Back to the Future of Ergonomics: Utilizing Inertial Motion Capture and Fatigue Failure Theory to Develop a Cumulative Damage Assessment Method for Estimating Risk of Low Back Injury in Industrial Settings

by

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Abstract

The central objectives of this dissertation are to critically evaluate the efficacy of a wireless sensor Inertial Motion Capture (IMC) system in estimating lumbar kinematics and kinetics within a controlled laboratory setting and to apply the IMC system in a manufacturing facility for data acquisition. Furthermore, it focuses on formulating and assessing a model based on fatigue failure theory for estimating cumulative damage to the lower back using continuous exposure data in a live manufacturing environment.

In the first study, "Assessing the Accuracy of a Wireless Sensor System for Estimating Lumbar Moments During Manual Lifting Tasks Considering the Effects of Load Weight, Asymmetry, and Height," the IMC system's accuracy is evaluated for estimating 3D moments at the L5/S1 joint during manual lifting tasks with load weight, asymmetry, and height variations. The analysis compares IMC-derived estimates to those obtained through bottom-up and top-down laboratory models using an Optical Motion Capture (OMC) and Force Plate (FP) system. This investigation establishes the benefits and limitations of the IMC system in terms of lumbar moment assessments.

The second study, "Estimating Compressive and Shear Forces at L5-S1: Exploring the Effects of Load Weight, Asymmetry, and Height using Optical and Inertial Motion Capture Systems", extends the examination to compression and anteroposterior shear forces at the L5/S1 joint. The IMC estimates are compared against a top-down laboratory musculoskeletal model using an OMC system, and additional kinematic variables such as trunk rotation, flexion, and lateral bending are assessed to understand discrepancies in force estimations. Moreover, an analysis of the distance between the handled box and the L5/S1 joint center is included to estimate segment length differences comprehensively.

In the third study, "Development of a Fatigue-Failure Based Continuous Risk Assessment Method for the Low Back Region Using Inertial Motion Capture Technology", the focus shifts to a real-world manufacturing environment, where a novel framework for processing IMC-collected data to estimate cumulative lumbar loading is developed and evaluated. Utilizing fatigue failure theory, cumulative damage is computed based on continuous low-back loading time-series data, offering an innovative approach to analyzing kinematic data and assessing cumulative loading exposure in complex real-world scenarios.

Overall, this body of work showcases the promising capabilities of IMC technology in lumbar kinematics and kinetics assessments while also introducing a pioneering approach for cumulative damage estimation. It also emphasizes the necessity for ongoing advancements in sensor technology and data processing methodologies to enhance accuracy and applicability in laboratory and field environments.

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And lastly, I dedicate this milestone to my father, Oscar Nail. His memory walks with me.

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List of Abreviations

ANOVA	Analysis of Variance
ASTM	American Society for Testing and Materials
BLS	Bureau of Labor Statistics
CD	Cumulative Damage
FP	Force plates
IMC	Inertial Motion Capture
IMU	Inertial Measurement Unit
MSD	Musculoskeletal Disorder
NIOSH	National Institute for Occupational Safety and Health
OMC	Optical Motion Capture
OSHA	Occupational Safety and Health Administration
RBPF	Randomized Block Partially Confounded

Chapter 1

1. Introduction

Musculoskeletal disorders (MSDs) are among the most common injuries across various demographics, afflicting individuals of diverse age groups with a broad spectrum of injuries. The Centers for Disease Control (CDC) defines MSDs as “diseases or disorders of the musculoskeletal system and connective tissue due to an event or exposure resulting in a bodily reaction” (Centers for Disease Control and Prevention, 2020). Low back pain, rotator cuff syndrome, and carpal tunnel syndrome are common examples of MSDs. Data collected by the Bureau of Labor Statistics (BLS) between 2011 and 2018 revealed that MSDs accounted for approximately 30% of occupational injuries or illnesses cases that involved days away from work (Bureau of Labor Statistics, 2020). This high prevalence underscores the gravity of work-related MSDs and the challenges they impose on the health and well-being of occupational workers.

The Occupational Safety and Health Administration (OSHA) estimates that employers in the United States allocate $15-20 billion to address the direct costs of MSDs in worker compensation (Occupational Safety and Health Administration, 2020) each year. Moreover, OSHA reports that the effects extend beyond direct expenditures, with indirect costs potentially soaring to $45-54 billion annually. In addition to the monetary ramifications, the human toll is also significant; MSDs frequently produce alterations in the lives of impacted workers, who might struggle to re-engage in their occupations or even to execute daily tasks (Miranda et al., 2010).

An analysis of the BLS data for non-fatal injury cases in 2020 that recorded absence from work shows that injuries to the trunk and upper extremities constitute 78% of all industry-related MSD cases (Bureau of Labor Statistics, 2020). The dominance of trunk and upper extremity injuries accentuates the importance of targeted ergonomic interventions and dedicated efforts in MSD prevention, especially for these critical body regions.

More than 132,000 occupational safety professionals in the United States concentrate on injury prevention in their workplaces (Bureau of Labor Statistics, 2023). One of their primary responsibilities is to understand the potential risk of injury for their employees when completing their daily jobs. Consequently, risk assessment becomes critical to understanding injury incidence, and various risk assessment tools are often used to quantify the exposure to physical risk factors (heavy lifting, awkward posture, highly repetitive tasks, and vibration, among others). Risk metrics obtained using these tools are then used to rank the risk of injury of the jobs or tasks from high to low. Several key characteristics govern the utility of ergonomic risk assessment tools in an industrial setting:

- Accuracy: To what extent does the tool precisely capture and quantify exposure information?
- Ease of use: Is the tool designed with an intuitive workflow that is simple to comprehend and execute?
- Validity: Does empirical evidence corroborate an association between the tool's risk scores and the prevalence or incidence of MSDs?
- Standardization: Is the tool capable of showing consistent results across industries?

In general, improving factors such as the accuracy and validity of assessment tools could mean using more complex methods. This can make the tool more difficult to understand and might require more resources for its application, such as training time, data collection, and analysis. A balance between these factors is required for successful risk assessment.

Low back pain (LBP) is the most common MSD individuals suffer (Vos et al., 2017). The prevalence of LBP has been estimated to be more than 25% of the United States Population (Deyo et al., 2006), while work-related MSDs for the back had an incidence rate of 9.6 per 10,000 full-time workers with 98,540 cases in 2019 (Bureau of Labor Statistics, 2020). Among the risk factors for LBP, mechanical loading of the spine and repetitive loading of surrounding musculoskeletal tissues have been identified as critical contributors (Callaghan et al., 2001; Coenen et al., 2013; da Costa & Vieira, 2009; Jäger et al., 2000; Kingma et al., 1996; Kumar, 1990; Norman et al., 1998). Understanding low back loading and the effect of its frequency during physical work is a central area of study in ergonomics. As a result, it is essential to measure cumulative exposure to physical risk factors (e.g., forceful exertions, repetition) to understand the relationship between these factors and the risk of adverse health outcomes. The term cumulative loading implies the integration of physical exposure over time (Waters et al., 2006).

Typically, practitioners gather exposure data regarding worker kinematics and kinetics through direct observation or review of video recordings (Lötters & Burdof, 2002; Spielholz et al., 2001). They then employ risk assessment tools to determine the risk level based on the exposure data. Conventional risk assessment methodologies, including the Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and the NIOSH Lifting Equation, are inherently constrained in handling discrete exposure information compared to continuous data. These tools were conceived with the primary intent of evaluating the most adverse-case scenarios within a job. They require analyzing each combination of postures and external forces in isolation. Notably, these tools do not incorporate computation methodologies to estimate cumulative exposure, a significant limitation in providing a holistic risk assessment.

Gallagher and Schall in 2017, followed by Gallagher and Barbe in 2022, compiled evidence that postulates material fatigue as a central factor in the development of MSDs. The fatigue failure phenomenon is substantiated by ex vivo studies, which involve examining tissues outside the living organism conducted on spinal segments, cartilage, tendons, and ligaments (Brinckmann et al., 1987; Gallagher et al., 2005, 2007; Gallagher & Marras, 2012; Schechtman & Bader, 1997; Thornton & Bailey, 2013). These studies observed fatigue failure behavior under repetitive loading, akin to regular materials subjected to repeated stress. Furthermore, in vivo studies, which entail examination within a living organism, conducted on animal models have corroborated these findings, showing fatigue failure in living musculoskeletal tissues (Andarawis-Puri & Flatow, 2011; Barbe et al., 2013, 2020; Fung et al., 2009, 2010; Sun et al., 2010). Epidemiological data also support this theory, highlighting the interplay between force and repetition as an indication of a fatigue failure process (Gallagher & Heberger, 2013). The fatigue failure theory is particularly valuable because it can handle and decipher complex loading patterns into fundamental components, such as stress cycles, which facilitates the estimation of cumulative loading. This makes the theory a well-adapted framework for integration with innovative continuous loading technologies and methodologies that have been validated in materials engineering.

Research conducted in laboratory settings has investigated the effects of spinal loading by estimating L5/S1 moments and forces (Desjardins et al., 1998; Faber et al., 2011, 2016, 2020; Fluit et al., 2014; Koopman et al., 2018; Lavender et al., 2003; Marras et al., 2010; Marras & Davis, 1998; Nail-Ulloa et al., 2021; Plamondon et al., 1996; Skals et al., 2017). However, assessing spinal loading *in vivo* is challenging and rarely performed due to the method's invasiveness (Wilke et al., 2001). Furthermore, the assessment is typically confined to controlled laboratory environments, limiting the ability to evaluate spinal loading in real-world field settings such as live production environments (Faber et al., 2011). Advancements in technology have made it easier and more cost-effective to collect continuous loading exposure data. Optical motion capture (OMC) technology provides an efficient means of obtaining kinematic data, such as segment orientation and position, linear and rotational acceleration and velocity, and joint angles by placing reflective markers on anatomical landmarks per the recommendations of the International Society of Biomechanics (Wu et al., 2002, 2005). In addition, kinetic analysis is made possible by using force plates, which measure ground reaction forces (GRF) and moments. However, implementing such technologies in workplace environments is often challenging or impractical, necessitating the exploration of alternative technologies that can better adapt to the dynamic nature of work environments (Lee & Lee, 2022). An alternative to this challenge is Inertial Motion Capture (IMC) systems, which employ small inertial measurement units (IMUs) and have shown potential in capturing continuous loading data, including L5/S1 moments (Faber et al., 2016, 2020; Koopman et al., 2018; Nail-Ulloa et al., 2021).

This dissertation has two main goals. The first is to evaluate the efficacy of a wireless sensor system in estimating kinematics and kinetics within a laboratory setting and to subsequently employ the system for data acquisition in a manufacturing facility. Secondly, this dissertation will formulate and assess a model based on fatigue failure theory for estimating cumulative damage to the lower back, utilizing continuous exposure history in the field. To complete these objectives, three specific aims, each constituting a distinct study, have been delineated:

Laboratory study 1: The first study is aimed at evaluating the accuracy of an Inertial Motion Capture (IMC) system in assessing 3D moments at the L5/S1 joint during lifting tasks that vary by three parameters: the weight of the load, degree of asymmetry, and height associated with the lifting and lowering tasks. The IMC system's estimates were compared against those derived from bottom-up and top-down laboratory models, which employed a gold-standard Optical Motion Capture (OMC) and Force Plate (FP) methodology.

Laboratory study 2: The second study extends the investigation to evaluate if the IMC system can accurately assess compression and anteroposterior shear forces at the L5/S1 joint, using musculoskeletal simulation, during lifting and lowering tasks with variations in mass, asymmetry, and height. Comparisons were made against a top-down laboratory model using a state-of-the-art OMC system. Additional aspects such as trunk rotation, flexion, and lateral bending were compared to gain insights into the discrepancies in force estimates. Furthermore, the study included a comparative analysis of the distance between the handled box and the L5/S1 joint center to estimate segment length differences comprehensively.

Field study: The third study, conducted in a live manufacturing environment, aimed to establish and evaluate a comprehensive framework for processing data to estimate cumulative lumbar loading. The study employed fatigue failure theory to calculate the cumulative damage from continuous low-back loading through time-series data gathered via IMC. This novel framework aims to enable the analysis of kinematic data and assessment of cumulative loading exposure associated with the involved loads, postures, and occupational tasks observed in the field.

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Chapter 2

2. Literature Review

2.1 Work-related musculoskeletal disorders

Work-related musculoskeletal disorders (WMSDs) can be attributed to a number of different risk factors broadly classified into three primary categories: individual, psychosocial, and physical. Individual risk factors include workers' health, fitness levels, sex, age, anthropometry, and work habits. Subtle differences in these personal attributes can result in varied exposure levels among workers executing the same tasks. On the psychosocial dimension, risk factors encompass inadequate social support within the workplace and personal life, stressors associated with leisure activities, and pre-existing health conditions (Hauke et al., 2011). In physical risk factors, elements such as force exertion, posture, task repetitiveness, and vibration are particularly significant and have been documented in the literature (Bernard et al., 1997; Jaffar & Rahman, 2017). In occupational settings, tasks involving lifting heavy objects, operating in awkward postures, engaging in highly repetitive tasks, and tools that expose workers to localized or full body vibrations contribute to the development of WMSDs. Notably, the development of WMSDs is often multifactorial, with a complex interplay among various risk factors (Bongers et al., 2006).

2.2 Assessment of physical risk factors

Considering the prevalent risk factors, ergonomic risk assessment methodologies have been developed to enable practitioners to quantify exposure to physical risk factors and subsequently estimate the potential risk of injury. These methodologies encompass self-reporting, observational analysis, and direct measurements. Essentially, the assessment process is divided into two major components: Quantifying the exposure to physical risk factors and estimating the risk of injury based on the quantified exposure.

Employing ergonomic risk assessment tools, practitioners can systematically evaluate the risk levels inherent with various tasks and occupations. This facilitates the reasonable allocation of resources for developing interventions prioritizing jobs with higher risk levels, and it also serves as a measure to evaluate the efficacy of intervention measures implemented. Nevertheless, it is imperative to acknowledge the limitations of current ergonomic risk assessment methodologies available to practitioners and researchers. These limitations and their ramifications will be scrutinized in the subsequent sections.

2.3 Methods for quantitative exposure to physical risk factors

When assessing risks associated with the execution of occupational tasks, engaging in a comprehensive evaluation of external loads applied on the body and the consequential effects of this load on musculoskeletal tissues is an essential requirement. Exposure to physical risk factors, referred to as external exposure, translates into biomechanical loading within the body, called internal loading (Winkel & Mathiassen, 1994). The forces exerted upon musculoskeletal tissues, as a consequence of internal loading, can inflict either reversible or irreversible damage to soft tissues, which may catalyze the development of MSDs.

Assessment techniques to estimate exposure to physical risk factors are broadly segmented into three categories as delineated by Burdorf & Van Der Beek (1999): Systematic observations, subjective self-reports, and direct measurements. The following sections will provide an overview of these three methods.

2.3.1 Systematic Observation

Systematic observation is a method that can be employed either in situ through direct observation at the workplace, or by utilizing video-based technology. Using this method, practitioners or researchers meticulously observe tasks executed by workers, either directly or via pre-recorded videos. A structured assessment of exposure to physical risk factors, encompassing data on posture, movement frequency, and force, is recorded employing checklists or specialized ergonomic risk assessment tools. Notably, video-based approaches offer several advantages over direct field observations, such as the ability to code and review data meticulously, culminating in a more thorough and reproducible analysis (Spielholz et al., 2001). While observational methods may not be as precise and reliable as direct measurements (De Looze et al., 1994; Juul-Kristensen et al., 2001), they are widely adopted by practitioners due to their relative ease of use, flexibility and cost effectiveness in field data collection (Chiasson et al., 2012; Takala et al., 2010).

Furthermore, an array of observational methods has been developed for the use of both practitioners and researchers (Burdorf, 2010; Colombini, 1998; David et al., 2008; Graves et al., 2004; Karhu et al., 1977; Kee & Karwowski, 2001; Kemmlert, 1995; Keyserling et al., 1992; G. Li & Buckle, 2000; McAtamney & Nigel Corlett, 1993; Monnington et al., 2003; Moore & Garg, 1995; Occhipinti, 1998; Waters et al., 1993). A list of examples of observational methods is depicted in Table 2.1, as summarized by David (2005).

Table 2.1. Examples of observational methods.

Method	**Main Feature**	**Reference**
OWAS	Time sampling for body postures and force	(Karhu et al., 1977)
Checklist	Assessment of legs, trunk and neck for repetitive task	(Keyserling et al., 1992)
RULA	Categorization of body postures and force, with action levels or assessment	(McAtamney & Nigel Corlett, 1993)
NIOSH lifting equation	Measurement of posture related to biomechanical load for manual handling	(Waters et al., 1993)
PLIBEL	Checklist with questions for different body regions	(Kemmlert, 1995)
The Strain Index	Combined index of six exposure factors for work tasks	(Moore & Garg, 1995)
OCRA	Measures for body posture and force for repetitive tasks	(Occhipinti, 1998)
QEC	Exposure levels for main body regions with worker responses, and scores to guide intervention	(David et al., 2008)
Manual Handling Guidance	Checklists for task, equipment, environment and individual risk factors	(Health and Safety Executive, 2016)
REBA	Categorization of body postures and force, with action levels for assessment	(Hignett & McAtamney, 2000)
FIOH Risk Factor Checklist	Questions on physical load and posture for repetitive tasks	(Ketola et al., 2001)
ACGIH TLVs	Threshold limit values for hand activity and lifting work	(ACGIH, 2001)
LUBA	Classification based on joint angular deviation from neutral and perceived discomfort	(Kee & Karwowski, 2001)
Upper Limb Disorder (ULD) Guidance, HSG60	Checklist for ULD hazards in the workplace	(Graves et al., 2004)
MAC	Flow charts to assess main risk factors to guide prioritization and intervention	(Monnington et al., 2003)

Outcomes from observational methods have been compared in the field (Chiasson et al., 2012; Takala et al., 2010), and while the applied methods displayed heterogeneity in performance and application scope, they commonly share strengths such as ease of learning and use. However, limitations include being time-consuming, often limited to static postures, difficulties in simultaneous observations of multiple body segments, a requirement for well-trained observers (Chiasson et al., 2012; Takala et al., 2010), and there is no general support for cumulative assessment (Huangfu, 2018). Recent advancements in computer vision have allowed the integration of this technology for estimating upper limb kinematics and hand activity

(Akkas et al., 2016, 2017; C. H. Chen et al., 2013; Chen et al., 2015), and its application in the construction industry for MSD risk assessment (C. Li & Lee, 2011). Researchers have also explored beyond the conventional two-dimensional (2D) videos, the Microsoft Kinect™, equipped with an RGB (red, green, and blue) camera and three-dimensional (3D) depth sensors, has been evaluated and suggested as a potentially valuable "portable" option for 3D motion capture for ergonomic assessment in the field (Dutta, 2012; Krüger & Nguyen, 2015). This technology has been used as an observational method for assessing work postures and as a real-time ergonomic assessment system (Diego-Mas & Alcaide-Marzal, 2014; Haggag et al., 2013; Nahavandi & Hossny, 2017). Using image processing algorithms to track pre-defined regions of interest, such as the elbow and shoulders, and to calculate segment motion information and joint kinematics by automating the estimation of movement speed, duty cycle, and exertion time, which could lead to a less time-consuming assessment, while also providing an objective and relatively reliable evaluation (Akkas et al., 2017). However, it is important to mention that the quality of results derived through computer vision is directly affected by environmental visibility and stable recording, which may be challenging in confined and highly dynamic industrial facilities.

2.3.2 Subjective self-report

Subjective self-report is a method where participants are asked regarding their perceptions and attitudes. Participants are provided with surveys or questionnaires, which they examine and respond to independently, without interference from the researcher or practitioner. Self-report questionnaires have been employed and critically assessed in several studies (Öberg et al., 1994; Spielholz et al., 1999; Torgén et al., 1997; Wiktorin et al., 1993, 1996) as a tool to estimate exposure to physical risk factors encompassing force, posture, and repetition. For instance, in one of the studies, workers were requested to estimate the duration they spent bending their wrists (Spielholz et al., 1999), and gauge and gauge the perceived level of force on a spectrum ranging from "very, very weak" to "very, very strong,", as illustrated in Table 2.2.

Table 2.2. Borg rating of perceived exertion scale (Borg, 1982).

Rating	Description

0	Nothing at all
0.5	Very, very weak
1	Very weak
2	Weak
3	Moderate
4	Somewhat strong
5	Strong
6	
7	Very strong
8	
9	
10	Very, very strong

The advantages of self-report questionnaires are their simplicity, time efficiency, cost-effectiveness, and aptitude to facilitate large sample sizes (McDowell, 2006). Nevertheless, the information obtained through self-reports is often susceptible to biases (Burdorf, 2010), as participants may inadvertently or intentionally provide inaccurate responses, and their perceptions may not always align with objective measures, as consistent over estimation of exposure have been reported for different risk factors (Spielholz et al., 2001).

2.3.3 Direct Measurement

Direct measurements employ hardware sensors that are physically connected to the subject in order to record exposure like force and posture (David, 2005). There is a variety of systems that have been developed and utilized in the realm of occupational ergonomics (Du & Duffy, 2007; Faber et al., 2016; Granata et al., 1996; Granata & Marras, 1995; Hansson et al., 2001; Lamooki et al., 2022; Lu et al., 2020; Marras et al., 1993; Matijevich et al., 2021; Radwin & Li Lin, 1993; Schall et al., 2016). Table 2.3 shows examples of direct measurement methods.

Table 2.3. Direct measurement methods examples

Method	Function	Reference
Lumbar motion monitor (LMM)	Assessment of spine posture and motion	(Marras et al., 1993)
Optical motion capture (OMC)	Measurement of 3D position	(Nagymáté & M. Kiss, 2018)
Inertial motion capture (IMC)	Measurement of segment orientation	(Faber et al., 2020)
Electronic goniometry	Measurement of angular displacement	(Radwin & Li Lin, 1993)
Electromyography (EMG)	Estimation of muscle activity levels	(Granata & Marras, 1995)
Force plates	Measurement of ground reaction forces	(Nail-Ulloa et al., 2021)
Inclinometers	Measurement of segment inclination	(Hansson et al., 2001)

2.3.3.1 Optical Motion Capture

Among motion capture technologies, Optical Motion Capture (OMC) is predominantly regarded as the benchmark or "gold-standard" in recording the position of body segment in a 3D space, with recent reports in the literature of errors below 200 µm for 97% of a 135 m^3 of capture volume (Aurand et al., 2017). OMC systems rely on employing image data captured by cameras fixed in a place, the data is then processed to determine the three-dimensional position of an object via triangulation using at least two cameras. To collect data, passive or active reflective markers are attached to the subject. The system records position data with three degrees of freedom per marker. Additionally rotational data for a body segment, like a joint angle, can be calculated using information from at least three markers whose relative positions are known. This facilitates tracking human movements by placing multiple markers on different body segments. There are different protocols for marker placement, one of the most used in contemporary biomechanics is the "Plug-in-gait" marker set, using 39 markers to track full body kinematics (Vicon®, 2002). The number of cameras, their placement, and resolution will define the capture volume for motion tracking. Generally, between six to ten cameras are utilized to study human motion will define a 5.5m*1.2m*2m capture volume (Eichelberger et al., 2016). OMC systems are predominantly used in laboratory environments where camera positions can be precisely managed. Calibration, employing markers with fixed and known relative positions, is essential to map the position of each camera within the global coordinate system. Researchers suggest as a good practice to always document the number of cameras and sample rate used to capture the data, as well as the reflective markers size (Nagymáté & M. Kiss, 2018). After calibration, it is critical not to move the cameras to preserve the accuracy and reliability of data recording. This requirement largely impacts the use of OMC in live industrial environments.

OMC systems are usually used in conjunction with force plate (FP) platforms, a force plate unit consists of one or more sensors attached in a plate to give an electrical output proportional to the force on the plate (Wardoyo et al., 2016). FPs measures the ground reaction force on each foot while standing, walking, running, and jumping. The application of OMC and FP methodology is commonly used in laboratory-based ergonomic studies due to its accuracy on kinematics and kinetic estimates when using biomechanical and musculoskeletal modelling (Faber et al., 2020; Koopman et al., 2018; Larsen et al., 2020; Nail-Ulloa et al., 2021; Skals, Bláfoss, de Zee, et al., 2021).

2.3.3.2 Inertial Motion Capture

Inertial Motion Capture (IMC) has become popular in the last decade for calculating human kinematics and kinetics (Faber et al., 2016, 2020; Karatsidis et al., 2016, 2019; Kobsar et al., 2020; Konrath et al., 2019; Koopman et al., 2018; Larsen et al., 2020; Lee & Lee, 2022; Matijevich et al., 2021; Nail-Ulloa et al., 2021; Paulich et al., 2018; Porta et al., 2020; Robert-Lachaine et al., 2017; Schall et al., 2022; Schepers et al., 2018; Skals, Bláfoss, Andersen, de Zee, et al., 2021). IMC employs inertial measurement units (IMUs), characterized by its lightweight, portability and low energy consumption. The sensors collect data that can be transmitted wirelessly to a host computer or saved directly to a memory card. This makes it an attractive option for applications that require human kinematics estimation outside the laboratory.

By integrating data from motion capture and external force measurements, such as force plates and in-shoe force sensors, IMC can estimate internal forces on joints and muscles using either rigid body models or advanced simulations (Faber et al., 2020; Karatsidis et al., 2019; Koopman et al., 2018; Larsen et al., 2020; Matijevich et al., 2021; Nail-Ulloa et al., 2021). Traditionally, using OMC alongside force plates units in laboratory settings has been considered the gold standard for analyzing human kinetics. However, IMC and in-shoe force sensors are gaining popularity with technological advancements because of their ability to estimate dynamic exposures in real-world settings (Faber et al., 2020; Matijevich et al., 2021). Faber et al., (2020) observed that the pair IMC system (Xsens™) and instrumented shoes presented root mean square errors (RMSE) < 20 Nm or 10% of the peak extension moment when compared against the gold standard. On the other hand, Matijevich et al. (2021) observed that a trunk IMU and pressure insoles could monitor time series lumbar moments across a broad range of material handling tasks with accurate results (up to r^2 = 0.89). These findings suggest that the degree of accuracy might be suitable for measurements across entire shifts in a workplace setting. Field-based exposure estimation paves the way for more intricate cumulative exposure estimation methods, potentially enhancing our understanding of the relationship between cumulative exposure and work-related MSDs.

2.4 Cumulative exposure to physical risk factors

Repetitive loading of musculoskeletal tissues contributes to workplace-related MSDs (Callaghan et al., 2001; Jäger et al., 2000; Norman et al., 1998). As a result, it is important to measure cumulative exposure to physical risk factors (e.g., forceful exertions, repetition) to understand the relationship between these factors and the risk of adverse health outcomes. The term cumulative loading implies the integration of physical exposure over time (Waters et al., 2006). Thus, cumulative loading indicates that load intensity, duration, and task repetition are critical factors in assessing risk (Koyuncu et al., 2021). Moreover, such an approach should provide a method to evaluate multi-task exposures, a prerequisite for understanding the relationship between work-related exposure and physical reactions such as MSDs (Veerasammy et al., 2022). There are several calculation methods for cumulative loading (Johnen et al., 2021) based on biomechanical modeling or musculoskeletal modeling approaches, as detailed in the following sections.

