected in two participants. To reduce interferences and missing data caused by external variables, such as excessive dryness of the participant's skin, a data filtering process was applied with a threshold of data ± 2SD.

After applying the filter, Figure 26 shows the data patterns for each participant's skin response to the no-stress condition.

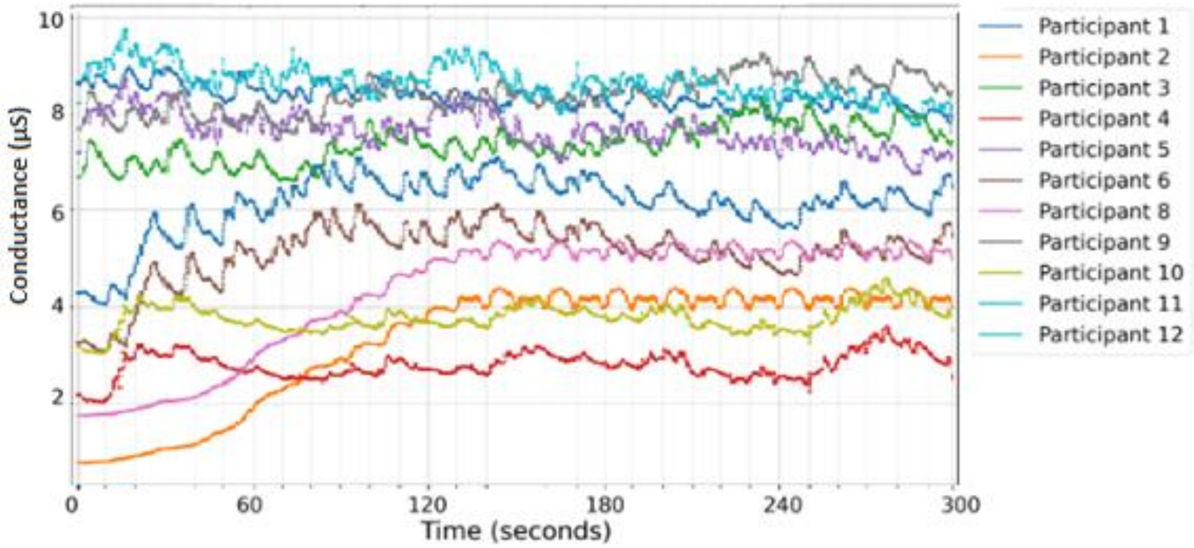


*Figure 26 Non-stress skin response after data filtering*

Figure 27 shows data patterns for all participants' skin reactions under stress following the filter's application.

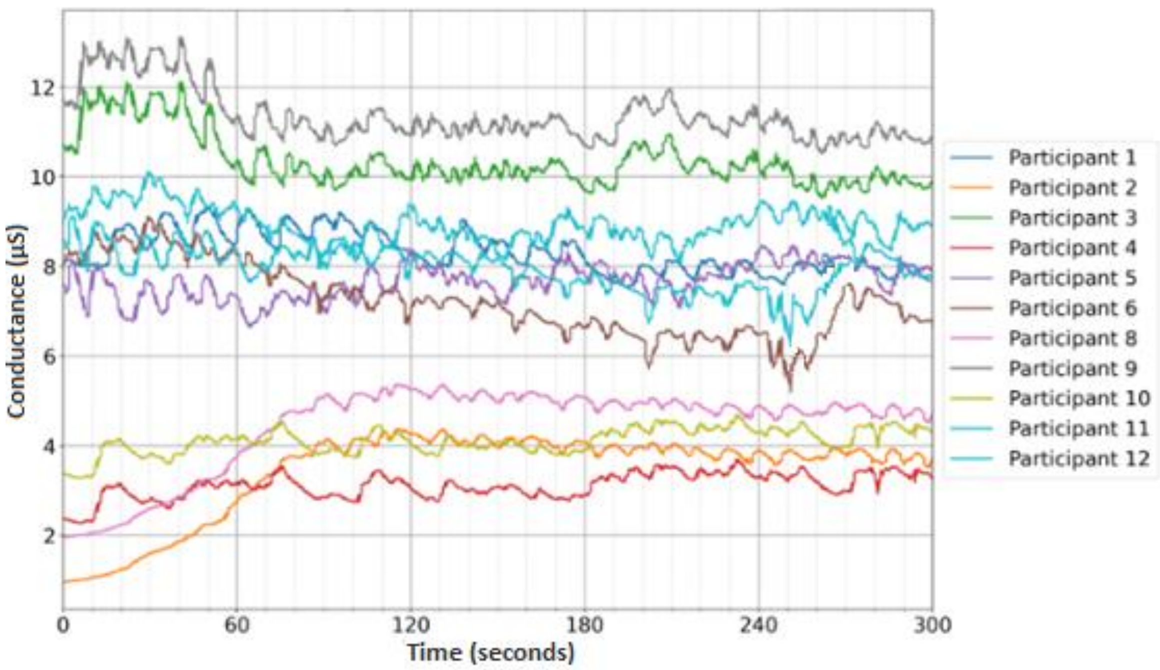


*Figure 27 Stress skin response after data filtering*

The new mean data set after filtering is shown in Figure 28. Where the "stress" condition shows values around 6.5-8 µS, the "non-stress" condition shows lower values, around 6 µS.

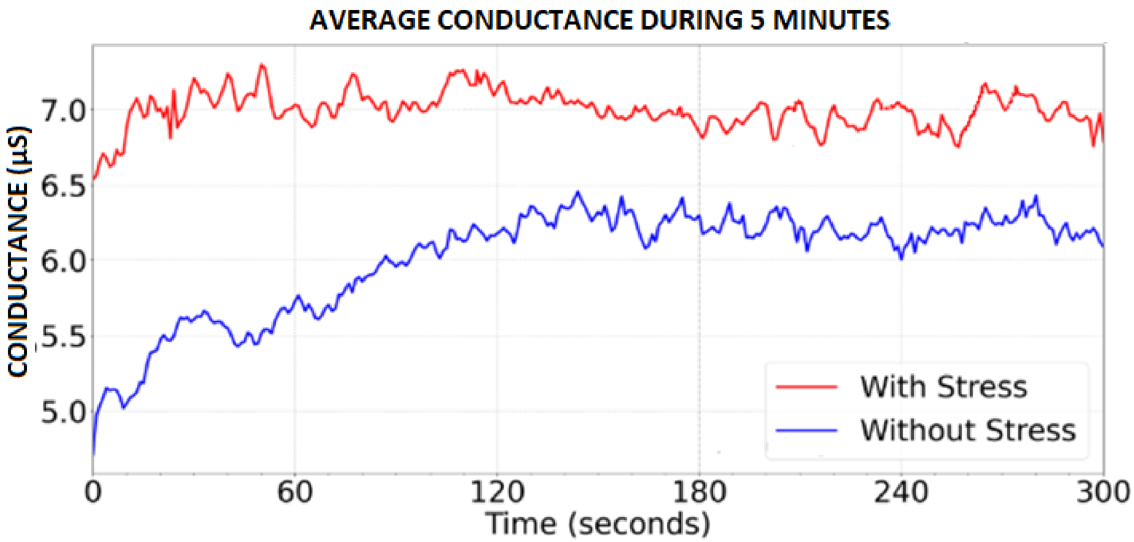


*Figure 28Average skin response after data filtering*

### 3.3.2 Heart rate stress detection

Heart rate is a direct physiological indicator of the body's reaction to stress, providing information about how the cardiovascular system responds to pressure, making it an essential tool for stress detection. A valuable technique for tracking both acute and chronic stress levels, heart rate variability, when combined with metrics such as mean beats per minute, aids in identifying patterns linked to stress. Under stress, the mean heart rate is higher (96 beats per minute) than it is under non-stress (92.15beats per minute). Measurement variability is higher under stress (standard deviation of 14.15). Stress causes a broader range of values, up to 98.9 beats per minute. The distribution of heart rates under stress and non-stress settings differs, as visualised in Figure 29.

Stress significantly affects cardiovascular responses, according to a statistical analysis of heart rate data. Under stress, the mean heart rate increases from 92.8 to 97.6, an increase of 5.72%. There is a moderate to high correlation (0.719) between stress-free and stress-induced heart rate readings. These results show that stress not only increases heart rate but also makes it more variable, suggesting increased physiological reactivity.

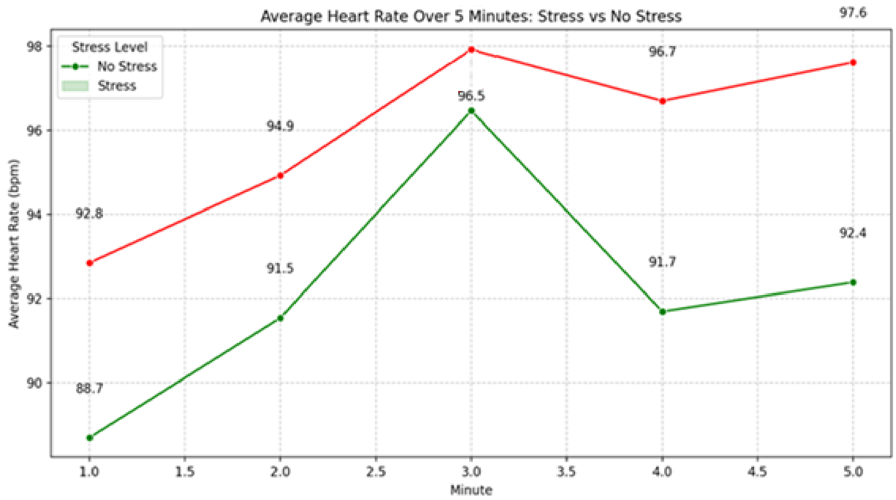


*Figure 29. Heart rate stress detection*

Without stress, the peaks are less perceptible and more widely distributed, with a mean of 88.7 beats per minute and a maximum of 96.15 beats per minute, based on trends in the behaviour of heart rate in both stressful and non-stressful environments. In this case, the trend line's slope (0.783) shows that the heart rate has been gradually declining over time. With a mean of 32.90 beats per minute and a maximum of 37.22 beats per minute, the peaks are more frequent and a bit higher during stressful situations. Given that the trend line is positive (1.1308), the heart rate appears to be gradually rising over time. In general, heart rate tends to increase during stressful situations and fall considerably during non-stressful ones. Furthermore, a more dynamic physiological reaction is shown in the stressed data's increased variability.

