



ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

DOCTORAL (PHD) THESIS

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Tool Sizing for Latin American People

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**DOCTORAL SCHOOL ON SAFETY AND
SECURITY SCIENCES**

Budapest, 2025. 09. 02

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INTRODUCTION

Personal motivation and interest: Since the establishment's inception, both industrial and non-industrial tasks have utilised hand tools to enhance the workers' power and achieve the required goals. In this context, during my childhood, my father worked and ran a workshop where he repaired crashed cars using various hand tools. I was his assistant and enjoyed this time, but as the years went by, I started to worry because I noticed that his hand shape and behaviour were changing due to the constant and repetitive work with these tools. I noticed that after a long shift, he was in continuous pain in his hand. In addition, my lovely cousin, who cared for me in the early years of my life, is a nurse and has worked all her life with patients and healing wounds with surgical hand tools doing repetitive tasks during the same shift, coincidentally after several years her hands had similar changes in muscle behaviour, and she suffered repeated muscle injuries. Nowadays, she has been diagnosed with a disease of the muscles and joints in her hands. On the other hand, Ecuador has special weather conditions and does not experience four distinct seasons (winter, spring, summer, and autumn) like the USA and Europe. Our location on the equator means that we only have two climate seasons: wet and dry. The weather conditions in my town are unique. Rose picking is the main activity. In this activity, workers are assigned to use hand tools or cutting hand tools to harvest roses. This repetitive task can lead to hand pain and fatigue among workers. Looking at the above situations, I felt the need to understand how these problems arise and how they can be solved or prevented.

Scientific motivation: Throughout my career, I have managed construction and automation technicians who work constantly with hand tools and who report hand fatigue during their shifts. For this reason, they request that necessary research be conducted to bridge the gap between factors contributing to hand fatigue and healthy working practices. The implications of this study are far-reaching: improving worker comfort and managing hand fatigue has the potential to improve work performance, reduce absenteeism, and reduce the risk of musculoskeletal disorders.

Actuality of the topic

The manufacturing industry is working to improve the management system and create an ideal healthy workplace, focusing on the best way to reduce accidents and maximise

resources [1], [2], [3]. Hand tools are increasingly being used as the primary tool in a wide range of industrial operations. One of the most critical control points in the industry is focused on the needs of specialised areas. Ergonomics and safety regulations are linked, as both contribute to a safe and healthy working environment. Ergonomic requirements include the design of workplaces, tools, and equipment to reduce the physical strain on workers and improve their well-being. In contrast, safety requirements concern the identification and mitigation of hazards that could contribute to accidents, injuries, or ill health. The high number of injuries each year is a significant concern for these types of businesses. By addressing ergonomic elements such as posture, equipment design, and work organisation, organisations can avoid ergonomic hazards and reduce the incidence of musculoskeletal disorders. Workers are trained to recognise and deal with ergonomic problems when ergonomic concepts are incorporated into safety practices, resulting in an integrated approach to occupational safety and health that improves worker safety, comfort, and productivity [1], [4].

Especially in sectors that depend on hand tools, ergonomics and appropriate risk management must be integrated to ensure worker safety and security. Long-term health problems and lost productivity are caused by musculoskeletal illnesses, which are exacerbated by poorly designed tools and repetitive manual labour. To reduce injuries and improve worker well-being, companies should evaluate ergonomic risks, choose the best tools, and provide appropriate training. In addition, acceptance of global safety regulations and risk-reduction strategies contributes to a decrease in workplace dangers, guaranteeing a more secure and effective setting that safeguards workers and corporate operations. To reduce the likelihood of a worker becoming ill in the future, it is necessary to assess the recurring and elemental forces during work and then design the workstation using methodical tool selection. The market's reliance on tool size will be a constraint in this situation, as tool manufacturers focus on designing for everyone, which can be challenging for specialist workers now, to reduce the possibility of getting a future illness due to the lack of a tailored device [5].

A two-stage process is used to identify management requirements. The aim of the first level is to group tasks according to the requirements of the project and application. This level involves main stages such as allocation, elicitation, analysis, specification, validation, and approval, ensuring that requirements are identified, analysed, documented, and validated before final approval. The second level consists of actions to

manage the process focuses on maintaining control over these requirements through configuration identification, baseline management, change control, library control, status accounting, and review audits to ensure consistency and traceability throughout the project lifecycle [6], [7], [8].

Industrial risk assessment tools aim to identify occupational diseases that affect different levels of the body. They are constantly refining their methods for identifying and mitigating the causes of accidents to reduce them, considering the requirements of Engineering [1], [9], [10], [11].

Industries have tracked musculoskeletal disorders in a variety of ways based on observation and workplace organisation, so tool selection is an essential feature of workplace design or organisation to reduce the possibility of future conditions [12]. Because it requires flexion and extension of the wrist, repetitive performance of the manual activity with excessive muscle effort is a serious ergonomic concern [13]. Cumulative trauma disorders of the extremities must be recognised as a serious ergonomic hazard by the ergonomics management of each factory.

According to the US Bureau of Labor Statistics, there are approximately 100,000 hand tool-related accidents per year, which illustrates the high frequency of accidents in this industry and the need to propose a viable solution strategy. The information provided relates to accidents involving hand-held power equipment and hand tools. The number of incidents and the average number of days lost due to work-related accidents involving equipment and hand tools will increase significantly between 2015 and 2021. From 59,830 cases in 2015 to 125,297 cases in 2021, equipment injuries resulted in an average of seven days lost from work. In comparison, hand tool-related injuries increased from 52,030 in 2015 to 108,903 in 2021, resulting in an average of five days off work. The total number of hand injury accidents, which includes accidents involving both equipment and hand tools, will increase from 111,860 in 2015 to 234,200 in 2021, indicating a worrying upward trend [15] - [18].

In a globalised environment, the quest for greater efficiency affects all organisational structures that seek to standardise the response to a similar activity across multiple locations. In this view, a "human reliability analysis" is used when the operator is at the centre of a cognitive process that leads to judgments, whose dependence increases the overall safety of the use of the equipment [18], [19]. Monitoring and controlling both

components of this combination to manage the "human factors" in the production process is the best way to achieve high safety standards, highlighting the need for risk prevention techniques targeted at specific hand tools.

Hand tool-related injuries, which make up a large portion of occupational incidents each year, are frequently caused by poor ergonomic practices, repetitive strain, and inadequate tool selection, which can result in long-term health risks and increased costs for businesses. Guaranteeing that ergonomic principles are followed in tool design, workstation setup, and work processes is crucial in reducing accidents, minimising musculoskeletal disorders, and improving overall worker well-being.

Physical damage caused by commonly used devices, such as pliers, hammers, chisels, and screwdrivers, as well as other hand tools, during the performance of regular work duties can be considered and classified into several groups based on the severity and medical care required, ranging from mild (Level I) to severe (Level IV). The trauma level percentage distribution is categorised by cause (cutting, machine-related, etc.). Machine-related injuries increase significantly from 11.61% to 88.2% when the trauma level rises from Level I to Level IV, whereas cut injuries fluctuate, reaching a peak of 38.39% at Level III before falling precipitously at Level IV [20].

The European Union Directive 89/391/EEC [21]. It encourages the adoption of policies to enhance employees' health and safety at work, thereby reducing the risk of job-related injuries. In addition to adherence to the mandates of numerous international standards, hand and wrist injuries account for over 17% (740 million) of total annual medical and production costs due to the above factors.

Adopting appropriate safety measures improves productivity by preventing lost workdays due to injuries, in addition to lowering the direct medical and compensation costs related to workplace injuries. It is even more critical to address ergonomic issues to create a safe and sustainable workplace as industries continue to change and strive for greater efficiency.

Occupational Safety in Hungary vs. Ecuador

Occupational safety strategies differ between Latin American and European countries due to differences in risk perception and tool use. Ultimately, workplace procedures, training methods, and technology adoption all affect worker safety outcomes, and cultural factors strongly influence these factors. Advances in technology, improvements in low-cost

manufacturing, and globalisation have been found to be strongly correlated. In Latin America, occupational safety regulations are often reactive, and with fewer resources and less emphasis on prevention, workers tend to take more risks. In contrast, proactive safety measures are typically prioritised in European countries, where they are supported by stricter regulatory frameworks and a greater focus on compliance, ensuring better risk reduction and preparedness [21], [22], [23].

Based on a culture that values personal accountability and following rules, Hungarian employees are more likely to prioritise safety and recognise possible risks, while Ecuadorian employees, who frequently deal with financial strains and less structured systems, may choose to accept or downplay risks to keep their jobs [24], [25], [26].

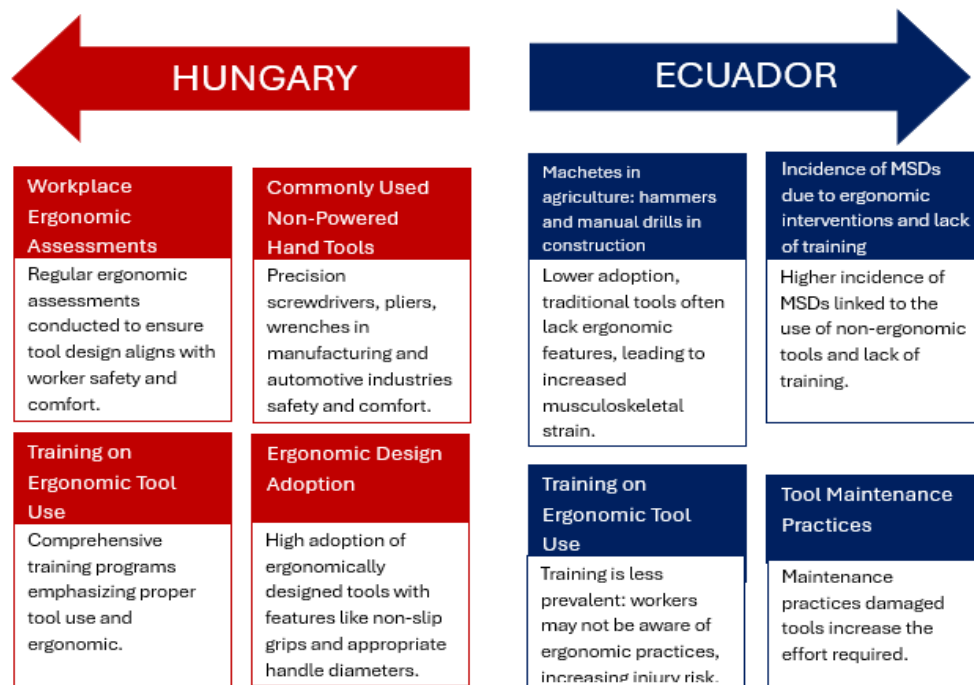


Figure 1 Occupational Safety in Hungary vs. Ecuador

In Hungary and Ecuador, non-powered hand tools exhibit significant differences in several aspects of ergonomics and occupational safety, as illustrated in Figure 1. Specifically, in Hungary, tools used in the industrial and automotive sectors are ergonomically designed with non-slip grips and optimal handle diameters. These tools are used in accordance with regular ergonomic assessments and training programmes. In contrast, in Ecuador, machetes, hammers, and hand drills are commonly used, often without ergonomic modifications and with limited assessment and training, especially in the informal sector. In contrast, machetes, hammers, and hand drills are commonly used in Ecuador, with minor ergonomic modification and limited assessment and training,

especially in the informal sector. This leads to higher rates of musculoskeletal disorders (MSDs), such as knee (7.4%) and hand (5.3%) osteoarthritis. In Hungary, regulations are in place but are not consistently enforced, and tools are not maintained, leading to a higher risk of injury [27], [28].

Older or less ergonomic equipment, more hazardous working conditions, and laxer enforcement of safety laws may all contribute to a greater awareness of potential risks in Ecuador. In addition, fewer people have access to organised training and medical care, which can make incidents seem more serious [21], [22], [23].

Formulation of the scientific problem

A complex problem requiring creative solutions at the interface of ergonomics, safety standards, tool design, workplace optimisation, and human reliability analysis. This complicated subject has several interrelated elements, each of which presents scientific difficulties and opportunities for progress. The large number of injuries that occur each year in the manufacturing industry, particularly those involving hand tools, has become a significant concern. The overall aim is to improve the management system and prevent future hand tool-related disorders.

Combining ergonomic concepts with safety requirements is a major scientific challenge. New approaches are needed to achieve a harmonious balance between designing workspaces, tools, and equipment that reduce the physical demands on workers (addressing ergonomic concerns) and identifying and mitigating hazards to prevent accidents and injuries (ensuring safety). The design of workstations requires a systematic and scientific strategy to measure recurrent and elemental forces during work. The scientific challenge is to develop effective methods for using tools in workstations, considering individual variations in tasks and applications, while meeting the varying needs of workers across multiple projects.

Hand tools are widely used in many different industries, especially in Latin America. However, there are still insufficient integrated ways to evaluate and reduce the ergonomic, physiological, and perception-related dangers associated with their repeated and prolonged use. Current procedures often overlook culturally influenced perceptions of occupational risk, the anatomical diversity of users, and the initial signs of muscle fatigue. The absence of formal examination techniques aggravates the high prevalence of musculoskeletal problems, hand injuries, and lost productivity. Specifically, there is a

lack of expert-driven frameworks for systematically classifying ergonomic hazards, culturally sensitive tools for evaluating worker risk perception are lacking, and surface electromyography (EMG) is not being used for real-time fatigue monitoring.

Understanding the physiological implications of flexion and extension of the wrist and excessive muscle effort is crucial in developing preventive measures and ergonomic management strategies to minimise the concern of cumulative trauma disorders.

Objectives

- Develop strategies and measures to prevent future hand tool-related disorders by applying cause identification.
- Establish systematic and scientific strategies for measuring forces during work and develop effective methods for the use of tools in workstations using new technology.
- Gain a comprehensive understanding of the physiological implications of repetitive manual activities on the wrist and muscles for avoiding possible degradation.

Hypotheses of the research

Hypothesis 1 (H1): Electromyography (EMG) can be used to identify the onset of muscle fatigue in individuals using hand tools by analysing changes in EMG signals during sustained gripping tasks to prevent injury and cumulative trauma disorders related to work.

Hypothesis 2 (H2): Risks associated with the use of non-powered hand tools can be effectively identified, categorised, and prioritised through the integration of individual factors using Multi-Criteria Decision-Making (MCDM) methods, by applying structured approaches like the Analytic Hierarchy Process (AHP) and the Best-Worst Method (BWM), to develop targeted risk reduction strategies that lead to a reduction in both the frequency and severity of hand-related injuries in the workplace.

Hypothesis 3 (H3): The probability of risk perception examined through the Domain-Specific Risk-Taking (DOSPERT) among users during tasks involving non-powered hand tools is significantly associated with individual factors such as previous hand-related injuries, task-specific variables such as tool complexity and duration of use, and ergonomic considerations such as tool design and workplace environment, which could lead to users experiencing hand-related disorders.

Hypothesis 4 (H4): By recording and analysing electromyography (EMG) signals from the muscles involved in using hand tools, an ML algorithm can accurately detect signs of muscle fatigue in individuals performing repetitive or prolonged manual tasks. This information can then be used to develop targeted interventions to prevent injuries and improve workplace safety.

Hypothesis 5 (H5): By training an artificial intelligence (AI) system using electromyography (EMG) data, we can teach the AI to accurately identify muscle fatigue signals and provide real-time feedback to workers, thereby improving their productivity and reducing the risk of injury.

Research methods

In preparing my thesis, I have divided my research into four parts, as shown in Figure 2. In the first part, I conducted a systematic review to determine the application methods of electromyography (EMG) and fatigue wave detection in the electromyographic response of hand muscles. In the second part, I developed a survey and data analysis to determine users' risk perceptions of different hand tool use scenarios and a country comparison to determine workers' behaviour in dealing with hand tool risks. In the third part, EMG data collection and machine learning (ML) techniques are applied to determine the muscle wave response, thereby identifying the best data identification method for AI data classification.

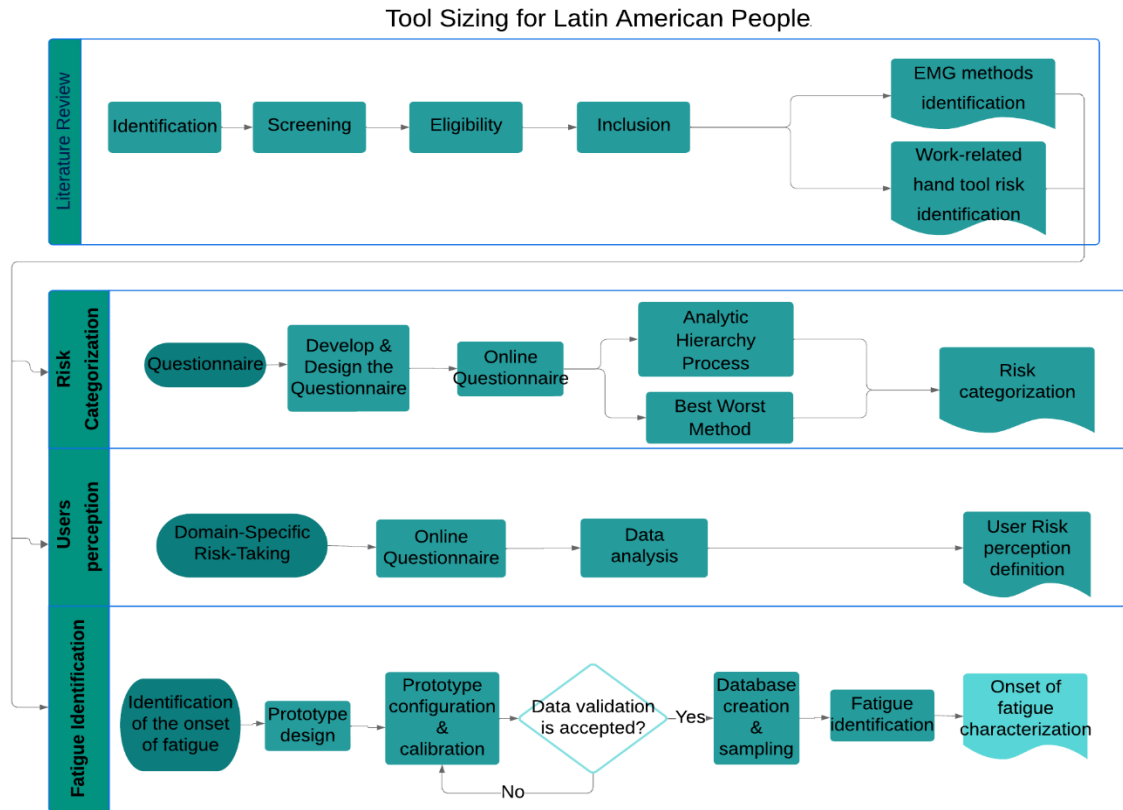


Figure 2 Tool Sizing for Latin American People Research Framework

Research limitations

The main limitations of the research are as follows: First, the variability in responses, particularly when experts are drawn from different industrial sectors or cultural backgrounds, may affect the consistency and reliability of the data used in multi-criteria decision-making methods when the categorisation of work-related risks in manual tool operation is made.

The DOSPERT scale could be limited by the fact that respondents might underreport risk-taking behaviour due to social overestimating the benefits of certain unsafe practices out of habit or necessity. Participants from different countries may interpret questions differently based on their language and workplace laws.

While EMG is a valuable tool for understanding muscle function in the hand to identify the early stages of fatigue, its limitations in directly studying nerve behaviour highlight the need for a multimodal approach that combines EMG with other techniques capable of providing a more comprehensive view of nerve control and interactions with hand muscles. In addition, a primary limitation is the indirect nature of EMG measurements. EMG records the electrical activity generated by muscle contractions, providing insight

into muscle function, but the recorded signals represent the collective output of motor units, making it difficult to isolate and analyse specific nerve behaviours.

EMG cannot distinguish between different types of nerves, such as sensory and motor nerves, limiting its ability to provide a comprehensive understanding of the neural mechanisms involved. This lack of precision limits the ability to differentiate between individual nerves or specific motor units within a muscle. In addition, studying nerve behaviour often requires invasive procedures that are not feasible in routine EMG studies. Direct insertion of electrodes into nerves or advanced imaging techniques, such as nerve ultrasound, are more suitable for studying nerve activity. However, there are ethical concerns, practical challenges, and potential risks associated with these methods that limit their widespread use.

Structure of the dissertation

The first part of this thesis presents an introductory description, presenting the formulation of the scientific problem, objectives, hypothesis, methods, and research limitations. The research continues in five chapters as follows:

In **Chapter 1**, a literature systematic review is presented to identify the methods used to apply electromyography to study hand muscle behaviour and to provide a comprehensive overview of the different techniques used to apply electromyography in other contexts and disciplines. It also includes methods for assessing and analysing risk perception and risk-benefit when using hand tools.

In **Chapter 2**, risk identification and assessment are combined with a mathematical categorisation method for risk reduction strategies. Data collected from surveys of ergonomics experts in workplaces where non-powered hand tools are used is used to determine risk grouping and categorisation to reduce hand injuries in the workplace using an Analytic Hierarchy Process (AHP).

In **Chapter 3**, the Domain-Specific Risk-Taking (DOSPERT) questionnaire is used to measure their risk perception and risk/benefit assessment of hand tool use. This study focuses on the health and safety domains relevant to the use of hand tools to gain a basic understanding of how workers in different cultural contexts perceive and evaluate the hazards associated with the use of hand tools in their unique work environments.

In **Chapter 4**, an electromyography (EMG) data collection method is specifically used to detect the onset of fatigue during hand tool use by detecting muscle electrical wave responses. Detecting the onset of fatigue during hand tool use using EMG data highlights the implications of the study for worker welfare.

In **Chapter 5**, Conclusions explain the significant contributions to the field by establishing a basic understanding and shedding light on the complex nature of risk perception in occupational settings related to the use of hand tools. The practical implications for worker well-being are underscored through the identification of fatigue onset during tool operation using EMG data and muscle electrical wave responses.

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 REVIEW OF FATIGUE AND RISK EVALUATION IN HAND TOOL USE

A comprehensive analysis of ergonomic solutions, injury prevention techniques, and biomechanical consequences in hand tool use provides an overview of the variables involved. The structured approach consists of an introduction, PRISMA methodology, presentation of results, and discussion.

1.1 Hand tools

In many professions, the use of hand tools is one of the leading causes of work-related illnesses and disorders. Uncomfortable postures and risky contact stressors are potential sources of injury. To avoid this, hand tools need to be hand-specific, considering the essential characteristics of the instrument. Excessive and repetitive use of these tools, especially when ergonomic design is unconsidered, puts users at considerable risk of developing musculoskeletal disorders (MSDs). Forceful exertions, uncomfortable wrist positions, and repeated hand movements are some of the main ergonomic risks associated with manual labour. Muscle exhaustion from such movements often leads to conditions such as De Quervain's disease, tennis elbow, tendinitis, tenosynovitis, and carpal tunnel syndrome (CTS). Collectively, these are referred to as repetitive strain injuries (RSIs) or cumulative trauma disorders (CTDs), and can result in diminished quality of life, loss of function, and chronic discomfort [29], [30].

1.1.1 Hand tools classification

Comfortably designed, effectively constructed hand tools used in balanced work environments reduce the incidence of hand and upper limb injuries. It also provides users with comfortable working conditions and high-quality products [31], [32].

The ergonomic function of the hand tool is the relationship between the characteristics of the user, the workstation, and the organisation of the task. By analysing the influence of several basic variables for each use situation, hand tools can be grouped and classified according to Table 1.

Table 1 Hand tools classification

Category	Non-Powered Hand Tools	Powered Hand Tools
Cutting Tools	Knives	Electric Saws
	Saws	Circular Saws
	Scissors	Jigsaws
	Shears	Reciprocating Saws
	Clippers	Chainsaws

	Chisels	Angle Grinders
	Axes	Power Drills
	Pliers	Impact Drivers
		Rotary Tools (Dremel)
Driving Tools	Screwdrivers	Power Screwdrivers
	Hammers	Electric Drills
	Mallets	Impact Wrenches
	Wrenches	Power Ratchets
	Spanners	Power Staplers
		Nail Guns
Holding Tools	Clamps	Bench Vises
	Vises	C-clamps
	Grips	Quick Clamps
Striking Tools	Hammers	Demolition Hammers
	Mallets	Rotary Hammers
	Sledgehammers	Power Nailers
	Mauls	Pneumatic Impact Tools
Measuring Tools	Tape measures	Laser Distance Measurers
	Rulers	Electronic Measuring Tools
	Callipers	Digital Levels
	Protractors	Ultrasonic Distance Measurers
	Levels	
	Squares	
	Gauges	
Finishing Tools	Sandpaper	Electric Sanders
	Files	Belt Sanders
	Rasps	Orbital Sanders
	Scrapers	Detail Sanders
	Planes	Power Planers
	Burnishers	Power Buffers
	Deburring tools	Rotary Polishers
Miscellaneous	Awls	Heat Guns
	Brushes	Electric Screwdrivers
	Pry bars	Electric Staplers
	Punches	

1.1.2 Hand tools selection

The risky contact shape of the tool could cause injury, so it's essential to be aware of it. Table 2 shows the main tool characteristics for the assessment criteria [25].

Table 2 Design Features Considerations in Ergonomic Hand Tools

Eligibility Parameter	Shape Device	Tool Characteristic	Handle Grip Material
Features	Adaptable and mouldable design	Lightweight structure	Enhanced grip with high-friction surface
	Smooth, non-sharp edges	Proportional dimensions for the task	Even force distribution on the handle

Way of handling the tool

Determining the job's tasks and methodology is the next step in the selection process. The physical attributes of the worker's hands are analysed in conjunction with the tool's and handle's applications to establish the tool's size for the hands [33], [34]. The fundamental safety of non-powered hand tools and the ergonomic handling of the tool are two ways to

evaluate the design features that encourage safer tool use and lower the chance of mishap or injury.

Intrinsic safety of non-powered hand tools

The proper safety measures in conjunction with inherent safety characteristics are essential for boosting efficiency, guaranteeing compliance, and enhancing overall operational efficiency and economy when choosing non-powered hand tools to lower the risk of accidents and foster safer working conditions. The best qualities of hand tools with basic security features are shown in Table 3 [26].

Table 3 Intrinsic safety aspects in non-powered hand tools.

Non-Powered Hand Tool Characteristics	Intrinsic Safety Features
Ergonomic	- Handle designed for comfort and reduced hand fatigue. - Grip surface prevents slipping for better control. - Magnetic tip ensures secure screw placement and reduces slippage. - Insulated grip enhances protection against electrical hazards.
Non-Slip	- Textured handle enhances grip and stability. - Integrated wire cutter guard prevents accidental injuries. - Anti-pinch mechanism reduces the risk of finger entrapment. - Locking joint mechanism ensures a firm and stable grip.
Retractable Utility	- Retractable blade allows safe storage and minimises accidental cuts. - Blade locking system prevents unintended movement. - Built with durable, impact-resistant materials for longevity.

Ergonomic way of handling the tool

Companies continue to invest in comfortable equipment and promote safe handling practices. Not only does this reduce workplace injuries and disorders, but it also promotes a healthier and more efficient working environment, increasing overall workplace success and well-being. The ergonomic grip of any hand tool is critical in all industrial tasks and helps workers achieve their job objectives.

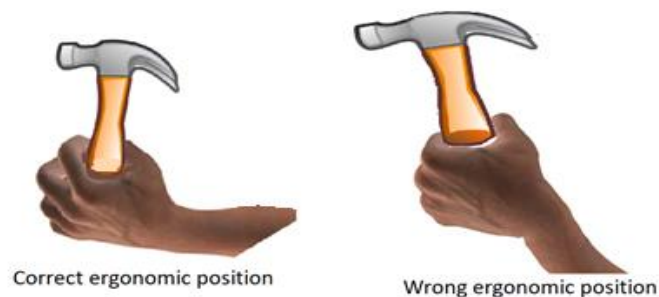


Figure 3 Power Grip.

Figure 3 shows the Power Grip, which is the style of tool holding used by both small and large hammers to provide the necessary force when striking materials. This style of holding a tool uses the entire palm to support the object, while the fingers and thumb provide the force [35].

