Advanced Musculoskeletal Modeling and Kinematic Assessments for Comparing Occupational Exoskeletons Effectiveness and Muscle Dynamics in Laboratory and In-Field Environments

By

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Master of Science

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Abstract

This thesis investigates the effectiveness of occupational exoskeletons and assistive tools in reducing ergonomic risks associated with physically demanding tasks, specifically focusing on the comparison of in-lab and in-field assessments and the utilization of advanced musculoskeletal modeling techniques. This thesis outlines its comprehensive investigation into the ergonomic risks associated with occupational tasks, organized across several chapters.

The first study explores the biomechanical impact of using a back support exoskeleton and assistive tools (Lever and Jake) in the task of manhole cover removal. The use of various tools and occupational exoskeletons was suggested to enhance physical capabilities of workers who regularly perform physically demanding tasks involving heavy lifting and awkward postures. Most of the studies aiming to explore the effectiveness of these tools and exoskeletons have been performed in confined and controlled laboratory spaces, which do not represent the real-world work environment. This study aimed to compare the outcome of biomechanical assessment of using a back support exoskeleton and assistive tools (Lever and Jake) in the procedure of manhole cover removal versus the results found by performing the same task in a laboratory. Ten able-bodied participants and ten able-bodied utility workers performed the same manhole removal task in-lab and in-field, respectively, with the aid of an exoskeleton and Lever and Jake tools. Muscle activity and Rapid Entire Body Assessment (REBA) scores were recorded using surface electromyography and inertial measurement units (IMUs), respectively, and compared between in-lab and in-field trials. The field experiments indicated significant differences ($p < 0.05$) in normalized muscle activity across most muscles when compared to lab data. These results revealed how muscle activity is affected by the controlled lab setting compared to real-world field conditions. However, REBA scores indicate similar ergonomic implications regardless of the utilization of exoskeletons or tools. These findings underscore that real-world field assessments are crucial for evaluating ergonomic risks and effects of occupational exoskeletons and tools to account for environmental factors and workers' skills in ergonomic evaluations of this nature.

The second study focuses on assessing lower back muscle and joint reaction forces during a common workplace task of lifting a weight using wearable IMUs and camera-based motion capture system (MCS). Low back pain is frequently associated with occupational factors, including heavy lifting and poor ergonomics, and can lead to substantial healthcare costs and reduced productivity. Assessment tools for human motion and ergonomic risk at the workplace are still limited. Therefore, this study aimed to assess lower back muscle and joint reaction forces in laboratory conditions using wearable IMU during weight lifting, a frequently high-risk workplace task. Ten able-bodied participants were instructed to lift a 28 lbs. box while surface electromyography sensors, IMUs, and MCS recorded their muscle activity and body motion. The data recorded by IMUs, and MCS was used to measure lower back muscle and joint reaction forces via musculoskeletal modeling. Lower back muscle patterns matched well with electromyography recordings. The normalized mean differences between muscle forces obtained based on measurements of IMUs and cameras were less than 25%, and the statistical parametric mapping results indicated no significant difference between the forces obtained by both systems. However, abrupt changes in motion, such as lifting initiation, led to significant differences ($p<0.05$) between the muscle forces obtained by these systems. Furthermore, the maximum L5-S1 joint reaction force calculated using IMU data was significantly lower ($p<0.05$) than those obtained by cameras during weight lifting and lowering. The study showed that wearable IMUs had a potential for in-field assessments of lower back muscle forces, enabling the evaluation of in-field ergonomic risk assessment, optimizing posture and workstation, and ultimately reducing the risk of work-related musculoskeletal disorders.

Integrating findings from both studies, this thesis highlights the potential of combining in-field and in-lab assessments using musculoskeletal modeling to better understand and mitigate ergonomic risks. This thesis introduces a novel approach by leveraging advanced musculoskeletal modeling techniques, such as the integration of IMU data and sophisticated statistical parametric mapping, to evaluate the potential of wearable sensors in ergonomic risks assessments. These advanced modeling techniques allow for a more precise simulation of human musculoskeletal dynamics under various real-world conditions, offering insights into muscle and joint forces that were previously challenging to obtain. By doing so, this innovative methodology not only enhances our understanding of ergonomic risk factors but also holds the potential to significantly reduce the prevalence of work-related musculoskeletal disorders. This marks a significant advancement in the biomechanics field by providing a comprehensive toolset for assessing and optimizing the use of occupational exoskeletons and assistive tools, contributing to safer work environments and better health outcomes for workers engaged in physically demanding tasks.

Preface

This thesis is an original work by Maryam Shakourisalim. The research project was approved by the Ethics Committee of the University of Alberta (protocol code Pro00109264, approved on 12 May 2022).

Parts of this thesis were presented as a presentation at the 24th Annual Alberta Biomedical Engineering Conference 2023 (Canada) and the 30th Annual Canadian Society for Mechanical Engineering Congress (CSME) in Canada.

Chapter 3 of this thesis has been submitted as short communication: M. Shakourisalim, X. Wang, K.B. Martinez, A. Golabchi, S. Krell, M. Tavakoli, H. Rouhani, "A Comparative Study of Biomechanical Assessments in Laboratory and Field Settings for Manual Material Handling Tasks Using Extractor Tools and Exoskeletons" Submitted, 2024.

Chapter 4 of this thesis has been published as short communication: M. Shakourisalim, K.B. Martinez, A. Golabchi, M. Tavakoli, H. Rouhani, "Estimation of lower back muscle force in a lifting task using wearable IMUs", 2024. Journal of Biomechanics, p.112077.

Dedicated to

My Family and Friends,

Whose unwavering support and influence have been pivotal in helping me overcome challenges and achieve my goals!

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Chapter 1

1. Introduction

1.1 Overview

This thesis delves into the critical evaluation of ergonomic risks associated with Work-related Musculoskeletal Disorders (WMSDs), emphasizing the role of occupational exoskeletons and assistive tools in mitigating these risks. WMSDs represent a significant concern within occupational health, encompassing a spectrum of conditions that affect muscles, nerves, tendons, and the musculoskeletal system, primarily due to or exacerbated by workplace activities and ergonomics [1]. WMSDs contribute to substantial medical costs, lost workdays, reduced productivity, and disability claims. This underscores the importance of prevention strategies [2]. Given the substantial impact of WMSDs on individuals' well-being, workplace productivity, and the broader economic landscape, this research aims to systematically assess how innovative ergonomic interventions, specifically occupational exoskeletons and assistive tools, can effectively reduce the incidence and severity of these disorders. By focusing on the ergonomic evaluation of such technologies in both laboratory and real-world settings, this study seeks to bridge the gap between theoretical research and practical applications, offering comprehensive insights into optimizing workplace ergonomics and enhancing worker safety.

Ergonomic interventions involving the redesign of workstations, tools, and tasks can be effective in reducing the incidence and severity of WMSDs. Although training programs emphasizing proper lifting techniques and body mechanics have shown some positive results, their long-term effectiveness is debated [3]. Moving forward, an integrated approach encompassing workplace wellness, training, and technological solutions like wearables may offer promising avenues for addressing WMSDs more holistically [4].

WMSDs have traditionally been studied in controlled laboratory settings, offering detailed analyses under standardized conditions. In laboratory settings, ergonomic assessments are conducted under controlled conditions designed to isolate and precisely measure specific variables related to WMSDs. This methodological approach ensures high degrees of measurement accuracy and repeatability, which are fundamental in understanding the biomechanical and physiological underpinnings of WMSDs. However, despite these advantages, laboratory-based assessments may fall short in capturing the complex nature of the workplace environment. Real-world conditions often involve a dynamic interplay of physical, environmental, and psychological factors that can significantly influence worker behavior, posture, and muscle activation patterns. For instance, the complexity of actual workspaces, varying environmental conditions such as temperature and noise, and the psychological stress of real-world tasks can all impact the development and management of WMSDs [5].

These factors are difficult, if not impossible, to replicate fully in a laboratory setting. As a result, while laboratory-based studies provide invaluable insights into the mechanisms and potential mitigation strategies for WMSDs, they might not offer a complete picture of how these disorders manifest and can be effectively addressed in real-world scenarios. Therefore, field assessments that incorporate the actual working conditions and environmental contexts in which workers operate, is essential to complement laboratory studies [6]. In-field evaluations bring in insights, unveiling unique challenges and risk factors that may be overlooked or underestimated in controlled settings [7]. Balancing the rigor of in-lab assessments with the realism of in-field observations can provide a more comprehensive understanding of WMSDs, which helps in designing effective training and assistive tools to address the specificities of workplace environments [7]. Figure 1.1 depicts the major differences between a laboratory and field assessment of wearable exoskeletons.

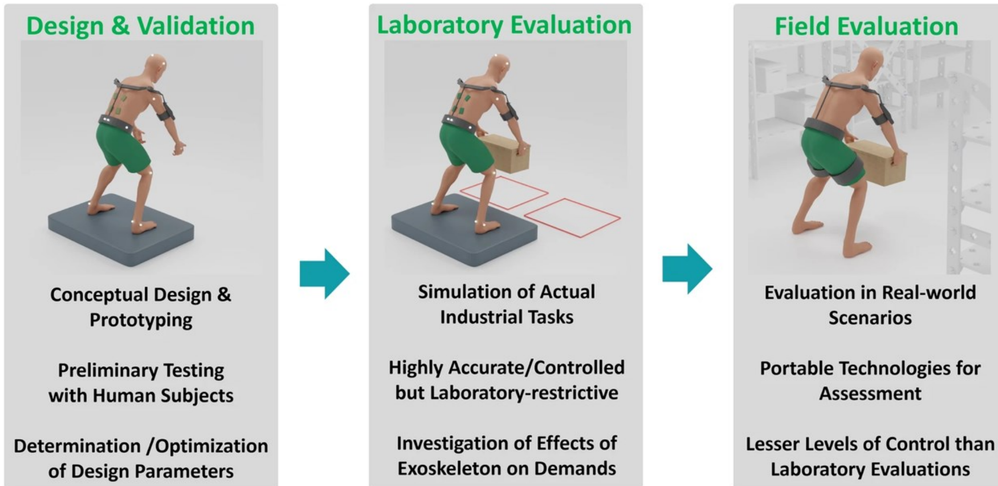


Figure 1.1. The three stages of industrial exoskeleton development: initial validation, laboratory testing, and field evaluation [7]. This figure is reproduced under license agreement from Springer Nature.

To this end, human motion assessment has long been a cornerstone of biomechanical research, and the technologies utilized for this purpose have witnessed significant evolution over time. One of the primary tools in the in-laboratory setting is the camera-based motion capture system (MCS). These systems, often based on optical tracking principles, use either marker-based or markerless methodologies. The marker-based approach involves placing reflective markers on specific anatomical landmarks of participants, allowing cameras to track their movement and, subsequently, recreate precise, high-resolution three-dimensional models of the human body in motion [8], [9]. Being set in controlled environments, these systems benefit from consistent lighting and minimal external disturbances, ensuring high-fidelity data capture. Furthermore, when integrated with force plates, they provide a comprehensive biomechanical analysis encompassing both kinematic and kinetic aspects [10].

On the other hand, inertial measurement units (IMUs) have revolutionized in-field human motion assessments. IMUs, compact sensors comprising accelerometers, gyroscopes, and occasionally magnetometers, offer the unparalleled advantage of capturing kinematics in real-world settings [11]. Their portability and wearability make them ideally suited for analyzing a vast range of activities, from athletic performances to everyday movements, outside the confines of a laboratory. This real-world data capture often results in more authentic and varied datasets. However, the flexibility of IMUs comes with challenges, such as ensuring absolute positional accuracy and mitigating sensor drift, issues absent in the controlled, static setup of MCS. While MCS is considered the gold standard for detailed biomechanical analyses in controlled settings, IMUs have bridged the gap, providing an avenue for assessing human motion in genuine, dynamic environments [11].

Despite the growing interest in and development of occupational exoskeletons and assistive tools aimed at reducing ergonomic risks in the workplace, there exists a notable gap in understanding their effectiveness in real-world settings as compared to controlled laboratory conditions. Much of the existing research emphasizes outcomes from lab-based evaluations, which may not fully account for the complexities and variability encountered in actual work environments. This gap underscores the need for comprehensive studies that bridge this divide, providing a detailed comparison of the effect of these interventions in both settings. Such insights are crucial for developing ergonomic solutions that are not only scientifically validated but also practically applicable and effective in the diverse conditions of the modern workplace, ensuring that the potential benefits of these tools are fully realized in reducing work-related musculoskeletal disorders.

1.2 Objective

The proposed research aims to integrate the findings and methodologies to develop and validate a comprehensive, in-field ergonomic risk assessment framework for occupational settings. The core research question driving this thesis is as follows: “How do occupational exoskeletons and assistive tools, when assessed in real-world work environments, impact the ergonomic risks associated with physically demanding tasks?” This inquiry aims to delve into the practical effectiveness of these interventions in reducing the incidence and severity of WMSDs among workers engaged in tasks that demand extensive physical effort. By examining the performance and impact of occupational exoskeletons and assistive tools within the authentic context of their intended use, this research seeks to uncover insights into their role in enhancing workplace ergonomics. Furthermore, it endeavors to bridge the gap between laboratory-based findings and their applicability in dynamic, real-world settings, thereby contributing to the development of more effective strategies for mitigating ergonomic risks in the workplace."

Specifically, this research will focus on assessing the effectiveness of occupational exoskeletons and other assistive tools in real-world environments, particularly in reducing the prevalence of WMSDs, with an emphasis on lower back pain. The research will employ a hybrid approach, combining the in-lab precision of biomechanical modeling, involving OpenSim software for musculoskeletal modeling, with the real-world relevance of in-field assessments, comparing in-lab and in-field ergonomic risk evaluations. The objective is to bridge the gap between laboratory-based ergonomic risk assessments and their real-world applicability, considering the variability of muscle activity patterns and ergonomic postures observed in different working environments.

Key elements of the research will include:

1. Utilizing IMUs and EMG to capture and analyze ergonomic risks in actual work settings, focusing on tasks that are known to cause WMSDs, such as lifting heavy objects.
2. Through this research, we aim to contribute to the development of more effective ergonomic interventions, improve the well-being of workers, and reduce the economic burden associated with WMSDs in the workplace.
3. Applying musculoskeletal modeling techniques to evaluate and predict muscle and joint reaction forces, particularly in the lower back, during occupational tasks.
4. Conducting a comparative analysis of kinetic data obtained using IMUs and MCS for ergonomic risk assessment. This element will focus on evaluating the accuracy and reliability of IMU-based measurements in capturing lower back muscle and joint forces during occupational tasks. The research will specifically examine the disparities in data obtained from these two methods, particularly during dynamic tasks such as lifting, to determine the extent to which IMU-based assessments can reliably substitute or complement MCS data in both laboratory settings. This comparison is crucial for establishing robust, non-invasive, and practical methods for ergonomic risk assessments in real-world work environments, thereby enhancing the feasibility and effectiveness of ergonomic interventions.

1.3 Structure

This thesis aims to bridge the gap between laboratory research and real-world application in four chapters (Figure 1.2). The initial chapter, Chapter 1, sets the stage for the research by outlining the significance of WMSDs and the potential of occupational exoskeletons and assistive tools in mitigating these risks. It presents the core research question, aiming to explore the impact of these interventions in real-world environments compared to controlled laboratory settings. This chapter lays the foundational understanding necessary for readers to grasp the complexity of ergonomic risks and the innovative approaches being investigated to address them.

