A framework to automate physical demand analysis based on artificial intelligence and motion capture for workplace safety improvement

by

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Abstract

Workers' safety and productivity and its affecting factors, such as ergonomics, are essential aspects of construction projects. Applying ergonomics and realizing the connections among workers and their assigned tasks have indicated a decrease in workers' injuries and discomforts, a beneficial effect on productivity, and a reduction in project costs. Workers in the construction zone are often subjected to awkward body postures and repetitive motions that cause musculoskeletal disorders. Accordingly, these disorders and circumstances lead to delays in production.

This research focuses on an automated and systematic Physical Demand Analysis (PDA) via Artificial Intelligence (AI) and Motion Capture system (MOCAP) for analyzing the working circumstances associated with physical demand. It enables the health and safety department to comprehend the construction tasks and the plant operation in detail for each task and production line to analyze the potential ergonomic risks for workers. Conventionally, ergonomists use an expensive and long time process to manually gather data to fill out the forms associated with the PDA technique, which involves observing and interviewing the different workers about the physical demands of a particular job. No study has yet been conducted to make an automated framework based on construction 4.0 for this action. This study uses a MOCAP system and an artificial intelligence technique to obtain joint angles and body segment positions in different working situations, convert them to activities, and detect their frequency. The framework is created to automatically fill a posture-based PDA

form and address the physiological side of the task demands. As a result, it can provide precise data about the physical demands of each job for different functions such as risk assessment, job matching, modified tasks for injured workers, and others. Also, the automated framework is created to reduce wastes related to costs and person-hours and improve the project's productivity.

Preface

This thesis is an original work by Ramin Aliasgari. The research project received research ethics approval from the University of Alberta Research Ethics Board. Project Name "ARTIFICIAL INTELLIGENCE AND MOTION CAPTURE BASED PHYSICAL DEMAND ANALYSIS FOR WORKPLACE SAFETY IMPROVEMENT," No. Pro00116445, DATE. January 27, 2022.

No part of this thesis has been previously published.

Dedication

To my family for their everlasting love and support, which contributed to my achievement.

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List of Abbreviations

Abbreviation	Explanation
3D	three-dimensional
AEC	architecture, engineering, and construction
AI	artificial intelligence
BVH	Biovision Hierarchy
CMU	concrete masonry unit
CPS	cyber-physical systems
IMU	inertial measurement unit
MOCAP	motion capture
PDA	physical demand analysis
REBA	rapid entire body assessment
RTLS	real-time locating systems
RULA	rapid upper limb assessment
sEMG	surface electromyography
UAV	unmanned aerial vehicles
UWB	ultra-wide bands
WCB	workers' compensation board
WMSD	work-related musculoskeletal disorder

Chapter 1 – Introduction

1.1 Background

Construction workers are often exposed to physically demanding duties, including awkward body position and repeated motion, resulting in work-related musculoskeletal disorders (WMSDs) that delay projects or manufacturing lines (CPWR, 2013b). Construction and manufacturing workers are more prone than workers in other sectors to be subjected to higher physical demands, such as awkward body positions, repetitive motion, and overexertion (Li et al., 2019). Additionally, Manual Material Handling (MMH) tasks are prevalent in these industrial sectors and maintenance workshops (Leung et al., 2004; Albers et al., 2005). Physical demand analysis (PDA) is a technique that allows the health and safety sector to thoroughly understand the construction jobs and plant operation for each task and production line and investigate potential ergonomic risks to workers. PDA collects data about the physical demands of work on particular parts of the human body via a systematic methodology (Li, 2017).

The 1950s and 1960s started the first research on the physical demands of construction tasks. These researches were focused on work physiology, and energy expenditure data for several trades were obtained (Lehmann, 1961; Durnin & Passmore, 1967; Astrand, 1967; Astrand et al., 1968; Christensen, 1983). These analyses showed that estimating the physiological demands of construction tasks is complicated. This difficulty was linked to the multiplicity of individual operations required in a single activity and the unpredictability among construction workers in adopting a method for performing an activity (Astrand & Rodahl, 1986).

Ergonomics focuses on a system of interacting components, including the worker, the physical and organizational work environment, the job, and the workplace (Sluiter, 2006). Also, ergonomics seeks to maximize worker comfort, safety, productivity, and efficiency by ensuring a good match between employees and their tasks. The rapid upper limb assessment (RULA) was created to evaluate the risk of work-related upper-limb disorders (McAtamney & Corlett 1993). Ergonomic designs were also examined with help from RULA. Also, the healthcare and service sectors use the rapid entire body assessment (REBA) to track and evaluate workers' shifting postures while on the job (Hignett & McAtamney 2000).

Lean construction was first defined in 1994 as applying Toyota Production concepts to the construction industry. Upon the onset of the "fourth industrial revolution," a significant study was conducted to determine the impact of industry 4.0 on the architecture, engineering, and construction (AEC) industry, including construction 4.0. with a primary emphasis on technology. To continue growing and supporting the AEC sector, Lean Construction must accept the changes brought about by Industry 4.0 while maintaining the people-processes-technology triangle at its foundation. The AEC industry has several issues, including a lack of innovation and management frameworks that are traditional and shortsighted (Hamzeh et al., 2021). Lean construction 4.0 should aim toward system efficiency despite being a challenge in the construction industry. This requires a balance of human demands, technological advancements, construction processes, and human ideals such as free choice, peace, and sustainability (Hamzeh et al., 2021).

According to construction 4.0, sensing technology advancements have allowed us to automatically gather and analyze body motion data. Ryu et al. (2018) propose an automated posture assessment approach based on inertial measurement units (IMUs) that enables ergonomic analysis via kinematic information. The experimental findings indicate that automated motion data collection and analysis may aid in comprehending working postures selected by workers with varying degrees of expertise (Ryu et al., 2018). Workers' body motions can be tracked using motion capture (MOCAP), which collects data for ergonomic studies. It is generally simple to post-process data collected by the instrument using direct measurement, as a MOCAP system. Joint angles and body segment positions are measured during various operations to determine the frequency accurately (Moeslund et al., 2006). Video recordings (Han & Lee, 2013b), wearable sensors (Yan et al., 2017), or vision-based sensing technologies like Microsoft Kinect are needed for extracting worker motions to do an automated ergonomic study (Han et al., 2013a). Once the motion data has been collected, an ergonomic and biomechanical analysis may be used to automatically identify potentially dangerous motions (Golabchi et al., 2015c).

Human observers' assessment of joint angles is highly imprecise. The standard deviation values demonstrate this for the various body joint angles (Golabchi et al., 2015b). Given the inherent imprecision in the human judgement of body joint angles utilized as inputs to posture-based ergonomic assessment tools, the subjective nature of these tools toward their inputs might result in discrepancies in outcomes. Golabchi et al. (2015b) assessed the inaccuracy of human assessment of joint angles characterizing worker postures and investigated how to improve ergonomic evaluation systems using fuzzy logic modelling approaches. The findings demonstrate the significant inaccuracy of human estimations and their influence on ergonomic study results while validating the use of fuzzy logic to mitigate their effects. Using automated fuzzy expert systems for ergonomic assessment, construction practitioners access a rapid, easy, and reliable technique for identifying and addressing risky worker movements to lower the incidence of WMSDs (Golabchi et al., 2015b).

The absence of new ideas in the AEC industry is only one of the sector's problems (Hamzeh et al., 2021). Throughout the preceding two decades, the industry has paid growing attention to artificial intelligence (AI) techniques, which are now used to bring innovation to the construction field and improve project efficiency and productivity (Guo, 2016). While efficiency is a challenge in the construction industry, lean construction 4.0 should emphasize system efficiency. Human demands, technology improvements, and construction procedures must work together (Hamzeh et al., 2021).

This research involves conducting a literature review on construction 4.0, PDA forms, WMSDs, MOCAP, and AI techniques. Then, in the subsequent sections, it proposes a framework for evaluating workers' body segment positions and joint angles during manual handling and operational tasks on construction sites by utilizing the Xsens MVN as an IMU, a type of MOCAP. It also uses an AI technique to convert the joint angles and body segment positions to different activities, identify their frequency, and automatically fill posture-based PDA forms. After that, it implemented the framework in a case study. Eventually, the results show that a posture-based PDA form is developed that enables users to get precise information about the physical demands of a particular job for different purposes such as ergonomic risk assessment, recruiting and training, job matching, and modified tasks for injured workers, and others. Moreover, by integrating Lean construction 4.0 into this framework, an automated PDA filling system is created to reduce wastes associated with costs and person-hours in subjective data collection and solve the issues related to inaccurate PDA.

1.2 Problem Statement

- No posture-based PDA form contains most of the construction workers' activities.
- There is a lack of definition on how to define activities by body postures.
- Ergonomists fill PDA forms manually.
- Ergonomists' techniques for data collecting to fill out the PDA forms are expensive, take a long time, subjective and imprecise.

1.3 Research Objectives

- Develop a posture-based PDA form that includes most of the activities construction workers do during work to enable users to get information about the physical demands of a particular job.
- Develop an AI-based algorithm to detect activities based on joint angles and body segment positions.
- Propose a framework to fill the PDA forms automatically and accurately.
- Reduce wastes related to cost and person-hours and improve the efficiency and accuracy in collecting data for physical demand analysis.

1.4 Research Contributions

Contributions from this research consist of:

1.4.1 Academic Contributions

- Developing a new posture-based PDA form.
- Using MOCAP and AI-based algorithm to objectively obtain postures and joint angles and body segment positions to define different activities.
- Using the definitions and a rule-based expert system to develop an automated PDA filling system.

1.4.2 Industry Contributions

- Reducing wastes associated with costs and person-hours for data collection and PDA form completion.
- Using the proposed framework will aid in the ergonomic design of a workstation or a manufacturing plant's production line. Also, instead of collecting data, ergonomists will concentrate their time on physical ergonomic interventions, such as improving the workplace's equipment and surroundings, reducing employees' exposure to ergonomic risks and enhancing worker health and safety.
- Helping workplace organizations and health care specialists to identify and modify occupations or activities as a customized, effective, and efficient return-to-work program to accommodate disabled or injured workers and assist them in returning to their prior positions.
- Identifying the most demanding activities to avoid assigning them to inexperienced or weak employees and matching jobs to specific persons within the worker's working capacity to increase practicality, efficiency, agility, operational effectiveness, and productivity.
- Analyzing the physical demands of alternate work methods and developing modified tasks or tactics to prioritize safety risks, mitigate ergonomic risks and prevent workplace accidents.

- Utilizing the framework may proactively reduce workers' insurance claims and injury reports and lower the industry's workers' compensation costs.
- Preparing a specific job demands documentation for training, recruiting, therapists to develop suitable treatment objectives, health care practitioners, and workers' compensation boards.

1.5 Organization of Thesis

This thesis comprises six chapters: Chapter 1 contains different parts such as background and problem statement, research objectives, and research contributions. Chapter 2 contains an overview of the relevant literature on construction 4.0, PDA, WSMD, MOCAP, and AI. Chapter 3 presents the methodology and its steps, including experimental design, data collection, processing data and automation, verification and validation. Chapter 4 presents the results of this study and a case study of using the AI/MOCAP framework in a masonry project. Chapter 5 discusses the results of the laboratory experiment and case study. Chapter 6 summarizes the study, makes suggestions and identifies areas for more investigation.

Chapter 2 – Literature Review

2.1 Construction 4.0

With the fast growth of technology and its applications across several disciplines, industries are undergoing a paradigm transition, with greater digitalization, increasing intelligent future-oriented technologies, automation, and the internet of things at the forefront (Lasi et al., 2014). The integration of Lean methods with Industry 4.0 technology has been studied in manufacturing, demonstrating the existing synergies (Sanders et al., 2016). On the other hand, the AEC industry has yet to obtain the benefits of current and developing technologies that comprise the fourth industrial revolution to provide more effective and efficient projects (Sawhney et al., 2020).

Industry 4.0 encompasses several ideas, including cyber-physical systems (CPS), autonomously managed and digitalized smart manufacturing, customized product and service making, and dispersed self-organization (Lasi et al., 2014). Industry 4.0 enables businesses to achieve greater agility, operational effectiveness, and productivity via machine-dominated production to digital, intelligent, and integrated manufacturing (Rosin et al., 2020; Oztemel & Gursev, 2020). According to Rüßmann et al. (2015), these nine technical ideas represent industry 4.0 in manufacturing. "automation, big data analytics, simulations, cybersecurity, system integration, the internet of things, augmented reality, additive manufacturing, and the cloud." Lean construction 4.0 will need to guarantee that people stay at the core of these implementations, emphasizing the user skill element and satisfaction conditions in new digitally-driven work conditions without jeopardizing work conditions or human connections (Hamzeh et al., 2021).

Construction 4.0 is a critical component of Industry 4.0 because it entails the application of numerous innovative technologies such as "sensor networks, virtual reality, automation, three-dimensional (3D) printing, prefabrication, unmanned aerial vehicles (UAV), augmented reality, and robotics to repetitive or dangerous procedures" (Sawhney, 2017; Ahmed, 2019). These intelligent technologies may enable construction stakeholders to gather data in an automated method, simulate various scenarios, conduct sophisticated analysis, display simulations, analyze findings, and operate the equipment. Construction 4.0's heart is CPS, and all these developments are CPS-based or CPS-enabled. Eventually, CPS is critical to achieving the aims of construction 4.0, which include safer, more practical, efficient, and environmentally friendly construction jobs (Sawhney, 2017).

The AEC industry began embracing some of these technologies in response. Data analytics techniques such as predictive modelling and machine learning are effective for decision-making for AEC projects (Mansouri et al., 2020). Additionally, simulation has been used extensively in the AEC industry for various objectives, including risk scheduling, process improvement, analysis, claims, and maintenance operations. Indeed, simulation is critical in developing a prospective idea of automated development planning and control (Abdelmegid et al., 2020). Also, construction 4.0 has been presented as a structure for more effective planning, design, and delivery of advanced facilities via physical-digital transitions (Sawhney et al., 2020).

Lean manufacturing is a solid basis for Industry 4.0 since lean principles encourage identifying inefficient processes and their simplification, facilitating automation and digitalization (Buer et al., 2018). A new manufacturing term has emerged since the convergence of lean production and industry 4.0: "Lean Automation." However, automation is not a new notion in lean, as the autonomy principles admit that repetitive and value-adding operations may be automated (Satoglu et al., 2018). Using lean-based techniques, Satoglu et al. (2018) aimed to show that waste reduction and adding value are prerequisites for implementing industry 4.0. This is known as production theory and is a problem-driven viewpoint based on lean-based approaches for using smart and digital technologies. Along with developing and implementing innovative solutions in manufacturing and logistics, the need for ergonomically advanced equipment continues to grow. It is possible to enhance working conditions and the quality of workplaces via the use of these technologies in an attempt to achieve Industry 4.0 compatibility across companies (Gašová et al., 2017).

2.2 Physical Demand Analysis

Numerous scientists have claimed that since physical exhaustion impairs performance, performance may be enhanced either by eradicating the sources of physical fatigue or by devising strategies to mitigate its effects (Brouha, 1967; Janaro, 1982; Itasca, 2000). Physical fatigue may reduce productivity and enthusiasm, distraction, imperfect quality work, job unhappiness, poor judgment, coincidences, and injuries while working in physically demanding environments (Brouha, 1967; Janaro, 1982; Itasca, 2000).

Physical and cognitive demands are the primary forms of task demands (Sluiter, 2006). The term "task demands" refers to the degree of difficulty, the time constraint, and the effort necessary to complete the task workload (Nixon et al., 2011). Also, task demands are a vital contributor to workplace physiological stress, and there is a significant association between increasing task workload fatigue and individual mistakes (Dorrian et al., 2011; Guastello et al., 2012). Additionally, task overload significantly contributes to mental and physical capacity failure in the job, such as mind and muscle fatigue (Nixon et al., 2011). Moreover, Dorrian et al. (2011) said that physical factors associated with work, such as high force while lifting, holding big things, and repetitiveness, contribute considerably to reducing muscular capacity.

According to Srinivasan et al. (2016), excessive physical activities have a detrimental effect on cognitive function, lowering focus and attention levels and increasing human mistakes. Numerous research has examined the influence of awkward postures and lifting task elements on musculoskeletal complaints; however, the relationships between these variables and individual fatigue and task demands have been neglected (Macdonald, 2003). However, physical fatigue caused by manual tasks, such as lifting, pushing, and pulling heavyweight items, affects attentional resources, cognitive processes, and muscular strength (Ahsberg et al., 2000; Guastello et al., 2012). As a result, it is essential to be aware of the physical demands of construction work to ensure the personnel's health and safety and boost productivity. The answer to the question of what a person may safely perform is based on this idea, according to Brouha (1967).

For example, some studies may highlight construction work as the best place to use physiology-based solutions to minimize the physiological demands of the task. These construction interventions include changing work techniques, such as investing in more automated tools and equipment, ensuring enough work-rest cycles, or even revising expectations of what workers can reasonably be expected to do. Using work physiology methodologies, Abdelhamid and Everett (1999) proved the capability of monitoring in-situ physical demands of construction operations for a concrete placement and finishing operation.

Eight ergonomic risks have been recognized by the Canadian Centre for Occupational Health and Safety (CCOHS, 2016), including " overtime work in the office, static body posture, WMSDs, manual material handling, usage of tools, poor lighting, shift work, and slips/trips/falls" which should be taken into account while creating production workstations. Also, awkward body position, repetition of action, and effort with force are the three major ergonomic risk factors (Jaffar et al., 2011; PSHSA, 2010). Because of this, it is critical to consider the operational processes and working conditions since they necessitate a wide range of varied physical positions, some of which might expose the worker to awkward body posture risks (Li et al., 2019). So, it is critical to conduct a thorough study and evaluate current and new workstations in the design phase to identify possible ergonomic risks (Li et al., 2019).

PDAs are used to record the environmental, cognitive, and physical demands of vital tasks, which is often advised to Canadian industry as well as other countries (OHCOW, 1998; Gagne, 2010; Workers' Compensation Board of Alberta, 2014; Workplace safety and prevention services, 2011; Li et al., 2019).

PDA aids in the identification of possible risk factors for injury and supports the design of activities that minimize these hazards (Workplace Safety and Insurance Board, 2018). Instead of reacting just when someone is hurt and takes time off work, the industry may be proactive rather than reactive by adopting preventive steps (WCB of Alberta, 2015a). As a result, the PDA is an essential tool for worker demand analysis and developing effective return-to-work programs that may be used in industries where physical demands are involved (Li et al., 2019). Workers who have been wounded in the workplace might continue contributing to their workstations and production if given modified work assignments (WCB of Alberta, 2015b).

PDAs for various equipment users are described in Workplace Safety North (2016). Furthermore, it is worth noting that PDAs may be tailored to suit any industry's specific needs. These ergonomic concerns were identified by Li et al. (2015), who used PDAs in an Alberta manufacturing plant to measure "environmental demands, sensory demands, frequency of activities, and physical strength demand." Some risk evaluation tools like the national institute for occupational safety and health (NIOSH) lifting equation must be used in conjunction with PDA, according to the occupational health clinics for Ontario Workers (OHCOW, 1998), to accurately recognize risk factors and determine whether a specific job duty necessitates overexertion. Workers' return to work is easier for injured employees when PDA is used with other evaluations, such as the fitness for work or functional ability evaluations (Gagne, 2010).

PDA employs a systematic approach to gathering data on the physical demands of work on specific parts of the human body. The prevention PDA is defined by the industrial accident prevention association (2009) as a systematic technique for assessing the physical, environmental, and cognitive demands of essential and non-essential professional responsibilities. This information provides step-by-step recordings of all physical demand data attained from plant observations. PDAs may be used to avoid injuries by detecting ergonomic risks and help rehabilitate after an occurrence (Li et al., 2015).

Each work is assigned a PDA, consisting of multiple tasks detailed in the PDA. A typical PDA typically contains "an overview of the job, a schedule of work shifts, and information about meals and breaks, job alternation, personal protective equipment (PPE), dangerous tasks, equipment used, strength requirements, repetitive motion demands, body posture necessities, sensory requirements, environmental situations, and ergonomic risks" (Li et al., 2017a). The PDA shows information in a suitable format for various occupational applications, ranging from rehabilitation to injury prevention. Companies have complete discretion over which jobs obtain a PDA form. PDA forms should be updated when a business innovates and improves its processes (Li et al., 2017a).

Having a functional PDA also benefits the manager, administrator, or plant nurse in that it helps them understand the job demands at the injured worker's workplace (Gagne, 2010). Occupational safety and health administration ergonomics led to PDA implementation in one organization, as Getty (1994) described, who asserts that PDA provides a basis for injury curb measures that improve quality and productivity. Other studies detail the Canadian Workers' Compensation Board's attempt to provide PDA templates for industry (Mallory, 2018). Also, PDA templates, such as the occupational health clinics for Ontario Workers (OHCOW, 1998) guideline for effective PDA implementation, have been developed.

Costs associated with getting PDA information vary according to the difficulty of the project and whether external consultants or internal employees are used (OHCOW, 1998). When working in a single place and doing repeated tasks, the PDA may be completed in less than an hour. However, the PDA may take several days to complete if the task requires travel to many areas and changes by day or season. The cost of a PDA might also vary depending on who conducts the PDAs. The least expensive option is to conduct a PDA using internal workers. However, internal employees educated about job analysis and injury risk variables may be restricted (OHCOW, 1998).

When establishing the cost of a PDA, the information should be priced according to the kind of work being analyzed. A PDA's cost should be calculated hourly when a job requires repeated tasks. A cost analysis should be undertaken per-PDA basis for jobs that vary daily. Additionally, if the PDA avoids an overexertion injury by job matching or ergonomic intervention, the cost savings may be as high as $6,000-$7,000 per instance. (OHCOW, 1998)

Collecting PDA information can be accomplished in two ways: reactively, by performing PDAs as the circumstance happens, or proactively, by performing PDAs in advance to build a databank for use when and if the need appears. If the PDA information is used for various purposes, proactive PDAs should be conducted. However, reactive PDA data gathering should be explored if resources are limited or precise information is necessary (OHCOW, 1998). Each of the options outlined above has some pros and cons. Table 1 shows the pros and cons of the two approaches for collecting PDA data.

Table 1: The pros and cons of two PDA data collection approaches (OHCOW, 1998).

Method	Advantages	Disadvantages
Proactive	Allows for the broadest possible range of uses.	Requires significant investment of resources and money
	PDA data may be valuable as early as the first day of the claim.	Maintaining a database of PDAs is complex such as the requirement to update PDAs when deviations arise.
	Allows for the finding of alternative employment placements through a database search.	The information included in current PDAs may not be as detailed as required in every accident situation.
	Prioritizes ergonomic intervention in occupations	-
	Affords applicable PDA data in job posters	-
Reactive	possibility of receiving specific, thorough information on an injury case.	The application range is the smallest.
	When doing a work analysis, accommodations might be addressed and researched.	Finding alternative work placements is challenging, such as task searches from the restricted record.
	Reduces resource and expense requirements	-

A PDA is a method for dissecting a job into its constituent parts. When investigators do a physical demand study, they objectively analyze and evaluate the ambient circumstances, the usage of machinery, work aids, equipment, and the physical demands of each operation. Direct and indirect observation methods are used to measure the physical and environmental demands of the work (OHCOW, 1998). In several instances, experience has shown a lack of uniformity among investigators. Due to the poor dependability of PDA information, the PDA's use and accuracy will be low. Additionally, when the PDA is contested in arbitration or on appeal, the data included in the PDA will be very problematic to approve (OHCOW, 1998).

Performing a PDA might be particularly challenging for very variable and occasional tasks. One approach is to collect videos of workers executing duties using video recorders. The recordings are then combined and evaluated, allowing the evaluator to analyze as though the worker performed a single continuous activity (Li et al., 2017a).

A time study may determine the frequency of various needed body positions. Additionally, the overall durations of assigned jobs are noted. Body postures are recorded using a spreadsheet at 1-minute intervals for each task in the time study. Direct observation is utilized with video recording since video cameras benefit from concurrently capturing hours of footage for several locations. The research team can then analyze this film to extract pertinent facts. Moreover, observers are aware of working hours and planned breaks in the case of video recording in order to prevent gathering footage during breaks. So, frequency is the number of times a worker performs a motion during a particular period, calculated by dividing the number of checkmarks in the spreadsheet by the time study period. Additionally, the length of action may be determined by accumulating the consecutive checkmarks in the time study spreadsheet. After calculating the percentage for each position, the following frequency descriptions are given to each percentage range: “Never” (0%), “Rare” (1–5%), “Occasional” (6–33%), “Frequent” (34–66%), and “Constant” (67–100%) (Li et al., 2019).

PDAs were constructed in stages, beginning with data collecting. To begin, the researchers installed a video camera around one worker's desk and performed direct observation to familiarise themselves with the procedure. The measuring instruments on hand sped up the process of completing the measurements. The next step was to create a time study spreadsheet and observe the worker for 60 minutes, with check marks every minute to capture the worker's movements where it is necessary to determine the frequency of actions (Li et al., 2019).

2.3 Work-Related Musculoskeletal Disorders

Painful illnesses are included under the umbrella term musculoskeletal disorders, affecting the body's soft tissues such as nerves, muscles, cartilage, tendons, ligaments, and joints (CCOHS, 2013). WMSD risk factors are elements in the workplace that contribute to the likelihood of developing WMSD (Jaffar et al., 2011). They are classified as physical stressors, psychological stressors, and individual variables. "Repetitive strain injuries, cumulative trauma disorders, overuse syndrome, and repetitive motion disorders" are other terms for them. In most cases, WMSDs result from either the job or the workers' work environment, and they tend to grow over time. WMSDs may be classified as sprains, strains, and cumulative trauma disorders, depending on the mechanism of injury (Inyang et al., 2012). Highly physical demand duties in the construction sector expose employees to well-known WMSD risk factors, including excessive force exertion, repetitive motion, vibration, awkward body position, and interaction force. Significant financial damage may result in wounded employees and managers (Wang et al., 2015).

Repetitive doing low-force activities may lead to WMSD, according to the Ontario safety association for community and healthcare (OSACH, 2010), without tiredness, abnormal body postures, pain, and tissue damage. Establishing break intervals to enable workers to eat and rest, automating or semi-automating operational chores, and ensuring that the activity is physically possible for the worker at the recruitment stage are effective alternatives for decreasing ergonomic problems (Safety and Health Authority, 2006).

In the United States, WMSD account for 33% of all work-related illnesses and injuries (Bureau of Labor Statistics, 2013). Researchers who interviewed 750 bricklayers randomly discovered that 67% of those tested had symptoms similar to WMSDs (Boschman et al., 2012). Injured workers, contractors, and civilization may incur high economic and human costs. Construction contractors often pay a higher premium for workers' compensation insurance than employees in most other businesses (AWCBC, 2012). According to one insurer, WMSDs accounted for 29% of covered contractors' workers' reimbursement claims. (Albers et al., 2006). Besides direct costs, contractors might have to pay for various indirect expenditures, such as compensation for missing personnel, lost productivity during a work stoppage, staff training, and replacement costs (OSHA, 2012).