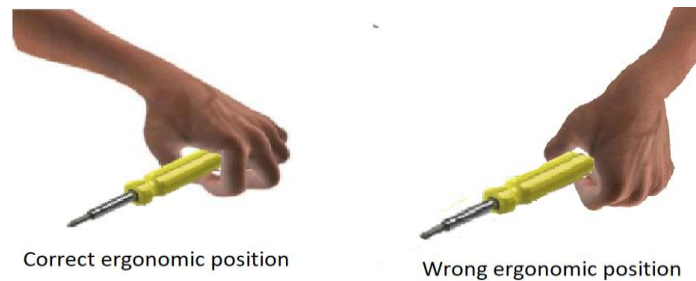


Figure 4: Single-handling tool.

The method for handling tubular tools based on handle diameter and length is depicted in Figure 4. While the fingers and thumb are employed to apply force, the entire palm is utilised when grasping a tool in this manner.



Figure 5 Pinch Grip handling tool.

The tool is held in a pinch grip for control, accuracy, and precision (see Figure 5). Holding the instrument between the thumb, index finger, and middle finger gives you the force you need to do the task. The contact pressure tool is another kind of grip that is shown in Figure 6. It is distinct from other grip methods in that force is applied to the tool against the component being fixed using the palm.

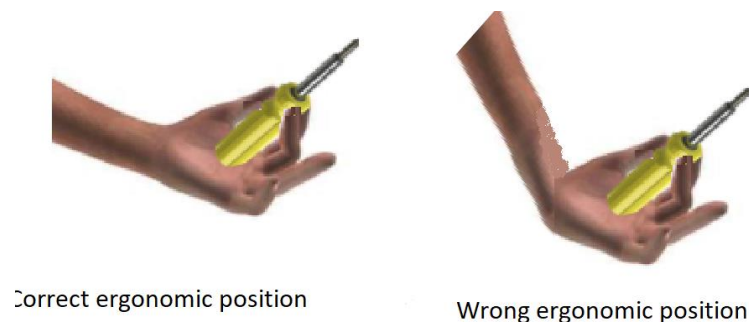


Figure 6 Contact pressure handling tool.

The complete hand is frequently employed to operate the double-handle tools depicted in Figure 7. To apply the proper force during the job, the pliers or forceps are held in this grip between the thumb, forefinger, and middle finger [36].

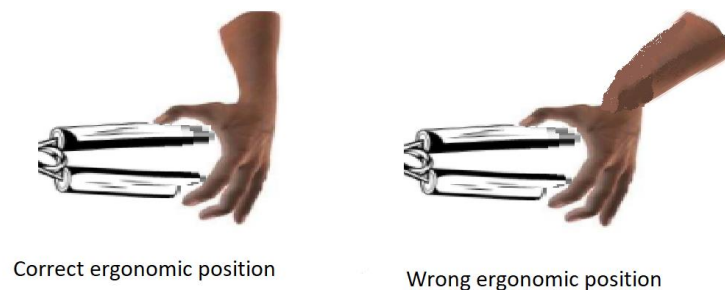


Figure 7: Double-handle tool.

1.1.3 Activating hand muscles using hand tools

According to the human studies, even the most skilled individuals cannot generate completely separate forces or movements with their four fingers; there is significant coupling between adjacent fingers [37], [38]. Previous studies have shown that each person maintains 52 different hand morphologies by combining intrinsic and extrinsic hand muscles. The principal component axes of the EMG (the 'muscle synergies') were then calculated, and the two orthogonal hand shape axes most closely associated with the most common muscle synergies were selected. This allowed us to examine muscle and motor unit membership patterns in muscle and postural synergies. The recording sites for this muscle were illustrated in Figure 8 [37], [39].

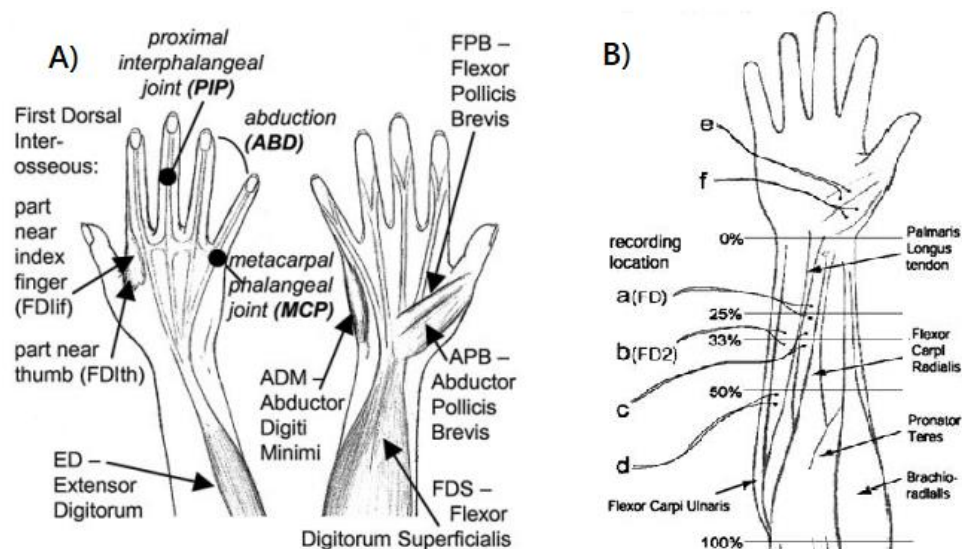


Figure 8 A) Anatomical locations of the seven muscles or muscle parts. B) Recording locations recommended and percentage of signal recovery quality.

Figure 8A, displays the muscles that are used to control hand movements using muscles. These include the flexor pollicis brevis (FPB), abductor digiti minimi (ADM), extensor digitorum (ED), abductor pollicis brevis (APB), and the portion of the first dorsal interosseus that is closest to the thumb (FDIth) and the index finger (FDIif). The APB and FPB are the thumb's intrinsic muscles. Activating Hand Muscles using Hand Tools. The intrinsic muscles of the little and index fingers are the ADM and FDI. The forearm contains the tendons of the extrinsic hand muscles ED and FDS, which are attached to the middle-to-distal phalanx (ED) or middle phalanx (FDS) of the four fingers [37].

1.1.4 Muscle fatigue

Muscle fatigue can be characterised as a decrease in optimal contractile force. Our body's ability to lift or move is impaired by extreme fatigue. Many studies have been carried out to detect and assess muscle fatigue. There are several methods of detecting fatigue based on muscle signals [40], [41]. Surface electromyography (sEMG) is the primary approach to recording and studying muscle activity, as it records the electrical signal from the muscles. Many other things can contribute to fatigue [42], such as muscle fibre structure, blood ion balance, energy supply, neurological variables, and many others. Research has shown that muscle fatigue is associated with the occurrence of musculoskeletal injuries during competition and training. Fatigue alters muscle activity patterns and kinematics, according to new research. Running fatigue could be linked to lower extremity injuries, as suggested by Nyland [43]. This can increase the likelihood of injury to both muscles and bones [44].

The kinematics can be modified as a result of physiological adjustments made to prevent or reduce the level of discomfort and the incidence of tiredness [45], [46]. Muscle strength can undergo various changes when sufficiently fatigued, controlling and ultimately determining the regulation of movement of the different parts, as demonstrated by Rodacki [47].

The mechanical properties of the hand play a role in the transmission of force produced by hand-held tools; this interaction is referred to as the tool-biological system, although it is widely recognised that the biological system changes over time in terms of fatigue and muscular precision [48], [49].

As a result, the above phenomenon suggests the existence of an underlying mechanism to mitigate the decreases that occur during the occurrence of force development

characteristics within the muscles due to fatigue. It highlights the importance of EMG signal processing and strategies for detecting muscle fatigue.

1.1.5 Assessments of Muscle Fatigue

The use of different training models, protocols, and techniques to quantify muscle fatigue may explain some of the differences in our understanding of the mechanism behind muscle fatigue. Our knowledge of ergonomics, work, and work-related injuries will be enhanced if we can develop an objective, quantifiable, and continuous technique for monitoring muscle fatigue [50], [51]. The maximal voluntary contraction (MVC) test is the most appropriate method for determining fatigue because it measures the force or power produced during a voluntary effort of maximal intensity. Short MVC tests are usually performed to record the decrease in maximal force production from a specific muscle as the subject continuously performs the fatiguing task or task of interest at pre, post and/or intermediate time points. This measures the pattern of muscle fatigue during the task performed. The pattern of muscle fatigue is represented by the rate of decline in power output assessed in these MVC tests. The force measurement equipment forms the basis of comparable tests that assist in direct assessment. However, muscle fatigue is indicated by a decrease in the power of maximal voluntary contractions. Nevertheless, the electrical impulses from the superficial muscle layer can be recorded by the surface electrodes, amplified, and finally used to determine the signal power spectrum when the response is observed in the sEMG.

1.1.6 Evaluation methods

Numerous non-invasive techniques exist for identifying muscle fatigue, with surface Electromyography (sEMG) and Mechanomyography (MMG) being the primary methods. sEMG captures the muscle's electrical activity signal, whereas MMG records its mechanical activity [52]. In addition, many other techniques are not as widely used in clinical or research settings. Examples include sonomyography (SMG), which uses ultrasound to measure haemoglobin absorption properties and detect fatigue during prosthesis control; near-infrared spectroscopy (NIRS); and acoustic myograph (AMG), which records muscle sound and is a specific application of MMG. Each technique attempts to document and study one or more muscle signals, symptoms and characteristics. However, surface electromyography is a more accurate way of identifying muscle fatigue [53].

1.2 Methodology

The main goal of using hand tools is to help find practical ways to lower hazards, lessen injuries, and enhance worker productivity and safety. Focusing primarily on any element influencing the assessment of muscular fatigue, the PRISMA 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 research and document selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards [54]. The articles in this meta-analysis were published between January 1990 and February 2024.

Web of Science, Scopus, PsycINFO, PubMed, Cochrane Library, and Excerpta Medica Database (EMBASE) were the multidisciplinary electronic databases from which English-language sources were retrieved for this meta-analysis. To find pertinent publications from these databases, the following keywords were used: (EMG OR surface OR electromyography OR myoelectric AND manifestations AND of AND fatigue OR surface AND emg OR multi-channel AND surface OR semg) OR (muscles AND fatigue OR exercise AND fatigue) AND (hand OR hand AND muscles) AND (machine AND learning OR ai OR artificial AND intelligence). Based on previous systematic reviews, the keywords identified were in the area of hand tool work-related illnesses [55], [56], [57], [58].

Figure 9 illustrates the steps involved in this meta-analytic investigation. 4827 documents in all were first obtained from the internet databases, and they were augmented by further human searches. Using Mendeley software, 1048 duplicates were removed, leaving 3779 records from the data sources. The remaining 291 papers were eliminated in the subsequent round of title and abstract screening, which eliminated 3488 papers deemed unrelated to the subject or centred on scale validation. 243 articles were eliminated following full-text screening by the exclusion criteria. After the eligibility evaluation was finished, thirteen full-text articles were eliminated. 35 journal articles were ultimately included for synthesis.

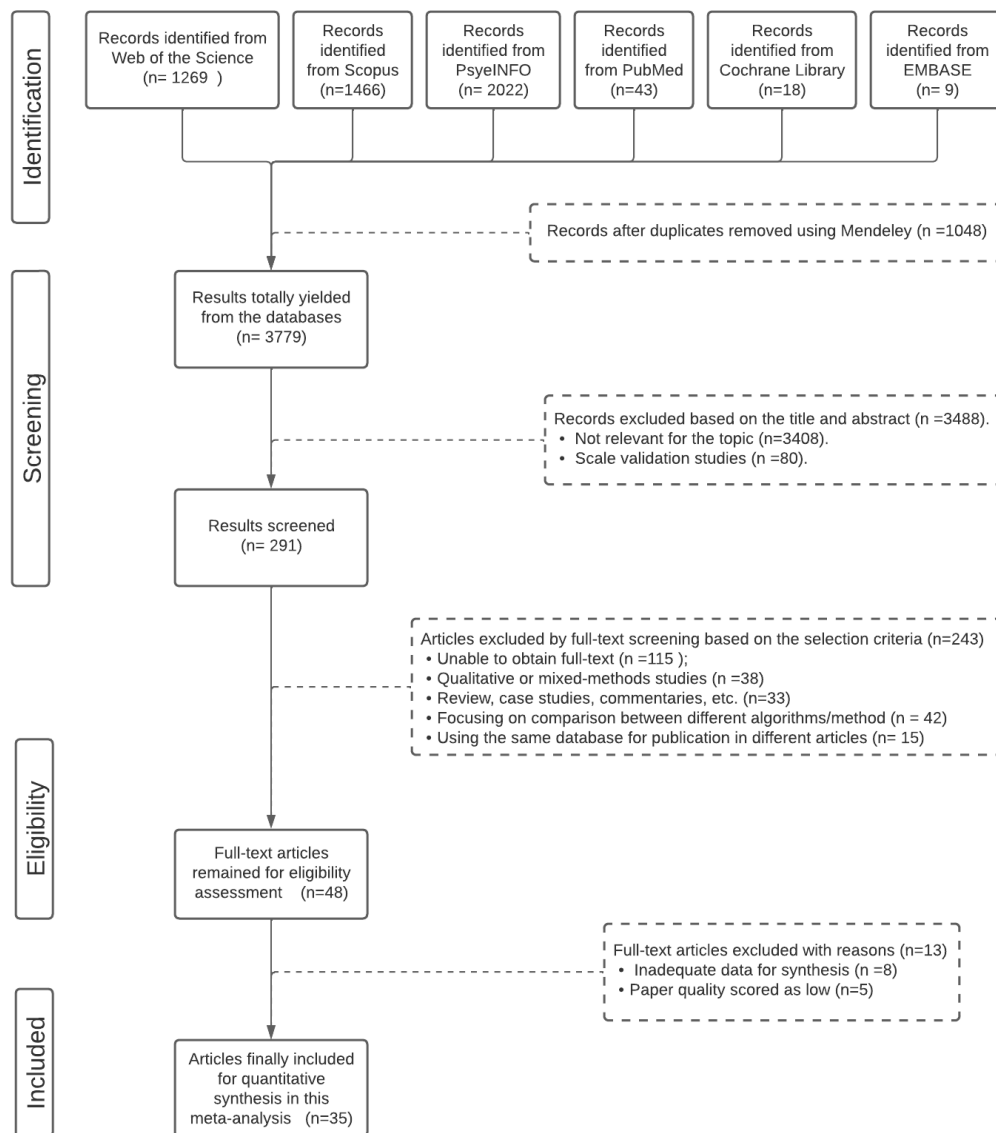


Figure 9 Flowchart of the selection and inclusion procedure

1.2.2 Eligibility Criteria

To be considered for inclusion, a study had to (a) primarily focus on any element that influences the assessment of muscular exhaustion; (b) be deemed empirical research; and (c) have a sample size of at least ten participants.

Key features of the selected studies were extracted and summarised in a consolidated report. 50% of the 35 studies were randomly selected to perform independent data extraction.

The extracted and coded items included (a) author(s) and year of publication; (b) sample size; (c) study design (EMG applied method and position); (d) effect size; and (e) EMG characteristics of AI applied principles. This study evaluates the muscle fatigue

assessment methods and data recognition algorithms to determine the required sample size.

The quality of the selected studies was assessed using the criteria of the Newcastle-Ottawa Scale (NOS). The NOS has been used extensively in previous physical health assessment reviews to evaluate the reliability of cross-sectional and cohort studies [59], [60] .

1.2.3 Analysis Procedures

Comprehensive Meta-Analysis (CMA, version 4.0, Biostat, Englewood, NJ, USA) software was used to conduct a meta-analysis. For the majority of studies included in this review, effect sizes were reported using Pearson's correlation coefficient (r) for correlational data or other convertible statistics such as normalised mean difference for continuous data and log odds ratios for binary data [60]. The p -value suggesting a moderating effect was evaluated using the Q_b test, and the meta-regression analysis employed the β -value. Fourth, a funnel plot was made to assess publication bias and see if the studies were evenly spaced around the effect size [61].

1.3 Results

This part displays the findings from the correlation test, which evaluates the impact of publications, as well as the information gathered about the risk assessment of hand tool use.

1.3.1 Correlation test

The publication bias of the chosen studies was then assessed using the Egger's correlation test and the Begg–Mazumdar rank correlation test.

The results of this meta-analysis indicated that the studies focused on preventing work-related diseases linked to hand muscles have a correlation with the sample effect and the myoelectrical evaluation method ($r = 0.520$, $Q = 27.04$, $p < 0.001$). There is a 95% confidence interval between 0.728 and 0.902, and the mean effect size is 0.834. The studies that were chosen were grouped into effect sizes that varied from -0.299 to 0.991

The null hypothesis that the mean impact size is zero is tested using the Z -value. The Z -value is 8.470, and p is less than zero. The Q -value is 27.04 with 17 degrees of freedom and $p < 0.001$.

1.3.2 Muscle fatigue detection

Several non-invasive methods, such as surface electromyography (sEMG) and mechanomyography (MMG), can identify muscle tiredness. MMG measures mechanical activity, while sEMG records electrical activity. Other techniques are also used, such as near-infrared spectroscopy (NIRS) and sonomicography (SMG). EMG data from muscles is gathered using statistical or machine learning methods, depending on the pattern of muscle exhaustion characteristics, as shown in Table 4.

Table 4 Overview of existing research on techniques using EMG signals to identify muscle fatigue during contraction

Studies	Consequence-Based Risk Identification	Muscles	Contraction Protocol	Analysis Methods
	Accidents / Physical Injuries	RF, BF, GM	Cycling 30 minutes constantly	IMNF
		Long Head BB	Exercise for 8 minutes during low-level isometric contraction.	Recurrence quantification analysis
		RF, BF	Run 400m on a tartan athletic track with a different intensity.	MPF, Linear Regression
		SEMBS, BF	Running over ground with maximal speed	EMG Peak, ANOVA
		BB, TB	Utilised the dumbbell as a burden	FFT, MPF
[62]	Long-term Ergonomic risk	Middle BB	Perform sixteen tasks with the fingers of the hand	RMS, Twin SVM
[63]		TB	Dumbbell curl exercise.	FFT & Spectral Density
[64]		RF, TA, BF, GM	Cycling with 100 watts	RAW EMG and statistical
		RF, VL, VM	5km running on a variable surface	iARV, iMAV, iRMS, WL, IMNF, IMDF
[64]		RF, GL, GM, VL, VM	Cycling for prolonged constant	RMS, MF
		Right RF	During walking.	DWT
	Physical Injuries and Tool Damage	RF, VL, BF, GL	Incremental running on a treadmill	RMS, Linear Regression
		GA	Running on a treadmill for 30 minutes	MDF, Linear regression
		RF, BF, TA, GAS	Running, 200m/outdoor and 400m/ treadmill.	MPF, Linear Regression
		GM, BF, VL, RF, TA, GA	Incremental running test on a treadmill	iEMG

Note: RF = quadriceps-rectus femoris; BF = biceps femoris (long head), GM = Gluteus Maximus, RA = rectus abdomini; ES = erector spinae; TA = tibialis anterior; VM = vastus medialis; SO = soleus. VL= vastus lateralis, GA= gastrocnemius, GL= Gluteal Muscles, SEMBS= semimembranosus, BB= Biceps Brachii, TB= Triceps Brachii.

Each method seeks to record and analyse different symptoms, indications, and properties of muscular exhaustion. Still, surface electromyography (EMG) is the gold standard for identifying muscle tiredness. BF, Medial Hamstrings (MH), GM, RF, Tibialis Anterior (TA), GL, Medial Gastrocnemius (GMS), semimembranosus (SEMBS), VM, GA, BB, Triceps Brachii (TB), and VL are among the muscles from which EMG signals have been obtained in numerous studies to generate fatigue indices using machine learning (regression) or statistical techniques (ANOVA test). Another issue is determining fatigue patterns from feature patterns, based on the particular usage.

1.3.3 Signal Processing

Electromyogram (EMG) signals are becoming increasingly important in a variety of applications such as healthcare, human-machine interfaces, and prosthetics. However, a significant obstacle to optimising these applications is dealing with distorted EMG signals [65]. Because EMG signals from muscles contain noise, appropriate filtering is required to ensure correct recording. This noise, which can come from a variety of sources, including amplifiers or external interference such as computers and radio broadcasts, can be low or high-frequency. While low-pass filters deal with high-frequency noise, high-pass filters reduce low-frequency noise. Bandpass filters are used to isolate specific frequency bands and deal with both types of noise [65], [66], [67]. These filtering methods are critical for improving performance in relevant applications and for accurate EMG signal analysis. A summary of the steps involved in processing EMG signals is shown in Table 5.

Table 5 EMG Signal Processing

Aspect	Details
Application	EMG signals are increasingly crucial in prosthetic devices, human-machine interactions, clinical/biomedical fields, and rehabilitation devices [63].
Challenge	Distorted EMG signals present a significant challenge in expanding performance applications [68].
Noise Removal	EMG signals collected from muscles by electrodes contain noise, which hampers signal recording [69].
Frequency of Noise	Noise in EMG signals can be low or high-frequency. Low-frequency noise often stems from amplifier direct current offsets, while high-frequency noise arises from nerve conduction, computers, and radio broadcasts [70].
Noise Removal Filters	High-pass filters remove low-frequency noise, while low-pass filters eliminate high-frequency noise [62].
Filter Band	Frequencies passed by a filter's transmission are known as the passband, while those blocked are the stop band [64].
Filter Concept	Low-pass filters remove frequencies above the cut-off value and transmit those below it, opposite to high-pass filters [71].

Bandpass Filter	Bandpass filters, unlike low or high-pass filters, transmit specific frequency bands determined by the user. They are ideal for EMG signal processing [72].
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EMG signal processing involves using electrodes to collect impulses from muscles, then pre-processing the signals to remove distortion and noise. The processed signals are then subjected to primary feature extraction, including amplitude, frequency, and time domain characteristics. Relevant features are selected to facilitate analysis. Machine learning algorithms are then used to classify the signals into appropriate categories, and post-processing methods can be used to improve the classification results. Finally, the signals are processed and interpreted to provide insights for a range of applications, including sports science, rehabilitation, and prosthetics [73].

1.3.4 Work-related hand tool risk identification

"Work-related health issues", "tool-related issues," and "work-related performance problems" are the main themes of the earlier studies. The main factors that appear to have prompted research into hand tool improvement were MSDs in any number of body regions (such as ulnar, upper extremity, carpal tunnel, etc.) [74].

Several studies examined work-related problems, which can be divided into three main categories: productivity, tool-related issues, and health and safety. Musculoskeletal disorders (MSDs) were the most common concern (36.2%), while health and safety issues were the most commonly examined (46.6% of articles). 8.6% of the studies looked at specific types of MSDs, while 3.4% looked at general health issues. Productivity and performance issues were addressed in 27.6% of the literature. Tool-related failure aspects were also extensively studied (32.8%), with particular attention paid to grip (15.6%), handle design (8.6%), tool characteristics (10.3%), and tool orientation (3.4%) [75].

Managers are very concerned about hand tool accidents because they have a direct impact on employee safety, output, and overall operational effectiveness. *'Physical injuries'* associated with the use of hand tools have a direct impact on employee safety, output, and overall productivity. These include immediate injuries such as cuts, fractures, and crush injuries, as well as chronic musculoskeletal disorders (MSDs). The possibility of these accidents is significantly increased by poor tool design, excessive force, vibration exposure, and improper maintenance; these factors result in lost workdays, reduced productivity, and increased compensation costs [76].

Another source of concern for managers is *Ergonomic risk* postures when using hand tools, which can lead to severe musculoskeletal disorders (MSDs) such as tendonitis,

carpal tunnel syndrome, and hand-arm vibration syndrome (HAVS). The strain on muscles, tendons, and nerves increases when workers use tools in awkward positions, such as extreme wrist flexion, forceful gripping, or repetitive motions. This can lead to long-term pain, reduced grip strength, and even permanent disability [76].

'Tool damage' is another primary concern for business managers because it has a direct impact on overall costs, worker safety, and operational efficiency. Workplace accidents and lost productivity can result from damaged tools, whether the result of inappropriate use, poor maintenance, or material fatigue. Workers may use extra force to compensate for worn or malfunctioning tools, increasing the risk of musculoskeletal injuries and product defects. Ignoring tool damage can lead to safety violations and reduced worker motivation [75], [76].

1.4 Discussions

Hand tools are essential in many professions; their misuse can lead to work-related illnesses and accidents. To reduce these hazards, this research presents how hand tools are properly categorised and selected. In addition, it presents hand tool features as either powered or non-powered, and then further into categories such as cutting, driving, holding, striking, measuring, finishing, and miscellaneous. Each category has a different function, and the ergonomic design of each is critical to ensuring user productivity and safety.

The study defined the selection process considering several variables, including the nature and technique of the task, the handle material of the tool, and its characteristics. The inherent safety features of hand tools, such as non-slip surfaces, insulated handles for electrical safety, and ergonomic handle designs, are essential in reducing the possibility of mishaps and promoting safer working environments. In addition, user efficiency and safety are improved by understanding different handling styles such as pressure handling, pinch grip, power grip, and single handling.

The physiological characteristics of using hand tools are explained by hand muscle activation and fatigue. Research has shown that hand muscles interact in complex ways when using tools and that muscle fatigue can reduce function and increase the risk of injury. There are many non-invasive techniques for detecting fatigue. Many articles describe and identify fatigue using surface electromyography (sEMG), a widely used method for determining fatigue and muscle performance [58], [63], [68], [77]. Despite

this, RMS, MNF, MPF, WL, MDF, iMAV, iRMS, IMNF, and IMDF are the most often used analysis techniques.

The analysis of electromyogram (EMG) signals to assess muscle fatigue requires the use of signal processing. EMG signals are filtered using a variety of techniques to reduce noise and distortion, enabling accurate analysis and interpretation. EMG signal processing is further enhanced by machine learning techniques that facilitate signal classification and provide insights for a range of healthcare, prosthetics, and rehabilitation applications. Based on the linear regression slope values that characterise the muscle fatigue index, statistical analysis or machine learning (ANOVA, regression line) is then applied [78].

The meta-analysis adds significantly to our knowledge of ergonomic risk factors and preventative measures by shedding light on the relationship between hand muscle fatigue and work-related illnesses. According to earlier research [79], [80], [81], tiredness is correlated with an increase in the EMG amplitude in the time domain, a shift towards lower frequencies in the frequency domain, and a mean drop in the spectrum when the amplitude increases in the time-frequency domain.

One finding from the research set is that MDF and MNF, which are based on power spectrum analysis of the EMG signals obtained from the FFT, are superior methods for detecting muscle fatigue because the spectral analysis of the data is more reliable and provides more information about muscle function than the other methods.

The research on hand tools, muscle activation, and fatigue assessment also highlights the importance of technological improvements, ergonomic design, and safety considerations in promoting health and safety in the workplace. The commonly evaluated muscles are GM, RF, BF, GMS, GL, VL, and VM. These muscles are superficial and easy to apply electrodes to; they are also very controllable when it comes to detecting fatigue. SEMG can detect fatigue during both dynamic and static contractions.

1.5 Main contributions

The amount of information we have on the ergonomic factors, muscle activation, and fatigue assessment associated with hand tools in many professional situations has been greatly enhanced by this research. The main contributions are presented below:

Hand Muscle Activation and Fatigue: The research identifies the role that muscle fatigue plays in occupational health. It examines the patterns of muscle activation, how adjacent fingers are coupled, and how fatigue affects muscle performance and the likelihood of injury. Several techniques for assessing muscular fatigue, such as surface electromyography (sEMG), are discussed, with an emphasis on the importance of accurately detecting fatigue to prevent work-related illnesses. In addition, the location of the electrodes is determined as the forearm, the area closest to the elbow, to obtain hand muscle signals from the muscles located in the forearm, including the flexor carpi radialis, flexor carpi ulnaris, and pronator teres.

Signal Processing for Muscle Fatigue Assessment: This study presents signal processing methods for properly assessing muscular tiredness by examining electromyogram (EMG) signals. It discusses how to extract features from EMG signals, remove noise from them, and use filtering techniques. It highlights how machine learning algorithms may be used to categorise patterns of fatigue. Signal processing makes it possible to accurately measure muscle exhaustion, offering information for use in prosthetics, rehabilitation, and healthcare.

Meta-analysis on Muscle Fatigue Studies: Demonstrates the link between hand muscle fatigue and work-related illnesses, highlighting the importance of understanding ergonomic risk factors and taking preventive action. The meta-analysis shows that there is a positive correlation ($r = 0.520$, $p < 0.001$) between the effectiveness of myoelectric evaluation methods and the prevention of work-related illnesses. According to this correlation, using the proper myoelectric diagnostic techniques can help to reduce the prevalence of work-related hand muscle disorders.