The literature review in Chapter 2 offers a comprehensive analysis of previous studies, distinguishing between the precision of laboratory assessments and the real-world applicability of field assessments. It examines the methodologies used in past research, emphasizing the advantages and limitations of each approach. Furthermore, it introduces musculoskeletal modeling as a pivotal tool for ergonomic risk evaluation, setting the stage for its application in subsequent studies. This chapter critically examines the gap between theoretical knowledge and practical implementation, highlighting the need for a more integrative approach that combines the strengths of both laboratory and field assessments.

Chapter 3 details the research design and methodologies employed to investigate the primary research question which explores the biomechanical impact of using a back support exoskeleton in the task of manhole cover removal. It describes the selection and use of occupational exoskeletons and assistive tools, participant recruitment, and the setup for both laboratory and field experiments. This chapter also presents the data collection and analysis methods, ensuring the reader understands how the research was conducted to maintain scientific rigor and relevance.

Chapter 4 presents an in-depth analysis and application of musculoskeletal modeling. This chapter presents the comparison between in-lab and in-field assessments, focusing on the differences in muscle dynamics and joint reaction forces measured through MCS technologies and wearable IMUs. By leveraging detailed musculoskeletal models, this chapter evaluates the potential of using IMUs under real-world conditions versus controlled environments. The outcomes offer critical insights into the practical effectiveness of these interventions in reducing ergonomic risks and highlight the potential for musculoskeletal modeling to enhance ergonomic assessment and intervention strategies.

Chapter 5 provides a discussion and conclusion on the research findings, discussing their implications for the design, selection, and implementation of ergonomic interventions in the workplace. It critically evaluates the research in the context of the existing literature, addressing the research question while highlighting limitations and areas for future research. This chapter concludes with recommendations for practitioners and researchers, aiming to contribute to the ongoing effort to reduce ergonomic risks associated with physically demanding tasks.

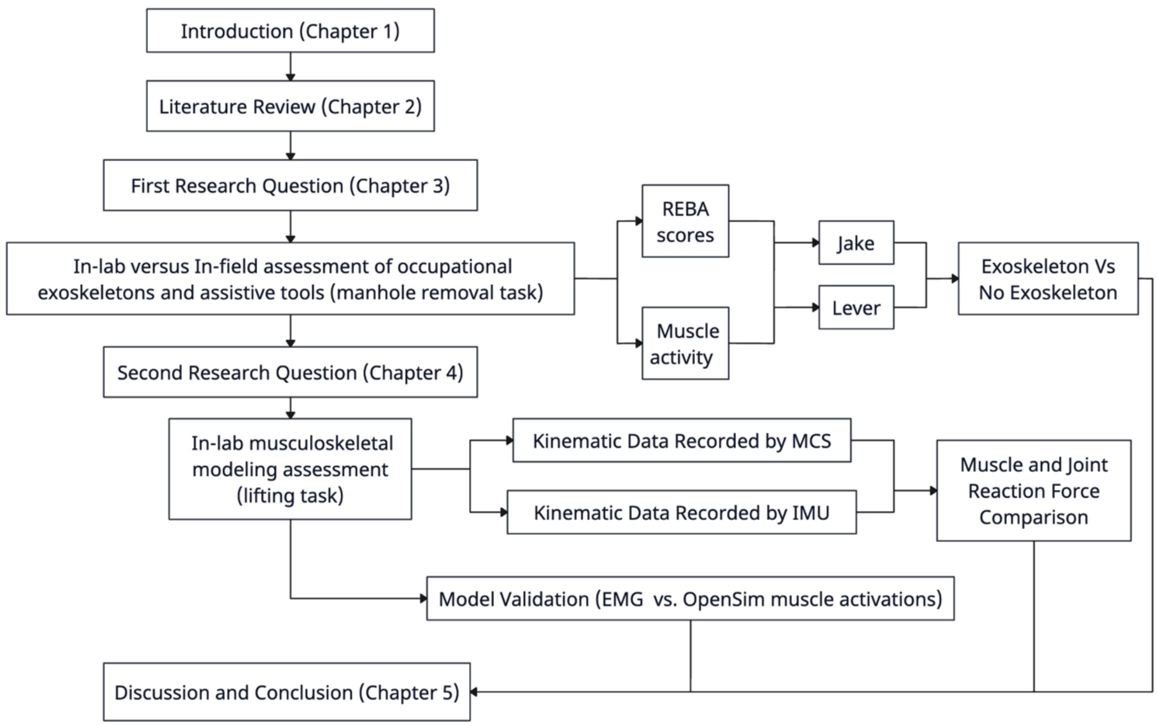


Figure 1.2. Flowchart demonstrating the relation between chapters of this thesis.

Chapter 2

2. Literature Review

This chapter offers a comprehensive review of the current research in biomechanical assessments, reviewing existing literature that explores the various approaches to evaluating ergonomic risks both in controlled laboratory settings and in the unpredictable real-world environments. This chapter bridges the theoretical foundation of musculoskeletal modeling with practical applications, delving into the precision and challenges inherent in laboratory assessments, the adaptability and technological constraints faced during field assessments, and the innovative methodologies aimed at combining these two worlds. It critically examines the role of advanced tools such as Statistical Parametric Mapping (SPM) and musculoskeletal modeling in transcending the traditional boundaries of ergonomic risk assessment.

2.1 Surface electromyography (EMG) measurements for biomechanical analysis

Surface EMG is a common technique that evaluates muscle function by measuring the electrical signals generated by muscles. This technique is non-invasive and measures the sum of the potentials generated by motor units, which are the basic functional units of muscle contraction. The technique involves placing electrodes on the skin over the muscles of interest. The recording process of EMG involves several steps [12]:

1. **Preparation of the Skin:** The skin is cleaned and, if necessary, shaved to reduce electrical impedance and improve signal quality.

2. **Electrode Placement:** Electrodes are placed over the belly of the muscle or along the muscle fibers, ensuring consistent placement across sessions or subjects for comparability.

3. **Signal Acquisition:** The electrical signals are then captured as the muscle contracts, either voluntarily or through stimulation.

Several considerations must be taken into account to as possible sources of error during surface EMG recordings. It is critical to avoid crosstalk from adjacent muscles. Movement artifacts can distort the signal, requiring participants to maintain specific postures or use of stabilization techniques during recordings. Skin impedance and sweat can also affect signal quality and are typically minimized through proper skin preparation. External electrical noise from other equipment can interfere with the signals and needs to be shielded or filtered out [12].

Muscle EMG measures the electrical activity of muscles which is related to, but not directly proportional to, muscle force. Muscle force refers to the mechanical force generated by the contraction of muscle fibers and can be influenced by factors like muscle size, type of muscle fibers, and biomechanical aspects of muscle and tendon structures. EMG provides insights into the timing and level of muscle activation rather than the force itself [13].

Estimating muscle force directly from EMG data is challenging due to several factors. First, the relationship between EMG signals and muscle force is non-linear. Second, individual variability affects the relationship, as differences in muscle size, fiber composition, and neuromuscular efficiency lead to unique EMG patterns. Third, muscle fatigue also complicates the interpretation as it changes EMG signal characteristics while reducing muscular efficiency. Fourth, crosstalk from adjacent muscles can contaminate EMG signals, inaccurately representing the targeted muscle's activity. Fifth, the distinction between static and dynamic contractions introduces further complexity; dynamic contractions involve changing muscle length and velocity, influencing the force output differently compared to static scenarios where the muscle length remains constant. Sixth, electrode placement and signal processing must be precise, as errors can lead to significant inaccuracies. Lastly, calibration and modeling are required to estimate force from EMG; however, these models often require individual calibration and provide only approximations of force, suitable for relative comparisons rather than absolute measurements. These complexities highlight why EMG is better suited for assessing trends in muscle activation rather than exact force measurements [10-13].

2.2 Laboratory Assessments in Biomechanics: Precision and Challenges

The assessment of human motion in biomechanics varies significantly between field and laboratory settings. Each environment offers unique advantages and faces distinct challenges, especially when analyzing complex movements and predicting the biomechanical impact of interventions. Lab settings offer controlled environments that are instrumental for detailed biomechanical analysis but often face challenges in replicating real-world conditions. Labs are equipped with high-tech tools that allow for the precise measurement of various biomechanical parameters. This controlled setting is ideal for studying specific aspects of human motion and understanding the underlying biomechanical principles [14].

Despite technological advancements, labs struggle to mimic the unpredictability and complexity of field conditions. For example, studies focusing on industrial tasks like overhead drilling use digital human models to replicate field tasks in a lab setting, highlighting the gap between lab-based simulations and real-world activities [15]. Labs facilitate comprehensive biomechanical analyses, such as the evaluation of joint angles, torques, and muscle activations. These detailed assessments are crucial for understanding the intricacies of human movement and for developing interventions to improve performance or reduce injury risk [16], [17].

2.3 Field Assessments in Biomechanics: Adaptability and Technological Limitations

On the other hand, field assessments, while adaptable, often struggle with the limitations of portable technology and the challenges of dynamic environments. Field assessments predominantly rely on wearable sensors to collect data. These devices are less intrusive and more practical for real-world settings but may lack the accuracy and comprehensiveness of lab equipment. To compensate for technological limitations, field assessments often employ predictive models and data analysis techniques [15].

2.4 Bridging the Gap Between Laboratory and Field Assessments

Efforts to bridge the gap between field and lab assessments are crucial for a holistic understanding of biomechanics. Validating models for specific tasks, such as lifting, ensures their accuracy in simulating real-world activities. For example, the development of an OpenSim full-body model for lifting tasks provides insights into lumbar loading during lifting, demonstrating the potential of these models for practical applications [18], [19]. Studies on overhead industrial tasks illustrate the ergonomic challenges workers face. Biomechanical analysis of such tasks informs the design of ergonomic solutions and assistance devices to mitigate the risk of WMSDs [20].

2.5 Comparative Analysis of Field and Laboratory Human Motion Assessments

Diverse perspectives on laboratory versus field assessments in the context of human motion analysis can be found in literature. For instance, the use of wearable devices for walking and running gait analysis outside of the lab was evaluated by [21]. This study focuses on the application of wearable technology for gait analysis outside of the laboratory setting. It highlights the shift from traditional lab-based assessments, which typically involve advanced equipment like 3D MCS, to field assessments using portable and affordable wearable devices. These devices enable the study of gait patterns in natural, real-world settings and are becoming integral in the analysis of daily movement patterns across diverse populations. The review underscores the need for more extensive studies involving large participant groups in their natural environments and the establishment of guidelines for the usability of wearable devices in gait analysis [21].

The study performed by Giannini et al. focuses on risk assessment for biomechanical overload in manual material handling. The Rapid Entire Body Assessment (REBA) score was employed as a key metric in this study. This scoring system is widely used in ergonomic risk assessment for identifying and quantifying biomechanical overload risks in manual material handling tasks (Figure 2.1). The study introduces a novel system that employs a sensor network consisting of IMUs and EMG sensors. This system gathers and processes data from three IMUs and two EMG capture devices, providing ergonomic risk scores, including the REBA score. The system's capabilities were tested in a challenging outdoor scenario involving the lifting and lowering of containers on a cargo ship. Comparisons between this new method and traditional evaluation methods demonstrate the system's consistency, time efficiency, and potential for deeper analysis, including variations among individuals and a more detailed biomechanical analysis [22].

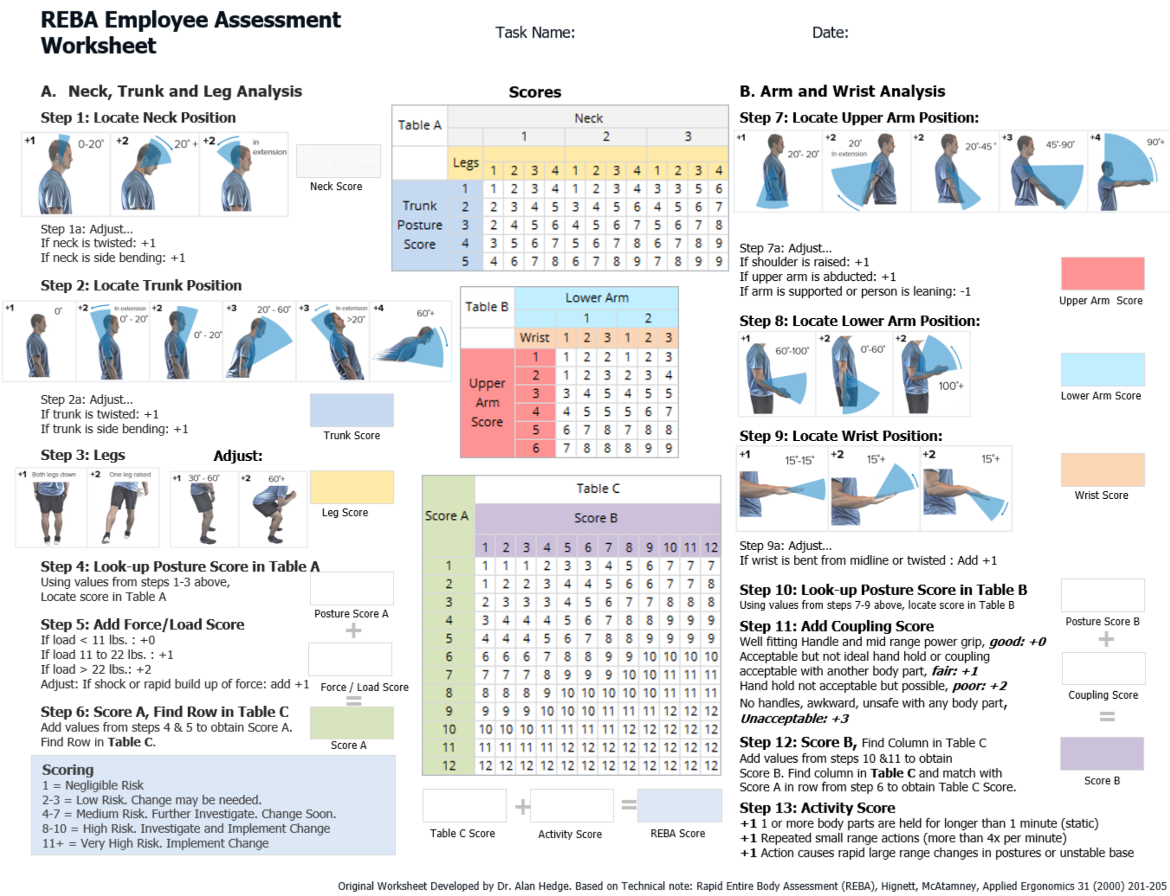


Figure 2.1. REBA worksheet and risk levels [23].

Table 2.1. Level of MSD risk based on REBA score.

Score	Level of MSD Risk
1	Negligible risk; no action required
2-3	Low risk; change may be needed
4-7	Medium risk; further investigation, change soon
8-10	High risk; investigate and implement change
11+	Very high risk; implement change

Moreover, a study on motion analysis in sports biomechanics deals with the comparison of in-field versus laboratory testing, specifically in cricket bowling. It emphasizes the accuracy and reliability of opto-reflective systems used in laboratories over video-based systems used in field settings. The paper discusses the technological advances in camera resolution and processing speeds that have improved biomechanical data collection and accuracy. However, it notes the challenges in implementing complex biomechanical models in field testing, thus favoring laboratory testing for certain precise measurements, such as the reconstruction of elbow angle data in cricket bowling [24].