One of the most considerable signs of the severity of injuries and illnesses is the median number of days away from work (Bureau of Labor Statistics, 2013). Injuries to the back received while working in construction are the third-highest among private firms regarding days away from work after only transportation and retail (CPWR, 2013a). Injuries to the lower back are responsible for more than half of all WMSDs resulting in days away from work (CPWR, 2013b). So, back WMSDs are the most prevalent injury in the construction industry. Construction workers with WMSDs may have decreased job abilities, and if the symptoms are not treated effectively, they are likely to return (Inyang et al., 2012). WMSDs, on the other hand, may result in lifelong impairment in the most severe instances (Albers & Estill, 2007).

Methods to estimate the risks of WMSDs may be divided into the following groups: expert observation, remote sensing, self-report, and direct measurement. Among these, self-report and observational approaches may discover only clearly recognizable risk variables like repetition and abnormal posture, leaving unresolved other workplace risks, such as excessive force exertion and vibration. Sensor and sensing technology advancements have resulted in approaches for collecting human movement data developed using marker-based and distant sensing techniques. (Wang et al., 2015). Moreover, Li and Buckle (1999) studied posture-based observational, direct measurement, and self-report approaches for assessing physical workload and related WMSD risk exposure. Most approaches for measuring exposure to possible WMSD risks were created for research purposes and are therefore unsuitable for application in many real-world work contexts. Also, David (2005) addressed the benefits and drawbacks of the strategies from workplace safety and health professionals. Observation-based assessments were shown to be the most effective for health practitioners and professional safety with limited sources and time. Furthermore, Inyang et al. (2012) used statistical data from Canada to examine the severity of WMSDs in the construction industry.

Ergonomic concepts should be included in workstations' design to decrease the risk of damage. Human body modelling and surface electromyography (sEMG) was used to establish a technique for evaluating fatigue development and muscle power during manual lifting exercises (Li et al., 2017b). Additionally, a repetitive lifting action is chosen, and the low back muscles' performance is examined using monitoring sEMG muscle activity. The kinematics of the lifting job is captured using AnyBody Technology software to create a human body model (Komeili et al., 2015).

On the other hand, although an ergonomically designed workplace may increase operational efficiency, it often requires unnatural body positions and activities potentially harmful to workers. Workers may suffer from WMSDs due to this incident, and their mental health may be exposed, resulting in considerable compensation costs (Hales, 1995; Golabchi et al., 2015a).

2.4 MOCAP

MOCAP is a technique for capturing people's movements and providing data for ergonomics investigation. Like the fast development and widespread implementation of MOCAP technology, improvements in WMSD evaluations have been achieved in construction research over several years, particularly in posture-oriented assessment. Two major research programs are focused on vision-based approaches and wearable sensor systems (Wang et al., 2015).

From a design standpoint, MOCAP can broaden the scope of user research in creating new products, designing more intelligent human-computer interfaces, and diagnosing mobility problems (Xin et al., 2007). Also, biomechanical knowledge and evaluation may better understand how people or groups interact with items and surroundings, allowing designers to project more efficient scenarios. MOCAP system may be used in the ergonomic work analysis context to examine posture, dynamic occupation, workflows, and reaches using a large amount of data, removing the need to analyze each frame of interest individually, limiting researcher bias, lessening effort, and preserving time (Pastura et al., 2012). The motion or kinematics data obtained may be input for current observational risk assessment methods that evaluate risk quantities on-site and biomechanical simulations that calculate tissue or joint loading related to WMSD hazards (Wang et al., 2015). Manual observation-based ergonomic analyses are helpful in stationary workplaces like manufacturing assembly sections and offices. However, they can provide incorrect data on construction worksites due to the wide range of manual activities implemented, the constantly shifting work environment, and the complication of exposure (Golabchi et al., 2016a).

When combined with virtual simulations, adding MOCAP to digital human models enables the assessment of novel work arrangements that do not exist physically. They may also be used to teach new employees if knowledge or the unique manner someone does a job is documented (Santos et al., 2013). The MOCAP is also utilized to stimulate the worker sample in the virtual world, ensuring that existing conditions are accurately represented (Golabchi et al., 2015a). When optimizing potential operating situations, the motion generation element visualizes worker activities using pre-recorded movements of ergonomically safe operations, allowing the virtual representation for safety exercise requests. Golabchi et al. (2015a, 2016b) thoroughly explain the safety analysis component.

Direct measurement techniques give precise information, but their high cost, data storage requirements, and processing time restrict their use on many patients or over a lengthy period. Direct measurement is pretty precise, and the post-processing of the information collected by the device is simple (Moeslund et al., 2006). The virtual model may be utilized to gather analytic inputs directly by measuring quantitative qualities such as distances or by observing various worksite components to gain qualitative features like body motion required to carry out a manual activity (Guo et al., 2016) and facilitating the design's correct perception (Golabchi et al., 2015a). The resultant MOCAP data are stored in the Biovision Hierarchy (BVH) file format, an ASCII (American Standard Code for Information Interchange) format that describes body joints' configurations and rotations for each time frame and allows the animation of bipedal figures. This may be achieved by specifying the virtual worker model's posture and position across time (Golabchi et al., 2015a). After applying loads to various body joints throughout the motion file, it is possible to detect postures that place excessive stress on a particular body joint and adjust the motion by redesigning the job until it is ergonomically safe. (Golabchi et al., 2015a).

The simulation model shows the present status of an ongoing operation and may be used for both objectives. First, it is a reference model for analyzing different operational scenarios, including existing operating safety and productivity, to find the company's optimal scenario. When predetermined motion time systems are included in the simulation environment, this method is considerably improved to accurately simulate varied conditions (Golabchi et al., 2018). The motion production component is likewise linked to the simulation model and thus produces the whole thing by combining gathered motions from a database (Golabchi et al., 2017). A trace message links the simulation model with motion generation and details the numerous motions executed. This data is then utilized as input for a process that searches for and constructs complete movements from a list of MOCAP data to develop a simulation model from the output of action recognition and use it for operation assessment and improvement (Golabchi et al., 2017). Generally, three types of MOCAP systems are used for different situations.

2.4.1 Optical System

In an optical system, sensors track reflective, optical, or magnetic markers placed in various areas on the body as the subject moves, and the markers' positions are collected by a series of sophisticated digital cameras (Rajput, 2013). The method's disadvantages include lengthy processes that can take considerably longer than the initial data gathering, including experimental setup time. While data collectors use many cameras, markers may be obscured by other portions of a subject's body. Three orthogonal coils are installed in a transmitter, each marker in a magnetic system. The difference in magnetic flux between the transmitter and receiver in the marker enables the position and orientation of the receiver to be determined. The magnetic system has the benefit of being line-of-sight independent. However, it is susceptible to magnetic fields and metallic items. (Rajput, 2013).

Despite the excellent precision with which optical MOCAP tracks marker trajectories, the method's reliance on laboratory equipment limits its potential applicability in everyday life activities or broader clinical practice (Karatsidis et al., 2019).

Direct measurement is often used in conjunction with or instead of expert observation to improve the accuracy of risk assessment. Direct measurement is accomplished by using accelerometers, force sensors, and goniometers. Researchers in the laboratory often use sensors directly connected to individual dress or skin to capture data such as joint and body segment motion in three dimensions, although this is seldom used in a real-world setting (Wang et al., 2015). In contrast to expert observation and self-report, direct measurement is objective. A broad range of typical direct measures, such as sound sensors, optical scanners, goniometers and inclinometers, and electromyography, examine biomechanics and tissue and joint stress (CPWR, 2013a).

Numerous commercially available measurements based on optical marker technologies are presented, including CODA, Vicon, Motion Analysis, APAS, and Qualisys. 3D markers attached to the body may track different body parts' positions and angular movement in real-time using particular algorithms (Li & Buckle, 1999).

Vicon is one of the most widely used 3D MOCAP. It entails positioning retroreflective indicators on the human skin or dress and several infrared cameras to monitor human movements (Richards, 1999). Marras et al. (1992) invented the lumbar motion monitor to quantify workers' risk of low back hurt. A triaxial electronic goniometer included in the device was used to capture a worker's 3D thoracolumbar spine movement while doing manual material-handling tasks. Additionally, using the lumbar motion monitor, the same group evaluated the features of trunk motion during repeated manual material handling (Marras & Granata, 1997).

2.4.2 Vision-Based System

As a marker-less assessment technique, vision-based evaluation utilizes depth sensors or numerous cameras to create 3D models of things. Computer vision techniques extract the skeleton and track its mobility (Wang et al., 2015). The use of two-dimensional kinematic data from a video camera was selected since it is the conventional method for determining kinematic parameters (Streit, 2013).

The currently existing devices are prohibitively costly, often require a lengthy learning curve, and are not customizable. With the debut of MS Kinect, the ability to change the biomechanical situation became available. This video game console has been investigated due to its well-known benefits including its cheap cost, marker-less design, and open-source nature (Berger et al., 2011; Chang et al., 2011; Fernandez-Baena et al., 2012).

2.4.3 Inertial Measurement Unit

The motion tracking techniques based on IMUs have been a practical method for predicting the kinematics of 3D body segments throughout the last decade (Luinge & Veltink, 2005; Roetenberg et al., 2005, 2009; Zhang et al., 2013). A significant advantage of such systems is their ability to operate in practically any environment without external equipment such as cameras. As a result of these advancements in inertial motion capture, researchers proved their capacity to assess 3D ground reaction forces and moments (Ren et al., 2008; Karatsidis et al., 2019).

Wearable measuring devices like those used with inertial motion capture were similarly utilized to monitor individual movement for ergonomic study due to their applicability to various circumstances such as varied indoor and outdoor temperatures and lighting (Kim & Nussbaum, 2013). Also, numerous experiments involving wearable sensor devices to evaluate WMSDs were conducted. Physiological status monitoring, anisotropic magneto-resistive sensors, real-time locating systems (RTLS), ultra-wide bands (UWB) and accelerometers were employed as sensors (Wang et al., 2015). Also, Alwasel et al. (2017) estimated joint forces and moments in a bricklaying operation using an IMU-based sensor suit and a 3D static strength prediction program. So far, research efforts in WMSDs in the construction sector have concentrated on posture detection, categorization, and comparison of working positions to ergonomic requirements using sensing technologies. Moreover, Li et al. (2016) present a methodology for using 3D motion-based ergonomic analysis to gather data on human body position.

Comparing marker-less optical technology using Kinect V2 with wearable technology utilizing IMUs for the RULA risk assessment tool shows that wearable technology is more accurate and reliable than marker-less optical equipment in on-site ergonomic risk assessment because self-occlusion and object occlusion creates inconsistency in marker-less optical technology (Humadi et al., 2021).

The Xsens MVN is a real-time inertial MOCAP device for the whole body that does not need a camera. One kind of it includes inertial sensors and a Lycra suit with integrated cabling to cover the whole body in this system, including up to twenty micro-electro-mechanical systems. The data from the magnetometer, gyroscope, and accelerometer are all integrated by the IMU to be calculated. Kim and Nussbaum (2013) state that this device can detect physical exposure from handling tasks relevant to inside and out situations. The inertial system MVN Biomech has proved reliable compared to other systems (Kider et al., 2008).

2.5 Artificial Intelligence

Researchers in various fields define AI; For instance, computer scientists are often interested in developing intelligent systems and programs that resemble human behaviour, such as experience-based learning and language comprehension. On the other hand, engineers place a more excellent value on using AI to solve problems. Systems that think like humans, act as individuals, think reasonably, and act realistically are all categories of AI, according to Russell and Norvig (1994).

AI is unique from other methods since it focuses on how computer programs mimic human mental functions, including memory, reasoning, learning, and contextual interpretation of data (Guo, 2013). AI is a multidisciplinary field that has drawn academics from various disciplines, including mathematics, computers, neurology, linguistics, and psychology. The acceptance of AI techniques has risen dramatically. They cover various topics in science and engineering, including logic reasoning, feeling, decision-making, illness detection, and robot control (Guo, 2013).

AI will continue to provide improved algorithms to construction operations to maximize production while minimizing costs and time. Holographic displays, virtual reality, and augmented reality will provide a new world of sensory experiences for system designers, practitioners, and users, advancing human-to-system interactions to previously unimagined data integration and usability (Hamzeh et al., 2019).

According to these descriptions, AI approaches can perform general intelligent action, simulate the human brain artificially, actively learn and adapt like a human, act intelligently, and process languages and symbols (Guo, 2013).

The five most suitable AI approaches for engineering challenges are "fuzzy logic, knowledge-based systems, inductive learning, genetic algorithms, and neural networks" (Pham, 1999).

In knowledge-based systems, data and information are necessary components of knowledge because they allow for inferences and conclusions. It might be implicit such as practical ability and competence, or explicit, like knowledge of a topic. Knowledge-based systems have been built based on the principle that once information is arranged and represented that computer programs can recognize, it often delivers decision-making answers that are the same or better than those generated by human specialists (Guo, 2013).

A further benefit of knowledge-based systems is that they may be used to create software that can draw logical conclusions and provide decisions about a problem area based on the information they have accumulated to assist humans in understanding, decision-making, and acting (Hembry, 1990). To build a knowledge-based system, one must prioritize "the representation, accumulation, acquisition," and application of task-particular information. Knowledge-based systems are made up of three main elements, as seen from the standpoint of the end-user: 1) Knowledge base: "heuristics, rules, facts, frames, and cases" make up the knowledge base, which is a vast repository of extremely certain and problem-particular information, 2) Knowledge-based reasoning: offers problem-solvers and decision-makers with solution suggestions, 3) User interface: provides a means of connecting the end-user to the system, and under its user-friendliness, encourages more people to utilize the system (Guo, 2013).

"Expert systems" are the most common knowledge-based system, and "case-based reasoning systems" are two kinds of knowledge-based systems that have been extensively used in numerous fields, such as software engineering, fashion matching advice, computer-aided design, computer vision, and production management (Guo, 2013).

A computer application is known as an expert system that can mimic the decision-making abilities of human experts by using explicit information acquired from experts, which may be used to execute complex decision tasks. The extracted information consists of factual and heuristic knowledge, including judgment, intuition, and logical reasoning. Numerous representations have been suggested for successfully representing knowledge in an expert system, including semantics, frames, and rules. Expert systems based on rules employ rules to represent their knowledge, called rule-based expert systems (Guo, 2013).

In a rule-based expert system, knowledge is represented by rules that reflect the expert opinion, including relations, suggestions, heuristics, directions, and tactics (Durkin, 1994). Two elements make up a rule: the IF section is referred to as the antecedent, which includes assumption or condition, and the THEN section is referred to as the consequent or inference. A rule's antecedent and consequent are built of two components: an object and its importance, which an operator connects such as "is, are, is not, and are not." They are often employed to give a linguistic expression a figurative meaning. Using mathematical operators, assigning a numerical value to an object is possible. Additionally, a rule may contain numerous antecedents connected by the logic operators AND as an aggregation, OR as a separation, and many consequents connected via the logic operator AND (Guo, 2013).

Chapter 3 – Methodology

The research methodology in this study is design science research (DSR). The methodology consists of three main scopes: 1) Finding gaps, 2) Developing a framework, and 3) Testing the framework (Hevner et al., 2004). Figure 1 shows the overall steps used to develop the framework. In the first step, the gaps related to physical demand analysis are detected by doing some literature review around this field, and a new posture-based PDA form is developed. In the second step, preliminary laboratory tests consisting of forty-one activities that are the most common in construction sites are simulated to determine the boundary numbers and tolerances of joint angles and body segment positions during the experiments using the MOCAP system. These activities include two primary parts: 1) Manual handling tasks and 2) Positional tasks. The next step defines different activities using the boundary numbers and tolerances and the MOCAP/AI-based framework. In the next stage, the definitions and rule-based expert systems are used to develop an automated PDA filling system. Next, a laboratory experiment is done for verification by comparing the results of five different observers and five expert ergonomists with the framework results. Eventually, on-site experiments are done to implement the framework and validation by comparing the results of the ergonomist with the framework results.

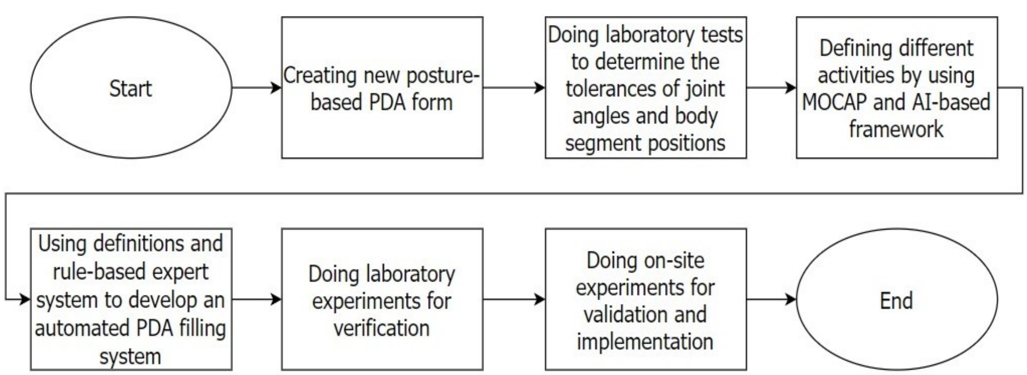


Figure 1: Methodology diagram

3.1. Experimental Design

3.1.1 Materials and Instrument

At least 200 concrete blocks are hand lifted each day by block masons (Hess et al., 2010). Given the 16.6 kg of a conventional concrete masonry unit (CMU) (CCMPA, 2013), masons physically lift more than 3,300 kg daily. The national institute for occupational safety and health developed a recommended weight limit for each lifting weight of 23 kg as the maximum weight that a person may lift during the typical working day without raising his or her risk of getting back discomfort for almost all health workers.

In the laboratory tests, 72 cardboard boxes of 400 × 200 × 200 mm are approximately similar to a kind of real CMUs that are CSA “A” - Type “A” (CCMPA, 2013). Also, some tables and chairs in different levels were used to provide conditions for doing different activities by participants.

In the actual experiment at the construction site, the CMUs were 20 cm standard masonry units with a normal weight of 18 kg and sizes of 390 × 190 × 190 mm.

The motion data of participants were collected using wireless MOCAP, the MVN Awinda from Xsens, and video cameras. The device consists of seventeen IMUs attached to each body segment: head, shoulders, upper arms, forearms, hands, upper legs, lower legs, feet, stern, and pelvis. Each sensor comprises a triaxial magnetometer, triaxial gyroscope, and triaxial accelerometer, which collect motion data at a sampling rate of 60 Hz (Xsens Technologies B.V., 2020). The tests were captured on video utilizing camcorders to identify and segment the data during the data processing step and observe the tasks manually filling the PDA form. Each participant had a calibration session to confirm that the models developed from the motion data were consistent with their bodies before the experiment. The sensors' data is extracted as BVH files, which provide the local three-dimensional coordinates of body joints. Also, an excel file that includes body segment positions, joint angles, and ergonomic joint angles in each frame is exported.

3.1.1.1 Coordinate Systems

The MVN fusion engine calculates the location and orientation of the sensor on each body segment concerning an earth-fixed coordinate system (*G*). The coordinate system is a right-handed Cartesian coordinate system with a global reference frame (Xsens Technologies B.V., 2020):

X is positive while directed to the local magnetic North (With red colour).
Y directed to the West regarding right-handed coordinates (With green colour).
Z is positive while directing upward (With blue colour).

When the person stands in T-pose, the body frames are aligned with the global reference frame. To calculate joint angles, an additional frame of reference is needed to establish the body frames based on the anatomical position defined by origin (the rotational center's proximity) (Xsens Technologies B.V., 2020):

X directed to the forward (With red colour).
Y pointing upward, from joint to joint (With green colour).
Z directed right (With blue colour).

Figure 2 shows the body segment coordinate system for each body segment origin when standing in T-pose, as used in MVN (Xsens Technologies B.V., 2020).

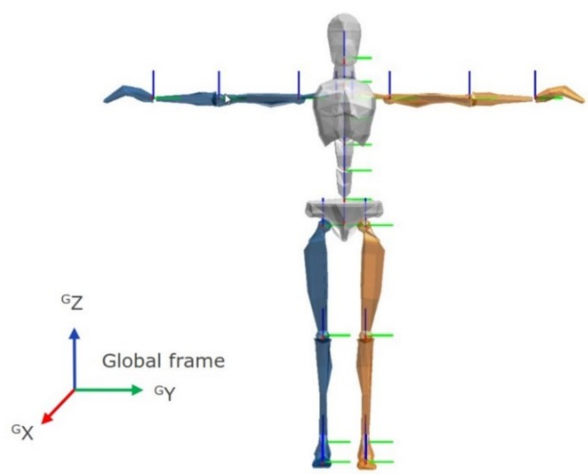


Figure 2: Body segment coordinate system for each body segment origin when standing in T-pose (Xsens Technologies B.V., 2020).

This alternate coordinate system is solely used to compute joint angles in an intermediate frame. The anatomical frame defines the joint origins, indicated in the functional axes' centers, with the *X*, *Y*, and *Z* axes associated with functional movements (Xsens Technologies B.V., 2020).

The joint angles and different coordinate systems in a leg are shown in Figure 3 as an example to show that global and local coordinate frames are used to calculate joint angles in MVN Analyze (Xsens Technologies B.V., 2020). Also, Figure 4 shows that at each joint origin, a body segment coordinate system is employed to derive the joint angles in MVN (Xsens Technologies B.V., 2020).

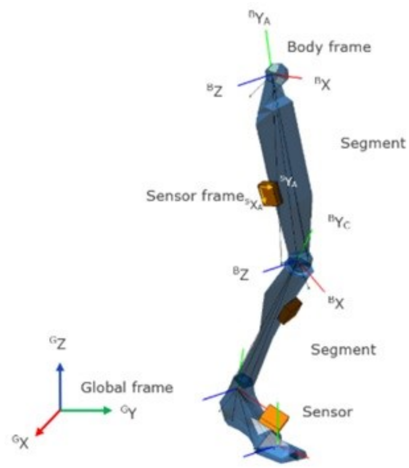


Figure 3: MVN software coordinates local and global frames to calculate joint angles (Xsens Technologies B.V., 2020).

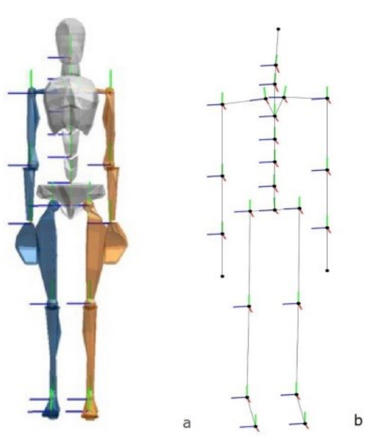


Figure 4: a) MVN's body segment coordinate system for determining joint angles, b) The skeleton comprises joint centers linked together. (Xsens Technologies B.V., 2020)

3.1.1.2 Body Planes

The three orthogonal planes split the human body and segments into diverse sectors to define a body segment position, organs and limb structures, and body parts' movements. The sagittal plane, also known as the median or lateral plane, is an *y-z* plane that divides the body into two halves (right and left). The *x-y* planes, called the frontal or coronal planes, split the body into two halves: a front and a back half, also referred to as the dorsal and ventral or posterior and anterior halves. The transverse plane, or horizontal plane, or axial plane, is an *x-z* plane parallel to the ground that separates the top and bottom sections of the body, also known as the superior and inferior sections (Mraz, 2015). Figure 5 shows these three body planes (Xsens Technologies B.V., 2020).

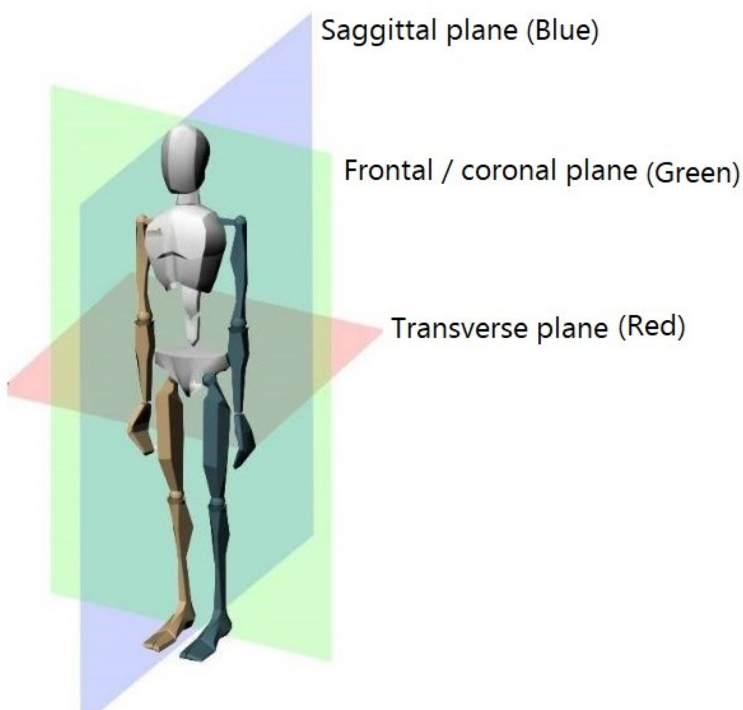


Figure 5: Body planes (Xsens Technologies B.V., 2020).

3.1.1.3 Body Segments

There are twenty-three segments in a body that the MOCAP system measures their positions. Figure 6 indicates these body segments in a 3D graphical simulation (Xsens Technologies B.V., 2020). Moreover, a schematic drawing of different body segments is shown in Table A-1.