Implications for Workplace Health and Safety: Identify the importance of safety considerations, ergonomic design, and technological developments in promoting health and safety in the workplace. Stakeholders can develop strategies to reduce workplace hazards and improve worker well-being.

Categorisation of identified risks based on their consequences: Establish a framework for understanding potential risks in categories such as accidents, Physical injury, Ergonomic risks, and Tool damage, and understand the wide range of possible outcomes associated with different activities.

Sample size: Determines the number of samples for the experimental selection in the identified categories. Considering that the experiment is a series of muscle repetitions, the adequate correlation between size and experimental result determines the group size of 12-20, as it allows the researchers to collect sufficient data to understand the factors that contribute to accidents.

- **Thesis (T1):** With a systematic PRISMA literature review and using correlation analysis of the studies (which presented an index $r = 0.520$ and $p < 0.001$), I have proved that:
 - Electromyography (EMG) collected in the forearm, including the flexor carpi radialis, flexor carpi ulnaris, and pronator teres, helps prevent work-related injuries and cumulative trauma disorders by identifying the onset of muscle fatigue during over 5-second gripping tasks.
 - The main identified categories of potential hand tool use-related risks include accidents, Physical injuries, Ergonomic risk, and Tool damage.

Own publications related to this chapter: [82], [83]

2 CATEGORISATION OF WORK-RELATED RISKS IN MANUAL TOOL OPERATION

In the field of hand tool use, a multicriteria categorisation of direct risk is essential for understanding the task. A structured methodology for categorising risk related to hand tools is presented, including an introduction, a detailed explanation of the methods, a presentation of the results, and a discussion of their implications.

2.1 Preventing CTDs through Tool Design and Risk Assessment

Work activities in several tasks have been associated with cumulative trauma disorders (CTDs) of the upper extremity. Poor posture has been identified as a major ergonomic risk factor for CTDs. In studies of musculoskeletal complaints in industrial assembly workers, ulnar deviation of the hand posture was shown to be the leading risk factor for hand symptoms. This hand position was found to be more common than other abnormal hand positions [84].

Musculoskeletal disorders (MSDs) and injuries among workers lead to a wide range of problems, including poor quality of life, reduced mobility, reduced strength, reduced income, and even difficult circumstances.

Hand tool use has generally been one area where ergonomic risk concerns are significant due to one of the main industrial goals being to prevent MSDS. That is why improvements in the design of hand tools have been essential in reducing pain and injury in the wrists and hands. A proven method for reducing workplace accidents is risk assessment. EN 292 /ISO 12100 risk reduction criteria and risk assessment form the conventional risk assessment methodology [85]. But when it comes to the risk assessment of a machine, it can be a challenge for users to identify and analyse hazardous actions.

Multicriteria decision-making

Ergonomics specialists have used multicriteria decision-making (MCDM) programs to identify ergonomic factors that can lead to MSDs and enhance subjects' quality of life through preventive initiatives. These models have helped create answers for a wide range of issues related to the avoidance of work-related illnesses, and the models themselves have addressed a significant number of issues with job scheduling in the sector. Researchers from all over the world have begun to examine this model in depth by connecting the mobility components with the MCDM models [86], [87].

The Analytic Hierarchy Process (AHP) technique is a relevant multi-criteria model that relies on the judgment and expertise of decision makers to make the right choices about how to solve a complex problem according to specific criteria. In effect, it assists decision makers in choosing the course of action that best suits their needs and assessment of the problem. As the AHP approach is subjective and an evaluation of expert knowledge, the study does not require a large sample size [87], [88].

However, since the answer can be viewed as a personal argument to some extent, the AHP approach has limitations, including the respondent's decision criteria. As the decision maker's preferences have a significant impact on the results, the criteria of perception, evaluation, correction, and choice in the AHP approach are rather ambiguous. Additionally, the interdependencies between AHP variables often lead to inconsistent weighting of criteria and results that do not reflect reality [88], [89]. To address these constraints, Pareto optimisation of AHP weight vectors was used. Thus, the authors modified the weights of the AHP vectors by using pairwise comparison matrices in a real-world case study. This showed that the AHP approach could be improved by integrating it with simulation-based sensitivity assessment and analytical network process (ANP) modelling [90].

The model used in addition to the AHP offers different advantages, depending on the type of study it is best suited for and the scenario to which it is applied. Therefore, several mathematical and optimisation techniques have been used to evaluate and improve the accuracy of the AHP results. Using a Monte Carlo simulation, statistical factors from sensitivity analysis and innovation have been incorporated into the AHP approach [91]. Few studies have examined the criteria for non-powered hand tools by combining the MCDM approaches with risk assessment. The choice of tool was made by the authors using an assessment based on the available materials.

This method is widely used to rank the risk factors associated with the onset of musculoskeletal problems in the shoulder and neck, OHS used APP to design a decision support system [92], [93].

2.2 Methodology

This section covers the components and materials used to conduct the research, together with an explanation of the survey methodology. To solve the Analytic Hierarchy Process (AHP) and Best Worst Method (BWM), we utilised algorithms created in Microsoft Excel from Office 365. The methodology used in this study followed the guidelines of previous

researchers [94], who provided a structured framework of algorithmic tools based on Excel for handling multi-criteria decision problems. Two researchers from the University of Obuda, R.P.A-R and V.C.E-C, each carried out a cross-check before confirming the results. This is followed by a detailed presentation of the study and an explanation of the approach used.

2.2.1 Survey

The survey was developed based on meetings and discussions with ergonomics experts to identify the key criteria for risk grouping and categorisation. The survey was then carried out in May 2023 through Google Forms (ANNEX 2) using the snowball sampling. Participants were selected from experts in the National Ergonomic Association of Ecuador, whose expertise characteristics in the safety field are detailed in Table 6. The expert category considered in this research was evaluated based on the rule provided by Malcolm Gladwell, which suggests that individuals need a minimum of ten years of experience. The survey was completed in 15 to 20 minutes per expert. Based on the criteria or groups identified in section 1.3.2, shown in Table 7, each expert categorised the risks according to their importance.

Table 6 Expert's description

Number	Expertise field	Years of working in the field	Gender	Education Level
1	Ergonomics	11	Male	PhD
2	Electrical ergonomics	10	Female	Master.
3	workplace	13	Male	Master.
4	safety engineering	11	Male	Master.
5	safety	10	Female	PhD
6	Accidents prevention	11	Female	Master.
7	safety and security	14	Male	Master.
8	safety	10	Male	Master.
9	safety and security	10	Female	Master.
10	ergonomics	15	Male	PhD

2.2.2 Design of Saaty Scale and Description Criteria

For the subsequent ranking of these criteria according to the requirements of the multicriteria technique used, one of the most important aspects of the study is the planning and selection of the criteria to be used or considered for the evaluation of the risk category associated with the use of hand tools. It is possible to examine the order of importance

chosen by the researchers, both individually and collectively, thanks to the creation of criteria. Our project's research identified three primary standards based on the literature on the hazards of using hand tools. An explanation of each criterion relating to the first level is also given in Table 7, together with the coding for each main criterion. The criteria are coded from C1 to C3.

Table 7 Main criteria and description of the criteria

Code	Explanation	Description
C1	Physical Injuries	Reflecting the immediate effects that injuries can have on worker health. It refers to direct harm caused by improper hand tool use, unsafe working conditions, or lack of protective measures.
C2	Ergonomic risk	Activities that have no immediate effects can result in long-term health issues and future illnesses. It refers to a tool's design, weight, or required force application that leads to physical strain or musculoskeletal disorders.
C3	Tool damage	It refers to the deterioration, malfunction, or breakage of hand tools due to excessive use, improper handling, or poor maintenance of tools used in the workplace.

Thus, they can be easily identified in Figure 10. The coding has been done to allow the reader to identify them with the criteria.

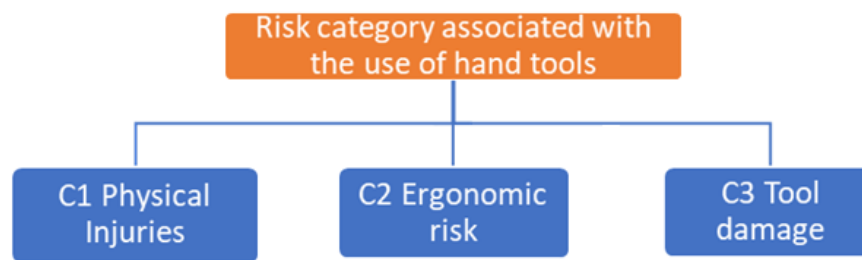


Figure 10 The hierarchical structure of hand tool use risk assessment.

Once the hierarchy has been constructed, respondents assign a numerical scale to each pair of alternatives (A_i, A_j), as shown in Table 8 [86]. By comparing the options in pairs in terms of how they affect an element higher in the hierarchy, numerical scales are assigned. Expert k personal preference for alternative A_i over alternative A_j is expressed by the term a_{ijk} .

Table 8 AHP scale for combinations.

Scale	Definition	Verbal Explanation
1	Both elements hold equal importance.	The two elements contribute equally to the characteristic being evaluated.
3	One element is slightly more important than the other.	Based on experience and judgment, one element is preferred, but the difference is minimal.
5	One element is significantly more important than the other.	Practical experience and evaluation strongly favour one aspect over the other.
7	One element dominates the other.	There is a strong preference for one element, backed by practical observations.

9	One element is overwhelmingly more important.	The superiority of one element is unquestionable, supported by substantial evidence.
2, 4, 6, 8	Intermediate values between adjacent levels.	The evaluation falls between two defined levels, representing a gradual increase in significance.
Reciprocals (1/x)	Assigned when comparing one activity to another.	The inverse value is used when the comparison direction is reversed.

According to Saaty (1990), one may also evaluate the consistency of judgments using the following equation [95]:

$$\text{Consistency ratio} = CR = \frac{CI}{RC} \quad (1)$$

And,

$$\text{Consistency index} = CI = \frac{\lambda_{max} - n}{n - 1} \quad (2)$$

Where λ_{max} represents the most influential eigenvalue. For a comparison to be considered reliable, the inconsistency of the comparison must be under 10 per cent.

The consistency ratio (CR) indicates how consistent the decisions made in the pairwise comparisons are; the consistency ratio forecasts the degree of inconsistency for random judgments of the same size; and the consistency ratio (CR) measures the degree of inconsistency observed in the pairwise comparisons.

2.2.3 Best Worst Method

Using the Best Worst Method (BWM), weights for the criterion and sub-criteria were generated with fewer pairwise comparisons and a more consistent comparison procedure. A criterion is considered best or most significant when it is most important in decision-making. In contrast, a criterion that is the least significant or worst has the opposite effect. The creation of BWM is just one of many MCDM strategies. The perceived efficiency of the technique can be attributed to its well-structured, transparent, and user-friendly nature, as well as its trustworthy results and minimal data requirements. A notable difference between the pairwise comparison-based BWM technique and other approaches is the way its core framework depends on the most and least important components. Higher performance accuracy, increased reliability of measured weight coefficients, and other features that facilitate estimation and interpretation with fewer paired comparisons than other methods are some of the advantages of BWM [96]. A summary of the key steps is given as:

Step 1: In decision-making is to choose a set of criteria. The criteria (C1, C2,..., Cn) must be determined before a decision can be made. These criteria are used to determine how well the alternatives perform.

Step 2: Determine the criteria that are the best and the worst for the context in which the decision is made. A criterion that is the most desirable may be the best; a criterion that is the least important or desirable may be the worst. This is about the criteria themselves, not the values of the criteria.

Step 3: Determine which criterion is most crucial. This value will be evaluated by a number between 1 and 9.

Step 4: Determine that the remaining criteria should take precedence over the least advantageous one.

Step 5: Establish the appropriate weights. To determine the best criterion weights, the most considerable absolute disparities are considered.

Step 6: The optimal optimisation ks_i^* in the Best Worst Method (BWM) is found by solving an optimization model.

$$CR = \frac{\xi^*}{\text{Consistency index}} \quad (3)$$

2.3 Results

As stated in the methodology, two multi-criteria were utilised to separate the results: the AHP approach and the Best-Worst method.

Best-Worst method

To classify the hand tools used at level one, the respondents were asked to compare the key requirements for risk categorisation, such as "Physical injuries" (C1) and "Ergonomic risk" (C2). Table 9 presents the input criteria established at the algorithm's starting point, which are used to initiate the BWM comparison as outlined in the methodology.

Table 9 Established criteria of hand tool use risk assessment

Criteria Number = 3	Criterion 1	Criterion 2	Criterion 3
Names of Criteria	Physical Injuries	Ergonomic risk	Tool damage

The analysed data provided by the experts identified the benchmarks illustrating the best and worst criteria in this analysis. In the next step, the best and worst identified criteria are needed as input. Table 10 shows the best and worst identified criteria in the method.

Table 10 Best and Worst identified criteria of hand tool use risk assessment.

Select the Best	Physical Injuries
Select the Worst	Tool damage

After obtaining all the aggregated weights of the 10 experts, pairwise comparisons (PCs) must be developed for each branch of the decision system according to the BWM technique, as shown below. As indicated in Table 11, the best criteria are compared to the other criteria at the beginning of the process with weighted values.

Table 11 Best criteria comparison of hand tool use risk assessment

Best to Others	Physical Injuries	Ergonomic risk	Tool damage
Physical Injuries	1	5	7

Using the scale provided by the assessors, Table 12 presents the comparison of the worst criterion against the other criteria with weighted values.

Table 12 Worst criteria comparison of hand tool use risk assessment

Others to the Worst	Physical Injuries	Ergonomic risk	Tool damage
Tool damage	7	5	1

The resulting weighting of the criteria according to the BWM is calculated in the established step 5 of the methodology. This data is presented in Table 13.

Table 13 Resulting weight criteria of hand tool use risk assessment

Weights	Physical Injuries	Ergonomic risk	Tool damage
	0.736	0.187	0.077

The ks_i^* represents the optimal consistency ratio, which measures the level of consistency in the decision-maker pairwise comparisons, leading to values typically ranging between 0 and 0.2 to indicate a correct consistency. The results' degree of dependability is indicated by the $ks_i^* = 0.198$, and their reliability is further demonstrated.

Figure 11 shows a strong difference between the criteria, where Physical Injuries dominate with over 73% of the total value, while the other two categories are smaller, contributing less than 20% and 8% respectively. This represents the distribution of risks when workers use hand tools.

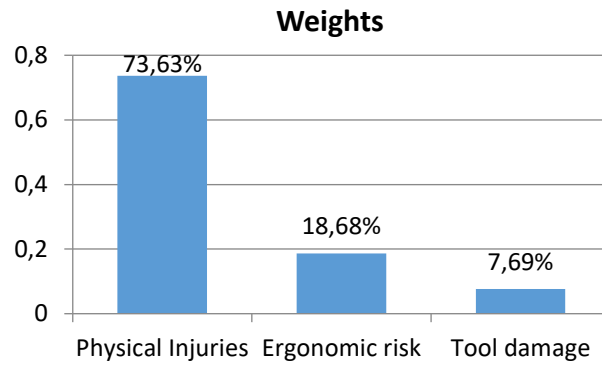


Figure 11 Results of BWM Criterion Weights of hand tool use risk assessment.

AHP Method

Using the scale provided by the evaluators, the Hierarchical Method for Weight Assignment, proposed by Saaty, will be used, which aims to "determine the weights or coefficients (C_i) with which a group of variables intervene. The weighted values are registered in Table 14, which presents the comparison of the worst criterion against the other criteria [97], [98]. The risk was rated by the experts using the method's guided scale, considering both the likelihood of future illness and its immediate impact on the worker's health.

Table 14 Matrix A= Risk evaluation ratio.

Matrix		Physical Injuries	Ergonomic risk	Tool damage	W_i	C_i	LAMD A_i
		1	2	3			
Physical Injuries	1	1	5	7	3,27	0,73	0,98
Ergonomic risk	2	1/5	1	3	0,84	0,19	1,19
Tool damage	3	1/7	1/3	1	0,36	0,08	0,89

The relationship between each risk and the scale to compare and determine the following steps to complete the calculation is represented by matrix A in Table 14. After establishing the matrix comparison, the presented data are normalised to ensure that the priority values (weights) assigned to criteria or alternatives are on a comparable scale. These normalised data are presented in Table 15.

Table 15 Normalized matrix

$$A^N = \begin{bmatrix} 0.74 & 0.79 & 0.64 \\ 0.91 & 0.16 & 0.27 \\ 0.41 & 0.10 & 0.09 \end{bmatrix}$$

To calculate the consistency ratio (CI) and the random consistency ratio (RCI), respectively, equations 1 and 2 are utilized. The findings are shown in Table 16.

Table 16 Resulting Consistency ratio for the AHP method

Ci=	0.03244379	
Rci=	0.66	
CR=	0.0492	Consistent

The risk level S^* was finally found by the Consensus indicator, and this number indicated the maximum risk that should be considered when choosing a tool. The general acceptance indicator S^* measures how well the decision criteria are generally agreed upon. The average judgments of the group are compared to the individual evaluations to ascertain the prevalence of each criterion [99].

In Figure 12, the results show that physical injuries account for the most significant percentage of injuries (73%), followed by ergonomics risk (18.8%) and tool damage (8.1%).

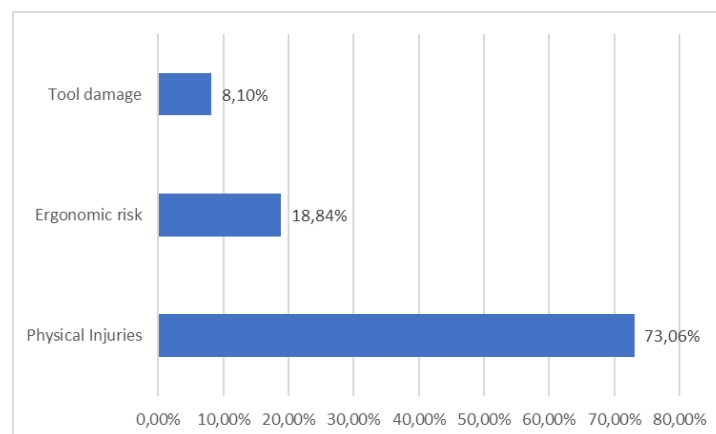


Figure 12 Results of AHP Criterion Weights of hand tool use risk assessment

2.4 Discussions

Poor posture and cumulative trauma disorders (CTDs), particularly in the upper extremities, are closely correlated. This correlation is particularly evident in areas such as industrial assembly, where repetitive manual handling is required. Specifically, it has been found that a significant risk factor for musculoskeletal disorders (MSDs) in workers is ulnar deviation of hand posture [100], [101], [102].

Preserving resources while increasing income is the first principle of the industry. Under this strategy, preventing employee illness is crucial to increasing output, and considerable effort is put into selecting the appropriate tools [103]. To reduce the potential risk, this study identified the main elements used in hand tool operations. According to current

research, injuries are the biggest concern for companies, with an average of 73.06%. This shows that organisations place a high priority on injuries because of the direct impact they can have on workers' health. Accidents and hazardous situations are often the cause of workplace injuries, which can result in physical pain and disability, lost productivity, increased healthcare costs, and employee downtime. In line with the researchers' findings about workplace injuries, physical pain, and disability [104], [105]

According to the study, ergonomic risks, which include things like repetitive motions and poor posture, are the second biggest concern, accounting for 18.84% of all hand tool-related injuries. This means that although they don't always cause immediate health problems, ergonomic risks, which include things like these, can lead to long-term health problems and future illnesses, in accordance with studies where the risk evaluation was proposed [106]. The expert opinions were consistently evaluated by the AHP method, as indicated by the comparatively high Consistency Ratio ($CR = 0.0492$).

Comparable results were also obtained using the Best Worst Method (BWM), where physical injury was considered the most important factor, accounting for 73.62% of the weight. This high weighting highlights how quickly physical injuries sustained during manual work with hand tools can have an impact. With weights of 18.68% and 7.69% respectively, the BWM analysis also found that ergonomic risks and tool damage were less important considerations.

This study shows that when selecting and designing hand tools, organisations should focus on reducing the immediate risk of physical injury. While ergonomic improvements should be considered to minimise long-term hazards, preventing injuries such as cuts, lacerations, and fractures caused by incorrect tool use should be a priority. It is in concordance with research to determine upper extremities MSDs [107].

The study's combined application of BWM and AHP demonstrates how MCDM techniques can be used to improve decision-making in occupational health and safety.

2.5 Main contributions

Worker safety must always come before other considerations. This is especially important in industrial environments where repetitive activities and physical handling are common. The high weighting of physical injuries reflects the industry's emphasis on minimising these risks. In settings where non-powered hand tools are often used, cuts, abrasions, and fractures are frequent injuries. Businesses must recognise that failing to take preventative

measures against such mishaps will lead to deteriorating employee health, increased production costs due to missed work, higher medical expenses, and decreased productivity.

The AHP and BWM models scored 73% and 73.62% respectively, indicating that physical injury posed the most significant risk associated with using hand tools. This demonstrates that misusing hand tools can have immediate and severe negative health repercussions on employees.

Ergonomic risk is the second most crucial component found in the study, accounting for 18.84% in the AHP model and 18.68% in the BWM model. Poor posture, repetitive tasks, and prolonged use of tools without adequate breaks are examples of ergonomic hazards that usually do not cause immediate injury.

Tool damage was the least essential criterion in both models, with 8.1% in the AHP model and 7.69% in the BWM model. Although this factor is critical, its low weight suggests that companies are more focused on the direct impact of tool use on worker health than on the potential for tool failure or damage.

The findings highlight the need for preventive methods in occupational health and safety management. Companies should invest in injury prevention by choosing equipment that reduces the likelihood of physical harm and by improving worker ergonomics. This can be achieved through the design of ergonomic equipment, worker training programmes that instruct workers in the correct use of equipment, and routine risk assessments that help identify potential hazards before they cause harm.

- **Thesis (T2):** By applying Multi-Criteria Decision-Making (MCDM) methods to categorize risks associated with hand tool use in a sample of 10 ergonomic experts, I demonstrated that integrating individual factors like 'tool damage', 'ergonomic risk', and 'physical injury' can effectively categorise to rank and assess the risks related to hand tool use, and it shows that 'physical injury' is the primary risk factor, with a weighted importance of 73.06% in the Analytic Hierarchy Process (AHP) (Consistency ratio: 0.0492) and cross-validated by the Best-Worst Method (BWM) at 73.62% (Reliability ratio: 0.1978).

Own publications related to this chapter: [17], [82], [108]

3 PERCEIVED WORK-RELATED RISKS OF USING HAND TOOLS

Understanding the task in the context of hand tool use requires an understanding of the user's perception of risk. A structured methodology for categorising risk related to hand tools is presented, including an introduction, a detailed explanation of the methods, a presentation of the results, and a discussion of their implications.

3.1 Ergonomic Assessment and Risk Perception of Hand Tools Use in Industrial Settings

Industrial businesses and tool suppliers have been able to forge new business partnerships in new areas because of the recent surge in the development of new information technologies—the use of hand tools in production processes, whether industrial or non-industrial, is growing in importance. Current trends show that hand tools, the main instrument utilised in the expansion of industrial activity, account for a sizable share of labour. One of the main issues facing the sector is the high incidence of hand tool-related injuries over time, which means that it will need to invest resources in remediation [29], [109], [110], [111].

When introducing new products to the market, industrial manufacturers specialising in hand tools pay particular attention to compliance with mechanical and legal requirements, depending on the conformity of these criteria with international standards. For ergonomics managers, a significant concern is how tools are selected to reduce the likelihood of workers becoming ill in the future. In this case, tool companies focus on designing for everyone, which can be problematic for certain operators and limits their reliance on the size of tools available on the market. [30], [112].

The identification of serious occupational diseases at various levels of the body is linked to the assessment of industrial risks. These tools, which range from virtual reality simulations to survey analysis, are constantly being improved to identify and reproduce the causes of accidents, thereby reducing the likelihood of such incidents [9], [10], [11].

The control of musculoskeletal disorders depends on the layout and design of the workstation; therefore, the method of tool selection plays a crucial role in the design or organisation of the workstation. As repetitive manual work requires significant muscle

tension and wrist flexion and extension, it poses a serious ergonomic risk [2], [13], [113], [114].

One of the main advantages of the DOSPERT scale is that it can be applied to a completely different setting, providing insightful information that can improve understanding of risk behaviour that is unique to a particular domain. [115]

A major issue affecting workers in the industry is risk attitudes related to hand tools. This issue has been examined by current researchers mainly from the employer's perspective, but there is limited research on workers' risk attitudes and how risk perceptions compare to expected benefits. There is a need to address this gap as the risk associated with the use of hand tools contributes to work-related musculoskeletal problems, in addition to their malfunctioning or less ergonomic design. The study seeks to assess employees' risk attitudes in relation to the selection of hand tools. Using the regression equation, the applied DOSPERT scale assesses employees' attitude to risk while providing information on their attitude to risk taking, risk perception, and expected benefits. It also assesses how employees perceive the hazards associated with the use of hand tools.

3.1.1 DOSPERT

The Domain-Specific Risk-Taking Scale, or DOSPERT scale, is a psychological assessment instrument used to measure risk-taking in several life domains. The purpose of the DOSPERT is to assess self-reported risk preferences in five domains. It assesses whether respondents are likely to engage in risky behaviour specific to a given domain [116].

3.1.2 Structure of the DOSPERT Scale

Each domain of the DOSPERT scale uses a series of items to assess a person's propensity to take risks. From "extremely unlikely" to "extremely likely", participants rate their likelihood of engaging in certain dangerous activities on a Likert scale (often 1-7) [116].

The five primary domains of the original DOSPERT scale are:

- Risks Related to Ethics involve actions that go against the law or moral principles.
- Investment and gambling risks are further subdivided under financial hazards. Options include making real estate or stock investments.

- Risks to Health and Safety refers to practices that may risk physical health or safety.
- Risks Associated with Recreation dangerous actions done in an attempt to have fun or get a thrill.
- Social risks are activities that could have an impact on a person's connections or social position.

3.1.3 Evaluation of the DOSPERT Scale

To assess "Risk perception (RPERC), Risk taken/risk probability (RPROB), and Expected Benefits (EXPB)" during tasks, the questionnaire items are evaluated three times. Comparisons between the two domains were done after a collective analysis of the responses was completed [116].

Regression analysis is then used to explore the relationship between the independent components and the risk-taking propensity. These effects' strength and direction are determined, along with the variables that significantly affect risk propensity.

To determine a person's risk attitude, risk-seeking or risk-aversion behaviour, one must analyse their conduct in the setting of uncertainty while taking into consideration their preferences and related utilities [115], [117]. A regression function represented in equation 14 can be utilised for this, per the DOSPERT evaluation:

$$Preference(X) = a \cdot (Expected\ Benefit(X)) + b \cdot (Perceived\ Risk(X)) + c \quad (4)$$

Where the risk attitude parameter of the individual is represented by a and b, it is the coefficients a and b that influence risk attitude. It serves as a signal in the DOSPERT equation (equation 4) that the level of risk is increasing or decreasing. A positive coefficient denotes risk-taking behaviour, whereas a negative coefficient denotes risk-averse conduct.

3.2 Methodology

There are several stages of implementation in the methodological protocol for the conduct of this research. Figure 13 illustrates the research process. Firstly, a centralised set of information selection criteria is used to gather the most critical aspects of occupational safety in hand tools, focusing on senior characteristics, reducing the risk of accidents, and

using non-powered tools as safety devices. After the initial research phase, problems and solutions are identified by systematising the data collected. The elements that should be utilised to evaluate the degree of risk in a particular domain were then determined using the DOSPERT (Domain-Specific Risk-Taking) scale. This was done using a survey. The data is then analysed to draw conclusions.