2.4.1 Biomechanical Models

The genesis of mathematical modeling concerning the inertial properties of the human body segments can be traced back to the pioneering work of Havanan (1964), when it became necessary to model the body for 3D analyses. After this, an array of biomechanical models has been developed, encompassing simple two-dimensional statics models to more sophisticated three-dimensional dynamic models, as employed in various studies (Jäger et al., 2000; Johnen, Mertens, et al., 2022; Kumar, 1990; Norman et al., 1998; Waters et al., 2006). Conventionally, rigid segment link models have been adopted to streamline the modeling of the human skeletal framework. In the realm of static models, Newton’s laws can compute the forces and moments acting on the joints, predicated on known joint positions and external forces. However, in static models the acceleration components of each segment are disregarded during computations. In scenarios characterized by leisurely motion, the repercussions of acceleration are deemed negligible due to the lower magnitude. Conversely, dynamic models factor in acceleration and leverage inverse dynamics to estimate joint kinematics, employing either a "bottom-up" (from the ground to the joint or segment of interest) or "top-down" (usually from the hands to the joint of segment of interest) strategy (Robertson et al., 2014).

2.4.2 Musculoskeletal modeling

Musculoskeletal simulations and dynamical modeling programs that can predict forces and moments acting on the musculoskeletal system during movement are plausible options in biomechanics (Damsgaard et al., 2006; Delp et al., 2007). These simulations typically involve the creation of a computer-based model of the human body, including its bones, joints, and muscles. Using equations of motion and principles of mechanics, the model can predict the forces and moments acting on the musculoskeletal system during movement, providing insights into the loading experienced by different body tissues. In a recent development, Karatsidis and colleagues, in 2019, pioneered and substantiated a workflow integrated within the Anybody™ software (Karatsidis et al., 2019)). This novel workflow is tailored to execute musculoskeletal model-based inverse dynamics, relying solely on input from Inertial Measurement Units (IMC). Notably, this workflow has been employed in both laboratory and field-based investigations, as exemplified by studies conducted by Larsen et al. in 2020, and Skals et al. in 2021 (Larsen et al., 2020; Skals et al., 2021).

2.4.3 Spinal Loading Methods

Several methods are utilized to estimate spinal loading, biomechanical models such as the Three-Dimensional Static Strength Prediction Program (3DSSPP) (Chaffin et al., 2006), and musculoskeletal models implemented through software like OpenSim™ or AnyBody™ (Damsgaard et al., 2006; Delp et al., 2007) allow for the estimation of muscle forces and spinal loads in various static and dynamic postures. Additionally, motion capture systems with specific marker configurations, such as the Plug-in Gait model and the Cleveland Clinic marker set, are used to track the kinematics of the lower back and provide insights into lumbar spine motion during occupational tasks (Vicon®, 2002). Recent studies in occupational biomechanics had used bottom-up and top-down approaches depending on the needs, resources available, and environmental limitations the studies face (Faber et al., 2011, 2020; Koopman et al., 2018; Larsen et al., 2020; Nail-Ulloa et al., 2021; Skals et al., 2021; Skals et al., 2021; Skals et al., 2017).

2.4.4 Methods of cumulative exposure integration

Employing an integration technique is the most common approach to ascertain the cumulative loading for time series data. Kumar (1990) integrated load over time, and developed a methodology for the estimation of spinal loading, using the following formula:

$$CL = \sum_{i}^{n} (L_i \times t_i)$$

Where:

CL: Denotes the cumulative load, encompassing compression or shear forces and is measured in Newton-seconds (Ns).

L_i: Represents the mean force exerted during the i^{th} segment of the task, quantified in Newtons (N).

t_i: Represents the temporal length of the i^{th} segment of the task, expressed in seconds (s).

The CL calculated ascertains the cumulative load pertinent to a singular task executed by a worker. To add together different tasks and compute the aggregate daily cumulative loading, the following equation was employed:

$$CDL = \sum_{j}^{n} \left(CL_j \times F_j\right)$$

Wherein:

CDL: denotes cumulative daily load.

CL_j: represents the overall load corresponding to task j.

F_j: denotes the frequency per day associated with task j.

In a different manner to the methodology used by Kumar, Norman et al. (1998), used the summation of peak spinal load for each respective task over time, while also incorporating loading during periods of rest to the computation, which uses the following formula:

$$Cumulative\ Load_{Total} = \sum_{i}^{n}(PL_i \times t_i \times F_i) + RL \times T$$

Where:

Cumulative Load$_{Total}$: Overall cumulative load of all tasks combined (N * s)

PL_i: Peak spinal compression load for task I (N)

t_i: duration of tasks I (s)

F_i: Frequency per day for task i

RL: Spinal compressive load during rest condition (upright standing posture)

T: Total rest time (s)

n: number of different tasks performed.

In congruence with the methodology employed by Norman et al. (1998), a study from Daynard et al. (2001), utilized the summation of peak spinal loads for each individual task, which was then multiplied by the respective duration, to calculate the cumulative spinal load. Notably, spinal loading during periods of rest was not considered.

$$Cumulative\ Spinal\ Compression\ Load = \sum_{i}^{n}(PSC_i \times t_i)$$

Where:

PSC_i: peak spinal compressive force for task i.

t_i: duration of task i.

To comprehend the efficacy of divergent integration methodologies in estimating cumulative spinal exposure, Callaghan et al. (2001) employed six (6) distinct methods to compute the cumulative loading exerted on the L4/L5 intervertebral segment. Markedly, all these methods were predicated on the linear integration of load over time:

- The product of peak load and the temporal duration of the task.

- The peak load multiplied by the work duration, compounded with the load experienced during upright stance, further multiplied by the duration of rest.
- The product of peak load with the temporal span during which load is held in hand.
- Segmentation of the lift cycle into four constituent components, with an attendant weighting of the load by each segment.
- Integration through rectangular approximation utilizing data samples acquired at a frequency of 5 Hz.
- Integration employing a rectangular approximation encompassing all frames amassed at a rate of 30 Hz.

Jager et al. (2000) deliberated on a fundamental assumption underlying the linear integration of lumbar disc compression forces over time to assess cumulative loading. There is an equivalence in injury risk between high-force, short-duration scenarios, and low-force, long-duration scenarios. The researchers postulated that "higher damage risk results from an increase of the compressive force amplitude than from a corresponding prolongation of time" (Jäger et al., 2000), as corroborated by the findings of Brinckmann et al. (1987). Based on this finding, Jäger et al. (2000) proposed the squared and tera-power methods, which are among the most used techniques to estimate cumulative damage in ergonomics (Johnen, Schaub, et al., 2022). The formulation for the linear, squared and tera-power methods is the following:

$$Linear = \sum_{i}^{n} (F_i \times t_i)/T$$

$$Squared = \sqrt{\sum_{i}^{n} \left(F_i^2 \times t_i\right)/T}$$

$$Tera - power = \sqrt{\sum_{i}^{n} \left(F_i^4 \times t_i\right)/T}$$

Where:

i: corresponds to the time interval.

F_i: compressive Force observed during i.

t_i: duration of i.

T: shift duration.

These computation methodologies, particularly the linear variant, commonly referred to as "non-weighted", have been demonstrated to be fairly inadequate for assessing physical exposure (Huangfu et al., 2018; Johnen, Mertens, et al., 2022). Instead, it is advisable to opt for approaches that weight the load intensity relative to load duration (Gallagher & Schall, 2017; Huangfu et al., 2018).

Additionally, the issue of methodological diversity has been highlighted previously (Johnen, Schaub, et al., 2022; Waters et al., 2006), emphasizing the challenge of comparing various work scenarios based on cumulative loading estimates. Johnnen et al. (2022), highlighted that weighted approaches are difficult to compare and must establish clear threshold values to estimate cumulative damage accurately.

2.4.5 Fatigue Failure Process in the development of MS tissue damage

Gallagher and Schall (2017) and Gallagher and Barbe (2022) synthesized the evidence suggesting that a material fatigue failure process plays a significant role in MSD development. The theory is supported by ex vivo studies on spinal segments, cartilage, tendons, and ligaments, where a consistent pattern of fatigue failure behavior under repetitive loading has been observed (Brinckmann et al., 1987; Gallagher et al., 2005, 2007; Schechtman & Bader, 1997; Thornton & Bailey, 2013). Another line of evidence is provided by in vivo animal studies where it has been reported fatigue failure processes in musculoskeletal tissues in a living state (Andarawis-Puri & Flatow, 2011; Barbe et al., 2013, 2020; Fung et al., 2009, 2010; Sun et al., 2010). Additionally, epidemiological evidence highlights the interaction between force and repetition as indicative of a fatigue failure process (Gallagher & Heberger, 2013). In recent times, there has been a surge in the development of tools by researchers that focus on fatigue failure for evaluating the risk of MSDs in the lower back, shoulders, and upper limbs (Bani Hani et al., 2021; Gallagher et al., 2017, 2018). These tools specifically analyze MSD risk in a discrete way throughout the work cycle by using peak moments, levels of perceived exertion, and the number of times a task is repeated. This discretized approach to tasks is seen as a limitation in ergonomic assessments, which leads to the interest of the possibility of looking into cumulative loading continuously using time series data. Figure 2.1 illustrates an example of an Stress (S) – number of cycles to failure (N) diagram.

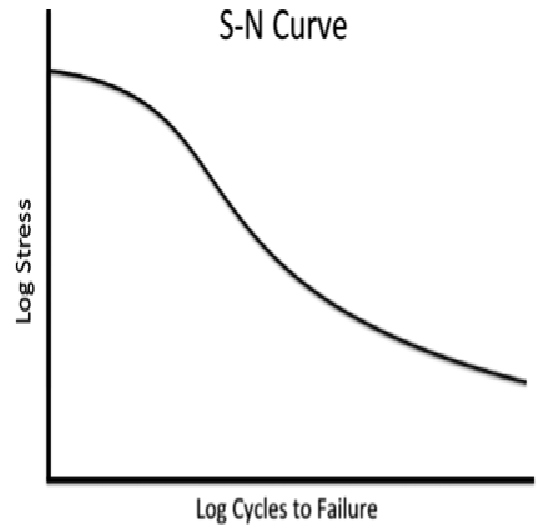

Figure 2.1. Example of an S-N diagram, relating the level of stress (S) to the number of cycles to failure (N) (Gallagher and Schall, 2017).

The significance of fatigue failure theory lies in its ability to deconstruct complex loading waveforms into stress reversals and cycles, enabling the estimation of cumulative loading. Therefore, fatigue failure theory is well-suited to utilize new continuous loading technologies and methods validated in material engineering science. Figure 2.2 illustrates a summary of the evidence from epidemiological studies according to Gallagher and Heberger (2013).

The critical techniques from fatigue failure theory that are relevant for processing time series data are highlighted in the following section.

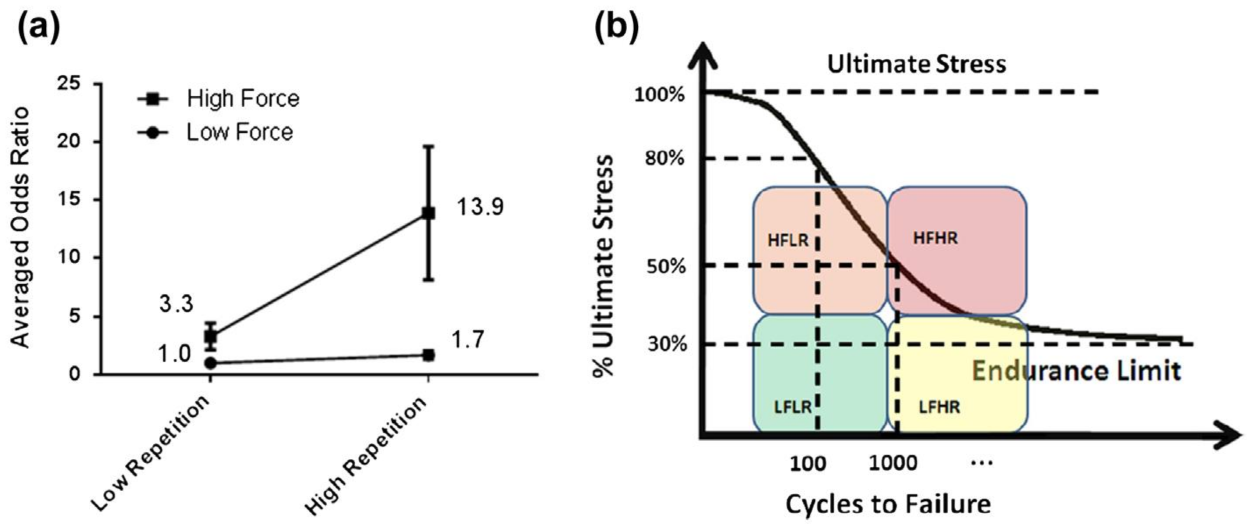

Figure 2.2. (a) Averaged odd ratios for seven studies examining quadrants of risk for force and repetition (Gallagher and Heberger,2013), and (b) the fatigue failure curve (Gallagher and Schall, 2017).

2.4.5.1 Rainflow Cycle Counting

Rainflow analysis, introduced by M. Matsuishi and T. Endo (1968), has found widespread application in studying material fatigue, and it has been described as the best cycle counting method (Stephens et al., 2001). This method can analyze continuous low back loading data and generate a “real-time” profile of the exposure distribution associated with a specific number of cycles through stress (or force or moment) range estimates and mean stress estimates. Using this technique, damage associated with each loading cycle could be estimated and summed as cumulative damage (CD). Comprehensive instructions on rainflow cycle counting have been issued by the American Society for Testing and Materials (ASTM E1049-85, 2017).

2.4.5.2 Cycle Loading Damage Estimation

In order to characterize the relationship between cycles to failure and different stress levels on lumbar motion segments, Gallagher et al. (2017) utilized studies on cadaveric lumbar spines (Brinckmann et al., 1987; Gallagher et al., 2005, 2007). The relationship between these variables follows an exponential pattern (Equation 1), similar to other materials like metals or plastics.

Equation 1:

$$N = 1{,}099{,}097.56 \times e^{-0.122 \text{ x } \%US}$$

Where:

- N = the number of cycles to failure.
- $\%US$ = percentage of the motion segment's ultimate strength.

Because the human spine is constantly subjected to a compressive load due to the body's weight in standing and sitting postures, the loading pattern can be classified as "fluctuating stress." As a result, modifications to the stress amplitude and mean stress are required for fully reversed sinusoidal loading. To achieve this, Goodman's method (Equation 2) was used to adjust the revised stress amplitude for each mean stress and stress range pair.

Equation 2:

$$\frac{S_a}{S_{Nf}} + \frac{S_m}{S_u} = 1$$

Where:

- S_a = alternating stress.
- S_m = the mean stress.
- S_{Nf} = the estimated value of the stress at failure for exactly Nf cycles as determined by an S-N diagram.
- S_u = the ultimate stress.

The adjusted stress amplitude was employed to indicate the stress level for each repetition classified by the rainflow analysis technique. Combining with Equation 1, it was possible to approximate the number of cycles required to cause failure at each stress amplitude and calculate the damage inflicted by each loading cycle. To estimate the CD sustained across a sequence of loading cycles, the Palmgren-Miner rule (Equation 3) was used, which is one of the most utilized models for predicting damage due to spectrum loading (Miner, 1945; Palmgren, 1924).

Equation 3:

$$c = \sum_{i}^{k} \frac{n_1}{N_1} + \frac{n_2}{N_2} + \cdots \frac{n_k}{N_k}$$

Where:

- c = a constant (usually set at 1, but potentially subject to variation). In this study, the threshold value for c is 1.
- n_i = the count of loading cycles experienced at force levels at which N_i … cycles would result in material fatigue failure.

2.5 Summary of literature review

The main findings of the literature review are summarized as follows:

- The multifactorial nature of the development of Musculoskeletal Disorders highlights the importance of comprehensive risk assessment methodologies for work-related MSDs within industrial environments.
- As for measuring exposure to physical risk factors, Inertial Motion Capture emerges as an efficient alternative, characterized by its minimal invasiveness, making it practical for field assessments.
- Existing assessment methods for measuring cumulative exposure in the low back are limited in scope, difficult to compare, and with no clear threshold values to estimate risk accurately.
- Fatigue Failure Theory presents a robust framework that holds promise in effectively estimating cumulative physical exposure.

References – Chapter 2

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Chapter 3

3. Assessing the Accuracy of a Wireless Sensor System for Estimating Lumbar Moments During Manual Lifting Tasks Considering the Effects of Load Weight, Asymmetry, and Height.

3.1 Introduction

Approximately 40% of all work-related musculoskeletal disorders (MSDs) in the US are attributed to back disorders (U.S. Department of Labor, 2016), and about 25% of workers experience low back pain (Luckhaupt et al., 2019; Yang et al., 2016). As a result, LBP remains a significant economic burden around the world (Bevan, 2015; Dagenais et al., 2008; Lo et al., 2021; Vos et al., 2012). It is generally believed that spinal loading resulting from biomechanical stress is a significant risk factor for this costly disorder (Coenen et al., 2013; da Costa & Vieira, 2009),

Research conducted in laboratory settings has investigated the effects of ergonomic interventions on the load placed on the spine, utilizing inverse dynamics analysis (Kingma et al., 1996) derived from laboratory-based instrumentation such as optical motion capture (OMC) systems, force plates (FPS), and instrumented boxes or pressure sensing devices (Corbeil et al., 2019; Hwang et al., 2009; Plamondon et al., 2010, 2014). However, the applicability of these methods in real-world environments is often cumbersome and not well replicated in the laboratory setting (Faber et al., 2011). Therefore, while it is desirable to perform these biomechanical studies in real-world settings (Burdorf & Lötters, 2002), utilizing the above-mentioned laboratory-based instrumentation is often not feasible or practical. To address this limitation, wearable measurement systems have been developed for ambulatory assessment of back loading (Freitag et al., 2007; Marras et al., 2010). However, these can be bulky and not practical for use in highly dynamic conditions. Inertial motion capture (IMC) systems consisting of small inertial measurement units (IMUs) have shown promise in assessing spinal loading, such as L5/S1 moments during trunk bending (Faber et al., 2016). It has also been tested that when combining IMUs sensors and force-sensing shoes, lumbar moments could be estimated within 10 to 20% of peak extension moments for manual lifting tasks (Faber et al., 2020). However, force-sensing shoes can be obtrusive in a real work environment, inviting us to consider an analysis approach solely using IMUs. Additionally, the effects of different loads, lifting heights, and the asymmetry of a lift have not been comprehensively assessed using IMC systems.

The current study investigates whether 3D L5/S1 moments can be accurately assessed using an IMC system during lifts involving three main factors: the weight of the load, degree of asymmetry, and height associated with the lifting and lowering tasks. Comparisons were made using bottom-up and top-down laboratory models constructed using a "gold-standard" OMC and FP methodology.

3.2 Methods

3.2.1 Participants

A total of 36 participants were recruited for the study, with an equal number of males and females, aged between 19 to 55 years old, and with a mean height of 173.54 cm (± 7.5 SD) and a mean body mass of 72.78 kg (± 12.1 kg SD). The participants were recruited from the Auburn University student body and the local Auburn/Opelika community. To be eligible, participants had to meet specific inclusion criteria, including 1) having no history of physician-diagnosed MSDs, injuries, or low back surgeries, 2) no low back pain in the past six months, and 3) no physician-diagnosed neurodegenerative disorders that may affect movement, such as Parkinson's disease or multiple sclerosis, among others. The study was approved by the Institutional Review Board of Auburn University (Protocol # 16-211 MR 1606). Details about the participants' anthropometry are provided in Table 3.1.

Table 3.1. Summary of participants' anthropometry.

	Body weight (kg)	Body height (cm)	Shoe length (cm)	Ankle height (cm)	Ankle width (cm)	Knee height (cm)	Knee width (cm)	Elbow width (cm)	Shoulder width (cm)	Shoulder height (cm)	Hip height (cm)	Hip width (cm)	Arm span (cm)
Mean	72.78	173.54	25.06	8.72	7.92	46.96	10.84	8.42	34.28	142.05	90.88	24.53	172.09
SD	12.1	7.5	1.3	10.0	6.8	9.8	6.5	10.1	3.3	6.8	8.9	2.0	9.1

3.2.2 Participant Preparation and Data Collection

In accordance with established protocols, the research team collected participants' anthropometric measurements, including weight, height, as well as lengths and circumferences of various major body segments (Haslegrave & Pheasant, 2018). The participants were equipped with 17 IMU sensors (MVN Awinda, Xsens Technologies B.V., Enschede, the Netherlands). These sensors are wireless, small, battery-powered, and capable of measuring and storing data on linear acceleration, angular velocity, and magnetic field. A combination of elastic neoprene straps and hypoallergenic athletic tape was used to secure the sensors. In addition, a full-body protocol of 50 reflective OMC markers were placed at specific reference points on the body to serve as the reference "gold-standard" for body segment position. The reflective marker trajectories were recorded by 16 cameras (Optitrack Prime 13, Natural Point, Inc.). The primary marker locations were defined using the full-body Plug-In Gait 39-marker set (Vicon®, 2002), while 11 additional markers were used to keep track of some segments that may be obstructed during lifting tasks due to the nature of the movement. These additional markers were placed on the inside of the elbows, ankles, knees, top of the feet, left and right sides of the pelvis, and between the sternum and clavicle markers (see Figure 3.1). The information obtained from the IMU sensors and anthropometric data was utilized to build a rigid link biomechanical model. This model was then evaluated against the full-body Plug-In Gait OMC model, using the data gathered from the reflective markers. An example of the participant setup and OMC and IMC avatars are shown in Figure 3.2.

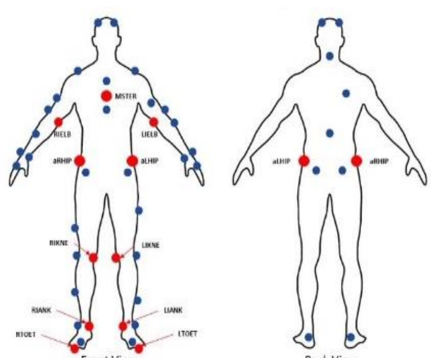

Fig 3.1. Adapted Plug-In Gait marker set.

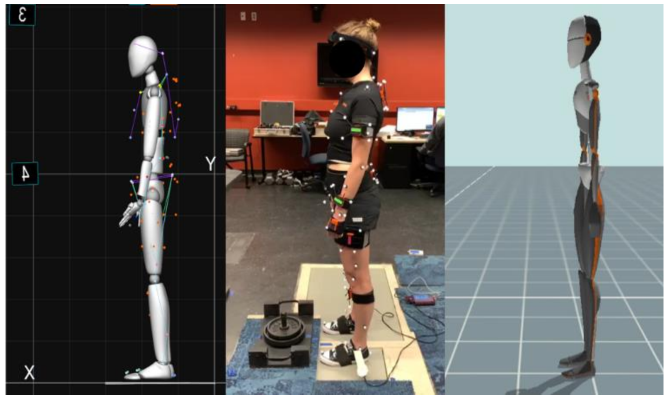

Fig 3.2. (Left) OMC model avatar, (Middle) Participant, (Right) IMC model avatar.

3.2.3 Systems Calibration

The OMC system was calibrated before each session of data collection, which involved defining the capture volume and establishing the origin and orientation of the global coordinate system. Before commencing the experimental procedure, participants were required to complete manufacturer-defined calibration protocols for both the IMC and OMC systems. Segment calibration was necessary for the IMC system to align the motion trackers to the participant body segments (Xsens®, 2021). This required the participant to assume a neutral posture (N-pose) for a brief period, then walk straight forward and return to the starting point. For the OMC system (NaturalPoint®, 2018), segment calibration required the participant to adopt an "A" pose (as depicted in Figure 3.1) to record a static trial. The static trial was then linked to the dynamic trials corresponding to each participant to enable subsequent biomechanical analysis.

3.2.4 Data synchronization and processing

The OMC software (Motive™) was defined as the master system to synchronously capture data from the FPs, OMC, and IMC. The OMC data was captured at a sampling rate of 120 Hz, while the IMC data was sampled at 60 Hz. The OMC signals were down-sampled offline to 60Hz, and the reflective markers' trajectory gaps were filled using the cubic interpolation methods (Xu et al., 2010). A bi-directional low-pass filter with a second-order Butterworth filter at 6Hz was used for the OMC system (Karatsidis et al., 2016) and 5Hz for the IMC system (Faber et al., 2020) to filter the forces and kinematics.

3.2.5 Experimental Procedure

The 36 participants completed the simulated manual material handling trials in a laboratory environment, where kinematic and kinetic data were collected. The duration of the trials varied from 10 to 30 seconds, depending on the participant's speed. Each participant performed three trials with a 2-minute rest period between them. Participants were instructed to lift a box with handles (similar to a standard milk crate) consisting of a load of 10 lbs. (4.54 kg), 20 lbs. (9.07 kg), or 30 lbs. (13.61 kg) both symmetrically and asymmetrically (i.e., 0°, 30° and 60° degrees from sagittal to the left) to one of three different heights (60 cm, 100 cm, and 140 cm). Each participant completed three different weight, height, and asymmetry combinations, using a lifting technique of their preference. An example of one of the trials is presented in Figure 3. The tested combinations were labeled using the following terminology: LXX (XX = Load of 10, 20, or 30 lbs.), AYY (YY = Angle of 00-, 30- or 60-degrees asymmetry), and HZZ (ZZ = Height of 60, 100, or 140 cm.). For example, L20_A30_H140 would represent a 20-pound load, picked up from a sagittal angle of 30° and lifted to a height of 140 centimeters. Loads and heights were randomized within levels of angle for 27 combinations (every combination was performed four times, a total of 108 trials). The combinations for the settings are shown in Table 3.2.

3.2.6 Biomechanical Modelling

Biomechanical models that combined both bottom-up and top-down approaches for the inverse dynamics were used to analyze the data. The biomechanical model from the OMC data consisted of 15 segments (hands, forearms, upper arms, upper legs, lower legs, feet, pelvis, thorax and head) and was developed in Visual3D software (C-Motion, Rockville, MD). The guidelines used to determine to location estimate for L5/S1 (Dumas et al., 2007; Reed et al., 1999) are based on proportions of the anterior superior iliac spine (ASIS) distance. This model was validated in a previous study (Nail-Ulloa et al., 2021). Visual3D developed the 15-segment biomechanical model used for the IMC system (C-Motion®, 2020). The external loads in the Top-Down calculations were divided equally between the hands, with half the weight assigned to each hand segment. This load distribution was adjusted accordingly during lifting and lowering of the load based on the changes in magnitude observed in the FPs data. The analysis involved calculating the total moments obtained by the vector summation of the L5/S1 moments (X, Y, Z) from each plane. The gold-standard OMC-BU estimates were used to identify the peak moments.

Table 3.2. Different combinations of load, height, and angle.