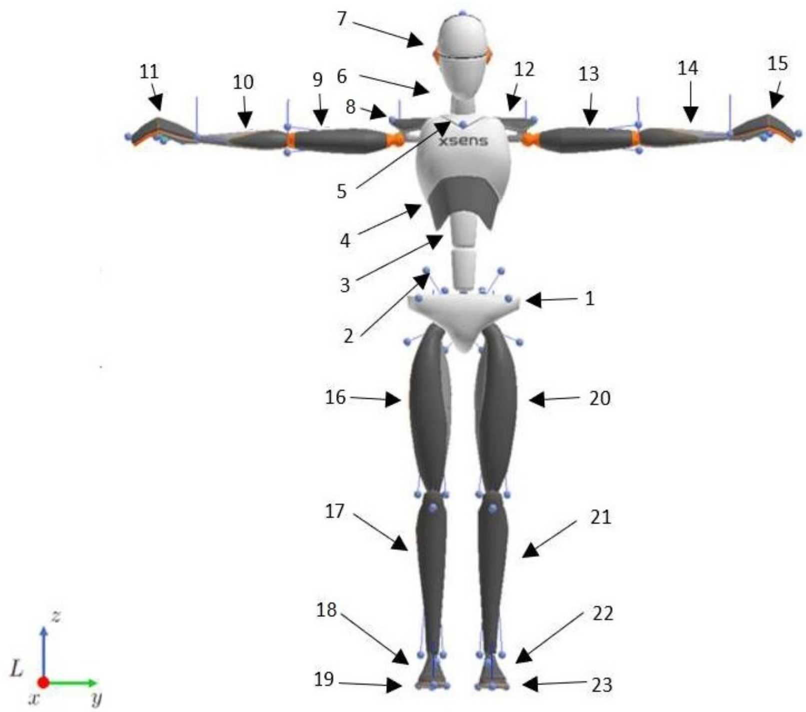


Figure 6: Indication of different body segments (Xsens Technologies B.V., 2020)

Table 2 shows the legend for defining the directions and body segments. Also, Table 3 prepared a list of twenty-three body segments and their descriptions (Xsens Technologies B.V., 2020).

Table 2: Legend table for body segments

Legend	
J	Joint
L	Lumbar spine segment
S	Sacral spine
C	Cervical spine segment
T	Thoracic spine segment
T8	Sternum

Table 3: Body segment Table (Xsens Technologies B.V., 2020).

Number	Body segment	Segment between	
1	Pelvis	Both hip joints	J L5S1
2	L5	J L5S1	J L4L3
3	L3	J L4L3	J L1T12
4	T12	J L1T12	J T9T8
5	T8	J T9T8	J T1C7 (Sternum)
6	Neck	J T1C7	J C1 Head
7	Head	End segment above J C1 Head	
8	Right Shoulder	J Right T4 Shoulder	J Right Upper Arm GH
9	Right Upper Arm	J Right Upper Arm GH	J Right Elbow
10	Right Forearm	J Right Elbow	J Right Wrist
11	Right Hand	End segment after J Right Wrist	
12	Left Shoulder	J Left T4 Shoulder	J Left Upper Arm GH
13	Left Upper Arm	J Left Upper Arm GH	J Left Elbow
14	Left Forearm	J Left Elbow	J Left Wrist
15	Left Hand	End segment after J Left Wrist	
16	Right Upper Leg	J Right Hip	J Right knee
17	Right Lower Leg	J Right Knee	J Right Ankle
18	Right Foot	J Right Ankle	J Right Toe
19	Right Toe	End segment after J Right Toe	
20	Left Upper Leg	J Left Hip	J Left knee
21	Left Lower Leg	J Left knee	J Left Ankle
22	Left Foot	J Left Ankle	J Left Toe
23	Left Toe	End segment after J Left Toe	

3.1.1.4 Body Joints

There are twenty-two joints in a body, and the MOCAP system measures their motion angles. Table 4 lists these joints and their descriptions (Xsens Technologies B.V., 2020). Also, a schematic drawing of them and ergonomic joint angles are shown in Table A-2.

Table 4: Joints Table (Xsens Technologies B.V., 2020).

Number	Joints	Joint between	
1	J L5S1	Lumbar spine segment five	Sacral spine one
2	J L4L3	Lumbar spine segment four	Lumbar spine segment three
3	J L1T12	Lumbar spine segment one	Thoracic spine segment twelve
4	J T9T8	Thoracic spine segment nine	Thoracic spine segment eight
5	J T1C7	Thoracic spine segment one	Cervical spine segment seven
6	J C1Head	Cervical spine segment one	Head segment
7	J T4 Right Shoulder	Thoracic spine segment four	Right shoulder MVN segment
8	J Right Shoulder	MVN shoulder segment	Upper arm
9	J Right Elbow	Upper arm	Forearm
10	J Right Wrist	Forearm	Hand
11	J T4 Left Shoulder	Thoracic spine segment four	Left shoulder MVN segment
12	J Left Shoulder	MVN shoulder segment	Upper arm
13	J Left Elbow	Upper arm	Forearm
14	J Left Wrist	Forearm	Hand
15	J Right Hip	Pelvis	Upper le
16	J Right Knee	Upper leg	Lower leg
17	J Right Ankle	Lower leg	Foot
18	J Right Ball Foot	Foot	Calculated toe
19	J Left Hip	Pelvis	Upper leg
20	J Left Knee	Upper leg	Lower leg
21	J Left Ankle	Lower leg	Foot
22	J Left Ball Foot	Foot	Calculated toe

3.1.1.5 Sensors

The MVN Awinda from Xsens is a real-time system that contains seventeen Wireless Motion Trackers (MTW) affixed to different body segments. Each sensor includes a triaxial magnetometer, triaxial gyroscope, and triaxial accelerometer, which collect motion data at a sampling rate of 60 Hz (Xsens Technologies B.V., 2020). Figure 7 shows the sensors that are attached to straps.

Figure 7: A picture of MVN sensors

Table 5 shows the name of the sensors and the related body segments. Also, Figures 8 and 9 show the positions of different body segments that each sensor needs to be attached to (Xsens Technologies B.V., 2020).

Figure 8: Position of MVN sensors (Xsens Technologies B.V., 2020)

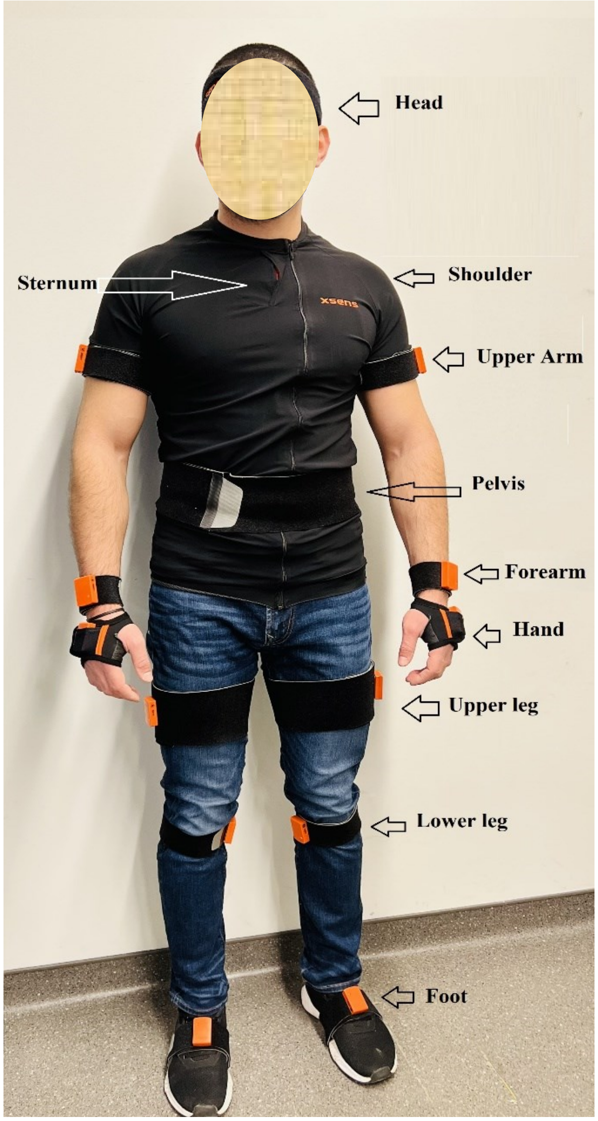


Figure 9: Position of MVN sensors attached to the body

Table 5: List of MVN sensors (Xsens Technologies B.V., 2020)

Number	**Sensors**	**Number**	**Sensors**
1	Pelvis	10	Left ForeArm
2	T8	11	Left Hand
3	Head	12	Right Upper Leg
4	Right Shoulder	13	Right Lower Leg
5	Right Upper Arm	14	Right Foot
6	Right ForeArm	15	Left Upper Leg
7	Right Hand	16	Left Lower Leg
8	Left Shoulder	17	Left Foot
9	Left Upper Arm		

3.1.2 Participants, Tasks, and Experimental Setup

This research has three kinds of experiments with different purposes and participants.

1) Preliminary laboratory tests consist of forty-one activities, including manual handling tasks and positional tasks, which are the most common in construction sites, to determine the boundary numbers and tolerances of joint angles and body segment positions during the experiments.
2) Laboratory tests simulate a symbolic construction task for manually and automatically completing a PDA form as an adjustment and verification of the proposed framework.
3) On-site validation of a real construction job for implementing the framework and completing the PDA form manually and automatically.

In the first kind of experiment, ten individuals with a dominant right hand were asked as volunteers via the University of Alberta’s graduate students in Edmonton, Alberta, Canada. Each participant was informed of the study's approach and completed an informed consent document approved by the University's Research Ethics Board. The tests took occurred in a University of Alberta laboratory. Each participant was informed of the experiment and instructed to do forty-one activities in the PDA forms separately upon arriving at the laboratory. Some tables, chairs, and cardboard boxes were used to provide different activities for participants. Definition and figures related to each activity are in appendix B.

In the second kind of laboratory test, one person with a dominant right hand was invited to the participant via the university and instructed to complete an 8 × 9 block wall using seventy-two cardboard boxes in the size of 400 × 200 × 200 mm, which is approximately similar to a kind of real CMUs (CSA “A” - Type “A”) at the University of Alberta laboratory. Figure 10 shows that the experimental setup with the pre-built wall was one course high and consisted of two boxes at the first and end of the course. Participants utilized seventy other boxes to build the wall from the first through the ninth courses.

Thus, each participant task consisted of seventy individual lifts. As shown in Figure 11, the participant performed laying blocks only. In the beginning, the blocks were placed≃100 cm away from the wall, arranged in three pallets, and each included twenty-four boxes.

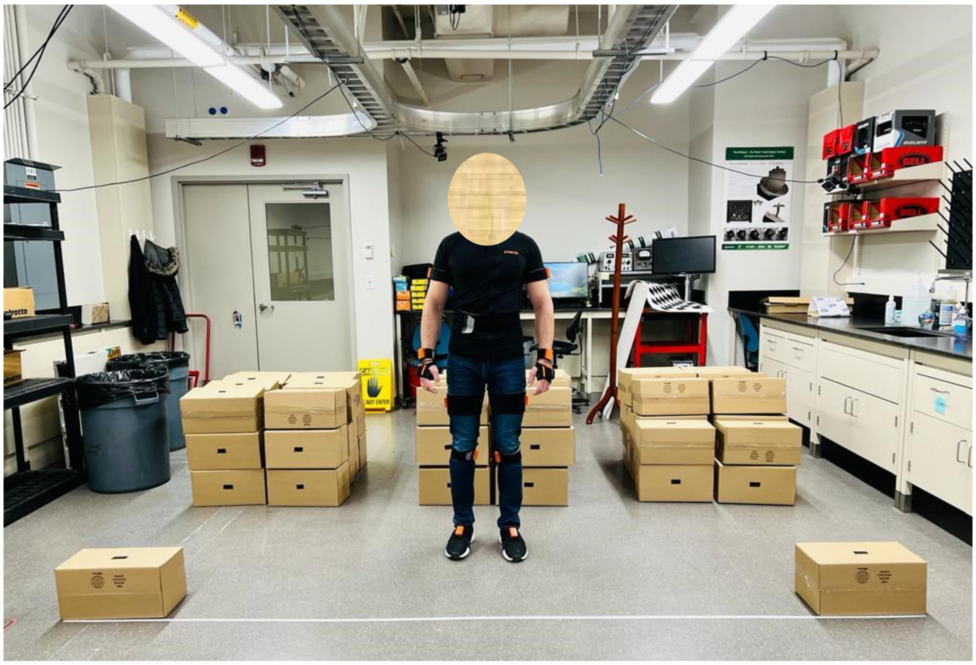


Figure 10: The experimental setup with the pre-built wall

Figure 11: The participant performed laying blocks to make an 8 × 9 block wall

In the third kind of test, the actual experiment at the construction site, the bricklayer with a dominant right hand was asked to build a 1 × 5 block line using five 20 cm standard masonry units with a normal weight of 18 kg and size of 390 × 190 × 190 mm on the earth at a construction site in Scorpio masonry company, Edmonton, Alberta, Canada. Figure 12 shows the experimental setup in that the bricklayer utilized five CMU blocks to build a line.

Figure 12: The bricklayer performed laying blocks to make a 1 × 5 block line

Also, he built a 1 × 3 block line using the same CMU blocks at 4.2 m above the earth on a scaffold. Figure 13 shows that the experimental setup with the pre-built wall was 15 courses high. The bricklayer utilized three other CMU blocks to build the wall in the sixteenth course.

Figures 12 and 13 show that the participant tasks included bringing blocks from pallets, laying them, spreading mortar between and on the blocks, scraping off excess mortar, and doing the alignment. The blocks were placed≃100 cm away from the wall.

Figure 13: The bricklayer performed laying blocks to make a 1 × 3 block line

3.2. Data Collection

Different strategies for collecting data in the workplace might provide wildly disparate findings. There are two types of data collection: subjective and objective. Apart from the financial strain placed on the enterprise, subjective risk evaluations can result in an exaggerated risk of injury or chronic discomfort based on evidence derived from anecdotes (Palmer et al., 2000). Descatha et al. (2009) show similarly that questionnaires often overestimate the degree of risk compared to what is present as measured by direct observation. While questionnaires are a less expensive option, they might not cover all possible health risks associated with exposure (Descatha et al., 2009). When an employer's primary goal is to minimize losses due to productivity and health hazards at the price of a more study, an objective technique is preferable (Palmer et al., 2000).

McCallig (2010) conducted research at a construction firm to assess three data collecting techniques for estimating exposure time to hand and whole-body vibration: questionnaire, interview, and direct observation. The research discovered that interviews and direct observation are more trustworthy than surveys or self-reported questionnaires (McCallig et al., 2010). Deros et al. (2011) observed a motorcycle component manufacturing factory, capturing video footage. The video was determined to provide sufficient time for observing the employees' posture and movement. Additionally, in-person interviews were undertaken to understand better the task, the difficulties encountered, and health issues. According to their observations, workers are regularly required to twist their necks and bend their spines because of the poor ergonomic design of workstations, which causes musculoskeletal disorders (Deros et al., 2011). Additionally, in conjunction with technical data, video-based observation may identify non-neutral and severe postures for repetitive motion that contribute to WMSDs (Juul-Kristensen et al. 2001).

In this research, there are two kinds of data collecting methods:

- For manual data collecting: gather data throughout the experiment by observation and video capture to gain information on the body's mobility, such as joint angles. In this manner, a stopwatch is used to record cycle time and job length, and a camcorder or more to study specifics of activities after the observation, as well as a description of the workplace structure, equipment, and work instruments, among other things. The video's duration varies according to the time necessary to complete the work under investigation, ranging from a few minutes to many hours.
- For data collecting automatically: Throughout the experiment, body kinematics were recorded using seventeen IMUs affixed to main body segments to gather data on body joint angles and body segment positions. Sensors are wireless, allowing for complete freedom and comfort during the experiment. After calibrating the motion sensors, the participant was directed to complete forty-one tasks included in the PDA form and begin constructing a block wall. They began by erecting the wall's first course, paying close attention to the planned alignment line to aid in alignment. Continuous motion and video data were gathered until the participant deemed the wall ready. After that, the data collecting was immediately stopped.

In the first kind of lab experiment, each participant's motion data resulted in BVH and excel files. Each file started when the participant began the first activity and ended when they finished the forty-one tasks. In the second kind of lab experiment, BVH and excel files were created for the participant's motion data. The file started while the participant stood in front of the first brick and ended behind the last block on the wall. Eventually, in the on-site experiment, BVH and excel files were created for the participant's motion data while standing in front of the mortar container and ended behind the last block on the wall.

3.3. Processing Data and Automation

The proposed MOCAP/AI-based framework is developed to define the activities and automated PDA filling system. Six components comprise the overall Rule-based Expert system: "knowledge base, knowledge acquisition facility, database, inference engine, explanation facility, and user interface" (Guo, 2013). 1) "Knowledge base": is a repository of information, like principles of problem-solving and insight, that an individual expert may utilize to solve issues in a particular problem area, and it may be used to aggregate the expertise of various human specialists. A set of IF-THEN rules represents the knowledge in the rule-based expert system. The rule is a conditional statement that establishes a connection between specified circumstances and actions or decisions. So, when the rule's condition section is convinced, the conclusion section is performed. 2) "Knowledge acquisition facility": offers a valuable and straightforward method for collecting and storing all IF-THEN rules. Additionally, various expert systems offer an interactive interface that enables a domain expert to add information directly into the system during runtime. 3) "Database": holds a collection of facts for matching the knowledge base's IF-THEN rules. 4) "Inference engine": performs the reasoning procedures necessary for the expert system to obtain a solution and connects knowledge base rules to database facts. The inference engine determines whether rules are fulfilled, assigns them a priority, and then executes the rules with the top preference. 5) "Explanation facility": helps the consumer comprehend the expert system's reasoning process. By keeping track of the rules that have been fired, the component creates a hint of reasoning that causes a particular inference. 6) "User interface": opens a contact line between the user and the system to pursue a solution. In addition, this decision is made during the system's design phase (Guo, 2013). So, the rules are obtained from the literature review and the results of the first kind of laboratory experiment.

After detecting the activities by the algorithm, the frequency of activities needs to be determined. It is accomplished by calculating the time spent on each task in minutes per shift or workday in the automated framework. Also, the same way is used to calculate the frequencies in manual techniques. Table 6 shows the range definition of five frequencies that are calculated automatically.

Table 6: Frequency based on percent shift or day activity is performed per task

Frequency during shift/workday	**Cumulative time per 8-hour workday**	
Not required	0 minute (0%)	
Rarely	More than 0 minutes (1%)	24 minutes (5%)
Occasionally	24 minutes (5%)	2.64 hours (33%)
Frequent	2.64 (33%)	5.28 hours (66%)
Continuous	5.28 hours (66%)	8 hours (100%)

3.4. Verification and Validation Method

Model verification and validation are techniques for evaluating and communicating the competence of models. Verification guarantees that a simulation model is accurately coded and implemented, while validation confirms that the simulation model generates a range of accuracy acceptable for the intended purpose.

This research has the support of five ergonomists for validation. For this purpose, five different observers and five expert ergonomists filled out the PDA forms related to the laboratory and on-site experiments using the time study method and other techniques to compare with the framework results. For the laboratory experiment, the standard deviation and the average of observers' results are calculated and compared with the results of the ergonomists and the framework. For the on-site experiment, the ergonomist's results, which provide the most detailed data, are compared to the framework results.

Chapter 4 – Results

4.1. Results of the Developed PDA Form

During this study, a new posture-based PDA form was created containing two primary parts: 1) Manual handling tasks and 2) Positional tasks. Additionally, each section has a variety of activities. Manual handling tasks are divided into lifting, carrying, and pushing/pulling parts, each of which is further subdivided into particular activities:

- There are five different actions in the lifting part: low-level lifting, knee-level lifting, waist-level lifting, shoulder-level lifting, and above-shoulder level lifting.
- There are five actions in the carrying part: front carry, side carry, side carry-right hand, side carry-left hand, and on shoulder carry.
- There are four actions in the pushing/pulling part: stationary pushing, stationary pulling, dynamic pushing, and dynamic pulling.

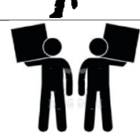
Positional Tasks contain mobility, back, shoulder, neck, elbow, wrist, and ankle parts that each of them breaks down into particular activities:

- There are ten different actions in the mobility part: sitting, standing, walking, climbing stairs, climbing ladders, climbing stools or other equipment, crouching, squatting, kneeling, and crawling.
- There are three actions in the back part: forward bending, trunk rotation, and backward bending.
- There are five actions in the shoulder part: below shoulder level reaching, forward shoulder level reaching, above shoulder level reaching, sideway shoulder reaching, and behind shoulder reaching.
- There are three actions in the neck part: forward bending, backward bending, and twist or tilt.
- In the elbow part, there is one action: flexion or extension.
- There are three actions in the wrist part: flexion or extension, bending, and rotation.

- There are two actions in the ankle part: flexion or extension, and rotation.

Tables 7 and 8 show the developed PDA form for manual handling tasks and positional tasks, respectively.

Table 7: Developed PDA form for manual handling tasks

Manual handling tasks	**Description of objects handled**	**Frequency of workday/shift**				
		Not required	**Rare**	**Occasional**	**Frequent**	**Constant**
Lifting						
Low level						
Knee level						
Waist level						
Shoulder level						
Above shoulder						
Carry						
Front						
Side						
Side, right hand						
Side, left hand						
On shoulder						
Pushing/pulling						

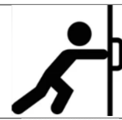
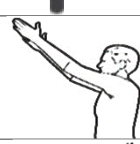
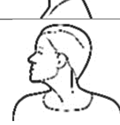
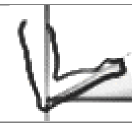
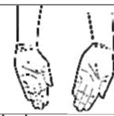
Stationary pushing						
Stationary pulling						
Dynamic pushing						
Dynamic pulling						

Table 8: Developed PDA form for positional tasks

Positional tasks	**Description of activity completed**	**Frequency of workday/shift**				
		Not required	**Rare**	**Occasional**	**Frequent**	**Constant**
Mobility						
Sitting						
Standing						
Walking						
Climbing – stairs	 					
Climbing – ladders						
Climbing – stools, etc.						
Crouching						

Squatting	
Kneeling	
Crawling	
Back	
Forward bending	
Trunk rotation	
Backward bending	
Shoulder	
Below shoulder level reaching	
Forward shoulder level reaching	
Above-shoulder level reaching	
Sideway shoulder reaching	
Behind shoulder reaching	
Neck	
Forward bending	
Backward bending	
Twist/tilt	

Elbow	
Flexion/extension	
Wrist	
Flexion/extension	
Bending (ulnar/ radial deviation)	
Rotation (supination/ pronation)	
Ankle	
Flexion/extension (dorsiflexion/ plantarflexion)	
Internal/external rotation	

4.2. Results of Rule-Based Expert System for Defining Activities and Automated Framework

The proposed framework in this study evaluates workers' body segment positions and joint angles during manual handling and operational tasks on construction sites by utilizing the Xsens MVN as an IMU type of MOCAP system. It also uses an AI technique to convert the joint angles and body segment positions to different activities, identify their frequency, and automatically fill the posture-based PDA form. A rule-based expert system as a kind of AI technique and Python as a high-level programming language is used for providing this automation.

For this purpose, movements in the *z*-direction are divided into five parts:

- Low level: is between the floor and knee height
- Knee level: is between the knee height and the middle of the hip
- Waist level: is between the middle of the hip and the middle of the back
- Shoulder level: is between the middle of the back and the shoulder level plus 10 centimetres
- Above-shoulder level: is above the shoulder level plus 10 centimetres

Figure 14 and Table 9 show the *z*-direction movement and definition of different body segments' height.