The t-test was used to compare heart rate data under stress and non-stress conditions, and the descriptive statistics explain the results, where t-statistic: -1,727 and p-value: 0,044. The p-value indicates a statistically significant difference between heart rate under stress and no stress conditions, which suggests that stress has a measurable effect on heart rate. These statistical summaries are presented in Table 28.

*Table 28. Descriptive Statistics*

| MEASURES | NO STRESS (1) | STRESS (2) |
|---|---|---|
| **COUNT** | 65.0 | 65.0 |
| **MEAN** | 92.15 | 96.0 |
| **STD** | 13.39 | 14.15 |
| **MIN** | 74.0 | 76.0 |
| **25%** | 81.0 | 86.0 |
| **50%** | 88.0 | 92.0 |
| **75%** | 103.0 | 111.0 |

| MEASURES | NO STRESS (1) | STRESS (2) |
|---|---|---|
| **MAX** | 132.0 | 126.0 |
| **RANGE** | 58.0 | 50.0 |
| **DEGREES OF FREEDOM** | 64 | |
| **T-STATISTIC** | -1,727 | |
| **P(T<=T) ONE-TAILED** | 0,044 | |
| **CRITICAL VALUE OF T (ONE-TAILED)** | 1,669 | |

To demonstrate the heart rate behaviour, the information from Participant 5, shown in Figure 30, provides insight into how stress affects their heart rate in a specific way, allowing for personalised monitoring. It shows how changes over time can be accurately tracked and trends assessed, which can be used as early warning signs of health problems or poor stress management.

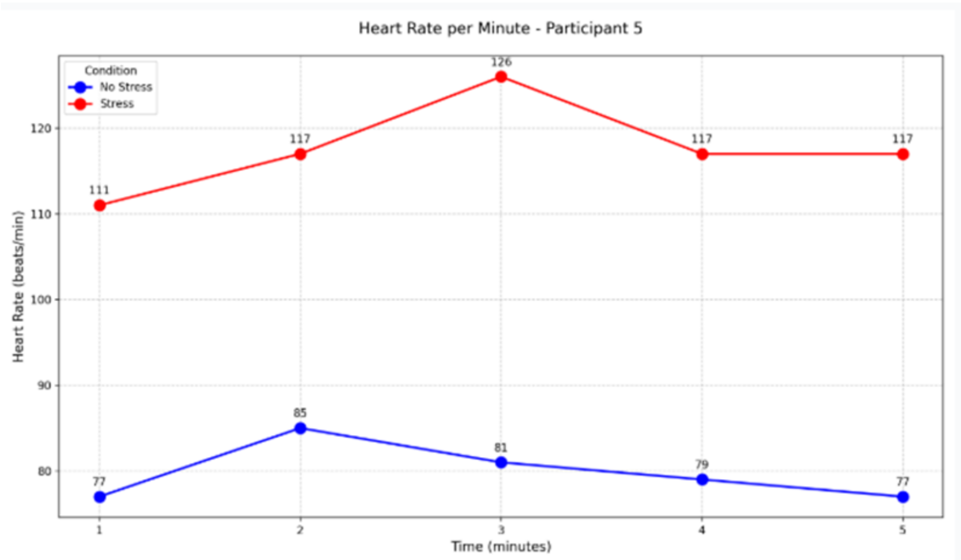


*Figure 30. Statistical Analysis for Participant 5*

There are noticeable differences between the heart rate readings taken under stressful and non-stressful conditions. A statistically significant difference between the two groups is indicated by a t-statistic of -13.364 and a p-value <0.05. Under stress, the median heart rate was 79.0 bpm and 117.0 bpm, while the mean heart rate increased by 37.8 bpm (from 79.8 bpm to 117.6 bpm). With a standard deviation of 4.8 bpm (compared to 2.99 bpm at rest) and a range of 15.0 bpm (compared to 8.0 bpm), the standard deviation and range show increased variability with exercise. These findings are supported by the variance and standard error, which show greater dispersion and reliable mean estimates. The effect of stress is clearly visible in the minimum and maximum values, where even the lowest stressed heart rate exceeds the highest non-stressed value. The presented descriptive statistical data are illustrated in Table 29.

*Table 29.Descriptive  Statistical Analysis for Participant 5*

| STATISTIC | NO STRESS | STRESS |
|---|---|---|
| T-STATISTIC | -13.3643 | |
| P-VALUE | 0.0000009400 | |
| MEAN (BPM) | 79.8 | 117.6 |
| MEDIAN (BPM) | 79.0 | 117.0 |
| STANDARD DEVIATION (BPM) | 2.99 | 4.8 |
| MINIMUM (BPM) | 77.0 | 111.0 |
| MAXIMUM (BPM) | 85.0 | 126.0 |
| RANGE (BPM) | 8.0 | 15.0 |
| VARIANCE | 8.96 | 23.04 |
| STANDARD ERROR | 1.5 | 2.4 |

### 3.3.3 Physiological signal comparison on Stage 2

Heart rate is a versatile tool for monitoring and evaluating recuperation, and over time, while skin conductance response offers information about the effects of stress on the skin. These assessments provide valuable insights into how the body reacts to stress, which can be utilised to detect possible health hazards, enhance productivity, and foster mental health. The analysis contrasts heart rate with µS for stress detection. The statistical tests for both measurements confirm significant differences between stress and non-stress situations. The results during the task under stress are presented in Table 30.

*Table 30. Descriptive Statistical variables under stress*

| | **Stress(2)** |
|---|---|
| **Sample** | 10905 |
| **Med** | 7.71 |
| **SD** | 3.559 |
| **Min** | 0.96 |
| **Q1** | 4.01 |
| **Median** | 7.81 |
| **Q3** | 9.98 |
| **Max** | 18.83 |

Stress and non-stress states differ significantly, according to statistical analysis, especially in skin conductance (measured in µS). Stress causes a 21.55% increase in the mean µS level, a higher standard deviation of variability, and noticeably higher maximum values. With a moderate effect size (Cohen's d = 0.44) and a highly significant difference ($p < 0.001$), statistical tests support this. 14 distinct state transitions are revealed by temporal analysis, with a mean of 1608.69 samples per state (minimum 1498, maximum 1980). In Figure 31, the zones, which have more variability and prominent peaks under stress, indicate tension. According to these results, µS are a strong and trustworthy stress detection indication that exhibits distinct statistical and temporal distinctions. Additionally, heart rate is higher during stress (96 vs. 92.15 beats/min on mean) with greater variability (standard deviation 14.1 vs. 13.3), further supporting the physiological distinction between stress and non-stress conditions.

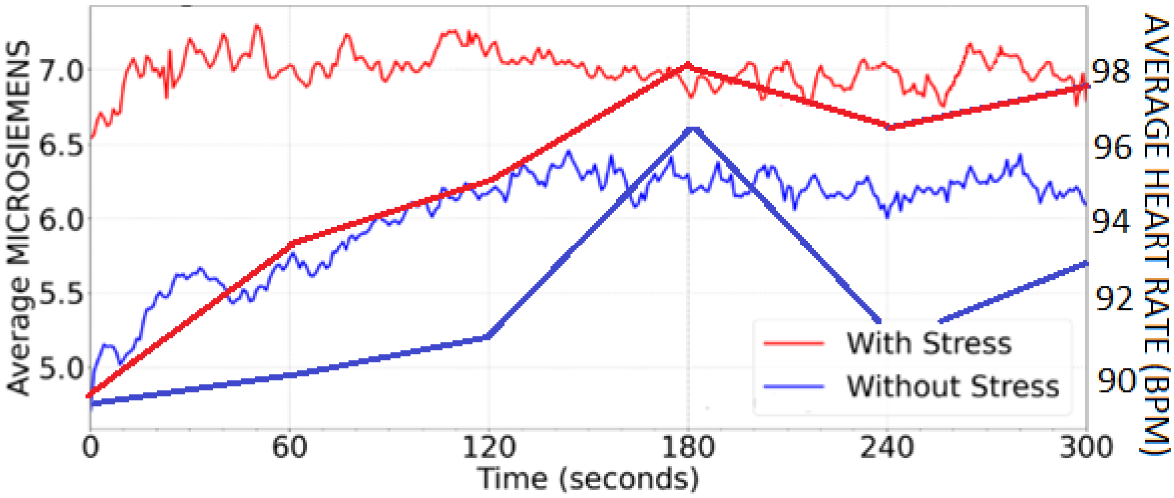


*Figure 31. Stress detection µS vs Heart rate*

### 3.3.4 Influence of Biophysical Data in the Manual Handling Predictions Model

The new biophysical data for manual handling prediction models, in this case, Garg created in 1978, is to increase the models' precision to evaluate worker safety and productivity. Garg's model was designed to measure metabolic energy expenditure and assess the physical demands of manual handling jobs [122]. The data from the original model went from 3.23 kcal/min to 8.7 kcal/min.

To calculate the energy consumed, used the method of Keytel et al. (2005) formula [123]. Calculation of kilocalories per minute (kcal/min) is based on heart rate in beats per minute (BPM), which correlates with metabolic equivalents and oxygen consumption. Weight is expressed in kilograms, age in years, and HR is the heart rate expressed in beats per minute in these calculations. These values are all multiplied by certain constants, then summed and corrected by subtracting a base value. Finally, the measurement is converted from kilojoules to kilocalories per minute by dividing the total by 4.184. The new biophysical data used to detect the stress influence are presented in Table 31, showing the descriptive statistical variables for comparison with the kcal values from the Garg model.