	Height		
Load	**60 cm**	**100 cm**	**140 cm**
	0°	0°	0°
10 lbs	30°	30°	30°
	60°	60°	60°
	0°	0°	0°
20 lbs	30°	30°	30°
	60°	60°	60°
	0°	0°	0°
30 lbs	30°	30°	30°
	60°	60°	60°

3.2.7 Data Analysis

The systems performance was evaluated using a randomized block partially confounded designs 3^3 (RBPF) with blocks of size three, these ANOVA were calculated by comparing the Absolute Peaks, RMSE, and absolute peak differences of the estimated moments. Confounded factorial designs are particularly appropriate because all main effects can be evaluated with equal precision. The interactions can be confounded with groups, reducing block size without sacrificing power in evaluating the treatments (Kirk, 2013). Due to the nature of the experimental design technique, groups (four groups of nine participants each) and the main effects (Load, Asymmetry Angle, Height, and their possible interactions) were analyzed to find potentially statistically significant differences. A Type I error rate of 0.05 was adopted across all the tests performed. Tukey's tests were employed for pairwise comparisons to assess significant main effects and interactions. All statistical analyses were performed using Minitab® software (version 19.2020.1, LLC, USA).

3.3 Results

Figure 3.3 presents typical results of moment estimates associated with the lifting (A) and lowering trials (B), showing the Bottom-Up Optical Motion Capture-based model (OMC-BU), the Top-Down Optical Motion Capture-based model (OMC-TD), and the Top-Down Inertial Motion Capture-based model (IMC-TD). Both figures from the lifting and lowering show two different peaks, with the higher one generally picking up or putting down the load from and to the floor level. The other peak was typically found when putting on or removing the load from the shelf. Measures of central tendency are shown in Tables 3.3, 3.4, and 3.5.

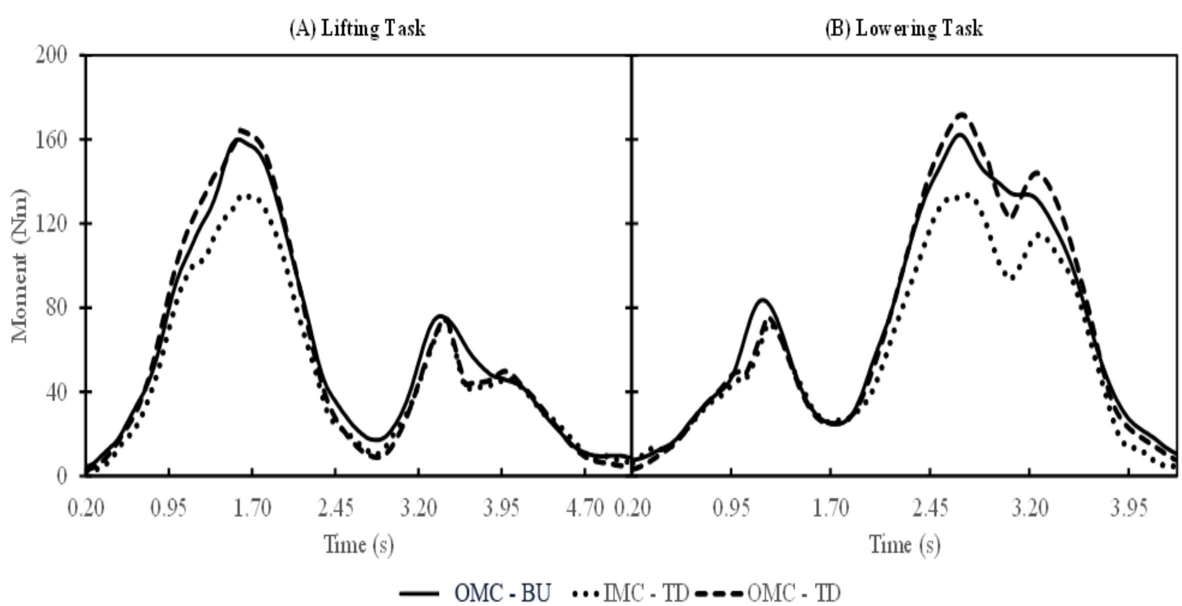

Fig 3.3. L5/S1 Moment during one of the lifting (A) and lowering (B) trials

Table 3.3. Measures of central tendency for the Absolute Peaks.

	Absolute Peaks (Nm)					
	Lifting			Lowering		
	OMC BU	IMC TD	OMC TD	OMC BU	IMC TD	OMC TD
Mean	197.59	171.63	208.59	188.47	166.24	200.57
Median	195.02	166.87	206.24	186.59	161.45	199.47
SD	45.09	42.5	44.3	41.1	39.74	40.93
Max	320.25	295.35	358.91	284.01	291.89	329.92
Min	110.91	97.66	121.12	96.55	98.14	120.45
IQR	69.38	63.85	56.47	62.11	58.65	53.05

Table 3.4. Measures of central tendency for the RMSE.

	RMSE (Nm)					
	Lifting			Lowering		
	OMC BU - OMC-TD	OMC BU - IMU TD	OMC TD - IMC TD	OMC BU – OMC TD	OMC BU - IMU TD	OMC TD - IMC TD
Mean	16.03	19.07	20.9	16.95	21.38	21.34
Median	15.5	18.05	19.78	16.06	20.74	19.49
SD	6.4	5.94	8.56	6.79	7.24	8.96
Max	39.64	34.74	46.95	43.3	41.72	47.12
Min	4.92	8.2	7.35	4.22	6.18	6

IQR	7.86	7.96	11.99	7.36	9.54	11.97

Table 3.5. Measures of central tendency for the Peak Differences.

	Peak Differences (Nm)					
	Lifting			Lowering		
	OMC BU - OMC-TD	OMC BU - IMU TD	OMC TD - IMC TD	OMC BU - OMC TD	OMC BU - IMU TD	OMC TD - IMC TD
Mean	-11.00	25.959	36.959	-12.10	22.224	34.324
Median	-10.81	26.178	36.655	-13.04	25.168	34.616
SD	16.83	19.627	20.055	17.63	19.796	19.438
Max	24.04	66.940	89.554	28.21	60.172	79.927
Min	-56.00	-36.412	-10.045	-61.42	-37.467	-17.325
IQR	23.30	20.362	27.129	19.40	21.023	22.092

3.3.1 Lifting Task

The results for the RBPF design for the Absolute Peaks were separated depending on the analyzed system and approach used (Table 3.6). When analyzing the Absolute Peaks for the OMC-BU calculations, the load ($p < 0.001$) and angle ($p = 0.02$) were identified as significant main effects, and no significant interactions were found. The load ($p < 0.001$) was a significant factor for the IMC-TD calculations. Again, the load ($p < 0.001$) was the only factor found as significant for the OMC-TD calculations. Groups ($p < 0.001$) was found as a significant factor for all systems. Tukey's test showed that for the three approaches, higher differences occurred between the pair including the 10 and the 30 lbs. loads.

For the RMSE analysis using the RBPF design (Table 3.7), the OMCBU-OMCTD results showed that the load ($p < 0.001$) was a significant factor. When comparing the OMCBU-IMCTD, groups ($p < 0.1$) and Load ($p < 0.001$) were significant, but we also observed the presence of the significant interaction Load x Height ($p = 0.003$). Tukey's test calculations suggested that the pair L30_H060 & L30_H100 were significantly different ($T = 4.825 > 4.602$). The comparison of the OMC-TD and IMC-TD showed that groups ($p < 0.001$), Load ($p = 0.014$), and Height ($p = 0.001$) were significant. The interaction between Load x Height was also observed as significant ($p = 0.01$). Tukey's test calculations suggested that the pair L20_H060 – L20_H100 was significantly different ($T = 7.260 > 5.953$). One of the interactions of Load x Height for OMC-TD and IMC-TD is shown in Figure 3.4.

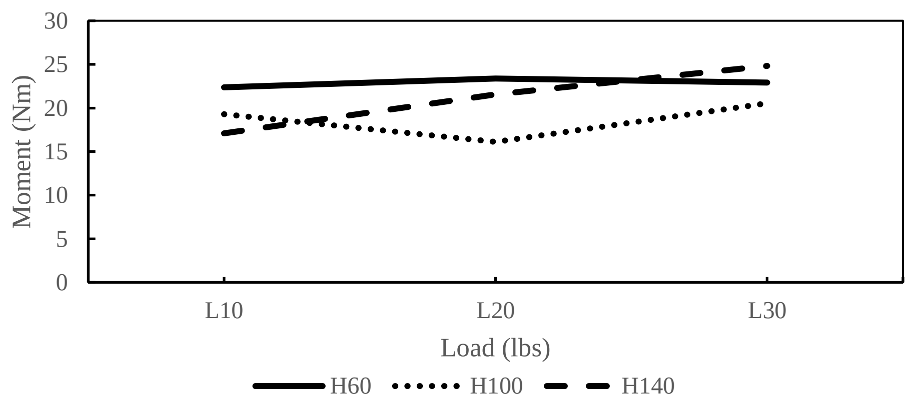

Fig 3.4. Load x Height Interaction for the OMC-TD and IMC-TD RMSE for the lifting portion of the trial

For the moment peak differences between models, there were no noteworthy variations observed for any of the primary factors for OMCBU-OMCTD and OMCBU-IMCTD (as indicated in Table 3.8). However, when comparing OMCTD-IMCTD, there was a significant difference in Load ($p = 0.020$). After performing post-hoc Tukey's test calculations, it was found that the L10 and L30 pairwise comparison exhibited a significant difference ($T = 8.037 > 6.536$).

3.3.2 Lowering Task

For the Absolute Peaks, as Table 3.6 shows, the load ($p < 0.001$) was identified as significant for the OMC-BU calculations. In the results for the IMC-TD calculations, as with the lifting trial, the load (p <

0.001) was found as a significant factor. Again, the load ($p < 0.001$) was the only factor found as significant for the OMC-TD calculations. Groups ($p < 0.001$) was found as a significant factor for all systems. As for the lifting part, the same situation was observed with the lowering estimates with Tukey's tests showing that for all systems, higher differences occurred between the pair including the 10 and the 30 lbs. loads.

Table 3.6. Results (p-values) of the ANOVA analyses, testing the effects of the Loads (A), Angle (B), Height (C), and their interactions on the Absolute Peaks (Absolute Peaks) for the L5/S1 total moment. Significant effects ($p < 0.05$) are indicated in bold/italics.

Factors	Absolute Peaks					
	Lifting			Lowering		
	OMC BU	IMC TD	OMC TD	OMC BU	IMC TD	OMC TD
Groups	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
A (LOAD)	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
B (ANGLE)	***0.020***	0.185	0.445	0.705	0.582	0.735
C (HEIGHT)	0.172	0.375	0.595	0.813	0.747	0.890
A*B	0.389	0.404	0.474	0.142	0.230	0.157
A*C	0.431	0.710	0.953	0.399	0.642	0.701
B*C	0.737	0.411	0.474	0.318	0.634	0.452
A*B*C	0.945	0.562	0.902	0.831	0.464	0.929

For the RMSE analysis using the RBPF design (Table 3.7), we started our comparison with the OMCBU-OMCTD; the results showed that the groups ($p < 0.025$) and load ($p < 0.001$) were significant factors. When comparing the OMCBU-IMCTD, groups ($p < 0.001$) and Load ($p < 0.001$) were significant, but we also observed the presence of the significant interaction Load x Height ($p = 0.032$) for the lifting trial. Tukey's test calculation did not suggest any pair as significantly different. The comparison of the OMC-TD and IMC-TD showed that groups ($p < 0.001$) and height ($p = 0.003$) were significant. The interaction between Load x Height was also observed as significant ($p = 0.028$). Tukey's test calculations suggested that the pair L20_H060 & L20_H100 (as for the lifting trial) was significantly different ($T = 7.429 > 6.136$). The interaction plot of Load x Height for OMC-BU and IMC-TD is shown in Figure 3.5.

When comparing the moment peak differences between models, no significant variations were observed for any of the primary factors in OMCBU-OMCTD, as indicated in Table 3.8. However, for OMCBU-IMCTD and OMCTD-IMCTD, there were significant differences observed for the interaction Load x Height ($p = 0.030$) and for Load ($p = 0.005$) and Angle ($p = 0.037$), respectively. The interaction for OMCBU-IMCTD did not demonstrate a clear trend. Nonetheless, post-hoc Tukey's test calculations for OMCTD-IMCTD revealed that the pairwise comparison for Load exhibited a significant difference between L10 and L30 ($T = 9.440 > 6.595$), while the pairwise comparison for Angle displayed a significant difference between A00 and A60 ($T = 7.184 > 6.595$).

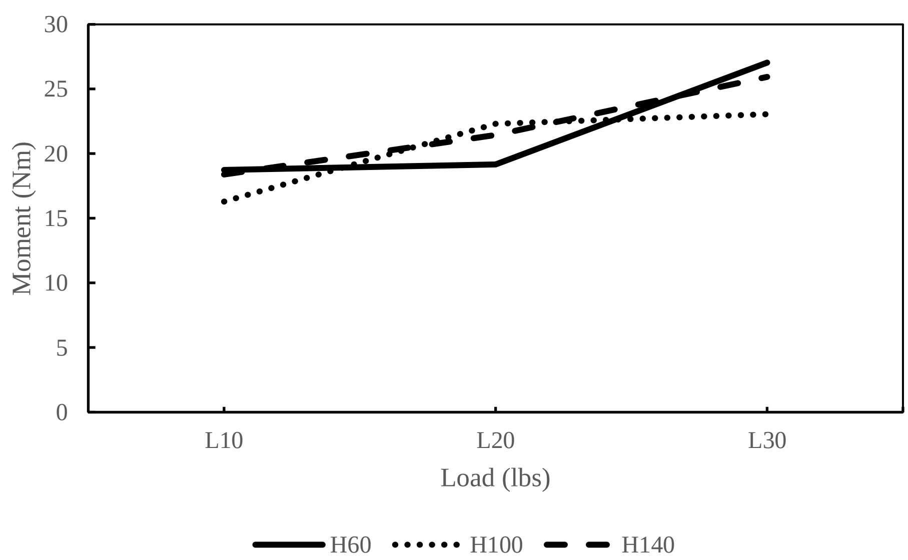

Fig 3.5. Load x Height Interaction for the OMC-BU and IMC-TD RMSE for the lowering portion of the trial.

Table 3.7. Results (p-values) of the ANOVA analyses, testing the effects of the Loads (A), Angle (B), Height (C), and their interactions on the RMSE of the L5/S1 total moment. Significant effects ($p < 0.05$) are indicated in ***bold/italics.***

	RMSE					
	Lifting			Lowering		
Factors	OMC BU - OMC-TD	OMC BU - IMU TD	OMC TD - IMC TD	OMC BU - OMC TD	OMC BU - IMU TD	OMC TD - IMC TD
Groups	0.148	***<0.001***	***<0.001***	***0.025***	***<0.001***	***<0.001***
A (LOAD)	***<0.001***	***<0.001***	***0.014***	***<0.001***	***<0.001***	0.563
B (ANGLE)	0.472	0.448	0.500	0.233	0.457	0.733
C (HEIGHT)	0.340	0.072	***0.001***	0.239	0.462	***0.003***
A*B	0.290	0.613	0.305	0.717	0.620	0.225
A*C	0.986	***0.003***	***0.010***	0.474	***0.032***	***0.028***
B*C	0.424	0.575	0.848	0.424	0.246	0.490
A*B*C	0.840	0.390	0.812	0.562	0.939	0.934

3.4 Discussion

The present study evaluated the performance of an IMC system for estimating L5/S1 moments with different load, height, and asymmetry angle configurations. Outcomes of a state-of-the-art laboratory system, consisting of an OMC and FPs, bottom-up OMC model, were compared against a top-down IMC model. L5/S1 moments were also calculated using a top-down OMC model for internal validation of the OMC system. For top-down estimates of L5/S1 moments, the load's weight was divided equally between each hand.

Table 3.8. Results (p-values) of the ANOVA analyses, testing the effects of the Loads (A), Angle (B), Height (C), and their interactions on the peak differences of the L5/S1 total moment. Significant effects ($p < 0.05$) are indicated in ***bold/italics.***

Factors	Peak Differences					
	Lifting			Lowering		
	OMC BU - OMC-TD	OMC BU - IMU TD	OMC TD - IMC TD	OMC BU - OMC-TD	OMC BU - IMU TD	OMC TD - IMC TD
Groups	***0.008***	0.384	0.458	***<0.001***	***0.002***	***0.001***
A (LOAD)	*0.536*	0.079	***0.020***	0.455	***0.003***	***0.005***
B (ANGLE)	0.336	0.081	0.524	0.243	***0.005***	***0.037***
C (HEIGHT)	0.071	0.414	0.557	0.974	0.552	0.647
A*B	0.872	0.224	0.549	0.737	0.449	0.303
A*C	0.348	0.159	0.755	0.172	***0.030***	0.600
B*C	0.182	0.196	0.424	0.306	0.267	0.456
A*B*C	0.244	0.723	0.633	0.111	0.096	0.903

The load was the most significant factor in almost all cases, influencing the Absolute Peaks and the RMSE, while the majority of non-significant differences observed between OMCBU and both of the TD models for the peak differences. We did not find any clear statistical trend regarding the Load x Height interactions observed for the RMSE (lifting and lowering), nor the Load x Angle interaction observed for the peak differences (lowering). We suspect this relates to participant variability or non-controlled variables such as lifting technique or speed. Hence, the influences of height and angle, were not a significant factor overall in the tested scenarios. Averaged over participants and trials, L5/S1 moment RMS errors remained around 15 to 20 Nm. The peak moment differences were 10 to 15% between the OMC and IMC-based models for lifting and lowering tasks. These results correspond closely with similar studies (Faber et al., 2020; Koopman et al., 2018). Considering the obtained results, distributing the load between the participants' hands seems promising with at least similar loads (symmetrical and evenly balanced). We recognize that tools have different shapes and weight distribution in industry. Nevertheless, we find these results worth exploring when analysis needs to be simplified.

When comparing the moment estimates of the trials, a consistent pattern emerged whereby the IMC system's estimates were consistently lower than those generated by OMC-based models (as shown in Tables 3 and 4). Similar observations were made in prior studies (Faber et al., 2016). The cause of this discrepancy may be attributed to the distinct approaches used by the two systems to track and define body segments. OMC-based models employ bony landmarks to estimate segment lengths, which may produce more precise outcomes than the IMC-based model estimates. The latter is computed using the participant's segment orientation and anthropometric data (e.g., height, arm span, shoulder height, hip height, etc.). Furthermore, during the analysis, it was observed that the lengths of the segments between the distal end of the hands and the proximal end of the thorax differed by as much as 15 centimeters between the two systems, with the IMC-based biomechanical model showing shorter segments. This variance in segment lengths (lever arm) might be a contributing factor to the lower moment estimates observed in the IMC model. Further research is needed to investigate the disparities in segment length estimation and their impact on moment estimates.

Another possible factor that could influence the variability among the models in this study is how the thorax is defined for TD calculations. As the trunk is not a rigid body in actuality, using a single rigid segment to model it may introduce potential sources of error. Nonetheless, it is feasible to employ a defined, rigid trunk in investigations of loading at the lower levels of the spine (Ignasiak et al., 2016). When calculating moments using BU inverse dynamics, the Ground Reaction Forces (GRF) tend to exert the most significant influence, which means that inertial properties are not as critical in these calculations. Conversely, when determining moments via a TD approach, the moments are primarily determined by inertial properties. Consequently, less precise estimates may be observed when large body segments assumptions are used (Desjardins et al., 1998; Plamondon et al., 1996).

The RMSE and Absolute Peaks showed similar results to those previously observed in the literature (Faber et al., 2016, 2020; Koopman et al., 2018). When comparing the mean values of the Absolute Peaks between the gold-standard OMC BU and the IMC TD for all trials (Table 2), the IMC TD moments were 13.14% smaller for the lifting tasks and 11.79% smaller for the lowering tasks.

It is also worth mentioning that the IMU system's sacrum sensor placement was somewhat problematic because there is not a prominent bony landmark that can be used for the IMU attachment point. We believe that due to the nature of the lifting and lowering tasks performed, which required forward bending, the sacrum sensor could have moved (mostly upwards) from its original location, affecting the estimated moment results. This challenge has been identified before in the literature (Larsen et al., 2020; Schall et al., 2021). Further research is needed to understand the nature of the variability and the potential options to reduce it, which would make the IMU system promising for field-based risk assessment.

3.4.1 Limitations

There are different constraints to consider in this study. First, it assumes that the weight is distributed evenly on both hands, which is improbable because the load's weight distribution may be uneven, particularly if the load has irregular shapes, as most tools in an industrial work environment. Moreover, this method neglects the potential effects of pushing or pulling loads. Second, the study's participants were all relatively young and healthy, and considering obese participants, a substantial proportion of the working population in the US (Ogden et al., 2014), may lead to more significant soft-tissue artifacts and affect the performance of the IMC system (Bolink et al., 2016). Third, possible imperfections in the scaling of the model may be another source of error that affects the accuracy of the estimates (Konrath et al., 2019). Fourthly, the participants were not restricted in their lifting technique or speed during the lifting and lowering tasks, which could affect the variability of the results (Fleron et al., 2019). Finally, during the study, IMC data was captured on a per-trial basis, with trials lasting around half a minute, so significant errors associated with magnetic disturbance and gyroscopic drift may not have been observed, as the literature has reported such errors in longer trials (Robert-Lachaine et al., 2017).

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Chapter 4

4. Estimating Compressive and Shear Forces at L5-S1: Exploring the Effects of Load Weight, Asymmetry, and Height using Optical and Inertial Motion Capture Systems.

4.1 Introduction

Low back disorders are a significant health problem affecting one out of four workers in the United States (Luckhaupt et al., 2019). Manual material handling tasks, such as lifting, impose high compression and shear forces on the spine (Wilke et al., 2001), which likely cause damage to spinal segments and surrounding tissues (Adams & Dolan, 2005; Van Dieën et al., 1999). Understanding low back loading is a central area of study in ergonomics, such as estimating moments and forces (compressive and shear) experienced by the lumbar spine during physical work. In order to protect workers and establish ergonomic safety limits for job design and intervention, the National Institute for Occupational Safety and Health (NIOSH) suggested a compressive force limit for the lumbar vertebrae of 3.4 kN (Waters et al., 1993). Also, there have been studies on the tolerance of the lumbar spine to shear force, contributing to a recommended limit of 1 kN (Gallagher & Marras, 2012; Marras, Davis, Kirking, & Bertsche, 1999; Marras & Davis, 1998). However, assessing spinal loading *in vivo* is challenging and rarely performed due to the methods' invasiveness (Wilke et al., 2001). Furthermore, the assessment is typically confined to controlled laboratory environments, limiting the ability to evaluate spinal loading in real-world field settings such as live production environments (Faber et al., 2011).

Musculoskeletal simulations and dynamical modeling programs that can predict forces and moments acting on the musculoskeletal system during movement are plausible options in biomechanics (Damsgaard et al., 2006; Delp et al., 2007). These simulations typically involve the creation of a computer-based model of the human body, including its bones, joints, and muscles. Using equations of motion and principles of mechanics, the model can predict the forces and moments acting on the musculoskeletal system during movement, providing insights into the loading experienced by different body tissues. Additionally, to address the "portability" limitation, some wearable measurement systems have been developed for ambulatory assessment of backloading (Freitag et al., 2007; Marras et al., 2010), but they can be bulky and not practical for use in highly dynamic conditions. In order to measure the motion associated with physical work in dynamic workplaces, inertial motion capture (IMC) usage has increased during the last decade (Lee & Lee, 2022; Schall et al., 2022).

Kinematic data obtained from IMC systems have been validated in several studies in the laboratory against data obtained from optical motion capture (OMC) systems (Bolink et al., 2016; Chang et al., 2022; Fleron et al., 2019; Larsen et al., 2020; Paulich et al., 2018; Schall et al., 2016). Estimating kinetic variables such as backloading from IMC systems has also been validated in the laboratory using force platforms or instrumented shoes to measure ground reaction forces (Faber et al., 2016, 2020; Koopman et al., 2018; Larsen et al., 2020; Nail-Ulloa et al., 2021). Recent advances in IMC technology, such as consistency of performance over time, accuracy, cost efficiency (Paulich et al., 2018; Schepers et al., 2018), and the availability of methods to predict ground reaction forces and moments from segment kinematics and dynamic properties have provided new opportunities for field assessment (Fluit et al., 2014; Konrath et al., 2019; Larsen et al., 2020; Skals, Bláfoss, Andersen, et al., 2021; Skals et al., 2017). Larsen et al. (2020) observed moderate to excellent correlations for the intraclass correlation coefficients for compression and anteroposterior shear forces, ranging from 0.65 to 0.92 during symmetrical and asymmetrical lifting, while the IMC-based model underestimated the trunk flexion compared to those measured with the OMC system. However, the combination of ambulatory IMC measurements and musculoskeletal modeling for estimating spinal loads during manual materials handling needs further evaluation before it can be used in the field. In particular, no studies have systematically evaluated the effects of key ergonomic variables such as load mass (Davis et al., 2010; Granata et al., 1999; Lavender et al., 2003; Plamondon et al., 2012), lifting and lowering height (Faber et al., 2009; Hoozemans et al., 2008), and asymmetry (Marras et al., 1999; Marras & Davis, 1998), and their potential interactions.

The current study aims to critically investigate the capability of an Inertial Motion Capture (IMC) system in accurately assessing compression and anteroposterior shear forces at the L5/S1 segment during lifting and lowering tasks. The tasks are varied across three primary factors: the mass of the load, the degree of asymmetry, and the height at which the load is handled. Within this context, the study is guided by two distinct hypotheses:

1. The IMC system will demonstrate comparable accuracy to the Optical Motion Capture system, considered the gold standard in estimating kinetics and kinematics.
2. The mass of the load, degree of asymmetry, and height will significantly affect the force estimates derived through the IMC system.

Clarifying and examining these hypotheses are essential in evaluating the effectiveness of IMC systems and understanding the factors that may impact their accuracy in assessing biomechanical loads during manual handling tasks. Additionally, trunk rotation, flexion, and lateral bending were compared to better understand the differences in force estimates. A measure of the distance between the handled box and the L5/S1 joint center was compared between systems as a comprehensive estimation of segment length differences.

4.2 Methods

A gender-balanced sample of 36 participants (19 to 55 years old; mean height = 173.54 ± 7.5 cm; mean body mass = 72.78 ± 12.1 kg) was recruited. Participants were from the Auburn University student body and the local Auburn / Opelika community. Inclusion criteria included 1) no history of physician-diagnosed MSD, injury, or surgery in the low back, 2) absence of low back pain during the previous six months, and 3) no history of a physician-diagnosed neurodegenerative disorder that may affect movement (e.g., Parkinson's disease, multiple sclerosis, among others). The study was approved by the Institutional Review Board of Auburn University (Protocol # 16-211 MR 1606).

4.2.1 Participant Preparation and Data Collection

Several anthropometric measurements were obtained, including height, weight, and the lengths and circumferences of several major body links following established guidelines (Pheasant & Haslegrave, 2006). Participants were fitted with 17 IMU Xsens Awinda sensors (Xsens Technologies, Enschede, Netherlands). Each IMU is a small wireless, battery-powered unit that measures and stores acceleration, angular velocity, and magnetic field information. The devices were secured using a combination of elastic neoprene straps and/or hypoallergenic athletic tapes. In addition to the IMU, the participants wore small, reflective motion capture markers used as a "gold-standard" reference of body segment position. The reflective markers' trajectories were recorded with sixteen cameras (Optitrack Prime 13, Natural Point, Inc), using a full body protocol for the OMC system. For this experiment, a total of 50 reflective markers were used. A full-body Plug-In Gait marker set was used to define the reflective markers' location; 11 markers were added to the set, including on the inside of the knees, elbows, and ankles, top of the feet, and left and right sides of the pelvis (Figure 4.1). The anthropometric data were used to build a rigid link biomechanical model using the information collected from the sensors. The model was compared against the one collected from the reflective markers. Major anthropometric measurements are summarized in Table 4.1. Figure 4.2 illustrates the experimental settings and the avatars from the respective systems.