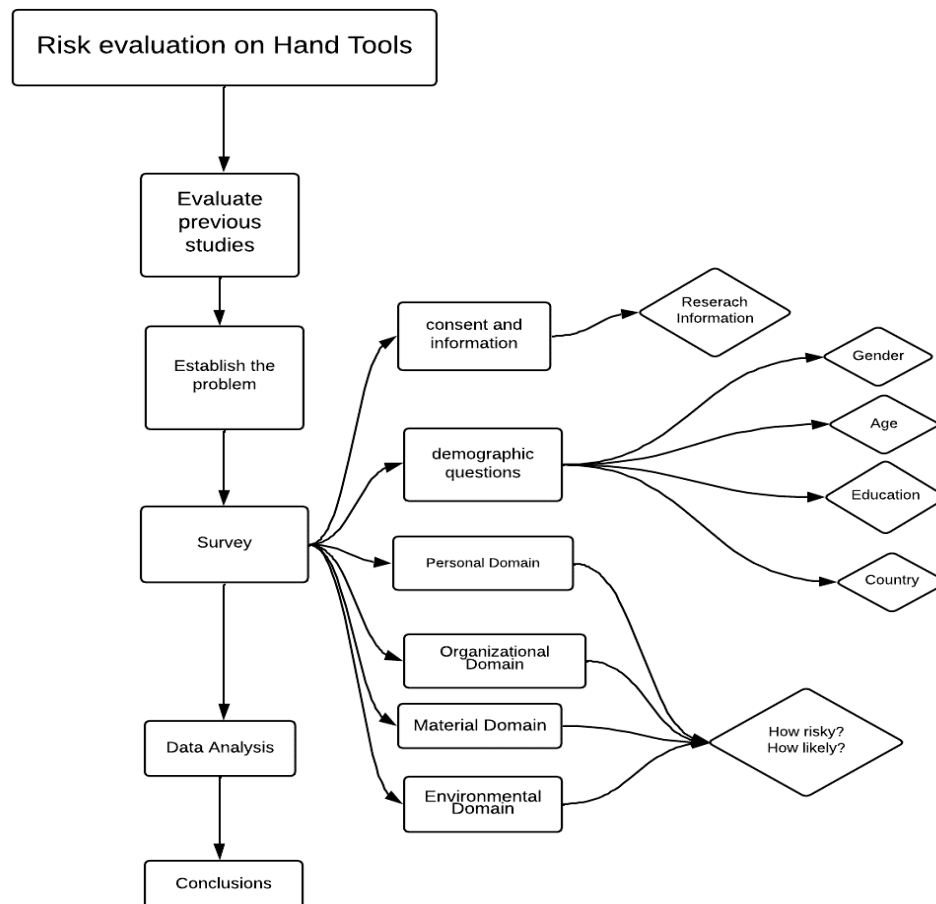


Figure 13 Research Process for Assessing Risk Perception in Hand Tool Use

The study was authorised by the Obuda University Ethics Committee (protocol code: OE-DI-205,2023, approved on November 28, 2022) and carried out in compliance with the Declaration of Helsinki (see ANNEX 1).

Every participant in the research gave their informed consent. Due to the particulars of the study, specific groups of people with relevant knowledge and experience had to be selected, such as safety engineers, ergonomists, and senior users themselves. To reduce the risk of injury and concentrate on non-powered equipment, purposive sampling was used to gather information on the most essential aspects of hand tool safety.

3.2.1 Survey

The online survey was conducted with willing participants, whose main commonality was that they had expertise with hand tools and had received training in their use across a range of industries. Given the changing nature of manufacturing, it is necessary to adopt new statements in place of the established financial, ethical, health and safety, and recreational categories. Following completion of the anonymous survey, the data were utilised to calculate perceived risk. It was sent directly to industrial managers via Google Forms.

A combined number of 123 replies from Ecuador and Hungary have been collected. The sample appears to be balanced based on the responses, with responses coming from Hungarian participants and respondents coming from Ecuador. The questionnaire in ANNEX 3 begins with demographic questions.

3.2.2 DOSPERT

The following section assesses risk-taking; four content areas are evaluated using the Domain-Specific Risk-Taking (DOSPERT) scale. To assess risk-taking behaviour in a new environment, the DOSPERT scale is modified for a completely new domain. To better reflect the characteristics of risk-taking relevant to this new domain, the original DOSPERT scale is modified in this transformation. The internal consistency is demonstrated by preliminary reliability tests on the modified questions. The number of questions also differs from the initial questionnaire.

A survey of twenty questions was created to assess the different categories [116], [118], [119]. The potential risk associated with the use of any hand tool or manually operated machine is determined by the first category, "Material Domain". The second category, 'Personal Domain', identifies the risk associated with individual characteristics such as aptitude and disposition when performing a task requiring hand tools. The risks associated with each physical aspect of the task activity, including temperature, humidity, light, and the arrangement of materials and tools, are described in the following category, 'Environmental Domain'. Finally, the risks associated with planning and documentation are explained in the "Organisational Domain". Figure 14 shows each of these criteria and groups.

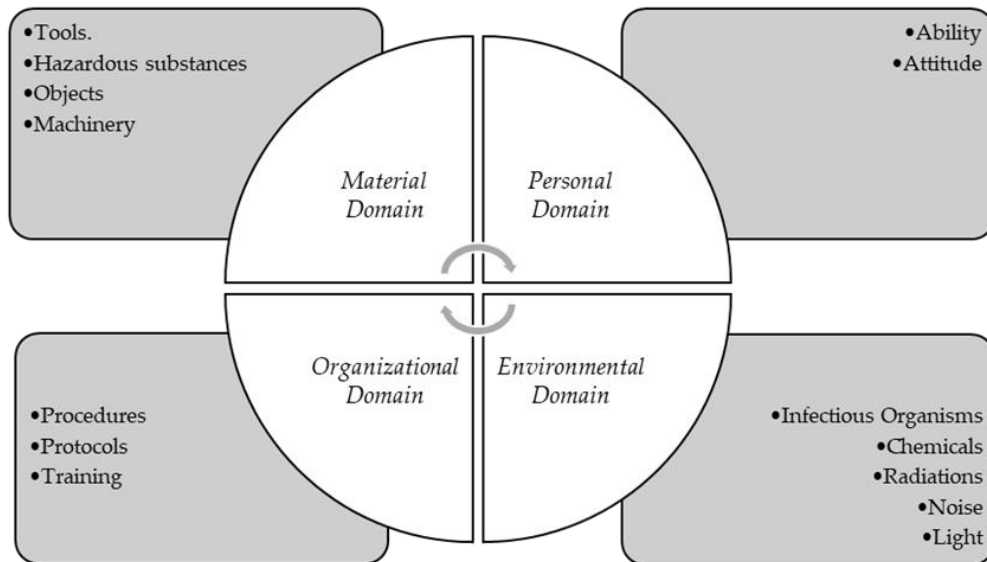


Figure 14 Risk categories and category examples

Table 17 lists the statements used for each of the survey's four subcategories [120]. Expected benefits, risk perception, and risk likelihood were all questioned using the same questions.

Table 17 Statements used for Risk Probability, Risk Perception, and Expected Benefits.

Index	Statements
<i>Material Domain (MD)</i>	
1	Work with incorrect hand PPE (Personal Protective Equipment).
2	Work with short tool handles that press into the palm of the hand?
3	Work with narrow tool handles that press deeply into the hand when the tool is used?
4	Work with a hand tool for the incorrect side? Example: if you are a right-hand person will you use a hand tool for left hand person.
5	Work with hand tools that require big effort or rotational movement to use?
6	Work with hand tools that require a bad or uncomfortable posture?
7	Work with hand tools that require big holding time?
8	Work with hand tools with handles made of slippery materials?
9	Work with heavy hand tools without hanging support?
10	Work with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?
<i>Environmental Domain (ED)</i>	
11	Work in spaces that are small or uncomfortable for the hand?
12	Work with the wrist in a flexed position?
13	Work with heavy hand tools in place where there are not hand support?
14	Work with heavy hand tools in a place where there is not good illumination?
<i>Personal Domain (PD)</i>	
15	Work fixing or adjusting mobile machine parts using hand tools?
16	Work with hand tools that have not been tested for proper operation?
<i>Organizational Domain (OD)</i>	
17	How probably could you work with hand tools without training before starting a new industrial task?
18	Work with hand tools in a place without structured industrial tasks?
19	Work with hand tools in a place without an accident prevention protocol?
20	How likely could you Work with hand tools in a place without a response protocol after suffering an accident?

Ten questions corresponding to the first category assess risk in relation to the physical dimensions of hand tools; the other four questions assess hazard perception about workplace characteristics and comfort during tasks. In the third category, two questions evaluate perceived risk in connection to aptitude and disposition. The final category consists of four questions that are especially made to assess risk in connection with the established protocols and procedures needed to carry out the job. On a numerical scale from 1 (very unlikely) to 7 (extremely likely), respondents are asked to rate the likelihood of engaging in the activity described in each question, which represents a risk-related scenario. Each question represents a specific risk-related event. The response range for expected benefits was 1 (no benefit at all) to 7 (great benefit), and the range for perceived risk was 1 (not at all risky) to 7 (very risky) [93].

People who use or are associated with hand tools in various ways make up the sample for the Hand Tools Survey. Users of hand tools, garden tools, construction tools, and related products are included. The voluntary nature of the questionnaire is the basis of the methodology.

3.2.3 Data evaluation

The number of independent variables has a significant impact on the analysis of risk behaviour. SPSS v25 and Microsoft Excel are used for this analysis. Next, to determine whether there are any notable differences in the different behaviours of Ecuador and Hungary, independent t-tests are used to compare the two countries. The reliability of the statements in each group was assessed by calculating Cronbach's alpha for the statements; all distributions were checked, and the three groups were evaluated. Equation 15 was used to check the internal reliability of the statements in the three groups (x, A, and B).

$$\alpha = \left(\frac{k}{k-1} \right) \left(\frac{S_y^2 - \sum S_i^2}{S_y^2} \right) \quad (15)$$

Where k is the measure's item count, α is Cronbach's alpha, the variance of the overall scores is S_y^2 , and the variance for each group is S_i^2 .

Three categories from which the responses received by the research are analysed: Scores below 0.6 indicate that the research is in its early stages and may not be robust enough or may need additional validation. This category, "Early stage research", contains these results. Scores between 0.5 and 0.7 fall into the second category, 'Applied research', which represents work that is beyond the preliminary stage and suggests that it could be used in

practice, although further work may be needed. Results between 0.9 and 1 are considered to have a high level of confidence and reliability, making the data suitable for use in making essential decisions [121], [122].

There is a latent risk of harm when carrying out industrial activities involving the use of hand tools. Risk perception, which includes the ability to identify hazards as well as the ability to perceive and evaluate risks, is a critical skill in maintaining safe working conditions when using hand tools. Knowledge and training are essential components of the development of industrial jobs [123], [124].

Given the different cultural perspectives on uncertainty, risk-taking, and safety between workers from Ecuador and Hungary, it is clear that assessing whether the former will behave in a more risk-averse manner than the latter is necessary. In addition, the use of assistive technology tools designed for the elderly will increase their ability to perform industrial and specialised tasks compared to tools that are not explicitly designed for their needs. Considering the purpose of the study and the need to investigate risk-taking, the study investigates workers' perceptions of hazards when using hand tools.

3.3 Results

Due to a lack of strict safety regulations and adequate training in the use of hand tools, the construction industry in the United States has an accident and injury rate 50% higher than any other industry. Risk awareness is on the rise in both countries, and to establish the starting point of workers' perceptions and gain insights for future workplace development, hand tools are used. The demographic profiles are presented first, followed by the research findings, considering the primary aspects of the study. Risk attitudes are assessed both across domains and between groups, after determining the level of risk in each domain (Domain-Specific Risk-Taking). Finally, a comparison is made between Ecuador and Hungary [125].

3.3.1 Demographic Profile

The number of respondents and the response rate for each nation are displayed in Figure 15. A total of 123 responses were obtained from Ecuador and Hungary. The replies show that 58.4% (73 persons) of the total respondents were Ecuadorian workers, and 41.46% of the respondents were Hungarian, providing a very balanced sample.

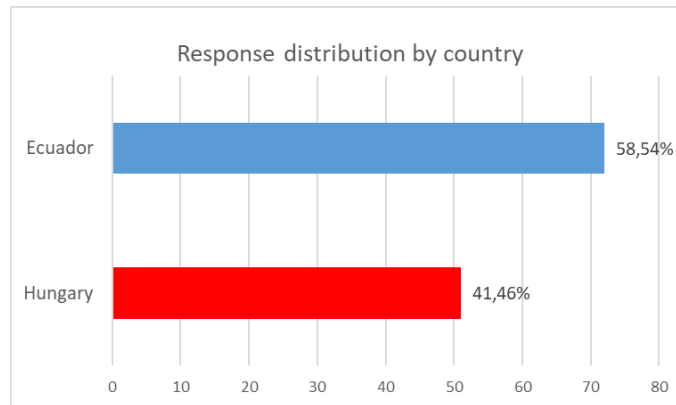


Figure 15 Response distribution by country

The number of women working in industry is rising. Figure 16 illustrates that of the respondents with hand tool experience, 13.82% (18 persons) are female, and 86.18% of the participants are male. Given that hand tools are utilised mainly in the engineering and construction sectors, it is not unexpected that a large proportion of men work in these fields.

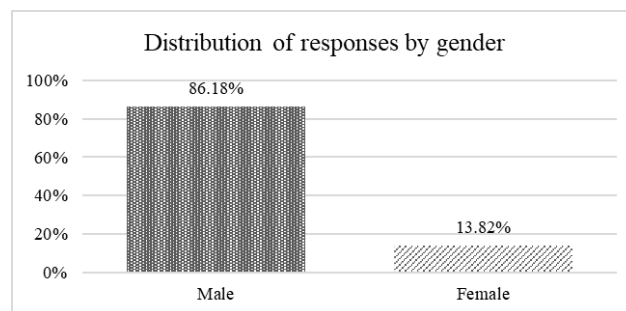


Figure 16 Gender distribution

Age is often the primary factor used in safety-related industries to categorise groups of workers. This classification considers the different stages of development, risk awareness, and experience of the workers. Figure 17 shows that young people make up the bulk of the industry's workforce. Most participants (63.41%) are between 19 and 26 years old, while the second largest group in the sample (15.45%) is even younger, i.e., between 15 and 18 years old, and the third largest group (10.57%) is made up of people between 27 and 35 years old. A common characteristic of the two youngest groups, representing 78.86% of the sample, is a low level of knowledge of work experience, indicating a lack of awareness of the impact of their work on occupational safety and health.

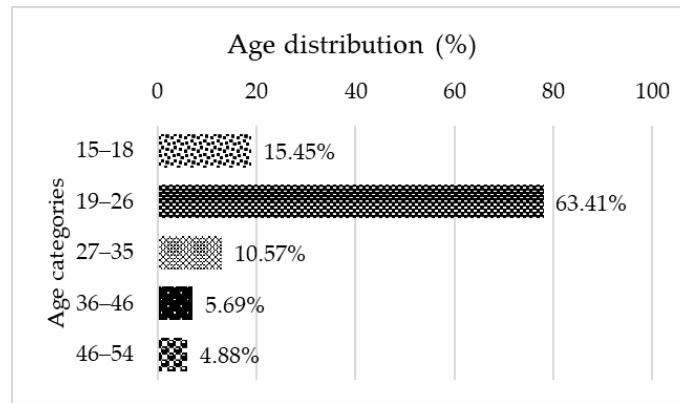


Figure 17 Age of participants

One of the most critical factors in ensuring that the sector has a specialised and competent workforce is the educational background of workers and engineers. Within this framework, the industry is divided into four primary levels of education: A Bachelor of Science (BSc), which focuses on technical and scientific fields. The Master of Science (MSc) programme is the next group and represents a higher level of education. The most prestigious academic degree is the Doctor of Philosophy (PhD). The 'Other' category also includes employees who have completed specialised training, technical colleges, and courses to cover all employees without a university degree. The fact that many employees in the sector do not have specialised vocational academic training, as shown in Figure 18, is indicative of the level of education in the industry. According to the data, 84.56% of the employees have a bachelor's degree or equivalent in technical sciences, and 15.45% of the respondents have completed higher education. The industry's heavy reliance on technical education is highlighted by this distribution, which may indicate a lack of specialised, professional or advanced knowledge and skills among the workforce. To promote innovation and meet the changing needs of the industry, these workforce characteristics highlight the need for decision support tools.

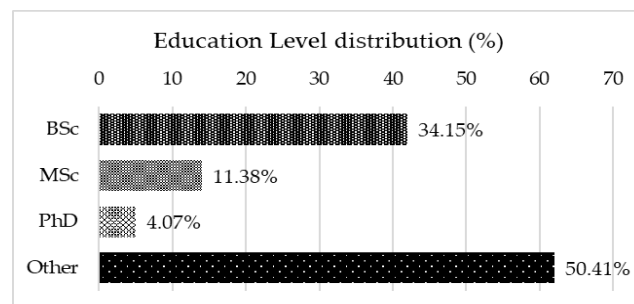


Figure 18 Education level of participants

Workers in the industrial sector consider the need for a personalised set of hand tools based on the changes they experience both at work and throughout their lives. This is due to age and the physical changes that come with experience. Workers' perceptions of the need for a consistent and specialised selection of tools for each age group are shown in Figure 19.

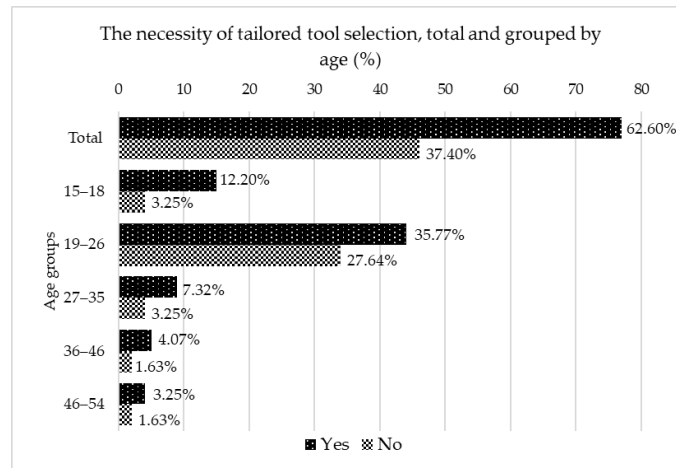


Figure 19 The necessity of tailored tool selection, total and grouped by age (%)

3.3.2 Descriptive statistics

In Ecuador and Hungary, workers who frequently use hand tools in their jobs were asked to complete the survey. The study of people who regularly use hand tools shows the median, mode, standard deviation, skewness, and standard error of skewness (see ANNEX 4), and these statistics show variability and distribution.

The Risk Probability domain reflects how participants think about ergonomic hazards when using tools. The average rating is about 3.56, suggesting regular exposure. The most concerning activities are "fixing mobile machine parts" (rating 4.19) and using "hand tools requiring force or rotation" (rating 4.07), both of which are linked to physical strain. Perceived risks are lower for lacking an "accident response protocol" (2.89) or "slippery handles" (3.09), while Ecuadorians consistently report risk values (4.07) related to incorrect PPE compared to Hungarians (2.80). Male participants report higher exposure (3.54) than women (3.35). The 15–18 age group reports the highest values (6.83) for fixing mobile parts. Those in healthcare and industrial jobs have the highest risk perception, 4.33 and 4.00, respectively, due to frequent exposure to risky tasks. Sales and admin roles show lower scores. Participants with PhDs/MScs report higher risk perception. This suggests that technical knowledge or exposure influences their perceptions.

Respondents identified how dangerous they felt ergonomic conditions were. The highest average risk perception was linked to "Slippery handles" (4.74), followed by "Poor grasp tools" (4.66) and "No support for heavy tools" (4.51). This reflects concerns about hand safety and load handling. The least risky were "No accident protocol" (2.89) and "Unstructured task sites" (3.48). Hungarians report a higher perception of risk (5.27 for "Slippery handles") than Ecuadorians (4.42). Both males (4.74) and females (4.76) showed identical recognition of tool-related hazards, with the most sensitive group (15-18 years) demonstrating the most significant awareness of poor-grasp tools (7.58). The older group (46-54 years) exhibited slightly elevated awareness due to experience. Health professionals reported the highest awareness (5.83). Those with PhDs and MScs consistently perceived greater risk.

Expected Benefits shows how people perceive the trade-off between the benefits and disadvantages of risky tasks. Hungarians generally report slightly lower benefits (3.48 vs 3.44). Younger respondents (15–18 years old) show significantly higher values than those aged between 36 and 54 (3.30 vs 3.22). Gender does not appear to influence the perception of risk, with both males and females reporting similar values. However, individuals with higher education tend to rate the benefits of risky tasks lower, indicating they are more aware of the risks involved, and health professionals report caution in comparison to industrial workers and those in sales/other roles (3.48 vs 3.44 for "Work with short handles").

3.3.3 Comparison of Hungary and Ecuador

A Comparison of Ecuadorian and Hungarian Risk Attitudes, along with aspects that influence risk attitudes across different domains, aids in designing targeted risk management strategies, enhancing safety at work, and refining decision-making models. This section presents: I) Risk Probability attitude Ecuador vs Hungary, II) Risk Perception behaviour Ecuador vs Hungary, III) Expected Benefits assessment Ecuador vs Hungary.

3.3.3.1 Risk Probability attitude Ecuador vs Hungary

Employee conduct in Ecuador and Hungary is shown by analysing their respective trend patterns. For each area, Figure 20 shows the likelihood of risk faced by Ecuadorian and Hungarian workers. The X-axis's numbers stand in for the statements. Comparing the two

countries is crucial because genetic variations lead to different human traits in each area, which can significantly alter how people perceive the likelihood of a risk.

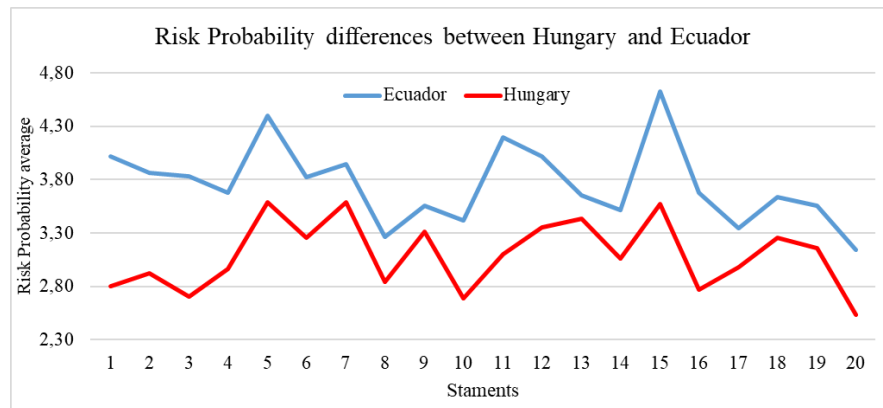


Figure 20 Comparison of Hungary and Ecuador: Risk probability

Table 18 summarises the significant differences and those that are not. The findings indicate that there were no significant differences ($p > 0.05$) in the two countries' workers' perceptions of the likelihood of danger for a variety of items. Long periods of standing, dangling or leaning hands, poor posture, and inadequate lighting are risk variables that affect how likely employees perceive their chances of becoming hurt. The use of a hand tool requires training. Tasks, work processes, and accidents must all adhere to established protocols. In evaluating danger, however, workers consider several physical attributes of hand tools. Whether you are left-handed or right-handed, the tool's dimensions, the range of motions and rotations you must perform, and whether the tool's handle is slippery are a few examples.

Another notable difference was the continuation of work after an incident without observing safety protocols. It is not as common in these countries to consider safety and protocol. This implies that Ecuadorians perceive a higher risk potential than the Hungarians, as all the test scores are favourable.

Table 18 Significant differences in risk probability by Hungarian and Ecuadorian workers.

No	Levene's Test for Equality of Variances		t-test for Equality of Means		
	F	Sig.	t	df	Sig. (2-tailed)
1	Equal variances not assumed		3.556	118.274	0.001
2	0.486	0.487	3.189	120	0.002
3	0.036	0.850	3.975	121	0.000
4	0.543	0.463	2.578	121	0.011
5	2.418	0.123	2.809	121	0.006
6	0.521	0.472	1.932	121	0.056*
7	0.417	0.519	1.212	121	0.228*
8	0.097	0.756	1.444	121	0.151*
9	0.082	0.775	0.770	121	0.443*

10	1.287	0.259	2.430	121	0.017
11	0.000	0.995	3.840	120	0.000
12	1.745	0.189	2.269	121	0.025
13	0.006	0.939	0.791	121	0.430*
14	0.155	0.695	1.584	120	0.116*
15	3.038	0.084	3.645	121	0.000
16	2.216	0.139	3.102	121	0.002
17	0.303	0.583	1.219	121	0.225*
18	1.058	0.306	1.404	121	0.163*
19	0.560	0.456	1.347	121	0.181*
20	0.951	0.331	2.139	121	0.034

* $p > 0.05$, the function is not significant

3.3.3.2 Risk Perception behaviour Ecuador vs Hungary

Figure 21 presents the following comparison, highlighting the main differences and similarities in the way the two countries surveyed perceive the risks associated with the use of hand tools.

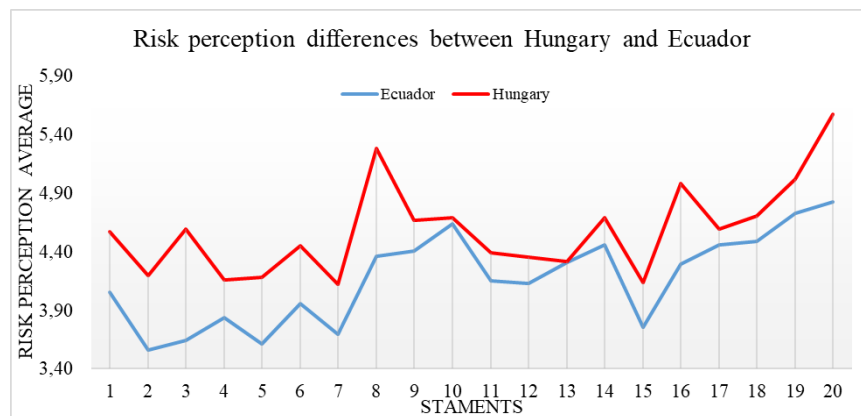


Figure 21 Comparison of Hungary and Ecuador: Risk perception

The responses of the Ecuadorian and Hungarian workers revealed substantial differences in their perceptions of risk in six areas. These areas include the size of tool handles, the possibility of slippage, the first testing of hand tools, and whether safety procedures are in place or not (Table 19). Employees' perceptions of risk differ between the two nations in other situations, but not substantially. Given that Ecuador served as the first sample and the test results were negative, it is presumed that employees in Hungary perceive danger more generally than employees in Ecuador. However, Ecuadorian workers believe that using hand tools that haven't been adequately inspected and working in settings without a response system are less unsafe, which calls for additional health and safety training.

Table 19 Significant differences in risk perception by Hungarian and Ecuadorian workers.

No	Levene's Test for Equality of Variances		t-test for Equality of Means		
	F	Sig.	t	df	Sig. (2-tailed)
1	0.034	0.854	-1.629	121	0.106*

2	0.005	0.945	-2.436	121	0.016
3	0.798	0.374	-3.505	121	0.001
4	0.020	0.887	-1.200	121	0.233*
5	2.329	0.130	-2.105	121	0.037
6	0.047	0.828	-1.824	121	0.071*
7	0.033	0.857	-1.661	121	0.099*
8	3.592	0.060	-3.349	121	0.001
9	Equal variances not assumed		-1.005	117.610	0.317*
10	1.904	0.170	-0.157	121	0.876*
11	0.831	0.364	-0.954	121	0.342*
12	0.312	0.577	-0.841	121	0.402*
13	0.698	0.405	-0.030	121	0.976*
14	0.796	0.374	-0.738	121	0.462*
15	0.746	0.389	-1.278	121	0.204*
16	Equal variances not assumed		-2.577	116.473	0.011
17	1.348	0.248	-0.484	121	0.629*
18	4.682	0.032	-0.803	121	0.424*
19	2.726	0.101	-1.026	121	0.307*
20	0.398	0.529	-2.586	121	0.011

* $p > 0.05$, the function is not significant

3.3.3.3 Expected Benefits Assessment Ecuador vs Hungary

Figure 22 shows the final rating of the employee's behaviour based on how they perceived the benefits. The findings are displayed according to the country of the employee and categorised by each domain.