An overview of wearable and non-wearable systems, highlighting clinical applications was studied by [25]. The results provide a comprehensive overview of the various methods used in gait analysis, contrasting wearable sensors and non-wearable sensors systems. The paper highlights the evolution and current state of gait analysis technologies, offering a detailed insight into both traditional and modern approaches to studying human gait. Non-wearable sensors are typically used in controlled laboratory environments. These systems, which include cameras, laser sensors, and pressure platforms, are designed to measure gait variables as the subject walks on a defined walkway. The main advantage of non-wearable sensors is that they allow for a more controlled analysis, isolating the study from external factors that could affect measurements. This results in high levels of repeatability and reproducibility for the gait parameters studied. The controlled setting, however, also means that these systems may not capture the natural gait patterns of individuals in their everyday environment [25].

In contrast, wearable sensors utilize a range of sensors attached to various parts of the body, such as the feet, knees, thighs, or waist. These sensors, which include accelerometers, gyroscopes, magnetometers, force sensors, goniometers, and electromyography, are designed to capture various signals that characterize human gait. Wearable sensors systems have the advantage of being able to analyze gait data outside the laboratory, capturing information about human gait during a person's everyday activities. This makes them particularly useful for long-term monitoring and evaluation in real-world settings. Wearable sensors systems have also been shown to provide benefits in fields like wearable gait retraining, extending the reach of laboratory-quality analysis to a broader population. However, they also have disadvantages, such as the complexity of analyzing IMU signals and the amplification of measurement errors in certain situations [23].

Another study focused on a novel approach to assess the risk of falling by measuring gait instability using wearable technology. The study consists of two parts: a laboratory-based analysis with MCS and a field assessment using wearable IMUs. In the lab, the gait of subjects was analyzed to establish normative thresholds for gait stability. The field assessment tested the accuracy of the wearable sensors in real-world conditions. Results showed high consistency between the wearable sensors and lab-based MCS, underscoring the potential of wearable technology for real-time monitoring of gait instability and fall risk (Figure 2.2). However, challenges in accuracy and applicability under different walking conditions were noted. The study highlights the comparison between controlled lab conditions and variable field settings in assessing gait stability [26].

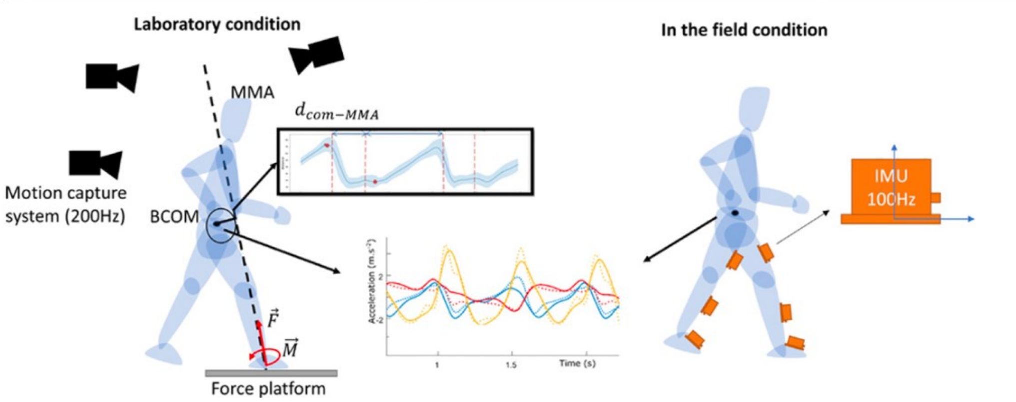


Figure 2.2. Graphical representation of a novel approach to assess the risk of falling by measuring gait instability using IMUs [24]. This figure is reproduced under the rights managed by Taylor & Francis.

Table 2.2 provides a side-by-side comparison of laboratory-based versus field-based human motion studies. Laboratory environments allow for a high degree of control and accuracy in measurements, though they may not fully reflect real-world scenarios. Field studies, conversely, capture the complexity of everyday movements but face challenges related to the control of variables and the precision of measurements. The aim is to facilitate an informed decision on which method best suits the research objectives, balancing the need for detailed analysis with the realism of natural settings.

Table 2.2. Comparative Overview of Laboratory-Based and Field-Based Human Motion Assessments

Aspect	Laboratory Assessments	Field Assessments
Environment	Controlled, consistent conditions	Real-world, variable conditions
Advantages	High precision and repeatability Controlled variables Detailed biomechanical analysis possible	Can assess natural behaviors and interactions Incorporates real-world variables

Limitations	Hard to replicate complex real-world conditions	Lower precision due to uncontrolled variables Technological limitations (e.g., sensor accuracy)
Technologies Used	Stationary motion capture systems	Wearable sensors (e.g., IMUs)
Data Collection	Requires specialized equipment and setup Data collected in specific tasks or simulations	Data can be collected during actual work or daily activities

2.5.1 Statistical Parametric Mapping (SPM)

Statistical Parametric Mapping (SPM) is a sophisticated analytical method used primarily in brain imaging studies, but its applications extend to other areas such as biomechanics. The core principle of SPM involves constructing and assessing spatially extended statistical processes to test hypotheses about functional imaging data. It has been implemented in a free and open-source software package known as SPM, which is designed for analyzing sequences of brain imaging data [27].

SPM's application is not limited to neuroimaging. For instance, SPM was used to identify differences between consensus-based joint motion patterns during gait in children with cerebral palsy. This study aimed to provide objective, quantitative data to support the identification of these patterns, which were initially defined based on expert opinion. By comparing kinematic waveforms of typically developing children with those of children with cerebral palsy, the study tested hypotheses about differences in joint motion patterns. This approach allowed for a detailed analysis of joint motion patterns, highlighting significant differences and locations within the gait cycle that were relevant to the classification of these patterns [28].

Another study presented MovementRx, a Python-based, GUI-enabled movement analysis decision support system that utilizes SPM. MovementRx is designed for the analysis of joint kinematics and kinetics in clinical gait analysis, providing a holistic view of all lower limb joints. It uses color maps to simplify the interpretation of complex statistical data, making it accessible to clinicians with limited statistical training. This application of SPM in MovementRx demonstrates its versatility beyond traditional neuroimaging, extending to biomechanics and movement analysis [29].

SPM and traditional statistical tests like the t-test are both used for hypothesis testing, but they have key differences. T-test typically used to compare means between two groups at a specific point or variable, while SPM analyzes data across an entire continuum, such as time or space. It is useful in situations where data are collected over time or space (like brain imaging or biomechanical motion analysis). T-test does not inherently account for multiple comparisons; separate adjustments (e.g., Bonferroni correction) may be needed when multiple t-tests are conducted. SPM integrates corrections for multiple comparisons across the entire dataset, reducing the risk of Type I errors (false positives) inherent in multiple testing. Furthermore, t-test results typically represent a single value or statistic (like a p-value), but SPM produces a statistical map where each point's value indicates the statistical significance, providing a more comprehensive view of data variations over time or space [30], [31].

SPM involves several advanced mathematical and statistical processes [27], [30-38]:

1. **General Linear Model (GLM):** GLM is a statistical linear model that generalizes various forms of linear regression models. It is used to describe a relationship between one or more independent variables and a dependent variable. In its simplest form, GLM can represent linear regression, but it can also be extended to represent ANOVA (for categorical outcomes) and ANCOVA (analysis of covariance). GLM is foundational in statistical analysis and is widely used in various fields, including biomedical research, for hypothesis testing, prediction, and inference [33]. SPM utilizes the GLM to model biomechanical data, such as joint angles or muscle activities. The model expresses the observed data as a linear combination of explanatory variables plus an error term.
2. **Time-Series Analysis:** Biomechanical data are often time-series (e.g., gait cycle data). SPM analyzes these data point-by-point across the entire cycle, applying statistical tests at each point.
3. **Statistical Tests:** Commonly, t-tests or F-tests are applied to assess the significance of differences in biomechanical variables at each time point in the cycle.

4. **Multiple Comparisons Correction:** Due to the large number of comparisons across a time series, SPM employs methods like Random Field Theory to adjust for multiple comparisons, controlling for false positives. Random Field Theory is a mathematical framework used primarily in the field of statistical analysis, especially within the context of neuroimaging and biomechanics. It is a key component in SPM. Random Field Theory helps to address the multiple comparison problem when making statistical inferences about spatial data. When applying statistical tests to a large number of spatially correlated data points (like voxels in neuroimaging or data points in biomechanical analysis), the chance of false positives increases. Random Field Theory provides a method to control for these false positives by considering the smoothness and correlation of the data across space. It adjusts the significance levels for spatially correlated tests, ensuring that the results of statistical tests are more reliable and accurate.
5. **Statistical Parametric Maps:** The results of these tests are assembled into a map, where each point's value represents the statistical significance of the observed effect, providing a comprehensive view of the biomechanical patterns and differences over time.

2.5.2 Musculoskeletal Modeling

Musculoskeletal modeling is central to both lab and field assessments, yet its application varies greatly due to environmental constraints. Comprehensive musculoskeletal models integrate detailed anatomical data, often derived from cadaver studies or MRI scans. This high level of detail allows for accurate simulations of human movement, particularly beneficial for understanding specific muscle coordination and joint dynamics during activities like walking or running [16], [17].

Advanced tools such as MCS and EMG provide granular data that enhances these models, allowing for precise replication of human motion and muscle activity in a controlled environment [16]. The dynamic and unpredictable nature of field settings complicates the direct application of detailed musculoskeletal models. The primary challenge lies in accurately capturing complex motion with portable and less intrusive technology. Wearable technologies, such as IMUs, are employed to gather movement data. However, integrating this real-world data with musculoskeletal models to simulate activities accurately remains a significant research area [16], [39]. Figure 2.4 shows a full-body musculoskeletal model and muscles designed in OpenSim software [40].

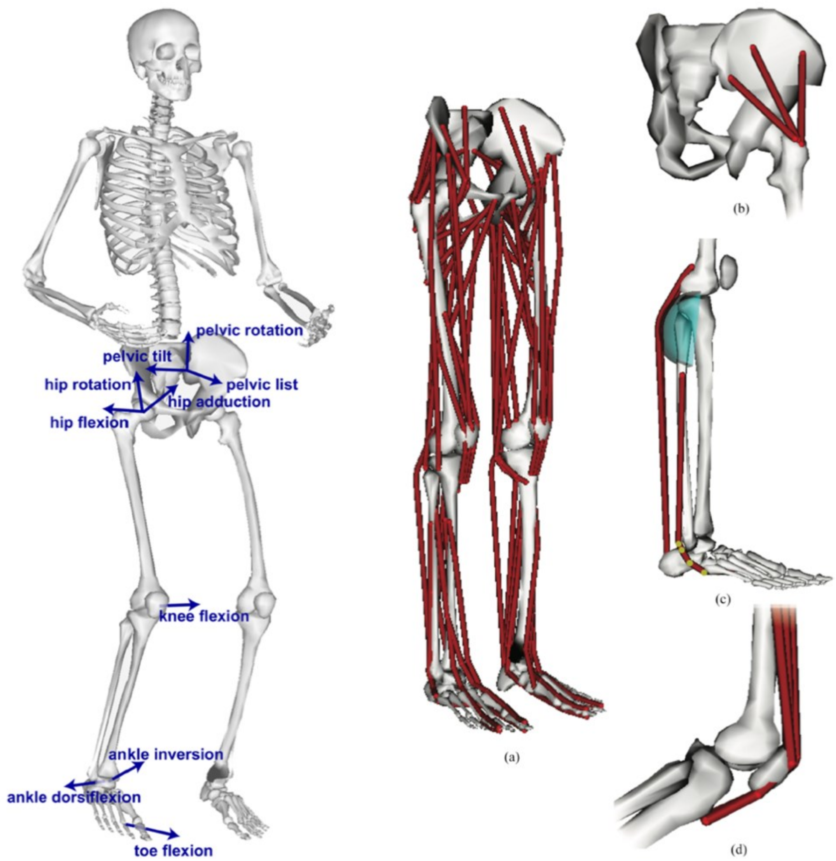


Figure 2.3. Full-body musculoskeletal model implemented in OpenSim with 22 rigid bodies. Lower body muscles were modeled as massless linear actuators (a-d) [40]. This figure is reproduced under IEEE copyright line © 2016.

2.6 Conclusion

While current research provides valuable insights into the biomechanical assessments conducted in both laboratory and field settings, a comprehensive understanding of how these environments influence the effectiveness of occupational exoskeletons and assistive tools in mitigating ergonomic risks remains elusive. This thesis, therefore, is positioned to bridge this gap by directly comparing the biomechanical impacts of these interventions across controlled and real-world conditions.

In summary, field and lab motion assessments each play a critical role in biomechanics. Laboratory assessments provide detailed, controlled analyses of human motion but often fall short in replicating the complexity of real-world environments. Field assessments, conversely, offer practicality and applicability but struggle with data accuracy and depth. The ongoing development of wearable technology and data analysis methods is key to enhancing field assessment accuracy. Integrating detailed lab findings with practical field applications remains a significant challenge, with musculoskeletal modeling serving as a pivotal tool in bridging these two domains for a comprehensive understanding of human biomechanics.

These studies collectively illustrate the evolving landscape of human motion analysis. While laboratory assessments offer high accuracy and control, particularly necessary in fields like sports biomechanics for precise measurements, they may not fully capture natural, real-world human movements. Field assessments, facilitated by advancements in wearable technology and computer vision, offer a more realistic and accessible approach to studying human movement patterns in everyday environments. However, challenges such as data accuracy, the complexity of dynamic environments, optimized musculoskeletal models, and the need for more comprehensive and standardized methodologies in field assessments remain areas for future research and development.

Chapter 3

3. In-lab versus In-field assessment

A Comparative Study of Biomechanical Assessments in Laboratory and Field Settings for Manual Material Handling Tasks Using Extractor Tools and Exoskeletons[1]

This chapter aims to illuminate the critical differences between laboratory and field assessments in ergonomic risk evaluation, thereby questioning and expanding upon traditional methodologies. It sets the stage to challenge the assumption that evaluations conducted exclusively in laboratory settings can fully encompass the effectiveness of occupational exoskeletons and assistive tools in mitigating ergonomic risks. By juxtaposing these two distinct assessment environments, the chapter aims to shed light on how each contributes uniquely to our understanding of ergonomic interventions' real-world applicability and effectiveness. As we navigate through the comparative analyses and discussions, the chapter lays a foundation for questioning and broadening the scope of traditional ergonomic evaluation methods. This exploration not only highlights the inherent limitations of lab-based assessments but also underscores the importance of incorporating real-world conditions into the evaluation process.

3.1 Introduction

To reduce the prevalence of WMSDs, employers are increasingly investing in equipment, tools, and training initiatives designed to minimize the physical strain associated with physically demanding tasks, and subsequently improve the well-being of the workers, enhance workplace productivity, and reduce the economic burden of injuries [41]. For example, occupational exoskeletons are proposed to reduce the risk of fatigue and chronic WMSDs. Exoskeletons are wearable devices constructed from lightweight materials that integrate mechanical components to

[1] This chapter has been submitted as short communication: M. Shakourisalim, X. Wang, K.B. Martinez, A. Golabchi, S. Krell, M. Tavakoli, H. Rouhani, "A Comparative Study of Biomechanical Assessments in Laboratory and Field Settings for Manual Material Handling Tasks Using Extractor Tools and Exoskeletons" Submitted, 2024.

enhance the physical capabilities of workers, addressing challenges like lifting heavy objects, performing repetitive tasks, or enduring extended periods of standing or kneeling [42][43].