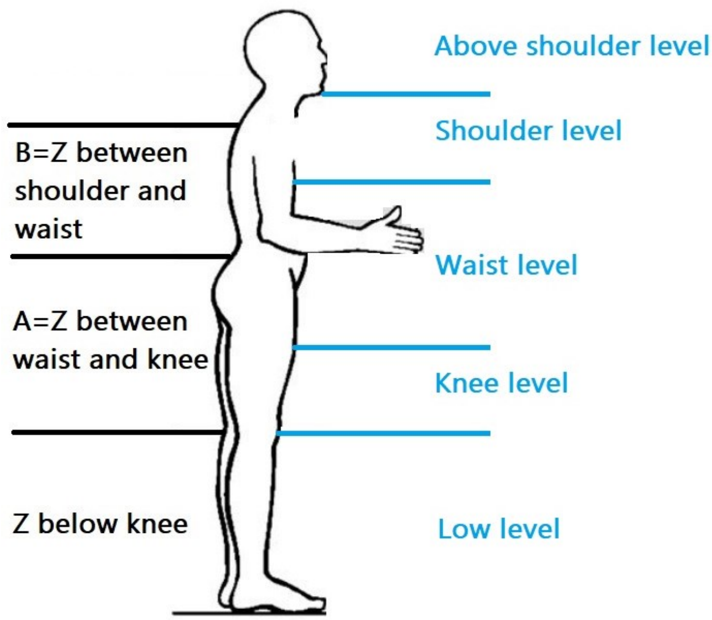
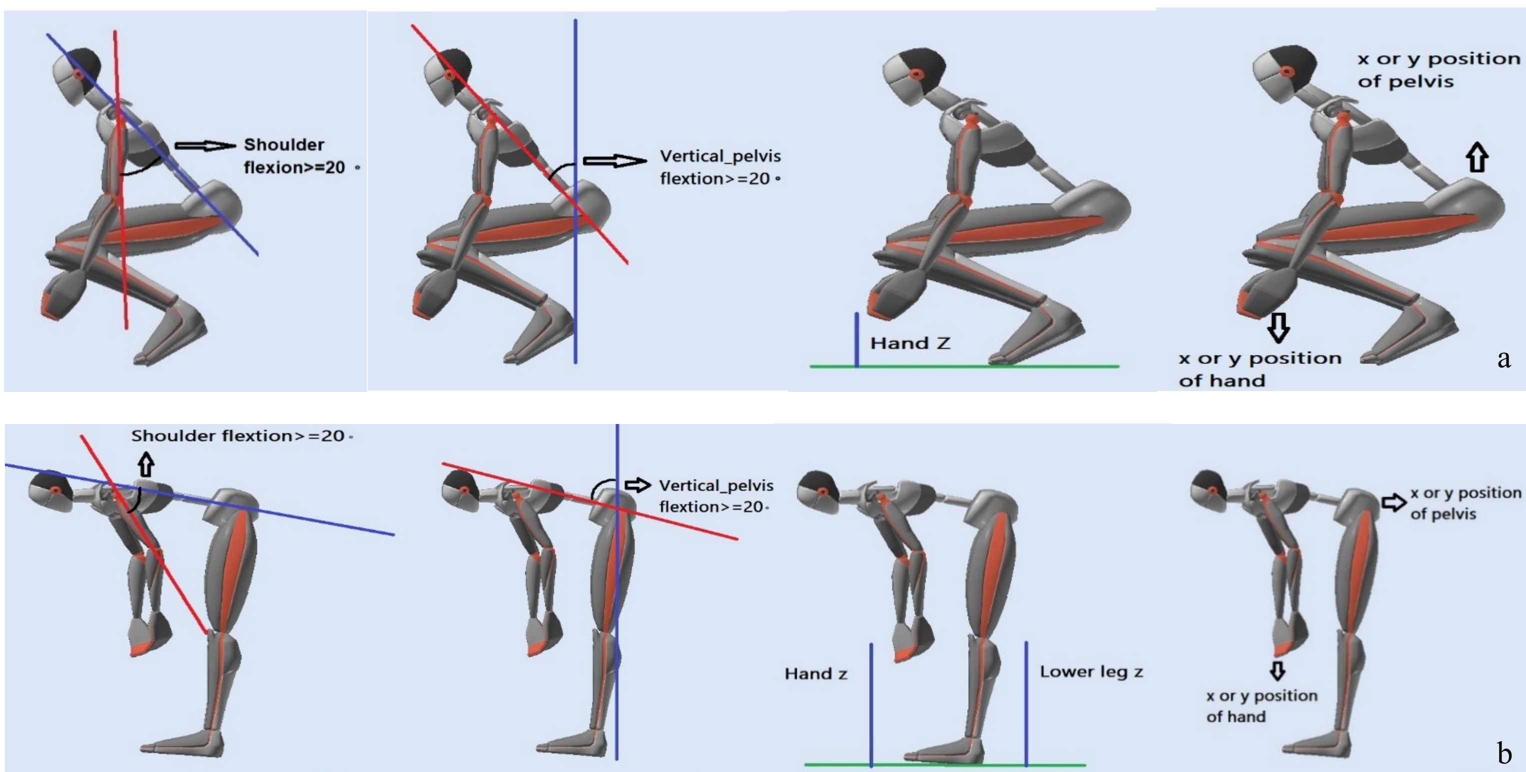


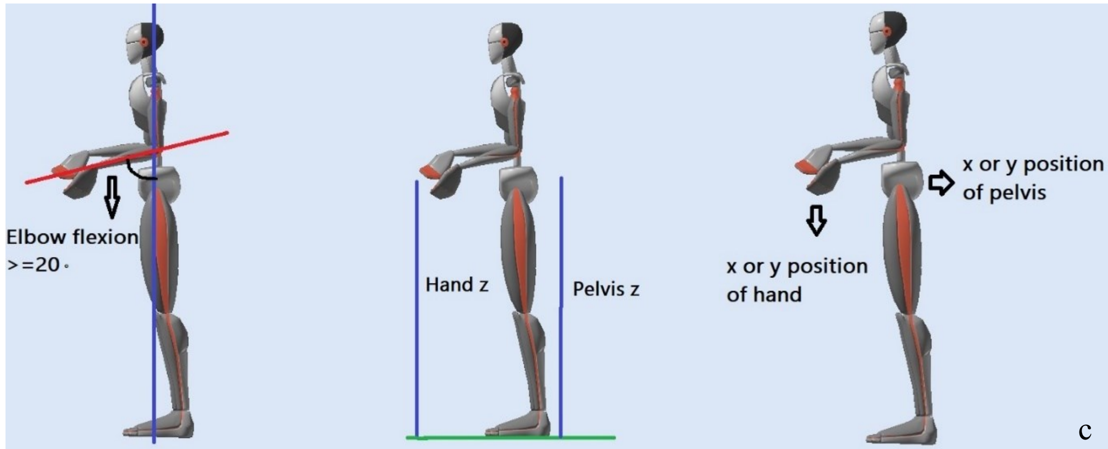
Figure 14: *Z*-direction movement for doing tasks

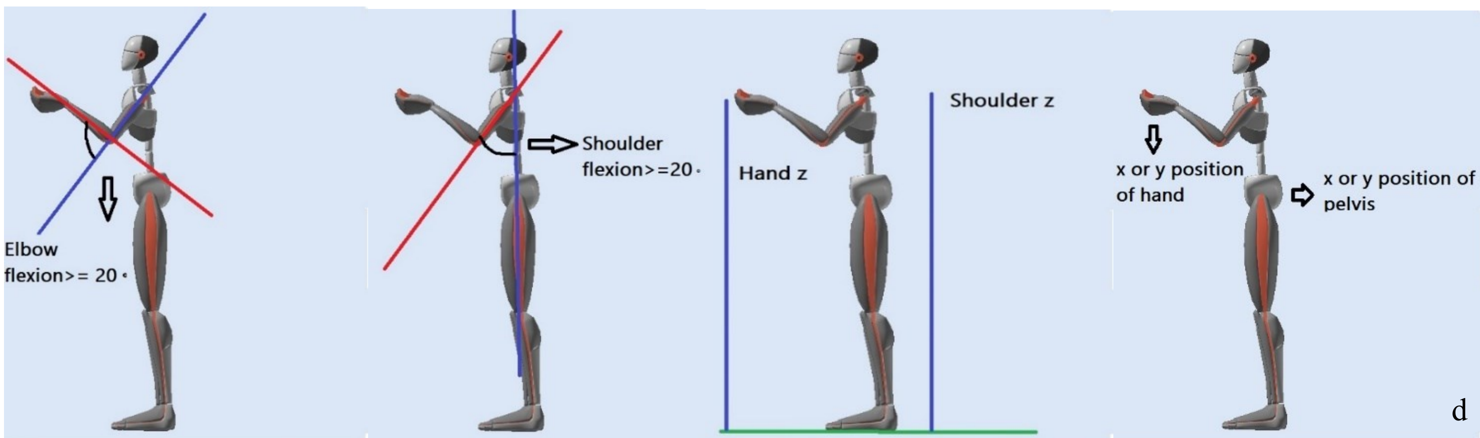
Table 9: Legend table for heights

Legend	
Waist_height	Height of waist in the natural position or first frame
Shoulder_height	Height of shoulder in the natural position or first frame
Knee_height	Height of knee in the natural position or first frame
Lower leg *z*	Knee height in the selected position or frame
A	Waist_height – Knee_height
B	Shoulder_height – Waist_height
Previous	The position in the previous frame

Tables 10–19 show the equations and rules that result from the first kind of laboratory experiment to detect different activities. The boundary and tolerance of joint angles and body segment positions obtained from the laboratory tests, RULA, REBA, and Occupational Health Clinics for Ontario Workers (OHCOW, 1998) guidelines, and results from previous research are used for generating these rules. Also, Figures 15-24 show 3D graphical explanations for different activities.




Elbow flexion
>=20◦
Hand z
Pelvis z
x or y position
of pelvis
x or y position
of hand
c


Elbow
flexion>= 20◦
Shoulder
flexion>=20◦
Hand z
Shoulder z
x or y position
of hand
x or y position of
pelvis
d

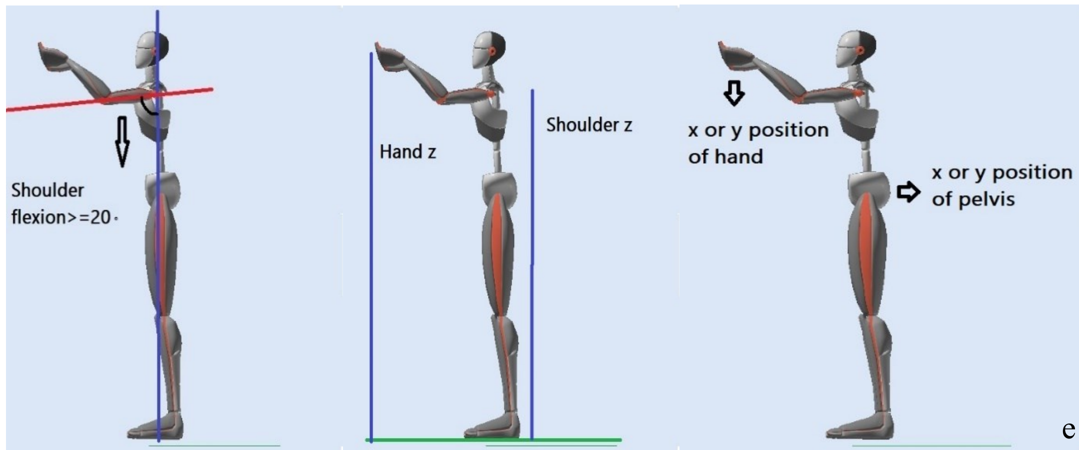


Figure 15: Different positions during lifting activities; a) Low-level, b) Knee level, c) Waist level, d) Shoulder level, e) Above-shoulder level

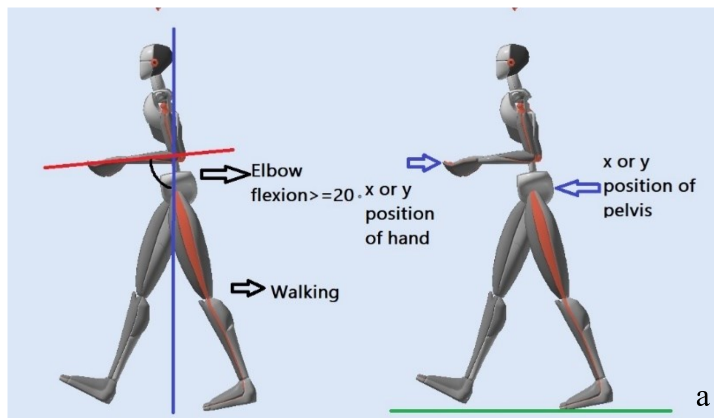
Tables 10a–d: Rules for different lifting activities

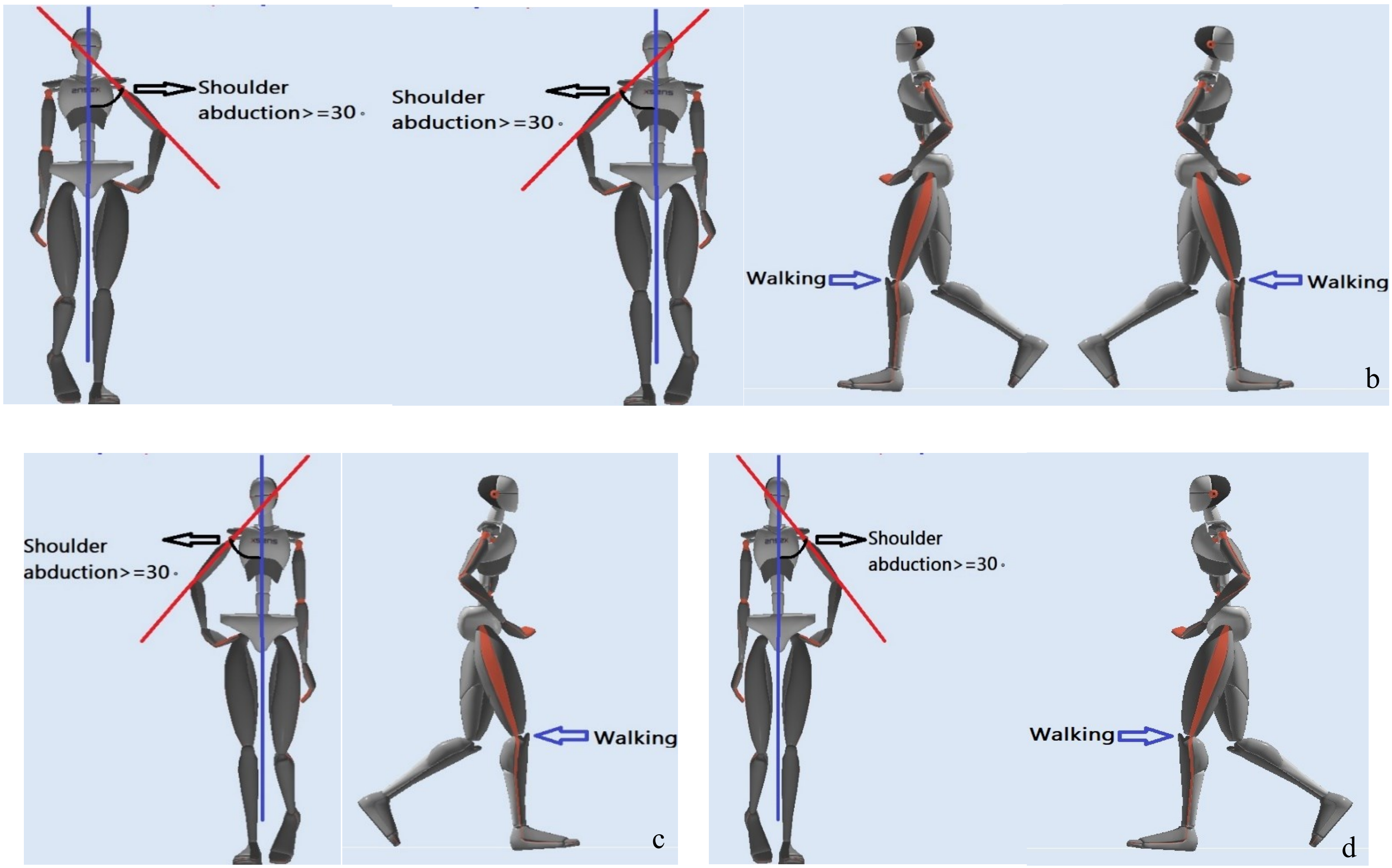
Manual handling tasks	**Condition 1**			
Lifting	Or	Or	Or	Or
Low-level	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	-	-
Knee level	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	-	-
Waist level	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Shoulder level	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Above-shoulder	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	-	-

Manual handling tasks	**Condition 2**			
Lifting	Or	Or	Or	Or
Low-level	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis x) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Knee level	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Waist level	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Shoulder level	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Above-shoulder	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m

Manual handling tasks	**Condition 3**		**And**	**Condition 4**	
Lifting	Or	Or		Or	Or
Low-level	Right Hand *z* < Right Lower Leg *z* m	Left Hand *z* < Left Lower Leg *z* m		Right Hand *z* – Previous Right Hand *z* ≥ 0.01 m	Left Hand *z* – Previous Left Hand *z* ≥ 0.01 m
Knee level	Right Lower Leg *z* ≤ Right Hand *z* < Right Lower Leg *z* + A/2	Left Lower Leg *z* ≤ Left Hand *z* < Left Lower Leg *z* + A/2		Right Hand *z* – Previous Right Hand *z* ≥ 0.01 m	Left Hand *z* – Previous Left Hand *z* ≥ 0.01 m
Waist level	Right Lower Leg *z* + A /2 ≤ Right Hand *z* < Pelvis *z* + B/2	Left Lower Leg *z* + A/2 ≤ Left Hand *z* < Pelvis *z* + B/2		Right Hand *z* – Previous Right Hand *z* ≥ 0.01 m	Left Hand *z* – Previous Left Hand *z* ≥ 0.01 m
Shoulder level	Pelvis *z* + B/2 ≤ Right Hand *z* < Right Shoulder *z* + 0.1 m	Pelvis *z* + B/2 ≤ Left Hand *z* < Left Shoulder *z* + 0.1 m		Right Hand *z* – Previous Right Hand *z* ≥ 0.01 m	Left Hand *z* – Previous Left Hand *z* ≥ 0.01 m
Above-shoulder	Right Hand *z* ≥ Right Shoulder *z* + 0.1 m	Left Hand *z* ≥ Left Shoulder *z* + 0.1 m		Right Hand *z* – Previous Right Hand *z* ≥ 0.01 m	Left Hand *z* – Previous Left Hand *z* ≥ 0.01 m

Manual handling tasks	Condition 5	Source
Lifting		
Low-level lifting	Vertical_Pelvis Flexion $\geq 20^{\circ}$	OHCOW, (1998)
Knee level lifting	Vertical_Pelvis Flexion $\geq 20^{\circ}$	OHCOW, (1998)
Waist level lifting	-	OHCOW, (1998)
Shoulder level lifting	-	OHCOW, (1998)
Above-shoulder lifting	-	OHCOW, (1998)




Shoulder
abduction>=30
Shoulder
abduction>=30
Walking
Walking
b
Shoulder
abduction>=30
Walking
c
Shoulder
abduction>=30
Walking
d

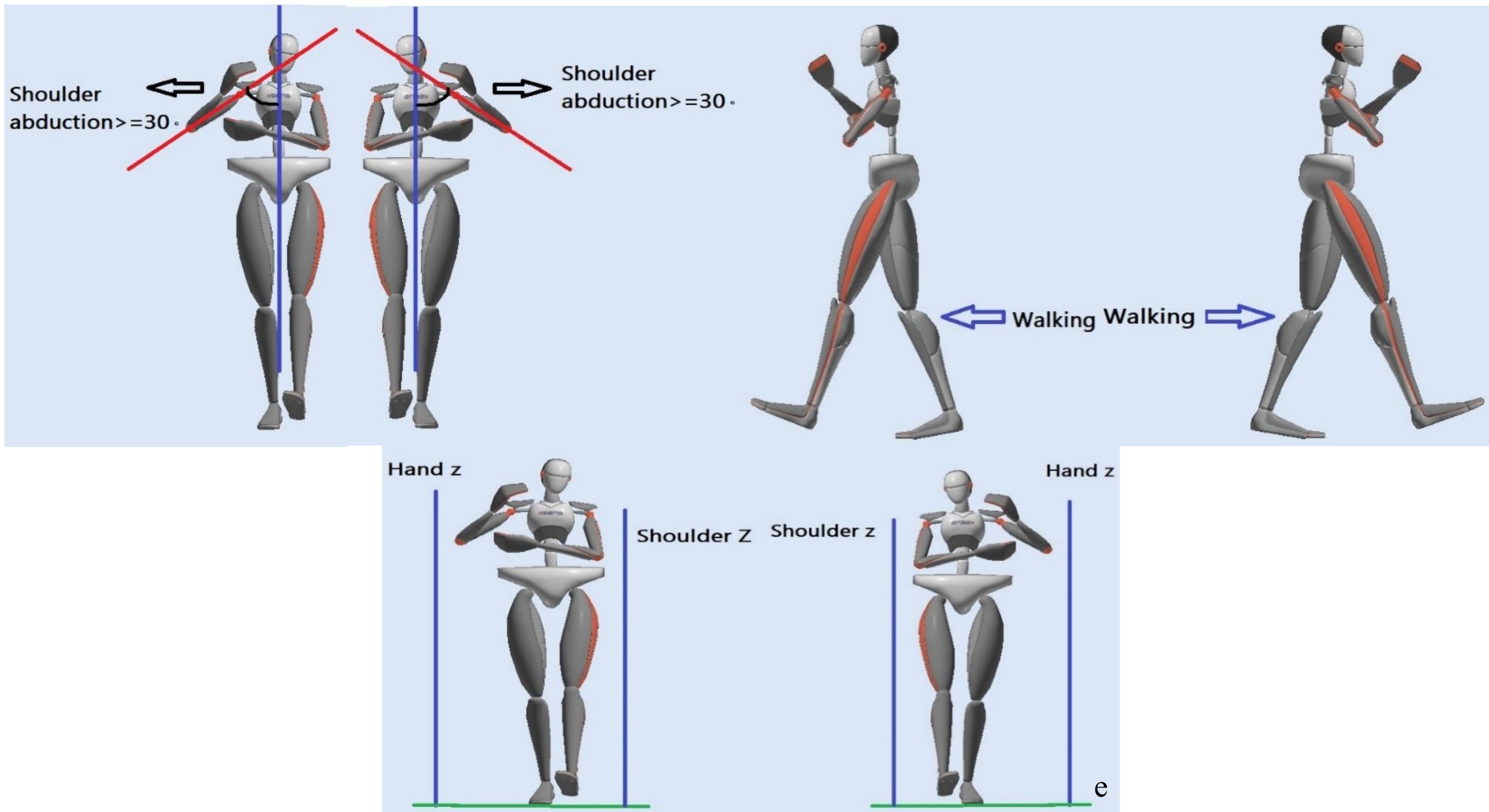


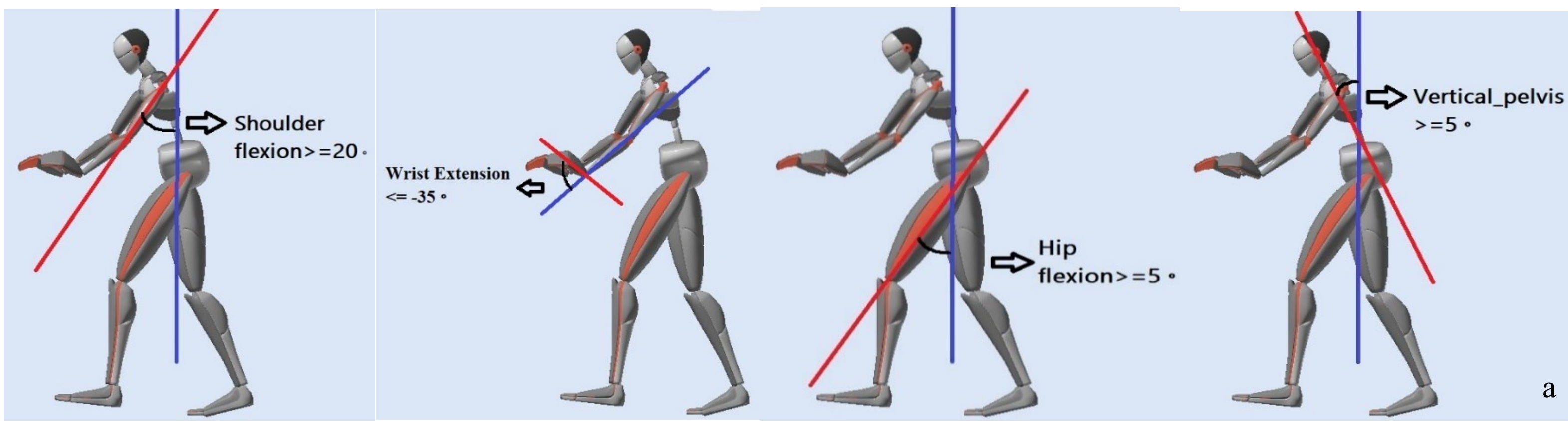
Figure 16: Different positions during carrying activities; a) Front, b) Side, c) Side, right-hand, d) Side, left-hand, e) On shoulder

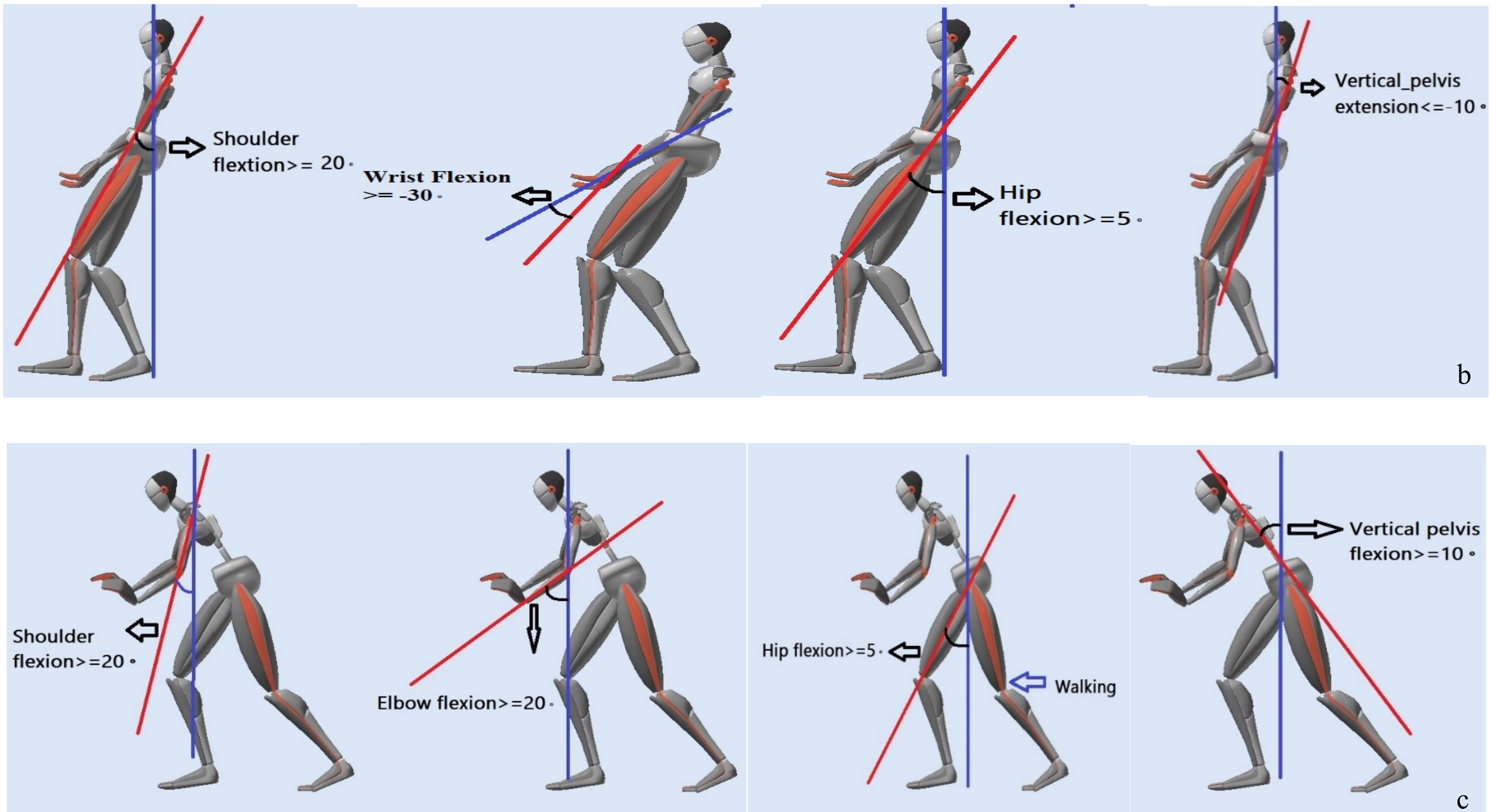
Tables 11a–c: Rules for different carrying activities

Manual handling tasks		**Condition 1**		
Carry	Or	Or	Or	Or
Front	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Side	Right Shoulder Abduction ≥ 30°	Left Shoulder Abduction ≥ 30°	-	-
Side, right hand	Right Shoulder Abduction ≥ 30°	-	-	-
Side, left hand	Left Shoulder Abduction ≥ 30°	-	-	-
On shoulder	Right Shoulder Abduction ≥ 30°	Left Shoulder Abduction ≥ 30°	-	-

Manual handling tasks		**Condition 2**		
Carry	Or	Or	Or	Or
Front	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.25 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.25 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.25 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.25 m
Side	Abs (Pelvis *x* – Previous Pelvis *x*) > 0.1 m	Abs (Pelvis *y* – Previous Pelvis *y*) > 0.1 m	-	-
Side, right hand	Abs (Pelvis *x* – Previous Pelvis *x*) > 0.1 m	Abs (Pelvis *y* – Previous Pelvis *y*) > 0.1 m	-	-
Side, left hand	Abs (Pelvis *x* – Previous Pelvis *x*) > 0.1 m	Abs (Pelvis *y* – Previous Pelvis *y*) > 0.1 m	-	-
On shoulder	Abs (Pelvis *x* – Previous Pelvis *x*) > 0.1 m	Abs (Pelvis *y* – Previous Pelvis *y*) > 0.1 m	-	-