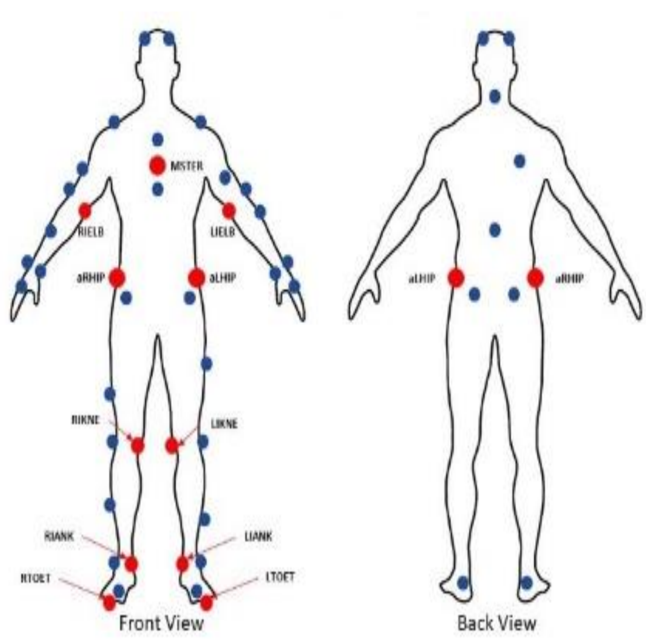

Fig 4.1. Adapted Plug-In Gait marker set.

Table 4.1. Summary of participants' anthropometry.

	Body weight (kg)	Body height (cm)	Shoe length (cm)	Ankle height (cm)	Ankle width (cm)	Knee height (cm)	Knee width (cm)	Elbow width (cm)	Shoulder width (cm)	Shoulder height (cm)	Hip height (cm)	Hip width (cm)	Arm span (cm)
Mean	72.78	173.54	25.06	8.72	7.92	46.96	10.84	8.42	34.28	142.05	90.88	24.53	172.09
SD	12.1	7.5	1.3	10.0	6.8	9.8	6.5	10.1	3.3	6.8	8.9	2.0	9.1

4.2.2 Systems Calibration

Standard procedures were used to calibrate the OMC and IMC systems. Segment calibration on the IMC system is necessary to align the motion trackers to the participants' segments. The procedure consisted of the participant holding a neutral posture for a few seconds, then walking straight forward and back to the point where they started. The OMC system was calibrated before each data collection session, defining the capture volume and the global coordinate system's orientation and origin.

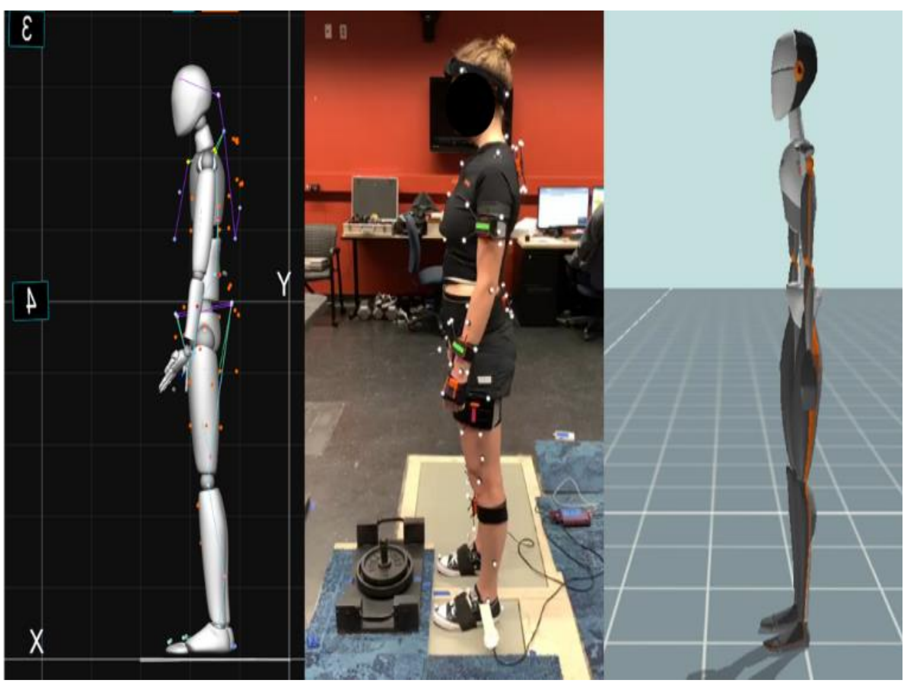

Fig 4.2. (Left) OMC model avatar, (Middle) Participant, (Right) IMC model avatar.

4.2.3 Musculoskeletal model

The biomechanical assessment was performed using a musculoskeletal modeling software, Anybody™ V.7.3.1 (AnyBody Technology, Aalborg, Denmark). The OMC-based template used for the analysis was the *Plug-in-gait Multitrial-StandingRef*. For the IMC system, the template used was the *BVH_Xsens*. The models were scaled according to the manually measured segment dimensions, which were inputted into the IMC software before initiating the data collection sessions. The BVH files from the Xsens software were exported containing information on the kinematic model static pose and the absolute position and orientation of the root pelvis segment as well as the joint angles between the segments for each time frame (Karatsidis et al., 2019). The Anybody Model Repository (AMR) used in this study to process BVH files is AMR v2.3.1. Compressive (proximo-distal, PD) and shear (antero-posterior, AP) forces were considered for the analysis. Medio-lateral (ML) shear forces were not considered due to their difference and smaller magnitude compared to the other two. The load lifted (box) was modeled in the software using the distance between the hands and the dimensions of the box as references, with the dimensions of the actual box being lifted (i.e., 10x25x40 cm).

4.2.4 Data Synchronization and Processing

Motion analysis was performed using the OMC and IMC systems simultaneously. OMC data was sampled at 120Hz, while IMC data was sampled at 60Hz. Forces and kinematics were bi-directionally low-pass filtered with a second-order Butterworth filter at 7 Hz for the forces system and 3 Hz for the kinematics. Gaps in the OMC markers' trajectory were filled using cubic interpolation methods in the Motive™ software. The force estimates for the OMC-based model were obtained using a top-down approach. In contrast, the IMC-based estimates were obtained through kinematics using the model utilized by Karatsidis et al. (2019).

4.2.5 Experimental Procedure

The 36 participants were instructed to perform different manual material handling tasks in a laboratory environment, where kinematic and kinetic data were collected. The duration of the trials varied from 10 to

30 seconds, depending on the participant. Each participant performed three trials with a 2-minute rest period between each other. Participants were instructed to lift boxes (similar to a standard milk crate) with handles consisting of three loads 10 lbs. (4.54 kg), 20 lbs. (9.07 kg), and 30 lbs. (13.61 kg) both symmetrically and asymmetrically (i.e., 0°, 30° and 60° degrees from sagittal to the left) to three different shelf heights (60 cm, 100 cm, and 140 cm). Each participant completed three different combinations, using a lifting technique of their preference. The tested combinations were labeled using the following terminology: LXX (XX = Load of 10, 20, or 30 lbs.), AYY (YY = Angle of 00-, 30- or 60-degrees asymmetry), and HZZ (ZZ = Height of 60, 100, or 140 cm.). For example, L20_A30_H140 would represent a 20-pound load, picked up from a sagittal angle of 30° and lifted to 140 centimeters. Loads and heights were randomized within levels of angle for 27 combinations (every combination was performed four times, resulting in 108 trials).

4.2.6 Measurements

L5-S1 compression and shear forces, flexion, lateral bending, rotation angles, and the distance between the joint and the box in X, Y, and Z axes were determined. These variables were measured in units of Newtons (N), degrees (°), and meters (m), respectively. The distance from the center of the L5-S1 joint was measured as indicated in Figure 4.3. The figure displays an example with the following coordinates (X_1, Z_1, Y_1) = (0.73, -0.31, -0.01), with X_1 = 0.73 m box in front of sacrum, Z_1 = 0.31 m box under sacrum, and Y_1 = 0.01 m box to the left of the sacrum

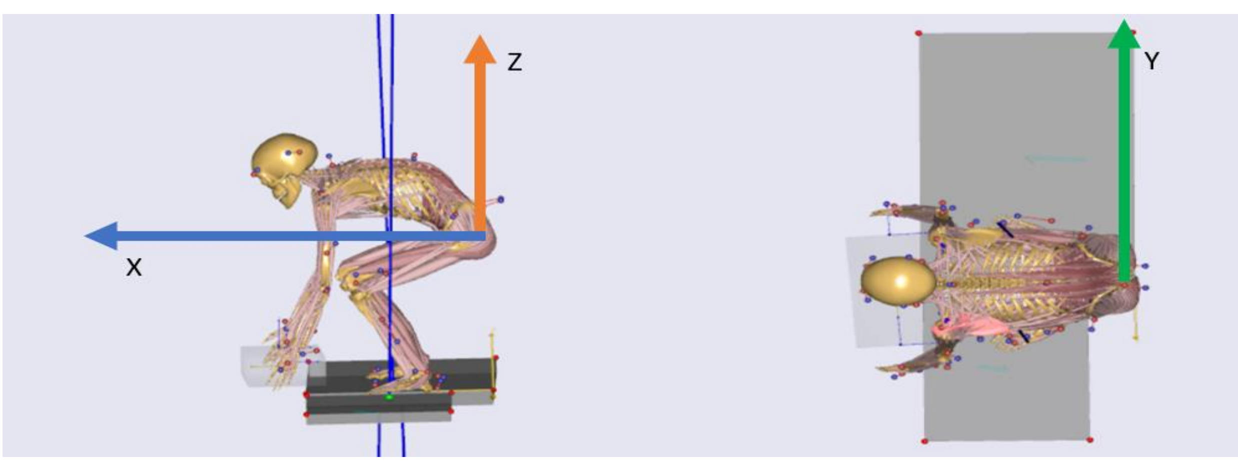

Fig 4.3. Distance of box to spine illustration from Plug-in-gait model template in Anybody™

4.2.7 Data Analysis

Boxplots, kernel density estimate (KDE) plots, simple linear regression analyses, and Bland-Altman plots were used to compare the level of agreement between systems. A 3^3 randomized block partially confounded design (RBPF) with blocks of size three was used to compare the ranges and the RMSE of the estimated moments. Confounded factorial designs are particularly appropriate if an interaction is expected to be negligible. The interactions can be confounded with groups, reducing block size without sacrificing power in evaluating the treatments (Kirk, 2014). Due to the nature of the experimental design technique, groups (four groups of nine participants each) and the main effects (Load, Angle, Height, and its possible interactions) were analyzed to find potentially significant differences. A type I error rate of 0.05 was used for all tests. Pairwise comparisons were performed using Tukey's test to analyze the RMSE and range for the main effects and interactions found as significant. Effect sizes were calculated to measure the strength of the relationship between variables. Omega-squared (ω^2) is recommended for complex designs with multiple variables (Kirk R. E., 1996). Statistical tests were conducted using Python.

4.3 Results

The results are divided into two main categories. First, descriptive statistics of compressive and anteroposterior shear forces, joint angles, and peak distances from the box to the spine are provided in Tables 4.2, 4.3, and 4.4. Second, are the experimental design (RBPF) results and post hoc analyses. Figure 4.4 shows an example of a full-duration trial considering the force estimates for the lifting and the lowering. The example corresponds to a female participant lifting a load of 10 lbs. (L10) with no asymmetry angle (A00) and a height of 1 m (H100).

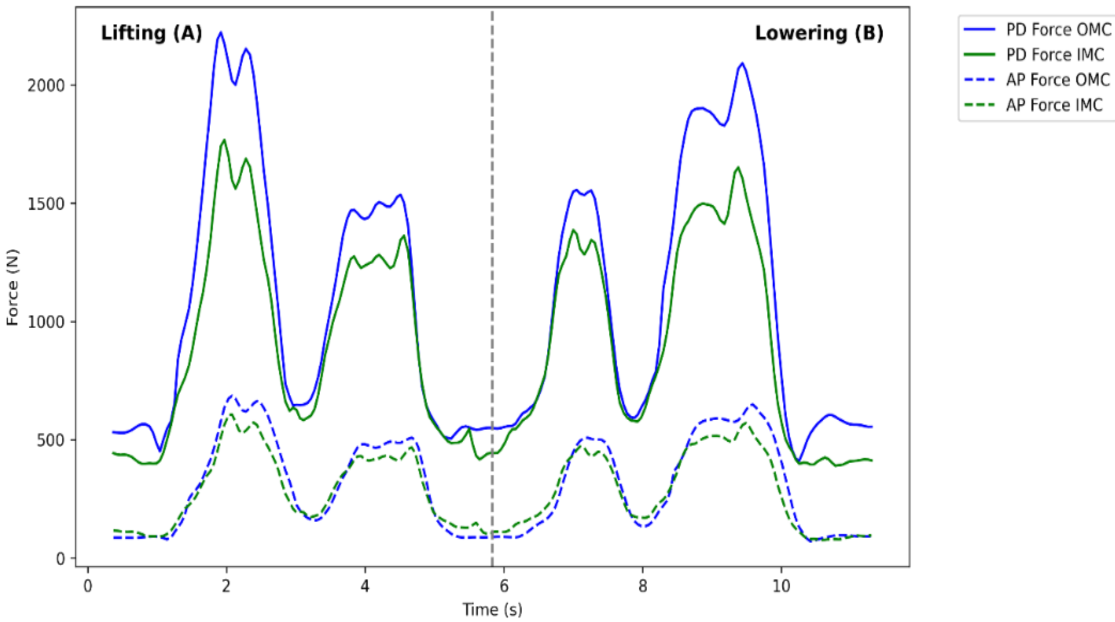

Figure 4.4. Compressive (PD) and Shear (AP) forces during one of the liftings (A) and lowering (B) trials.

Table 4.2. Summary of measures of the force estimates for both motion capture systems.

Summary measure	Peak OMC Lift	Peak IMC Lift	Peak OMC Lower	Peak IMC Lower	RMSE Lift	RMSE Low
Force PD (N)						
Mean	2798.52	1823.36	2644.29	1741.59	544.66	556.86
SD	666.71	433.61	614.82	391.68	156.83	161.03
Max	4864.02	3010.83	4262.28	2773.24	871.70	920.28
Min	1623.87	1063.77	1354.51	917.27	224.15	161.26
25th percentile	2279.24	1516.67	2214.72	1448.62	420.45	436.55
50th percentile	2708.36	1759.61	2628.07	1722.28	524.98	546.58
75th percentile	3195.15	2096.70	2963.76	1969.03	648.16	684.75
90th percentile	3651.78	2435.74	3524.45	2232.75	773.54	756.67
Force AP (N)						
Mean	944.99	653.22	898.91	624.99	147.83	154.68
SD	233.66	152.72	216.34	136.69	51.06	51.28
Max	1684.01	1103.53	1524.13	989.27	284.40	293.85
Min	532.51	393.01	485.71	354.05	47.06	39.49
25th percentile	770.15	549.01	742.61	532.08	109.62	121.24
50th percentile	920.16	627.84	887.49	600.62	144.97	149.71
75th percentile	1116.86	750.22	1032.33	715.50	178.16	187.52
90th percentile	1266.48	866.29	1214.76	807.75	223.52	225.44

Table 4.3. Summary of measures of the joint angles estimates for both motion capture systems.

Summary measure	Peak OMC Lift	Peak IMC Lift	Peak OMC Lower	Peak IMC Lower	RMSE Lift	RMSE Lower
Joint Angles (Degrees)						
Flexion/Extension Angle						
Mean	62.62	44.64	63.68	46.52	10.92	11.19
SD	10.64	10.34	11.28	10.62	4.79	4.90
Max	81.91	63.47	86.57	65.02	28.18	28.55
Min	39.77	16.27	36.93	15.53	3.73	2.45
25th percentile	54.40	37.83	57.38	39.22	7.07	7.53
50th percentile	64.29	46.02	64.86	47.55	10.21	10.69
75th percentile	71.76	52.30	72.32	54.09	13.14	12.99
90th percentile	74.77	56.94	75.27	60.14	16.86	18.14
Lateral Bending Angle						
Mean	9.88	8.90	9.95	8.45	4.19	4.16
SD	5.11	4.09	4.76	3.86	2.12	2.16
Max	27.83	20.81	25.61	18.27	11.42	11.33
Min	3.08	2.61	3.03	2.57	1.04	0.93
25th percentile	6.56	5.66	6.62	5.59	2.75	2.61
50th percentile	8.78	8.24	9.08	8.22	3.70	3.74
75th percentile	10.96	11.18	11.63	10.41	5.01	5.17
90th percentile	16.94	15.12	16.33	13.93	7.21	7.24
Rotation Angle						
Mean	9.11	14.62	8.76	14.95	5.93	6.07
SD	4.41	6.51	4.23	7.21	3.19	2.97
Max	22.24	36.44	23.04	35.78	16.31	13.86
Min	2.23	4.91	2.56	3.77	0.95	1.02
25th percentile	6.11	9.80	5.46	9.21	3.61	3.93
50th percentile	7.74	14.01	7.80	13.45	5.05	5.65
75th percentile	11.51	18.80	11.41	19.16	7.54	7.77
90th percentile	14.58	22.09	14.58	23.88	9.67	10.22

4.3.1 Descriptive results

4.3.1.1 Compressive Forces

The compressive force estimates varied significantly between systems, as shown in Table 4.2. The OMC results were between 1,000 to 1,800 N higher than the IMC estimates. Figure 4.5 shows the resultant box plots with the force estimates, where a difference increases as observed forces increase. The KDE plots display the distribution of observations, shown in Figure 4.6. Due to the comparison of distribution shapes, it is noticeable that the OMC estimates showed a wider range of values than the IMC estimates for both lifting and lowering scenarios. Figure 4.7 presents the Bland-Altman plots, highlighting a trend wherein increases in the magnitude of the force estimates increase the differences in agreement between systems.

Table 4.4. Summary of the differences in peak distance estimates for both motion capture systems.

Summary measure	X OMC - IMC Lift	Z OMC - IMC Lift	Y OMC - IMC Lift	X OMC - IMC Lower	Z OMC - IMC Lower	Y OMC - IMC Lower
Differences of Spine to load distance (m)						
Mean	0.08	0.12	0.03	0.08	0.13	0.04
SD	0.05	0.07	0.03	0.05	0.07	0.04
Max	0.27	0.34	0.17	0.28	0.35	0.17
Min	0.00	0.00	0.00	0.00	0.00	0.00
25th percentile	0.04	0.07	0.01	0.04	0.07	0.01
50th percentile	0.07	0.11	0.03	0.07	0.12	0.03
75th percentile	0.11	0.16	0.04	0.11	0.17	0.05
90th percentile	0.15	0.21	0.07	0.15	0.22	0.08

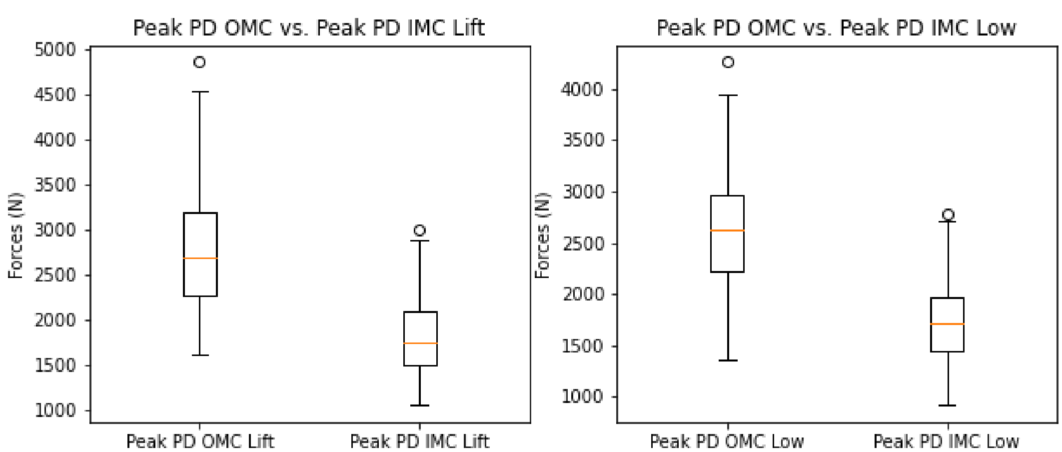

Figure 4.5. Box plots for peak compressive force for the OMC and IMC systems for the lifting and lowering tasks.

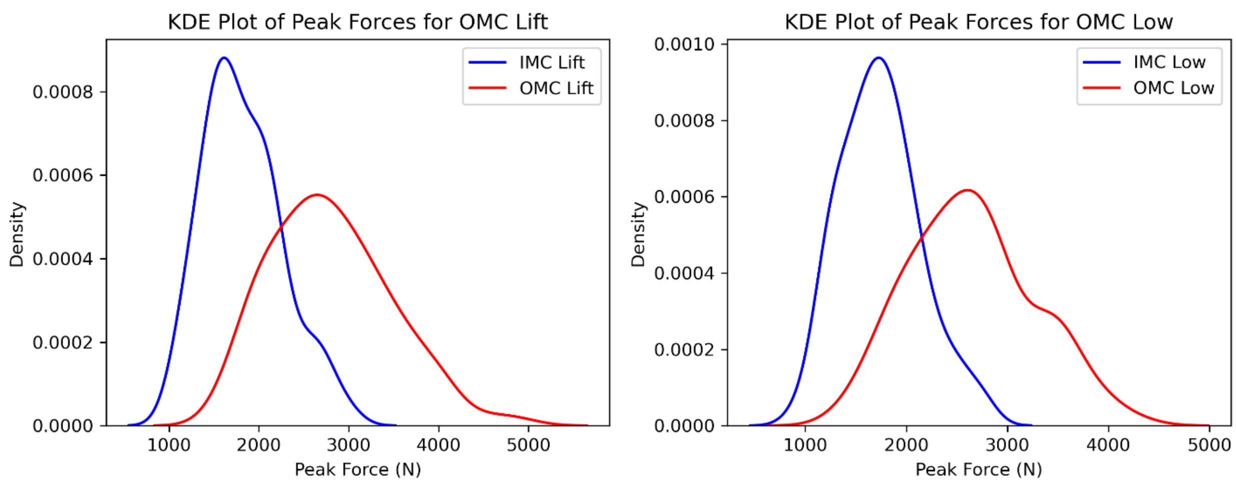

Figure 4.6. KDE plots for peak compressive force for the OMC and IMC systems for the lifting and lowering tasks.

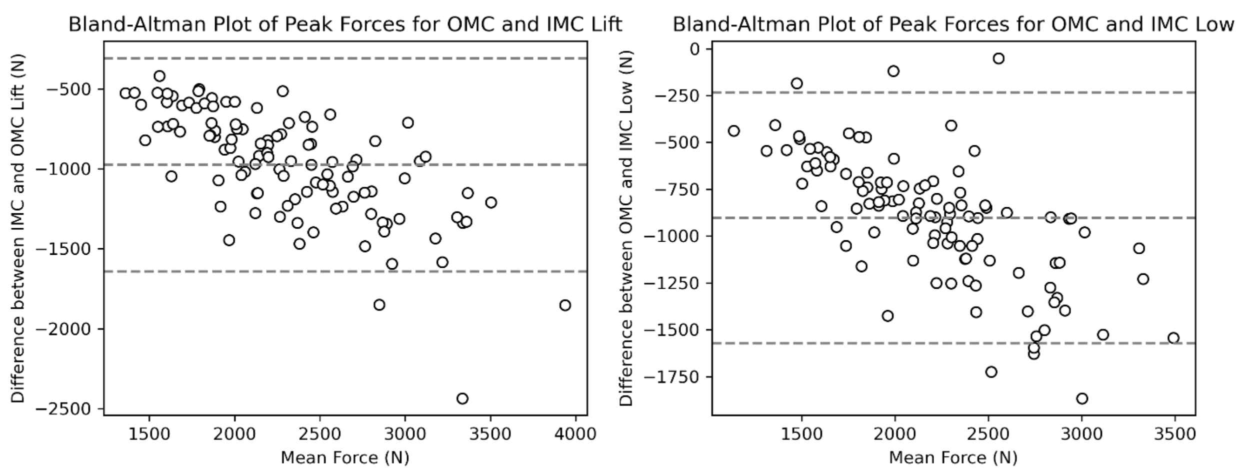

Figure 4.7. Bland-Altman plots for OMC and IMC system peak compressive force estimates for lifting and lowering tasks.

The simple linear regression analysis for the tasks is shown in Figure 4.8. For the lifting task, the regression line equation suggests a multiplication of 1.37 (95% CI: 1.24 – 1.51) and 1.35 (95% CI: 1.20 – 1.51), respectively, for the force estimates with 293.66 (95% CI: 293.52 – 293.79), and 289.03 N (95% CI: 288.88 – 289.18) added as the intercepts.

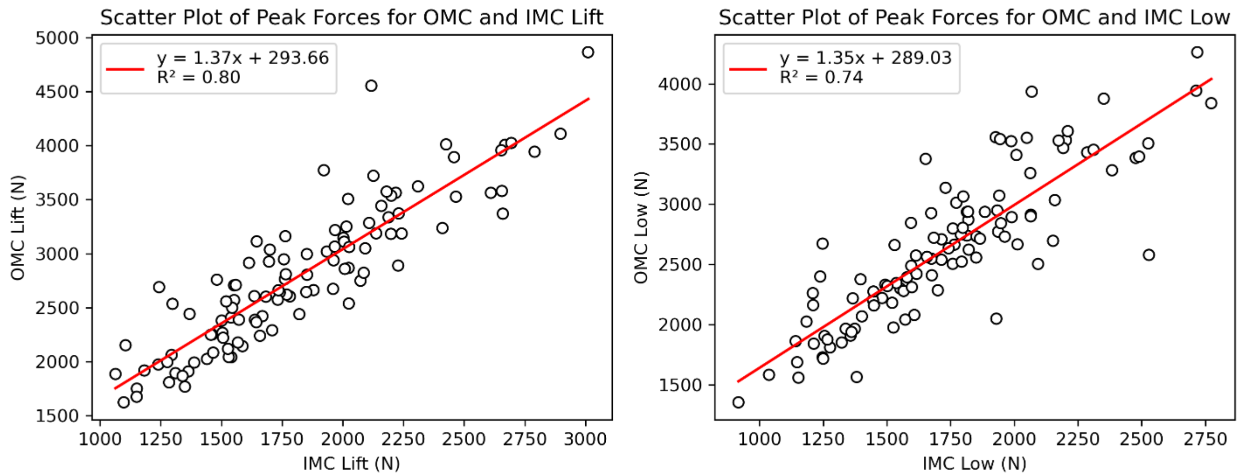

Figure 4.8. Scatter plots of peak compressive forces between systems for the lifting and lowering tasks.

The RMSE of the compressive forces for the time series data for all observations is shown in Figure 4.9 and Figure 4.10. The RMSE varied mainly between 420 N to 756 N (25th to 90th percentiles) for the lifting and lowering tasks.