Table 31. Comparison of the New biophysical data to the Garg model

| Minutes | New under Stress Kcal/min | Garg Predicted Metabolic Rate (Kcal/min) |
|---|---|---|
| **1** | 6,57142857 | 3,23 |
| **2** | 13 | 4,65 |
| **3** | 19,7142857 | 6,03 |
| **4** | 25,4285714 | 7,4 |
| **5** | 33,2857143 | 8,7 |

The data from Garg's model was used as the basis for the NIOSH equation to analyse the recommended weight limit. These data were compared with the newly obtained biophysical data introducing stress to understand the influence of psychosocial factors. The t-test results indicate a statistically significant difference between Variable from Garg model (mean: 6.002) and New biophysical data (mean: 19.6). The t-statistic of -3.68 exceeds the critical values for both one-tailed (2.13) and two-tailed (2.78) tests, with corresponding p-values of 0.011 and 0.021, respectively, both below the 0.05 significance threshold. This confirms that the difference in means is unlikely due to random chance. New biophysical data show much greater variability (variance: 108.65) compared to the Variable from the Garg model (variance: 4.69), and the Pearson correlation coefficient of 0.998 highlights a powerful positive relationship between the paired observations.

New biophysical data exhibit significantly higher values with greater variability, suggesting a meaningful difference between the two conditions or groups represented by the variables. These results are shown in Table 32.

Table 32. T-test results comparing original data from the Gangs model and new biophysical data.

| | Variable from the Garg model | New biophysical data |
|---|---|---|
| Media | 6,002 | 19,6 |
| Variance | 4,68657 | 108,646939 |
| Observations | 5 | 5 |
| Pearson Correlation Coefficient | 0,99838024 | |
| Hypothetical Mean Difference | 0 | |
| Degrees of Freedom | 4 | |
| t-Statistic | -3,67980145 | |
| P(T<=t) One-Tail | 0,01060383 | |
| Critical t Value (One-Tail) | 2,13184679 | |
| P(T ≤ t) Two-Tail | 0,02120766 | |
| Critical t Value (Two-Tail) | 2,77644511 | |

## 3.4 Discussions

Heart rate variability (HRV) and galvanic skin response (GSR) are two biological indicators that are being used in stress detection. This method of detection is becoming more and more dependable and non-invasive. These physiological measures are valuable tools for industrial applications because they show quantifiable changes in response to stress as the autonomic nervous system's reaction.

Stress detection by GSR involves the analysis of micro-Siemens values, with the mean micro-Siemens value being 8.13, ranging from 0.96 to 18.83 µS. The variability of these measurements, reflected in a standard deviation of 3.56, underlines the diversity of individual stress responses. Statistical trends, such as a linear regression slope of 0.000244587 and a highly significant p-value of 2.009096241e-68, confirm a consistent increase in skin conductance under stress, which increases with sweat gland activity, a response typically triggered in this condition. Clusters for stress and no-stress circumstances can be distinguished by pattern recognition in GSR data. Under stress, these clusters exhibit more variable behaviour and more observable peaks. The statistically significant differences between stress and no-stress states ($p < 0.001$) validate GSR as a robust and non-invasive tool for stress detection. The assessments of µS values demonstrate the method's sensitivity and reliability in identifying stress.

Significant changes in heart rate patterns during stress are indicative of the cardiovascular system's response to stress and the body's increased physiological sensitivity. In response to stress, the mean heart rate increases from 76 to 126 beats per minute, while the standard deviation is higher, 14.15. In addition, stress causes more frequent and pronounced peaks in heart rate compared to the smoother, more stable patterns seen in non-stressful situations. Statistical analysis confirms the significance of these differences. A t-test comparing heart rate data under stress and no-stress conditions yields a p-value of 0,044, indicating a statistically significant difference. This finding supports the validity of heart rate as a reliable indication of physiological stress by demonstrating the quantifiable effect of stress on heart rate. Heart rate trends further support this conclusion. When under stress, the heart rate gradually rises (a positive slope of 1.13), but when not under stress, it grows more slowly (a slope of 0.7). These patterns highlight how stress affects the body's autonomic functions and show how it dynamically affects cardiovascular activity. The 5-minute duration considered in the test captures body changes before the heart rate stabilises during warm-up. This emphasises that under stress conditions, the stabilised heart rate after warm-up time for the body for long-period tasks will be higher than in non-stress conditions. This time and BPM factor is consistent with the factors identified in studies of body stabilisation time during exercise [124], [125].

Data from galvanic skin conductance (GSC) and heart rate are used to provide a comprehensive view of stress responses. This combination of signals enhances the precision and reliability of stress detection by capturing distinct aspects of physiological reactivity. The body's increased autonomic nervous system activity during stress is reflected in both measurements' increased variability. With clear transitions observed in visual representations, such as the red zones for stress in Figure 31, the temporal patterns additionally show the clear differences between stress and no-stress states.

This study offers a nuanced understanding of how stress affects metabolic rates and overall worker efficiency by integrating biophysical data from manual handling under stress into established models, such as Garg's manual handling framework, thereby enhancing our comprehension of stress's impact on physical performance.

With a mean of 19.6 kcal/min under stress as opposed to the model's projected mean of 6.002 kcal/min, a comparison with Garg's original model shows that stress dramatically increases metabolic rates. Despite greater variability under stress, the high Pearson correlation coefficient (0.998) shows a tight alignment between the observed and projected data, and the t-test findings suggest that this difference is statistically significant. These results highlight the significant effects that stress can have on energy consumption and physical exertion.

The use of the eSense skin conductance device for GSR monitoring and a consumer-grade smartwatch for heart rate tracking introduces certain limitations in measurement accuracy compared to medical-grade equipment because they are designed for ease of use, portability, and non-invasive real-time monitoring, which makes them suitable for repeated manual handling tasks, considering it has shown acceptable reliability in previous research on stress detection [126]. To address this, the experimental design emphasised consistent sensor placement and signal preprocessing or data filtering.

GSC, heart rate monitoring and metabolic rates together provide a robust and efficient basis for stress analysis and detection. In addition to advancing the study of stress-related outcomes, these technologies open the door to targeted therapies that reduce the adverse effects of stress on performance and health. This study combines GSR and HR monitoring, which are based on physiological signals, to offer a more concrete and objective method of identifying psychosocial stressors during manual handling tasks. The results consistently show increased heart rate (HR) and galvanic skin response (GSR) activity under high-stress conditions. As earlier research focused on the impact of psychosocial factors, such as workload and job control, on the development of musculoskeletal diseases, the accuracy of stress detection was limited as it mainly depended on self-report questionnaires and observational correlations [127], [128]. Additionally, the impact of work-related stress on musculoskeletal disorders (MSDs) was examined; however, physiological data were not employed to verify stress in real time [129]. Earlier ergonomic evaluations of manual handling activities have relied on subjective techniques like the NASA Task Load Index and the Job Content Questionnaire, which collect self-reported information on stress, control, and perceived workload [130], [131]. These methods have helped establish a correlation between work-related stress and psychosocial elements, but they are unable to measure physiological reactions in real time. Studies have shown, for example, how job pressures affect musculoskeletal health, but their methods lacked real-time biological data, which prevented them from directly capturing physiological changes as they occur.

This study, on the contrary, presents a novel empirical technique that uses wearable technology to record GSR and HR while individuals conduct regulated manual handling tasks in stressful situations. This configuration allows for the measurement of stress-related autonomic nervous system reactions, providing insights that are time-synchronised with tasks. Similar physiological monitoring research used biofeedback to detect driver stress, but they weren't used in the context of manual handling or workplace ergonomics [132]. Additionally, they recommended integrating biomechanical and psychosocial elements, but they failed to create an experimental model as multidisciplinary and robust as the one this chapter suggests [133].

## 3.5 Main contributions

The study demonstrated the efficacy of Heart Rate Variability (HRV) and Galvanic Skin Conductance (GSC) as physiological indicators for non-invasive stress detection. The study showed the sensitivity and reliability of these measures in discriminating between stressful and non-stressful situations by measuring responses using heart rate variability and µS levels. Significant changes were validated by statistical analysis, confirming their viability for use in industrial settings.

- **Thesis (T3):** Applying a bio data (GSR and BPM) system in a controlled laboratory setting with 13 participants. I proved that the 'Overcontrol' psychosocial risk factors introduced during manual handling tasks produce a variation in the autonomous nervous system response, generating a heart rate mean increase from 76 to 126 beats per minute, thus a higher mean of GSR under a stressful environment with a $p < 0.01$. The Skin response represented by the peak impedance mean significantly different under stress and non-stress conditions with impedance values of 8.13 μS and 6.62 μS, respectively.

Own publications related to this chapter:[134], [135].

# 4 MACHINE LEARNING METHODS FOR STRESS DETECTION DURING MANUAL HANDLING TASKS

In manual handling, the sites and types of injury vary from the knee, lower back, shoulder and biceps. Muscle strains from lifting loads and cartilage and tendon injuries from higher repetitive movements are common, highlighting the fatigue, stress and conditioning risk factors in this industrial activity [136].

## 4.1 Stress detection

Sensors are now crucial to medical research and related fields. These are typically used to measure and identify different diseases and their severity. Wearable sensors are gadgets that use one or more sensors, such as GSR sensors. Scientists accept stress as a significant contributor to several health issues, some of which can be fatal if undetected [137].

Depending on the time, stress can be classified into three categories: acute stress, episodic acute stress, and chronic stress. Acute stress goes away fast, while chronic stress persists for a long time [138].

The analysis of medical signals is typically complex, especially when long-term signal recordings are involved. To identify relevant signal features, a variety of signal processing techniques are employed. A supervised classifier, or cluster analysis, is directly fed the values of the collected features. By categorising these bio signals, medical professionals can read the signals more effectively and provide the proper care [139].