Manual handling tasks	**Condition 3**		**Source**
Carry	Or	Or	
Front	Abs (Pelvis *x* – Previous Pelvis *x*) > 0.1 m	Abs (Pelvis *y* – Previous Pelvis *y*) > 0.1 m	OHCOW, (1998)
Side	-	-	OHCOW, (1998)
Side, right hand	-	-	OHCOW, (1998)
Side, left hand	-	-	OHCOW, (1998)
On shoulder	Right Hand $z \geq$ Right Shoulder $z - 0.05$ m	Left Hand $z \geq$ Left Shoulder $z - 0.05$ m	OHCOW, (1998)




Shoulder flextion>= 20
Wrist Flexion >= -30
Hip flexion>=5
Vertical_pelvis extension<=-10
b
Shoulder flexion>=20
Elbow flexion>=20
Hip flexion>=5
Walking
Vertical pelvis flexion>=10
c

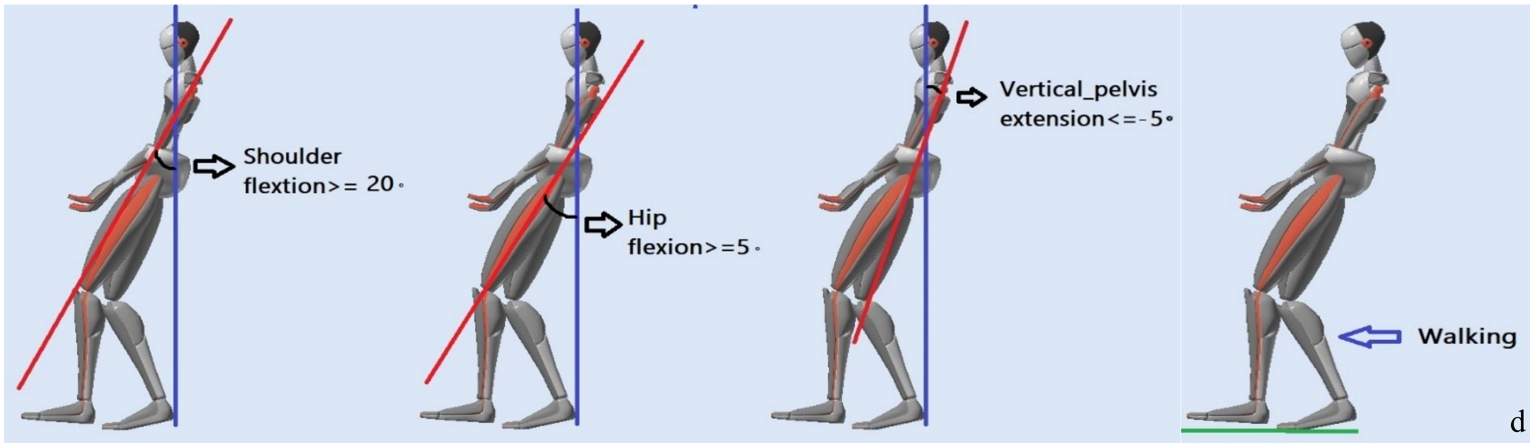


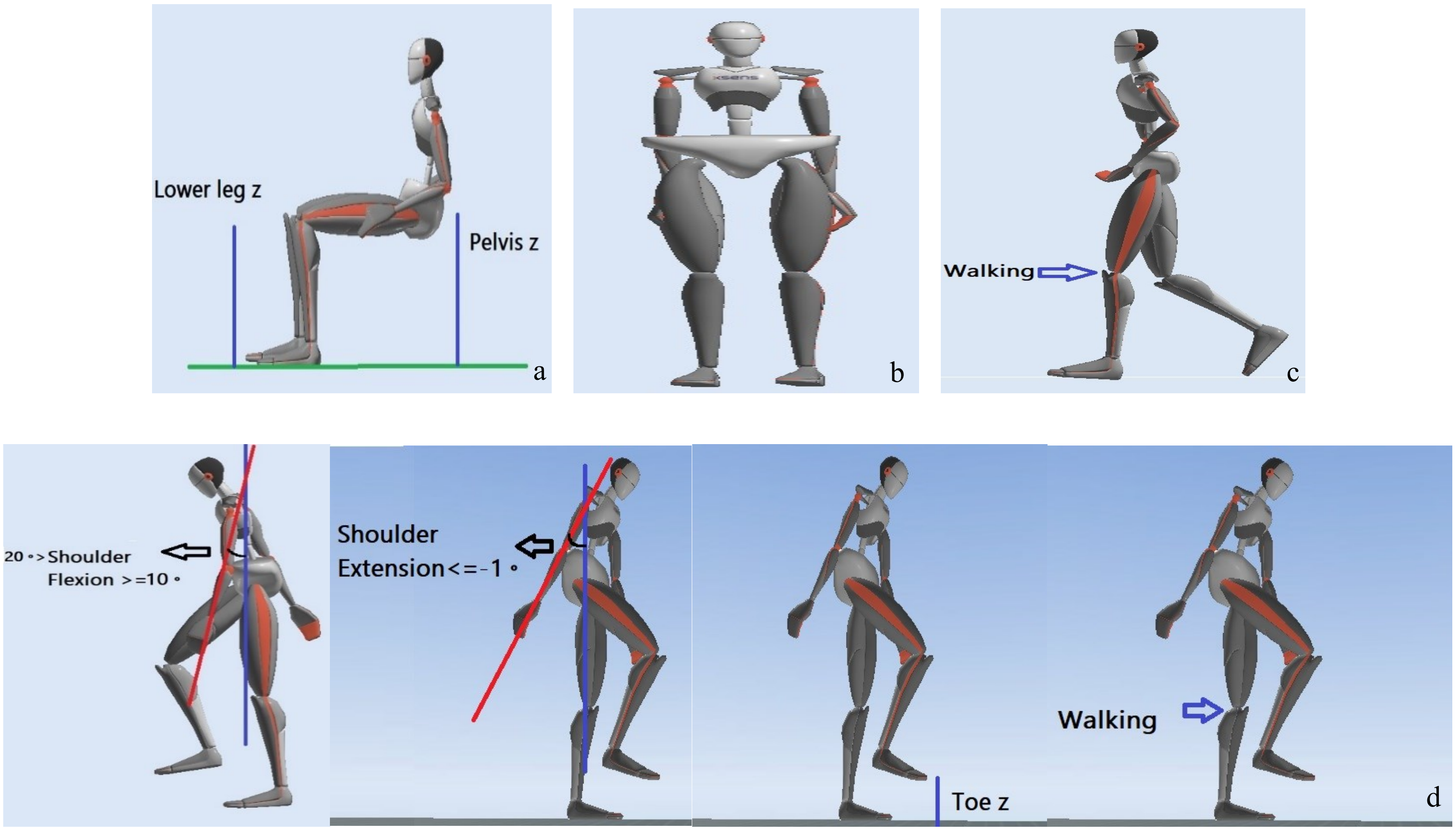
Figure 17: Different positions during; a) Stationary pushing, b) Stationary pulling, c) Dynamic pushing, d) Dynamic pulling

Tables 12a–c: Rules for different pushing and pulling activities

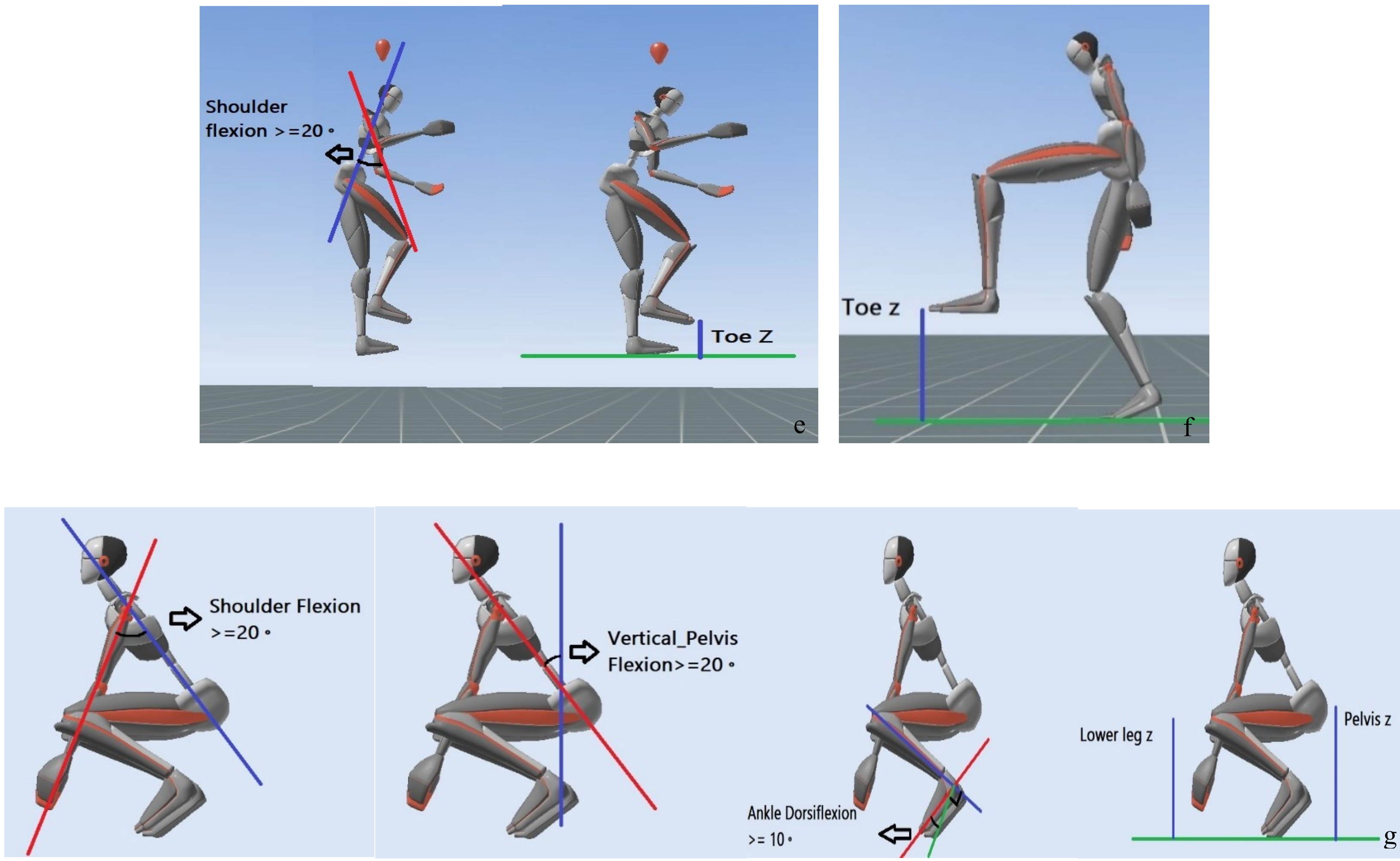
Manual handling tasks	**Condition 1**			
Pushing/Pulling	Or	Or	Or	Or
Stationary pushing	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	-	-
Stationary pulling	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Dynamic pushing	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Dynamic pulling	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°	Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°

Manual handling tasks	**Condition 2**		**And**	**Condition 3**
Pushing/pulling	Or	Or		
Stationary pushing	Abs (Pelvis x – Previous Pelvis x) ≤ 0.05 m	Abs (Pelvis y – Previous Pelvis y) ≤ 0.05 m		Vertical_Pelvis Flexion $\geq 5^{\circ}$
Stationary pulling	Abs (Pelvis x – Previous Pelvis x) ≤ 0.05 m	Abs (Pelvis y – Previous Pelvis y) ≤ 0.05 m		Vertical_Pelvis Extension $\leq -10^{\circ}$
Dynamic pushing	Abs (Pelvis x – Previous Pelvis x) > 0.05 m	Abs (Pelvis y – Previous Pelvis y) > 0.05 m		Vertical_Pelvis Flexion $\geq 10^{\circ}$
Dynamic pulling	Abs (Pelvis x – Previous Pelvis x) > 0.05 m	Abs (Pelvis y – Previous Pelvis y) > 0.05 m		Vertical_Pelvis Extension $\leq -5^{\circ}$

Manual handling tasks	**Condition 4**		**And**	**Condition 5**		**Source**
Pushing/Pulling	Or	Or		Or	Or	
Stationary pushing	Right Hip Flexion $\geq 5^{\circ}$	Left Hip Flexion $\geq 5^{\circ}$		Right Wrist Extension $\leq -35^{\circ}$	Left Wrist Extension $\leq -35^{\circ}$	OHCOW, (1998)
Stationary pulling	Right Hip Flexion $\geq 5^{\circ}$	Left Hip Flexion $\geq 5^{\circ}$		Right Wrist Flexion $\geq -30^{\circ}$	Left Wrist Flexion $\geq -30^{\circ}$	OHCOW, (1998)
Dynamic pushing	Right Hip Flexion $\geq 5^{\circ}$	-		Left Hip Flexion $\geq 5^{\circ}$	-	OHCOW, (1998)
Dynamic pulling	Right Hip Flexion $\geq 5^{\circ}$	-		Left Hip Flexion $\geq 5^{\circ}$	-	OHCOW, (1998)



Lower leg z
Pelvis z
a
b
Walking
c
20 ∘> Shoulder
Flexion >=10 ∘
Shoulder
Extension<=-1 ∘
Toe z
Walking
d


Shoulder
flexion >=20 ∘
Toe Z
e
Toe z
f
Shoulder Flexion
>=20 ∘
Vertical_Pelvis
Flexion>=20 ∘
Ankle Dorsiflexion
>= 10 ∘
Lower leg z
Pelvis z
g

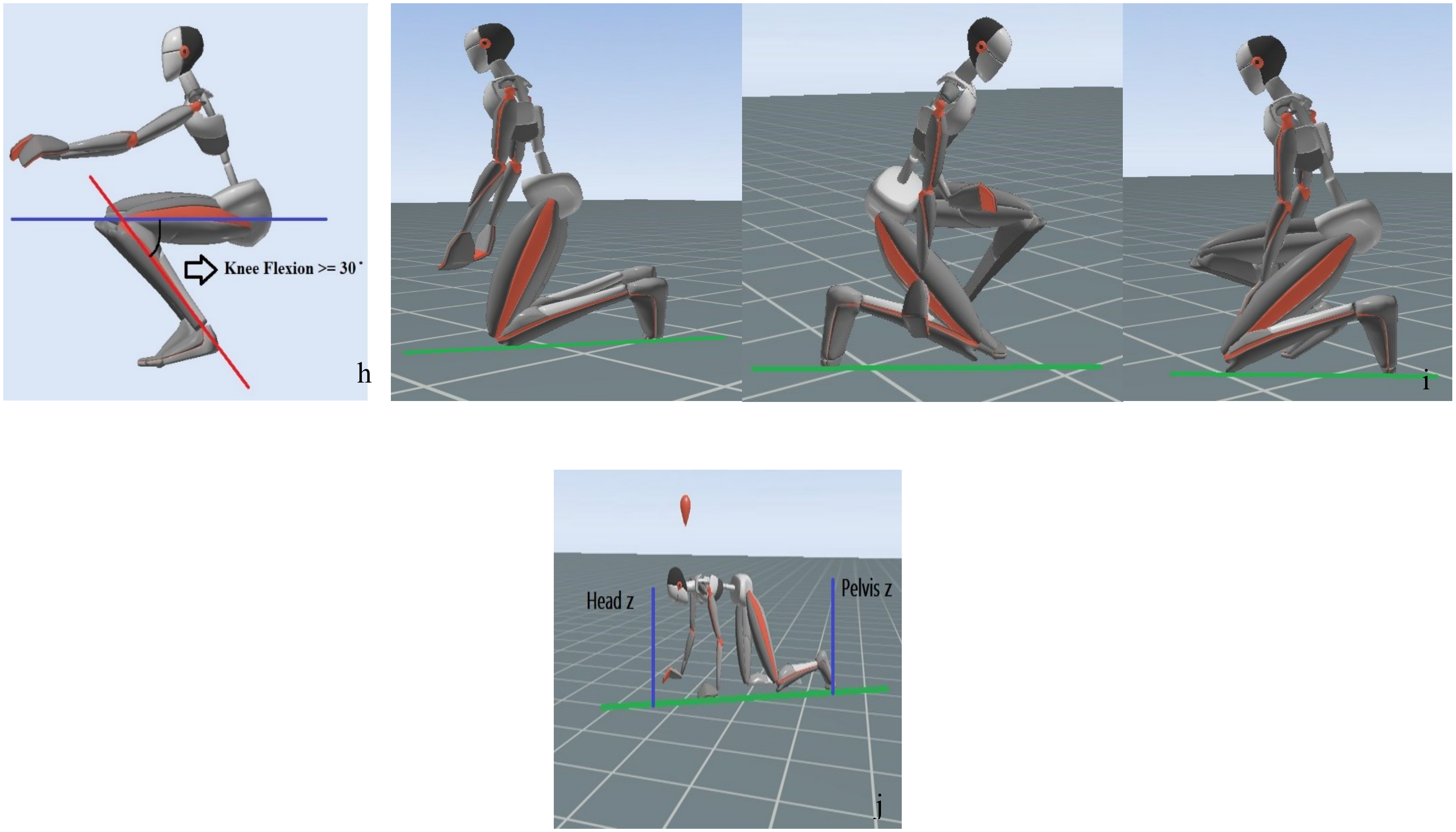


Figure 18: Different positions during mobility activities; a) Sitting, b) Standing, c) Walking, d) Climbing–stairs, e) Climbing–ladders, f) Climbing–stools, g) Crouching, h) Squatting, i) Kneeling, j) Crawling

Tables 13a–d: Rules for different mobility activities

Positional tasks	Condition 1			
Mobility	Or	Or	Or	Or
Sitting	Abs (Pelvis z – Right Lower Leg z) ≤ 0.15 m	-	-	-
Standing	Whole frames – walking – climbings – carryings – sitting – crouching – kneeling – low – level lifting – knee level lifting – Pulling – pushing – crawling – squatting – Dynamic Pushing – Dynamic Pulling – trunk forward bending – backward trunk bending	-	-	-
Walking	Abs (Pelvis x – Previous Pelvis x) > 0.05 m	Abs (Pelvis y – Previous Pelvis y) > 0.05 m	-	-
Climbing – stairs	20°>Right Shoulder Flexion ≥ 10°	20°>Left Shoulder Flexion ≥ 10°	Right Shoulder Extension ≤ –1°	Left Shoulder Extension ≤ –1°
Climbing – ladder	Right Shoulder Flexion ≥ 20°	-	-	-
Climbing – stools, etc.	Abs (Right Toe z – Previous Right Toe z) ≥ 0.1 m	Abs (Left Toe z – Previous Left Toe z) ≥ 0.1 m	-	-
Crouching	Vertical_Pelvis Flexion ≥ 20°	-	-	-
Squatting	Right Knee Flexion ≥ 30°	Left Knee Flexion ≥ 30°	-	-
Kneeling	Right Lower Leg z ≤ 0.15 m	Left Lower Leg z ≤ 0.15 m	-	-
Crawling	Abs (Head z – Pelvis z) ≤ 0.1 m	Abs (Head z – Pelvis z) ≤ 0.1 m	-	-

Positional tasks	Condition 2			
Mobility	Or	Or	Or	Or
Sitting	Abs (Pelvis z – Left Lower Leg z) $\leq$ 0.15 m	-	-	-
Standing	-	-	-	-
Walking	-	-	-	-
Climbing – stairs	Abs (Right Toe x – Previous Right Toe x) > 0.01 m	Abs (Right Toe y – Previous Right Toe y) > 0.01 m	Abs (Left Toe x – Previous Left Toe x) > 0.01 m	Abs (Left Toe y – Previous Left Toe y) > 0.01 m
Climbing – ladder	Left Shoulder Flexion $\geq$ 20°	-	-	-
Climbing – stools, etc.	-	-	-	-
Crouching	Abs (Pelvis z – Right Lower Leg z) $\leq$ 0.15 m	-	-	-
Squatting	-	-	-	-
Kneeling	-	-	-	-
Crawling	Abs (Right Hand z – Right Foot z) $\leq$ 0.1 m	Abs (Left Hand – Left Foot z) $\leq$ 0.1 m	-	-

Positional tasks	Condition 3		And	Condition 4	
Mobility	Or	Or		Or	Or
Sitting	-	-		-	-
Standing	-	-		-	-
Walking	-	-		-	-
Climbing –	Abs (Right Toe z – Previous	Abs (Left Toe z – Previous Left		-	-

stairs	Right Toe z) ≥ 0.1 m	Toe z) ≥ 0.1 m		
Climbing – ladder	Abs (Right Toe z – Previous Right Toe z) ≥ 0.1 m	Abs (Left Toe z – Previous Left Toe z) ≥ 0.1 m	-	-
Climbing – stools, etc.	-	-	-	-
Crouching	Abs (Pelvis z – Left Lower Leg z) ≤ 0.15 m	-	Right Shoulder Flexion ≥ 20°	Left Shoulder Flexion ≥ 20°
Squatting	-	-	-	-
Kneeling	-	-	-	-
Crawling	Abs (Right Lower Leg z – Right Foot z) ≤ 0.1 m	Abs (Left Lower Leg z – Left Foot z) ≤ 0.1 m	-	-

Positional tasks	**Condition 5**		**Source**
Mobility	Or	Or	
Sitting	-	-	OHCOW, 1998
Standing	-	-	OHCOW, 1998
Walking	-	-	OHCOW, 1998
Climbing – stairs	-	-	OHCOW, 1998
Climbing – ladders	-	-	OHCOW, 1998
Climbing – stools, etc.	-	-	OHCOW, 1998
Crouching	Right Ankle Dorsiflexion ≥ 10°	Left Ankle Dorsiflexion ≥ 10°	OHCOW, 1998
Squatting	-	-	Mallor, 1998
Kneeling	-	-	OHCOW, 1998
Crawling	-	-	OHCOW, 1998

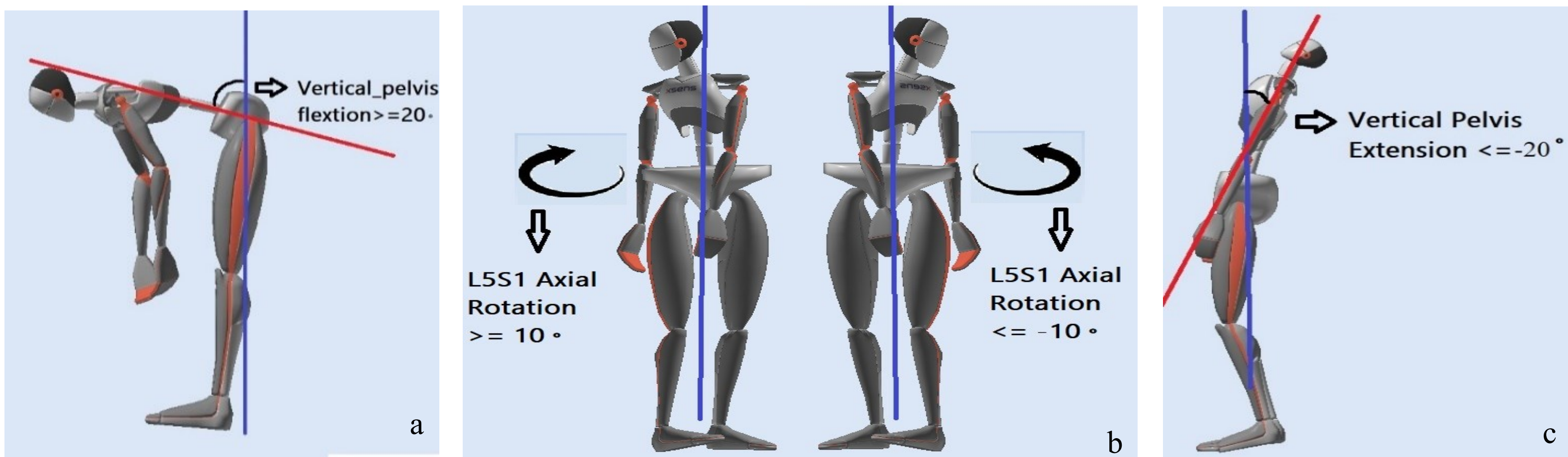
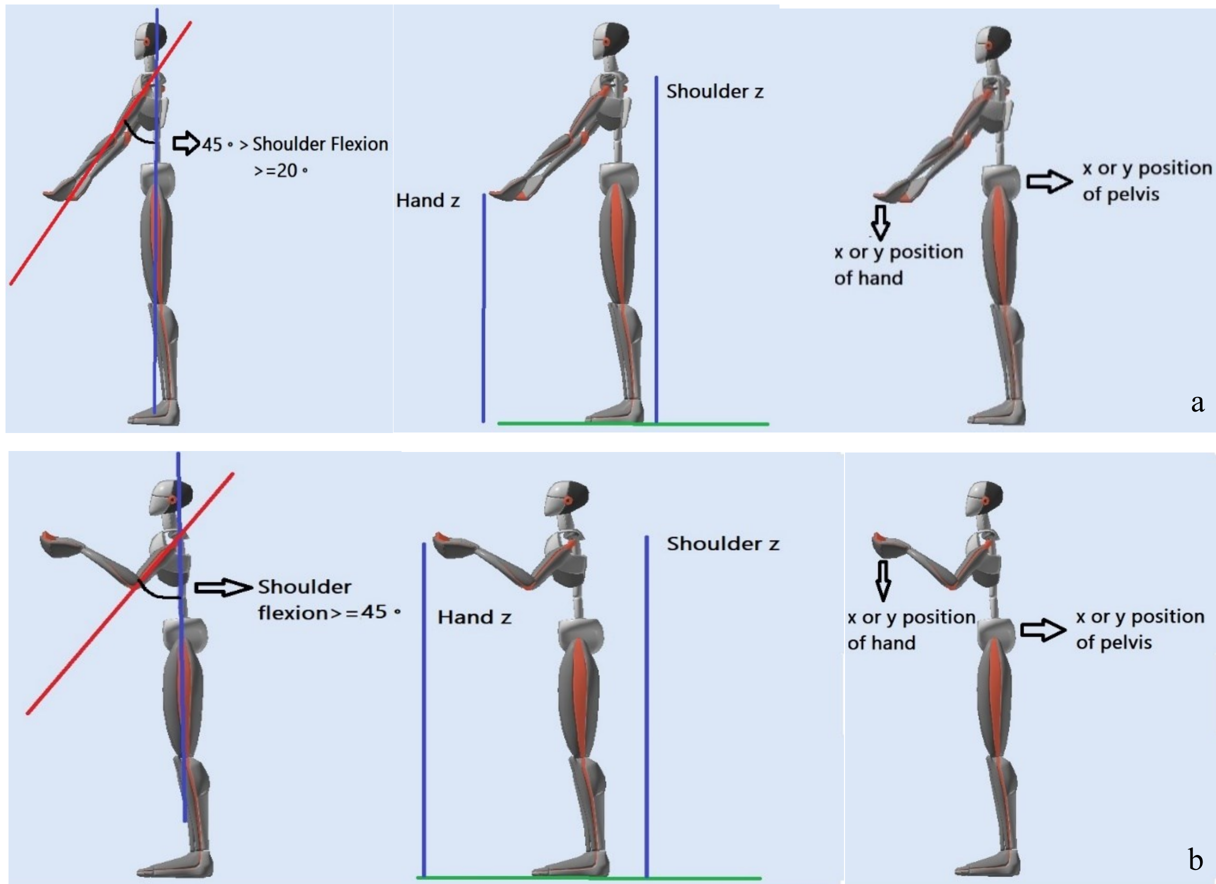
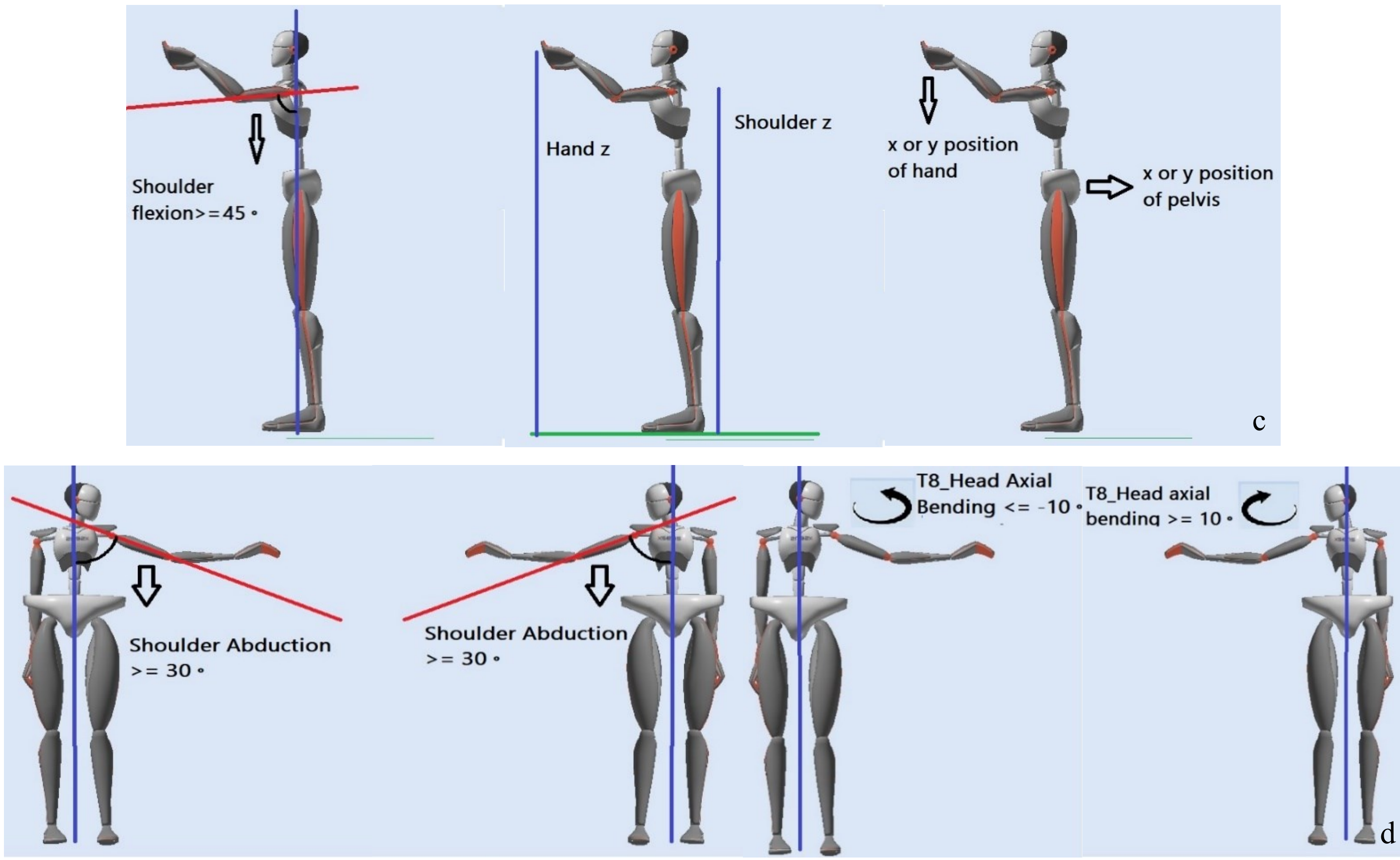