Numerous studies have focused on ergonomic risk analysis and the effect of physical assistance devices, such as occupational exoskeletons. However, these studies are mostly conducted in laboratory settings [44], [45], [46]. Laboratory assessments provide controlled environments for detailed biomechanical and physiological measurements, isolating the exoskeleton's effects from other variables and allowing for precise and repeatable measurements [45]. However, these controlled conditions may not accurately represent the complexities and variability of real-world tasks, which can limit the generalizability of findings and impact the validity of assessments [47], [48]. In contrast, field evaluations, conducted in actual work environments, allow researchers to observe and evaluate workers in their natural settings, which ensures that the assessments are contextually relevant and offer crucial insights into the exoskeleton's real-world performance, usability, and user acceptance [49], [50], [51]. However, in-field ergonomic risk assessments are also subject to limitations, such as the influence of uncontrolled environmental variables and limited measuring equipment [14].

The discrepancies identified between laboratory and field assessments pose a significant challenge to current methodologies by potentially mischaracterizing the safety and effectiveness of certain tasks, postures, and the use of exoskeletons. For example, a task or posture deemed safe in a laboratory setting, based on specific biomechanical parameters, might not account for the cumulative stress on the body over time or the influence of external conditions, leading to an erroneous classification of safety. Similarly, the effect of an exoskeleton designed to reduce ergonomic risks may be overestimated in controlled settings, failing to account for practical challenges such as user compliance, comfort, and the adaptability of the device to various tasks and environments. These oversights can result in the endorsement of practices or tools that may not provide the expected protection or could even intensify the risk of injury when implemented in the field.

This study critically examines the discrepancies in biomechanical assessments of manual material handling tasks in laboratory versus field settings, focusing on the potential for varied interpretations of ergonomic risks and the effectiveness of assistive devices, including exoskeletons. An experimental approach was adopted by evaluating measurements of muscle activities and body posture for a manhole cover removal task. This task is a representative high-demand, frequent manual handling activity commonly performed by utility workers. Experiments were conducted both in lab and field environments, utilizing assistive tools and a passive back-support exoskeleton.

Our objectives are to compare biomechanical outcomes in laboratory and field conditions, to evaluate the effectiveness of back support exoskeletons in mitigating ergonomic risks in varied settings, and to contribute to the development of more effective ergonomic assessments and tools in real-world work environments. We hypothesize significant variances in biomechanical assessments between lab and field environments and expect the exoskeleton's effectiveness in reducing ergonomic risks to differ across these settings. The anticipated results are expected to deepen our understanding of ergonomic risk factors across different environments. These insights are crucial for designing more effective ergonomic tools and practices, especially for manual tasks such as manhole cover removal, ultimately contributing to the prevention of work-related musculoskeletal disorders.

3.2 Methods

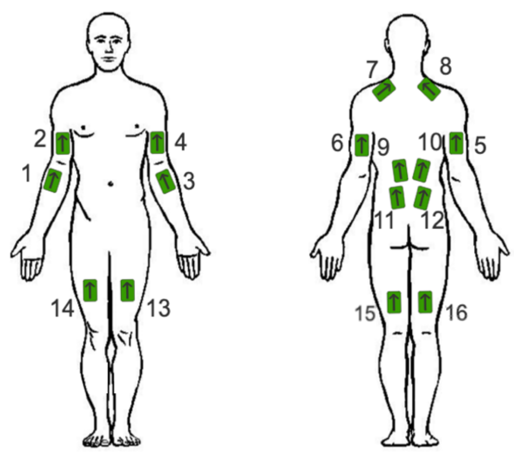
3.2.1 Study Design and Participants

For the in-field assessment, ten able-bodied male participants (body mass: 73 ± 18 kg, body height: 180 ± 5 cm, age: 33 ± 7 years) from the drainage and construction workers volunteered to perform the manhole removal task on their jobsite. The in-lab data was recorded from ten able-bodied participants (6 males, 4 females, body mass: 63 ± 13 kg, body height: 170 ± 7 cm, age: 26 ± 1 years) among university students. The in-lab setup was designed to replicate the tasks performed by workers on the job site. Participants had no clinical history of lower back pain up to six months prior to the study, and written consent was collected from the participants after they were informed of the experimental procedures. The study was approved by the research ethics board of the University of Alberta, ID: Pro00109264.

3.2.2 Experimental Procedure

Surface electromyography (EMG) data was captured bilaterally from the Brachioradialis, Biceps Brachii, Triceps Brachii, middle branch of the Trapezius, Latissimus Dorsi, Thoracolumbar Fascia, Rectus Femoris, and Bicep Femoris muscles using 16 Trigno Avanti sensors provided by Delsys Inc., USA (Figure 6). In addition to this, a Rapid Entire Body Assessment (REBA) was conducted to evaluate ergonomic risks, with body joint angles being measured using 11 IMUs from Xsens Technologies, NL. These units were attached to various body parts, including the head, upper trunk (over the sternum), upper arms, forearms, lower back, thighs, and shanks (Figure 3.1).

a)



Sensor #	Muscle
Upper limbs	
1	Right Brachioradialis
2	Right Biceps Brachii
3	Left Brachioradialis
4	Left Biceps Brachii
5	Right Triceps Brachii
6	Left Triceps Brachii
Back	
7	Left Trapezius
8	Right Trapezius
9	Left Latissimus dorsi
10	Right Latissimus dorsi
Lower limbs	
11	Left Thoracolumbar fascia
12	Right Thoracolumbar fascia
13	Left Rectus femoris
14	Right Rectus femoris
15	Left Bicep femoris
16	Right Bicep femoris

b)

Sensor #	Location
Upper limbs	
1	Head
2	Chest
3	Pelvis
4	Right Upper arm
5	Right Forearm
6	Left Upper arm
7	Left Forearm
Lower limbs	
8	Right Thigh
9	Right Shank
10	Left Thigh
11	Left Shank

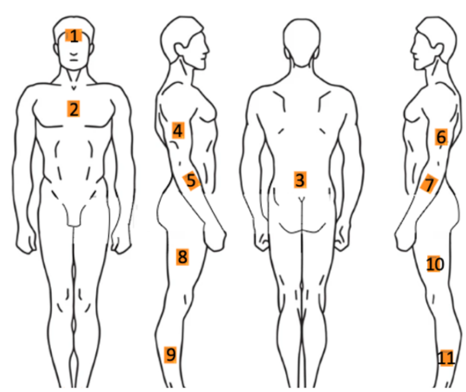


Figure 3.1. Sensor placement of (a) EMG sensors and (b) IMU sensors on the participants.

The activity being assessed involved moving a manhole cover using either a sledgehammer and a pick bar tool called the "Jake" tool or an in-house lever-based tool called the "Lever" tool. Each participant engaged in two repetitions of the task, with a resting period of five seconds of standing still between each repetition, as illustrated in Figure 3.2. To explore the effectiveness of an exoskeleton in minimizing ergonomic risks, the participants repeated the trials while wearing a passive back-support exoskeleton, the BackX from SuitX, USA. The BackX exoskeleton is designed to support the wearer's lower back by providing assistive torque during activities that involve bending and lifting. BackX offers a significant reduction in the load on the lower back, with maximum net torques of 24.8 Nm during flexion, thereby enhancing ergonomic safety [52]. This exoskeleton had two modes: the standard mode, which activates when the trunk is bent between 30° and 45°, and the instant mode, which is always activated. To assess the performance of these modes, each task was performed two times with the standard mode and two times with the instant mode of the exoskeleton.

In-field data was collected from utility workers removing manhole covers on the job-site. The in-lab trial was designed to duplicate the in-field trials by employing a total of 60 lbs. weight plates within the laboratory environment, aiming to replicate the 60 lbs. manhole cover used in-field. Furthermore, we maintained consistency by utilizing identical Jake and Lever tools for both the in-field and in-lab tests, ensuring a seamless comparison between the two scenarios. This approach allowed us to assess the performance of the tools and the exoskeleton in a controlled setting, mirroring real-world conditions as accurately as possible. However, there were some inconsistencies, such as differences in the experience level between workers and student participants. In addition, the in-field manhole covers are flushed with the ground, which was not possible to exactly replicate in-lab.

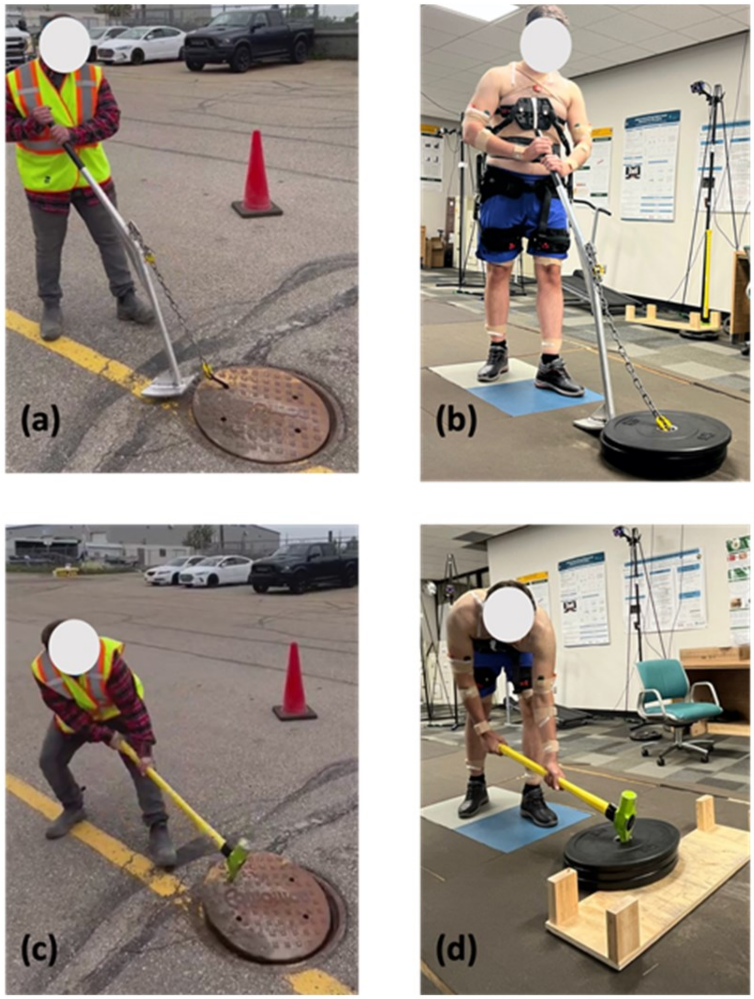


Figure 3.2. Experimental procedures in-field (a & c), in-lab (b & d) using Jake tool (c & d), and Lever tool (a & b).

3.2.3 Data analysis

The analysis of muscle activities while removing a manhole cover was conducted using EMG sensors. The EMG data was gathered at a rate of 2000 Hz and then subjected to a band-pass filter, isolating frequencies in the range of 10 to 500 Hz. Subsequently, the signal was rectified and smoothed using a moving average filter with a window size of 500 data points. In order to standardize the amplitude of the EMG signal, a Maximum Voluntary Contraction (MVC) technique was applied to each of the muscles under observation [53]. MVC is a critical technique in biomechanics, denoting the maximum force that a muscle or group of muscles can exert voluntarily. It is essential for assessing an individual's capacity for physical tasks and normalizing muscle activity to evaluate muscle function and prevent injuries. One of the ways to measure MVC is by having an individual perform a strength exercise while connected to EMG sensors. The measurement process includes several maximum effort contractions with rest in between to prevent fatigue. The peak value of the filtered and processed EMG recording is MVC [54]. Finally, we determined the Root Mean Square (RMS) value for the normalized amplitude of the EMG signal across the duration of the activity.

The data recorded by IMU, underwent a low-pass filtering process using a 2nd order Butterworth filter set at a 6 Hz cut-off frequency. This filtered data was then used to ascertain the sensor orientations through the application of a sensor fusion algorithm, as described in [55], [56]. In addition to this, the orientation of the sensor relative to the body was determined through a functional calibration procedure, as outlined in [57]. Following these initial steps, the orientations of different body segments were calculated, considering both the adjusted sensor orientations and the sensor-to-body orientation. Finally, using the obtained body segment orientations, the angles of various joints during the trials were computed and expressed within the Joint Coordinate System (JCS), as referenced in [58].

The calculated joint angles were used for Rapid Entire Body Assessment (REBA) based on the participants' body posture and joint angles. REBA is an evaluation tool employed to assess the risk of WMSDs linked to specific job activities. REBA score is used to assess ergonomic risk through the observation of body postures, using the measured joint angle. Each body region is scored separately, and these scores are combined in a two-step table, leading to a single REBA score [59]. The accuracy of REBA score calculated by IMUs was previously validated for manual handling tasks [59], [60].

The REBA scores measured using IMU data and the RMS values of normalized EMG amplitudes for each task were compared between in-field and in-lab experiments. These comparisons were performed with both Lever and Jake tools, with and without the exoskeleton. The data did not exhibit a normal distribution, as determined by the Shapiro-Wilk test. Therefore, we chose to employ the Wilcoxon rank-sum test with a significance level of 5% to investigate whether there were any significant differences in the dependent variables among the paired comparisons [61].

3.3 Results

The analysis of normalized muscle activity during in-field experiments revealed significant differences ($p < 0.05$) when compared to the in-lab data for most of the muscle groups. Specifically, when participants used the Jake and Lever tools with and without the exoskeleton, the muscle activity levels were notably different in the field compared to the laboratory settings (Figures 3.3 and 3.4). This suggests that the muscle engagement required for the same task can vary considerably depending on the environment in which the task is performed. Interestingly, despite these differences in muscle activity levels, the REBA scores, which are used to assess posture-related ergonomic risk, showed no statistically significant difference between in-field workers and their in-lab counterparts. This was consistent across scenarios, whether the workers were using the Jake and Lever tools with or without the exoskeleton (Figure 3.5). This aspect of the results indicates that while the ergonomic posture risk remained consistent across both environments, the actual muscle exertion and patterns of activity differed.

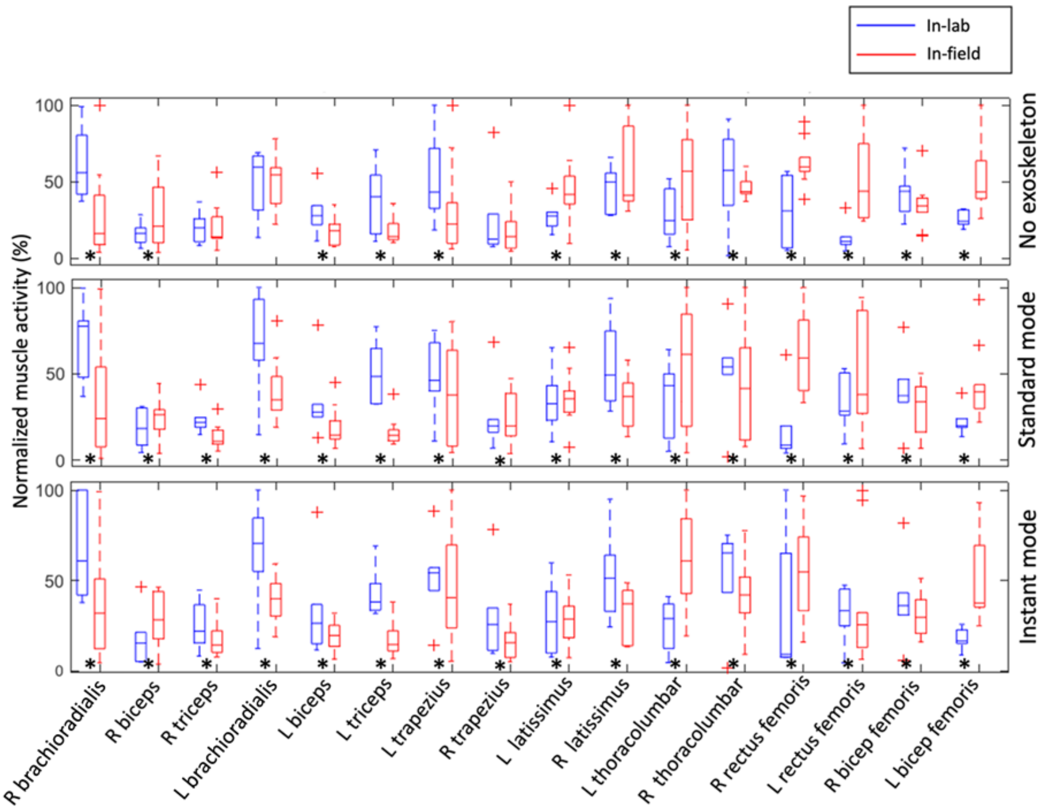


Figure 3.3. Comparison between normalized muscle activation amplitudes during in-field and in-lab experiments with and without the exoskeleton while using the Jake tool. The results for all participants are presented as boxplots. Crosses indicate an outlier. Black asterisks indicate a significant difference with zero with p-values < 0.05.