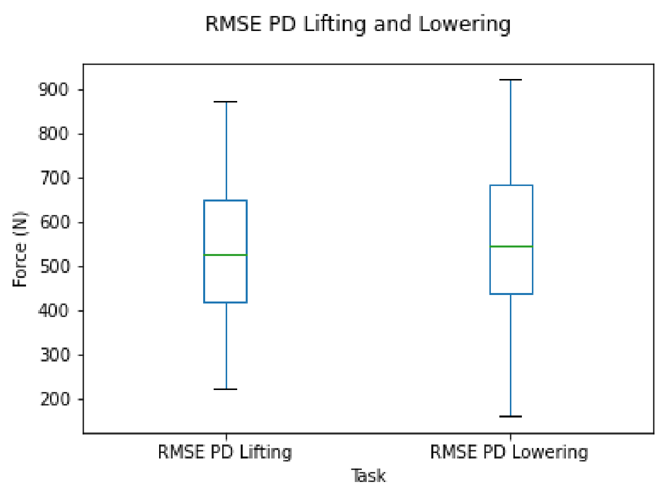

Figure 4.9. Box plots for the RMSE of the compressive force for the OMC and IMC systems for the lifting and lowering tasks.

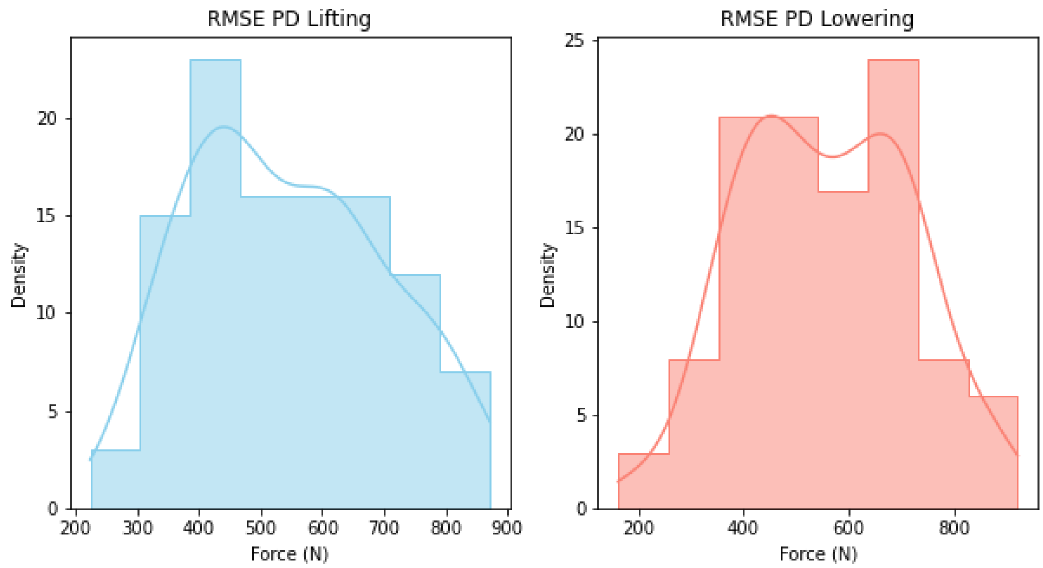

Figure 4.10. Histograms of the compressive force for the OMC and IMC systems for the lifting and lowering tasks.

The peak compressive force differences were also calculated, mostly between 696 N to 1397 N, with most observations being between the 25th and the 90th percentile, as seen in Figure 4.11.

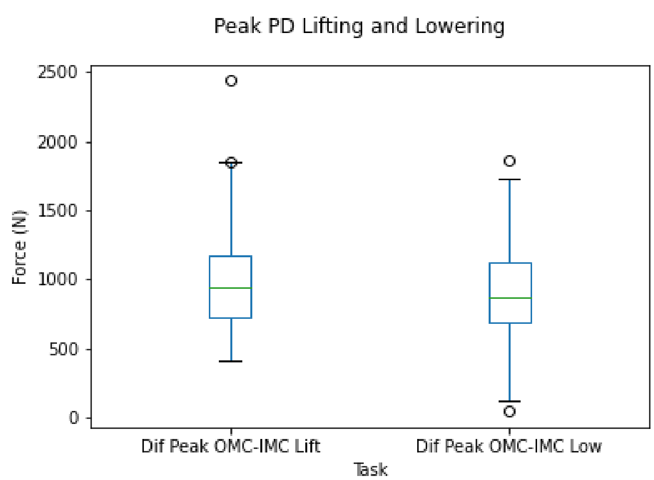

Figure 4.11. Peak compressive force differences between systems for every pair of observations.

4.3.1.2 Shear Forces

As with the compressive forces, the shear forces exhibited significant variation between systems. The maximum peak shear force observed was around 1,600 N in the OMC system, while the IMC system had a maximum peak shear force of 1,200 N for both lifting and lowering tasks, respectively. Differences between 200 to 400 N were observed for the values between the 25th and 90th percentiles. Figure 4.12 displays the shear force estimates for each system, with noticeable differences between the estimates, especially at the higher end of the observed forces. Additionally, the probability density functions for the observations displayed in the KDE plots (Figure 4.13) show a similar situation to the one observed for the compressive forces, with the OMC estimates having a wider range of values and generally higher estimates than the IMC-based estimates. As for the compressive force estimates, the Bland-Altman plots in Figure 4.14 reveal noticeable differences between the observations for the shear forces, highlighting the trend of higher differences with higher force estimates.

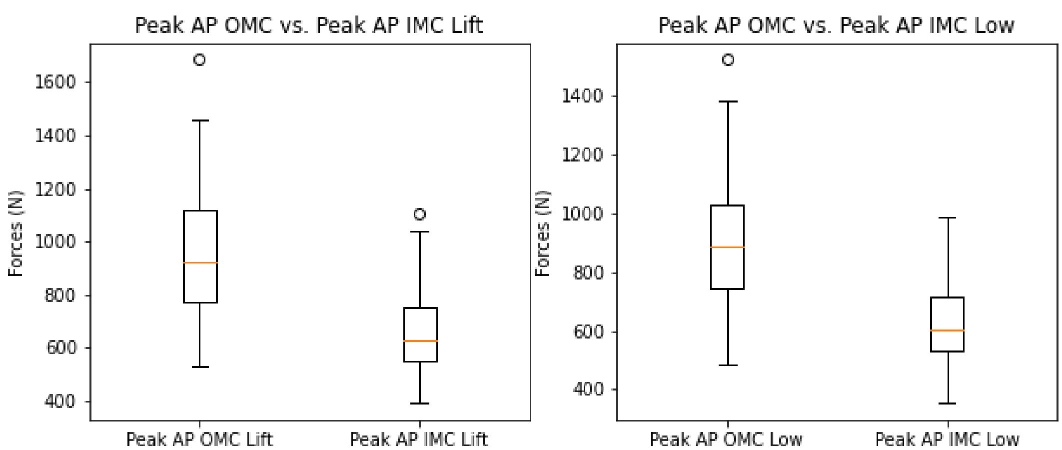

Figure 4.12. Box plots for peak shear force for the OMC and IMC systems for the lifting and lowering tasks.

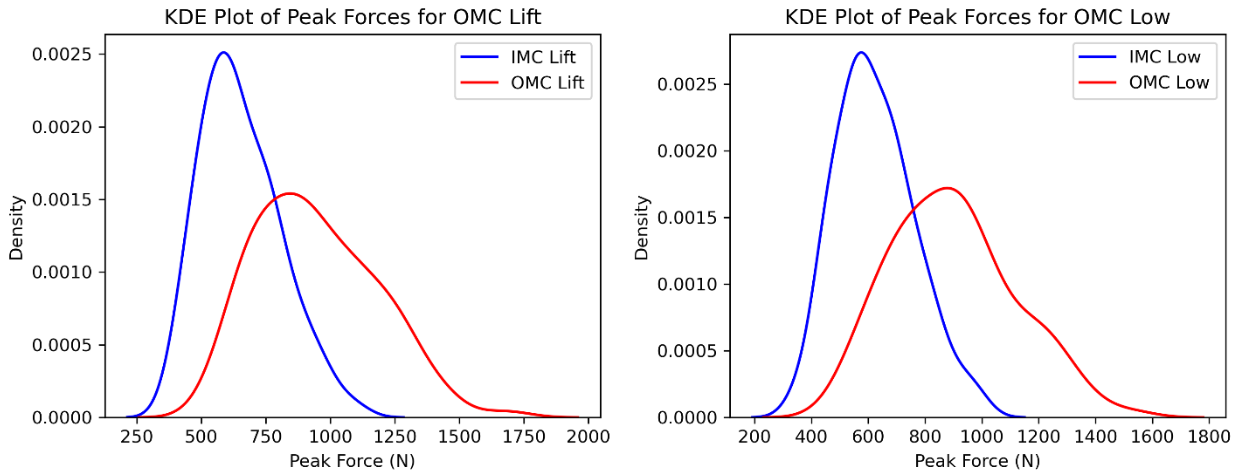

Figure 4.13. KDE plots for peak shear force for the OMC and IMC systems for the lifting and lowering tasks.

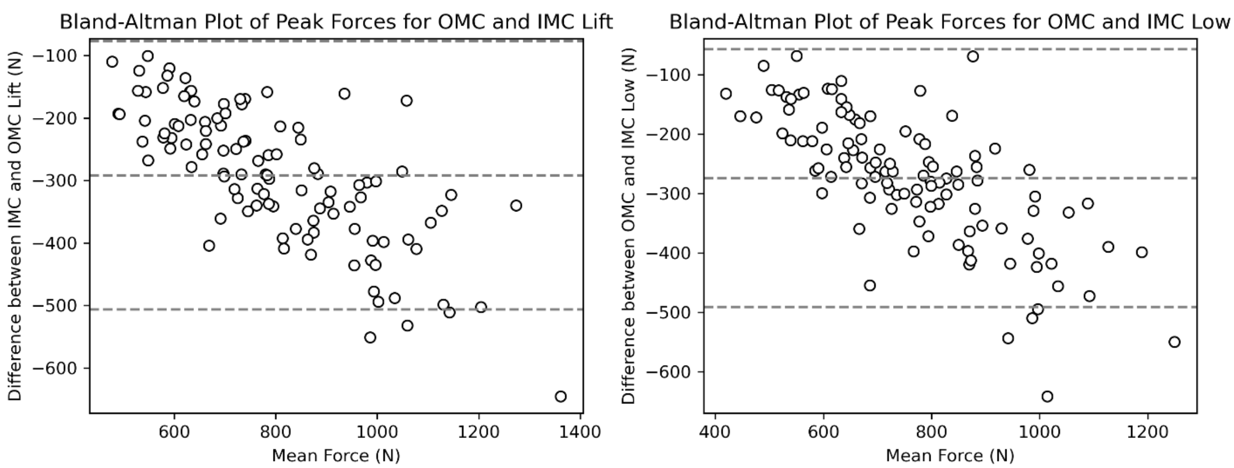

Figure 4.14. Bland-Altman plots for OMC and IMC system shear force estimates for lifting and lowering tasks.

Figure 4.15 displays the results of the simple linear regression analysis for the tasks. For the lifting task, the regression line equation suggests a slope of 1.41 (95% CI: 1.30 – 1.53) and 1.42 (95% CI: 1.29 – 1.56) for the force estimates. The intercepts were 21.40 N (95% CI: 21.29 – 21.52) and 8.87 N (95% CI: 8.74 – 9.00).

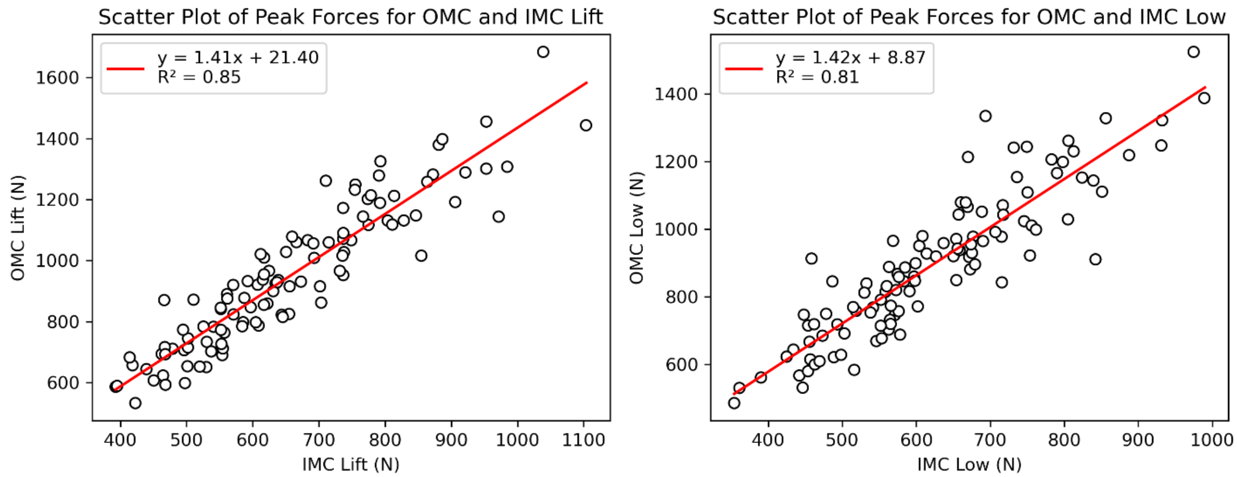

Figure 4.15. Scatter plots of peak shear forces between systems for the lifting and lowering tasks.

The RMSE of the shear forces for the time series data for all observations is shown in Figure 4.16 and Figure 4.17. The RMSE varied mainly between 109 N to 225N (25th to 90th percentiles) for the lifting and lowering tasks.

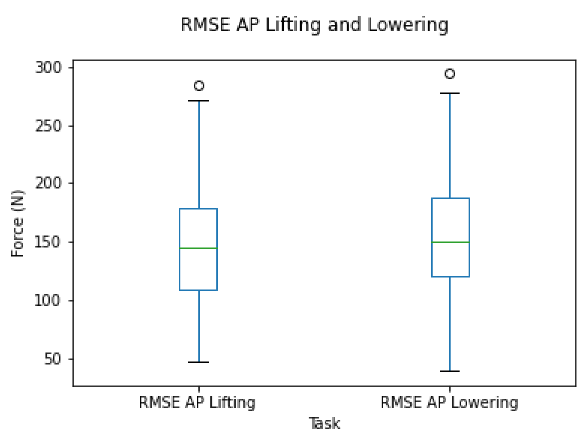

Figure 4.16. Box plots for the RMSE of the shear force for the OMC and IMC systems for the lifting and lowering tasks.

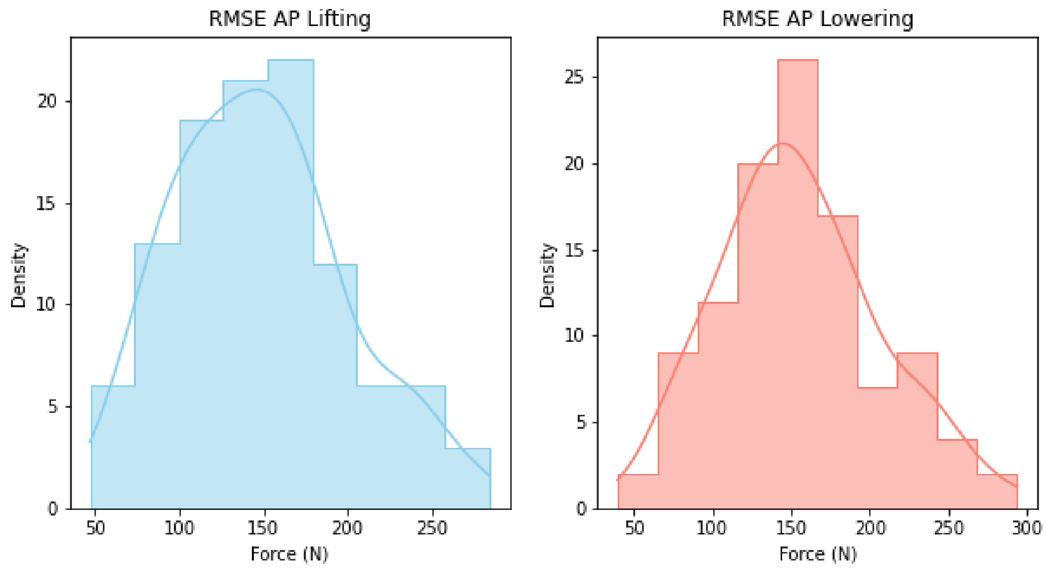

Figure 4.17. Histograms of the shear force for the OMC and IMC systems for the lifting and lowering tasks.

The peak shear force differences were also calculated, mostly between 205 N to 435 N, with most observations being between the 25th and 90th percentile, as seen in Figure 4.18.

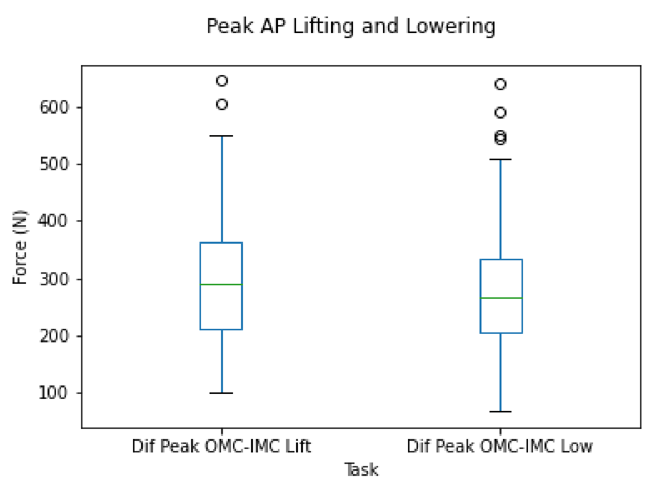

Figure 4.18. Peak shear force differences between systems for every pair of observations.

4.3.2 Joint Angles

4.3.2.1 Flexion

The peak flexion angle comparison for every system showed that the OMC-based estimates were higher than the IMC-based by around 14 to 18 degrees. Figures 19 and 20 display the differences observed. Figure 4.21 shows the Bland-Altman plots where it is displayed that the mean differences are 17,9 and 17,1 degrees for the lifting and the lowering tasks, respectively.

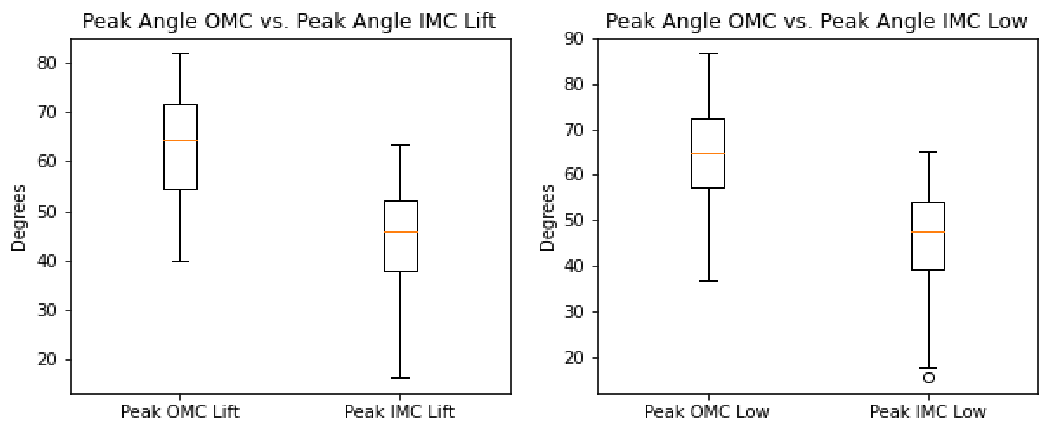

Figure 4.19. Box plots of the peak flexion angle for the OMC and IMC systems for the lifting and lowering tasks.

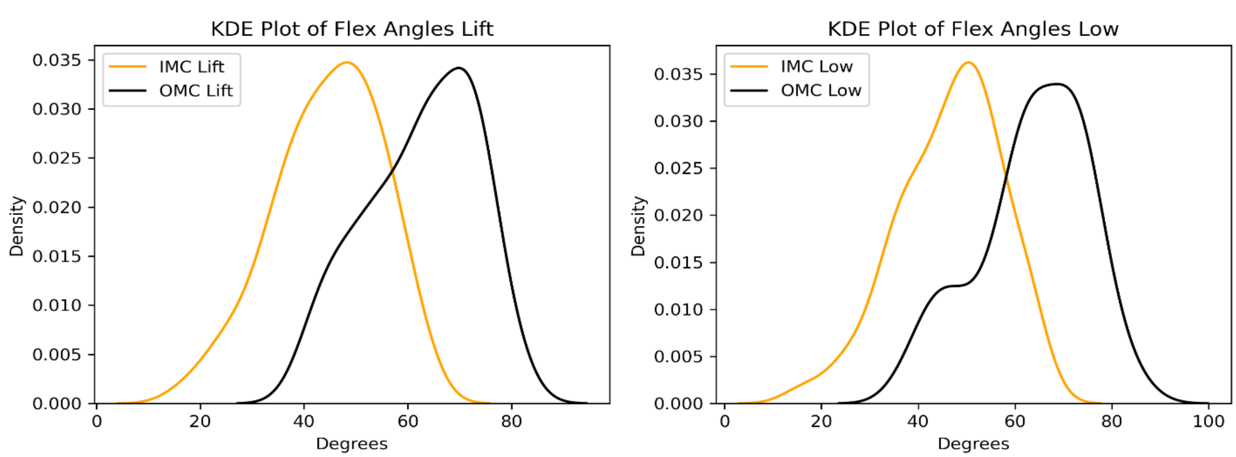

Figure 4.20. KDE plots of the peak flexion angle for the OMC and IMC systems for the lifting and lowering tasks.

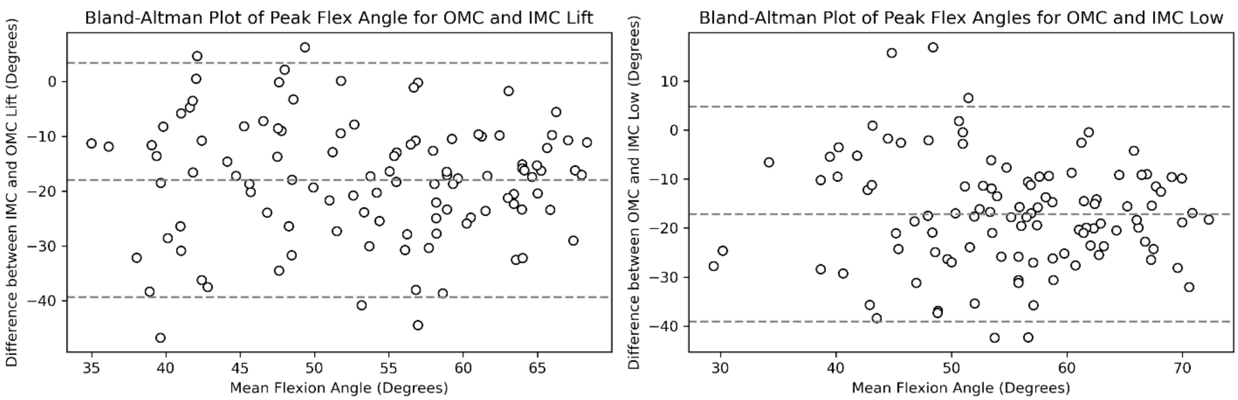

Figure 4.21. Bland-Altman plots for OMC and IMC system peak flexion angle estimates for lifting and lowering tasks.

The root mean square error (RMSE) of the flexion angle for the entire time series dataset is displayed in Figure 4.22. The RMSE ranged from 2.45 to 28.54 degrees for both the lifting and lowering tasks, with most values falling between the 25th and 75th percentiles (7.06 to 13.13 degrees).

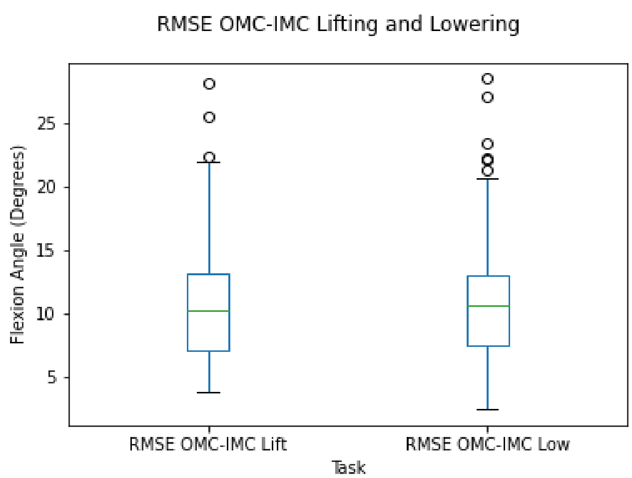

Figure 4.22. Box plots for the RMSE of the flexion angle for the OMC and IMC systems for the lifting and lowering tasks.

4.3.2.2 Lateral Bending

The comparison of peak lateral bending angles across the different systems revealed that estimates based on the OMC and IMC methods were generally similar, with median values of approximately 8.5

degrees falling within the interquartile range for all scenarios. However, the OMC-based estimates were higher than those of the IMC system for the lifting and lowering tasks. The observed differences are illustrated in Figures 4.23 and 4.24. Bland-Altman plots were generated and displayed in Figure 4.25. The plots indicate that the mean differences in peak lateral bending angles between the two systems were approximately -1 degrees for the lifting and lowering tasks.

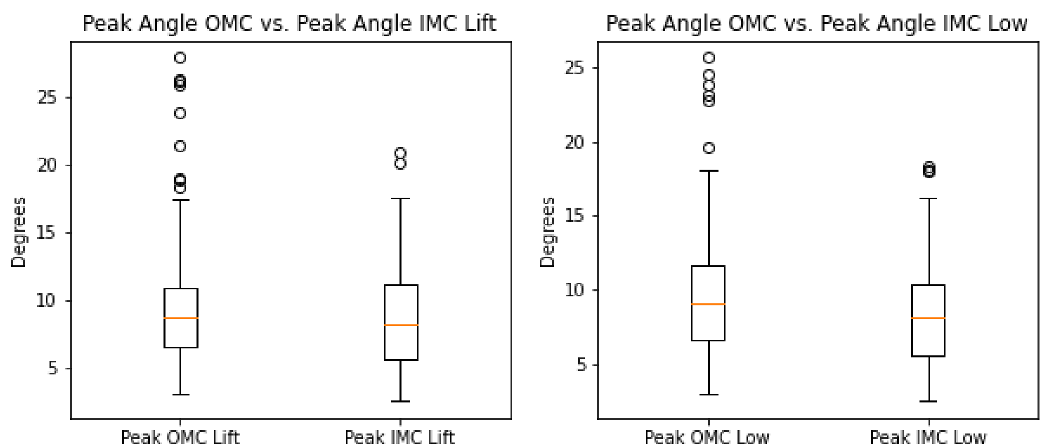

Figure 4.23. Box plots of the peak lateral bending angle for the OMC and IMC systems for the lifting and lowering tasks.