Figure 19: Different positions during trunk activities; a) Forward Bending, b) Trunk Rotation, c) Backward Bending

Table 14: Rules for different back activities

Positional tasks	**Condition 1**		**Source**
Back	Or	Or	
Forward bending	Vertical_Pelvis Flexion $\geq 20^{\circ}$	-	REBA
Trunk rotation	L5S1 Axial Rotation $\leq -10^{\circ}$	L5S1 Axial Rotation $\geq 10^{\circ}$	assumption
Backward bending	Vertical_Pelvis Extension $\leq -20^{\circ}$	-	REBA


45 ∘ > Shoulder Flexion
>=20 ∘
Hand z
Shoulder z
x or y position
of pelvis
x or y position
of hand
a
Shoulder
flexion>=45 ∘
Hand z
Shoulder z
x or y position
of hand
x or y position
of pelvis
b


Shoulder
flexion>=45 ∘
Hand z
Shoulder z
x or y position
of hand
x or y position
of pelvis
c
Shoulder Abduction
>= 30 ∘
Shoulder Abduction
>= 30 ∘
T8_Head Axial
Bending <= -10 ∘
T8_Head axial
bending >= 10 ∘
d

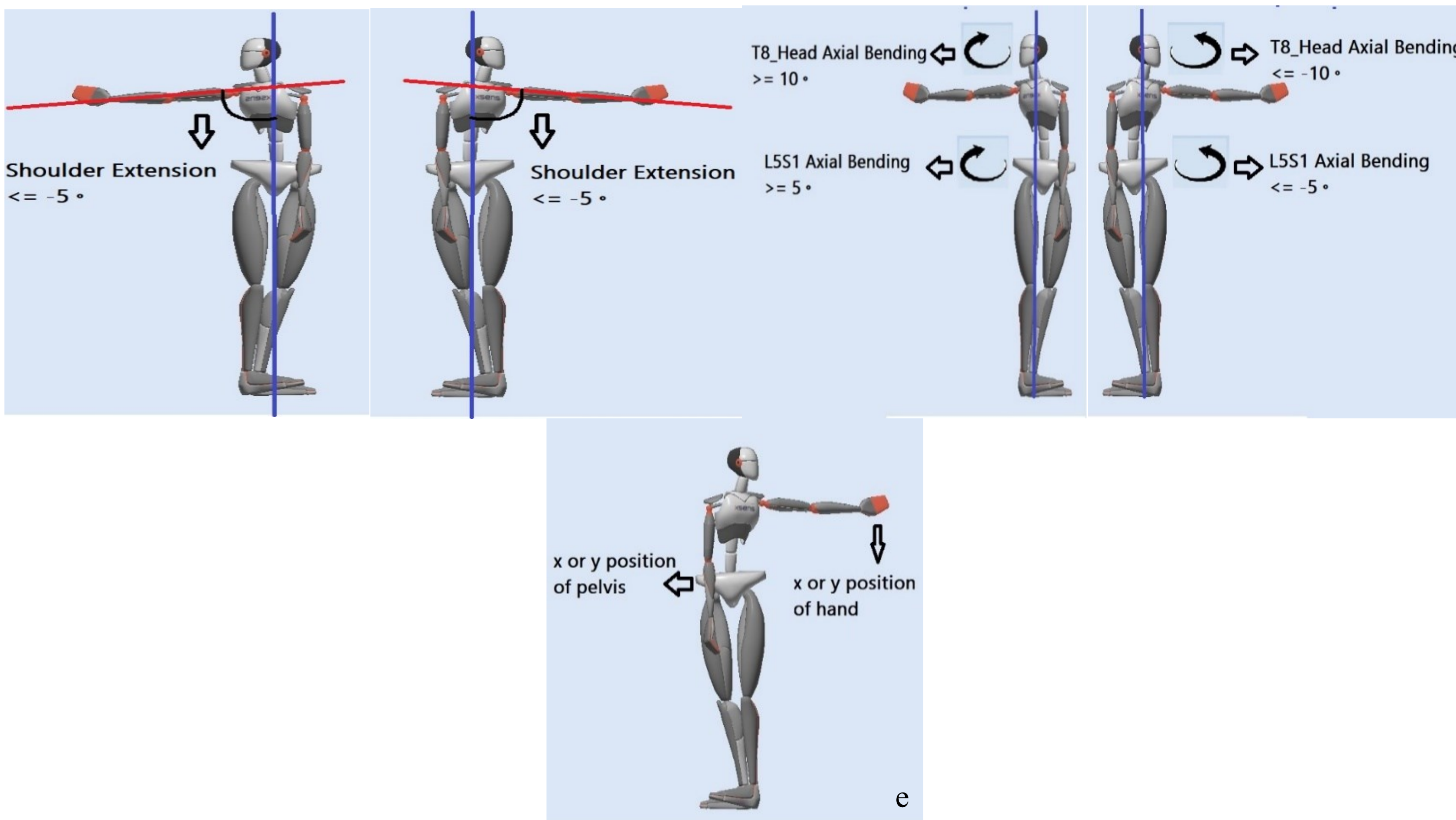


Figure 20: Different positions during reaching activities; a) Below shoulder level, b) Forward shoulder level, c) Above-shoulder level, d) Sideway shoulder, e) Behind shoulder

Tables 15a–f: Rules for different shoulder activities, for reaching

Positional tasks	**Condition 1**			
Shoulder	Or	Or	Or	Or
Below shoulder level reaching	Abs (Left Hand x – Pelvis x) ≥ 0.30 m	Abs (Left Hand y – Pelvis y) ≥ 0.30 m	Abs (Right Hand x – Pelvis x) ≥ 0.30 m	Abs (Right Hand y – Pelvis y) ≥ 0.30 m
Forward shoulder level reaching	Abs (Left Hand x – Pelvis x) ≥ 0.30 m	Abs (Left Hand y – Pelvis y) ≥ 0.30 m	Abs (Right Hand x – Pelvis x) ≥ 0.30 m	Abs (Right Hand y – Pelvis y) ≥ 0.30 m
Above– shoulder level reaching	Abs (Left Hand x – Pelvis x) ≥ 0.30 m	Abs (Left Hand y – Pelvis y) ≥ 0.30 m	Abs (Right Hand x – Pelvis x) ≥ 0.30 m	Abs (Right Hand y – Pelvis y) ≥ 0.30 m
Sideway shoulder reaching	Abs (Left Hand x – Pelvis x) ≥ 0.30 m	Abs (Left Hand y – Pelvis y) ≥ 0.30 m	Abs (Right Hand x – Pelvis x) ≥ 0.30 m	Abs (Right Hand y – Pelvis y) ≥ 0.30 m
Behind shoulder reaching	Abs (Left Hand x – Pelvis x) ≥ 0.30 m	Abs (Left Hand y – Pelvis y) ≥ 0.30 m	Abs (Right Hand x – Pelvis x) ≥ 0.30 m	Abs (Right Hand y – Pelvis y) ≥ 0.30 m

Positional tasks	**Condition 2**		**And**	**Condition 3**	
Shoulder	Or	Or		Or	Or
Below shoulder level reaching	45° > Right Shoulder Flexion ≥ 20°	45° > Left Shoulder Flexion ≥ 20°		Right Hand z < Right Shoulder z – B/2	Left Hand z < Left Shoulder z – B/2
Forward shoulder level reaching	Right Shoulder Flexion ≥ 45°	Left Shoulder Flexion ≥ 45°		Right Shoulder z – B/2 ≤ Right Hand z < Right Shoulder z + 0.1 m	Left Shoulder z – B/2 ≤ Left Hand z < Left Shoulder z + 0.1 m
Above-shoulder level reaching	Right Shoulder Flexion ≥ 45°	Left Shoulder Flexion ≥ 45°		Right Hand z ≥ Right Shoulder z + 0.1 m	Left Hand z ≥ Left Shoulder z + 0.1 m
Sideway shoulder reaching	Right Shoulder Abduction ≥ 30°	Left Shoulder Abduction ≥ 30°		Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°
Behind shoulder reaching	Right Shoulder Extension ≤ –5°	Left Shoulder Extension ≤ –5°		Right Elbow Flexion ≥ 20°	Left Elbow Flexion ≥ 20°

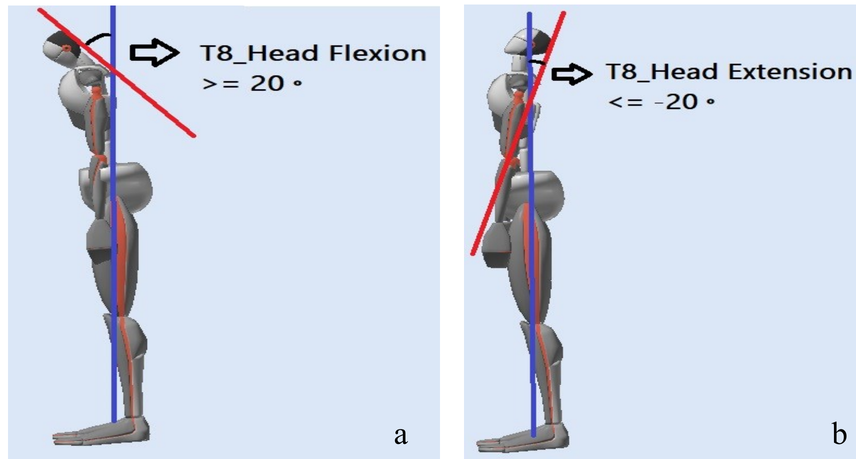
Positional tasks	Condition 4		And	Condition 5		Source
Shoulder	Or	Or		Or	Or	
Below shoulder level reaching	Vertical_Pelvis Flexion < 45°	-		-	-	REBA
Forward shoulder level reaching	Vertical_Pelvis Flexion < 45°	-		-	-	REBA
Above-shoulder level reaching	Vertical_Pelvis Flexion < 45°	-		-	-	REBA
Sideway shoulder reaching	T8_Head Axial Bending ≥ 10°	T8_Head Axial Bending ≤ –10°		-	-	assumption
Behind shoulder reaching	T8_Head Axial Bending ≥ 10°	T8_Head Axial Bending ≤ –10°		L5S1 Axial Bending ≥ 5°	L5S1 Axial Bending ≤ –5°	REBA

Table 16a–c: Rules for different shoulder activities, for reaching, if Vertical_Pelvis Flexion/Extension ≥ 45° (second position)

Positional tasks	Condition 1			
Shoulder	Or	Or	Or	Or
Below shoulder level reaching	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Forward shoulder level reaching	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m
Above-shoulder level reaching	Abs (Left Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Left Hand *y* – Pelvis *y*) ≥ 0.30 m	Abs (Right Hand *x* – Pelvis *x*) ≥ 0.30 m	Abs (Right Hand *y* – Pelvis *y*) ≥ 0.30 m

Positional tasks	Condition 2			
Shoulder	Or	Or	Or	Or
Below shoulder level reaching	Abs (Right Hand x – Right Shoulder x) > 0.05	Abs (Left Hand x – Left Shoulder x) > 0.05	Abs (Right Hand y – Right Shoulder y) > 0.05	Abs (Left Hand y – Left Shoulder y) > 0.05
Forward shoulder level reaching	Abs (Right Hand x – Right Shoulder x) ≤ 0.05	Abs (Left Hand x – Left Shoulder x) ≤ 0.05	Abs (Right Hand y – Right Shoulder y) ≤ 0.05	Abs (Left Hand y – Left Shoulder y) ≤ 0.05
Above-shoulder level reaching	Abs (Right Hand x – Right Shoulder x) > 0.05	Abs (Left Hand x – Left Shoulder x) > 0.05	Abs (Right Hand y – Right Shoulder y) > 0.05	Abs (Left Hand y – Left Shoulder y) > 0.05

Positional tasks	Condition 3		Source
Shoulder	Or	Or	
Below shoulder level reaching	45°>Right Shoulder Flexion ≥ 20°	45°>Left Shoulder Flexion ≥ 20°	REBA
Forward shoulder level reaching	Right Shoulder Flexion ≥ 45°	Left Shoulder Flexion ≥ 45°	REBA
Above-shoulder level reaching	Right Shoulder Flexion ≥ 45°	Left Shoulder Flexion ≥ 45°	REBA



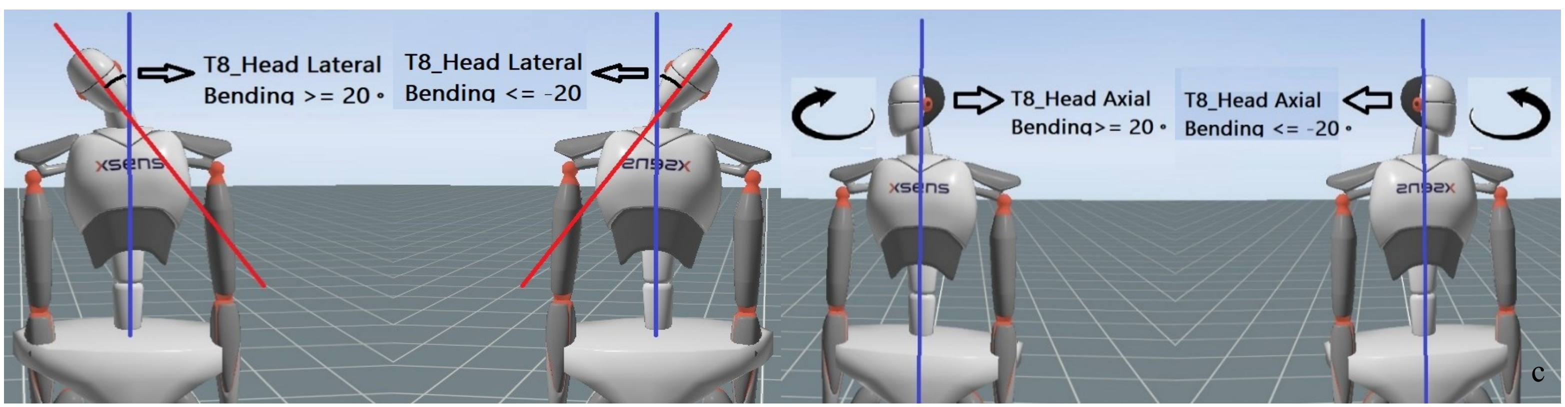


Figure 21: Different positions during neck activities; a) Forward bending, b) Backward bending, c) Twist/tilt

Table 17: Rules for different neck activities

Positional tasks	Condition 1				Source
Neck	Or	Or	Or	Or	
Forward bending	T8_Head Flexion $\geq 20^{\circ}$	-	-	-	REBA
Backward bending	T8_Head Extension $\leq -20^{\circ}$	-	-	-	REBA
Twist/tilt	T8_Head Lateral Bending $\geq 20^{\circ}$	T8_Head Lateral Bending $\leq -20^{\circ}$	T8_Head Axial Bending $\geq 20^{\circ}$	T8_Head Axial Bending $\leq -20^{\circ}$	REBA

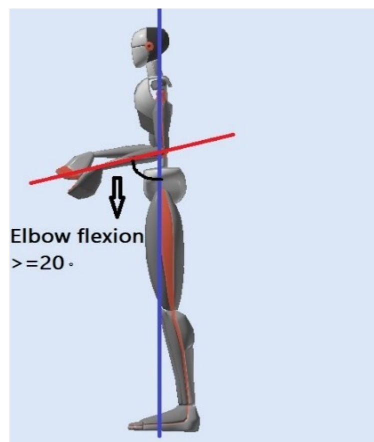
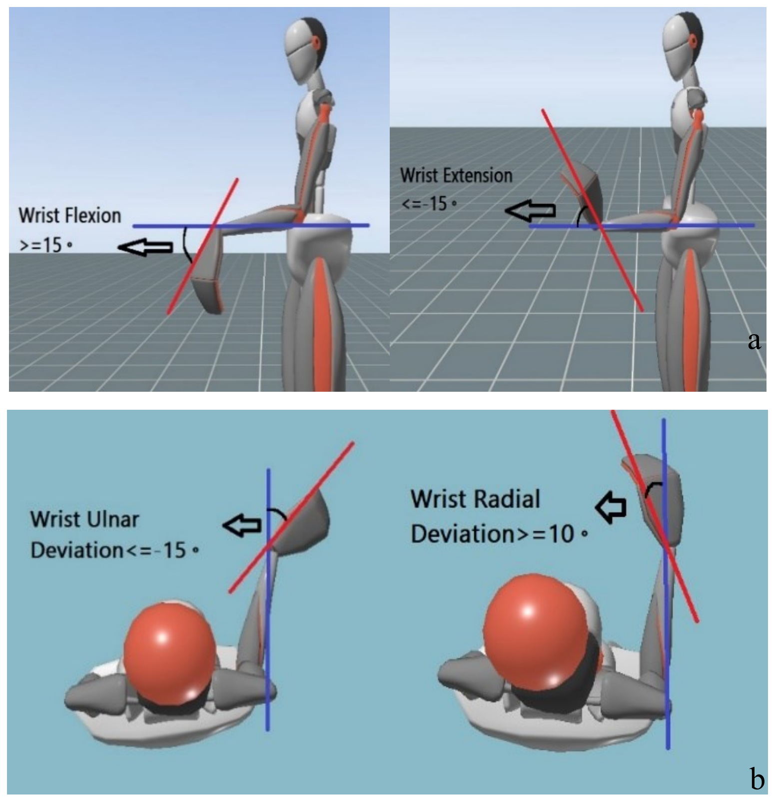


Figure 22: Position during elbow activity

Table 18: Rules for elbow activity

Positional tasks	**Condition 1**		**Source**
Elbow	Or	Or	
Flexion/extension	Right Elbow Flexion $\geq 20^{\circ}$	Left Elbow Flexion $\geq 20^{\circ}$	REBA



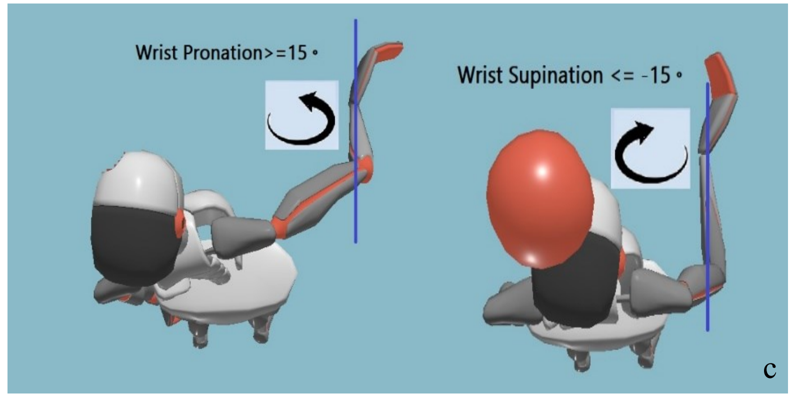


Figure 23: Different positions during wrist activities; a) Flexion/ extension, b) Bending (ulnar/ radial deviation), c) Rotation (supination/ pronation)

Table 19: Rules for different wrist activities

Positional tasks	**Condition 1**				**Source**
Wrist	Or	Or	Or	Or	
Flexion/extension	Right Wrist Flexion ≥ 15°	Right Wrist Extension ≤ −15°	Left Wrist Flexion ≥ 15°	Left Wrist Extension ≤ −15°	REBA
Bending (ulnar/radial deviation)	Right Wrist Radial Deviation ≥ 10°	Right Wrist Ulnar Deviation ≤ −15°	Left Wrist Radial Deviation ≥ 10°	Left Wrist Ulnar Deviation ≤ −15°	Lind et al. (2020)
Rotation (supination/pronatio n)	Right Wrist Pronation ≥ 15°	Right Wrist Supination ≤ −15°	Left Wrist Pronation≥ 15°	Left Wrist Supination≤ −15°	assumption

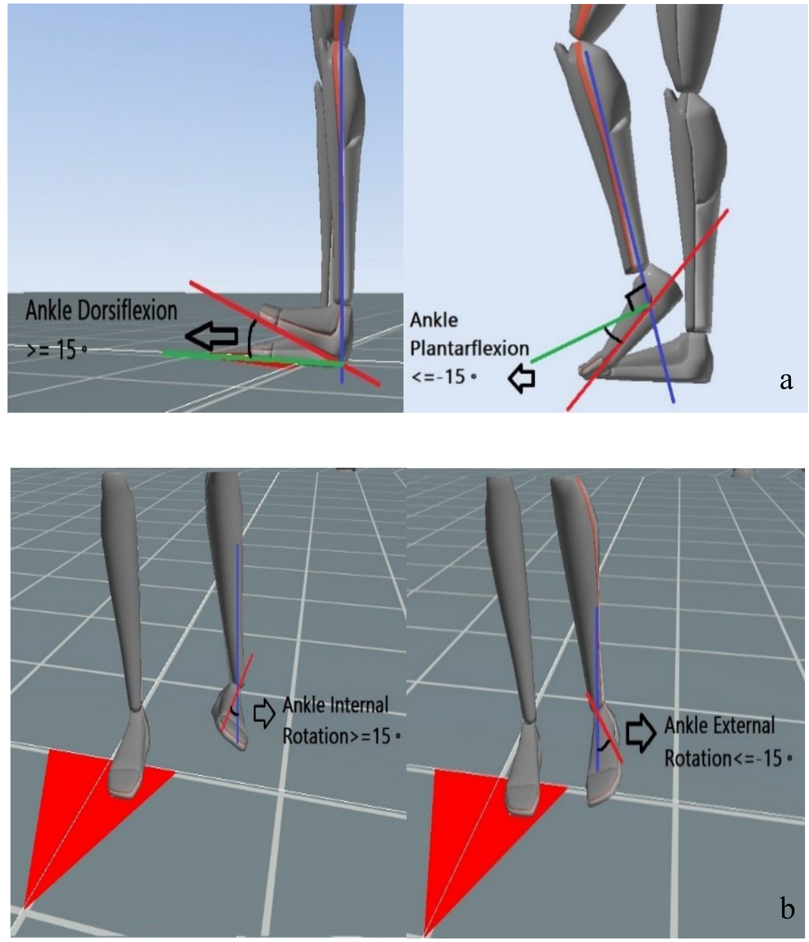


Figure 24: Different positions during ankle activities; a) Flexion/extension (dorsiflexion/ plantarflexion), b) Internal/ external rotation

Table 20: Rules for different ankle activities (assumptions)

Positional tasks	**Condition 1**			
Ankle	Or	Or	Or	Or
Flexion/extension (dorsiflexion/plantarflexion)	Right Ankle Dorsiflexion ≥ 15°	Right Ankle Plantarflexion ≤ –15°	Left Ankle Dorsiflexion ≥ 15°	Left Ankle Plantarflexion ≤ –15°
Internal/external rotation	Right Ankle Internal Rotation ≥ 15°	Right Ankle External Rotation ≤ –15°	Left Ankle Internal Rotation ≥ 15°	Left Ankle External Rotation ≤ –15°

4.3. Results of the Laboratory Experiment

This section shows the results of three different methods of implementing the PDA form.