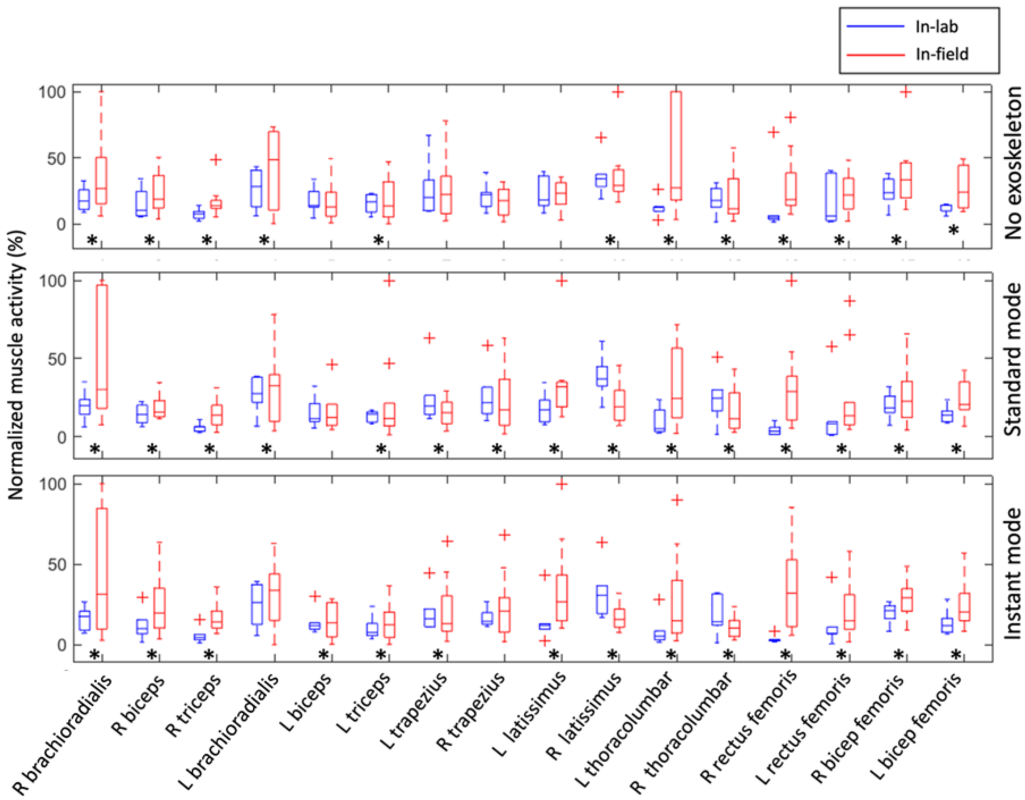


Figure 3.4. Comparison between normalized muscle activation amplitudes during in-field and in-lab experiments with and without the exoskeleton while using the Lever tool. The results for all participants are presented as boxplots. Crosses indicate an outlier. Black asterisks indicate a significant difference with zero with p-values < 0.05.

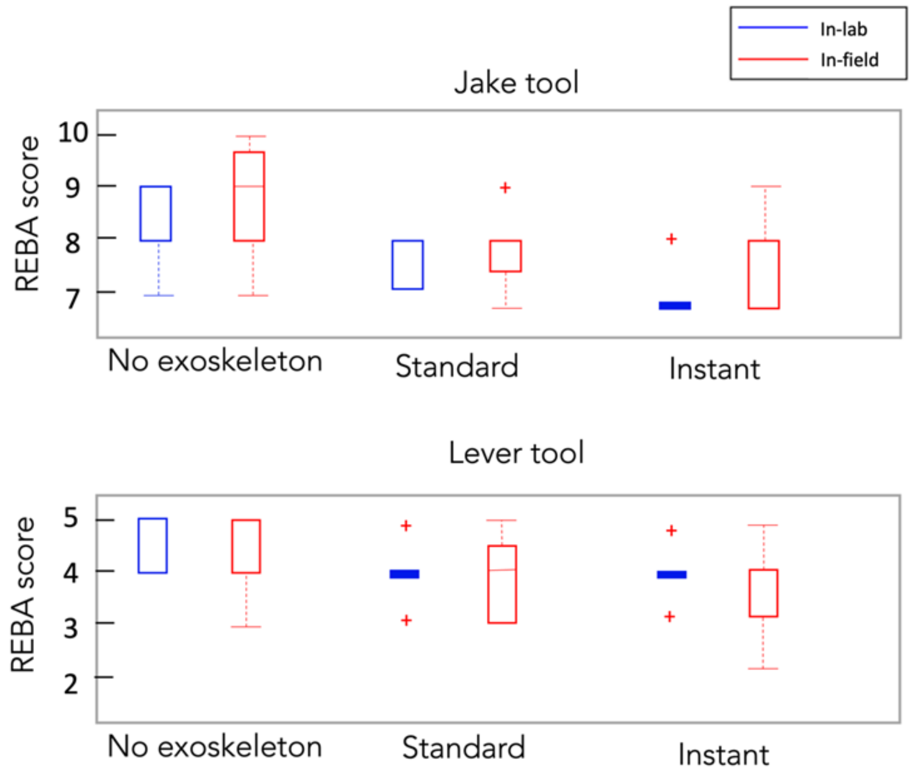


Figure 3.5. Comparison between REBA scores during in-field and in-lab manhole cover removal experiments using different tools and with and without Exoskeleton (in both Standard and Instant modes). The results for all participants are presented as boxplots. Red crosses indicate an outlier, and there are no significant differences with zero.

Furthermore, we conducted a comparison between the exoskeleton's real-world impact on manhole removal, as documented in [62], and our controlled laboratory findings using the Wilcoxon rank-sum test. Our laboratory experiments revealed that wearing the exoskeleton while using either tool for manhole cover removal generally had little to no effect on most muscle activities. However, when participants used the Jake tool with the exoskeleton, significant ($p < 0.05$) changes in muscle activity of the right Trapezius, right Latissimus, left Rectus Femoris, and Biceps Femoris were observed (Figure 3.6). Similarly, as illustrated in Figure 3.7, when the Lever tool was employed, we observed significant differences ($p < 0.05$) in muscle activity, specifically in the left Triceps, right Trapezius, right Thoracolumbar, and left Biceps muscles, when participants wore the exoskeleton compared to when they did not. Based on the in-lab results, the back support exoskeleton had little to no effect on participants performing the manhole cover removal task. However, the exoskeleton was reported to be useful for the same task performed in the field by utility workers [62].

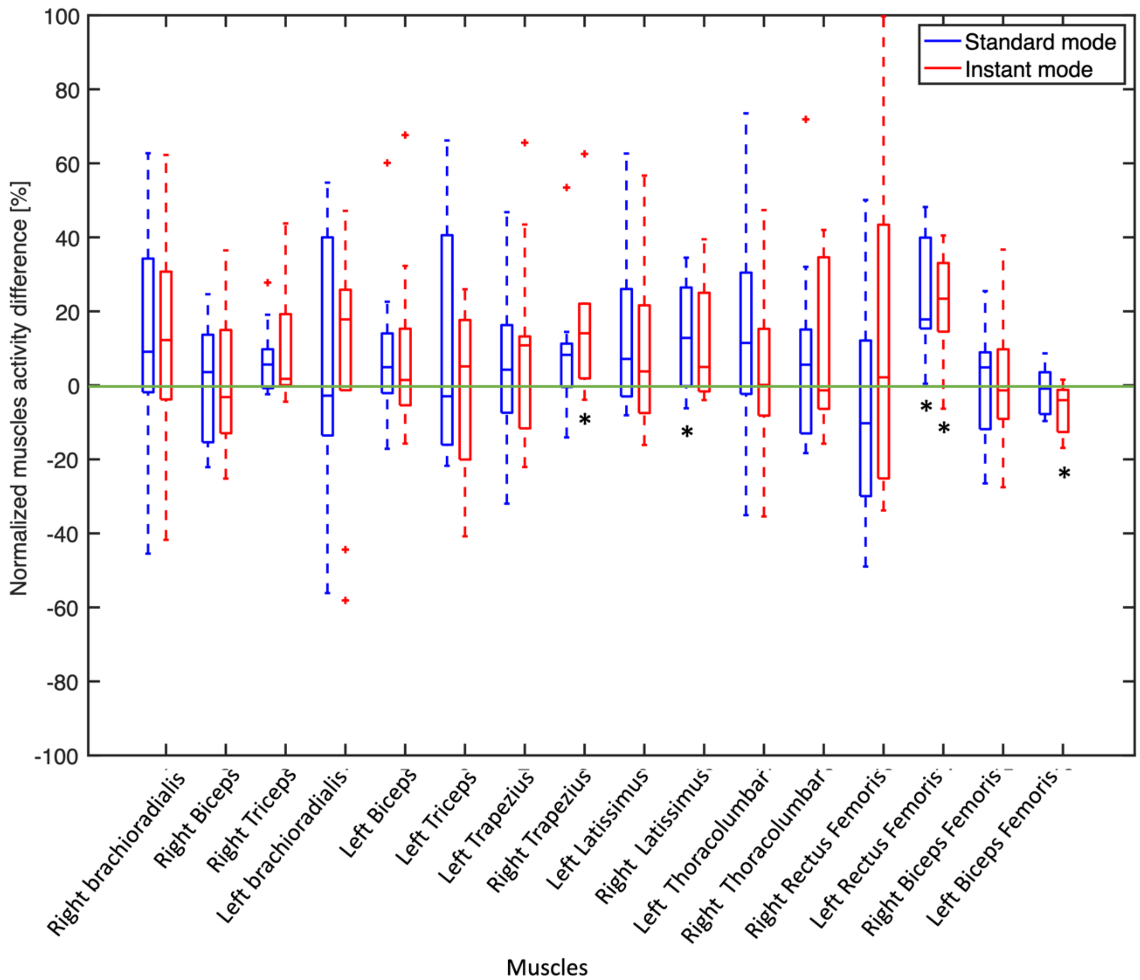


Figure 3.6. The percentage of normalized muscle activity when a manhole cover was removed using a Jake tool while wearing an exoskeleton (instant and standard mode) compared to not wearing an exoskeleton. The results for all participants are presented as boxplots. A positive percentage is an increase in muscle activity when the exoskeleton is worn. Red crosses indicate an outlier. Black asterisks indicate a significant difference with zero with p-values < 0.05.

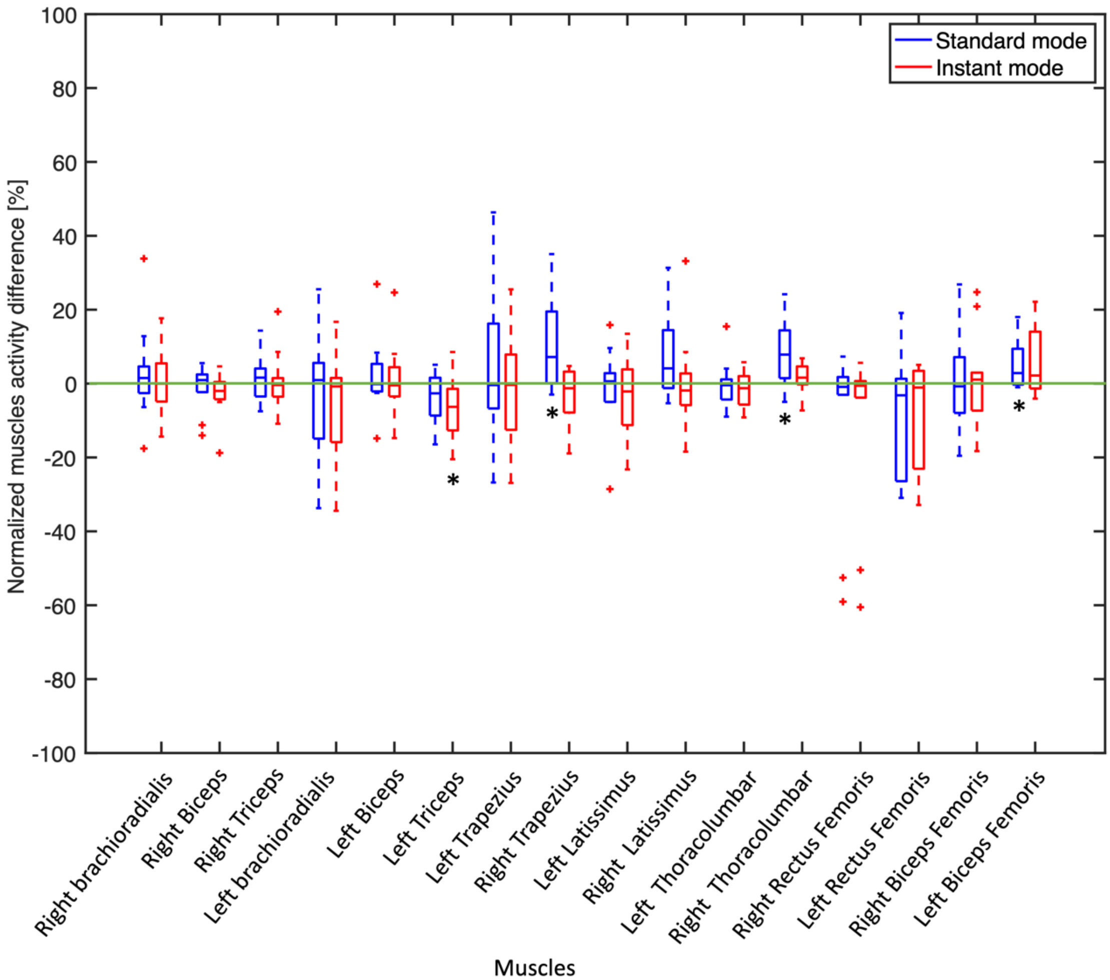


Figure 3.7. The percentage of normalized muscle activity when a manhole cover was removed using a Lever tool while wearing an exoskeleton (instant and standard mode) compared to not wearing an exoskeleton. The results for all participants are presented as boxplots. A positive percentage is an increase in muscle activity when the exoskeleton is worn. Red crosses indicate an outlier. Black asterisks indicate a significant difference with zero with p-values < 0.05.