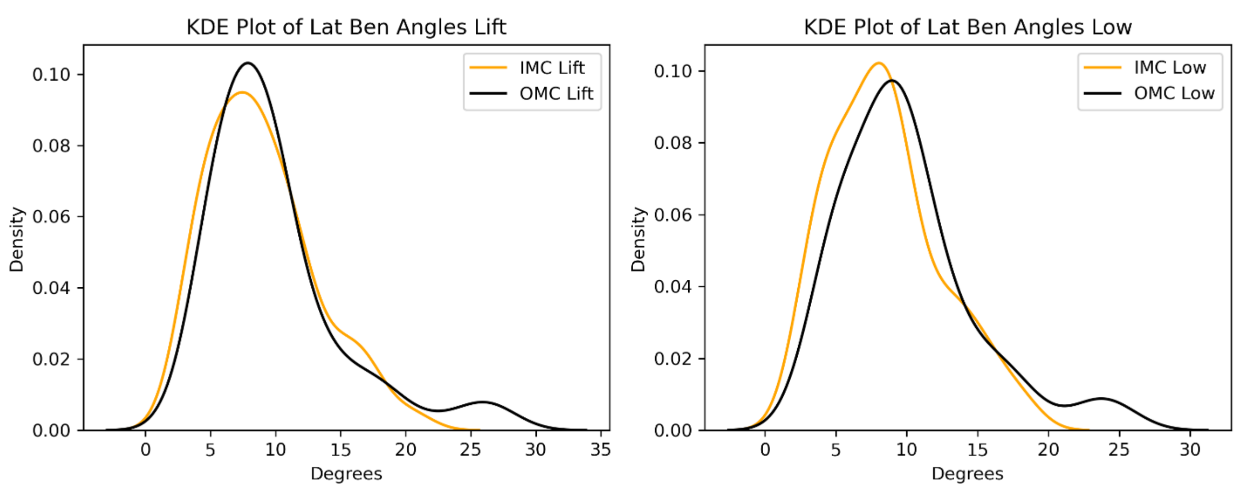

Figure 4.24. KDE plots of the peak lateral bending angle for the OMC and IMC systems for the lifting and lowering tasks.

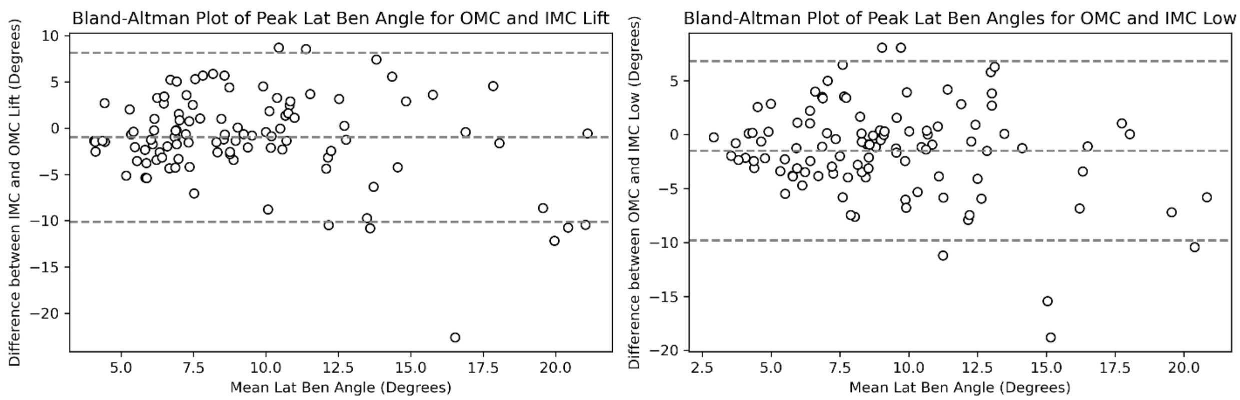

Figure 4.25. Bland-Altman plots for OMC and IMC system peak lateral bending angle estimates for lifting and lowering tasks.

Figure 4.26 illustrates the root mean square error (RMSE) of the lateral bending angle for the trials. In the lifting and lowering tasks, the RMSE ranged from 0.92 to 11.42 degrees, with values between the 25th and 75th percentiles ranging from 3.79 to 5.16 degrees.

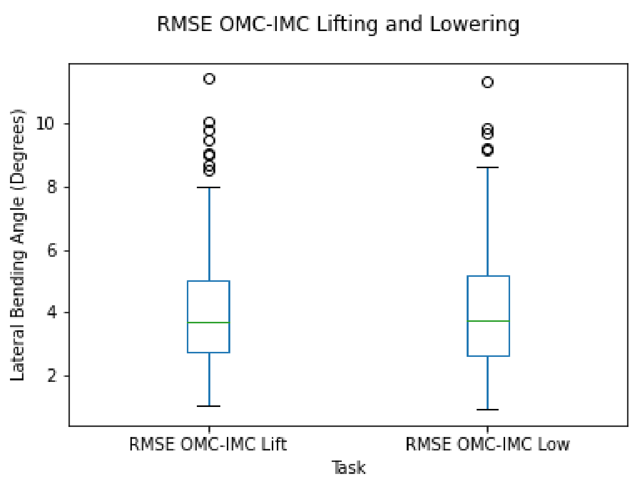

Figure 4.26. Box plots for the RMSE of the lateral bending angle for the OMC and IMC systems for the lifting and lowering tasks.

4.3.2.3 Rotation

In terms of peak rotation angles, the comparison between the OMC and IMC methods showed that the IMC estimates were generally higher for the lifting and lowering tasks, with median values of approximately 7.74 and 13.44 degrees, respectively. These differences are illustrated in Figures 4.27 and 4.28. Bland-Altman plots were generated and displayed in Figure 4.29 to assess the agreement between the two systems. The plots reveal that the mean differences in peak rotation angles between the OMC and IMC systems were 5.51 degrees (limits of agreement: -5.65, 16.67) for the lifting task and 6.19 degrees (limits of agreement: -5.98, 18.35) for the lowering task.

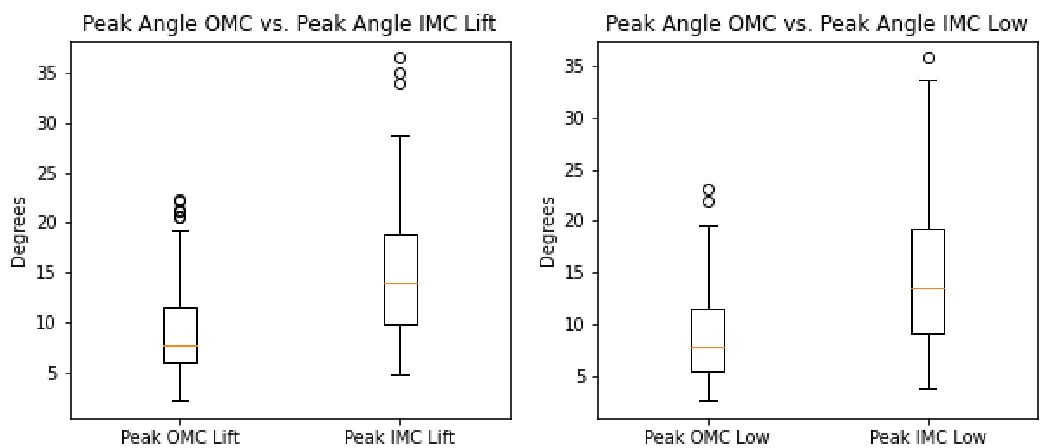

Figure 4.27. Box plots of the peak rotation angle for the OMC and IMC systems for the lifting and lowering tasks.

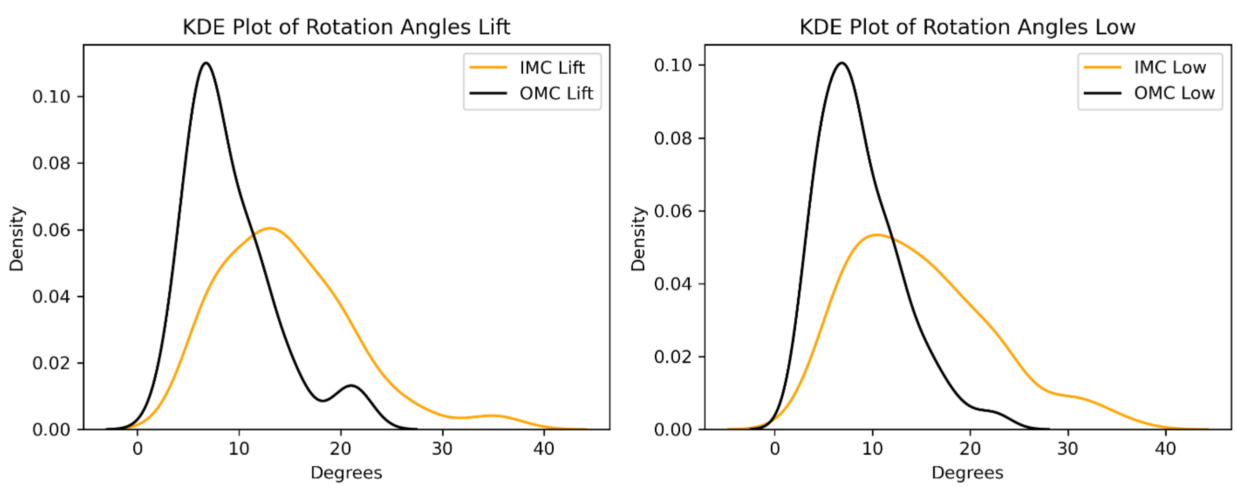

Figure 4.28. KDE plots of the peak rotation angle for the OMC and IMC systems for the lifting and lowering tasks.

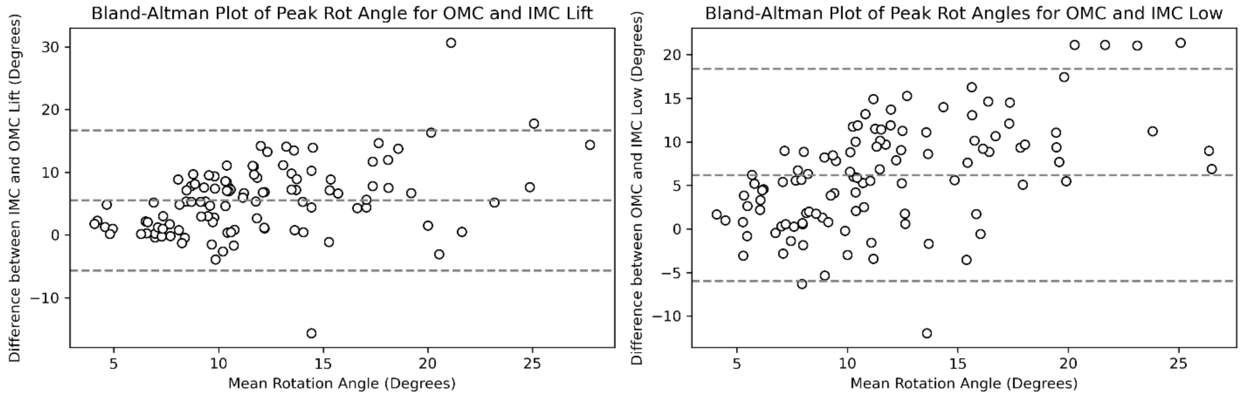

Figure 4.29. Bland-Altman plots for OMC and IMC system peak rotation angle estimates for lifting and lowering tasks.

The RMSE of the rotation angle for the trials is presented in Figure 4.30. The lifting and lowering tasks had RMSE values ranging from 0.94 to 16.31 degrees, with the 25th to 75th percentile values ranging from 3.61 to 7.77 degrees.

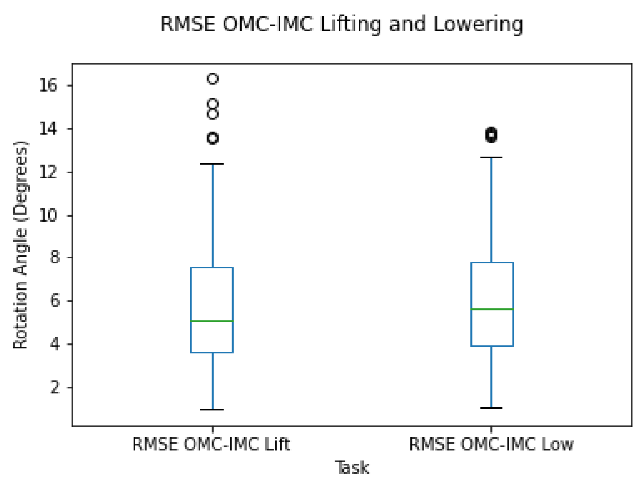

Figure 4.30. Box plots for the RMSE of the rotation angle for the OMC and IMC systems for the lifting and lowering tasks.

4.3.2.4 Distance from the spine to the load

The distance between the spine and the load was analyzed in the X, Y, and Z axes. The results are presented in Figure 4.31. The mean peak distance difference was 7.90 cm for the lifting task and 7.93 cm for the lowering task in the X-axis, with a range of 0 to 27.94 cm. The mean peak distance difference in the Z-axis was higher, with 11.51 cm for the lifting task and 12.53 cm for the lowering task, and a range of 0.1 to 34.80 cm. The Y-axis showed smaller differences, with a mean of 3.41 cm for the lifting task and 3.71 cm for the lowering task, and a range of 0 to 17.34 cm.

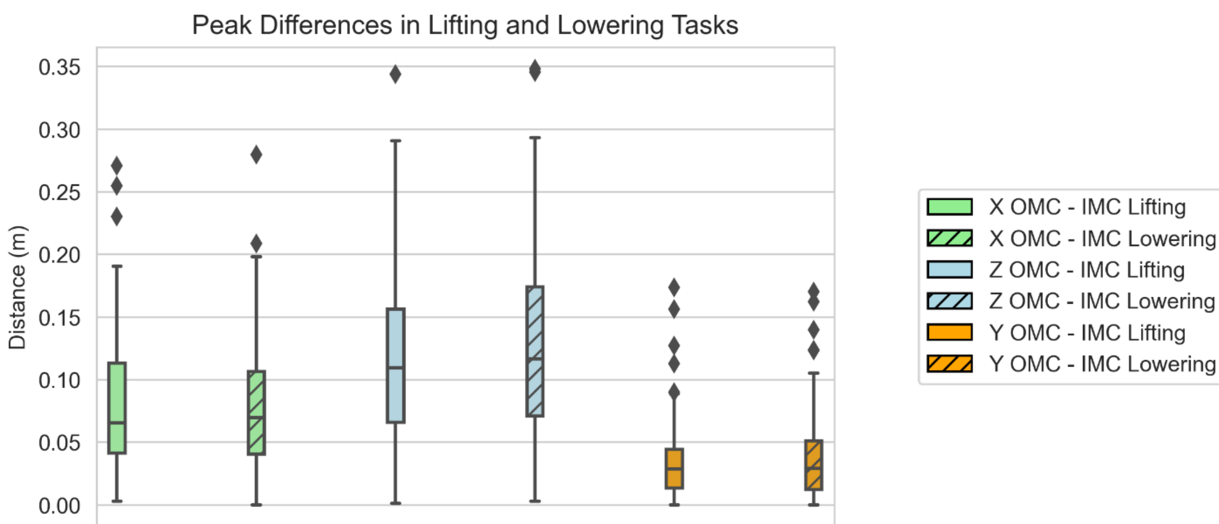

Figure 4.31. Box plots for the peak distance differences from the center of the L5-S1 joint to the lifted object for the lifting and lowering tasks.

4.3.3 ANOVA results

The RBPF 3^3 ANOVA results are divided into forces and joint angles. The analyses compared the peaks (forces and angles), RMSE, and peak differences for the lifting and lowering tasks. The summary of the forces on the analysis of the effect of load's weight, height, and asymmetry and their potential interactions are displayed in Tables 4.5 and 4.6.

4.3.3.1 Compressive Forces

The statistical analysis revealed significant differences between the participant groups across all scenarios, as presented in Table 6. Furthermore, among the three main factors investigated, the load was significant for the individual peaks, the RMSE, and the peak differences between systems in both the lifting and lowering tasks. Post hoc tests using Tukey's method demonstrated significant differences between all load levels, with the greatest difference observed between L10 and L30. Additionally, height was found to be a significant factor for the estimates of RMSE in both tasks, with H60 showing significant differences from H100 and H140. The observed trends were consistent across both lifting and lowering tasks.

4.3.3.2 Shear Forces

The trends observed for the shear forces were similar to those for the compressive forces. The groups and load factors were significant for all estimates in both task scenarios. Moreover, the RMSE for the lifting and lowering tasks had height as a significant factor, with H60 showing significant differences from H100 and H140 in both cases. A notable difference between the two force types was observed in the Peak IMC estimate for the lifting task, where an interaction effect between Load and Height was significant ($p=0.047$), indicating that a higher load and height level led to higher shear force estimates, however, the effect size was small ($\omega^2 = 0.035$).

4.3.4 Joint Angles

The summary of the ANOVA results for the joint angles is shown in Tables 4.7 and 4.8.

4.3.4.1 Flexion/Extension

The flexion/extension angle analysis revealed significant differences between groups for both systems. The lifting task also showed significant effects for Load on the peak IMC ($p=0.028$) and Angle on the peak OMC ($p=0.003$) and IMC ($p=0.014$), with increasing flexion values as the Angle increased, and A00 being significantly different from A60. However, Angle did not affect any of the peaks for the lowering task, but Height did for the Peak IMC ($p=0.017$), with H100 significantly different from H140. The RMSE for both tasks did not show significant differences. Although peak differences did not significantly affect the lifting task, a significant effect of Height was observed for the lowering task ($p=0.002$). Tukey's test indicated that H140 was significantly different from H060 and H100.

Table 4.6. ANOVA results testing the effects of Loads (A), Angle (B), Height (C), and interactions for the compressive and shear forces at L5/S1 during the lifting tasks. Significant effects ($p < 0.05$) are indicated in ***bold/italics.*** Large effect sizes ($\omega^2 > 0.14$) are indicated in **bold**.

Lifting	Peak OMC		Peak IMC		RMSE		Peak Dif	
Factors (df)	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2
Force PD								
Groups (3)	***<0.001***	**0.544**	***<0.001***	**0.551**	***0.049***	0.138	***0.005***	**0.262**
A - Load (2)	***<0.001***	**0.938**	***<0.001***	**0.873**	***<0.001***	**0.614**	***<0.001***	**0.767**
B - Angle (2)	0.117	0.007	0.280	0.002	0.216	0.005	0.121	0.021
C - Height (2)	0.499	-0.002	0.994	-0.008	***<0.001***	**0.234**	0.383	0.000
A*B (4)	0.570	-0.003	0.062	0.022	0.146	0.014	0.120	0.032
A*C (4)	0.974	-0.010	0.122	0.014	0.258	0.007	0.496	-0.005
B*C (4)	0.404	0.000	0.802	-0.009	0.144	0.014	0.570	-0.009
A*B*C (8)	0.819	-0.011	0.420	0.001	0.639	-0.009	0.874	-0.037
Force AP								
Groups (3)	***<0.001***	**0.518**	***<0.001***	**0.477**	***0.017***	**0.197**	***<0.001***	**0.397**
A - Load (2)	***<0.001***	**0.916**	***<0.001***	**0.868**	***<0.001***	**0.576**	***<0.001***	**0.576**
B - Angle (2)	0.399	0.000	0.814	-0.009	0.155	0.010	0.079	0.041
C - Height (2)	0.282	0.002	0.994	-0.011	***<0.001***	**0.259**	0.121	0.029
A*B (4)	0.864	-0.009	0.764	-0.012	0.574	-0.006	0.984	-0.044
A*C (4)	0.827	-0.009	***0.047***	0.035	0.220	0.011	0.172	0.033
B*C (4)	0.099	0.015	0.385	0.001	0.277	0.007	0.362	0.006
A*B*C (8)	0.636	-0.006	0.796	-0.018	0.528	-0.005	0.252	0.032

Table 4.7. ANOVA results testing the effects of Loads (A), Angle (B), Height (C), and interactions for the compressive and shear forces at L5/S1 during the lowering tasks. Significant effects ($p < 0.05$) are indicated in ***bold/italics.*** Large effect sizes ($\omega^2 > 0.14$) are indicated in **bold**.

Lowering	Peak OMC		Peak IMC		RMSE		Peak Dif	
Factors	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2
Force PD								
Groups (3)	***<0.001***	**0.475**	***<0.001***	**0.427**	***0.011***	**0.217**	***0.020***	**0.187**
A - Load (2)	***<0.001***	**0.826**	***<0.001***	**0.934**	***<0.001***	**0.630**	***<0.001***	**0.836**
B - Angle (2)	0.269	0.004	0.586	-0.002	0.454	-0.002	0.922	-0.020
C - Height (2)	0.848	-0.010	0.688	-0.003	***<0.001***	0.125	0.926	-0.020
A*B (4)	0.274	0.008	0.077	0.012	0.051	0.035	0.236	0.019
A*C (4)	0.541	-0.005	0.370	0.001	0.249	0.009	0.936	-0.034
B*C (4)	0.695	-0.011	0.349	0.001	0.078	0.028	0.860	-0.029
A*B*C (8)	0.183	0.024	0.721	-0.006	0.180	0.023	0.848	-0.043
Force AP								
Groups (3)	***<0.001***	**0.457**	***<0.001***	**0.428**	***0.002***	**0.296**	***<0.001***	**0.386**
A - Load (2)	***<0.001***	**0.928**	***<0.001***	**0.875**	***<0.001***	**0.628**	***<0.001***	**0.698**
B - Angle (2)	0.655	-0.004	0.518	-0.004	0.604	-0.007	0.758	-0.029
C - Height (2)	0.574	-0.003	0.861	-0.010	***0.001***	0.104	0.913	-0.037
A*B (4)	0.250	0.005	0.356	0.003	0.377	0.002	0.757	-0.043
A*C (4)	0.364	0.001	0.576	-0.006	0.121	0.025	0.720	-0.039
B*C (4)	0.316	0.003	0.407	0.000	0.078	0.033	0.766	-0.044
A*B*C (8)	0.913	-0.015	0.669	-0.013	0.143	0.034	0.712	-0.053

Table 4.8. ANOVA results testing the effects of Loads (A), Angle (B), Height (C), and interactions for joint angles during the lifting tasks.

Significant effects ($p < 0.05$) are indicated in ***bold/italics.*** Large effect sizes ($\omega^2 > 0.14$) are indicated in **bold**.

Lifting	Peak OMC		Peak IMC		RMSE		Peak Dif	
Factors (df)	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2
Flexion/Extension								
Groups (3)	***<0.001***	**0.392**	***<0.001***	0.369	0.546	-0.024	0.783	-0.056
A - Load (2)	0.063	0.091	***0.028***	0.127	0.675	-0.052	0.886	-0.087
B - Angle (2)	***0.003***	**0.261**	***0.014***	0.163	0.578	-0.038	0.803	-0.077
C - Height (2)	0.435	-0.007	0.051	0.096	0.994	-0.085	0.449	-0.018
A*B (4)	0.385	0.006	0.880	-0.062	0.279	0.054	0.222	0.096
A*C (4)	0.676	-0.039	0.288	0.026	0.346	0.025	0.477	-0.022
B*C (4)	0.250	0.037	0.557	-0.021	0.455	-0.012	0.811	-0.119
A*B*C (8)	0.378	0.020	0.211	0.075	0.564	-0.051	0.661	-0.105
Lateral Bending								
Groups (3)	0.140	0.074	0.674	-0.042	0.776	-0.056	0.251	0.035
A - Load (2)	0.093	0.039	0.733	-0.015	0.339	0.013	0.108	0.080
B - Angle (2)	***<0.001***	**0.626**	***<0.001***	**0.731**	0.715	-0.079	0.804	-0.047
C - Height (2)	0.549	-0.010	0.979	-0.021	0.493	-0.033	0.574	-0.026
A*B (4)	0.415	0.000	0.455	-0.003	0.578	-0.065	0.132	0.104
A*C (4)	0.142	0.042	0.680	-0.019	0.933	-0.188	0.184	0.075
B*C (4)	0.788	-0.029	0.373	0.004	0.601	-0.073	0.206	0.064
A*B*C (8)	0.547	-0.013	0.265	0.027	0.755	-0.180	0.632	-0.055
Rotation								
Groups (3)	0.672	-0.041	***<0.001***	**0.440**	0.240	0.038	***<0.001***	**0.478**
A - Load (2)	0.420	-0.002	0.558	-0.008	0.124	0.097	0.23	0.027
B - Angle (2)	***<0.001***	**0.775**	***<0.001***	**0.802**	0.475	-0.020	0.071	0.096
C - Height (2)	***0.008***	0.081	0.785	-0.014	0.600	-0.039	***0.018***	**0.180**
A*B (4)	0.970	-0.033	0.409	0.001	0.784	-0.092	0.469	-0.010
A*C (4)	0.909	-0.028	0.961	-0.031	0.471	-0.016	0.847	-0.070
B*C (4)	0.650	-0.014	0.633	-0.013	0.500	-0.024	0.871	-0.073
A*B*C (8)	0.824	-0.035	0.311	0.016	0.464	-0.007	0.141	0.134

Table 4.9. ANOVA results testing the effects of Loads (A), Angle (B), Height (C), and interactions for joint angles during the lowering tasks. Significant effects ($p < 0.05$) are indicated in ***bold/italics.*** Large effect sizes ($\omega^2 > 0.14$) are indicated in **bold**.

Lowering	Peak OMC				Peak IMC			
Factors (df)	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2	p-value	Effect Size ω^2
Flexion/Extension								
Groups (3)	***<0.001***	**0.361**	***<0.001***	**0.379**	0.494	-0.015	0.755	-0.053
A - Load (2)	0.111	0.093	0.076	0.094	0.542	-0.042	0.851	-0.051
B - Angle (2)	0.156	0.066	0.118	0.067	0.899	-0.098	0.412	-0.006
C - Height (2)	0.614	-0.036	***0.017***	**0.187**	0.694	-0.069	***0.002***	**0.369**
A*B (4)	0.760	-0.076	0.753	-0.057	0.412	0.002	0.156	0.091
A*C (4)	0.379	0.011	0.225	0.052	0.686	-0.094	0.867	-0.083
B*C (4)	0.573	-0.038	0.504	-0.017	0.502	-0.033	0.422	-0.001
A*B*C (8)	0.394	0.023	0.677	-0.062	0.715	-0.144	0.894	-0.137
Lateral Bending								
Groups (3)	0.343	0.012	0.992	-0.088	0.728	-0.049	0.257	0.033
A - Load (2)	***0.020***	0.066	0.971	-0.024	0.438	-0.018	0.139	0.106
B - Angle (2)	***<0.001***	**0.654**	***<0.001***	**0.709**	0.641	**-0.063**	0.769	-0.074
C - Height (2)	0.517	-0.007	0.620	-0.013	0.461	-0.024	0.702	-0.064
A*B (4)	0.382	0.003	0.776	-0.027	0.592	-0.067	0.422	-0.002
A*C (4)	0.166	0.028	0.370	0.005	0.843	-0.149	0.774	-0.111
B*C (4)	0.391	0.002	0.363	0.005	0.674	-0.095	0.367	0.020
A*B*C (8)	0.634	-0.019	0.355	0.014	0.677	-0.130	0.897	-0.228
Rotation								
Groups (3)	0.202	0.049	<0.001	0.373	0.238	0.039	***<0.001***	**0.460**
A - Load (2)	0.158	0.024	0.505	-0.004	0.128	0.086	***0.049***	0.087
B - Angle (2)	***<0.001***	**0.739**	***<0.001***	**0.876**	0.130	0.085	***<0.001***	**0.463**
C - Height (2)	0.167	0.023	0.929	-0.013	0.589	-0.035	0.501	-0.012
A*B (4)	0.939	-0.043	0.343	0.004	0.921	-0.116	0.700	-0.035
A*C (4)	0.942	-0.043	0.932	-0.022	0.637	-0.054	0.776	-0.043
B*C (4)	0.633	-0.019	0.651	-0.011	0.537	-0.031	0.621	-0.026
A*B*C (8)	0.775	-0.043	0.728	-0.019	0.336	0.052	0.291	0.040

4.3.4.2 Lateral Bending

In terms of lateral bending, both the RMSE and peak differences for the lifting and lowering tasks did not exhibit any significant effects. However, the peaks for both systems in both tasks demonstrated a significant association with the Angle ($p < 0.001$). Further analysis using Tukey's test revealed significant differences between every angle level for the IMC (lifting and lowering) and the OMC (lowering). Additionally, A60 exhibited a significant difference from A00 and A30 for the OMC in the lifting task. Regarding the Peak OMC in the lowering task, the Load also displayed significance ($p=0.020$). Tukey's test indicated that L10 was significantly different from L20 and L30.