Computers learn from previous work in the field of machine learning, using computational techniques to extract knowledge from data without explicit programming or reliance on a pre-defined formula. The system uses both supervised and unsupervised learning methods to acquire knowledge. Unsupervised learning involves the machine identifying a pattern in unlabelled input data. Choosing the best machine learning algorithm for model training can be challenging; therefore, the experimental method is commonly used to identify the most effective algorithm. The first step in building a machine learning algorithm is to clean the data and apply various preprocessing techniques to improve the data. This stage ensures better algorithm performance. The next stage is feature extraction, where the machine learning algorithm is given the descriptive features that have been extracted from the data [137].

Skin conductivity (electrodermal activity or EDA) data is categorised using the K-Nearest Neighbours (KNN) method based on its similarity to labelled samples to identify stress. EDA signals have characteristics such as signal entropy, mean conductivity and derived peaks. By calculating distances (such as Euclidean) between a fresh sample and stored data points, the technique places the sample in the majority class of its k nearest neighbours. Although KNN is efficient and straightforward for stress detection, it can be computationally expensive on large datasets and sensitive to unimportant factors. To achieve accurate classification, k-value tuning and feature selection must be done correctly.

To identify stress, the Convolutional Neural Network (CNN) technique automatically learns patterns in skin conductance (also known as electrodermal activity, or EDA) signals by using convolutional layers to identify spatial and temporal patterns, in contrast to traditional techniques that require manual feature extraction. CNNs process raw EDA signals. These layers use filters to extract essential features, which are then sent through pooling layers to increase computational efficiency and reduce dimensionality. The extracted features are categorised into weighted and unweighted groups by fully connected layers.

Artificial neural networks with numerous layers are used in deep learning, a form of machine learning, to automatically identify patterns in massive data sets. It excels at analysing complex, high-dimensional data, such as physiological signals.

## 4.2 Methods

A wearable is used to collect the stress data from the subjects during squatting to assess the biodata metrics involved in manual handling tasks. The wearable has two electrodes to measure undetectable electrical voltage from the skin, which are connected to a dedicated smartphone. Researchers then collect the data to train several machine learning (ML) models. These models were then tested to identify the best option based on computational parameters such as execution time and memory usage.

The wearable used in the Obuda University laboratories is described in section 3.2. A total of 13 people (12 men and 1 woman) with no history of upper extremity MSDs volunteered for this study.

The specialist then evaluated the data annotation. The specialists identify the tests and the data of each exercise sequence according to their intrinsic properties, labelling the exercise without stress as 1 and the exercise under stress conditions as 2. Thus, the presence of stress when its value is 2 and the absence of stress when it is 1.

### 4.2.1 Wearable Design

The design of the wearable experiment is a detailed representation of all its systems and the steps to determine the presence of stress. The created design utilises several phases, as shown in Figure 32.

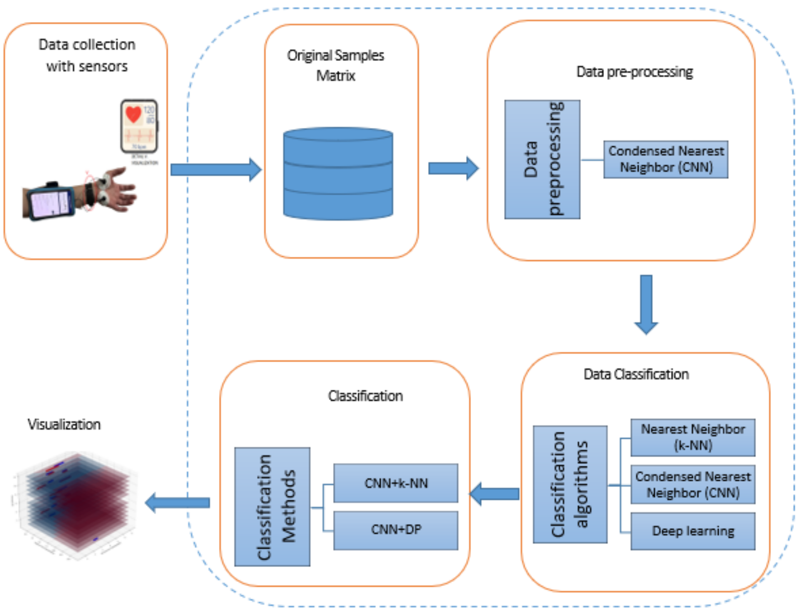


*Figure 32 Developed experiment to determine the presence of stress*

### 4.2.2 Preparing Data

The squat session begins when the electronic device detects skin conductance. Machine learning models can be affected by outliers, which are samples that show errors and drift, even with calibrated sensors. We therefore adopted two different strategies to identify and remove outliers [140]. Condensed Nearest Neighbour (CNN) is an algorithm that keeps the points closest to the edge points of the decision boundary in the first method, known as the prototype selection technique [141]. The use of models for the detection of outliers is the second method. These models can identify data that differs from the rest in terms of distribution. In this approach, unsupervised analysis is performed, and the model determines which samples should be removed. An approach called One-Class SVM (OSVM) detects the density of the majority class and labels instances at the extremes of the density function as outliers [142].

### 4.2.3 Classification Algorithms

The methods have embraced the following classification: (i) A new instance's distance from a training base is calculated using the k-nearest Neighbour (k-NN) algorithm, which then allocates it to the closest group according to its association. (ii) The following models use the Convolutional Neural Network (CNN) algorithm, which finds patterns in images to recognise objects, classes, and categories. This means that any data can be used with it. (iii) Deep learning to detect pattern data using fully connected neural network designs.

## 4.3 Results

The wearable should have a memory to store participants' data, export it and apply appropriate machine learning models that can test, identify and classify stress. To differentiate between stress and non-stress conditions, models have been developed using supervised learning.

### 4.3.1 K-Nearest Neighbours (KNN)

The K-Nearest Neighbours (KNN) technique was used to discriminate between stress and non-stress conditions using the μS variable. Cross-validation, performed after scaling the data, yielded accuracy scores ranging from 41.37% to 73.56%, with a mean accuracy of 56.06% and a standard deviation of 11.44%. The results presented in Table 33 suggest that the accuracy of the model was moderate, although it was able to discriminate between different levels of stress to some extent. To facilitate understanding of the categorisation results, a confusion matrix and a decision boundary visualisation were also produced.

*Table 33KNN Classifier Results for Performance on Stress Detection*

| Features | k | Test Accuracy | CV Mean Accuracy | Non-Stress Precision | Stress Precision |
|---|---|---|---|---|---|
| μS + relative seconds | 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| μS only | 10 | 0.6629 | 0.6549 | 0.6416 | 0.6994 |

The model showed a slight bias towards more reliable detection of stress states when using μS alone. It was more accurate in detecting stress situations (69.94%) compared to non-stress conditions (64.16%).

### 4.3.2 Convolutional Neural Network (CNN)

The convolutional neural network (CNN) model demonstrated highly predictive characteristics, achieving 100% accuracy in identifying stress levels from skin conductance data and relative time. With 5,469 true negatives, 5,136 true positives, and zero false classifications, the confusion matrix verified flawless classification. The model showed a good fit, converged rapidly, and the loss fell below 0.001 within fifty cycles, as shown in Table 34. To pre-process the data, participants 7 and 13 were eliminated, time was converted to relative seconds, features were standardised, and a 70/30 train-test split was applied while maintaining class balance.

*Table 34 Convolutional Neural Network accuracy on stress detection*

| **Metric** | **Non-Stress** | **Stress** | **Note** |
|---|---|---|---|
| Precision | 1.00 | 1.00 | |
| Recall | 1.00 | 1.00 | |
| F1-Score | 1.00 | 1.00 | |
| Support | 5,469 | 5,136 | Number of test samples |
| **Overall Accuracy** | **1.00** | | **100% accuracy on test data** |

### 4.3.3 Deep Learning

The deep learning model achieves 100% classification accuracy by effectively differentiating between stress and non-stress conditions using skin conductance data. Following the exclusion of participants 7 and 13, the final dataset comprised 35,350 samples, exhibiting a balanced distribution of 18,230 non-stress and 17,120 stress samples, a reduction from its original 13 participants. The absence of false positives and false negatives, coupled with the presence of 5,469 true negatives and 5,136 true positives, was further validated by a confusion matrix that demonstrated impeccable categorisation. A notable conclusion was that the µS measurement (importance: 0.2233) was less predictive than relative time (importance: 0.7058). This finding indicates that temporal patterns in skin conductance are significant for the detection of stress. The model attained an optimal ROC AUC score of 1.0, thereby demonstrating its remarkable capacity to differentiate between stress and non-stress conditions accurately.

### 4.3.4 KNN and Deep Learning

The Deep Learning model and the K-Nearest Neighbours (KNN) model with k = 1 both obtained 100% accuracy and a Receiver Operating Characteristic Area Under the Curve (ROC AUC) of 1.0, thereby demonstrating flawless classification of stress and non-stress states. Due to its superior simplicity, speed, and interpretability, the KNN model is a favourable option for simple applications. Furthermore, the evaluation of feature importance in the Deep Learning model revealed that relative time (0.7058 important) emerged as a superior predictive metric compared to the µS measurement (0.2233 importance). This finding underscores the critical role of temporal patterns in skin conductance data in the identification of stress, as shown in Table 35.

*Table 35 KNN and Deep Learning for stress detection*

| **Aspect** | **Finding** |
|---|---|
| **Model Accuracy** | Both KNN and Deep Learning achieved 100% accuracy (1.0000). |
| **ROC AUC Score** | Both models reached an AUC of 1.0000. |
| **Interpretability** | KNN: High interpretability and simplicity; Deep Learning: More complex, but provides feature importance insights. |
| **Feature Importance** | Deep Learning highlighted that **relative_seconds** (0.7058) is more influential than **µS** (0.2233). |
| **Overall Comparison** | Both models perform equally well, achieving perfect classification results on this dataset. |

### 4.3.5 Comparison Of Machine Learning Methods for Stress Detection

After comparing machine learning models for stress detection, CNN and KNN + DL outperformed the others, achieving nearly perfect accuracy with an $R^2$ score of 0.9996, mean square error (MSE) of 0.0031, and mean absolute error (MAE) of approximately 0.035, as illustrated in Table 36. This suggests that these models are almost accurate in predicting stress levels. Although it had a slightly lower $R^2$ (0.99993) and slightly larger errors (MSE = 0.0053, MAE = 0.0458), the KNN model also performed well. The SVR (Deep Learning) model, on the other hand, did not perform well on this dataset, as evidenced by its negative $R^2$ score (-0.0397) and large prediction errors (MSE = 7.9388, MAE = 2.1218).