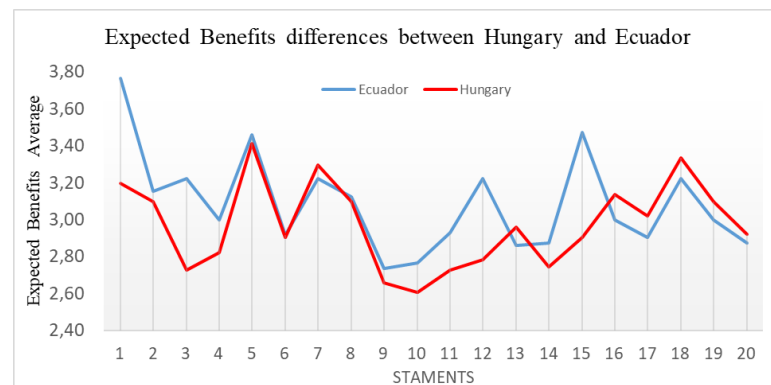


Figure 22 Comparison of Hungary and Ecuador: Expected Benefits

The perceived advantages of the assertions did not differ significantly ($p > 0.05$ for each statement), as Table 20 demonstrates. The most significant variation in the impression of the positive characteristic is seen in statement number 15, "Work fixing or adjusting mobile machine parts using hand tools?" However, this difference in perception is not statistically significant. The statements about testing, pre-operational training, and safety practice (with Ecuador as the first sample) had a negative mean difference, as Table 20 demonstrates. This implies that requests and demands for testing, training, and the presence of a safety plan were less common among Hungarian workers than among Ecuadorian workers. In these cases, more investigation is necessary because the

difference can be due to better working conditions, greater worker awareness, or better worker education.

Table 20 Differences in expected benefits by Hungarian and Ecuadorian workers.

No	Levene's Test for Equality of Variances		t-test for Equality of Means		
	F	Sig.	t	df	Sig. (2-tailed)
1	0.080	0.777	1.459	121	0.147
2	1.583	0.211	0.170	121	0.865
3	0.113	0.737	1.572	121	0.119
4	0.037	0.847	0.601	121	0.549
5	2.893	0.092	0.145	121	0.885
6	1.268	0.262	0.047	121	0.963
7	0.246	0.620	-0.221	121	0.825
8	0.155	0.695	0.074	121	0.941
9	0.085	0.771	0.242	120	0.809
10	0.209	0.648	0.561	121	0.576
11	2.458	0.120	0.674	121	0.502
12	0.101	0.751	1.469	121	0.144
13	0.090	0.765	-0.319	121	0.750
14	0.497	0.482	0.426	121	0.671
15	0.843	0.360	1.836	121	0.069
16	0.283	0.595	-0.420	121	0.675
17	2.033	0.156	-0.378	121	0.706
18	0.556	0.457	-0.342	121	0.733
19	0.025	0.874	-0.274	121	0.785
20	0.245	0.622	-0.139	121	0.890

3.3.4 Domain-Specific Risk-Taking Evaluation

Domain-Specific Risk-Taking is the assessment of an individual's willingness to take risks in different industrial task domains, recognising that risk tolerance varies across contexts. This section presents: I) a Reliability analysis, II) a General view of Risk Probability of hand tool usage, III) a General view of Perceived Risk of hand tool usage, IV) a General view of Expected Benefits of hand tool usage.

3.3.2.1 Reliability analysis

The reliability of the statements was checked before applying the DOSPERT scale to score them. Table 21 shows the excellent reliability of each set of statements; Cronbach's alpha is greater than 0.92 for each of the three categories (probability of risk, risk perception, and expected benefits). Exceptionally high reliability is indicated by values above 0.9. Tables 18, 19, and 20 show the Cronbach's alpha values for each item when it is removed. Each question is pertinent and significantly influences risk perception, risk likelihood, and the advantages of hand tools, since each scenario's Cronbach's alpha values drop when the item is eliminated.

Table 21 Cronbach's alpha value for Risk Probability (RPROB), Risk Perception (RPERC), and Benefits (EXPB)

Risk Assessment Domains	variance associated with the total scores	Sum of individual variances	Cronbach's Alpha
RPROB	434.94	53.82	0.924
MD			0.877
ED			0.802
PD			0.762
OD			0.884
RPERC	502.85	47.15	0.954
MD			0.914
ED			0.844
PD			0.683
OD			0.877
EXPB	783.33	61.65	0.970
MD			0.940
ED			0.943
PD			0.655
OD			0.939

MD= Material Domain. ED= Environmental Domain. PD= Personal Domain. OD= Organizational Domain.

A check for a reasonable level of reliability was also performed on the reliability of the statements within the categories. The most reliable questions in the group were those relating to the material and organisational domains. In contrast, the few questions in the human characteristics category resulted in a somewhat low but still acceptable level of reliability.

3.3.2.2 Overview of the Risk Probability of Using Hand Tools

At this point, an analysis was conducted of the responses' descriptive attributes, including the mean, mode, median, and standard deviation (Table 22). Table 17 contains a list of the actual statements. Higher numbers indicate greater hazards and fewer benefits, while lower numbers indicate lower probability and likelihood, and fewer benefits received.

Table 22 Descriptive features of the statements (Risk probability (X))

x	x (Mean)	Median	Mode	SD	Skewness	Cronbach's α and Cronbach's α if the item is deleted
1. Material Domain (MD)						
Incorrect hand PPE	3.5121	3	1	2.01	0.316	0.923
Short tool handles	3.4754	3	2	1.66	0.219	0.922
Narrow tool handles	3.3658	3	2	1.64	0.242	0.921
Incorrect hand (left/ right side)	3.3821	3	5	1.56	0.104	0.922
Big effort or rotational movement	4.065	4	5	1.63	-0.13	0.922
Uncomfortable posture	3.5853	3	5	1.61	0.117	0.918
Big holding time	3.7967	4	5	1.61	-0.107	0.922
Handles made of slippery materials	3.0894	3	3	1.6	0.28	0.919
Heavy hand tools	3.4552	3	3a	1.71	0.137	0.920
Difficulty grasping the tool	3.1138	3	3	1.68	0.423	0.919
2. Environmental Domain (ED)						
Small spaces	3.7377	4	5	1.65	0.023	0.920

x	$\bar{x}$ (Mean)	Median	Mode	SD	Skewness	Cronbach's α and Cronbach's α if the item is deleted
Wrist in a flexed position	3.7398	4	5	1.62	-0.04	0.920
Not hand support	3.5609	3	3	1.53	0.016	0.919
Not good illumination	3.3278	3	3	1.57	0.122	0.920
3. Personal Domain (PD)						
Mobile machine parts	4.1869	5	5	1.66	-0.194	0.922
Not tested for proper operation	3.3008	3	3	1.67	0.468	0.921
4. Organizational Domain (OD)						
Work without training	3.1951	3	2	1.65	0.442	0.920
Work without structured tasks	3.4796	3	3	1.5	0.247	0.918
Work without an accident prevention	3.3902	3	3	1.62	0.223	0.920
Work without a response protocol.	2.8861	3	3	1.58	0.571	0.922

^a Multiple modes exist. The smallest value is shown.

The mode and median have been adjusted to 'more likely' based on the responses, indicating that participants are more likely to use hand tools from the wrong side or with more effort, twisting or adopting an uncomfortable posture. Working with the wrong hand or with short or narrow tool handles is unacceptable to them. Although the mean and median are below the mode, the mode is 5 (out of 7). For the last set of participants, the median and mode are both 3 (out of 7) for those who do not think that there is a significant chance of slick handles, heavy tools used without hanging support, or hand tools that are difficult to grasp. Even though they were probably working with their wrists bent, participants frequently complained about the space being tiny or unpleasant. The workspace has enough lighting and illumination (the negative statement's mode and median are both 3). It also has a hand support. Participants are more likely to use hand tools to inspect and maintain the machine's moving parts correctly after receiving some instruction (see mode and median for questions 15–17). The responses indicate that some workplaces have no accident prevention measures in place, while others have mechanisms for responding to accidents (see mode and median for questions 18-20). Several workplaces lack clearly structured industrial activities.

3.3.2.3 Perspective on the Perceived Risk of Using Hand Tools

Descriptive statistics of the perceived risk of the participants about the statements (Table 17) are given in Table 23.

Table 23 Descriptive features of the statements (B (Perceived Risk(X)))

x	B (Perceived Risk(X))	Median	Mode	SD	Skewness	Cronbach's α if item deleted
1. Material Domain (MD)						
1	4.2683	5	5	1.732	-0.125	0.971
2	3.8211	4	5	1.466	0.236	0.969

x	B (Perceived Risk(X))	Median	Mode	SD	Skewness	Cronbach's α if item deleted
3	4.0325	4	5	1.547	-0.042	0.969
4	3.9675	4	5	1.476	0.072	0.969
5	3.8455	4	3	1.488	0.057	0.969
6	4.1626	4	5	1.49	0.064	0.968
7	3.8699	4	4	1.402	0.018	0.968
8	4.7398	5	6	1.552	-0.465	0.968
9	4.5122	5	5	1.479	-0.241	0.969
10	4.6585	5	5	1.644	-0.28	0.969
2. Environmental Domain (ED)						
11	4.252	4	5	1.371	-0.137	0.968
12	4.2195	5	5	1.48	-0.155	0.969
13	4.3089	4	5	1.494	-0.2	0.968
14	4.5528	5	4	1.685	-0.041	0.969
3. Personal Domain (PD)						
15	3.9106	4	4	1.66	0.232	0.97
16	4.5772	5	6	1.531	-0.385	0.968
4. Organizational Domain (OD)						
17	4.5122	5	5	1.462	-0.16	0.968
18	4.5772	5	5	1.493	-0.295	0.968
19	4.8455	5	6	1.584	-0.333	0.968
20	5.1301	5	7	1.619	-0.367	0.968

The participants rated most of the scenarios under the Material Domain subscale as dangerous (mode and median range between 4 and 6 for these statements). These scenarios included using hand tools designed for the wrong hand, being too big, too short, too narrow, having a slippery handle, being heavy without hanging support, or requiring an awkward posture. The most frequent answers exceed the risk perceived by half of the respondents, indicating that respondents generally view the scenarios produced by the statements as relatively dangerous and risky. The only exception is that inadequate lighting and a large amount of extra work because of rotation are not regarded as hazardous. In contrast, the absence of accident response methods and processes is viewed as a dangerous and detrimental occurrence.

3.3.2.4 Overall perception of the anticipated advantages of using hand tools

Table 24 displays the anticipated advantages that participants thought would be connected to the exact phrases.

Table 24 Descriptive features of the statements (A (Expected Benefits (X)))

x	A (Expected Benefits(X))	Median	Mode	SD	Skewness	Cronbach's α if item deleted
1. Material Domain (MD)						
1	3.5284	3	2	2.14	0.419	0.953
2	3.13	3	2	1.75	0.618	0.953
3	3.0162	3	1	1.74	0.547	0.954
4	2.9268	3	1	1.6	0.390	0.952
5	3.439	3	4	1.75	0.352	0.952
6	2.9105	2	1	1.7	0.637	0.951
7	3.252	3	2	1.77	0.496	0.952
8	3.1138	3	1	1.98	0.470	0.950
9	2.7049	2	1	1.7	0.854	0.951
10	2.6991	3	1	1.52	0.683	0.950

x	A (Expected Benefits(X))	Median	Mode	SD	Skewness	Cronbach's α if item deleted
2. Environmental Domain (ED)						
11	2.8455	3	1	1.66	0.589	0.951
12	3.0406	3	1	1.64	0.367	0.951
13	2.9024	3	1	1.7	0.541	0.951
14	2.8211	3	1	1.66	0.804	0.952
3. Personal Domain (PD)						
15	3.2357	3	2	1.71	0.331	0.953
16	3.0569	3	1	1.78	0.471	0.951
4. Organizational Domain (OD)						
17	2.9512	2	2	1.68	0.654	0.952
18	3.2682	3	4	1.77	0.404	0.951
19	3.0406	2	1	1.95	0.537	0.951
20	2.8943	2	1	1.82	0.736	0.951

3.3.5 Factor Analysis

Figure 23 shows the risk probability analysis, the factor analysis included 10 items from the material domain, 4 items from the environmental domain, 2 items from the personal domain, and 4 items from the organisational domain. The Bartlett's sphericity test was highly significant ($p < 0.001$), and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.8873, indicating that the data were suitable for factor analysis. Factor loadings for RPROB showed a mixed pattern for MD, with items distributed across several factors, three items loading highly on Factor 1 and one item on Factor 3. ED performed well, with most items (3/4) loading on Factor 1, confirming a clear grouping. However, PD did not show strong factor groupings, with items loading on different factors. OD showed excellent factor validity, with all four items loading on Factor 4, creating a perfect grouping.

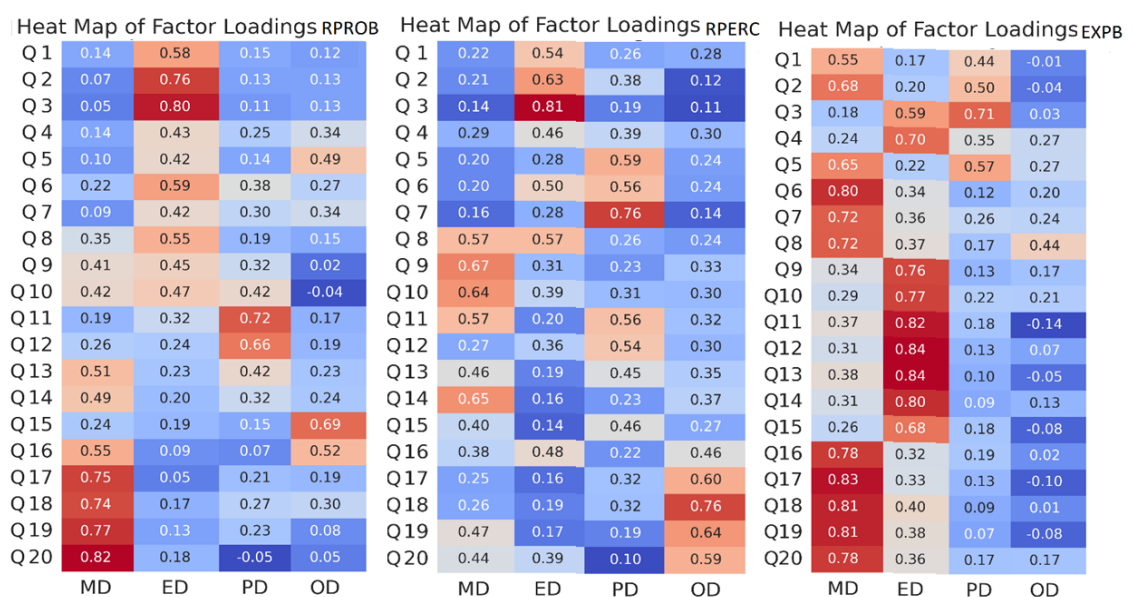


Figure 23 RPROB factor analysis

Figure 23 shows risk perception with a similarly structured factor analysis. The Bartlett's test was again highly significant ($p < 0.001$), and the KMO was 0.9204, indicating strong suitability for factor analysis. The results showed that the MD items were distributed across several factors, with no clear grouping into a single factor. ED again performed well, with all 4 items loading on Factor 1, confirming the consistency of this grouping. PD had two items with weak factor loadings, as they did not clearly load onto a single factor. OD performed excellently, with all four items loading on Factor 4, providing a coherent and clear grouping.

The EXPTB factorial analysis in Figure 23 is similar. The Bartlett's sphericity test is significant ($p < 0.001$), and the KMO measure is 0.9248. This shows that the data is suitable for factor analysis. The factor loadings for MD are clearer in this block, with six of ten items loading onto Factor 1. ED also shows clear grouping, with all four items loading onto Factor 2. PD items have weak factor loadings, as in previous blocks. OD has an excellent result, with four items loading onto Factor 1.

3.3.6 Attitude to risk by domain and across groups

Risk Attitude by Domain across different domain groups. Understanding these variations helps in designing targeted risk management strategies, improving workplace safety, and enhancing decision-making models. This section presents: I) Correlation of Risk-taking, Risk Perception, and Expected Benefit of hand tool usage, II) Risk Attitude in the case of hand tool usage, III) Risk Attitude across the groups.

Correlation of Risk-taking, Risk Perception, and Expected Benefit of Hand Tool Usage

Asking about the perceived value of utilising a hand tool in connection to the circumstances outlined in the statements yields results at the other end of the spectrum. The relationships between the three groups are graphically depicted based on the responses: Risk Probability vs. Risk Perception vs. Expected Benefit. Pairs of relationships are displayed. The perceived risks and expected benefits for each domain are categorised in Figure 24. The Material Domain focuses on tool design and usability, presenting moderate risks (4.0-4.5) and benefits (3.0-3.5). With an emphasis on ergonomics, the Environmental Domain offers fewer hazards (~4.0) and advantages (~2.9-3.1). Fluctuation is shown in terms of rewards (~3.0) and risks (4.0-4.5) in the personal domain. The organisational domain has the highest risks (4.5-5.0) and the lowest

rewards (~2.7-3.1). This is due to structural issues such as inadequate safety procedures and training.

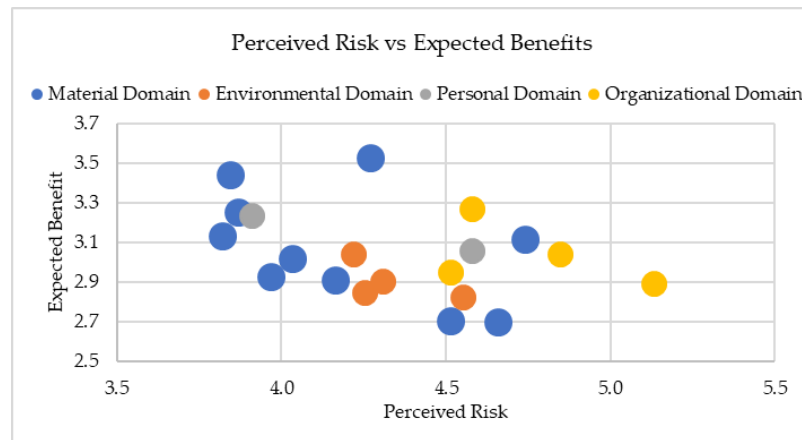


Figure 24 Risk Perception and Expected Benefit of Hand Tool Usage

The connection between risk perception and risk benefits is shown in Figure 25. Moderate risk perception (3.5–4.0) and relatively low risk-taking levels (~4.0) are consistent in the Material Domain, suggesting cautious behaviour brought on by tool design issues. Ergonomic problems with moderate risk taking are indicated by the lower risk perception (~3.5) but comparable risk taking in the Environmental domain. Variety is evident in the Personal Domain, where more risk-taking (~4.5) is associated with risk perception (~3.5–4.0), which is a consequence of self-confidence in one's own abilities. The highest risk perception (4.0–4.5) and risk-taking (~5.0) are seen in the Organizational Domain, which is a sign of organisational issues such as a lack of established protocols that push employees to take more risks.

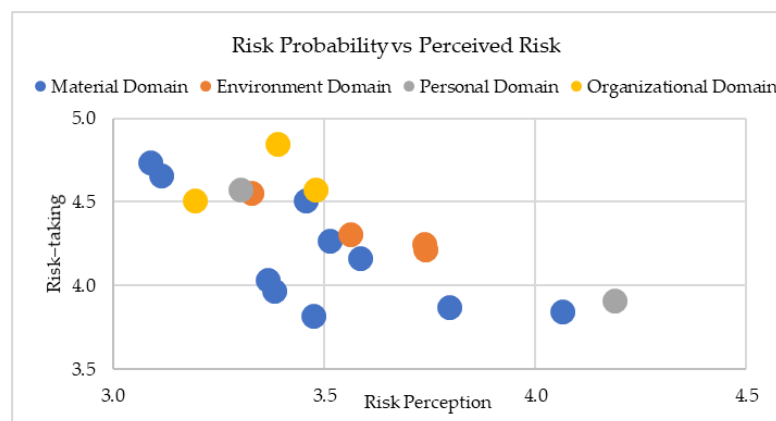


Figure 25 Risk Perception vs Risk-taking of hand tool usage

Risk-taking and perceived benefits are shown in Figure 26. The balance between tool benefits and associated risks is reflected in the material domain, where moderate risk-

taking (~3.9-4.3) is associated with greater perceived benefits (~3.0-3.5). Similar patterns are seen in the environmental domain, where modest ergonomic benefits are seen despite significant risk taking (~3.9-4.3) and lower perceived benefits (~2.9-3.1). Due to people's confidence in risk management, the personal domain shows fluctuation, with moderate benefits (~3.1-3.3) corresponding to higher risk-taking (~4.3-4.5). The organisational domain has the highest risk-taking (~4.7-5.3) and the lowest perceived benefits (~2.7-3.1).

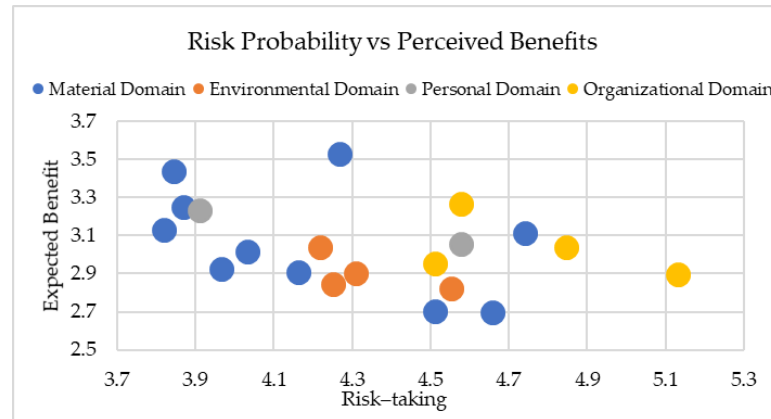


Figure 26 Risk-Taking vs Expected Benefit of Hand Tool Usage

Perceived danger, taking risks, and projected benefits are all adversely connected, according to the study. Based on a pairwise analysis of the connections, Table 25 displays the correlation coefficients across the categories. Perceived risk and risk-taking have a substantial negative correlation (-0.75), suggesting that people are deterred from utilising the hand tool due to the perceived risk. Perceived risk and expected benefits, however, have a negative correlation (-0.4), suggesting that consumers are aware that employing "faulty" hand tools could result in mishaps. In summary, the correlation between taking risks and the anticipated rewards is positive (0.48). This implies that people could act carelessly when utilising imperfect hand tools or when their employer requires them to use hand tools, even if they are aware of the possible risks. In comparison, if employees believe they would benefit, they are more likely to take risks. This third association is the worst one displayed in Figure 26. The multiple correlation of 0.77, which indicates that risk perception and projected benefits have a 60% influence on risk taking, suggests a moderately strong explanatory effect.

Table 25 Risk statement values used for DOSPERT evaluation

	Risk-taking	Perceived risk	Expected benefit
Risk-taking	1		
Perceived risk	-0.75	1	
Expected benefit	0.48	-0.40	1

3.3.7 Risk Attitude in the case of hand tool usage

The bounded means calculated for the DOSPERT scale regression analysis are shown in Table 26. The use of the bounded mean avoids bias and distortion calculated after removing the lowest and highest 15% of data values. For each response item, these values represent the results for the whole group. To assess the regression and ascertain the coefficients for perceived risk (X2) and expected benefit (X1), they supply the initial values for the DOSPERT equation.

Table 26 Risk statement values used for DOSPERT evaluation

Statements	x	A (Expected Benefits(X))	B (Perceived Risk(X))
1. Material Domain (MD)			
1	3.4286	3.4476	4.2952
2	3.4423	3	3.7619
3	3.3143	2.8952	4.0286
4	3.3524	2.8381	3.9333
5	4.0762	3.3524	3.8476
6	3.5714	2.7619	4.1333
7	3.8286	3.1524	3.8571
8	3.0095	2.9714	4.7905
9	3.4286	2.5577	4.5238
10	3.019	2.5905	4.6952
2. Environmental Domain (ED)			
11	3.7308	2.7238	4.2667
12	3.7524	2.9429	4.2286
13	3.5524	2.7905	4.3238
14	3.2885	2.6571	4.5714
3. Personal Domain (PD)			
15	4.1905	3.1524	3.8667
16	3.219	2.9333	4.619
4. Organizational Domain (OD)			
17	3.1143	2.8095	4.5238
18	3.4476	3.1714	4.6095
19	3.3333	2.8952	4.9238
20	2.7714	2.7333	5.2381

The Dospert values by domains and the total Dospert value for the components before the regression analysis are evaluated in Figure 27 and 24.

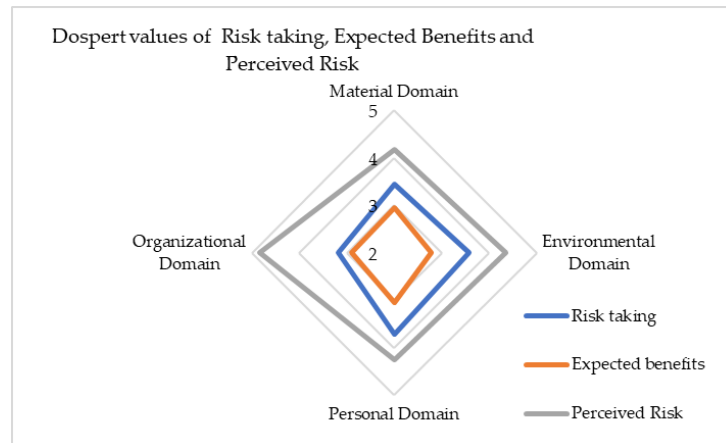


Figure 27 Dospert values by domains (developed by authors)

By averaging the statement values within each domain, the average scores for each domain are first determined to obtain the DOSPERT value. As a result, a new average matrix is produced, with each column denoting a particular factor and each row representing a domain. Every column across all domains is averaged to determine the final DOSPERT number.

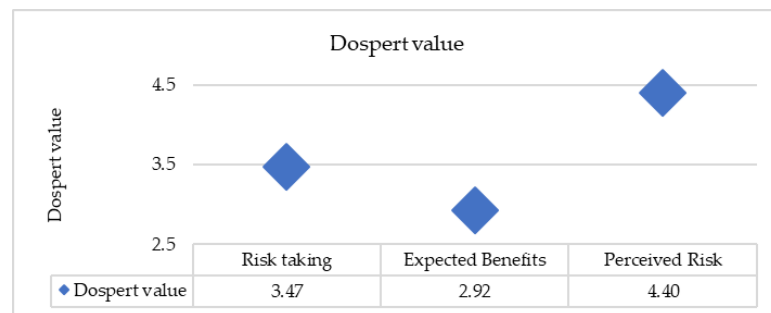


Figure 28 The combined Dospert value (developed by authors)

To determine if people who use hand tools are risk-seeking or risk-averse, equation 14 is completed, and the DOSPERT scale assessment is used in the form of linear estimates. When Equation 1 was applied to the data gathered for the first domain (material domain), as Table 27 illustrates, the "b" factor in the equation (perceived risk) had a negative coefficient, signifying risk aversion.

Table 27 Risk assessment evaluation – Material Domain

	Coefficients	SE	t-Statistic	Probability	Lower 95%	Higher 95%
Interception	4.7494	1.5853	2.9960	0.0201	1.0009	8.4979
Expected Benefits	0.3079	0.2977	1.0341	0.3355	-0.3961	1.0118
Perceived Risk	-0.5285	0.2367	-2.2323	0.0608	-1.0883	0.0313

The data collected for the second domain (the environmental domain) generated a negative coefficient as well in the 'b' term of the equation when the identical equation 1 was applied, again indicating risk aversion. Table 28 shows the result in terms of perceived risk.

Table 28 Risk assessment evaluation – Environmental Domain

	Coefficients	SE	t-Statistic	Prob.	Lower 95%	Higher 95%
Interception	10.3143	2.9811	3.4599	0.1791	-27.5640	48.1925
Expected Benefits	-0.1500	0.5111	-0.2936	0.8182	-6.6441	6.3440
Perceived Risk	-1.4528	0.4052	-3.5852	0.1732	-6.6018	3.6961

Finally, a negative factor was found for the "b" component of the equation for the Organisational Domain, the fourth domain, which indicates a risk-aversion attitude once more. The information in Table 29 represents perceived risk.

Table 29 Risk assessment evaluation - Organizational Domain

	Coefficients	SE	t-Statistic	Prob.	Lower 95%	Upper 95%
Interception	1.2131	4.2830	0.2832	0.8243	-53.2076	55.6337
Expected Benefits	1.0979	0.8508	1.2905	0.4197	-9.7123	11.9082
Perceived Risk	-0.2556	0.4999	-0.5113	0.6991	-6.6076	6.0963

According to the risk attitude by category, employees exhibited risk-averse behaviour in the material, environmental, and organisational domains. The Personal Domain had to be excluded because it contained two statements and three variables, making it impossible to run the regression model. However, the Personal domain was also part of the whole model.