4.3.1 Results of the Time Study Method

The following tables present the results of the time study method used by five different observers. Table 21 shows the frequency of different activities as a percentage. Also, standard deviation quantifies the variation or dispersion of the observers' results.

Table 21: Frequency of different activities for the time study method

Activity	Frequency/percentage					Standard deviation
	Obs. 1	Obs. 2	Obs. 3	Obs. 4	Obs. 5	
Lifting						
Low-level	100.00	100.00	100.00	100.00	100.00	0.00
Knee level	85.71	28.57	100.00	85.71	100.00	26.50
Waist level	85.71	0.00	42.86	85.71	71.43	32.58
Shoulder level	42.86	0.00	28.57	0.00	42.86	19.38
Above-shoulder	42.86	0.00	28.57	0.00	42.86	19.38
Carry						
Front	100.00	100.00	100.00	100.00	100.00	0.00
Side	0.00	0.00	0.00	0.00	0.00	0.00
Side, right hand	0.00	0.00	0.00	0.00	0.00	0.00
Side, left hand	0.00	0.00	0.00	0.00	0.00	0.00
On shoulder	0.00	0.00	0.00	0.00	0.00	0.00
Pushing/pulling						
Stationary pushing	0.00	0.00	0.00	0.00	0.00	0.00
Stationary pulling	0.00	0.00	0.00	0.00	0.00	0.00
Dynamic pushing	0.00	0.00	0.00	0.00	0.00	0.00
Dynamic pulling	0.00	0.00	0.00	0.00	0.00	0.00
Mobility						
Sitting/driving	14.29	14.29	14.29	14.29	14.29	0.00
Standing	14.29	100.00	0.00	0.00	100.00	46.95
Walking	100.00	100.00	14.29	100.00	100.00	34.29
Climbing – stairs	0.00	0.00	0.00	0.00	0.00	0.00
Climbing – ladders	0.00	0.00	0.00	0.00	0.00	0.00
Climbing – stools, etc.	0.00	0.00	0.00	0.00	0.00	0.00
Crouching	0.00	0.00	0.00	0.00	0.00	0.00

Squatting	0.00	0.00	100.00	0.00	0.00	40.00
Kneeling	0.00	0.00	0.00	0.00	0.00	0.00
Crawling	0.00	0.00	0.00	0.00	0.00	0.00
Back						
Forward bending	100.00	100.00	100.00	85.71	100.00	5.71
Trunk rotation	0.00	0.00	100.00	85.71	100.00	46.95
Backward bending	0.00	14.29	0.00	0.00	0.00	5.71
Shoulder						
Below shoulder level reaching	100.00	100.00	42.86	85.71	100.00	22.13
Forward shoulder level reaching	28.57	28.57	28.57	0.00	0.00	14.00
Above-shoulder level reaching	42.86	42.86	28.57	0.00	0.00	19.38
Sideway shoulder reaching	0.00	0.00	0.00	0.00	0.00	0.00
Behind shoulder reaching	0.00	0.00	0.00	0.00	0.00	0.00
Neck						
Forward bending	0.00	100.00	100.00	100.00	100.00	40.00
Backward bending	0.00	0.00	28.57	0.00	0.00	11.43
Twist/tilt	0.00	71.43	100.00	0.00	100.00	45.54
Elbow						
Flexion/extension	100.00	100.00	100.00	100.00	100.00	0.00
Wrist						
Flexion/extension	100.00	57.14	0.00	0.00	100.00	44.81
Bending (ulnar/ radial deviation)	71.43	100.00	100.00	0.00	0.00	45.54
Rotation (supination/ pronation)	100.00	42.86	100.00	85.71	100.00	22.13
Ankle						
Flexion/extension (dorsiflexion/ plantarflexion)	0.00	57.14	0.00	100.00	100.00	44.81
Internal/external rotation	100.00	14.29	100.00	85.71	100.00	33.32

Table 22 shows the average frequency of manual handling tasks in percentage and categorizes them as “Not required,” “Rare,” “Occasional,” “Frequent,” or “Constant.” Table 23 gives the frequency and categories for positional tasks.

Table 22: Average frequency of activities for the time study method (% and range), for manual handling tasks

Manual handling tasks	Average of frequency/ percentage	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Lifting						
Low-level	100.00					C
Knee level	80.00					C
Waist level	57.14				F	
Shoulder level lifting	22.86			O		
Above-shoulder lifting	22.86			O		
Carry						
Front	100.00					C
Side	0.00	N				
Side, right hand	0.00	N				
Side, left hand	0.00	N				
On shoulder	0.00	N				
Pushing/pulling						
Stationary pushing	0.00	N				
Stationary pulling	0.00	N				
Dynamic pushing	0.00	N				
Dynamic pulling	0.00	N				

Table 23: Average frequency of activities for the time study method (% and range), for positional tasks

Positional tasks	Frequency/ percentage	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Mobility						
Sitting/driving	14.29			O		
Standing	42.86				F	
Walking	82.86					C
Climbing – stairs	0.00	N				
Climbing – ladders	0.00	N				
Climbing – stools, etc.	0.00	N				
Crouching	0.00	N				
Squatting	20.00			O		
Kneeling	0.00	N				

Crawling	0.00	N				
Back						
Forward bending	97.14					C
Trunk rotation	57.14				F	
Backward bending	2.86		R			
Shoulder						
Below shoulder level reaching	85.71					C
Forward shoulder level reaching	17.14			O		
Above-shoulder level reaching	22.86			O		
Sideway shoulder reaching	0.00	N				
Behind shoulder reaching	0.00	N				
Neck						
Forward bending	80.00					C
Backward bending	5.71			O		
Twist/tilt	54.29				F	
Elbow						
Flexion/extension	100.00					C
Wrist						
Flexion/extension	51.43				F	
Bending (ulnar/ radial deviation)	54.29				F	
Rotation (supination/ pronation)	85.71					C
Ankle						
Flexion/extension (dorsiflexion/ plantarflexion)	51.43				F	
Internal/external rotation	80.00					C

4.3.2 Results of an Ergonomist Method

The following results are related to a method used by the first ergonomist. The ergonomist measured each activity's frequency percentage and determined their range definitions. Table 24 shows the frequency of activities in percentage and range definition for the ergonomist's technique, for manual handling tasks. Table 25 gives this information for positional tasks.

Table 24: Frequency of activities for ergonomist's method (% and range), for manual handling tasks

Manual handling tasks	Frequency	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Lifting						
Low-level	8.21			O		
Knee level	18.21			O		
Waist level	7.50			O		
Shoulder level	8.39			O		
Above-shoulder	7.23			O		
Carry						
Front	35.89				F	
Side	0.00	N				
Side, right hand	0.00	N				
Side, left hand	0.00	N				
On shoulder	0.00	N				
Pushing/pulling						
Stationary pushing	0.00	N				
Stationary pulling	0.00	N				
Dynamic pushing	0.00	N				
Dynamic pulling	0.00	N				

Table 25: Frequency of activities for ergonomist's method (% and range), for positional tasks

Positional tasks	Frequency	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Mobility						
Sitting/driving	10.72			O		
Standing	19.37			O		
Walking	35.89				F	
Climbing – stairs	0.00	N				
Climbing – ladders	0.00	N				
Climbing – stools, etc.	0.00	N				
Crouching	0.00	N				
Squatting	22.23			O		
Kneeling	0.00	N				
Crawling	0.00	N				
Back						

Forward bending	30.18		O
Trunk rotation	5.36		O
Backward bending	0.00	N	
Shoulder			
Below shoulder level reaching	15.00		O
Forward shoulder level reaching	27.32		O
Above-shoulder level reaching	7.23		O
Sideway shoulder reaching	0.00	N	
Behind shoulder reaching	0.00	N	
Neck			
Forward bending	11.25		O
Backward bending	0.00	N	
Twist/tilt	16.34		O
Elbow			
Flexion/extension	23.03		O
Wrist			
Flexion/extension	26.43		O
Bending (ulnar/ radial deviation)	23.12		O
Rotation (supination/ pronation)	0.00	N	
Ankle			
Flexion/extension (dorsiflexion/ plantarflexion)	8.21		O
Internal/external rotation	30.09		O

4.3.3 Results of the Proposed Framework

The following results are related to the proposed framework in this research. Table 26 shows the frequency of activities in percentage and range definition for the proposed framework, for manual handling tasks. Table 27 gives this information for positional tasks.

Table 26: Frequency of activities for the proposed framework (% and range), for manual handling tasks

Manual handling tasks	Frequency	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Lifting						
Low-level	2.18		R			
Knee level	7.50			O		
Waist level	8.90			O		
Shoulder level	8.08			O		
Above-shoulder	4.90		R			
Carry						
Front	34.58				F	
Side	1.71	N				
Side, right hand	1.01	N				
Side, left hand	1.48	N				
On shoulder	1.86	N				
Pushing/pulling						
Stationary pushing	1.63	N				
Stationary pulling	12.63			O		
Dynamic pushing	0.43	N				
Dynamic pulling	3.54		R			

Table 27: Frequency of activities for the proposed framework (% and range), for positional tasks

Positional tasks	Frequency	Frequency of workday/shift				
		Not required	Rare	Occasional	Frequent	Constant
Mobility						
Sitting/driving	9.91			O		
Standing	25.87			O		
Walking	47.51				F	
Climbing – stairs	0.00	N				
Climbing – ladders	1.17	N				
Climbing – Stools, etc.	1.17	N				
Crouching	0.00	N				
Squatting	44.76				F	
Kneeling	0.00	N				

Crawling	0.00	N			
Back					
Forward bending	34.34			F	
Trunk rotation	7.15		O		
Backward bending	9.29		O		
Shoulder					
Below shoulder level reaching	10.64		O		
Forward shoulder level reaching	24.86		O		
Above-shoulder level reaching	21.64		O		
Sideway shoulder reaching	1.17	N			
Behind shoulder reaching	0.00	N			
Neck					
Forward bending	43.78			F	
Backward bending	0.19	N			
Twist/tilt	32.79		O		
Elbow					
Flexion/extension	86.13				C
Wrist					
Flexion/extension	82.40				C
Bending (ulnar/radial deviation)	90.52				C
Rotation (supination/ pronation)	8.08		O		
Ankle					
Flexion/extension (dorsiflexion/plantarflexion)	12.86		O		
Internal/external rotation	23.43		O		

4.3.4 Results Analysis of Laboratory Experiment

The following results are related to comparing three methods used for filling the PDA form. Table 28 shows the frequency of different activities in percentage and range definition for three methods, for manual handling tasks. Table 29 gives this information for positional tasks.

Table 28: Frequency of activities for three methods (% and range), for manual handling tasks

Manual handling tasks	Frequency per shift (percentage)			Frequency per shift (N-R-O-F-C)		
	AI model	Ergonomist 1	Time study	AI model	Ergonomist 1	Time study
Lifting						
Low-level	2.18	8.21	100.00	R	O	C
Knee level	7.50	18.21	80.00	O	O	C
Waist level	8.90	7.50	57.14	O	O	F
Shoulder level	8.08	8.39	22.86	O	O	O
Above-shoulder	4.90	7.23	22.86	R	O	O
Carry						
Front	34.58	35.89	100.00	F	F	C
Side	1.71	0.00	0.00	N	N	N
Side, right hand	1.01	0.00	0.00	N	N	N
Side, left hand	1.48	0.00	0.00	N	N	N
On shoulder	1.86	0.00	0.00	N	N	N
Pushing/pulling						
Stationary pushing	1.63	0.00	0.00	N	N	N
Stationary pulling	12.63	0.00	0.00	O	N	N
Dynamic pushing	0.43	0.00	0.00	N	N	N
Dynamic pulling	3.54	0.00	0.00	R	N	N

Table 29: Frequency of activities for three methods (% and range), for positional tasks

Positional tasks	Frequency of workday/shift			Frequency per shift (N-R-O-F-C)		
	AI model	Ergonomist	Five observers	AI model	Ergonomist	Five observers
Mobility						
Sitting/driving	9.91	10.72	14.29	O	O	O
Standing	25.87	19.37	42.86	O	O	F
Walking	47.51	35.89	82.86	F	F	C
Climbing – stairs	0.00	0.00	0.00	N	N	N
Climbing – ladders	1.17	0.00	0.00	N	N	N
Climbing – stools, etc.	1.17	0.00	0.00	N	N	N
Crouching	0.00	0.00	0.00	N	N	N

Squatting	44.76	22.23	20.00	F	O	O
Kneeling	0.00	0.00	0.00	N	N	N
Crawling	0.00	0.00	0.00	N	N	N
Back						
Forward bending	34.34	30.18	97.14	F	O	C
Trunk rotation	7.15	5.36	57.14	O	O	F
Backward bending	9.29	0.00	2.86	O	N	R
Shoulder						
Below shoulder level reaching	10.64	15.00	85.71	O	O	C
Forward shoulder level reaching	24.86	27.32	17.14	O	O	O
Above-shoulder level reaching	21.64	7.23	22.86	O	O	O
Sideway shoulder reaching	1.17	0.00	0.00	N	N	N
Behind shoulder reaching	0.00	0.00	0.00	N	N	N
Neck						
Forward bending	43.78	11.25	80.00	F	O	C
Backward bending	0.19	0.00	5.71	N	N	O
Twist/tilt	32.79	16.34	54.29	O	O	F
Elbow						
Flexion/extension	86.13	23.03	100.00	C	O	C
Wrist						
Flexion/extension	82.40	26.43	51.43	C	O	F
Bending (ulnar/radial deviation)	90.52	23.12	54.29	C	O	F
Rotation (supination/ pronation)	8.08	0.00	85.71	O	N	C
Ankle						
Flexion/extension (dorsiflexion/ plantarflexion)	12.86	8.21	51.43	O	O	F
Internal/external rotation	23.43	30.09	80.00	O	O	C

Bar charts of distribution discrepancies in frequencies help quickly compare the different sets of frequencies among different methods in each activity. Figures 25–34 show bar charts for comparing the frequency of different activities (as percents) between the AI model, ergonomist, and time study methods used.

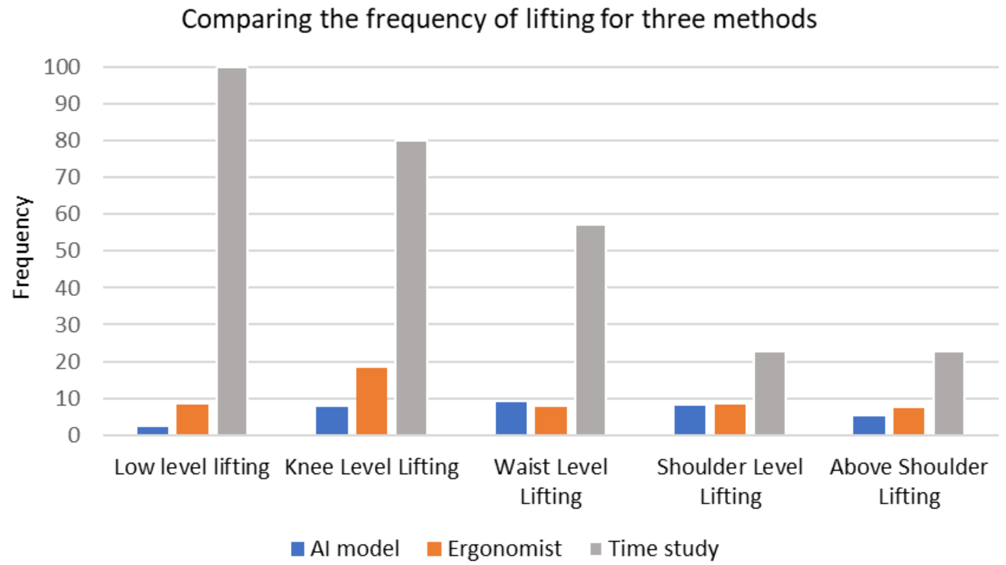


Figure 25: Comparison of frequency of lifting activities

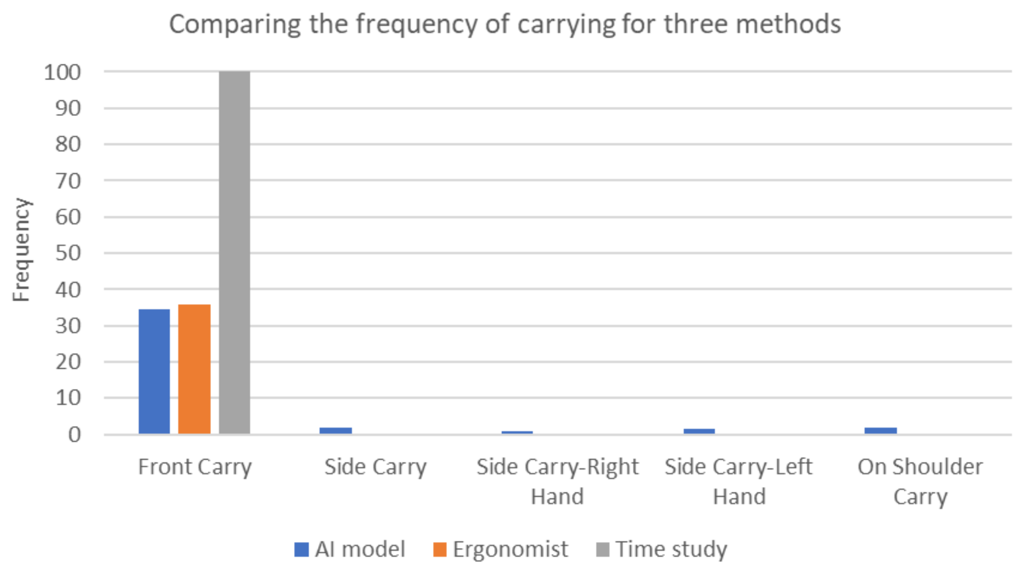


Figure 26: Comparison of frequency of carrying activities between three methods used.

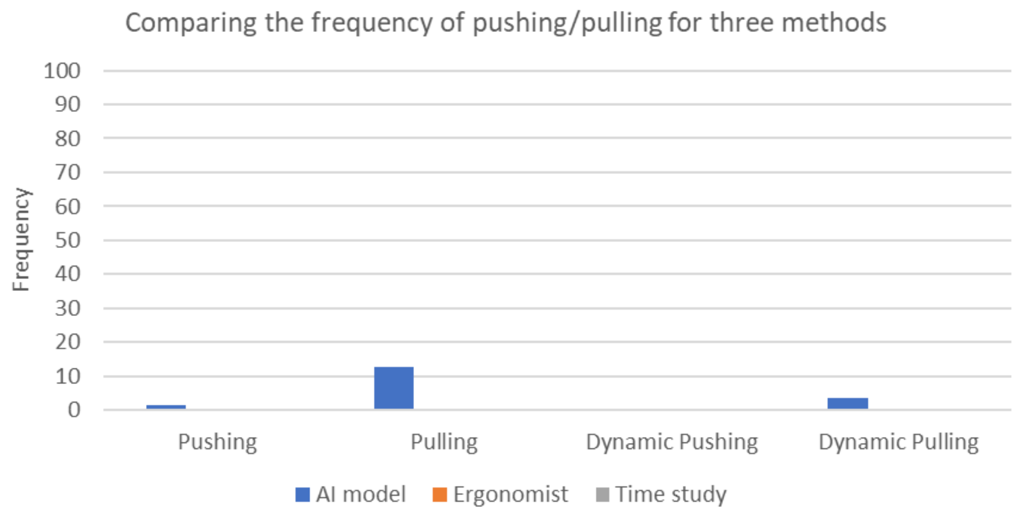


Figure 27: Comparison of frequency of pushing/pulling activities between three methods used.

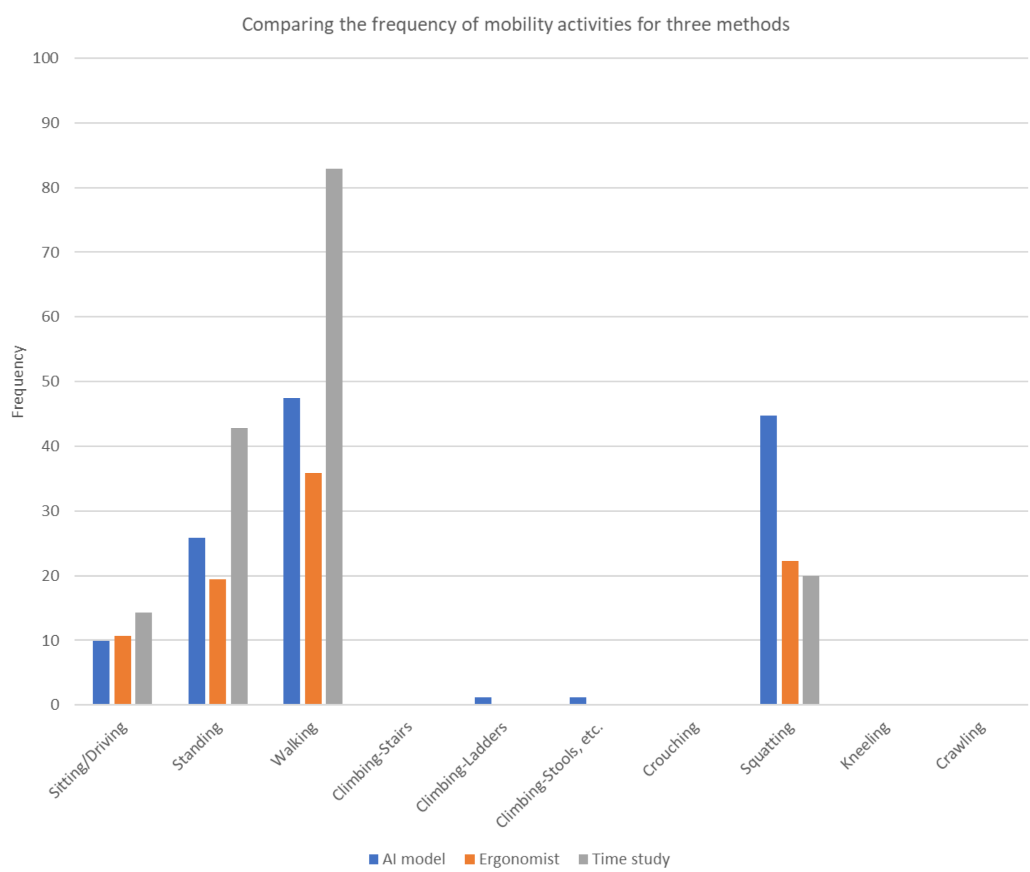


Figure 28: Comparison of frequency of mobility activities in percentage between three methods used.

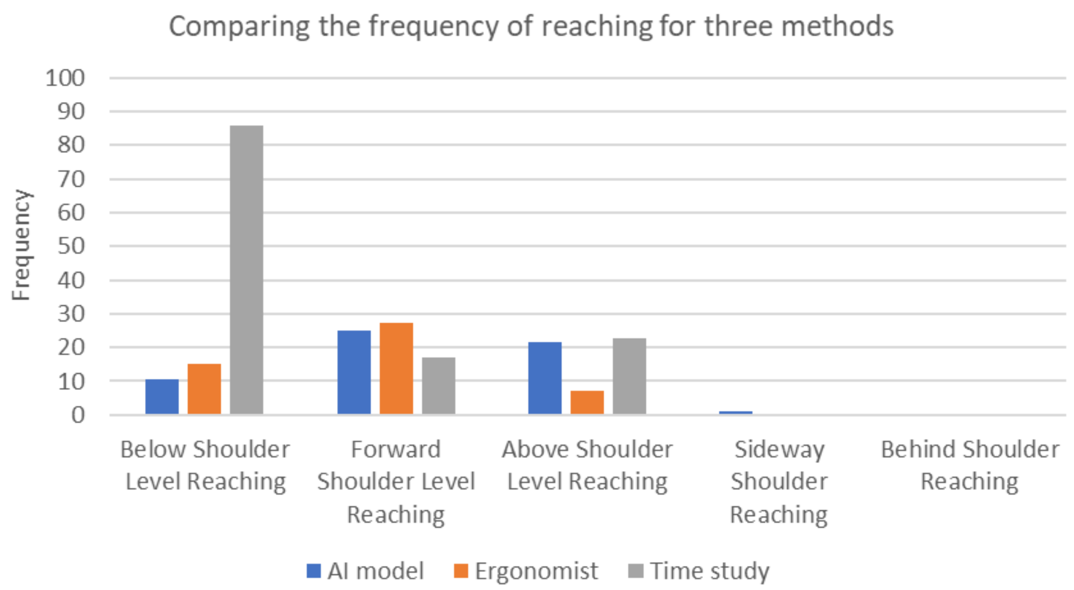


Figure 29: of frequency of reaching activities between three methods used.

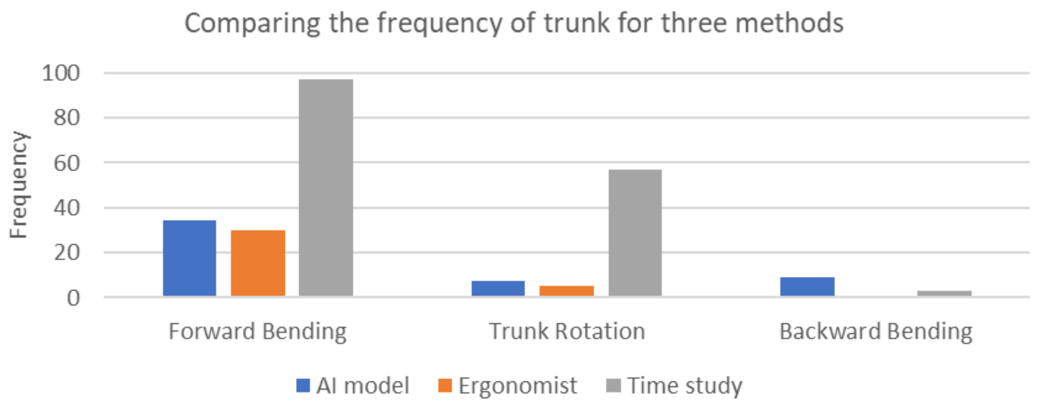


Figure 30: Comparison of frequency of trunk activities between three methods used.