*Table 36 Comparison of Machine Learning Methods on Stress Detection*

| **Method** | **Mean Squared Error (MSE)** | **Mean Absolute Error (MAE)** | **R² Score** | **Rank** |
|---|---|---|---|---|
| KNN + DL | 0.0031 | 0.0358 | 0.9996 | 1 |
| CNN | 0.0031 | 0.0352 | 0.9996 | 2 |
| KNN | 0.0053 | 0.0458 | 0.9993 | 3 |
| SVR (Deep Learning) | 7.9388 | 2.1218 | -0.0397 | 4 |

The 3D visualisation of stress classification data in Figure 33 shows the relationship between skin conductance measurements. Each layer corresponds to a different participant, while the z-axis shows the skin conductance response (SCR) as an indicator of physiological stress levels. Red areas represent stress, while blue areas represent non-stress states. This structured pattern shows the models that achieve 100% classification accuracy. A highly significant link between the variables under analysis was indicated by the incredibly small p-value ($6.847 \times 10^{-1026}$) obtained from the Chi-square test.

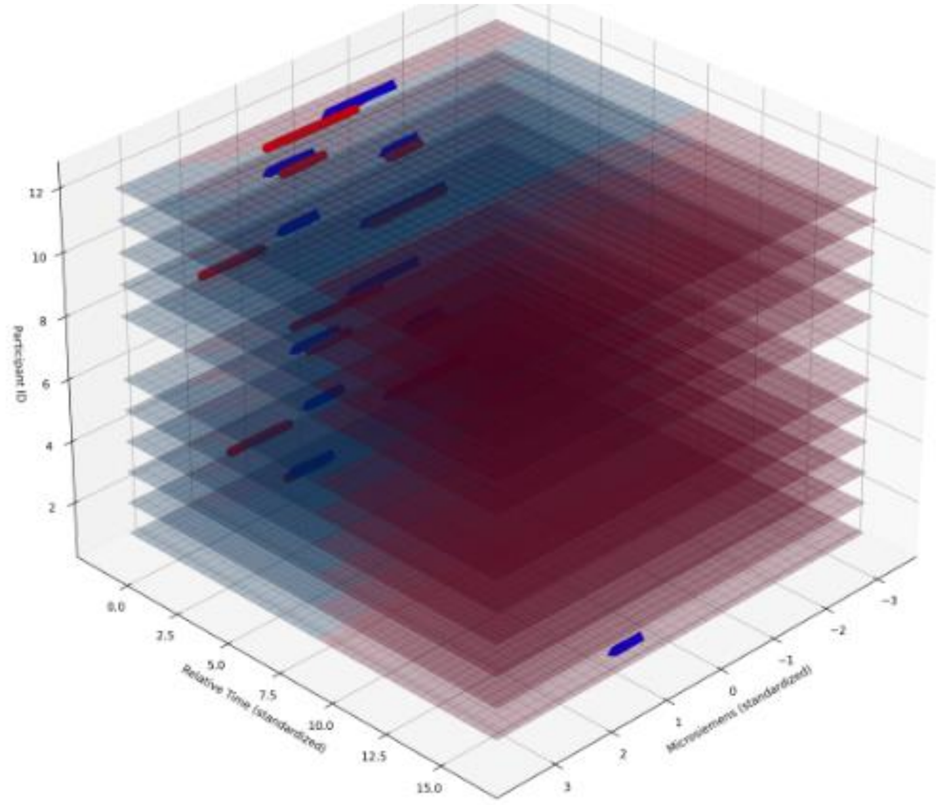


*Figure 33 Stress classification 3D model*

## 4.4 Discussion

Using skin conductance (µS) and relative temporal features, this study investigated how well different machine learning models classified stress and non-stress scenarios. K-Nearest Neighbours (KNN), Convolutional Neural Networks (CNN) and Deep Learning models were all presented and compared[143], [144].

The KNN model showed reasonable classification accuracy, with cross-validation scores ranging from 41.37% to 73.56%, with a mean of 56.06% and a standard deviation of 11.44%. There was a small bias in the confusion matrix to identify stress states (69.94%), as opposed to non-stress states (64.16%). On the other hand, KNN achieved 100% accuracy when both relative seconds and µS were used as functions. This suggests that the model works best when the data set is appropriately scaled and organised in accordance with the behaviour of the studies about accuracy [134], [143].

In comparison, the CNN and deep learning models performed better, classifying everything perfectly with 100% accuracy. There were no false positives or false negatives because of the CNN model's successful differentiation of stress levels. The fact that the

CNN converged quickly - the loss value fell below 0.001 in 50 cycles - was a key finding. The importance of relative time (0.7058) in stress classification was also shown by deep learning approaches to be greater than that of μS (0.2233). This emphasises the importance of temporal patterns in stress detection [137].

The best model, according to the comparison in the study, as indicated (Table 36), was KNN + deep learning, followed by CNN. The low prediction errors of these models (MSE = 0.0031, MAE = 0.035) allowed them to achieve an R2 value of 0.9996. The single KNN model had slightly larger errors (MSE = 0.0053, MAE = 0.0458), but still performed well. However, the SVR-based Deep Learning model fell short with a negative R2 score (-0.0397) and significant prediction errors (MSE = 7.9388, MAE = 2.1218).

The findings demonstrate the efficiency of machine learning in stress detection, mainly when temporal features are used. Additionally, supporting the robustness of the findings was the Chi-square test, which verified a very significant association between the variables under study ($p=6.847e^{-1026}$).

By integrating the machine learning models created in this study into wearable technology, they can be implemented in practice and used to assess stress in real time during manual handling tasks. When signs of excessive stress are detected, interventions such as task modification or rest periods can be initiated to minimise the risk of musculoskeletal disorders (MSDs) and reduce fatigue. The results of the combined model can also inform managerial decisions and long-term ergonomic improvements.

## 4.5 Main contributions

The study provided a comprehensive assessment of the advantages and disadvantages of KNN, CNN and Deep Learning models by methodically comparing their performance using skin conductance (μS) and relative time data. The study's findings highlighted the importance of temporal patterns in physiological stress detection, with relative time (0.7058) being a more significant predictor of stress than μS (0.2233), as revealed by feature importance analysis. The CNN and deep learning models demonstrated their applicability for high-fidelity stress classification by achieving 100% accuracy, no false positives and fast convergence (loss < 0.001 in 50 cycles).

The study presented detailed performance metrics (MSE, MAE, and R2) that demonstrated the superior predictive performance of KNN + Deep Learning models (R2

= 0.9996). With a highly significant p-value of $6.847 \times 10^{-1026}$, the Chi-square test was used to validate the models' dependability.

- **Thesis (T4):** In a controlled laboratory setting with 13 participants, comparing the 4 most common machine learning models for stress data classification, I have proved that KNN+Deep Learning models have the highest level of accuracy of 100%, showing 0.9996 as $R^2$ (coefficient of determination) and a p-value of $3.66e^{-06}$ for stress detection.

Own publications related to this chapter: [134], [135]

# 5 CONCLUSIONS

The contributions and innovations presented in the thesis are presented in this section. It highlights the significance of the study and reinforces its impact on the advancement of occupational safety and health (OSH). This section focuses on summarising the research objectives, the novelty of the approach and how the results validate the hypotheses outlined at the beginning of the study.

## 5.1 Novelty

My thesis explores a novel approach to understanding and addressing muscle and bone problems that occur during physical activities (MSDs), focusing on the stressors associated with work. While previous studies have primarily focused on biomechanical or physical ergonomic factors, this research uniquely integrates psychosocial factors, such as worker control, conflict resolution and scheduling, into the evaluation of workplace safety risks. This complete approach to thinking about MSDs makes a new definition. It goes beyond thinking about physical strain to include thinking about stress that is cognitive and emotional. These factors have a significant impact on how well workers perform their jobs and how they feel.

In my thesis, I have presented an analysis of distractions influenced by psychosocial factors in manual handling aimed at preventing MSD in the workplace. The approach is novel, as occupational safety and health (OSH) targets workplace risk issues that are both psychological and physical [145]. To prevent workplace accidents, organisational structures will be strengthened, and the integration of ergonomic concepts with safety standards will be highlighted. A comprehensive and integrative approach to occupational safety and health (OSH) focusing on physical and psychological risk factors is presented. This study examines the influence of cognitive and psychological factors, such as mental workload and stress, on the effectiveness of manual handling tasks. The psychosocial stressors can act as distractors, impairing workers' ability to maintain proper ergonomic techniques and increasing the risk of injury. By examining these elements, the research highlights a critical but often overlooked link between mental and physical well-being in the workplace.

A significant contribution of my thesis is the development and application of a hybrid methodological approach that combines a PRISMA-based systematic review with meta-analytic correlation analysis and multicriteria decision-making techniques (AHP and

BWM). This integration allows for the quantitative synthesis of data and the subjective prioritisation of risk factors as perceived by workers, providing a dual perspective that has not been used in this context before. Additionally, the use of wearable biophysical galvanic skin response and heart rate monitor sensors to assess real-time physiological responses during manual tasks is a novel, minimally invasive method of evaluating stress-induced fatigue.