3.4 Discussions

This study aimed to investigate if in-lab experiments with non-workers as participants for ergonomic risk assessment in various tasks and using various tools and exoskeletons can be a reliable surrogate for in-field experiments with actual workers. The findings highlighted that the body postures (assessed by the REBA Score) were comparable between the in-lab experiments with non-workers as participants and the in-field experiments with actual experienced workers, regardless of the use of exoskeletons or tools. Yet, the muscle activity levels significantly differed between these two conditions, showcasing a variance in muscle engagement patterns when tasks were performed with and without the aid of tools and exoskeletons. These differences suggest that the controlled laboratory environment with the use of weights instead of the actual manhole and non-workers as participants instead of actual workers does not fully capture the complexity of real-world tasks, leading to potential discrepancies in ergonomic assessment. This raises intriguing questions about the interpretation of muscle activity data in isolation and highlights the importance of a holistic approach to ergonomic assessment, considering both muscle activity and body posture to gain a comprehensive understanding of the impacts on worker health and safety.

Notably, the observed muscle activities were not higher or lower across all muscle groups in lab experiments compared to the real-world experiments. When using tools and exoskeleton in both modes, the activity level of some muscles increased in lab compared to the real world and decreased for other muscles. This may indicate that actual workers in field employed different muscle recruitment strategies and synergies compared to non-workers in the lab, while both participant groups had comparable body postures and performed similar tasks. This might partially be due to demographic differences (such as body height, body mass, age, and sex) between the two participant groups and their different physical fitness and experience level for manual handling task execution. This experience might have led to more efficient movement patterns and muscle use in the field, which were not replicated in the lab setting.

Future research should thus aim for a deeper understanding of these patterns and their implications for ergonomic interventions. Given that occupational exoskeletons are ultimately intended for use in field environments, it becomes evident that a detailed field analysis with actual workers is essential and likely to yield more insightful results compared to controlled in-lab studies. In addition, due to the observed different outcomes or exoskeletons among users of different demographics, it is recommended to consider a diverse population in the design and validation of occupational exoskeletons, to ensure that the findings are broadly applicable and inclusive. This diversity should encompass not just gender and age but also physical conditioning and professional experience, as these factors contribute to the effectiveness of movement patterns and muscle use.

Besides the differences between the study participants, the differences between experimental conditions can contribute to the observed difference in muscle activities. In a real-world context, numerous uncontrollable variables come into play, such as the varied layers of clothing worn by participants, which can affect movement and muscle engagement. Beyond these, environmental conditions like weather, temperature, and even the time of day may impact the results, which are often unaccounted for in laboratory settings. Moreover, the psychological state of participants, influenced by real-world stressors or the artificial environment of a lab, can also alter performance and outcomes. These discrepancies highlight the need for future studies to perform comprehensive evaluations to understand how each of these factors might influence results differently across various measurement conditions.

In our study, we utilized circular weights with central holes to simulate the lifting of manhole covers, different from manhole covers that often have holes at the edge. In addition, the circular weight was not flush with the ground, similar to the real-world manhole cover. This design choice may affect the torque dynamics experienced during actual lifting operations, potentially influencing the ergonomic assessment outcomes. This limitation of our experimental design highlights the importance of designing future studies with closer alignment to real-world conditions to fully understand the ergonomic implications of lifting tasks in utility work.

In this study, we focused on a single material handling task: the removal of utility manhole covers. This task was selected due to its relevance and high occurrence in manual material handling. However, we recognize this as a limitation, as our findings may not fully extend to other types of material handling tasks. Future research could benefit from including a diverse range of scenarios, allowing for a broader understanding of biomechanical and ergonomic impacts across different tasks and enhancing the applicability and generalizability of our findings. In addition, in our study, each participant was tested only twice in each scenario. While this was sufficient to gain preliminary insights, it may impact the overall data reliability and the generalizability of the findings. Future studies should consider increasing the number of repetitions to enhance data robustness.

In summary, our study design introduced multiple variables, such as differing environments, experimental setups, and participant demographics, which may influence the research outcomes. While this approach provides valuable insights into the real-world application of exoskeletons and tools, it complicates the isolation of single variables to understand their specific impacts. For future research, we recommend controlled studies that isolate and examine an individual factor that may affect the effectiveness of exoskeletons and tools in real-world settings. Such studies would complement our findings by providing a deeper understanding of how each variable contributes to the overall effectiveness of tool and exoskeleton interventions in improving worker safety and productivity.

3.5. Conclusion

This study emphasizes the need to evaluate occupational exoskeletons and assistive tools in real-world settings, as muscle activity differs significantly between controlled lab environments and actual field conditions. These insights contribute to a more comprehensive understanding of the practical implications of various tools and exoskeletons employed for physically demanding tasks, such as manhole cover removal and emphasize the importance of considering environmental factors in such ergonomic assessments.

Chapter 4

4. In-lab musculoskeletal modeling assessment

Estimation of lower back muscle force in a lifting task using wearable IMUs[2]

In this chapter, we delve into the application of IMUs and musculoskeletal modeling to assess muscle and joint forces in real-time, showcasing their potential in the realm of in-field ergonomic risk assessment. This examination provides a detailed insight into how leveraging IMUs, coupled with musculoskeletal models, can revolutionize the way we understand and evaluate the biomechanical impacts of occupational tasks. The findings presented here not only pave the way for a deeper understanding of ergonomic risks associated with various work-related activities but also offer a substantial contribution to the development of more effective workplace interventions. By exploring the capabilities and limitations of these technologies, the chapter highlights their significance in designing ergonomic solutions that are both scientifically grounded and practically applicable. This discussion extends beyond theoretical implications, aiming to equip practitioners and researchers with the knowledge to implement advanced assessment methods that enhance worker safety and health.

4.1 Introduction

Low back pain is a widespread issue, affecting up to 84% of the general population during their lifetime [63]. In 2020, there were 619 million reported cases of lower back pain worldwide, and with the aging population, this number is expected to reach 843 million by 2050 [64]. Many of these cases are attributable to occupational factors like heavy lifting and poor ergonomics, leading to a significant economic impact through increased healthcare costs, workday absences, and reduced productivity. In Europe, WMSDs, including low back pain, account for half of all work absences lasting more than three days and approximately 60% of reported cases of permanent

[2] This chapter has been submitted as short communication: M. Shakourisalim, K.B. Martinez, A. Golabchi, M. Tavakoli, H. Rouhani, "Estimation of lower back muscle force in a lifting task using wearable IMUs" Submitted, 2024.

incapacity. WMSDs primarily affect the lower back but can also impact upper limbs, particularly in professions involving repetitive tasks, heavy lifting, and suboptimal ergonomic conditions. This results in added healthcare expenses, workers' compensation claims, and the need for investments in workplace improvements [65].

For a comprehensive ergonomic and biomechanical assessment of common tasks performed in a workplace, such as lifting a heavy load, measurements of muscle and joint reaction forces, such as spinal loads, are required [66]. These measurements were historically invasive, involving surgery to implant sensors in the body [16]. Alternatively, researchers developed musculoskeletal models that simulated the complex musculoskeletal structure of body parts, such as the spine and vertebral joints, to characterize how the body joints experience internal loads during activities like lifting. Various musculoskeletal modeling software packages have been developed [39], [17], [67]. that can contribute to the assessment of human motion kinematics and kinetics and, thus, ergonomic risk assessment. In musculoskeletal modeling packages such as OpenSim, muscle and joint reaction forces can be calculated from kinematic data recorded by non-invasive methods such as camera-based MCS to evaluate different tasks, such as lifting [16] and overhead industrial tasks [68]. While MCS cameras are acknowledged for their accuracy, they are confined to controlled laboratory settings and are often impractical for real-world field assessments. Therefore, in out-of-lab applications of human motion measurement, the preference is to employ wearable sensors, such as IMUs [69]. More importantly, it was reported that the outcomes of in-lab ergonomic risk assessments and human motion analysis were not always comparable with the field evaluations [70]. Thus, there is a need for in-field ergonomic risk assessment based on human motion kinetics assessment using musculoskeletal modeling and wearable sensors.

Previous studies investigated the use of wearable sensors to provide kinematic data and machine learning to classify correct and incorrect postures toward enhancing workplace ergonomics and injury prevention [71]. Moreover, wearable IMUs were used to detect fatigue-related changes in spine motion with the ultimate goal of preventing musculoskeletal injuries in workplaces and sports settings [72]. In general, kinematic parameters obtained by wearable IMUs have been validated against those obtained by MCS. However, the propagation of error in kinematics assessment when using IMUs into error in muscle forces and joint reaction forces estimation has not been evaluated for many tasks such as trunk flexion and extension during lifting. Given the impact of inertial and geometrical properties of the body sections, in addition to their kinematics, on the muscle forces and joint reaction forces estimation, the relative contribution of the kinematic assessment errors to the force estimation error is still unknown.

This research study is focused on a comparative analysis of lower back muscle and joint (L5-S1) forces computed by OpenSim when using kinematic data captured from MCS versus IMUs. Furthermore, the results of our musculoskeletal modeling were validated by comparing the muscle activations estimated by musculoskeletal modeling with those measured by surface electromyography (EMG) to validate the implementation of musculoskeletal modeling.

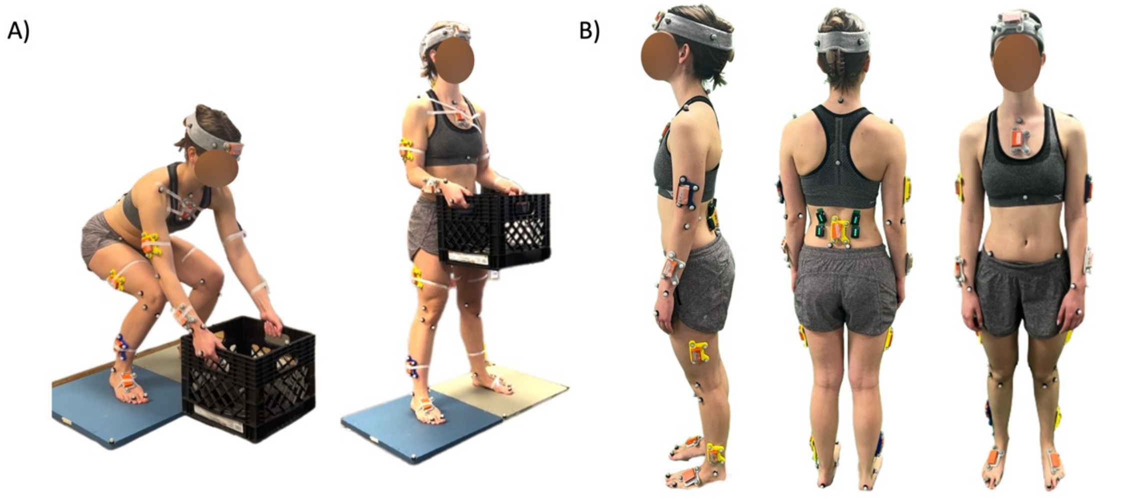
4.2 Method

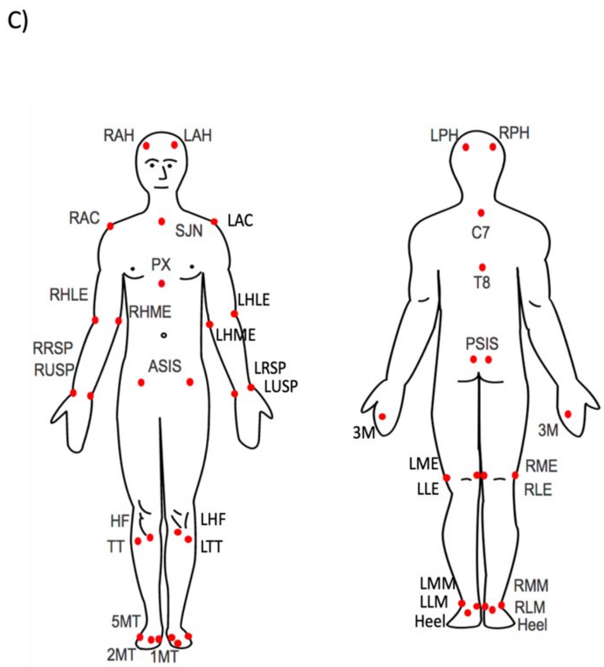
4.2.1 Study Design and Participants

Ten participants (five males and five females; age: 26 ± 2 years old, height: 171 ± 10 cm, body mass: 66 ± 15 kg) with no clinical history of lower back pain were recruited. The experimental procedure was approved by the research ethics board of the University of Alberta, and participants provided their written consent after being informed of the testing procedure.

4.2.2 Experimental Procedure

Participants were asked to lift a 28 lbs. box from the floor to their pelvis height while standing with each foot on a force plate (Figure 4.1 (A)). They were fitted with 40 reflective markers and 13 IMUs (MTws, Xsens Technologies, NL) to calculate their body joint angles while performing the task. Reflective markers were used to capture movements using MCS (Vicon, Oxford Metric, UK) as a gold standard. In addition, ground reaction forces were measured by two force plates (OR 6-7, AMTI, USA). IMUs were placed on several body segments (left and right upper and lower arm, left and right upper and lower leg, left and right foot, head, chest, and pelvis). For validation purposes, EMG of lower back muscles was measured using four sensors (Trigno Avanti, Delsys, USA) placed bilaterally over the Latissimus dorsi (LD) and Thoracolumbar fascia (TF) [53]. The data recorded by cameras, IMU, force plate, and EMG were collected synchronously at 100 Hz, 40 Hz, 1200 Hz, and 2000 Hz, respectively. Figure 4.1 (C) shows the marker and sensor placements on a participant.





Abbreviation	Meaning
RAH	Right Anterior Head
LAH	Left Anterior Head
LPH	Left Posterior head
RPH	Right Posterior head
RAC	Right acromion
SJN	Incisura jugulars
C7	Seventh cervical
PX	Processus xiphoideus
T8	8^{th} thoracic vertebra
RASIS	Right anterior superior iliac spine
LASIS	Left anterior superior iliac spine
RPSIS	Right posterior superior iliac spine
LPSIS	Left posterior superior iliac spine
RHLE	Right humerus lateral epicondyle
RHME	Right humerus medial epicondyle
RRSP	Right radial styloid
RUSP	Right ulnar styloid
3M	3^{rd} phalange
HF	Head of fibula
TT	Tibial tuberosity
RME	Right medial epicondyle
RLE	Right lateral epicondyle
RMM	Right medial malleolus
RLM	Right lateral malleolus
HEEL	Right heel
5MT	5^{th} metatarsal
2MT	2^{nd} metatarsal
1MT	1^{st} metatarsal

Figure 4.1. (A) The lifting task was performed by a participant while wearing IMUs and reflective markers. (B) Placement of reflective markers, IMUs, and EMG sensors on a participant. (C) Reflective marker positions, abbreviation and meaning.

4.2.3 Data Processing

EMG recordings were band-pass filtered (10-500 Hz), rectified, and normalized to the maximum voluntary contraction amplitudes. EMG, kinetic, and kinematic data were all low-pass filtered using a 2nd order Butterworth filter with a 6 Hz cut-off frequency [53]. Joint angles were found using MCS recordings by calculating the local coordinate system of each segment based on the ISB recommendations [73], [74], [58]. To find the comparable joint angles using IMUs, a functional calibration, according to [57], was performed to align the inertial frames of the IMUs with the anatomical frames of the body. To this end, after wearing IMUs, participants were asked to stand still for 5 seconds and then perform 10 leg and arm flexions/extensions while locking their knee and elbow joints. Then, segment orientations were estimated using the sensor fusion algorithm proposed by [55], [56]. The joint angles obtained by both MCS and IMUs were used as input to OpenSim software.