Risk attitude across the groups

Regression analysis was used to assess the risk attitude across all the statements. The analysis (Table 30) reveals that respondents generally exhibited a risk-averse attitude, and that while using hand tools for work, risk aversion outweighs risk seeking. Employees want a safe working environment and safe hand tools.

Table 30 Risk attitude evaluation - coefficients

	Coefficients	SE	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5.0525	1.1488	4.3980	0.0004	2.6287	7.4763
Expected Benefits	0.3098	0.2477	1.2507	0.2280	-0.2128	0.8323
Perceived Risk	-0.5775	0.1468	-3.9338	0.0011	-0.8872	-0.2678

The following regression formula can be used to calculate risk attitude based on the calculations:

$$\text{Risk Attitude} = 5.0525 + 0.31 \cdot \text{Expected benefit (X)} - 0.58 \cdot \text{Perceived Risk(X)} \quad (3)$$

According to the regression values, the Organizational Domain has lower values, and the Material Domain has greater values (Figure 29).

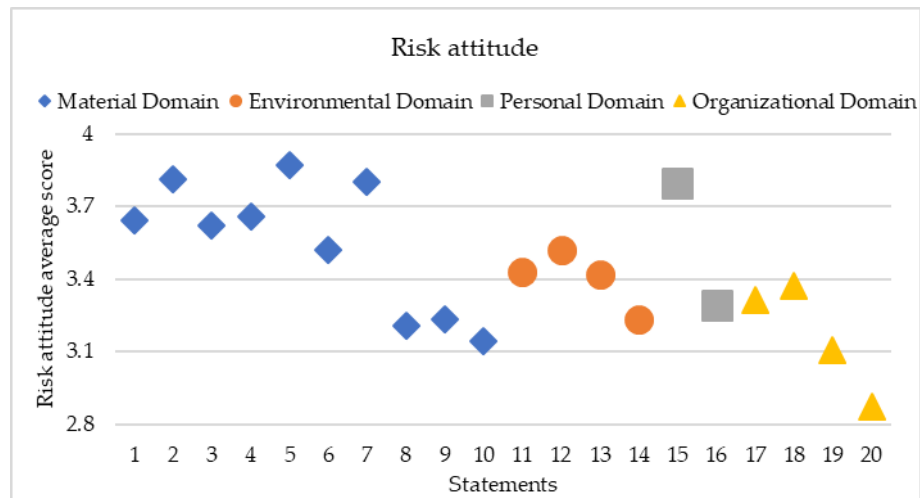


Figure 29 Risk Attitude values by domains according to the regression function (developed by authors) (Note: the numbers denote the individual statements in the questionnaire)

The regression model's coefficients can be examined to identify trends in risk-taking behaviour. The aggregate results clearly show that the respondents preferred safety over hand tools and the workplace.

3.4 Discussions

The selection and customisation of hand tools for jobs and personnel is an essential concern in industry. This study provides a framework for grouping hand tool risks into four categories: organisational, material, personal, and environmental. Each of these categories highlights the various components of tool use that can pose risks to workers, which must be understood to prevent hand-related diseases and accidents.

Perceived hazards influence the desire for safer devices, and the cautious use of these devices depends on several variables, including age, tool quality, worker qualifications and skills, and the type of manufacturing process [126], [127], [128].

Risk aversion is common in the material and environmental spheres, according to the study. This implies that employees value using tools properly to avoid accidents and choose safer equipment and working environments. Numerous factors, including the task's nature, the worker's expertise, and the tool's quality, affect this caution.

The study found significant differences in risk attitudes when comparing the risk perceptions of workers from Ecuador and Hungary. The size of tool handles, their

slickness, and the presence of safety laws were all factors that Hungarian workers frequently viewed as posing greater risks. However, Ecuadorian workers were less worried about other risks, such as working in unregulated environments or utilising untested equipment. This implies that for Ecuador's safety protocols to meet worldwide standards, more education and awareness initiatives are required.

The study identified several domains, including material risks related to the manufacturing of tools and machinery, personal risks caused by individual factors like prior injuries, environmental risks caused by physical aspects like the workplace layout, and organisational risks related to planning and documentation. In Tables 27-30, the coefficients show that instruments considered safe improve worker satisfaction and productivity, demonstrating the dependability of the relationship between perceived risk and predicted benefits.

Perceived risk in the organisational domain is lower than in the other domains, according to Figure 29, which displays the outcome. According to this, the group of organisational domains has a lower perceived risk than the material, environmental, and human features. The results presented in Table 27 demonstrate that workers do not have a risk-taking attitude toward the risk associated with the hand and any hand-held tool or hand-held machine because of the identified risk aversion in the material domain, which implies that users feel the need to understand how to use the tool while also paying attention to potential failures.

Employees in Ecuador may perceive less risk while using hand tools that have not been evaluated or when working in settings without established safety protocols, according to the results displayed in Figure 21. This implies that Hungarians are more inclined than Ecuadorian workers to behave in a risk-averse manner.

3.5 Main contributions

Nowadays, selecting hand tools specifically designed for jobs and employees is a significant concern for ergonomics specialists and industry managers. By classifying the risks connected to using hand tools for industrial tasks, this study aims to assist ergonomics managers. The four categories of risks are organisational, environmental, human, and physical. Organisational risks are linked to planning and documentation, people risks are related to specific elements, environmental risks are linked to physical conditions, and material risks are linked to tools and equipment.

By understanding these categories, users can reduce their risk of hand-related ailments and complaints associated with non-powered hand equipment. Table 27 findings indicate that risk aversion was noted in the Material domain. Given the possibility of failure, this implies that users are driven to become proficient with the instrument.

Workers may select other instruments that initially appear riskier but, despite the apparent risk, turn out to be more accurate, efficient, or cost-effective. The findings in Table 28 for the environmental domain similarly demonstrate risk aversion, indicating that hand tool users think it's critical to take the workplace's quality and atmosphere into account. The Organizational Domain group was viewed as having less risk, according to the data displayed in Figure 29. This is due to the established protocols and training programs that are specific to each industrial work. Risk-taking was also observed in the personal realm, which is the third area (Table 28). This implies that workers are very confident in their capacity to complete the task at hand after obtaining the required training.

In general, Hungarian workers felt more risky than Ecuadorian workers, the survey found. The two nations' views of danger in some hand tool safety situations, such as tool handle size, slipperiness, and the existence of safety procedures, differed noticeably.

- **Thesis (T3):** By applying modified DOSPERT risks perception evaluation related to hand tool uses in a sample of 123 participants. I determined four domains: 'Material Domain', 'Personal Domain', 'Environmental Domain', 'Organizational Domain', and I proved that risk aversion was more likely in the Material and Environmental domains (b coefficient -0.0729 and -2.1639 , respectively) and risk-taking behaviour in the Organizational and Personal domains (b coefficient 0.2985 and 0.2985 , respectively).

Own publications related to this chapter: [120], [129]

4 ELECTROMYOGRAPHIC FATIGUE MONITORING DURING MANUAL TOOL OPERATION

In the field of hand tool use, the risk related to fatigue among users is essential for understanding the task. A structured methodology for analysing fatigue on set risk related to hand tools is presented, including an introduction, a detailed explanation of the methods, a presentation of the results, and a discussion of their implications.

MSDs induced by hand tool use were primarily caused by hard exertion, uncomfortable postures, vibrations, and repetition. Additionally, most tasks involving hand tools involve one or more of these characteristics. The discomfort that tool users endure leads to physical stress [130]. Since these varieties of variables can cause musculoskeletal disorders (MSDs), ergonomic tool design is essential. Stress and chronic injuries can be avoided by using ergonomic tools to lessen the physical strain on the body.

4.1 Ergonomic Pliers Gripping Design

In the design of hand tools, the grip width plays a crucial role in minimising the stress on the hand. Improving work efficiency and reducing work-related illnesses, therefore, depends on hand tools having the right grip span. Research has been carried out to determine the ideal grip span to achieve the strongest possible grip. In particular, the grip width influences the individual finger force. In other words, each finger has a unique grip span for applying the most force [130].

ISO 5745, together with DIN 5745, sets standards for the dimensions and usability of pliers and nippers to ensure they fit comfortably in the hand, reduce strain, and support natural hand movements, which is essential for ergonomics. By defining grip requirements, handle lengths, and force distribution, this standard helps prevent repetitive strain injuries and musculoskeletal disorders (MSDs) among tool users [131]. The primary dimensions of gripping and handling pliers are outlined in this International Standard, together with test values that confirm the suitability of the pliers for use in accordance with ISO 5744 [132].

The correct handle length ensures that the tool can be used comfortably with less risk of musculoskeletal disorders, as it helps to distribute the force more evenly across the hand, reducing fatigue and discomfort with prolonged use. The standardised dimensions of the pliers are presented, and the standardised measurement position is shown in Figure 35.

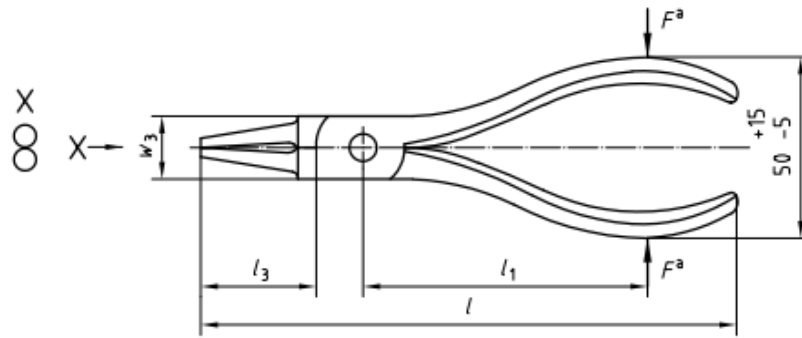


Figure 30. Standardised Pliers Dimensions

Table 35 provides specifications for pliers based on their nose length, nominal length (l), and handle length (l_1), along with performance standards for torque, twist, load, and permanent deformation. The l_1 handle length is critical for ergonomics as it directly affects the leverage, comfort, and ease of applying force. The l_1 length allows users to generate adequate gripping force without excessive strain or awkward hand postures, ensuring that the tool can be comfortably used with less risk of musculoskeletal disorders, as it helps distribute force more evenly across the hand, reducing fatigue and discomfort in prolonged use.

Table 31. Standardised Pliers Dimensions according to ISO DIN 5745

Length of nose	Nominal length		Torsion test		Load test	
	l (mm)	l_l (mm)	Torque T (N·m)	Maximum twist α_{max}	Load F (N)	Maximum permanent set s_{max}^a (mm)
Short nose	125	63	0.5	20°	630	1
	140	71	1.0		710	
	160	80	1.25		800	
Long nose	140	63	0.25	25°	630	
	160	71	0.5		710	
	180	80	1.0		800	
$a \quad s = w_l - w_2$ (see ISO 5744)						

4.2 Method

This section covers the components and materials used to conduct the research, together with an explanation of the device implementation methodology. This is followed by a detailed presentation of the study and an explanation of the approach used.

4.2.1 Sample

A sample of 12 men who had never had upper extremity MSDs volunteered for this investigation. The study began with a summary of the experiment's goals and procedures and an informed consent form for each participant (see ANNEX 5). The signal was

captured as the reference measurement from the forearm. Each subject's Pronator Teres was used as the measurement site and was attached to the electrodes.

4.2.2 Procedure

Participants completed an upper extremity MSD questionnaire before the experiments. Then, prior to the experiments, all participants were given a brief description of the experimental procedure and completed a practice test to familiarise them with the grasping task.

For this study, participants exerted their maximum grip force by grasping the handles of the pliers. All participants were instructed to exert their maximum force from an initial relaxed state and then to perform 40 repetitions of this movement. After the trial, they were asked to relax. Participants were given five minutes' rest between each trial to minimise muscle fatigue. The grasping task was repeated twice for each grip range (45 mm, 65 mm), so that each participant performed 80 trials. Trials were selected in random order. After performing a grasping task, each participant was asked to provide a subjective rating of discomfort for each grip span using the Borg CR10 scale, which ranges from 0 to 10 and represents different levels of effort intensity. A score of 0 indicates complete relaxation, with 0.5 suggesting a barely perceptible level of effort and 1 reflecting very low effort where one might feel slightly uncomfortable. At 2, low effort is manageable, while 3 represents moderate effort, signalling noticeable pressure but still under control. 4 indicates somewhat intense effort, affecting concentration, and 5 indicates intense effort, with discomfort and significant worry. As effort increases, 7 reflects a very intense level, characterised by overload that's difficult to ignore. Near the top, 9 represents extreme effort, bordering on unbearable, and 10 is maximum effort, an overwhelming state that can't be sustained for long.

The electrical signal outputs from the EMG sensors were converted to digital signals and then sent to a computer.

4.2.3 Statistical comparison

The t-test is used to determine whether the means of two groups are significantly different. First, formulate the alternative hypothesis that there is a significant difference and the null hypothesis that there is no difference. The next step is to choose between a paired t-test, an independent t-test (two-sample), or a one-sample t-test. This is followed by confirming equal variance for independent tests and checking normality assumptions before

computing the test. Degrees of freedom, which vary with sample size, are then determined after the t-statistic has been calculated using group means, variances, and sample sizes. The p-value associated with the computed t-statistic is then found to determine significance: if the p-value is less than or equal to the chosen significance level (often 0.05), the null hypothesis is rejected, indicating a significant difference between the groups; if it is greater, the null hypothesis is not rejected, indicating no significant difference.

4.3 Results

To select the most appropriate hand tools and ensure both efficiency and user safety, force and fatigue detection are used to determine the force requirements that can lead to muscle strain, while prolonged use of tools that cause excessive fatigue can lead to long-term injury or reduced productivity. The results are presented with a focus on force and fatigue detection by EMG evaluation.

4.3.1 EMG evaluation

The analysis presented tracks muscle activity over time for each repetition or muscular contraction during a task using hand tools. The variables identify the participant and represent the measurement of muscular activity value, indicating the EMG reading of muscular strength, to be analysed by an algorithm to determine the presence of fatigue. The Activity and its response are presented in Figure 31.

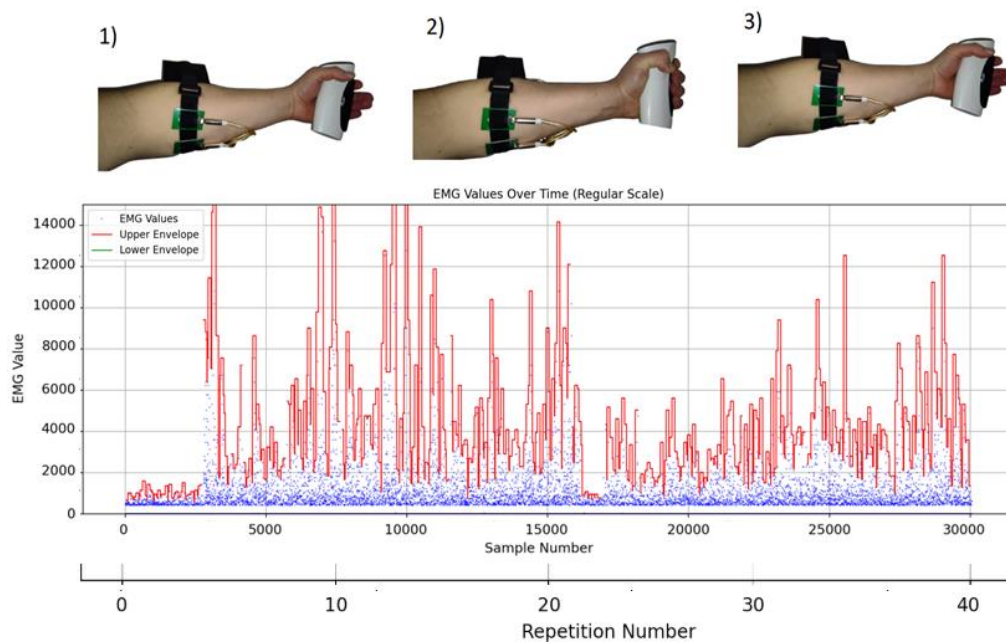


Figure 31. EMG captured data during hand tool use. 1) relaxed grasping of the handles, 2) Full force grasping of the handles, 3) Initial position recovery and muscle relaxation

To analyse the data, it is divided into four groups by assigning a tag during the exercise according to the type of hand tool usage (45mm or 65mm). Group 1 represents non-fatigue using a 45mm hand tool, while Group 3 represents non-fatigue using a 65mm hand tool. Fatigue is indicated by a value of 2 or 4, representing its influence during the task: 2 means the onset of fatigue using a 45mm hand tool, and 4 indicates the onset of fatigue using a 65mm hand tool. When analysing fatigue, focus on cases where the class is 2 or 4 to identify possible patterns in the EMG signals, such as changes in amplitude or frequency, compared to non-fatiguing cases. The descriptive analysis of the measured data is presented in Table 32.

Table 32. Descriptive analysis for data used to identify fatigue

	Participant	Repetition EMG values	Class values	Fatigue	Non-Fatigue
count	11808.0	11796.0	11808.0	11,802.0	18,239.0
mean	3.7007960705	35.7414377755	2.8770325203	320.60	390.62
std	1.1401313194	9.4492391668	0.9924527262	948.01	1,031.75
min	1.0	3.0	2.0	0.0	0.0
25%	3.0	30.0	2.0	0.0	0.0
50%	3.0	34.0	2.0	0.0	0.0
75%	5.0	39.0	4.0	0.0	484
max	12.0	83.0	4.0	29,24	29,92
P (one tail)	2.22e-07				
t-statistic	-5.9285				
Cohen's d	-0.070				

The data is evaluated and classified to proceed with the rows of fatigue (class = 2 or 4) that have been filtered.

Figure 32 provides significant findings related to the evolution of EMG values over the range of the 40 trials. In the initial range around 25 repetitions, there is considerable variability in EMG values for both the fatigued and non-fatigued conditions, with more pronounced spikes in the fatigued condition. This reflects peaks in muscle activity as participants adjust their effort. Over time, EMG values gradually decrease in both conditions, suggesting a reduction in muscle activation due to fatigue. In the fatigue condition, the EMG values have higher peaks, indicating moments of increased effort. In contrast, in the non-fatigue condition, the values are steadier and lower in amplitude, reflecting more consistent muscle activity without extreme effort. After about 20 repetitions, EMG values stabilise at lower levels, particularly in the non-fatiguing condition. This analysis suggests that fatigue is characterised by greater variability and higher peaks in EMG values, particularly in the early repetitions, before both conditions stabilise.

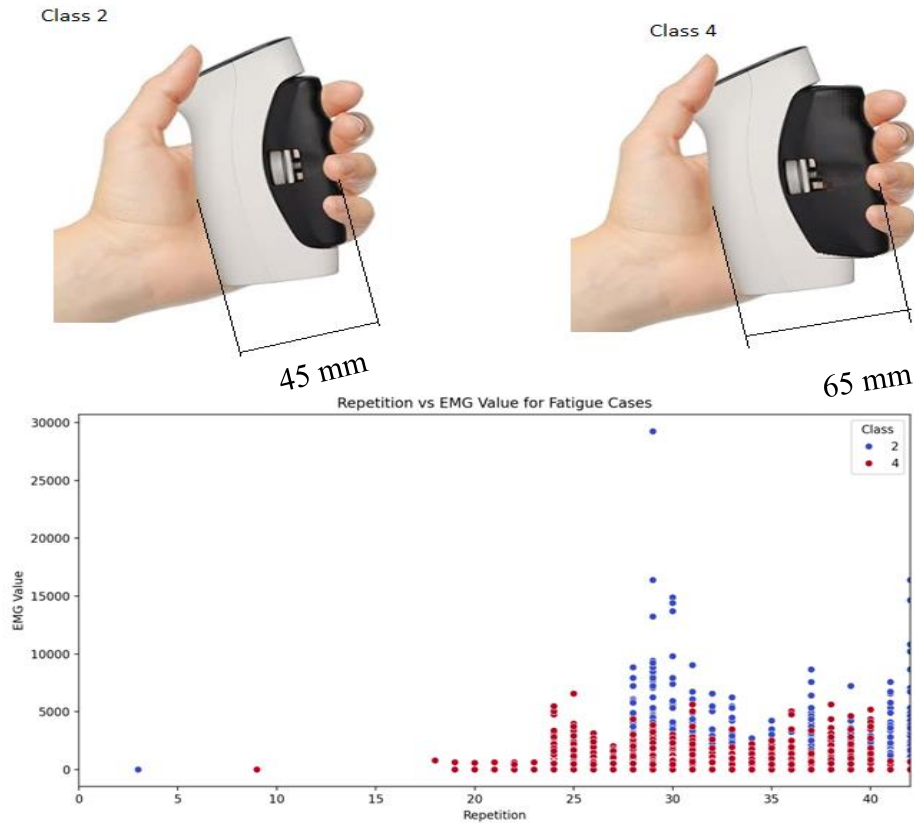


Figure 32. EMG values for the fatigued condition.

The Kolmogorov-Smirnov (KS) test evaluates distributional differences between two datasets. In this sense, the p-value ($2.22e-07$) indicates a statistically significant difference between the two groups, though the effect size (Cohen's $d = -0.07$) suggests the difference is negligible. On the other hand, the left-tail KS test explicitly has a high p-value (0.9941) and a minimal statistic (0.0006). As a result, even though the overall distributions vary somewhat, the difference appears to be insignificant.

Individual Participant Analysis

The next step is to analyse data from a random participant in a hand tool fatigue experiment to understand how fatigue manifests itself in the observed metrics, such as grip strength, force application, or tool handling efficiency. In addition, the sensitivity of detecting fatigue-related changes will be determined. The selected subject is Participant 3, and the compared data is the repetition 1 compared to the last repetition, as shown in Figure 33, to analyse the changes in EMG data. The effects of fatigue are highlighted in Repetition 1 (blue) and Repetition 40 (orange). At Repetition 1, the muscle initially shows stronger contractions, with higher and more frequent EMG peaks, reflected in a maximum of 6241.0. At repetition 40, these values decrease significantly to a maximum of 2916.0

(a decrease of 53.3%), indicating reduced muscle activity due to fatigue. The number of samples increases from 261 to 316, which suggests more fragmented signal patterns, possibly due to irregular contractions.

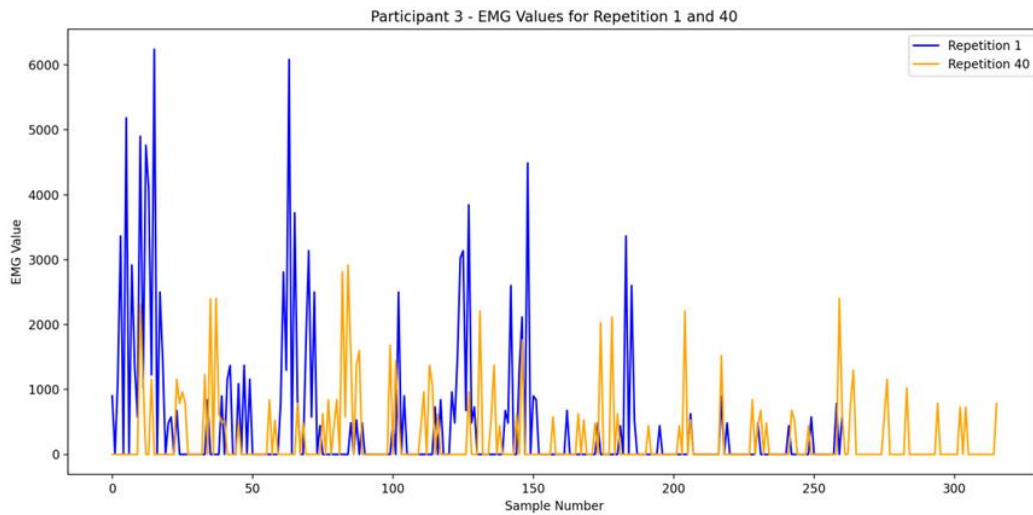


Figure 33. EMG values during Repetition 1 and Repetition 40

Figure 34 compares the EMG peak values during the first (R1) and fortieth (R40) repetition of a task, showing changes in muscle activation over time. The mean peak values for repetition 1 are significantly higher at 1866.27, while the mean for repetition 40 is 1142.48, indicating a 38.8% decrease in mean peak values, suggesting muscle fatigue or adaptation as activation levels decrease with repeated effort. The peaks are sorted by magnitude, and while both conditions show a steep initial decline that levels off, the R1 peaks consistently exceed those of R40 until they converge at lower magnitudes and peak count of 51 for R1 and 54 for R40.

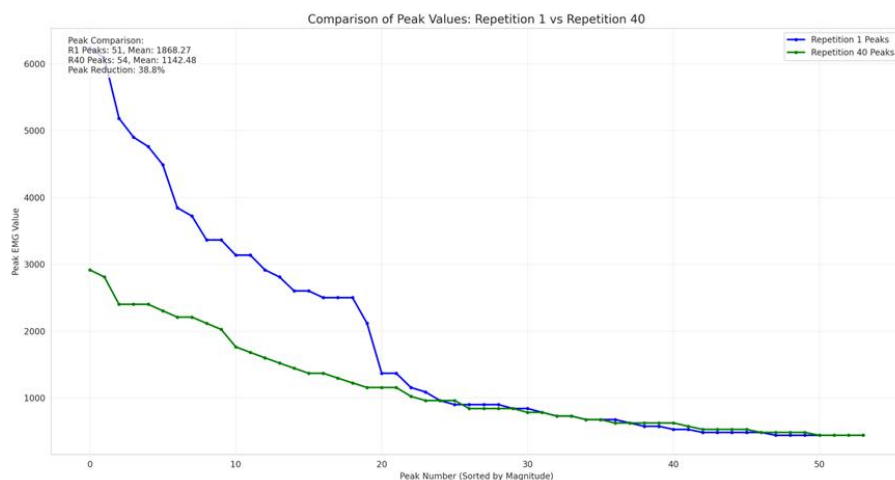


Figure 34. Comparison of the peaks between Repetition 1 and Repetition 40

The EMG values for participant 3 between the first (R1) and fortieth (R40) repetition show significant differences in muscle activation, as shown in Figure 35. The mean EMG value decreases from 474.35 in R1 to 239.90 in R40, a reduction of 49.4% and a mean difference of 234.45. The R1 distribution is broader and shows greater variability, whereas the R40 distribution is narrower with a higher peak, indicating more consistent but reduced muscle activation during later repetitions. A t-test confirms the statistical significance of this difference, with a t-statistic of 3.391 and a p-value of less than 0.0001. These results suggest that muscle fatigue occurs over repetitions, leading to reduced activation and possibly more stable movement patterns.

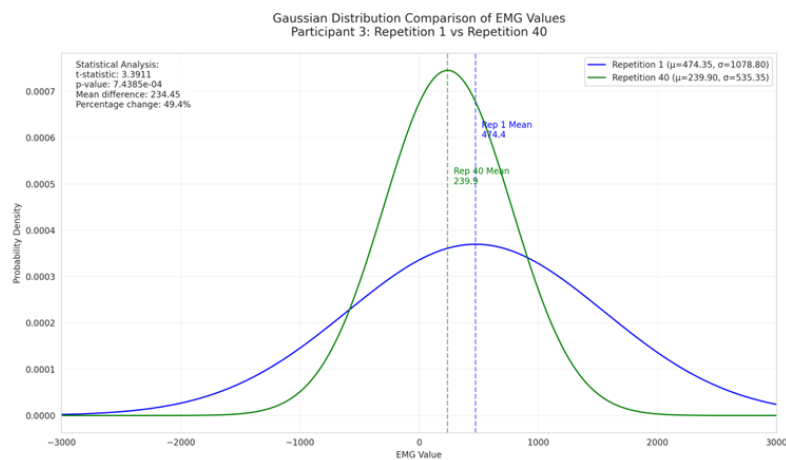


Figure 35. Gaussian distributions plotted for Repetition 1 and Repetition 40

The statistical significance of the difference between repetition 1 and repetition 40. The distribution corresponds to a p-value of approximately 0.0004 (0.04%). The t-statistic (3.3911) emphasises the right tail. The overall two-tailed p-value is approximately 0.0008 (0.08%), well below the $\alpha = 0.05$ threshold, confirming that the difference is statistically significant. These data are expressed in Table 33.