To prevent musculoskeletal disorders (MSDs), in my thesis, I examined physical ergonomics, psychological demands, and cognitive load to improve worker performance and safety, particularly in manual handling. The research uses an evidence-based methodology and tools, including the NIOSH lifting equation and systematic literature reviews, to identify key ergonomic issues. This contribution to the body of occupational safety and health knowledge will enhance the ability to develop comprehensive, human-centred safety measures that prioritise the physical and mental well-being of workers. In addition, I presented an analysis based on the lightweight machine-learning model to detect proper ergonomic squatting techniques during manual handling tasks. This application of machine learning is innovative because it provides real-time, data-driven insights into workers' posture and movements to prevent injuries proactively by offering immediate feedback or corrective measures, a step beyond traditional observational ergonomics.

To address occupational safety challenges, the systematic use of tools such as the Analytic Hierarchy Process (AHP) allows research to categorise and prioritise neurocognitive and psychosocial factors based on worker perceptions. The APH method provides a structured decision-making framework in line with the best-worst method, ensuring that the most impactful stressors and distractors in manual handling tasks are systematically identified and ranked, enabling targeted interventions.

Finally, the integration of laboratory stress measurement during lifting tasks ensures that theoretical findings are consistent with industrial conditions, tasks that have been proven through validation in controlled, real-world simulations. This approach bridges the gap between theoretical research and practical application. By combining systematic reviews, worker-centred categorisation techniques and advanced computational tools, the study sets a new standard in occupational health research, emphasising precision and adaptability.

My thesis contributes to scientific knowledge by confirming the relationship between psychosocial stressors and muscle activity reduction (SMAR). Correlation analysis revealed a statistically significant association ($r = 0.480$, $p < 0.001$), providing robust evidence that psychosocial factors can directly affect physiological performance during repetitive lifting tasks. The study recorded an increase in heart rate of 65.79%, from 76 to 126 beats per minute. This indicates that task demands have a significant impact on the autonomic nervous system. Skin response, as represented by peak impedance, showed a significant difference between stress and non-stress conditions, with mean values of 8.13 μS and 6.62 μS, respectively. These results support the hypothesis that unmanaged stress contributes to the early onset of fatigue and increases the risk of musculoskeletal disorders (MSDs). In addition, the thesis illustrates the practical application of machine learning in occupational health, applying stress classification models (KNN, CNN, and deep learning algorithms) to collected physiological data. This innovative application of artificial intelligence facilitates the prediction of stress patterns and the detection of risk, establishing the basis for intelligent, technology-driven interventions in workplace design and management of workloads. These findings represent an advance for the field through the establishment of a measurable, physiological link between workplace stressors and musculoskeletal performance decline.

## 5.2 New scientific results

My research aimed to demonstrate the importance of making workplaces more comfortable in preventing and reducing work-related illnesses, such as musculoskeletal disorders (MSDs), particularly in situations involving manual handling. Additionally, it explored how psychosocial factors influence neurocognitive elements in the NIOSH (National Institute for Occupational Safety and Health) MSD prevention equation.

Therefore, my new scientific results are as follows:

- **Thesis (T1):** With a systematic PRISMA literature review and using a correlation analysis of the studies (which presented an index $r = 0.480$ and $p < 0.001$), I proved that psychosocial distractor factors, mainly worker control, conflict resolution, and scheduling, induce mental stress causing muscular activity reduction (SMAR), which has a direct impact on the risk of musculoskeletal disorders (MSDs) in manual handling.

- **Thesis (T2):** By applying MCDM to categorize the psychosocial factors in a sample of 283 participants (185 men and 98 women), with a 95% confidence level and 5.83% margin of error, I proved that 'Worker control' is the main psychosocial category affecting manual handling tasks since its weight of importance is 67.42% in the AHP method (CI: 0.065), and cross-validated by the BWM at 68.52% (${ks_i}^*$: 0.13). And inside the 'Worker control' class 'Overcontrol' is the most important factor with 71.72% in the AHP method (CI: 0.071), cross-validated by 71.43% in the BWM method (${ks_i}^*$: 0.159).
- **Thesis (T3):** Applying a bio data (GSR and BPM) system in a controlled laboratory setting with 13 participants. I proved that the 'Overcontrol' psychosocial risk factors introduced during manual handling tasks produce a variation in the autonomous nervous system response, generating a heart rate mean increase from 76 to 126 beats per minute, thus a higher mean of GSR under a stressful environment with a $p < 0.01$. The Skin response represented by the peak impedance mean significantly different under stress and non-stress conditions with impedance values of 8.13 µS and 6.62 micro µS, respectively.
- **Thesis (T4):** In a controlled laboratory setting with 13 participants, comparing the 4 most common machine learning models for stress data classification, I have proved that k-NN+Deep Learning models have the highest level of accuracy of 100%, showing 0.9996 as $R^2$ (coefficient of determination) and a p-value of 3.66e-06 for stress detection.

## 5.3 Recommendations

Industries need to take a methodical and structured approach to address the psychological and physical risk factors that affect the health and well-being of their employees. Prioritising the integration of ergonomic principles into workplace operations and design is essential. This involves reducing musculoskeletal disorders (MSDs) by using tools such as the NIOSH lifting equation and teaching employees safe manual handling practices. Additionally, industries should leverage technology, such as machine learning models, to monitor workplace ergonomics and ensure proper techniques are used during manual handling tasks.

To mitigate the detrimental consequences of overcontrol on manual handling tasks, companies should concentrate on enhancing employee autonomy and modernising management procedures. This can be achieved through participatory decision-making, which gives workers autonomy in task completion, and by educating managers on leading with cooperation rather than micromanagement or overcontrol.

Future research should investigate how Psychosocial factors associated with manual handling tasks may be affected after prolonged exposure. It should also focus on the use of advanced technologies, such as wearable sensors, AI-based ergonomic assessments and augmented reality tools, to provide real-time feedback and improve workers' posture and movement during manual tasks.

Future studies should use larger and more varied samples of participants to validate the machine learning models and apply them in real employment settings. This would involve incorporating the models into mobile or wearable platforms and assessing their performance in providing managers and employees with real-time feedback. Studies should also investigate the long-term effects of such systems on reducing psychosocial stress and preventing musculoskeletal disorders (MSDs), as well as issues with user acceptance, data privacy, and alert fatigue.

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# LIST OF ABBREVIATIONS

AM. *Asymmetric Multiplier*

CM. *Coupling Multiplier*

DM. *Distance Multiplier*

FM. *Frequency Multiplier*

HM. *Horizontal Multiplier*

HPA. *hypothalamic-pituitary-adrenal*

ILO. *International Labour Organisation*

LBP. *low back pain*

LC. *Load Constant*

MCDM. *multicriteria decision-making*

OSVM. *One-Class SVM*

SMAR. *stress and muscular activity reduction*

VM. *Vertical Multiplier*

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# APPENDIX

*ANNEX A Ethical approval*

ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

Bánki Donát Gépész és
Biztonságtechnikai Mérnöki Kar,

Budapest, 2022. november 28.

**ETIKUS KUTATÁSI NYILATKOZAT**

*Alulírott Prof. Dr. Rajnai Zoltán egyetemi tanár, az Óbudai Egyetem Bánki Donát Gépész és Biztonságtechnikai Mérnöki Kar dékánja nyilatkozom, hogy*

*Vanessa Cristina Erazo Chamorro PhD hallgató*
*„Safe & Healthy workplace"*

*című kutatásait a Biztonságtudományi Doktori Iskola keretei között, támogatott kutatásként végzi. Kutatásai során etikus módszereket alkalmaz, amelyet Dr. Szabó Gyula kutatásvezető figyelemmel kísér.*

ÓBUDAI EGYETEM Bánki Donát Gépész és Biztonságtechnikai Mérnöki Kar * Budapest

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*ANNEX B Stress factors grouping*

| No | GROUP OF FACTORS | MENTIONS | CATEGORY | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | inadequate social support | | Management practices | | | Lack of security | | |
| 2 | Bad management style | | Management practices | | | | | |
| 3 | bad organisational characteristics (such as climate, culture, and communication | | Management practices | Physical Work Environment | | | | |
| 4 | conflict resolution/bad interpersonal interaction | 3 | | | Interpersonal interaction | | | |
| 5 | decision making | | | | | | | |
| 6 | diversity | | | | | | | |
| 7 | inadequate management style/inadequate management practices | | Management practices | | | | | |
| 8 | insecurities concerning career | | | | | Lack of security | | |
| 9 | insecurity | | | | | Lack of security | | |
| 10 | job mobility | | | Physical Work Environment | | | | |
| 11 | machine-paced/pacing | 2 | | Physical Work Environment | | | | |
| 12 | negative values (technology, employee growth/development, and valuing the individual | | Management practices | | Interpersonal interaction | | | |
| 13 | no sense of belonging | | | | | | | |
| 14 | non-participation | | Management practices | | | Lack of security | | |
| 15 | organizational effectiveness | | Management practices | | | | | |
| 16 | Perceived stress was continuous improvement at work/pressure to improve your skills. | | | | | | | Worker over control |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 17 | physical environment | | | Physical Work Environment | | | | |
| 18 | quantitative workload/overload | 2 | Management practices | | | | | |
| 19 | resource inadequacy | | Management practices | | | | | |
| 20 | role ambiguity | 2 | Management practices | | | | | |
| 21 | scheduling/shift work/night working | 4 | Management practices | | | | | |
| 22 | task complexity/job demand/stressful job/hazardous job/concentration demand | 2 | | | | | Complexity/job demand | |
| 23 | underutilization | | Management practices | | | | | |
| 24 | worker control/control over tasks/supervision | 3 | | | | | | Worker over control |

# Stressors

My name is Vanessa Erazo, and I am researching at the Safety and Security doctoral school. You are invited to take part in a research study. The purpose of the study is to determine the psychosocial factors or stressor parameters that affect manual handling activities and how they affect a workplace to rate whether it is safe and healthy.

As part of my data collection procedures, I am soliciting voluntary participation from you. This means you may choose to participate or not. You will be asked to answer a survey about psychosocial stressors categorization.

All information will be kept anonymous and confidential. This means that your name will not appear anywhere and no one except me will know about your specific answers. In my writing or any presentations, I will use a made-up name or code for you, and I will not reveal identifying details about you. The data will be used only in the context of the study.