OpenSim is a free and accessible open-source software package, for musculoskeletal modeling and simulation. It integrates advanced computational capabilities within its application framework, complemented by a user-friendly graphical interface. OpenSim contains a vast collection of models previously created by researchers, freely available for public use (Delp et al., 2007). We used a recently developed lifting full-body (LFB) musculoskeletal model to estimate muscle forces and joint reaction forces. This LFB model was previously validated for similar lifting tasks, and it consists of 238 Hill-type musculotendon actuators, 30 segments, and 29 degrees of freedom [16]. Furthermore, eight muscle groups (the erector spinae, rectus abdominis, external obliques, internal obliques, multifidus, quadratus lumborum, psoas major, and latissimus dorsi (LD)) were defined for the trunk, while upper and lower limbs were activated by ideal torque actuators and did not have any muscles [16].

4.2.4 Simulation Steps

The steps taken to calculate muscle and joint reaction forces using OpenSim are as follows:

1. The LFB model was loaded in OpenSim (version 4.4).
2. The model was scaled for each participant based on their anthropometric and MCS data during a static pose.

3. The lower back muscle forces were calculated by performing a static optimization (SO) method while minimizing the sum of muscle activations squared. The inverse kinematic data (joint angles) was given as a motion input to static optimization. Moreover, external forces applied to each participant's body were an additional input to this method. The external forces consist of forces applied on each hand and the ground reaction forces. There are different ways to calculate the external forces on each hand when a person is lifting a box. Here, we used a simple method for dividing the weight of the box and applying the corresponding force to each hand according to [75].
4. Joint reaction analysis was performed through OpenSim to calculate the L5-S1 reaction force using kinematic data and muscle forces (calculated in Step 3) as input.
5. Steps 3 and 4 were repeated, but this time the kinematic data (joint angles) was measured using IMUs calculated from the data obtained by IMUs.

4.2.5 Muscle and Joint Reaction Force Comparison: Kinematic Data Recorded by MCS vs. IMU

To compare the lower back muscle forces and L5-S1 joint reaction force using kinematic data captured by MCS and IMU, the difference between forces was calculated and averaged over time for each participant and normalized to the range of the force obtained using MCS. Furthermore, since lifting is a dynamic task and values of the measured muscle and joint reaction force vary during a task cycle, statistical parametric mapping (SPM) paired t-test ($p < 0.05$) was used to compare the difference between forces calculated using MCS and IMU data [30], [76].

4.2.6 Model Validation: EMG Recordings vs. Muscle Activations Estimated by OpenSim

To validate the muscle activations obtained by our musculoskeletal modeling, muscle activations calculated using the model were compared to those recorded using EMG sensors [16]. Since EMG recordings cannot be directly compared to predicted muscle activations from the simulation, the onset/offset timing in our experiment and simulation was evaluated to explore whether they are in good agreement [77]. We performed a correlation analysis (using xcorr function in MATLAB 2017a, The MathWorks Inc., USA) to compare the pattern and timing of the muscle activations between the activations obtained by the model and the EMG recordings. To assess the EMG measurements against the various bundles of muscle in the model, we added up the activation of these muscle bundles (longissimus thoracis pars thoracis and longissimus thoracis pars lumborum) within the model that corresponded to the region where the electrodes were placed in the experiment. Furthermore, the sum activity of muscle bundles was normalized to the maximum muscle activation during the lifting cycle, similar to [16].

4.3 Results

4.3.1 Muscle and Joint Reaction Forces

SPM results suggested no significant differences ($p > 0.05$) in the measurement of muscle forces when using kinematic data measured by MCS compared to IMU for most parts of the task. However, when there was a sudden jerk in the motion, such as a sudden change in external forces when the box was lifted, a significant difference could occur between muscle forces estimated by MCS and IMU (Figure 4.2). Also, the difference between the left and right longissimus thoracis muscle forces obtained by MCS and IMU was less than 25% for all participants (Table 4.1).

SPM results for L5-S1 joint reaction forces suggested significant differences ($p < 0.05$) between MCS and IMU estimations while the person was lifting or lowering the box. However, there was no significant difference between the forces when the person was standing upright while holding the box (Figure 4.3). Also, the difference between the L5-S1 joint reaction forces obtained by MCS and IMU ranged between 8% and 36% for all participants (Table 4.1).

Table 4.1. Normalized difference between estimated (by OpenSim) muscles and L5-S1 joint reaction forces obtained by motion caption system and those obtained by IMU. The results are presented as the MAE of the difference between force time-series normalized by the peak force obtained by MCS, expressed in percentage. In addition, the mean value and standard deviation (SD) of these MAE values among participants are presented.

Muscles and joint forces	Participants										
	1	2	3	4	5	6	7	8	9	10	Mean	SD
Right Longissimus Thoracis	6.7	12.1	13.6	5.4	12.6	14.8	8.4	3.8	5.3	14.7	9.7	4.0
Left Longissimus Thoracis	5.6	0.7	12.8	4.1	10.5	13.7	7.4	4.4	4.8	11	7.5	4.1
Right Iliocostalis lumborum	24.3	12.7	22.5	20.1	17.8	19.5	18.2	20.7	23.8	13.8	19.3	3.7
Left Iliocostalis lumborum	23.6	18.4	18.5	20.5	24.7	22.7	15.9	23.5	18.4	14.9	20.1	3.2
L5-S1 Joint	26	36.4	25.7	7.5	20.5	31.4	24.3	13.4	18.5	27.4	23.1	8.0

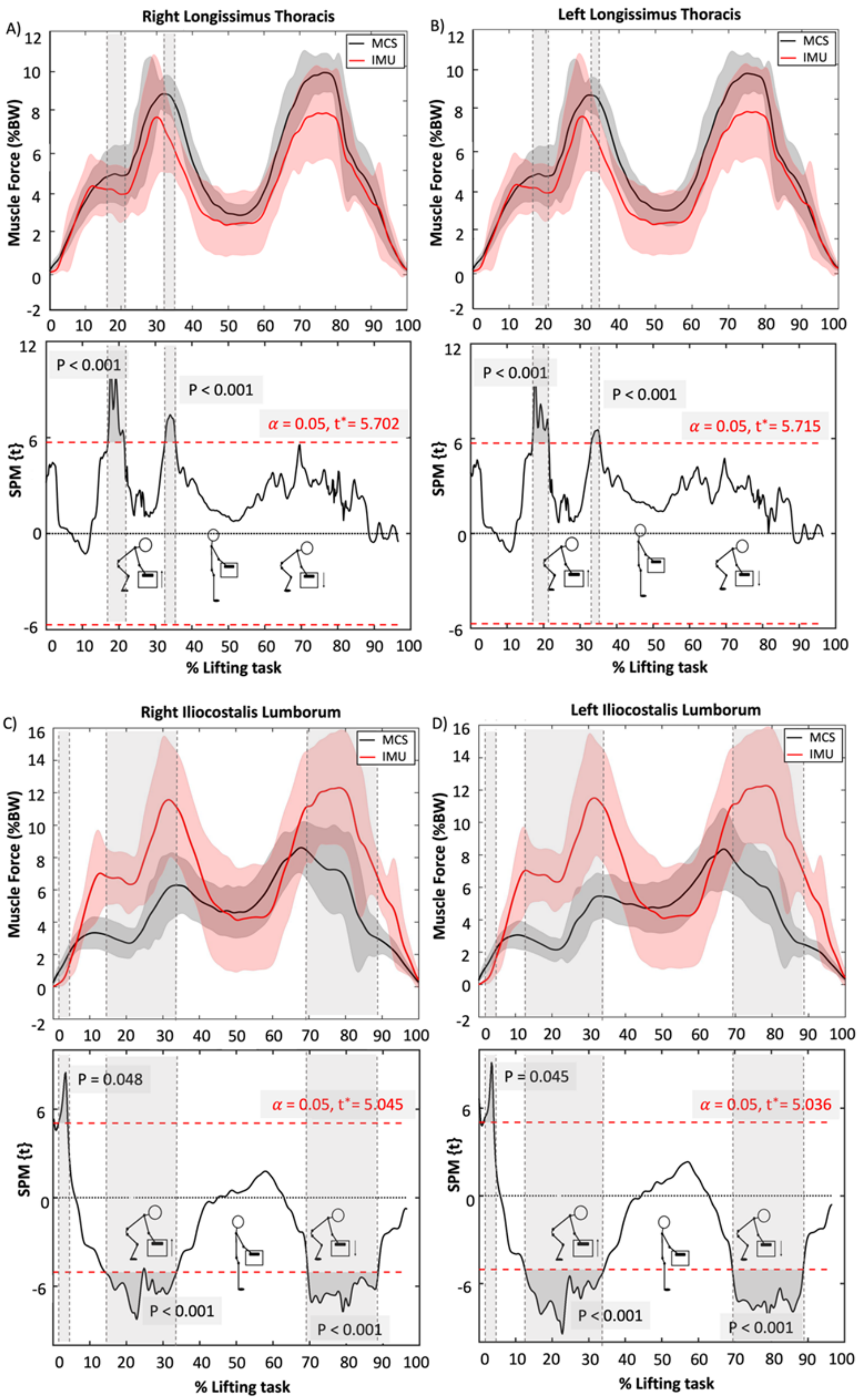


Figure 4.2. The Statistical Parametric Mapping (SPM) analysis results (t-statistics) were calculated using MCS (black) and IMU (red), depicting the mean muscle force and standard error of (A) right Longissimus Thoracis, (B) left Longissimus Thoracis, (C) right Iliocostalis Lumborum and (D) left Iliocostalis Lumborum for all the participants.

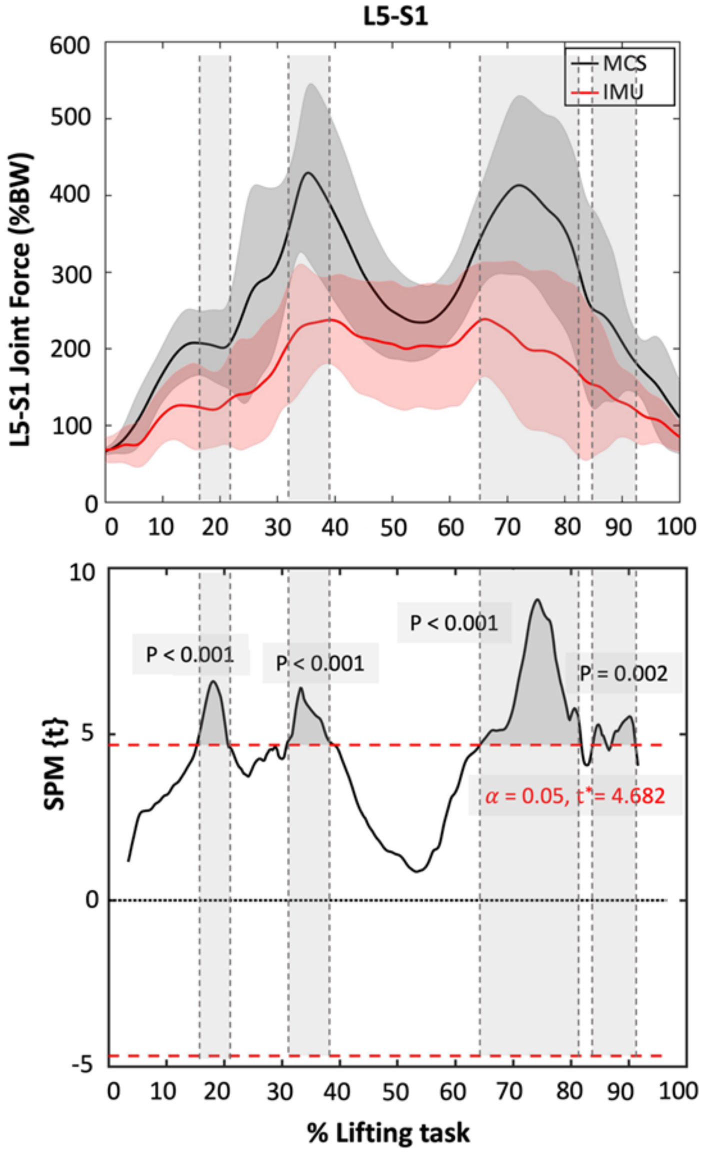


Figure 4.3. The Statistical Parametric Mapping (SPM) analysis results (t-statistics) were calculated using MCS (black) and IMU (red), depicting the mean joint reaction force and standard error of the L5-S1 joint for all the participants. The X-axis represents the percentage of the lifting task cycle (%). The grey-shaded areas show the significantly different parts of waveforms ($p < 0.05$) between MCS and IMU.

4.3.2 Model Validation

The model's estimations were consistent with the recorded EMG recordings from the left and right LD and TF during the lifting task (Figure 4.4 (A)). The mean correlation coefficients across all participants were between 0.82 and 0.86. Among the four muscles, the EMG recording from the right TF showed the highest correlation with the model's estimated muscle activation. Figure 4.4 (B) illustrates the peak correlation values of each measured muscle for all the participants. Since the measured EMG signals are an amalgamation of activities from multiple muscles beneath the sensor's surface, to enhance the accuracy of the comparison of muscle activities estimated by the musculoskeletal model and those measured by the EMG sensors, we aggregated the activities of all model muscles located beneath the EMG sensor area. As we are aware of potential inaccuracies due to EMG crosstalk in recording muscle activities, our primary objective is to validate the model's ability in terms of reflecting similar muscle activation patterns rather than determining the exact values of muscle activations. Although there are potential inaccuracies due to EMG recordings crosstalk, our primary objective was to validate the model's capability in reflecting similar muscle activation patterns rather than determining the exact values of muscle activations.