4.3.4.3 Rotation

Regarding the rotation angle, the analysis revealed significant effects of groups on the peak IMC and peak differences for both the lifting and lowering tasks. Furthermore, the load factor was found to be significant only for the peak differences in the lowering task ($p = 0.004$), specifically with L10 showing a significant difference from L20. Additionally, the angle factor demonstrated significance for the peaks in both the OMC and IMC systems for both tasks ($p < 0.001$), with each angle level displaying significant differences. The peak difference between systems in the lowering task also exhibited a significant association with the angle factor ($p < 0.001$). Further analysis using Tukey's test revealed that A60 significantly differed from A00 and A30, indicating higher differences as the angle level increased. Height was observed as a significant factor in the lifting task, specifically in the estimates of the peak OMC ($p = 0.008$). Post hoc analysis using Tukey's test revealed that H140 significantly differed from H100 and H060. Similarly, in the peak difference between systems, height was found to be significant ($p = 0.018$), with post hoc analysis indicating that H140 was significantly different from H060.

4.4 Discussion

This study assessed the accuracy of compressive and shear force estimates at the L5/S1 level obtained by a musculoskeletal model using data from an ambulatory measurement system consisting of inertial motion capture (IMC) during manual lifting. The outcomes of the IMC-based model were compared against a Top-Down optical motion capture (OMC) based model.

4.4.1 Accuracy of force estimates

The results revealed significant differences between the compressive (PD) and anteroposterior (AP) shear force estimates obtained from the OMC and IMC systems. On average, the OMC estimates were 975.16 N higher for the compressive forces and 291.77 N higher for the shear forces. Additionally, the values obtained from the OMC system exhibited a broader range than those from the IMC system for both force estimates. These discrepancies between the IMC and OMC systems carry significant practical implications, particularly when the estimates are utilized to contextualize activities within ergonomic thresholds, such as the recommended limits for compression and shear forces during manual material handling tasks, which are 3,400 N and 1,000 N respectively (Gallagher & Marras, 2012; Granata et al., 1999; Marras & Davis, 1998; Waters et al., 1993). The linear regression analysis of the force estimates (Figures 4.8 and 4.15) indicates that obtaining a PD force of 2,300 N with the IMC system would be equivalent to approximately 3,400 N. In comparison, an AP force of 700 N would be equivalent to approximately 1,000 N. In other words, the IMC-based forces were approximately 30% lower than the OMC estimates. Another observed trend revealed by the Bland-Altman plots (Figures 4.7 and 4.14) showed that as the force estimates increased, the discrepancies between estimates increased. Consequently, underestimating the forces at L5/S1 by the IMC system could be problematic and lead to a misinterpretation of injury risk assessment in occupational settings.

In a laboratory study by Marras and Davis (1998), participants were instructed to lift a 13.7 kg load (30 lbs) at various asymmetric angles using one or two hands. Compressive and shear forces at L5/S1 were measured using electromyography (EMG) and a back electrogoniometer that measured joint angles relative to the thorax and pelvis. The results demonstrated that compressive forces ranged from 3700 N for a symmetrical lift to 4200 N for a 60-degree angle. In contrast, our analysis of the average compression forces for the 13.7 kg load, considering different combinations of height and angles, yielded an average of approximately 3200 N for the OMC system and 2000 N for the IMC system.

In a recent study by Skals et al. (2021), musculoskeletal modeling and an IMC system were utilized to estimate compressive and anteroposterior shear forces in manual material handling activities in the supermarket sector. The study involved handling loads ranging from 5.3 kg to 20.2 kg, considering different starting positions and shelf heights. The authors reported noteworthy force estimates for loads of 10.2 kg (reaching up to 3,442 N for compression), 17.3 kg (3,854 N for compression and 1,113 N for shear), and 20.2 kg (4,188 N for compression and 1,191 N for shear). Although their results were not directly compared against an OMC model, and the loads and lifting parameters differed from those in our study, it is important to note that the observations from their IMC-based model exhibited higher magnitudes than those observed in the present study for similar loads. We suspect these significant force discrepancies may be attributed to kinematic variations, differences in flexion/extension and rotation joint angles, as well as disparities in model scaling or segment length.

The IMC-based model template used in the current study has been reported to underestimate trunk flexion angle in previous research (Larsen et al., 2020). Larsen et al. (2020) reported root mean square errors (RMSEs) ranging from 12.43 to 16.54 degrees for symmetrical and asymmetrical lifting tasks. These results align with our observations. The mean RMSE for lifting in our study was 10.92 degrees; for lowering, it was 11.19 degrees. However, it is important to note that the degree of underestimation varied. As indicated in Table 4, the RMSE values were as low as 3.73 degrees for lifting and 2.45 degrees for lowering but also reached as high as 28 degrees for both tasks.

In addition to trunk flexion angle, Larsen et al. (2020) also investigated the comparison of lateral bending and rotation angles. They reported RMSE values ranging from 1.8 to 2.79 degrees for lateral bending and 4.58 to 7.75 degrees for rotation. Our study also examined these angles, and the mean values for lateral bending were 4.19 degrees for lifting, 4.16 degrees for lowering, and 5.93 degrees for rotation, as shown in Table 4.4. These findings reinforce a similar pattern of discrepancy in angle estimates as reported in existing literature.

To evaluate the differences in position error between the systems, peak differences in the distance from the lifted box to L5/S1 (at peak force) were calculated. The most considerable discrepancies were observed in the X and Z axes. Specifically, there was an average difference of 8 cm on the X-axis and 12 cm and 13 cm on the Z-axis for lifting and lowering, respectively. Importantly, these differences indicated underestimations by the IMC system compared to the OMC system. There was no single instance where the IMC-based distance exceeded that of the OMC system. These findings are consistent with a study conducted by (Faber et al., 2020), which also reported similar differences between IMC and OMC estimates in the context of biomechanical models used to estimate moments at L5/S1.

The assessment of spine-to-box distance provided a comprehensive evaluation of segment length, revealing a consistent underestimation, particularly in the trunk\torso, across most IMC-based models. This consistent underestimation of segment lengths, coupled with the underestimated joint angles, especially in flexion/extension, has important implications for the kinematic inputs used to estimate kinetics, potentially explaining the observed differences in forces as previously presented. One potential source of this issue may be attributed to the location and placement of the sacrum sensor in the IMC system, as guided by the manufacturer. Unlike the OMC system, which tracks bony landmarks to measure trunk length, the IMC sacrum sensor is placed in a region without prominent landmarks for identification, making its placement and stability challenging. Moreover, the sacrum sensor may experience motion and upward shift during flexion, further complicating its accurate placement and stability (Larsen et al., 2020; Schall et al., 2021).

In general, the consistently shorter torso observed in the IMC-based model could be related to changes in the position of the sacrum sensor, which may be influenced by the dynamic and varied nature of the evaluated tasks that require significant forward bending. We suspect the sacrum sensor may shift primarily upwards from its original placement, impacting segment definitions. Our results indicate that the IMC-based model underestimates torso flexion, overestimates rotation, and shows similar estimates to the OMC-based system for lateral bending. These observations could be explained by the differences in the range of motion among different spinal regions. For instance, if the torso is defined above the lumbosacral joint and closer to the thoracic region, a decrease in flexion and an increase in rotation would be expected. Researchers have observed these differences, with flexion decreasing from 20 degrees at L5/S1 to 10 degrees at T11-T12 and rotation increasing from approximately five degrees at the lumbosacral level to nine degrees in the thoracic region (White & Panjabi, 1978). Users of the IMC system should exercise caution regarding how sensor positioning affects torso dimensions and, by extension, not just kinematics but also kinetic estimates. It may be beneficial for IMC system manufacturers to propose improved placement methods or suggest additional adjustments during pre- or post-data processing.

4.4.2 Impact of load, height, and asymmetry

To our knowledge, the current study represents the first attempt to assess the differences in force and kinematics estimates between IMC and OMC systems using musculoskeletal models within a systematic statistical framework. We analyzed the results in relation to load, height, and asymmetry levels, as well as their potential interactions. When comparing both systems, our main findings indicate that the root mean square error (RMSE) of both compressive (PD) and anteroposterior (AP) forces were significantly influenced by load levels and height levels. Specifically, the RMSE values were higher as load levels increased and lower as height levels increased (with no significant differences between H100 and H140). We attribute these higher differences at lower heights to the increased flexion angle associated with retrieving and placing the load from the shelf compared to the other heights. Since this level involved more flexion/extension movements, the differences between the OMC and IMC-based estimates were more pronounced.

Regarding the impact of variables on the compressive and shear force estimates for each system, our findings align with previous studies (Davis et al., 2010; Granata et al., 1999; Lavender et al., 2003; Plamondon et al., 1996; Skals et al., 2021), indicating that load mass has the most substantial effect. However, our results differ regarding the impact of asymmetry on AP forces. While Skals et al. found that load and asymmetry affected these forces, our study did not observe a significant effect of angle on the estimates from either the IMC or OMC-based models. A Load*Height interaction effect for the shear forces during the lifting tasks was observed for the IMC-based model, suggesting that higher load and height levels lead to higher AP peak forces. However, the small effect size estimate suggests it may not be practically meaningful.

Future research should extend the comparison and analysis of kinetics and kinematics to other pertinent body parts, such as the shoulder and knees, which are known to be susceptible to MSDs (U.S. Department of Labor, 2016). Examining the forces and movements in these areas would provide a more comprehensive assessment of the overall biomechanical impact. Additionally, exploring how changes in variables such as lifting technique, exertion speed, and postures (e.g., squatting or bent postures) can impact the forces and moments experienced by the body could provide valuable insights. Understanding these relationships would allow for more targeted and effective ergonomic interventions.

Furthermore, future studies should incorporate the assessment of muscular demands. Considering factors such as muscle activation levels and fatigue during various tasks would provide a deeper understanding of the physiological aspects of ergonomic assessment. By integrating muscular demands into the analysis, researchers can better comprehend the interaction between muscular activity, forces, and kinematics, leading to more comprehensive and accurate ergonomic evaluations, as Skals et al. (2021) suggested.

In conclusion, when comparing compressive and anteroposterior shear forces using musculoskeletal modeling with OMC and IMC-based models, significant differences were observed, making ergonomic assessment challenging. However, improving the scaling of the IMC-based model to reduce differences in joint angle and segment length could enhance the quality of the estimates. As expected, increasing load levels significantly impacted force estimates, while the lower lifting height showed higher force values than other levels.

4.4.3 Limitations

The present study has several limitations that should be acknowledged. Firstly, the tasks evaluated in this study focused on asymmetry levels of 0, 30-, and 60-degree angles to the left of the initial box position during a two-handed lift. However, it is important to note that going beyond 60 degrees or considering right-sided asymmetry instead of left-sided could yield different force profile trends (Marras & Davis, 1998). Furthermore, the lifting technique and exertion speed were not controlled variables in the experiment, introducing potential variability in the results (Dehghan & Arjmand, 2022; Fleron et al., 2019). The analysis did not consider whether squatting or bent postures were utilized during load lifting, which could impact the force estimates (Dehghan & Arjmand, 2022).

Additionally, an acknowledged issue when using inertial measurement units (IMUs) over time is the effect of magnetic disturbance and gyroscopic drift, which can affect the accuracy of the estimates (Robert-Lachaine et al., 2017). Although the impact of this effect was not directly measured in our study, it is important to note that the IMC system was re-calibrated between trial combinations, and the trials lasted no more than 30 seconds. Another limitation of our study was the significant time investment required to process the data using the applied methodology. Similar observations have been reported in recent literature (Skals et al., 2021), suggesting that musculoskeletal simulation tools may not be feasible as a standard for industrial ergonomic assessments. However, as researchers and practitioners continue to benefit from the advantages of musculoskeletal modeling, advancements will likely be made to address and overcome these limitations.

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Chapter 5

5. Development of a Fatigue-Failure Based Continuous Risk Assessment Method for the Low Back Region Using Inertial Motion Capture Technology.

5.1 Introduction

Repetitive loading of musculoskeletal tissues contributes to workplace-related musculoskeletal disorders (MSDs) (Callaghan et al., 2001; Jäger et al., 2000; Kumar, 1990; Norman et al., 1998). As a result, it is important to measure cumulative exposure to physical risk factors (e.g., forceful exertions, repetition) to understand the relationship between these factors and the risk of adverse health outcomes. The term *cumulative loading* implies the integration of physical exposure over time (Waters et al., 2006). Thus, cumulative loading indicates that load intensity, duration, and task repetition are critical factors in assessing risk (Koyuncu et al., 2021). Moreover, such an approach should provide a method to evaluate multi-task exposures, a prerequisite for understanding the relationship between work-related exposure and physical reactions such as MSDs (Veerasammy et al., 2022). As enumerated by prior authors, there are several calculation methods for cumulative loading (Johnen et al., 2021). The issue of methodological diversity has been highlighted previously (Waters et al., 2006; Johnen et al., 2022), emphasizing the challenge of comparing various work scenarios based on cumulative loading estimates.

Gallagher and Schall (2017) and Gallagher and Barbe (2022) synthesized the evidence suggesting that a material fatigue failure process plays a significant role in developing MSDs. The theory is supported by ex vivo studies on spinal segments, cartilage, tendons, and ligaments, where a consistent pattern of fatigue failure behavior under repetitive loading has been observed (Brinckmann et al., 1987; Gallagher et al., 2005, 2007; Schechtman & Bader, 1997; Thornton & Bailey, 2013) failure processes in musculoskeletal tissues in a living state (Andarawis-Puri & Flatow, 2011; Barbe et al., 2013, 2020; Fung et al., 2009, 2010; Sun et al., 2010). Additionally, epidemiological evidence highlights the interaction between force and repetition as indicative of a fatigue failure process (Gallagher & Heberger, 2013). The significance of fatigue failure theory lies in its ability to deconstruct complex loading waveforms into stress reversals and cycles, enabling the estimation of cumulative loading. Therefore, fatigue failure theory is well-suited to utilize new continuous loading technologies and methods validated in material engineering science.

Typically, practitioners gather exposure data regarding worker kinematics and kinetics through direct observation and/or review of video recordings (Burdorf et al., 1997; Spielholz et al., 2001). They then employ risk assessment tools to determine the risk level based on the exposure data. Nonetheless, an assessment of existing methods for calculating incremental loading suggests that even relative differences in cumulative loading values due to an ergonomic improvement measure are not comparable (Johnen et al., 2021). Advancements in technology have made it easier and more cost-effective to collect continuous loading exposure data. Optical motion capture (OMC) technology provides an efficient means of obtaining kinematic data, such as segment orientation and position, linear and rotational acceleration and velocity, and joint angles by placing reflective markers on anatomical landmarks per the recommendations of the International Society of Biomechanics (Wu et al., 2002, 2005). In addition, kinetic analysis is made possible through the use of force plates, which measure ground reaction forces (GRF) and moments. However, implementing such technologies in workplace environments is often challenging or impractical, necessitating the exploration of alternative technologies that can better adapt to the dynamic nature of work environments (Lee & Lee, 2022). An alternative to this challenge is Inertial Motion Capture (IMC) systems, which employ small inertial measurement units (IMUs) and have shown potential in capturing continuous loading data, including L5/S1 moments (Faber et al., 2016, 2020; Koopman et al., 2018; Nail-Ulloa et al., 2021).

The primary objective of this study was to establish and evaluate a comprehensive framework for processing data to estimate lumbar loading. To achieve this objective, the study utilized methods from fatigue failure theory to calculate the cumulative damage resulting from continuous low-back loading time-series data collected through Inertial Motion Capture (IMC). The proposed framework offers a novel approach for analyzing kinematic data and assessing cumulative loading exposure associated with complex loads, postures, and occupational tasks observed in field settings, which could lead to the development of more effective interventions aimed at reducing the risk of low back injuries in various occupational settings.

5.2 Methods

5.2.1 Participants

A sample of eight participants, six males and two females (mean age = 33.11, SD = 10.59), was recruited (Table 1). All participants were workers at an automotive manufacturing facility. Inclusion criteria included 1) being an employee in the manufacturing facility, 2) having no history of physician-diagnosed MSD, injury, or surgery in the low back, 3) having no history of a physician-diagnosed neurodegenerative disorder that may affect movement (e.g., Parkinson's disease, multiple sclerosis, among others), and 4) not presenting any health conditions that would put the person at heightened risk of severe illness from COVID-19. The health conditions included cancer, chronic kidney disease, chronic obstructive pulmonary disease, a weakened immune system due to an organ transplant, obesity (Body mass index, BMI, of 30 or higher), serious heart conditions, such as heart failure or coronary artery disease, sickle cell disease, and type 2 diabetes mellitus. Details about participants' anthropometry are shown in Table 5.1. This study was reviewed and approved (Protocol # 19-165 EP 1904) by the Institutional Review Board at Auburn University. During the consenting process, participants were informed that the research team had established protocols for securing the data and that no individual results would be identifiable from anyone outside the research team.

Table 5.1. Summary of participants' anthropometry (n = 8).

	Weight (kg)	Height (cm)	Shoe Length (cm)	Shoulder Height (cm)	Shoulder Width (cm)	Arm Span (cm)	Hip Height (cm)	Hip Width (cm)	Knee Height (cm)	Ankle Height (cm)
Mean	79.32	174.17	30.69	145.21	36.38	158.66	91.08	25.38	52.21	10.34
SD	10.61	10.33	2.42	8.60	4.05	52.19	7.17	2.63	4.34	0.96

5.2.2 Types of Occupational Tasks

The study was conducted in a live production environment, where workers performed routine tasks during their regular workday. The setting accurately represents workers' real-world conditions and challenges while performing their jobs. Manufacturing vehicles in the facility where the study occurred is a complex multistep process involving automated and manual steps. The manual steps involve multiple repetitive movements, including bending at the waist to pick up/install parts, working above shoulder level, repetitive hand, and wrist motion, and handling different loads which vary in weight and shape. Workers performed their respective jobs for two hours and then changed to a different station after the break. Every employee worked on average in four different stations in a typical day.

5.2.3 Epidemiological Evaluation

Epidemiological data were collected from participants through a survey assessing low back disorders. In addition, the facility provided injury data from January 1, 2018, through September 2, 2020, allowing the researchers to focus data collection on those lines and stations where injuries were recently recorded. The primary guideline for developing the surveys in this study was the Oswestry Disability Questionnaire (Fairbank JC & Pynsent P, 2000). Modifications were made during editing to reduce the potential risk for leading questions and survey complexity.

Participants completed the epidemiology surveys individually. Employees were pulled out of their working lines for 25 to 45 minutes to complete surveys after the consenting process. They were asked to answer all questions carefully, following the survey instructions. Researchers were present only to provide clarification on instructions. If participants did not indicate low back pain (LPB), aches, or burning in the past year, they could skip the Oswestry Disability Questionnaire section of the survey, as this questionnaire would not be relevant. When completing the surveys, it was made clear to all participants that specific individual data would not be shared with anyone outside the research team.

5.2.4 Biomechanical Assessment

5.2.4.1 Participant Preparation and Data Collection

After completing the informed consent process, participants were fitted with a full-body IMC system of 17 sensors (MVN Awinda, Xsens Technologies B.V., Enschede, Netherlands). Each sensor is a small, wireless, battery-powered unit that measures and stores acceleration, angular velocity, and magnetic field information. The sensors were secured using a combination of elastic neoprene straps and hypoallergenic athletic tape (Figure 5.1). Anthropometric measurements were used to build a rigid link biomechanical model using the information collected from the IMC system. During the data collection phase of the study, workers wore the IMC system for no longer than one hour while performing various tasks at different workstations. Each collected trial lasted approximately one minute on average, depending on the specific tasks required at each station and the car model being assessed.

5.2.4.2 System Calibration

Participants were required to follow calibration protocols for the IMC system. Segment calibration on the IMC system is necessary to align the motion trackers to the subject segments (Xsens®, 2021). The procedure consists of each participant holding a neutral posture for a few seconds (N-pose), then walking forward, turning around, and returning to where they started. Every participant was required to calibrate after completing the data collection at each station.

5.2.4.3 Data Cleaning and Processing

IMC data was sampled at 60Hz. Force and kinematic data were bi-directionally low-pass filtered with the IMC system's second-order Butterworth filter at 5 Hz (Faber et al., 2020). Trials were smoothed using a moving average of 10 frames as an additional measure to reduce noise in the data.

5.2.4.4 Experimental Procedure

The participants were instructed to perform their manual material handling jobs as they would typically; they were also instructed to inform the team if they noticed any difference when performing their tasks because of the IMC system. Each participant worked on a particular production line, typically cycling through five stations, on average, during a given eight-hour shift. Three car models were manufactured while the research team collected data at the plant. In order to ensure quality data, data was captured at least twice for each of the three models for each worker for every station they were working.

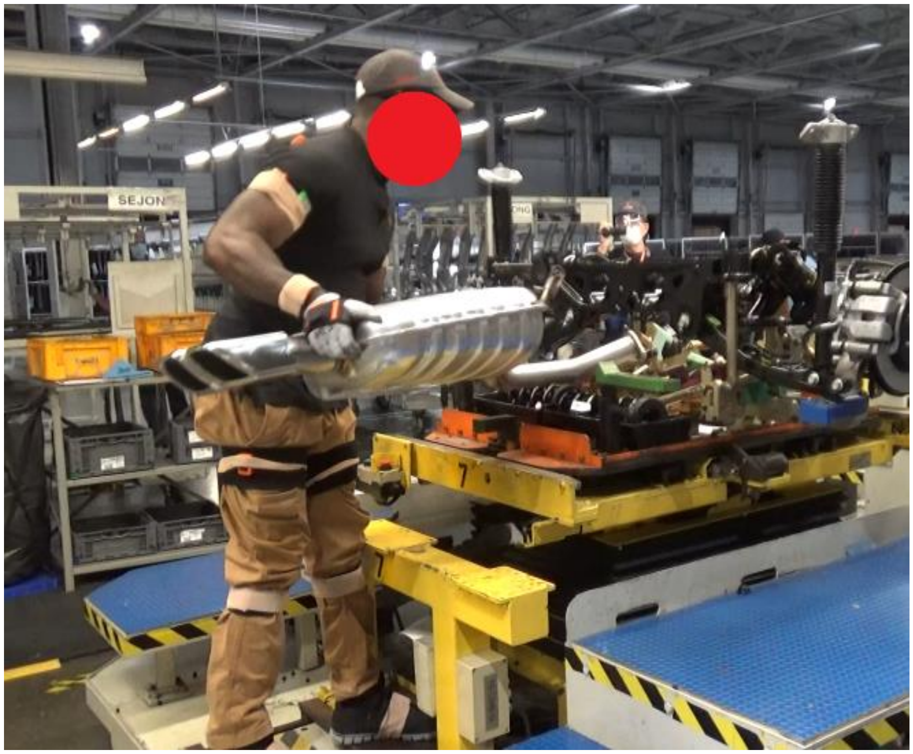

Figure 5.1. A participant working at a station while wearing the IMC system.

5.2.5 Experimental Procedure

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5.2.5.1 Biomechanical Modeling and task identification

Inverse dynamics were calculated using a top-down analysis approach. A 15-segment biomechanical model was developed in the biomechanical analysis software Visual3D (C-Motion®, 2020). Total moments were calculated for the analyses. The total moment is the vector summation of each plane's L5/S1 moments (X, Y, Z).

Videos of each participant’s work postures and activities were recorded. Two camcorders were used for recording to ensure the analysis of all work postures could be identified from at least two angles. These videos also provided a method to cross-reference biomechanical data. Two researchers independently performed a video-based job analysis. First, research team members’ observations analyzed worker postures and movements. Various work postures were defined and characterized for different body regions, including the shoulder, wrist, back, neck, and leg. Upper extremity actions, such as grasping and pinching, were identified. Awkward postures included reaching, body twisting, bending, neck twisting, hyper-extended or flexed back positions, overhead work, and kneeling. The researchers defined manual material handling tasks as lifting/lowering, horizontal pulling/pushing, and forward pulling/pushing. Also, hand-held tools were often used as part of the work tasks studied. Thus, researchers also observed hand-arm vibration exposure during biomechanical data collection. However, this vibration was not considered in the subsequent analysis. As most works involved attaching parts to cars, the team also obtained the weights of both handled parts and hand-held tools, which were essential to the biomechanical analysis. The repetition and duration of each task were also analyzed for each participant. External loads were assigned to the hands when the participants were lifting, lowering, or carrying (using recorded videos and the IMC visual representations). If loads were handled with two hands, the load was assumed to be divided evenly between the hands (Nail-Ulloa et al., 2021).

Figure 5.2 depicts a framework for data processing. The initial step involves gathering exposure information, which includes posture, task frequency, and external force. A dynamic biomechanical model was used to estimate continuous low back stress from time series moment data.

5.2.5.2 Rainflow Cycle Counting

Rainflow analysis, introduced by [i]Matsuishi and T. Endo (1968), has found widespread application in studying material fatigue, and it has been described as the best cycle counting method (Stephens et al., 2001). This method can analyze continuous low back loading data and generate a “real-time” profile of the exposure distribution associated with a specific number of cycles through stress (or force or moment) range estimates and mean stress estimates. Using this technique, damage associated with each loading cycle could be estimated and summed as cumulative damage (CD). The authors completed the rainflow analysis using a Microsoft Excel-based tool (Microsoft Corporation).