The benefit of this research is that you will be helping to identify elements like stress, workload, time pressure, or interpersonal conflicts that may negatively impact workers' health, safety, and productivity. If you have any questions about participation in this study, you may contact me at erazo.vanessa@uni-obuda.hu

This study was approved by the Ethical Review Board of Banki Faculty. If you agree to participate in this research study after fully reading and understanding the statements above, please mark the box below to indicate your acceptance to participate.

* Indica que la pregunta es obligatoria

1. I confirm that I received the necessary information about the research and I consent to the publication of my answers without any data that could identify to me.(Confirmo que recibí la información necesaria sobre la investigación y doy mi consentimiento para la publicación de mis respuestas sin ningún dato que pueda identificarme.) *

   *Marca solo un óvalo.*

   ◯ Yes. (Si)

2. Age. (Edad)

*Marca solo un óvalo.*

- 15-18 years old
- 19-26 years old
- 27-35 years old
- 36-46 years old
- 46-54 years old
- over 55 years old

3. Choose the continent where you were born (Where your country is from?):. ( Elige el continente donde naciste (¿De dónde es tu país?):

*Marca solo un óvalo.*

- Africa
- Europe
- America
- Asia
- Oceania

4. Gender. (Genero)

*Marca solo un óvalo.*

- Female. (Femenino)
- Male. (Masculino)
- Other. (Otro)

5. Education. (Educación)

*Marca solo un óvalo.*

- PhD. (Doctor)
- MSc. (Master o Magister)
- BSc. (Ingeniero, licencido,etc)
- Other(Otro)

Lifting loads/ levantamiento de cargas

6. 1. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Worker Control / Control Over Tasks / Supervision ( Eg: Timing control alarms, Remote Supervision, Over control) in comparison to Conflict resolution / bad interpersonal interaction (Eg: Wrong conflict resolution way, Not balance between, instructions vs punishment, Not clear instructions)

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | | | | | | | | | | very relevant |

Stressors

7. 2. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Worker Control / Control Over Tasks / Supervision ( Eg: Timing control alarms, Remote Supervision, Over control) in comparison to Scheduling / shiftwork / night working (Eg: Early morning task, Midday task, Late night task). *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

stressors

8. 3. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Conflict resolution / bad interpersonal interaction (Eg: Wrong conflict resolution way, Not balance between, instructions vs punishment, Not clear instructions) in comparison to Worker Control / Control Over Tasks / Supervision ( Eg: Timing control alarms, Remote Supervision, Over control). *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

Sección sin título

9. 4. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Conflict resolution / bad interpersonal interaction (Eg: Wrong conflict resolution way, Not balance between, instructions vs punishment, Not clear instructions) in comparison to Scheduling / shiftwork / night working (Eg: Early morning task, Midday task, Late night task). *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

Sección sin título

10. 5. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Scheduling / shiftwork / night working (Eg: Early morning task, Midday task, Late night task) in comparison to Worker Control / Control Over Tasks / Supervision ( Eg: Timing control alarms, Remote Supervision, Over control). *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

Sección sin título

11. 6. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Scheduling / shiftwork / night working (Eg: Early morning task, Midday task, Late night task) in comparison to Conflict resolution / bad interpersonal interaction (Eg: Wrong conflict resolution way, Not balance between, instructions vs punishment, Not clear instructions) *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

Worker Control / Control Over Tasks / Supervision

12. 7. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Timing control alarms (e.g. Pomodoro Timer, Shift Change Alarms, countdown Timer ) in comparison to Remote Supervision ( e.g: Management Platforms, Performance Dashboards )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

13. 8. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Timing control alarms (e.g. Pomodoro Timer, Shift Change Alarms, countdown Timer ) in comparison to Over control ( e.g: Bossy Supervisors, Checking in on every small detail of a task, Rigid Task Instructions, requiring workers to submit constant progress )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

14. 9. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Remote Supervision ( e.g: Management Platforms, Performance Dashboards ) in comparison to Timing control alarms (e.g. Pomodoro Timer, Shift Change Alarms, countdown Timer )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

15. 10. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Remote Supervision ( e.g: Management Platforms, Performance Dashboards ) in comparison to Overcontrol ( e.g: Bossy Supervisors, Checking in on every small detail of a task, Rigid Task Instructions, requiring workers to submit constant progress )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

16. 11. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Overcontrol ( e.g: Bossy Supervisors, Checking in on every small detail of a task, Rigid Task Instructions, requiring workers to submit constant progress ) in comparison to Timing control alarms (e.g. Pomodoro Timer, Shift Change Alarms, countdown Timer )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

17. 12. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Overcontrol ( e.g: Bossy Supervisors, Checking in on every small detail of a task, Rigid Task Instructions, requiring workers to submit constant progress ) in comparison to Remote Supervision ( e.g: Management Platforms, Performance Dashboards )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

Conflict resolution / bad interpersonal interaction

18. 13. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Wrong conflict resolution way (e.g. Avoiding the Issue, Avoiding the Issue, Imposing Solutions ) in comparison to Not balance between, instructions vs punishment ( e.g: Reactive Punishment, Public Shaming, Punishment for Unclear Expectations)? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

19. 14. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Wrong conflict resolution way (e.g. Avoiding the Issue, Avoiding the Issue, Imposing Solutions ) in comparison to Not clear instructions ( e.g: Inconsistent Communication, Lack of Written Guideline, Assuming Knowledge )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

20. 15. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Not balance between, instructions vs punishment ( e.g: Reactive Punishment, Public Shaming, Punishment for Unclear Expectations) in comparison to Wrong conflict resolution way (e.g. Avoiding the Issue, Avoiding the Issue, Imposing Solutions )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

21. 16. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Not balance between, instructions vs punishment ( e.g: Reactive Punishment, Public Shaming, Punishment for Unclear Expectations) in comparison to Not clear instructions ( e.g: Inconsistent Communication, Lack of Written Guideline, Assuming Knowledge )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | very relevant |

22. 17. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Not clear instructions ( e.g: Inconsistent Communication, Lack of Written Guidelines, Assuming Knowledge ) in comparison to Wrong conflict resolution way (e.g. Avoiding the Issue, Avoiding the Issue, Imposing Solutions )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

23. 18. In activities related to lifting loads or manual handling, on a scale of 1-9, how stressful (or relevant) do you consider the stressors defined as Not clear instructions ( e.g: Inconsistent Communication, Lack of Written Guideline, Assuming Knowledge ) in comparison to Not clear instructions ( e.g: Inconsistent Communication, Lack of Written Guideline, Assuming Knowledge )? *

*Marca solo un óvalo.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very relevant |

*ANNEX D Descriptive statistics of the categorisation of the stressors in the manual handling tasks*

| **Question** | **x̄** | **SE** | **SD** | **Var** | **γ2** | **γ1** | **CI 95%** | x̄ Africa | x̄ America | x̄ Asia | x̄ Europe | x̄ Female | x̄ Male | x̄ 15-18 | x̄ 19-26 | x̄ 27-35 | x̄ 36-46 | x̄ 47-54 | x̄ >55 | x̄ BSc | x̄ MSc | x̄ PhD | x̄ Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| How stressful do you consider the stressors defined as Worker Control / Control Over Tasks / Supervision in comparison to Conflict resolution / bad interpersonal interaction | 5.71 | 0.07 | 1.20 | 1.44 | 1.86 | -0.77 | 0.14 | 5,50 | 5,86 | 5,29 | 5,72 | 5,57 | 5,79 | 5,55 | 5,65 | 5,88 | 5,72 | 5,72 | 6,00 | 5,68 | 5,50 | 5,43 | 5,82 |
| How stressful do you consider the stressors defined as Worker Control / Control Over Tasks / Supervision in comparison to Scheduling/shiftwork / night working | 5.18 | 0.06 | 1.06 | 1.13 | 3.40 | 0.40 | 0.12 | 5,83 | 5,00 | 5,41 | 5,18 | 5,19 | 5,17 | 5,25 | 5,47 | 5,44 | 5,06 | 4,95 | 5,00 | 5,41 | 5,30 | 4,29 | 4,99 |
| How stressful do you consider the stressors defined as Conflict resolution / bad interpersonal interaction in comparison to Worker Control / Control Over Tasks / Supervision | 4.40 | 0.07 | 1.18 | 1.40 | 2.11 | 1.34 | 0.14 | 4,83 | 4,08 | 4,53 | 4,40 | 4,65 | 4,28 | 4,20 | 4,88 | 4,35 | 4,67 | 4,07 | 4,13 | 4,83 | 4,03 | 3,71 | 4,15 |

| Question | $\bar{x}$ | SE | SD | Var | $\gamma 2$ | $\gamma 1$ | CI 95% | $\bar{x}$ Africa | $\bar{x}$ America | $\bar{x}$ Asia | $\bar{x}$ Europe | $\bar{x}$ Female | $\bar{x}$ Male | $\bar{x}$ 15-18 | $\bar{x}$ 19-26 | $\bar{x}$ 27-35 | $\bar{x}$ 36-46 | $\bar{x}$ 47-54 | $\bar{x}$ >55 | $\bar{x}$ BSc | $\bar{x}$ MSc | $\bar{x}$ PhD | $\bar{x}$ Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| How stressful do you consider the stressors defined as Conflict resolution / bad interpersonal interaction in comparison to Scheduling/shiftwork / night working | 5.16 | 0.06 | 1.07 | 1.14 | 2.96 | 0.33 | 0.12 | 5,58 | 5,02 | 5,53 | 5,16 | 5,21 | 5,13 | 5,15 | 5,39 | 5,21 | 4,86 | 5,11 | 4,88 | 5,27 | 5,13 | 5,43 | 5,05 |
| How stressful do you consider the stressors defined as Scheduling/shiftwork / night working in comparison to Worker Control / Control Over Tasks / Supervision | 3.78 | 0.09 | 1.47 | 2.15 | 1.52 | 1.51 | 0.17 | 5,42 | 3,17 | 4,35 | 3,78 | 4,10 | 3,61 | 3,35 | 4,33 | 4,00 | 4,47 | 3,21 | 3,50 | 4,50 | 3,30 | 3,71 | 3,24 |
| How stressful do you consider the stressors defined as Scheduling/shiftwork / night working in comparison to Conflict resolution / bad interpersonal interaction | 5.14 | 0.06 | 0.99 | 0.99 | 3.28 | 0.50 | 0.12 | 5,25 | 5,04 | 5,65 | 5,14 | 5,14 | 5,14 | 5,35 | 5,24 | 5,03 | 5,17 | 5,07 | 5,00 | 5,27 | 4,97 | 5,14 | 5,06 |
| How stressful do you consider the stressors defined as Timing control alarms in comparison to Remote Supervision | 5.14 | 0.06 | 1.07 | 1.14 | 2.22 | 0.15 | 0.12 | 5,33 | 4,99 | 5,24 | 5,14 | 5,09 | 5,17 | 4,70 | 5,51 | 5,12 | 5,17 | 4,98 | 5,00 | 5,26 | 5,33 | 4,86 | 5,01 |