Table 33. Statistics for Participant 3, Repetition 1 vs Repetition 40

	Repetition 1	Repetition 40
	Value	Value
count	261.0	316.0
mean	4.743.524.904.215	2.398.987.341.772
Std	1.078.801.203.564	5.353.450.889.995
Min	0.0	0.0
25%	0.0	0.0
50%	0.0	0.0
75%	484.0	0.0
Max	6241.0	2916.0
Two-tailed p-	0.0008043728222952851	
t-statistic	33.911	
One-tail area	4.02E ⁻⁰⁴	

4.3.2 Force evaluation

Ergonomic gripping of hand tools is a concern in industry for prolonged or repetitive use. The tool comparison, as shown in Figure 36, is used to observe the force trend and determine the influence of hand tool size in the selection process.

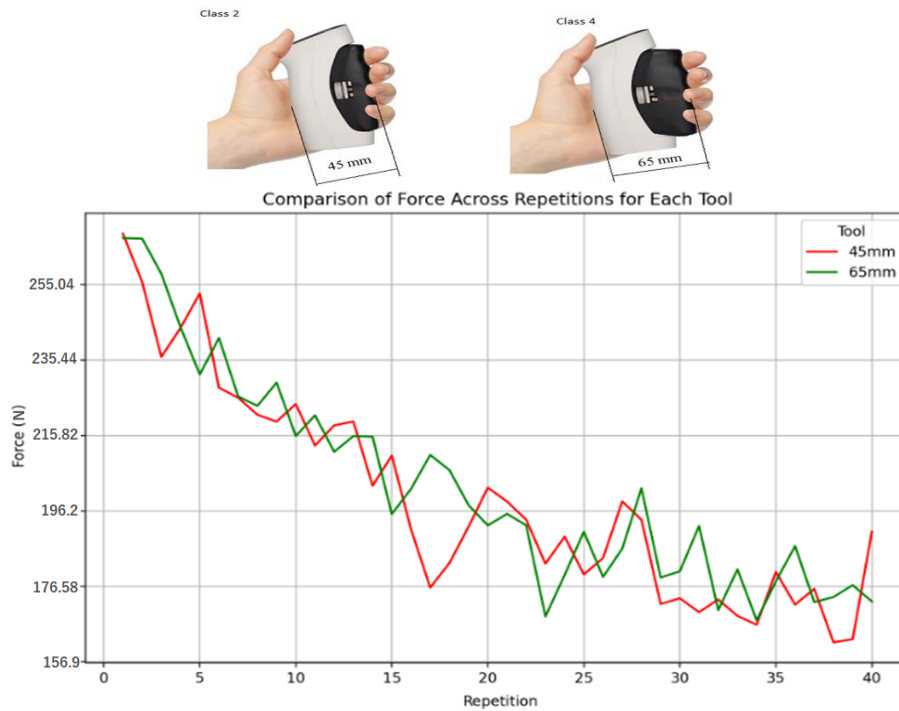


Figure 36. Force throughout the reps for tools 45mm and 65 mm

The rate of force reduction for the 45mm tool is -1.9N, whereas the rate of force reduction for the 65mm tool is more prominent at -2.42N. This implies that because the force needed decreases more quickly with each repetition, participants reduce the force more quickly when using the 65mm tool. In this sense, the 65mm tool allows users to achieve a little higher peak force values in terms of performance and variability (maximum of 370.8 N as opposed to 342.3 N for the 45mm tool). However, a standard deviation of 54.25 N for the 65mm tool vs 50.13 N for the 45mm tool suggests that the force measurements are less reliable.

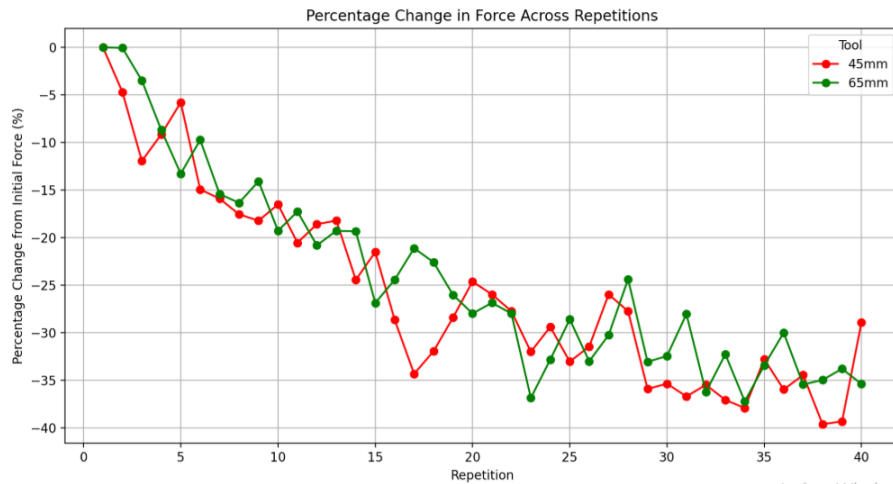


Figure 37. Percentage change in force over repetitions

The percentage change in force over repetitions for the 45mm and 65mm tools is shown in Figure 37. With the 45mm tool weighing 251.33 N and the 65mm tool weighing 253.5 N, comparable force levels are established. The initial variability of the 65mm tool is marginally higher, though. Both gadgets show a noticeable decrease in force as fatigue increases with the number of repeats. The 45mm tool's starting force is reduced by 31.3%, resulting in a drop to 172.66 N. In a similar vein, the 65mm tool decreases by 30.3% to 176.58 N.

Table 34. Force distribution statistics and statistical comparisons.

Metric	Tool 45mm	Tool 65mm
Non-Fatigue Mean	251.33 N	253.5 N
Non-Fatigue Std	50.13 N	54.25 N
Fatigue Mean	172.66 N	176.58 N
Force Reduction	78.68 N (31.3%)	76.9 N (30.3%)
Non-Fatigue (t-statistic)	9.46	8.16
Non-Fatigue (p-value)	3.74×10^{-16}	4.19×10^{-13}
Fatigue Effect Cohen's d (Tool 45mm)	1.73	
Fatigue Effect Cohen's d (Tool 65mm)		1.49

Table 34 compares the force distribution statistics of the 45mm and 65mm tools in both fatigued and non-fatigued conditions. The initial force levels of the two tools are comparable; however, the 45mm tool reduces the force a bit more (78.68 N vs 76.9 N). Strong fatigue effects are seen in both states, with larger Cohen's d values (1.73 for 45mm and 1.49 for 65mm). With p-values below the significance level ($p < 0.001$), both tools show very significant effects. The 45mm tool reflected a p-value of 3.74×10^{-16} . The 65mm tool also shows a substantial effect with a p-value of 4.19×10^{-13} . The force reductions observed for both tools are statistically significant and unlikely to be the result of chance, as confirmed by these incredibly low p-values.

To detect changes, the focus is on the application of force, comparing the data from the initial phase with the data from the final phase, as shown in Figure 38. The data were collected from the selected participants.

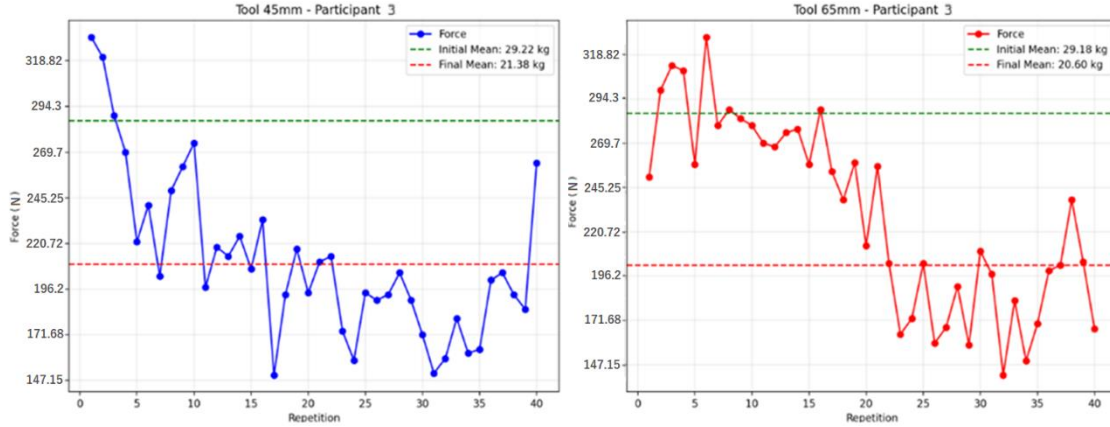


Figure 38. Force across repetitions from Participant 3 for hand tools use.

Significant force reductions for both tools over the repetitions are shown in Table 35. With a mean force of 286.65 N at the start and 209.74 N at the end, the 45mm tool reduced by 76.91 N (26.8%). Similarly, the 65mm tool shows a reduction of 84.17 N (29.4%) from its initial mean force of 286.26 N to 202.09 N. The 45mm tool gave a t-statistic of 3.20 and a p-value of 0.0127, while the 65mm tool showed greater significance with a t-statistic of 4.84 and a p-value of 0.0013, confirming the importance of these reductions. With the 65mm tool showing greater reductions, these data demonstrate the significant influence of fatigue on force.

Table 35. Statistical force analysis for Participant 3

Metric	Tool 45mm	Tool 65mm
Initial Mean Force (first 5 reps)	286.65 N	286.26 N
Final Mean Force (last 5 reps)	209.74 N	202.09 N
Force Reduction	76.91 N	84.17 N
Percentage Reduction	26.8%	29.4%
t-statistic	3.20	4.84
p-value	0.0127	0.0013

4.3.3 Machine Learning Fatigue detection

The information needed to identify the underlying patterns and relationships between the features and their labels is extracted by the KNN algorithm. This knowledge is then used to classify new, unseen data points. In this case, data pre-processing was the first step. This involved selecting relevant parameters such as standard deviations, moving averages and EMG values. The information was then separated into training and test sets after being classified as 'fatigue' or 'non-fatigue' [133], [134], [135].

The initial strategy, called the prototype selection strategy, uses the Condensed Nearest Neighbour (CNN) algorithm to keep the points nearest to the decision boundary's edge points. The second approach is the use of models to identify outliers. These models can detect data that has a different distribution from the others. With this method, unsupervised analysis is carried out, and the model decides which samples need to be eliminated.

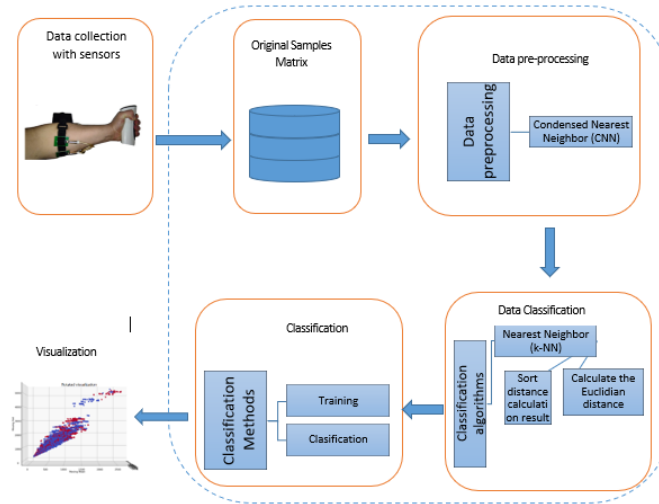


Figure 39 KNN classification method structure

The design of the experiment involves a detailed representation of all its systems and the steps to determine the onset of fatigue. The design consists of several phases, as shown in Figure 39. Several specialised libraries and Python were used to analyse muscular fatigue using electromyography (EMG) data obtained from various sizes of hand tools. First, the necessary modules were imported: `scipy.stats` for statistical analysis, `matplotlib.pyplot` and `seaborn` for data visualisation, `numpy` for numerical operations and `pandas` for managing and modifying the dataset. We imported the dataset using `pandas.read_excel()` with the `engine="odf"` option to correctly interpret the ODS file format. After loading the data, we filtered it using the 'Class' column, with classes 1 and 3 denoting non-fatigue and classes 2 and 4 denoting fatigue. As a result, we were able to separate and contrast fatigued and non-fatigued samples. To visually examine the differences between these two states, we generated Gaussian distribution plots of the EMG data using `seaborn.kdeplot()`. We applied the Mann-Whitney U test using `scipy.stats.mannwhitneyu()`, which can be set up for a two-tailed or one-tailed test depending on the hypothesis (e.g. whether tiredness values were predicted to be lower), to assess the statistical significance of these differences.

To prepare the data for K-Nearest Neighbours (KNN) machine learning classification, two additional features were created: a moving average and a moving standard deviation of the EMG signal. The `series.rolling(window=50).mean()` and `.std()` functions were used in Pandas to compute these features, respectively, smoothing the signal and aiding the identification of fatigue-related patterns. The K-nearest neighbours (KNN) classifier was initialised using `KNeighborsClassifier(n_neighbors=5)`, where `n_neighbors=5` indicates that the output label would be determined by taking the five closest data points into account. After training the model using `fit()`, the test data was classified using `predict()`. We used `sklearn.metrics.accuracy_score()` and `sklearn.metrics.classification_report()` to evaluate the model's performance, yielding precision, recall, F1-score and accuracy metrics.

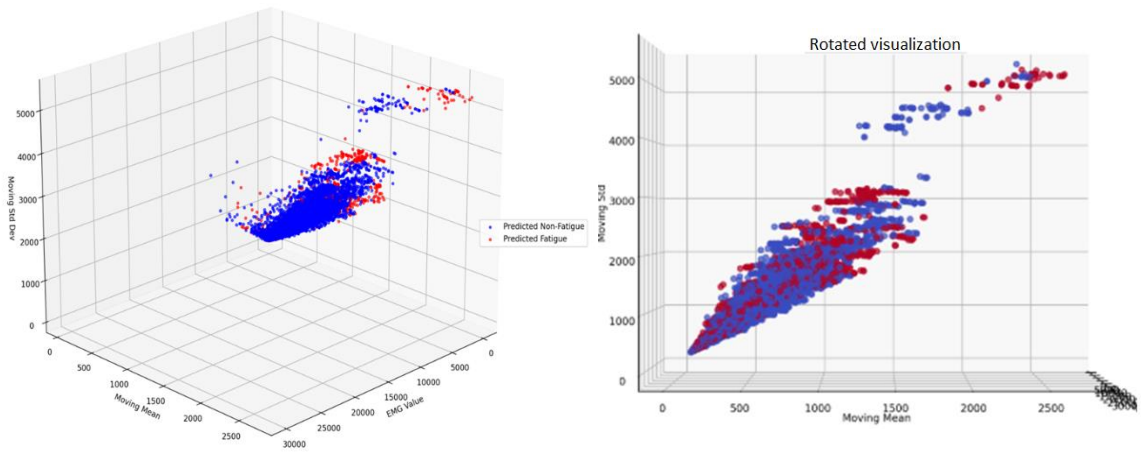


Figure 40. KNN classification results

The clustering result of the KNN model trained on the training data and then evaluated on the test set is shown in Figure 40. The overall accuracy of the model was 76.4%, indicating that it accurately predicted the state of fatigue in 76.4% of the situations. Additional investigation showed that the model performed better at detecting non-fatiguing states (81% F1 score) than fatiguing states (68% F1 score).

Table 36. KNN classification analysis of the EMG data

Class	Precision	Recall	F1-score	Support
0	0.79	0.83	0.81	5403
1	0.71	0.66	0.68	3404
Accuracy	0.76			8807
Macro Avg	0.75	0.74	0.75	8807
Weighted Avg	0.76	0.76	0.76	8807
Average distance to nearest neighbours	0.03828786168904291			
Min distance to nearest neighbours	0.0			
Max distance to nearest neighbours	5.119779473991095			

Table 36 shows the descriptive behavioural parameters of the model. The average distance to nearest neighbours was relatively small, indicating that the data points are generally clustered together; it shows clear clustering patterns between predicted fatigued and non-fatigued states. The average distance to nearest neighbours is relatively small (0.038), indicating a good clustering density.

The presence of points with zero distance to their nearest neighbours indicates high similarity or even identical patterns within the data. Conversely, the maximum distance observed indicates the presence of outliers or isolated data points. The maximum distance of 5.12 indicates some outliers or isolated points in the data set.

4.4 Discussions

The study demonstrates how important it is to use electromyography (EMG) analysis to detect force and fatigue when choosing hand tools that strike a compromise between user safety and efficiency. Insights to reduce the risk of chronic injuries, increase productivity, and support ergonomic designs can be obtained by assessing the degree of muscular activity and exhaustion during tool use. These findings are in concordance with previous research about Muscular synchronisation and hand-arm fatigue [136], [137], [138]

Twelve male participants with no history of upper extremity musculoskeletal disorders (MSDs) were selected to reduce risk factors for confounding and to provide a controlled group. By reducing the variability associated with pre-existing problems, this homogeneity ensures the trustworthiness of the strength and EMG data. The inclusion of individuals with different fitness levels may shed light on how these variables affect tool ergonomics and fatigue.

Based on ergonomic concepts and research that tracks muscle activity, EMG data, and clustering detection techniques over multiple tool use cycles [134], [139], [140]. A thorough examination of the effects of varying hand tool sizes (45mm vs. 65mm) on muscle strain is made possible by the classification of fatigue levels (class 2 and 4 for fatigue, class 1 and 3 for non-fatigue). EMG measurements show patterns, including higher peaks during fatigue and increased variability.

Significant variability and significant peaks can be seen in the EMG data during fatigue. These trends show an increase in muscular effort as the user adapts to the demands of the task. Muscle activity stabilises with the number of repetitions. Even after this period of adaptation, fatigued conditions still show higher EMG signal amplitude and variability

than non-fatigued conditions. These changes are crucial markers of the onset of fatigue and help determine when users need to take a break or change tasks. The examination of participant 3 provides a particularly clear understanding of how fatigue develops over time. A significant decrease in muscle activation is observed when comparing the mean EMG values from repetition 1 (R1) and 40 (R40), which show a 49.4% decrease.

The p-value (0.0008) in the t-test for EMG values between repetitions 1 and 40 is below the typical significance threshold ($\alpha = 0.05$). This indicates a statistically significant reduction in muscle activation as fatigue progresses over repetitions. The distributions of EMG values in fatigued and non-fatigued conditions differ significantly, according to the Kolmogorov-Smirnov (KS) Test, which has a p-value of 2.22×10^{-7} . This low p-value validates the presence of variations in muscle activation patterns brought on by tiredness, even though the effect magnitude is tiny (Cohen's $d = -0.07$).

For statistical comparison of force measurements between fatigued and non-fatigued states, the p-values for the 45mm and 65mm tools are incredibly small (e.g. 3.74×10^{-16} and 4.19×10^{-13}). These results support the idea that the decreases in force seen during repetitions are not random but rather reflect the effects of fatigue. Both tools show significant fatigue effects, and the statistical comparisons are highly significant ($p < 0.001$). The higher fatigue effect of the 45mm tool may be due to its closer approximation to natural hand ergonomics, allowing users to exert effort for more extended periods of time at a higher cumulative cost. As the 65mm tool initially allows for higher peak forces, the faster force reduction indicates that fatigue is induced more quickly. This result highlights the trade-off between diameter and peak force in tool design.

K-Nearest Neighbours (KNN) machine learning approach in ergonomics is used to characterise fatigue states. The model's accuracy (76.4%) and precision (81%) for non-fatiguing states, and for identifying fatigue (68% F1 score). The presence of outliers (the highest distance is 5.12) suggests some noise in the data, but the clustering patterns and modest average distances to nearest neighbours suggest strong internal consistency. This could be reduced in the future with improved feature selection and pre-processing.

4.5 Main contributions

Preventing worker fatigue during industrial operations with hand tools is a strategic risk prevention measure for worker health and safety. This work primarily contributes to enhancing knowledge of muscle fatigue and force application during repetitive gripping

tasks with hand tools of different sizes. The study offers comprehensive knowledge into how tool design affects user performance, fatigue, and ergonomics by utilising machine learning approaches, statistical comparisons, and electromyographic (EMG) analysis.

This research bridges the knowledge gap between biomechanical analysis and real-world tool design and occupational health applications. The novel use of EMG data to measure muscle activity and identify fatigue during repetitive gripping tasks is one of the key contributions of the study. When comparing fatigued and non-fatigued states, the data show patterns in muscle activation, including increased EMG peaks and variability. In addition, a comparison between the 45mm and 65mm tool sizes shows that the larger tool allows slightly higher peak forces and develops fatigue more quickly, as evidenced by greater decreases in force and variability.

- **Thesis (T4):** Applying an EMG smart wearable device in a controlled laboratory setting with 12 participants using standardised hand tool dimensions of 45 and 65mm. I proved that:
 - Fatigue onset occurs around 25 repetitions with a probability of fatigue detection ($p\text{-value} = 2.22 \times 10^{-7}$)
 - A pattern comparison in mean peak EMG values decrease significantly during the exercise.
 - Electromyography (EMG) signals from forearm muscles in gripping tasks show a probability of force reduction detection of 3.74×10^{-16} and 4.19×10^{-13} , using standardized hand tool dimensions of 45 and 65mm.
- **Thesis (T5):** I have proved that an artificial intelligence (AI) system trained on electromyography (EMG) data can accurately detect muscle fatigue signals with K-NN method, that achieved an accuracy of the model to predict the state of fatigue of 76.4% to provide real-time feedback to workers, reducing the risk of MSDS.

Own publications related to this chapter: [17].

5 CONCLUSIONS

This part presents the innovations and contributions of the thesis. It emphasises the importance of the study and reaffirms how it will promote occupational safety and health (OSH). This chapter focuses on providing an overall description of the objectives of the study, the novelty of the approach and how the results support the initial hypotheses.

5.1 Novelty

In my thesis, I have presented risk assessment and reduction strategies that focus specifically on non-powered hand tools that integrate ergonomic principles, safety regulations, and human reliability analysis to create a robust framework for minimising hand tool injuries. My thesis also included approaches to addressing hand tool-related injuries in the manufacturing sector, using new technologies and multidisciplinary management strategies.

In my research, I established the integration of electromyography (EMG) for the monitoring of muscle activity and the detection of early signs of fatigue. By using EMG signals, the study proposes real-time detection of physiological strain during prolonged or repetitive tasks, enabling intervention before injury or cumulative trauma disorders can be observed.

To meet the challenges of occupational safety, systematic analysis of physiological factors is a key element of fatigue analysis. By studying the effects of wrist flexion, extension and excessive muscle effort during repetitive manual tasks, my research identifies the biomechanical factors that contribute to injury. This kind of information helps to develop tools and procedures that better match human capabilities, thereby significantly reducing risk.

A comprehensive and multi-dimensional approach to risk assessment and reduction has been developed in my research, using ergonomic principles, safety regulations and human reliability analysis to furnish a comprehensive methodology for the attenuation of injuries sustained in the use of hand tools. The mathematical categorisation technique and the Analytic Hierarchy Process (AHP), together with the Best Worst Method to systematically evaluate and rank risk factors, demonstrate a novel, expert perception, evidence-based strategy for workplace safety.

In my dissertation, I presented a risk assessment using the Domain-Specific Risk-Taking (DOSPERT) questionnaire, which provides psychological and behavioural findings for understanding risk perception and its impact on workplace safety measures, taking into account the attitudes of users of non-powered hand tools. Finally, I have presented practical applications by collecting and analysing EMG data to develop fatigue reduction protocols using innovative technologies for a deep understanding of ergonomic and physiological principles to minimise injuries and improve productivity in the manufacturing sector.

5.2 New scientific results

My research aimed to develop scientific strategies and methods for measuring forces during work, as well as to develop efficient workstation tool use techniques using new technologies. In addition, I aimed to develop strategies and measures to prevent hand tool-related disorders by gaining a detailed understanding of the physiological effects of repetitive manual activities on the wrist and muscles, as well as identifying their causes.

Therefore, my new scientific results are as follows:

- **Thesis (T1):** With a systematic PRISMA literature review and meta-analyses, I have proved that electromyography (EMG) collected in the forearm, including the flexor carpi radialis, flexor carpi ulnaris, and pronator teres, helps prevent work-related injuries and cumulative trauma disorders by identifying the onset of muscle fatigue during over 5-second gripping tasks.
- **Thesis (T2):** By applying Multi-Criteria Decision-Making (MCDM) methods to categorize risks associated with hand tool use in a sample of 10 ergonomic experts, I demonstrated that integrating individual factors like 'tool damage', 'ergonomic risk', and 'physical injury' can effectively stratify to rank and assess the risks related to hand tool use, and it shows that 'physical injury' is the primary risk factor, with a weighted importance of 73.06% in the Analytic Hierarchy Process (AHP) (Consistency ratio: 0.0492) and cross-validated by the Best-Worst Method (BWM) at 73.62% (Reliability ratio: 0.1978).
- **Thesis (T3):** By applying modified DOSPERT risks perception evaluation related to hand tool uses in a sample of 123 participants. I determined four domains: 'Material Domain', 'Personal Domain', 'Environmental Domain', 'Organizational Domain', and I proved that risk aversion was more likely in the Material and

Environmental domains (b coefficient -0.0729 and -2.1639 , respectively) and risk-taking behaviour in the Organizational and Personal domains (b coefficient 0.2985 and 0.2985 , respectively).

- **Thesis (T4):** Applying a EMG smart wearable device in a controlled laboratory setting with 12 participants using standardized hand tool dimensions of 45 and 65mm. I proved that:
 - Fatigue onset occurs around 25 repetitions with a probability of fatigue detection ($p\text{-value} = 2.22 \times 10^{-7}$)
 - A pattern comparison in mean peak EMG values decrease significantly during the exercise.
 - Electromyography (EMG) signals from forearm muscles in gripping tasks show a probability of force reduction detection of 3.74×10^{-16} and 4.19×10^{-13} , using standardized hand tool dimensions of 45 and 65mm.
- **Thesis (T5):** I have proved that an artificial intelligence (AI) system trained on electromyography (EMG) data can accurately detect muscle fatigue signals with K-NN method, that achieved an accuracy of the model to predict the state of fatigue of 76.4% to provide real-time feedback to workers, reducing the risk of MSDS.

5.3 Recommendations

The study could benefit the industry in tasks involving the use of hand tools by providing insight and knowledge into the appropriate tool for each worker. The results will provide information on how individual differences affect muscle fatigue and tool usability.

More tool designs and a greater range of sizes and shapes can be considered when seeking to make recommendations for ergonomic tool design that are effective. By considering these elements, a more comprehensive understanding of how tool weight, material, and grip texture can impact workers when they are in danger and impact performance may be achievable.

Designing ergonomically optimised tools with improved grip and force distribution should be prioritised. In addition, training programs for workers on proper tool-handling techniques and periodic ergonomic evaluations are provided to enhance workplace safety and productivity.

Implementing AI-driven EMG monitoring solutions in industrial environments can help identify early fatigue onset and adjust work-rest cycles, including a tailored hand tool selection according to workers' anthropometrics.

As future research, the study could integrate the effects of recovery interventions, such as stretching, rest breaks, or cooling techniques, on mitigating fatigue during repetitive tasks. This would provide a complete understanding of risk prevention for workers using hand tools.

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LIST OF ABBREVIATIONS

AI. *artificial intelligence*
 ANP. *analytical network process*
 CTDs. *cumulative trauma disorders*
 DOSPERT. *Domain-Specific Risk-Taking*
 MCDM. *Multicriteria decision-making*
 ML. *machine learning*
 MSDs. *Musculoskeletal disorders*
 NIRS. *near-infrared spectroscopy*
 sonomicography. *sonomicography*

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APPENDIX

ANNEX 1 Ethical approval of the research



ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

Bánki Donát Gépész és
Biztonságtechnikai Mérnöki Kar,

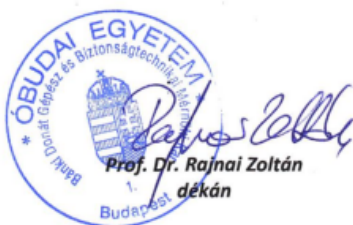
Budapest, 2022. november 28.

ETIKUS KUTATÁSI NYILATKOZAT

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

Ricardo Patricio Arciniega Rocha PhD hallgató
„Tools size selection for Elderly People”

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



Risk scale

My name is Ricardo Arciniega, and I am researching at the Safety and Security doctoral school. You are being invited to take part in a research study. The purpose of the study is to develop a methodology to select the correct hand tool size oriented to reduce and prevent the injuries and diseases produced by repetitive works.

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 exerted to fulfill a survey about risk categorization when using hand tools in the workplace

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 develop a methodology to select the correct non-powered hand tool size. If you have any questions about participation in this study, you may contact me at arciniega.ricardo@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 your acceptance in 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. *

Marca solo un óvalo.