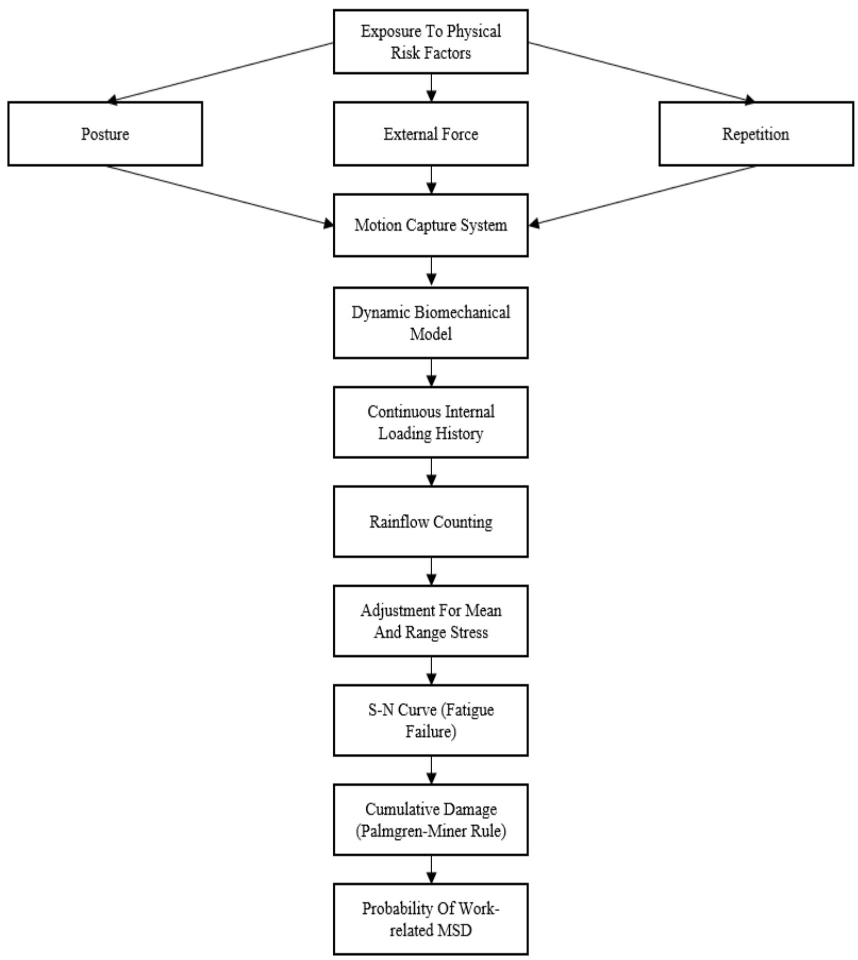

Figure 5.2. Technology-assisted framework for data processing using fatigue failure methods.

5.2.6 Cycle Loading Damage Estimation

In order to characterize the relationship between cycles to failure and different stress levels on lumbar motion segments, Gallagher et al. (2017) utilized studies on cadaveric lumbar spines (Brinckmann et al., 1987; Gallagher et al., 2005, 2007). The relationship between these variables follows an exponential pattern (Equation 1, see page 28), similar to other materials like metals or plastics.

Equation 1:

$$\mathrm{N} = 1{,}099{,}097.56 \times \mathrm{e}^{-0.122 \text{ x } \%\mathrm{US}}$$

Where:

- N = the number of cycles to failure.
- %US = percentage of the motion segment's ultimate strength.

Because the human spine is constantly subjected to a compressive load due to the body's weight in standing and sitting postures, the loading pattern can be classified as "fluctuating stress." As a result, modifications to the stress amplitude and mean stress are required for fully reversed sinusoidal loading. To achieve this, Goodman's method (Equation 2, page 28) was used to adjust the revised stress amplitude for each mean stress and stress range pair.

Equation 2:

$$\frac{S_a}{S_{Nf}} + \frac{S_m}{S_u} = 1$$

Where:

- S_a = alternating stress.
- S_m = the mean stress.
- S_{Nf} = the estimated value of the stress at failure for exactly Nf cycles as determined by an S-N diagram.

- S_u = the ultimate stress.

The adjusted stress amplitude was employed to indicate the stress level for each repetition classified by the rainflow analysis technique. Combining with Equation 1, it was possible to approximate the number of cycles required to cause failure at each stress amplitude and calculate the damage inflicted by each loading cycle. To estimate the CD sustained across a sequence of loading cycles, the Palmgren-Miner rule (Equation 3, page 29) was used, which is one of the most commonly utilized models for predicting damage due to spectrum loading (Miner, 1945; Palmgren, 1924).

Equation 3:

$$c = \sum_{i}^{k} \frac{n_1}{N_1} + \frac{n_2}{N_2} + \cdots \frac{n_k}{N_k}$$

Where:

- c = a constant (usually set at 1, but potentially subject to variation). In this study, the threshold value for c is 1.
- n_i = the count of loading cycles experienced at force levels at which N_i … cycles would result in material fatigue failure.

5.2.7 Statistical Analysis

Stepwise logistic regression was used to examine the relationship between reported low-back pain and recorded injury data to the continuous fatigue failure assessment method estimates. The controlled variables for the stepwise logistic regression were the CD, line, station, car model, and subject (participant). An alpha level of 0.05 was used for all tests. Statistical tests were conducted in Statistix® (version 9, Analytical Software, Tallahassee, FL, USA).

5.3 Results

Participants worked on eight production lines and 49 stations with two or three car models in production during the site visits, depending on the day's schedule. The research team collected data for a total of 108 trials (one trial corresponds to an individual worker completing the required tasks for a single car model at a specific station on a given line).

5.3.1 Example of the Continuous Fatigue Failure-based Risk Assessment Model

In this example, a worker performed their job at one of the trimming stations; the only external load associated with this trial is a pneumatic rachet (1.5 kg, handled with the right hand). The estimated total moment is shown in Figure 5.3. The duration of the task is one minute.

With the moment loading history associated with the exertions performed at that workstation when manufacturing a particular car model, forces at the L5/S1 level were estimated using a lever arm for the erector spinae muscle of 5 cm (Chaffin et al., 2006). The line of action of the erector spinae muscles was assumed to act parallel to the normal compression force on the L5/S1 disc.

Next, the obtained forces were applied to an average cross-sectional area of 16.2 cm of the L5/S1 disc (Jager M & Luttmann A, 1991) to get the corresponding stress loading history. The stress loading history was processed using the rainflow analysis to obtain the number of cycles, mean and range for the stress history. The stress magnitudes were adjusted using Goodman's method based on the stress range and mean stresses (Equation 2). Then, the revised stress ranges were used to calculate damage per loading cycle, using the average ultimate strength for a 35-year-old male (closest estimate to the average worker who participated in the study) of 7.3 kN (4.51 MPa) (Jager M & Luttmann A, 1991).

The cumulative damage was calculated using the Palmgren-Miner rule (Equation 3), summing the individual cycles. After obtaining estimates of cumulative damage, the final result corresponding to an average workday is obtained by multiplying the cumulative damage by 480 (8 hours of work converted to minutes, the working period at the manufacturing facility).

Lastly, if the result is greater than or equal to 1.0, the worker would be considered at increased risk of a low-back injury because the cumulative damage would be higher than the critical threshold. An example of the adjusted stress range loading history after applying the rainflow cycle counting method is shown in Figure 5.4.

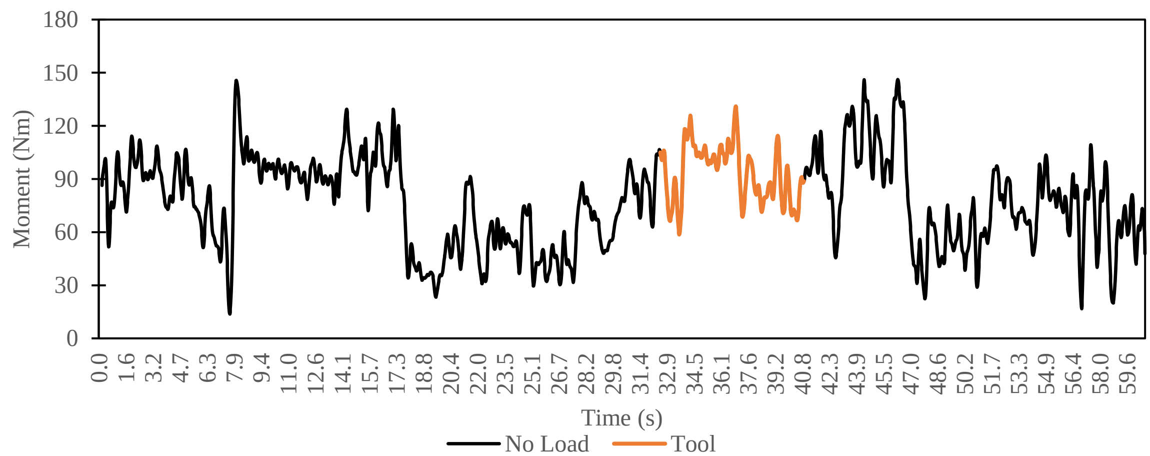

Figure 5.3. Example of the estimated total moment.

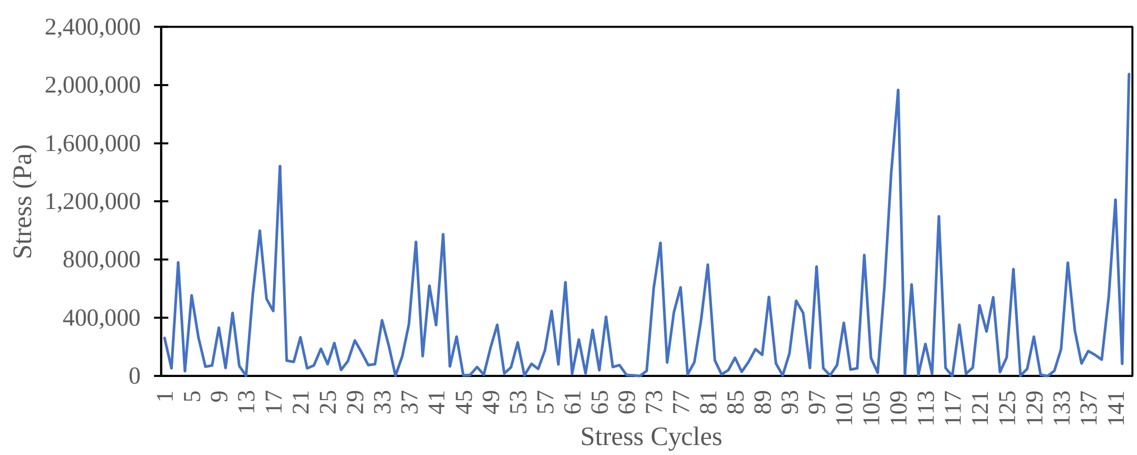

Figure 5.4. Stress range adjusted by compression after applying rainflow analysis.

In the example, the final result showed a total damage calculation of 0.412, indicating that the worker would not be exposed to a high risk of low-back pain while working at that particular station for that specific car model.

Table 5.2. Stepwise Logistic Regression Results for Self-reported Low Back Injuries

Step	Variable	Coefficient	Std Error	Coef/SE	Deviance	Difference	p
1	Constant	-4.81	2.05	-2.35	54.02		
	CD	0.96	0.29	3.34			
	Line	-0.42	0.29	-1.47			
	Model	-0.12	0.46	-0.25			
	Station	0.14	0.08	1.80			
	Subject	0.08	0.03	2.91			
2	Constant	-5.02	1.88	-2.66	54.09	0.06	0.80
	CD	0.95	0.29	3.33			
	Line	-0.41	0.28	-1.45			
	Station	0.14	0.08	1.79			
	Subject	0.08	0.03	2.90			
3	Constant	-6.56	1.83	-3.58	56.28	2.20	0.14
	CD	0.87	0.28	3.11			
	Station	0.09	0.06	1.43			
	Subject	0.08	0.03	2.44			
4	Constant	-4.95	1.22	-4.07	58.28	0.00	0.16
	CD	0.77	0.26	3.00			
	Subject	0.06	0.03	2.27			

Resulting Stepwise Model

Variable	Coefficient	Std Error	Coef/SE	p
Constant	-4.95	1.22	-4.07	<0.001
CD	0.77	0.26	3.00	0.002
Subject	0.06	0.03	2.27	0.023

Deviance	58.28
p-Value	0.9999
Degrees of Freedom	105

Table 5.3. Stepwise Logistic Regression Results for Low-Back Injuries

Step	Variable	Coefficient	Std Error	Coef/SE	Deviance	Difference	p
1	Constant	-1.19601	0.84697	-1.41	137.33		
	CD	0.43356	0.24599	1.76			
	Line	0.38212	0.15518	2.46			
	Model	-0.00807	0.26069	-0.03			
	Station	-0.07024	0.04169	-1.68			
	Subject	-0.01716	0.01496	-1.15			
2	Constant	-1.21156	0.68210	-1.78	137.33	0.00	0.9753
	CD	0.43339	0.24593	1.76			
	Line	0.38262	0.15435	2.48			
	Station	-0.07033	0.04160	-1.69			
	Subject	-0.01721	0.01488	-1.16			
3	Constant	-1.43658	0.66544	-2.16	138.72	1.39	0.2386
	CD	0.48982	0.24636	1.99			
	Station	0.28505	0.12624	2.26			
	Subject	-0.04772	0.03607	-1.32			
4	Constant	-1.55538	0.65858	-2.36	140.49	1.77	0.1829
	CD	0.49246	0.24319	2.02			
	Subject	0.22269	0.11632	1.91			
5	Constant	-0.39938	0.24338	-1.64	144.31	3.82	0.0507
	CD	0.48619	0.23506	2.07			

Resulting Stepwise Model

Variable	Coefficient	Std Error	Coef/SE	p
Constant	-0.39938	0.24338	-1.64	0.1008
CD	0.48619	0.23506	2.07	0.0386

Deviance	144.31
p-Value	0.0079
Degree of Freedom	106

5.3.2 Summary of Results

Four participants who completed the surveys reported low-back pain, while the others did not. Of the 108 processed trials, 18 indicated a high injury risk exceeding the critical threshold of 1.0. After including participants, lines, and stations as covariates, a stepwise logistic regression was performed to determine the relationship between the calculated cumulative damage (CD) and the injury data (both recorded and self-reported). The results revealed significant associations between the CD and injury data. The relationship found between the CD estimates, and the self-reported low-back pain presented the following results: $p = 0.002$, $OR = 2.16$, (95% Confidence Interval: 1.30, 3.57); while, for the CD estimates and the recorded injuries, the analysis showed the following results: $p = 0.038$, $OR= 1.65$, (95% Confidence Interval: 1.03, 2.63). Tables 5.2 and 5.3 show the analysis results after performing the stepwise logistic regression.

5.4 Discussion

This study is the first attempt to demonstrate a fatigue failure-based *continuous risk assessment* method that can accommodate low back compressive force history generated using a biomechanical model fed by an IMC system. The model provides flexibility in measuring cumulative damage when dealing with different loads, postures, and occupational tasks observed in the field that could affect the development of occupational low-back disorders. The initial results for this first attempt at estimating continuously cumulative damage using a fatigue failure-based approach are promising, as the estimates of risk from the cumulative damage total showed a significant association with self-reported low back pain and with the low back injuries reported by the manufacturer, for both stepwise logistic regression analyses.

Non-weighted or linear (Norman et al., 1998a) and weighted (Jäger et al., 2000) integration methods for estimating CD have been proposed in the literature. Practitioners and researchers currently use them. However, Huangfu et al. (2018) suggested that the non-weighted or linear integration method may be unsuitable for evaluating high physical exposure. Additionally, there is a precedent of comparison between the CD estimation approaches mentioned above and fatigue failure. Huangfu (2018) compared CD estimates generated by using compressive force estimates from a simple biomechanical model as an input for a fatigue failure-based model, linear, and weighted (squared) integration methods against health outcomes from two different epidemiological databases (Sesek, 1999; Zurada et al., 1997). The fatigue failure-based model exhibited superior performance across the testing scenarios compared to the linear and squared integration approaches, particularly for assessing “low-risk” jobs (Huangfu, 2018).

On the other hand, Johnen et al. (2022) highlighted that weighted approaches are difficult to compare and must establish clear threshold values to estimate cumulative damage accurately. The presented fatigue failure-based framework offers several advantages, including clear threshold values and a comprehensive methodology for accurately estimating cumulative damage.

This method could also account for personal characteristics like sex or age, which affect critical factors in our analysis, like cross-sectional areas of the L5-S1 disc, muscle lever arms (Chaffin et al., 2006), and the ultimate strength of the spine (Jager M & Luttmann A, 1991). Future adjustments for workers' personal characteristics could be added with existing data sources. Further research is needed to validate these potential improvements.

The approach used in this study could be applied to other body parts. For example, some data could be utilized as a reference for the ultimate strength of tendons on fatigue failure-based discrete risk assessment tools already published in the literature for the shoulders or the upper extremities (Bani Hani et al., 2021; Gallagher et al., 2018). Injury data and biomechanical estimates of shoulder forces or moments could be obtained from a musculoskeletal biomechanical modeling software such as Anybody™ modeling system (Aurbach et al., 2020; Damsgaard et al., 2006). Such an approach may be advantageous in justifying the effort of working with a full-body model instead of trying less accurate or simplified methods for assessing low back loading (Coenen et al., 2015).

The external loads workers handled on their respective lines and stations were between one and three kilograms, on average (except for car parts weighing around 10 kg). Our study revealed an interesting finding regarding the influence of posture on risk assessment. We observed many stations where workers performed tasks in non-neutral postures, particularly involving torso flexion, which coincided with high peak moments and elevated estimates of cumulative damage and reported injuries. The results suggest that posture may be critical in accurately estimating cumulative damage.

In contrast, ergonomic risk assessment tools that rely solely on evaluating peak load moment may overlook and underestimate the importance of trunk motion. The finding is especially crucial when workers are not handling loads but are still in an awkward posture, which may be more critical for the analysis. Overall, our study emphasizes the need to consider posture when estimating cumulative damage and provides a valuable tool for practitioners in the field of ergonomic risk assessment.

It may be noted that the using this continuous loading data processing framework for risk assessment offers numerous benefits. For example, it accounts for changes in key risk factors influencing significantly the risk of low back disorders, including lateral trunk velocity, load moment, lifting frequency, trunk twisting velocity, and sagittal trunk angle, as noted by Marras et al. (1995). Another key advantage is that the framework enables the analysis of various working conditions, such as lifting with one hand or handling two different loads simultaneously, thereby providing a more comprehensive risk assessment. Also, typical ergonomics risk factor analysis (used by many MSD risk assessment tools) often requires subjective estimation of the level of forces being exerted (by either researcher or study participant), which may lead to significant errors in risk estimation. Using more quantitative methods to evaluate such loads may help eliminate this error in risk assessment. A recent alternative to the full-body 17 IMU sensors setup was studied by Matijevich et al. (2021), where the authors suggest that a single trunk IMU sensor and a pair of pressure insoles to estimate forces could reach high accuracy when assessing lumbar moments compared to the whole-body setup, using gold-standard laboratory equipment as a reference. Such an alternative could offer a faster donning and doffing of the system (in our study, 15-20 minutes were required to measure and record anthropometry and secure the sensors) and less potential obstruction to the jobs from the hardware on parts of the body that are sensitive to highly dynamic motion like the hands or the forearms. Because the IMC data was captured on a per-trial basis, with trials lasting around a minute, we did not observe or have any reason to believe substantial errors associated with magnetic disturbance and gyroscopic drift were present like in longer trials (Robert-Lachaine et al., 2017). According to the system's manufacturer, the research team recalibrated the IMC system between stations, which could help prevent gyroscopic drift. There are still some hurdles to implementing quantitative methods such as those discussed here. However, such techniques may promise to improve quantitative risk assessment methods in the future.

5.4.1 Limitations

The COVID-19 pandemic significantly affected the performance of this research project, from the industry partner having a constant workforce shortage which prevented the team from capturing data on some of the lines and stations that were initially planned, to the anticipated final closeout of the data collection because of outbreaks at the manufacturing facility. Although ending the data collection affected the study's sample size and analysis, the significant results from our analysis make further research promising.

One limitation of this study is the assumption of even weight distribution on the hands. It is not likely that a load's weight will be evenly distributed between both sides of the body, especially when loads present irregular geometries. Additionally, this approach does not consider the potential impact on pushing or pulling loads. This limitation could be faced by utilizing a system that provides ground reaction force estimates from pressure insoles (Matijevich et al., 2021). Another limitation is associated with the individual characteristics of the participants. The IMC system performance might be affected by participants' characteristics, such as being obese, as soft-tissue artifacts may be common (Bolink et al., 2016). Additionally, we might not have captured enough postural exposure data to avoid biases in the evaluated tasks. A longer sampling duration of 50-60 minutes may be considered in future research (Porta et al., 2020).

It is worth noting that positioning the sacrum sensor for the IMU system presented certain challenges. The trunk has few anatomical features that can be a stable attachment point for an IMU. Considering the dynamic and varying nature of the evaluated tasks requiring forward bending, we suspect that the sacrum sensor may have shifted (primarily upwards) from its original placement, impacting the results of the moment calculations. Previous studies have raised similar concerns (Larsen et al., 2020; Schall et al., 2021).

This model does not account for the remodeling and healing of musculoskeletal tissues and the impact on these by psychosocial stress, which are factors to consider when developing programs to prevent chronic low back pain (Buruck et al., 2019). However, fatigue failure theory could be suited to address and incorporate the effect of damage development and healing in our model (Gallagher & Barbe, 2022).

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References – Chapter 5

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Chapter 6

6. Conclusions and future research.

6.1 Conclusions

This research aimed to critically assess the efficacy of an inertial motion capture system under controlled laboratory conditions and subsequently deploy the system in a real-world production setting. Also, the body of work sought to develop, test, and validate a data processing framework for continuous loading data to evaluate cumulative damage in the lumbar region by applying fatigue failure techniques. The major conclusions derived from these studies are:

The first study aimed to systematically assess the accuracy of 3D L5/S1 moment estimates during simulated manual lifting tasks using an Inertial Motion Capture (IMC) wearable system by comparing how load weight, asymmetry, and height affected the estimates individually, as well as their possible interactions. The reference moments were calculated using inverse dynamic bottom-up and top-down laboratory models based on data from a measurement system that included Optical Motion Capture (OMC) and Force Plates (FPs). Thirty-six participants performed tasks consisting of lifting and lowering one of three loads to one of three different heights and three different asymmetrical angles. A Randomized Block Partially Confounded design was used to compare the RMSE, absolute peaks, and peak differences of the moments between the IMC and OMC-based reference systems. Regarding the findings:

- The load was the most significant factor in almost all cases. No solid statistical trends were found regarding the interactions observed for the RMSE nor peak differences. The RMSE remained around 15-20 Nm, and the peak moment differences observed were 10-15% between the OMC and IMC-based models for lifting and lowering tasks.

- A close correspondence between the IMC and OMC-based moment estimates was established, with the load being the main factor affecting the differences between systems.

- The IMC system shows potential for use in occupational settings to capture data on the lumbar moments of workers, which could be utilized to assess ergonomic risk.

The second study aimed to assess the accuracy of a wearable inertial motion capture system in estimating compressive and shear forces at the L5/S1 level during manual lifting tasks. Reference forces at L5/S1 were obtained using an inverse dynamics top-down laboratory musculoskeletal model based on data from an optical motion capture measurement system. The experimental setup mirrored that of the first study. The main findings are as follows:

- The results revealed that the wireless sensor system underestimated peak compressive and shear forces by an average of 30%, respectively. The observed RMSE averaged 550 N for compressive forces and 150 N for shear forces. To identify potential biomechanical factors contributing to these differences, the peak angles of lumbar flexion, rotation, and lateral bending were analyzed. Additionally, the distance in X, Y, and Z coordinates from the center of the lumbar joint to the center of the lifted box was evaluated as a proxy for segment length differences. The findings suggest that load mass and lifting height have a significant impact on force estimates.

- Furthermore, significant differences in force estimates may be attributed to discrepancies in joint angles and position estimates. These results provide insights into the limitations of the inertial motion capture system in accurately estimating forces at the L5/S1 level during manual lifting tasks.

- Understanding these limitations is important for improving the system's accuracy and enhancing its utility in ergonomic assessments.

- The biomechanical modeling approach, employing inverse dynamics for the estimation of L5/S1 moments, is more aptly equipped for capturing physical exposure within a live production environment, as compared to the tested methodology based on musculoskeletal simulation.

The primary objective of the third study was to establish and evaluate a comprehensive framework for processing data to estimate lumbar loading. To achieve this objective, the study utilized methods from fatigue failure theory to calculate the cumulative damage resulting from continuous low-back loading time-series data collected through Inertial Motion Capture (IMC). Eight workers from an automotive manufacturing facility volunteered to participate while they performed their work. Time-series estimates of moments at the lumbosacral joint (L5/S1) were calculated using a top-down approach. These moments were processed using cycle counting methods to obtain estimates of cumulative damage. A total of 108 trials were evaluated. Each trial consisted of one complete working cycle of a specific vehicle model at a particular workstation. Low back injury data provided by the company and self-reported injuries from surveys completed by the workers were compared against fatigue failure-based cumulative damage estimates using stepwise logistic regression models.

- Results indicated a statistically significant relationship between the cumulative damage estimates and both self-reported low-back pain (OR = 2.16, [95% CI: 1.30, 3.57]) and recorded injuries (OR= 1.65, [95% CI: 1.03, 2.63]).

- The proposed framework offers a novel approach for analyzing kinematic data and assessing cumulative loading exposure associated with complex loads, postures, and occupational tasks observed in field settings.

Collectively, these studies represent pioneering efforts in evaluating an IMC system through biomechanical and musculoskeletal modeling, systematically addressing critical variables such as load mass, height, asymmetry, and their interactions. Moreover, the field assessment employing the IMC system laid the groundwork for developing and validating a cutting-edge approach to measuring cumulative exposure.

6.2 Future Research

These studies hold promising implications but also reveal limitations that warrant further investigation. Future laboratory-based research should examine factors such as lifting technique, speed, and posture in laboratory studies. Including a more diverse range of weights and asymmetry levels that mimic real-world scenarios is advisable.

In the context of the field study, the fatigue failure model introduced represents a pioneering step in the quest for more extensive research on estimating cumulative damage, and the preliminary outcomes signal promise for future research pursuits. However, automation is essential to mitigate the extensive data processing time requisite for the model to provide outcomes. Additionally, it would be advantageous to stay alert to emerging advancements such as more accurate or cost-efficient IMU technologies, computer vision-centric cameras, machine learning, and artificial intelligence to enhance the practical applicability of this approach. Moreover, refining our understanding of musculoskeletal tissue properties, such as healing dynamics and variations across sex and age, could significantly enrich the personalization of results. Personalization is a crucial aspect given the diverse anthropometrics encountered in industrial settings. Lastly, it is essential to conduct a broader range of epidemiological studies to substantiate the robustness of the proposed method. Moreover, incorporating risk assessments and health outcomes from diverse industrial sectors is crucial for establishing a standardized framework for results, an indispensable attribute for the practical applicability of risk assessment methodologies.

6.3 Summary

Quantifying cumulative exposure to physical risk factors remains a formidable challenge in modern ergonomics. The present research demonstrated the efficacy of utilizing an inertial motion capture system for data acquisition in field settings, which was subsequently processed by employing an innovative method for estimating cumulative damage in low back loading through continuous loading history and fatigue failure theory. The employment of biomechanical modeling for the estimation of moments at the lumbar region exhibited superior accuracy compared to the estimation of compressive and shear forces via musculoskeletal modeling when the IMC system was juxtaposed with the gold standard OMC. Consequently, low back moments were incorporated as input in the fatigue failure-based continuous loading assessment methodology. This model was tested and validated within an automotive manufacturing environment, revealing an association between cumulative damage (CD) estimates and health outcomes reported by the company and participating individuals.

The development and application of this method was the first attempt toward a more sophisticated, scientific-based ergonomic risk assessment model. Future endeavors appear promising with the potential integration of cutting-edge data capture technologies and personal attributes, including age, gender, anthropometry, and possibly the recuperative properties of musculoskeletal tissues.

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