| Question | $\bar{x}$ | SE | SD | Var | γ2 | γ1 | CI 95% | $\bar{x}$ Africa | $\bar{x}$ America | $\bar{x}$ Asia | $\bar{x}$ Europe | $\bar{x}$ Female | $\bar{x}$ Male | $\bar{x}$ 15-18 | $\bar{x}$ 19-26 | $\bar{x}$ 27-35 | $\bar{x}$ 36-46 | $\bar{x}$ 47-54 | $\bar{x}$ >55 | $\bar{x}$ BSc | $\bar{x}$ MSc | $\bar{x}$ PhD | $\bar{x}$ Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| How stressful do you consider the stressors defined as Timing control alarms in comparison to overcontrol | 4.41 | 0.07 | 1.16 | 1.34 | 1.91 | 1.16 | 0.14 | 5,17 | 4,13 | 4,59 | 4,41 | 4,52 | 4,36 | 4,00 | 4,79 | 4,35 | 4,83 | 4,13 | 4,25 | 4,77 | 4,07 | 4,29 | 4,18 |
| How stressful do you consider the stressors defined as Remote Supervision in comparison to Timing control alarms | 5.72 | 0.07 | 1.16 | 1.34 | 2.64 | -0.81 | 0.14 | 6,58 | 5,87 | 5,18 | 5,72 | 5,64 | 5,75 | 5,60 | 5,53 | 5,59 | 5,64 | 5,92 | 5,75 | 5,63 | 5,40 | 4,86 | 5,91 |
| How stressful do you consider the stressors defined as Remote Supervision in comparison to Overcontrol | 3.58 | 0.08 | 1.28 | 1.63 | 3.23 | 1.90 | 0.15 | 5,17 | 3,18 | 3,76 | 3,58 | 3,69 | 3,52 | 2,95 | 4,04 | 3,62 | 4,03 | 3,23 | 3,50 | 4,06 | 3,23 | 3,00 | 3,26 |
| How stressful do you consider the stressors defined as Overcontrol in comparison to Timing control alarms | 5.21 | 0.06 | 1.05 | 1.09 | 2.24 | 0.67 | 0.12 | 5,42 | 5,07 | 5,29 | 5,21 | 5,22 | 5,20 | 5,10 | 5,41 | 5,47 | 5,14 | 5,04 | 5,00 | 5,37 | 5,43 | 4,57 | 5,05 |
| How stressful do you consider the stressors defined as Overcontrol in comparison to Remote Supervision | 5.88 | 0.06 | 0.94 | 0.88 | 4.16 | -0.78 | 0.11 | 6,08 | 6,01 | 5,12 | 5,88 | 5,74 | 5,95 | 5,65 | 6,01 | 5,74 | 5,67 | 5,93 | 6,00 | 5,72 | 6,10 | 5,71 | 5,98 |

| **Question** | **$\bar{x}$** | **SE** | **SD** | **Var** | **γ2** | **γ1** | **CI 95%** | $\bar{x}$ Africa | $\bar{x}$ America | $\bar{x}$ Asia | $\bar{x}$ Europe | $\bar{x}$ Female | $\bar{x}$ Male | $\bar{x}$ 15-18 | $\bar{x}$ 19-26 | $\bar{x}$ 27-35 | $\bar{x}$ 36-46 | $\bar{x}$ 47-54 | $\bar{x}$ >55 | $\bar{x}$ BSc | $\bar{x}$ MSc | $\bar{x}$ PhD | $\bar{x}$ Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| How stressful do you consider the stressors defined as the Wrong conflict resolution way in comparison to Not balance between instructions vs punishment | 5.01 | 0.06 | 1.01 | 1.03 | 5.28 | 1.26 | 0.12 | 5,83 | 5,04 | 5,00 | 5,01 | 4,87 | 5,09 | 5,25 | 5,28 | 4,68 | 4,78 | 4,96 | 5,13 | 5,11 | 4,60 | 4,57 | 5,05 |
| How stressful do you consider the stressors defined as the Wrong conflict resolution way in comparison to Not unclear instructions | 5.20 | 0.06 | 0.94 | 0.88 | 3.40 | 0.56 | 0.11 | 5,75 | 5,08 | 5,24 | 5,20 | 5,19 | 5,21 | 5,50 | 5,17 | 5,53 | 5,28 | 5,07 | 4,88 | 5,32 | 5,23 | 5,43 | 5,08 |
| How stressful do you consider the stressors defined as Not balanced between instructions vs punishment, in comparison to the Wrong conflict resolution way | 5.77 | 0.06 | 0.95 | 0.89 | 3.07 | -1.24 | 0.11 | 5,92 | 5,98 | 4,88 | 5,77 | 5,66 | 5,83 | 5,90 | 5,67 | 5,62 | 5,56 | 5,92 | 6,00 | 5,57 | 5,77 | 6,00 | 5,94 |
| How stressful do you consider the stressors defined as Not balanced between instructions vs punishment in comparison to Not clear instructions | 5.88 | 0.06 | 0.98 | 0.96 | 3.21 | -0.88 | 0.11 | 6,33 | 5,99 | 5,00 | 5,88 | 5,65 | 6,00 | 5,65 | 5,84 | 5,91 | 5,81 | 5,95 | 6,00 | 5,82 | 5,83 | 5,14 | 5,98 |

| **Question** | **$\bar{x}$** | **SE** | **SD** | **Var** | **γ2** | **γ1** | **CI 95%** | $\bar{x}$ Africa | $\bar{x}$ America | $\bar{x}$ Asia | $\bar{x}$ Europe | $\bar{x}$ Female | $\bar{x}$ Male | $\bar{x}$ 15-18 | $\bar{x}$ 19-26 | $\bar{x}$ 27-35 | $\bar{x}$ 36-46 | $\bar{x}$ 47-54 | $\bar{x}$ >55 | $\bar{x}$ BSc | $\bar{x}$ MSc | $\bar{x}$ PhD | $\bar{x}$ Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| How stressful do you consider the stressors defined as Not clear instructions in comparison to Wrong conflict resolution way | 5.76 | 0.06 | 1.00 | 1.00 | 2.18 | -0.90 | 0.12 | 6,17 | 5,96 | 5,12 | 5,76 | 5,66 | 5,82 | 5,80 | 5,59 | 5,68 | 5,61 | 5,93 | 6,13 | 5,57 | 5,63 | 6,29 | 5,94 |
| How stressful do you consider the stressors defined as Not clear instructions in comparison to Not clear instructions | 5.27 | 0.06 | 1.10 | 1.20 | 2.80 | 0.83 | 0.13 | 6,50 | 4,99 | 5,00 | 5,27 | 5,39 | 5,21 | 5,25 | 5,45 | 5,35 | 5,58 | 5,04 | 5,00 | 5,50 | 5,27 | 5,57 | 5,04 |

Bánki Donát Gépész és
Biztonságtechnikai Mérnöki Kar
OE-DI-206,2023

**INFORMED CONSENT FORM**

**"The Distraction Influenced by Psychosocial Factors in Manual Handling Aimed to Prevent MSD in the Workplace"**

My name is Vanessa Erazo, and I am researching at the Safety and Security doctoral school. You are invited to take part in a research study. The purpose of the study is to *Determine the psychosocial factors or stressor parameters that affect manual handling activities and how they affect a workplace to rate whether it is safe and healthy.*

As part of my data collection procedures, I am soliciting voluntary participation from you. This means, you may choose to participate or not. You will be asked to lift a load from the floor to a height of 75 cm 5 times per minute for 5 minutes. This will take approximately *ten* of your time. *For the study video- recording will be used for data analysis.*

All information will be kept *anonymous and confidential. This means that your name will not appear anywhere and no one except me will know about your specific answers. In my writing or any presentations, I will use a made-up name or code for you, and I will not reveal identifying details about you. The data will be used only in the context of the study.*

The benefit of this research is that you will be helping to *identify elements like stress, workload, time pressure, or interpersonal conflicts that may negatively impact workers' health, safety, and productivity.* If you have any questions about participation in this study, you may contact me at erazo.vanessa@uni-obuda.hu

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This study was approved by the Ethical Review Board of Banki Faculty. If you agree to participate in this research study after fully reading and understanding the statements above, please sign below to indicate your acceptance to participate.

| | | |
|---|---|---|
| ______________________ | ______________________ | __________ |
| Name of Participant | Signature | Date |
| __Erazo-Chamorro Vanessa C. ___ | ______________________ | __________ |
| Name of Principal Investigator | Signature | Date |

Participant code _____OE-BD-SSDS-PFMH-_____________

Heart rate per minute (HRM):

Non stressors included

Minutes: 1 2 3 4 5

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| | | | | |

Including stressors factors:

Minutes: 1 2 3 4 5

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| | | | | |

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I want to express gratitude to my PhD classmates for the friendship, teamwork, and experiences that have made this journey much simpler and more rewarding. Both academically and personally, the innumerable conversations, brainstorming sessions, and times of mutual support have been helpful.

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