☐ Yes

2. What is your expertise field?

3. How many years are you working in your field?

8. Please rate the risk importance. Of the following three listed risks which one is the last one of importance?

⌵ Dropdown

Marca solo un óvalo.

- ☐ Physical Injuries
- ☐ Ergonomic risk
- ☐ Tool damage

9. Please compare the importance of the selected first option in relation to the second option.

Marca solo un óvalo.

	1	2	3	4	5	6	7	
same	☐	☐	☐	☐	☐	☐	☐	Extremely important

10. Please compare the importance of the selected first option in relation to the third option.

Marca solo un óvalo.

	1	2	3	4	5	6	7	
same	☐	☐	☐	☐	☐	☐	☐	Extremely important

11. Please compare the importance of the selected second option in relation to the third option.

Marca solo un óvalo.

	1	2	3	4	5	6	7	
same	☐	☐	☐	☐	☐	☐	☐	Extremely important

Hand Risk taking

My name is Ricardo Arciniega, and I am researching at the Safety and Security doctoral school. You are being invited to take part in a research study. The purpose of the study is to develop a methodology to select the correct hand tool size oriented to reduce and prevent the injuries and diseases produced by repetitive works.

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 exerted to fulfill a survey about risk perception when using hand tools in the workplace

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 develop a methodology to select the correct non-powered hand tool size. If you have any questions about participation in this study, you may contact me at arciniega.ricardo@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 your acceptance in 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. Gender. (Genero)

Marca solo un óvalo.

☐ Male. (Masculino)

☐ Female. (Femenino)

☐ Other. (Otro)

6. Education Level. (Nivel de estudios) *

Marca solo un óvalo.

- ☐ PhD
- ☐ Master. (Maestría)
- ☐ BSc. (Ingeniería, Licenciatura, etc)
- ☐ Other. (otro)

Material Agent

7. How likely could you Work with incorrect hand PPE (Personal Protective Equipment). (Trabajar con EPI (Equipo de Protección Individual) de manos incorrecto.) *

Marca solo un óvalo.

- ☐ 1 Highly unlikely. (Sumamente improbable)
- ☐ 2 Moderately unlikely. (Moderadamente Improbable)
- ☐ 3 Something unlikely. (Algo improbable)
- ☐ 4 Uncertain. (Incierto)
- ☐ 5 Somewhat likely. (Algo probable)
- ☐ 6 Moderately likely. (Moderadamente probable)
- ☐ 7 Highly likely. (Sumamente probable)

16. How probably could you Work with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.(¿Con qué probabilidad podría trabajar con herramientas manuales pesadas de modo que la mano y los dedos no puedan agarrar fácilmente la herramienta?) *

Marca solo un óvalo.

- ☐ 1 Highly unlikely. (Sumamente improbable)
- ☐ 2 Moderately unlikely. (Moderadamente Improbable)
- ☐ 3 Something unlikely. (Algo improbable)
- ☐ 4 Uncertain. (Incierto)
- ☐ 5 Somewhat likely. (Algo probable)
- ☐ 6 Moderately likely. (Moderadamente probable)
- ☐ 7 Highly likely. (Sumamente probable)

Environmental Agents

17. How likely is it that you will be able to work in spaces that are small or uncomfortable for the hand?.(¿Qué tan probable es que puedas trabajar en espacios pequeños o incómodos para la mano?.) *

Marca solo un óvalo.

- ☐ 1 Highly unlikely. (Sumamente improbable)
- ☐ 2 Moderately unlikely. (Moderadamente Improbable)
- ☐ 3 Something unlikely. (Algo improbable)
- ☐ 4 Uncertain. (Incierto)
- ☐ 5 Somewhat likely. (Algo probable)
- ☐ 6 Moderately likely. (Moderadamente probable)
- ☐ 7 Highly likely. (Sumamente probable)

36. How risky do you consider Working with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.(¿Qué tan arriesgado considera trabajar con herramientas manuales pesadas de modo que la mano y los dedos no puedan agarrar fácilmente la herramienta?) *

Marca solo un óvalo.

- ☐ 1 Nothing risky. (Nada arriesgado)
- ☐ 2 Slightly risky . (Ligeramente arriesgado)
- ☐ 3 Something risky. (Algo arriesgado)
- ☐ 4 Moderately risky. (Moderadamente arriesgado)
- ☐ 5 Risky. (Arriesgado)
- ☐ 6 Very risky. (Muy arriesgado)
- ☐ 7 Extremely risky. (Extremadamente arriesgado)

Environmental Agents

37. How risky do you consider working in spaces that are small or uncomfortable for the hand?.(¿Qué tan arriesgado consideras trabajar en espacios pequeños o incómodos para la mano?) *

Marca solo un óvalo.

- ☐ 1 Nothing risky. (Nada arriesgado)
- ☐ 2 Slightly risky . (Ligeramente arriesgado)
- ☐ 3 Something risky. (Algo arriesgado)
- ☐ 4 Moderately risky. (Moderadamente arriesgado)
- ☐ 5 Risky. (Arriesgado)
- ☐ 6 Very risky. (Muy arriesgado)
- ☐ 7 Extremely risky. (Extremadamente arriesgado)

40. How risky do you consider Working with heavy hand tools in a place where there is not good illumination?.(¿Qué tan arriesgado considera trabajar con herramientas manuales pesadas en un lugar donde no hay buena iluminación?) *

Marca solo un óvalo.

- ☐ 1 Nothing risky. (Nada arriesgado)
- ☐ 2 Slightly risky . (Ligeramente arriesgado)
- ☐ 3 Something risky. (Algo arriesgado)
- ☐ 4 Moderately risky. (Moderadamente arriesgado)
- ☐ 5 Risky. (Arriesgado)
- ☐ 6 Very risky. (Muy arriesgado)
- ☐ 7 Extremely risky. (Extremadamente arriesgado)

Personal Characteristics

41. How risky do you consider Work fixing or adjusting mobile machine parts using hand tools?.(¿Qué tan arriesgado considera usted que trabaja arreglando o ajustando partes móviles de máquinas usando herramientas manuales?) *

Marca solo un óvalo.

- ☐ 1 Nothing risky. (Nada arriesgado)
- ☐ 2 Slightly risky . (Ligeramente arriesgado)
- ☐ 3 Something risky. (Algo arriesgado)
- ☐ 4 Moderately risky. (Moderadamente arriesgado)
- ☐ 5 Risky. (Arriesgado)
- ☐ 6 Very risky. (Muy arriesgado)
- ☐ 7 Extremely risky. (Extremadamente arriesgado)

55. How beneficial do you consider Working with heavy hand tools without hanging support?.(¿Qué tan beneficioso considera trabajar con herramientas manuales pesadas sin soporte colgante?)

Marca solo un óvalo.

	1	2	3	4	5	6	7	
no b	☐	☐	☐	☐	☐	☐	☐	substantial benefits. (Cuantiosos beneficio)

56. How beneficial do you consider Working with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.(¿Qué tan beneficioso considera trabajar con herramientas manuales pesadas de modo que la mano y los dedos no puedan agarrar fácilmente la herramienta?) *

Marca solo un óvalo.

	1	2	3	4	5	6	7	
no b	☐	☐	☐	☐	☐	☐	☐	substantial benefits. (Cuantiosos beneficio)

Environmental Agents

57. How beneficial do you consider working in spaces that are small or uncomfortable for the hand?.(¿Qué tan beneficioso consideras trabajar en espacios pequeños o incómodos para la mano?) *

Marca solo un óvalo.

	1	2	3	4	5	6	7	
no b	☐	☐	☐	☐	☐	☐	☐	substantial benefits. (Cuantiosos beneficio)

ANNEX 4 Descriptive statistics for hand tool risk perception

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
How likely could you Work with incorrect hand PPE (Personal Protective Equipment).	3,51	3,43	2,01	4,02	2,80	4,07	3,54	3,35	3,65	5,71	4,38	2,29	2,00	2,00	1,50	3,31	4,33	3,75	3,58	2,81	2,79	4,80	3,94
How probably Work with short tool handles that press into the palm of the hand?.	3,48	3,44	1,66	2,76	2,80	3,92	3,45	3,24	2,95	5,73	4,23	2,71	2,17	2,00	1,50	3,31	4,00	3,75	3,48	2,60	2,79	3,60	4,00
How probably could you Work with narrow tool handles that press deeply into the hand when the tool is used?.	3,37	3,31	1,64	2,69	2,71	3,89	3,42	3,06	3,65	5,48	3,15	2,29	3,50	1,00	1,50	3,62	4,00	3,75	3,39	3,02	2,57	3,80	3,63
How probably could you Work with a hand tool for the incorrect side? Example: if you are a right-hand person will you use a hand tool for left hand person.	3,38	3,35	1,56	2,43	2,96	3,73	3,42	3,18	3,40	5,23	4,08	3,71	3,00	2,50	1,50	4,00	3,83	3,50	3,35	3,05	2,93	3,20	3,62
How probably could you Work with hand tools that require big effort or rotational movement to use?.	4,07	4,08	1,63	2,65	3,59	4,46	4,19	3,29	4,00	6,52	3,92	5,29	3,17	2,00	2,50	4,08	5,33	4,00	4,09	3,53	3,14	4,40	4,48
How probably could you Work with hand tools that	3,59	3,57	1,61	2,61	3,25	3,87	3,62	3,35	3,20	5,85	3,31	4,57	3,50	2,00	1,50	4,38	4,00	4,00	3,54	3,16	3,14	3,40	3,87

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
require a bad or uncomfortable posture?.																							
How probably could you Work with hand tools that require big holding time?	3,80	3,83	1,61	2,59	3,59	4,00	3,81	3,71	3,60	6,06	4,00	4,43	3,50	2,00	2,50	4,62	3,67	4,00	3,77	3,19	3,71	2,60	4,21
How probably could you Work with hand tools with handles made of slippery materials?.	3,09	3,01	1,6	2,56	2,84	3,31	3,12	2,88	2,80	5,10	2,54	3,71	3,33	2,00	1,00	3,38	3,17	3,25	3,11	2,95	2,57	3,40	3,17
How probably could you Work with heavy hand tools without hanging support ?	3,46	3,43	1,71	2,94	3,31	3,61	3,52	3,06	3,40	5,48	3,77	3,29	3,67	2,00	1,50	3,92	3,67	4,25	3,38	3,12	3,21	3,60	3,62
How probably could you Work with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.	3,11	3,02	1,68	2,81	2,69	3,46	3,21	2,53	3,05	5,04	2,92	3,29	3,17	2,00	2,00	3,38	3,00	3,25	3,13	2,37	2,79	3,80	3,54
How likely is it that you will be able to work in spaces that are small or uncomfortable for the hand?.	3,74	3,73	1,65	2,71	3,10	4,20	3,74	3,53	3,45	5,92	3,54	4,43	4,33	1,50	4,00	4,31	3,00	4,75	3,69	2,93	3,93	4,60	4,00
How likely is it that you will be able to work with the wrist in a flexed position?.	3,74	3,75	1,62	2,62	3,35	4,07	3,75	3,71	3,35	5,83	4,15	4,43	4,67	2,50	4,50	4,31	3,33	5,25	3,65	3,19	3,93	4,20	3,92
How probably could you Work with heavy hand	3,56	3,55	1,53	2,33	3,43	3,70	3,53	3,76	3,25	5,73	3,31	4,57	3,83	2,00	3,50	3,77	3,50	3,75	3,57	3,05	3,07	3,80	3,89

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
tools in place where there are not hand support?.																							
How probably could you Work with heavy hand tools in a place where there is not good illumination?.	3,33	3,29	1,57	2,45	3,00	3,56	3,40	2,71	3,75	5,31	2,31	3,57	3,50	2,00	1,00	3,54	2,50	3,25	3,41	2,98	2,57	3,20	3,59
How probably could you Work fixing or adjusting mobile machine parts using hand tools?.	4,19	4,19	1,66	2,76	3,57	4,69	4,28	3,59	4,25	6,83	3,62	4,29	4,17	2,50	2,50	3,46	4,17	4,00	4,38	3,77	2,86	4,40	4,62
How probably could you Work with hand tools that have not been tested for proper operation?.	3,30	3,22	1,67	2,79	2,76	3,73	3,42	2,59	3,15	5,60	2,08	3,43	3,83	2,00	2,00	2,77	2,00	3,75	3,51	3,05	2,50	4,60	3,44
How probably could you Work with hand tools without training before starting a new industrial task?	3,20	3,11	1,65	2,72	2,98	3,39	3,25	2,82	2,90	5,27	2,77	4,43	2,50	2,50	3,00	3,46	2,17	2,00	3,32	2,70	2,93	4,20	3,41
How probably could you Work with hand tools in a place without structured industrial tasks?,	3,48	3,45	1,5	2,25	3,25	3,69	3,57	2,94	3,35	5,71	2,85	4,14	3,50	2,50	2,50	3,69	2,33	3,50	3,59	2,98	3,00	3,80	3,79
How probably could you Work with hand tools in a place without an accident prevention protocol?,	3,39	3,33	1,62	2,63	3,16	3,61	3,42	3,18	3,05	5,63	2,54	4,86	3,17	3,00	1,50	3,85	2,17	3,50	3,45	2,95	3,14	4,20	3,57

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
How likely could you Work with hand tools in a place without a response protocol after suffering an accident?	2,89	2,77	1,58	2,50	2,53	3,18	2,98	2,29	2,45	4,90	2,23	3,86	2,50	3,00	1,50	2,92	2,33	2,50	2,98	2,40	2,64	3,20	3,16
How risky do you consider Working with incorrect hand PPE? (Personal Protective Equipment).	4,27	4,30	1,73	3,00	4,57	4,11	4,33	3,88	3,65	7,04	4,85	4,14	3,67	3,50	4,00	3,85	4,50	3,25	4,35	4,53	3,79	4,80	4,02
How risky do you consider Work with short tool handles that press into the palm of the hand?.	3,82	3,76	1,47	2,15	4,20	3,61	3,83	3,76	3,75	5,90	4,31	4,43	4,17	4,50	5,00	4,08	3,67	3,50	3,76	3,95	4,29	3,40	3,54
How risky do you consider Work with narrow tool handles that press deeply into the hand when the tool is used?.	4,03	4,03	1,55	2,39	4,59	3,69	4,02	4,12	3,85	6,42	4,23	4,14	4,50	5,00	4,50	4,00	3,83	4,50	3,99	4,21	4,21	3,40	3,79
How risky do you consider Working with a hand tool for the incorrect side? Example: if you are a right-hand person will you use a hand tool for a left-hand person.	3,97	3,93	1,48	2,18	4,16	3,89	4,00	3,76	3,30	6,42	4,62	3,86	4,50	4,00	3,50	4,38	3,17	4,50	3,96	3,95	4,07	4,00	3,83
How risky do you consider Working with hand tools that require big	3,85	3,85	1,49	2,21	4,18	3,66	3,87	3,71	3,05	6,27	4,46	3,86	4,33	5,50	4,00	4,08	3,67	4,75	3,74	4,02	4,21	3,00	3,59

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
effort or rotational movement to use?.																							
How risky do you consider Working with hand tools that require a bad or uncomfortable posture?.	4,16	4,13	1,49	2,22	4,45	4,01	4,21	3,88	3,75	6,88	4,15	4,14	4,00	4,00	4,50	4,15	4,00	3,75	4,17	4,53	3,79	3,80	3,89
How risky do you consider Working with hand tools that require big holding time?.	3,87	3,86	1,4	1,97	4,12	3,75	3,95	3,35	3,40	6,29	4,38	3,57	4,00	4,50	3,50	4,00	4,50	3,75	3,80	3,98	3,71	3,60	3,73
How risky do you consider Working with hand tools with handles made of slippery materials?.	4,74	4,79	1,55	2,41	5,27	4,42	4,74	4,76	4,30	7,48	5,62	5,29	4,67	5,00	4,50	5,38	5,83	5,00	4,56	4,79	4,93	4,00	4,57
How risky do you consider Working with heavy hand tools without hanging support?.	4,51	4,52	1,48	2,19	4,67	4,46	4,54	4,35	4,15	7,38	4,77	4,00	4,67	4,50	3,50	4,31	4,83	4,50	4,55	4,63	3,86	4,20	4,46
How risky do you consider Working with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.	4,66	4,70	1,64	2,70	4,69	4,70	4,71	4,35	4,40	7,58	5,00	4,14	4,50	5,00	4,00	4,54	5,50	4,00	4,66	4,65	4,14	4,40	4,65
How risky do you consider working in spaces that are small or	4,25	4,27	1,37	1,88	4,39	4,21	4,33	3,76	3,95	6,81	5,00	3,71	4,33	5,00	4,00	4,23	5,33	4,50	4,16	4,23	4,14	4,00	4,17

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
uncomfortable for the hand?.																							
How risky do you consider working with the wrist in a flexed position?.	4,22	4,23	1,48	2,19	4,35	4,18	4,27	3,88	4,15	6,75	4,77	3,43	4,33	4,00	3,50	4,00	4,83	4,00	4,23	4,30	3,79	4,40	4,11
How risky do you consider Working with heavy hand tools in place where there is no hand support?.	4,31	4,32	1,49	2,23	4,31	4,37	4,42	3,59	4,10	7,02	4,69	3,43	4,33	4,50	3,50	3,69	5,00	3,75	4,39	4,51	3,50	4,20	4,22
How risky do you consider Working with heavy hand tools in a place where there is not good illumination?.	4,55	4,57	1,69	2,84	4,69	4,52	4,53	4,71	3,70	7,25	5,54	5,00	5,17	4,00	5,00	5,08	5,50	5,25	4,40	4,30	4,71	4,20	4,57
How risky do you consider Work fixing or adjusting mobile machine parts using hand tools?.	3,91	3,87	1,66	2,75	4,14	3,80	3,99	3,41	3,00	6,42	4,69	4,00	4,00	4,00	3,00	4,31	4,50	3,75	3,86	4,02	3,93	3,20	3,76
How risky do you consider Working with hand tools that have not been tested for proper operation?.	4,58	4,62	1,53	2,34	4,98	4,35	4,62	4,29	4,10	7,44	5,31	4,29	4,17	4,00	4,00	4,62	5,33	4,25	4,54	4,72	4,07	4,20	4,48
How risky do you consider Working with hand tools without	4,51	4,52	1,46	2,14	4,59	4,52	4,53	4,41	3,85	7,42	5,31	3,43	4,83	4,50	4,00	4,23	5,67	4,75	4,47	4,42	4,07	4,60	4,52

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
training before starting a new industrial task?.																							
How risky do you consider Working with hand tools in a place without structured industrial tasks?.	4,58	4,61	1,49	2,23	4,71	4,55	4,58	4,53	3,85	7,48	5,62	3,57	4,83	5,00	4,00	4,31	5,67	5,50	4,51	4,72	4,29	4,00	4,44
How risky do you consider Working with hand tools in a place without an accident prevention protocol?.	4,85	4,92	1,58	2,51	5,02	4,79	4,93	4,29	4,15	7,90	5,85	4,29	4,67	4,00	5,00	4,62	6,00	4,75	4,81	4,81	4,36	4,60	4,84
How risky do you consider Working with hand tools in a place without a response protocol after suffering an accident?.	5,13	5,24	1,62	2,62	5,57	4,89	5,09	5,35	4,45	8,13	6,31	5,43	5,33	5,00	5,00	5,54	5,33	6,00	5,01	5,14	5,36	4,80	4,94
How beneficial do you consider Working with incorrect hand PPE? (Personal Protective Equipment).	3,53	3,45	2,14	4,56	3,20	3,82	3,67	2,65	3,60	5,96	3,00	3,00	2,67	2,00	1,50	2,69	4,83	2,00	3,72	3,16	2,07	3,80	3,97
How beneficial do you consider Work with short tool handles that press into the palm of the hand?.	3,13	3,00	1,75	3,06	3,10	3,20	3,19	2,76	2,95	5,38	2,69	3,00	2,00	2,50	1,50	2,92	4,17	1,75	3,22	3,02	2,50	3,60	3,21

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
How beneficial do you consider Work with narrow tool handles that press deeply into the hand when the tool is used?.	3,02	2,90	1,74	3,02	2,73	3,27	3,18	2,00	2,65	5,21	2,92	2,71	1,83	2,50	1,00	2,77	3,50	1,75	3,15	2,56	2,07	3,80	3,38
How beneficial do you consider Working with a hand tool for the incorrect side? Example: if you are a right-hand person will you use a hand tool for a left-hand person.	2,93	2,84	1,6	2,56	2,82	3,04	3,08	1,94	2,40	5,06	2,31	3,00	3,00	2,50	1,00	2,62	1,67	2,50	3,14	2,74	2,21	3,80	3,05
How beneficial do you consider Working with hand tools that require big effort or rotational movement to use?.	###	3,35	1,75	3,05	3,41	3,51	3,58	2,53	3,20	5,83	3,23	3,29	2,33	3,00	1,50	3,38	3,67	1,75	3,58	3,14	2,64	3,60	3,70
How beneficial do you consider Working with hand tools that require a bad or uncomfortable posture?.	2,91	2,76	1,7	2,90	2,90	2,96	2,99	2,41	2,65	4,98	2,23	3,00	2,67	3,00	2,50	2,38	3,00	2,25	3,03	2,95	2,43	3,80	2,83
How beneficial do you consider Working with hand tools that require big holding time?.	3,25	3,15	1,77	3,12	3,29	3,27	3,36	2,59	2,85	5,54	2,85	3,71	2,33	3,00	1,50	2,92	3,33	2,25	3,40	3,00	2,71	4,00	3,38
How beneficial do you consider Working with hand tools with handles	3,11	2,97	1,98	3,92	3,10	3,17	3,24	2,35	2,60	5,46	2,62	2,57	2,83	3,50	1,00	2,85	2,50	2,25	3,28	3,00	2,57	4,40	3,11

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
made of slippery materials?.																							
How benefical do you consider Working with heavy hand tools without hanging support?.	2,70	2,56	1,7	2,89	2,61	2,77	2,74	2,35	2,35	4,48	2,08	3,86	2,33	2,50	1,50	2,92	1,33	1,75	2,82	2,40	2,86	2,60	2,76
How benefical do you consider Working with heavy hand tools so that the hand and fingers are not able to easily grasp the tool?.	2,70	2,59	1,52	2,29	2,61	2,80	2,78	2,18	2,25	4,65	2,23	3,14	2,17	2,50	1,00	2,54	1,83	2,50	2,84	2,58	2,36	3,20	2,73
How benefical do you consider working in spaces that are small or uncomfortable for the hand?.	2,85	2,72	1,66	2,75	2,73	2,97	2,95	2,18	2,70	4,79	2,15	3,00	2,83	2,00	1,50	2,38	2,00	3,00	3,02	2,65	2,43	3,40	2,94
How benefical do you consider working with the wrist in a flexed position?.	3,04	2,94	1,64	2,68	2,78	3,27	3,16	2,29	2,55	5,23	2,77	3,00	2,50	2,50	1,50	2,69	2,50	2,75	3,20	2,86	2,57	3,40	3,14
How benefical do you consider Working with heavy hand tools in place where there is no hand support?.	2,90	2,79	1,7	2,89	2,96	2,90	2,98	2,41	2,25	4,98	2,46	3,29	3,00	3,50	2,00	2,77	2,33	2,25	3,01	2,67	2,93	3,80	2,89
How benefical do you consider Working with heavy hand tools in a	2,82	2,66	1,66	2,75	2,75	2,92	2,92	2,24	2,05	4,81	2,62	3,43	2,83	3,00	2,00	2,77	2,33	2,00	2,93	2,67	2,71	2,80	2,86

Descriptive Statistics																							
Questions per domain: Risk Probability Risk Perception Expected Benefits	Central tendency				Country		Gender		Age					profession					Education				
	$\bar{x}$	$\bar{x}_b$	SD	σ	$\bar{x}$ Hun	$\bar{x}$ Ecu	$\bar{x}$ male	$\bar{x}$ female	$\bar{x}$ 15- 18	$\bar{x}$ 19- 26	$\bar{x}$ 27- 35	$\bar{x}$ 36- 46	$\bar{x}$ 46- 54	$\bar{x}$ academic	$\bar{x}$ health	$\bar{x}$ industrial	$\bar{x}$ other	$\bar{x}$ sales	$\bar{x}$ student	$\bar{x}$ BSc	$\bar{x}$ Master	$\bar{x}$ PhD	$\bar{x}$ Other
place where there is not good illumination?.																							
How benefical do you consider Work fixing or adjusting mobile machine parts using hand tools?.	3,24	3,15	1,71	2,94	2,90	3,52	3,35	2,53	3,05	5,52	2,62	3,29	2,50	2,00	1,00	2,62	2,33	2,25	3,52	2,84	2,29	4,00	3,56
How benefical do you consider Working with hand tools that have not been tested for proper operation?.	3,06	2,93	1,78	3,17	3,14	3,04	3,11	2,71	2,75	5,04	2,85	3,71	2,67	2,00	1,00	3,08	4,00	2,00	3,13	2,88	2,71	3,80	3,10
How benefical do you consider Working with hand tools without training before starting a new industrial task?.	2,95	2,81	1,68	2,83	3,02	2,94	3,00	2,65	2,95	5,00	1,92	3,43	2,50	2,00	1,50	2,77	2,67	2,00	3,11	3,05	2,57	3,40	2,84
How benefical do you consider Working with hand tools in a place without structured industrial tasks?.	3,27	3,17	1,77	3,13	3,33	3,27	3,31	3,00	2,90	5,42	3,00	3,86	3,00	2,50	1,50	3,46	3,17	2,75	3,35	3,07	3,00	3,80	3,32
How benefical do you consider Working with hand tools in a place without an accident prevention protocol?.	3,04	2,90	1,95	3,79	3,10	3,04	3,08	2,76	2,55	5,17	2,69	3,43	2,67	2,00	2,00	2,85	3,33	2,50	3,14	2,84	2,71	3,60	3,11



Bánki Donát Gépész és
Biztonságtechnikai Mérnöki Kar
OE-DI-205,2025

INFORMED CONSENT FORM

"Tool Sizing"

My name is Ricardo Arciniega, and I am researching at the Safety and Security doctoral school. You are being invited to take part in a research study. The purpose of the study is to *Develop a methodology to select the correct hand tool size oriented to reduce and prevent the injuries and diseases produced by repetitive works.*

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 exert your maximum grip force by grasping the pliers' handles. You are to exert your maximum force from an initial relaxed state and then perform 40 repetitions of this movement. 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 *Develop a methodology to select the correct non-powered hand tool size*. If you have any questions about participation in this study, you may contact me at arciniega.ricardo@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 sign below to indicate your acceptance to participate.

Name of Participant

Signature

Date

Arciniega-Rocha Ricardo P.
Name of Principal Investigator

Signature

Date



Participant code OE-BD-SSDS-NPHTS-1

Force data for each grasping repetition 45mm:

1	2	3	4	5	6	7	8	9	10
24.9	25.9	27.2	22.0	26.8	23.0	22.5	21.2	22.5	25.3
11	12	13	14	15	16	17	18	19	20
21.8	24.0	22.1	21.3	22.3	20.6	20.1	22.0	22.6	21.4
21	22	23	24	25	26	27	28	29	30
22.0	21.5	20.0	22.1	21.2	21.2	20.9	21.5	19.6	21.2
31	32	33	34	35	36	37	38	39	40
19.8	20.9	20.0	19.1	20.2	21.1	21.2	17.1	20.8	21.6

Force data for each grasping repetition 65mm:

1	2	3	4	5	6	7	8	9	10
29.2	29.9	26.5	26.4	26.4	25.6	25.3	23.9	28.9	29.2
11	12	13	14	15	16	17	18	19	20
30.2	25.7	25.7	25.8	27.0	23.3	27.9	25.6	24.4	26.5
21	22	23	24	25	26	27	28	29	30
28.0	25.0	22.8	25.0	27.1	25.6	24.5	25.5	23.1	25.4
31	32	33	34	35	36	37	38	39	40
23.5	25.5	22.4	20.5	23.4	23.3	21.7	20.3	22.8	20.5

ACKNOWLEDGMENT

This process during my doctoral program was an incredible and difficult dream come true. This dissertation has been a challenging experience, and it would not have been possible without the support, guidance, and encouragement of numerous others.

To begin with, I would like to thank my supervisor, Dr. Habil Szabó Gyula, whose advice, valuable critique, and constant patience have been invaluable throughout this process. Your dedication to my academic development has had a significant impact on both this dissertation and my own development as a researcher.

To my family, who's always being supporting me and giving me the best wishes. To my mother, who always taught me to never give up, and my father, who taught me to work with patience step by step.