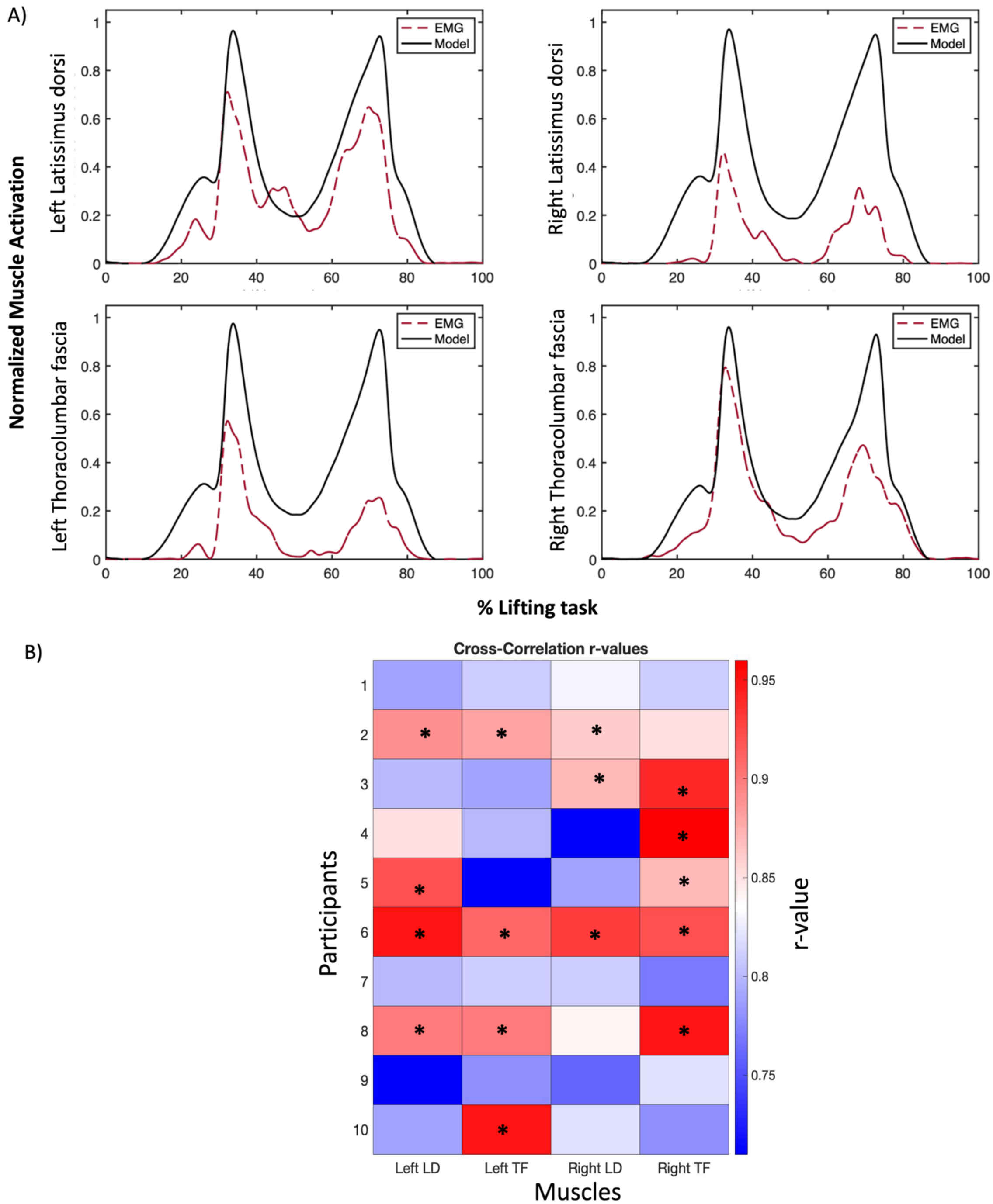


Figure 4.4. (A) Normalized EMG signals (red dashed lines) and model muscle activation estimates (solid black lines) for left and right LD and TF for one participant. (B) The peak cross-correlation values of the lower back muscle for all the participants. * denotes r-values higher than 0.86.

4.4 Discussion

In this study, we estimated human motion kinetics (muscle and joint reaction forces) using musculoskeletal modeling (OpenSim package) based on kinematics data captured by MCS vs. IMU and compared them together.

Muscle forces and L5-S1 joint reaction forces estimated using MCS and IMU recordings in this study were consistent with what has been found in the literature for different lifting tasks [66], [78], [79]. Also, the model's predictions of muscle activations aligned well with the measured EMG sensors for the lower back muscles in terms of activation patterns and timing. The highest external force exerted on the back was when the participant raised and lowered the box, which resulted in the model's output and the EMG recordings exhibiting a similar pattern with two distinct peaks. The correlation coefficients and the average time differences between the peak muscle activation and the peak EMG magnitude were comparable to the values reported in a previous study [16]. These observations indicated the validity of our musculoskeletal modeling.

Our findings underscore the critical nature of dynamic tasks such as lifting and lowering objects, which not only mimic real-world ergonomic settings but also present a higher risk of injury compared to static postures. These dynamic movements are not only more representative of typical workplace tasks but are also associated with a higher risk of musculoskeletal injuries. The increased biomechanical demands during these activities emphasize the importance of focusing our modeling efforts on dynamic tasks to better reflect the complexities and risks inherent in real-world ergonomic settings.

The outcome of this study demonstrated the extent of accuracy of lower back muscle forces estimated using IMU recordings compared to those obtained by the MCS and assessed the effect of kinematic error propagation. These findings reinforced the potential of wearable IMUs, combined with musculoskeletal modeling tools like OpenSim, for in-field assessments of muscle forces, marking a significant step in advancing occupational health and safety practices. However, researchers must proceed with caution, as some sudden changes in movement and external forces (such as grabbing or releasing an external load) may lead to inaccurate results obtained by IMUs. At the same time, spinal joint loads such as L5-S1 estimated using IMUs resulted in significant errors compared to MCS results. Therefore, more steps need to be taken to decrease sources of error, mainly reducing the sources of error in body segment orientation measurement using IMU measurements.

In conclusions, it's crucial to delineate the specific conditions under which IMUs yield reliable data, alongside scenarios where their accuracy may be compromised. Firstly, the nature of the task at hand plays a pivotal role in determining the precision of IMUs. Activities characterized by rapid or complex movements present a higher likelihood of error, attributable to sensor drift and the inherent challenges in accurately capturing swift kinematic changes. This limitation underscores the need for careful consideration of the activity's nature when employing IMUs for ergonomic assessment.

Secondly, environmental conditions significantly influence the performance of IMUs. Specifically, magnetic interference from external sources can detrimentally impact the sensors' magnetic components within IMUs, resulting in data inaccuracies. This phenomenon highlights the importance of evaluating the ambient environment where IMUs are deployed to mitigate potential interference and ensure data integrity.

Thirdly, the accuracy of IMUs heavily depends on their precise alignment and calibration on the wearer's body. Misplacement or incorrect orientation can introduce substantial errors, misleading the assessment outcomes. Therefore, meticulous attention to the correct placement and calibration of IMUs is essential for obtaining dependable data and effectively leveraging these devices in ergonomic risk assessment. By addressing these factors (task specificity, environmental influences, and device alignment) we can enhance the reliability and applicability of IMUs in real-world ergonomic evaluations.

While we used IMU sensors produced by Xsens in this study, other IMUs may have lower measurement accuracy and reliability for various body motions compared to MCS cameras. Yet, we did not use the sensor fusion algorithm and biomechanical model embedded in this system and implemented our custom-made, previously published sensor fusion algorithm on the IMUs' raw data. As such, we expect similar results when other IMUs are used for muscle and joint force estimation using musculoskeletal modeling [55, 56].

To enhance accuracy in future investigations, researchers could consider incorporating an EMG-informed model where muscle activation estimates are derived from the EMG data [78]. Additionally, the hand modeling approach used in this study was a simplified model in which the lifted object's mass was directly added to the hands of the lifter in the OpenSim model. This simplistic approach did not account for the dynamics of the object being lifted, such as how its movement with respect to the hands might affect the lifter's posture or muscle activation. This computationally efficient modeling approach thus may not be accurate for all real-world lifting scenarios and might result in large residual forces and moments compared to other hand-box modelling approaches [75].

Yet, in our study, the object's motion with respect to the hand was negligible, the lifting acceleration was not high, and our primary goal was to analyze the overall load effects rather than the dynamic interactions between the lifter and the object. Therefore, we expect minor impact of this simplified modeling approach on our study results and conclusions. Nevertheless, it may be valuable to explore alternative models for hand-mass interaction to assess the importance of external force modeling, in future studies [75].

The outcomes of this study have the potential to assist researchers with in-field ergonomic risk assessment and guide them in optimizing workers' posture and tools for more effective support during strenuous tasks while also reducing the risk of WMSDs.

4.5 Residuals

The analysis of residual forces and moments reveals insights into the dynamic inconsistencies inherent in musculoskeletal modeling. Residuals, representing the discrepancy between modeled and actual forces and moments, are pivotal for assessing model fidelity (Hicks et al., 2015). In our study, we evaluated the average root mean squared error (RMSE) values of residuals obtained by OpenSim for both IMU and MCS. This analysis contributes to a growing body of literature, aligning with previously reported values and emphasizing the importance of refining model predictions to closely mirror actual physical behavior.

Comparative analysis with existing studies on similar tasks underscores the relevance of our approach. In our study, focused analysis on the lifting task dynamics specifically highlights the residual forces in the vertical direction (FY) and the moments about the vertical axis (MZ), reflecting pivotal components of the load handling mechanics. This focus is driven by literature that identifies FY and MZ as critical for understanding the effectiveness and safety of lifting strategies. The average RMSE values are reported in Table 4.2. When comparing these outcomes with similar studies, specifically the RMSE values of 84 N for FY and 32 N.m. for MZ reported in related research [75], our results underscore a comparable level of precision in capturing the vertical forces and moments about the vertical axis crucial for evaluating the biomechanical aspects of lifting tasks. The agreement between our results and those documented in related research suggests that the methodologies employed are robust and effective in capturing the complexities of lifting box tasks.

Table 4.2. Average RMSE of residual forces (FY (N)) and moments (MZ (N.m)) across participants during a lifting task cycle, as measured by OpenSim for IMU and MCS.

	FY (N)	MZ (N.m)
MCS	34.6	10.1
IMU	36.6	51.7

Chapter 5

5. Discussions and conclusion

5.1 Discussion

The research presented in this thesis offers a comprehensive examination of WMSDs, emphasizing the need for a holistic approach to ergonomic risk assessment in both laboratory and real-world settings. Central to this discussion is the exploration of different technologies used for human motion assessment, such as MCS and IMUs, and their application in understanding and mitigating WMSDs. The key findings of this study are:

1. Laboratory vs. Field Assessments: A significant insight from the study is the variation in muscle activity patterns between in-lab and in-field conditions, despite similar postural ergonomic risks (REBA scores). This finding highlights the complexity of replicating real-world conditions in a laboratory setting. It underlines the importance of conducting ergonomic assessments in actual work environments to obtain more relevant and accurate data.
2. Technological Advancements in Motion Analysis: The evolution of technologies like IMUs has made it feasible to assess human motion in real-world settings. However, the study revealed limitations, such as inaccuracies in capturing absolute positions and dealing with sensor drifts. These technological challenges need to be addressed for more reliable in-field assessments.
3. Role of Exoskeletons and Assistive Tools: The research underscores the potential of occupational exoskeletons and assistive tools in reducing the risk of WMSDs. However, it also indicates the necessity for these tools to be evaluated in the field, considering the different outcomes observed among users with varying demographics and physical conditioning.
4. Musculoskeletal Modeling: The use of musculoskeletal models, particularly in estimating lower back muscle forces, has been validated as a useful tool. The study also pointed out the discrepancies in muscle and joint reaction forces between the data captured by MCS

and IMU, suggesting the need for further refinement in these models, especially for in-field applications.

5.2 Limitations and Future Steps

The study's participant demographics, primarily university students for in-lab assessments, might not accurately represent the physical conditioning and work experience of actual utility workers. This demographic variation can lead to differences in task execution and ergonomic risk. Technological limitations, particularly concerning the accuracy and reliability of IMUs in field assessments, also pose a challenge.

Future research should focus on enhancing the fidelity of in-field assessments, possibly through the development and integration of more advanced wearable sensor technologies. To enhance the depth and utility of future research in ergonomic risk assessment, especially considering the findings and limitations identified in this study, the following expanded recommendations are proposed:

1. Enhancement of Wearable Sensor Technologies: Future investigations should prioritize the advancement and incorporation of cutting-edge wearable sensor technologies to heighten the fidelity of in-field assessments. The development of sensors with higher accuracy, reduced drift, and enhanced durability will be critical in capturing more reliable data in dynamic work environments. This initiative should aim to overcome the limitations associated with current IMU technologies, such as issues with sensor drift and the challenge of accurately capturing rapid movements in complex work tasks.
2. Broadening Participant Demographics: There is an imperative need to expand the scope of participant demographics in ergonomic research to encompass a broader spectrum of the workforce. This expansion would involve recruiting participants from various age groups, genders, and occupational backgrounds to ensure the research findings are reflective of and applicable to the diverse real-world workforce. Addressing this recommendation will help overcome the current study's limitation of potentially narrow demographic representation, thereby enhancing the generalizability of research outcomes to a wider array of work settings.

3. Refining Musculoskeletal Models: Future research should also focus on the refinement of musculoskeletal models to enhance their integration with wearable sensor data, aiming for increased accuracy in ergonomic risk assessments conducted under field conditions. This could involve the incorporation of more sophisticated algorithms for data processing and the modeling of complex muscle interactions and joint dynamics. Such advancements would directly address the identified gap in the current study regarding the precision of musculoskeletal assessments, facilitating more accurate predictions of ergonomic risk.
4. Long-term Effectiveness and User Acceptance: Investigating the long-term effectiveness and user acceptance of occupational exoskeletons and assistive tools across diverse work environments should be a central focus of future studies. This research should not only assess the biomechanical benefits of these interventions over extended periods but also explore workers' perceptions, compliance rates, and the practicality of implementing such tools in everyday work routines. Highlighting this aspect responds to the need for a deeper understanding of the long-term impact and viability of ergonomic interventions, as identified in the limitations of the current study.
5. Advanced Machine Learning Algorithms for Data Interpretation: Exploring the application of advanced machine learning algorithms to improve the interpretation of data collected via IMUs, especially in dynamic and unpredictable work environments, should be a pivotal area of future research. Machine learning techniques have the potential to uncover complex patterns within the sensor data that may not be evident through traditional analysis methods. This approach can significantly enhance the accuracy and depth of ergonomic risk assessments, addressing the complexities and variabilities of real-world work activities.

By addressing these focused areas, future research can build upon the limitations and findings of the current study, driving forward the development of more accurate, generalizable, and practical solutions for mitigating ergonomic risks in the workplace.

5.3 Conclusion

This thesis has successfully bridged the gap between theoretical research and practical application in the realm of ergonomic risk assessment for WMSDs. The comprehensive analysis of both laboratory and field assessments, along with the evaluation of modern technologies like IMUs and

MCS, provides valuable insights into the complexities of WMSDs in the workplace. The research underscores the importance of conducting real-world assessments for more accurate and relevant data, considering the inherent limitations of laboratory simulations.

Integrating the research findings into practical applications within real-world settings amplifies their value and impact, particularly in enhancing workplace ergonomics. A vital aspect of this application is the involvement of end-users in the selection process of ergonomic tools and interventions. By incorporating feedback and preferences from the workers who will directly engage with these tools, the selection process becomes inherently more user-centric, ensuring that the chosen interventions are not only effective biomechanically but also meet the usability criteria essential for daily operation.

Accompanying the implementation of ergonomic interventions with comprehensive, context-specific training programs further ensures that workers are well-prepared to utilize these tools effectively. Training should extend beyond mere usage instructions to include education on maintaining proper posture and adopting techniques that mitigate the risk of musculoskeletal disorders. Additionally, the design and deployment of ergonomic solutions must account for the complex and variable nature of workplace tasks. Solutions that are flexible and adaptable to a range of work environments, tasks, and user needs stand a better chance of being effectively integrated into daily work routines.

Central to our findings is the application of musculoskeletal modeling, a powerful tool that has significantly advanced our ability to assess and mitigate ergonomic risks. By accurately simulating muscle and joint forces, this modeling approach has unveiled precise biomechanical insights that are used for designing targeted interventions. These interventions, aimed at reducing the ergonomic risks associated with specific work tasks, are grounded in a detailed understanding of the biomechanical loads that workers face. Furthermore, musculoskeletal modeling's predictive capability is instrumental in tailoring the development and adjustment of occupational exoskeletons and assistive devices, ensuring they meet the specific needs of the workforce.

This thesis underscores the indispensable role of musculoskeletal modeling in ergonomic risk assessment and intervention design. It lays a robust foundation for future research aimed at enhancing in-field assessments and developing more effective WMSD prevention strategies across diverse occupational settings. By focusing on the capabilities of musculoskeletal modeling, we take a significant stride towards a future where workplace ergonomics are not just understood but are dynamically improved, paving the way for safer, healthier work environments for all.

In conclusion, this research contributes significantly to the understanding of WMSDs and ergonomic risk assessment. It lays a foundation for future studies to build upon, particularly in enhancing in-field assessments and developing more effective interventions for preventing WMSDs in various occupational settings.

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