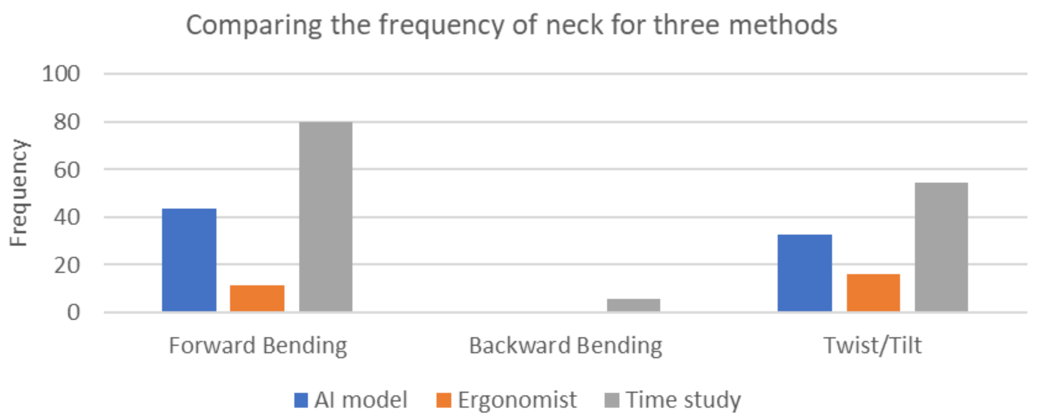


Figure 31: Comparison of frequency of neck activities between three methods used.

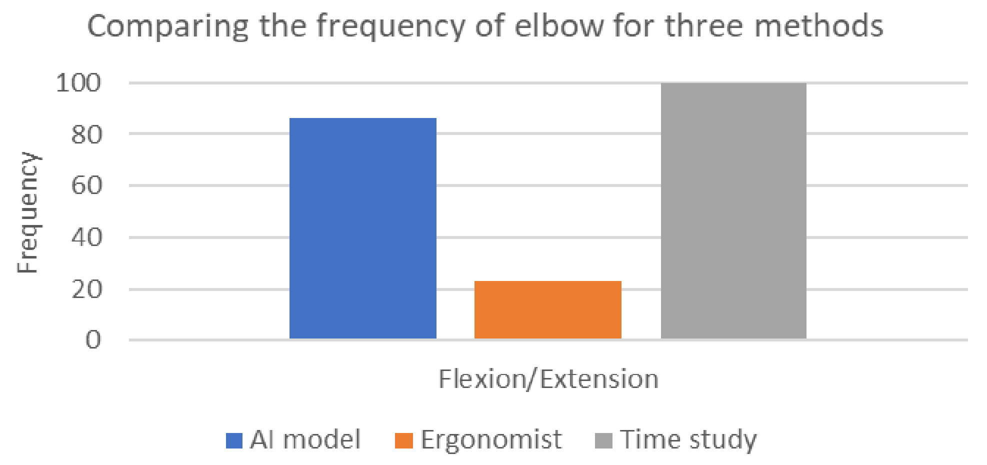


Figure 32: Comparison of frequency of elbow activities between three methods used.

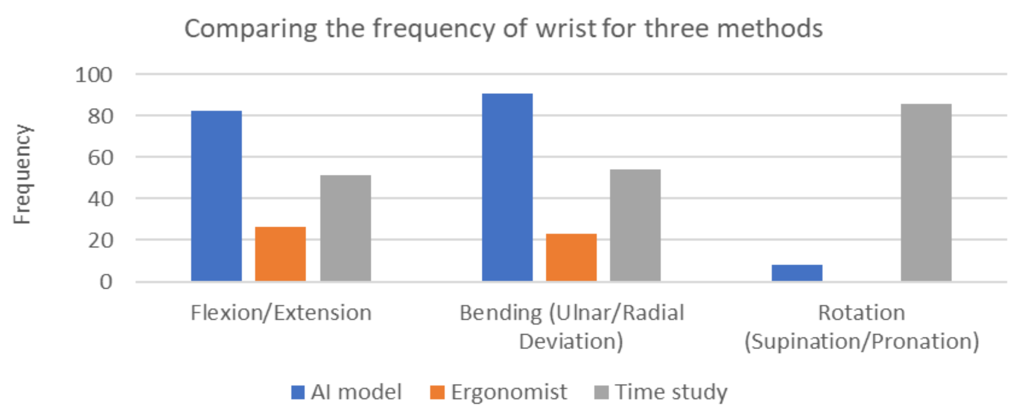


Figure 33: Comparison of frequency of wrist activities between three methods used.

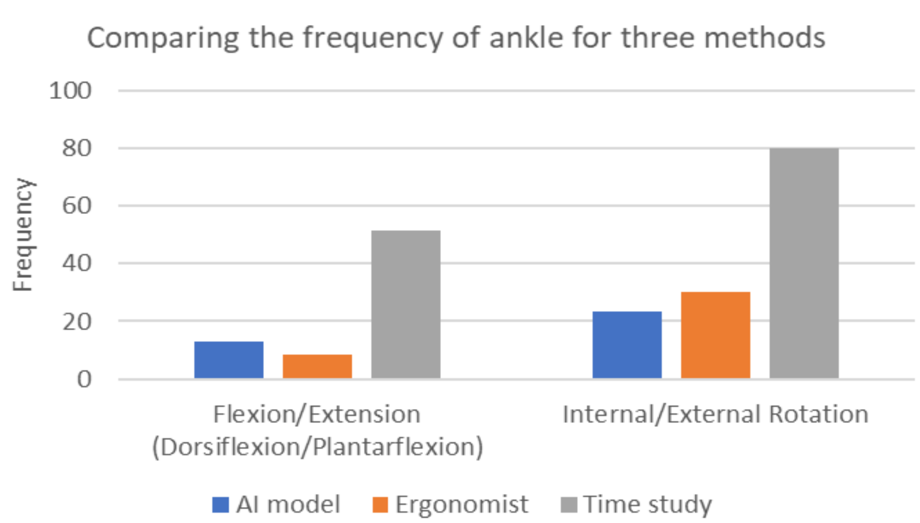


Figure 34: Comparison of frequency of ankle activities between three methods used.

The following findings compare the results of the suggested technique to those of five different ergonomists. In this experiment, four ergonomists used their specific techniques to determine the range definition of each frequency, and only one ergonomist determined both percentage and the range definition of activities' frequency. Table 30 shows the frequency of activities in the range definition measured by five ergonomists and automated framework. Table 31 gives this information for positional tasks.

Table 30: Comparing the AI model's results with five different ergonomists' results, for manual handling tasks

Manual handling tasks	**Frequency per shift (N-R-O-F-C)**					
	AI model	**Ergonomist 1**	**Ergonomist 2**	**Ergonomist 3**	**Ergonomist 4**	**Ergonomist 5**
Lifting						
Low-level	R	O	O	O	O	C
Knee level	O	O	O	O	O	F
Waist level	O	O	O	O	O	F
Shoulder level	O	O	N	O	O	N
Above-shoulder	R	O	O	O	O	N
Carry						
Front	F	F	C	C	F	C
Side	N	N	N	N	N	N
Side, right hand	N	N	N	N	N	N
Side, left hand	N	N	N	N	N	N
On shoulder	N	N	N	N	N	N
Pushing/pulling						
Stationary pushing	N	N	N	N	N	N
Stationary pulling	O	N	N	N	N	N
Dynamic pushing	N	N	N	N	N	N
Dynamic pulling	R	N	N	N	N	N

Table 31: Comparing the AI model's results with five different ergonomists' results, for positional tasks

Positional tasks	Frequency per shift (N-R-O-F-C)					
	AI model	**Ergonomist 1**	**Ergonomist 2**	**Ergonomist 3**	**Ergonomist 4**	**Ergonomist 5**
Mobility						
Sitting/driving	O	O	O	O	O	O
Standing	O	O	C	C	F	C
Walking	F	F	C	O	F	C
Climbing – stairs	N	N	N	N	N	N
Climbing – ladders	N	N	N	N	N	N
Climbing – stools, etc.	N	N	N	N	N	N
Crouching	N	N	N	O	N	F
Squatting	F	O	F	O	O	O
Kneeling	N	N	N	N	N	N
Crawling	N	N	N	N	N	N
Back						
Forward bending	F	O	F	F	O	C
Trunk rotation	O	O	O	O	N	O
Backward bending	O	N	R	N	N	O
Shoulder						
Below shoulder level reaching	O	O	O	F	F	O
Forward shoulder level reaching	O	O	O	F	O	O
Above-shoulder level reaching	O	O	O	O	O	O
Sideway shoulder reaching	N	N	N	N	N	N
Behind shoulder reaching	N	N	N	N	N	N
Neck						
Forward bending	F	O	F	C	O	C
Backward bending	N	N	O	N	O	O
Twist/tilt	O	O	O	O	R	O
Elbow						
Flexion/extension	C	O	C	N	F	C
Wrist						
Flexion/extension	C	O	F	F	O	C
Bending (ulnar/radial deviation)	C	O	N	O	F	O
Rotation (supination/ pronation)	O	N	N	N	R	O

Ankle						
Flexion/extension (dorsiflexion/ plantarflexion)	O	O	C	N	O	C
Internal/ external rotation	O	O	F	N	O	O

Figure 35–44 show the bar charts to compare the frequency range definition of different types of activities between the automated framework and five ergonomists.

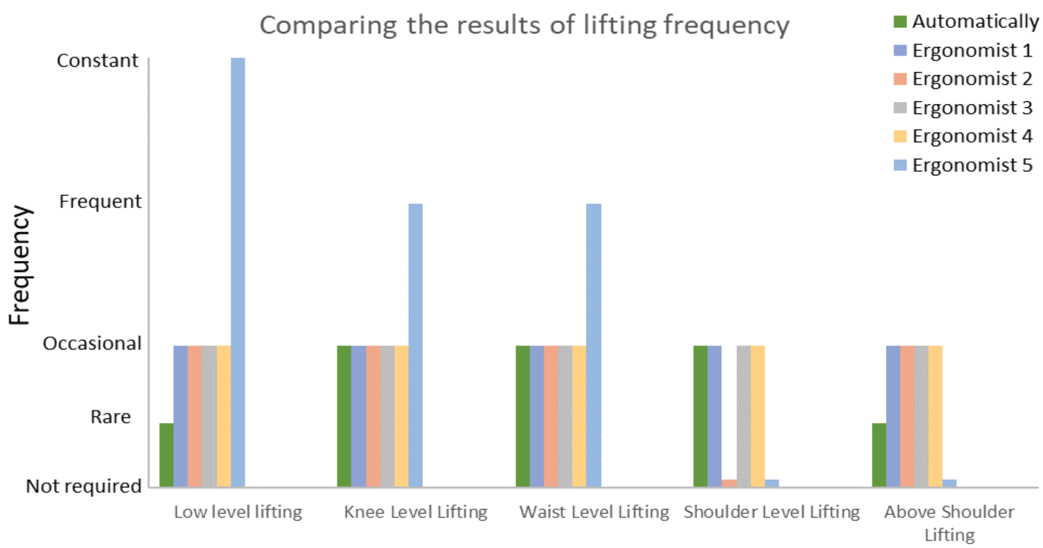


Figure 35: Comparison of the frequency of lifting activities between the automated framework and five ergonomists.

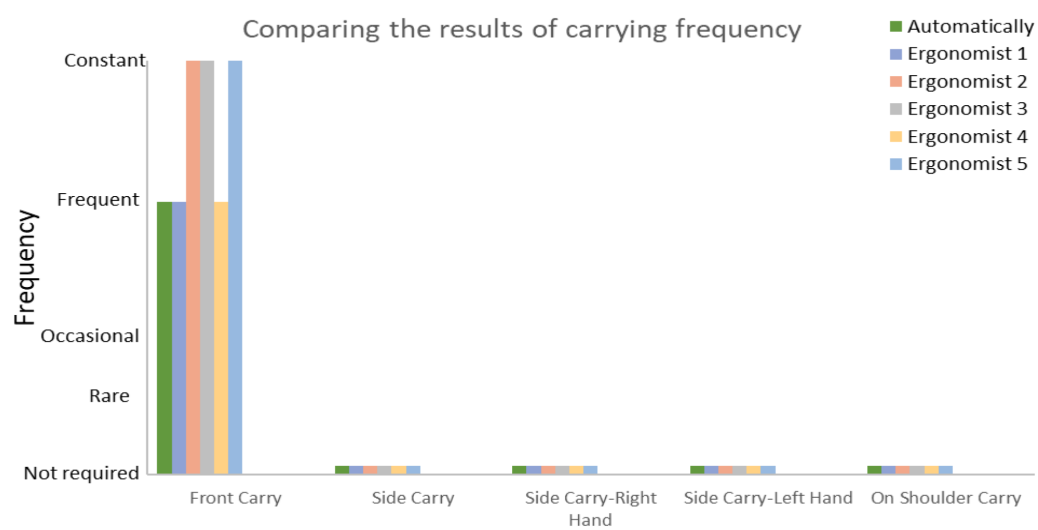


Figure 36: Comparison of the frequency of carrying activities between the automated framework and five ergonomists.

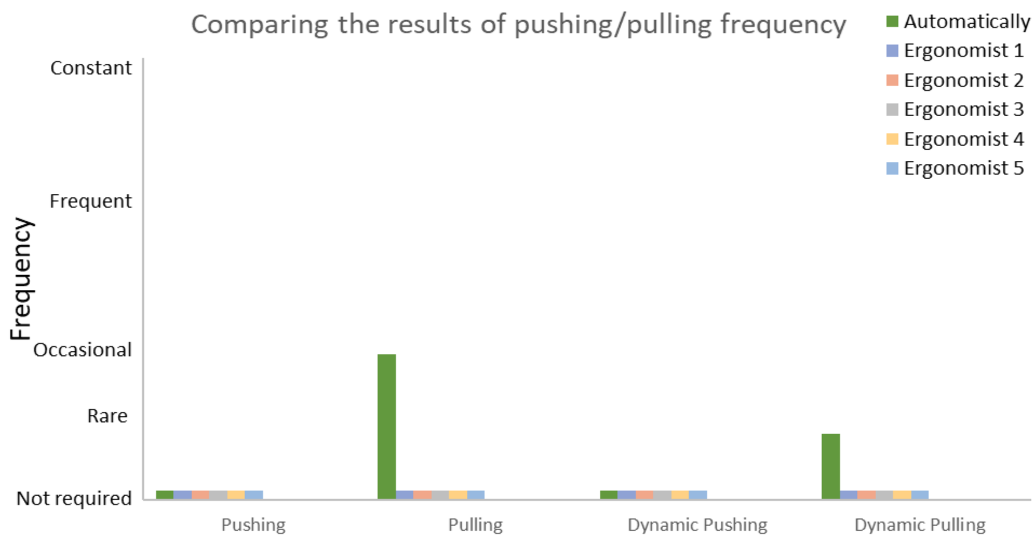


Figure 37: Comparison of the frequency of pushing/pulling activities between the automated framework and five ergonomists.

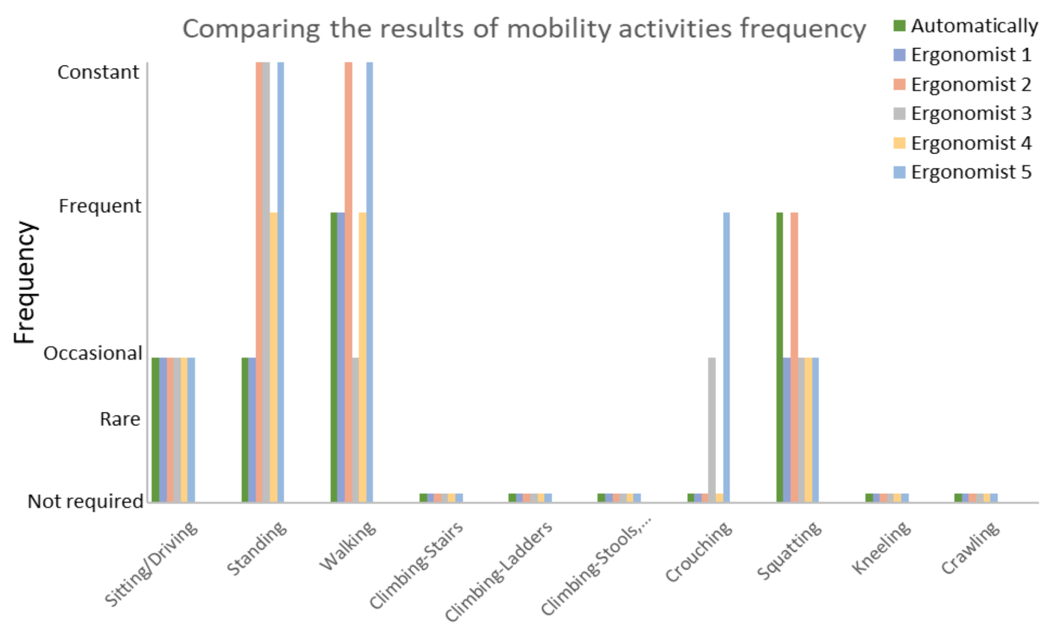


Figure 38: Comparison of the frequency of mobility activities between the automated framework and five ergonomists.

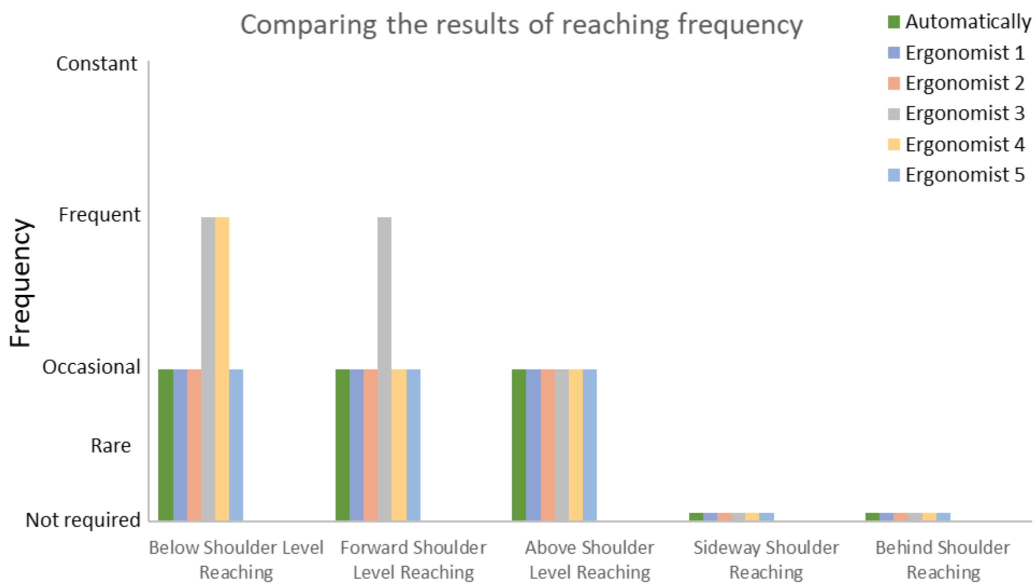


Figure 39: Comparison of the frequency of reaching activities between the automated framework and five ergonomists.

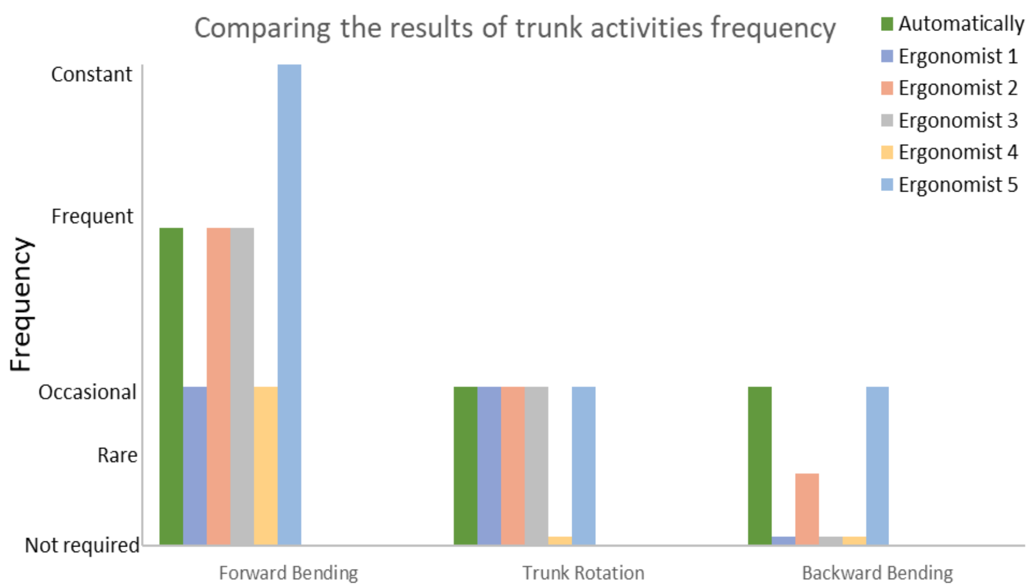


Figure 40: Comparison of the frequency of trunk activities between the automated framework and five ergonomists.

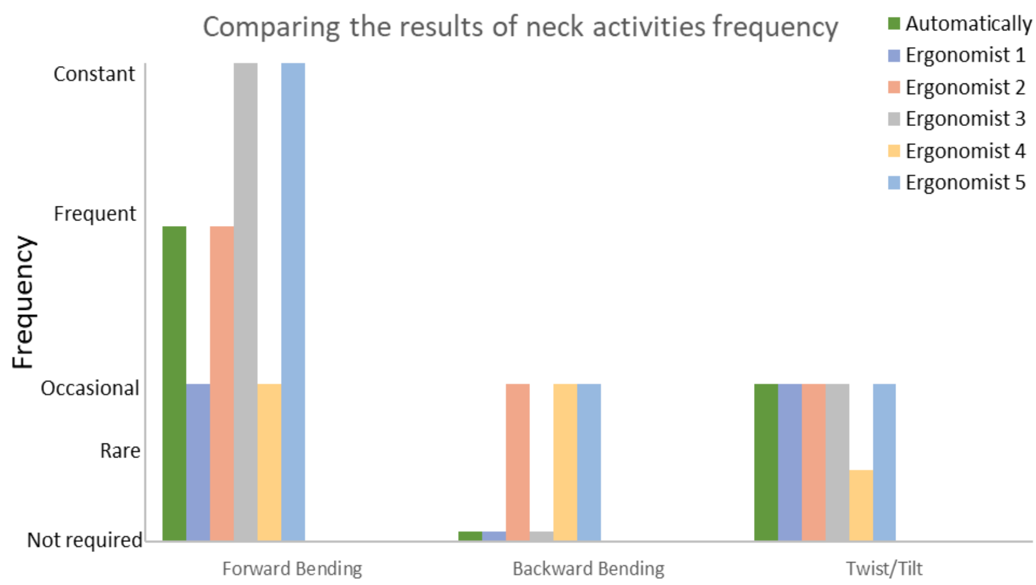


Figure 41: Comparison of the frequency of neck activities between the automated framework and five ergonomists.

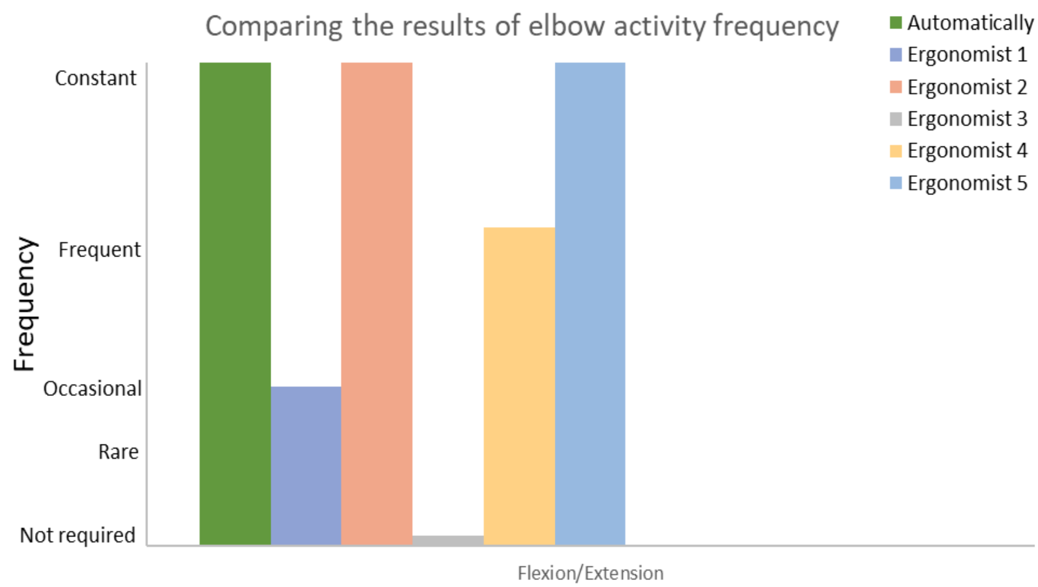


Figure 42: Comparison of the frequency of elbow activities between the automated framework and five ergonomists.

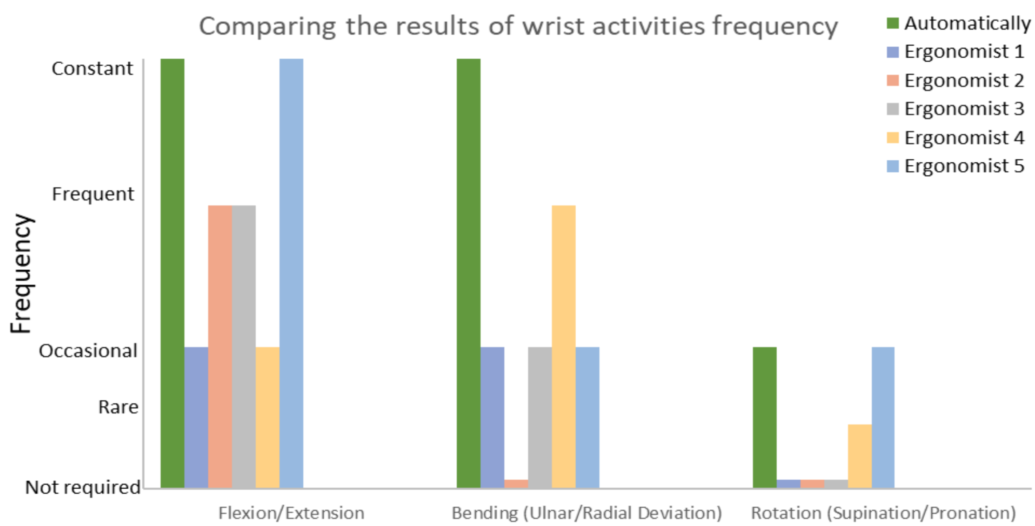


Figure 43: Comparison of the frequency of wrist activities between the automated framework and five ergonomists.

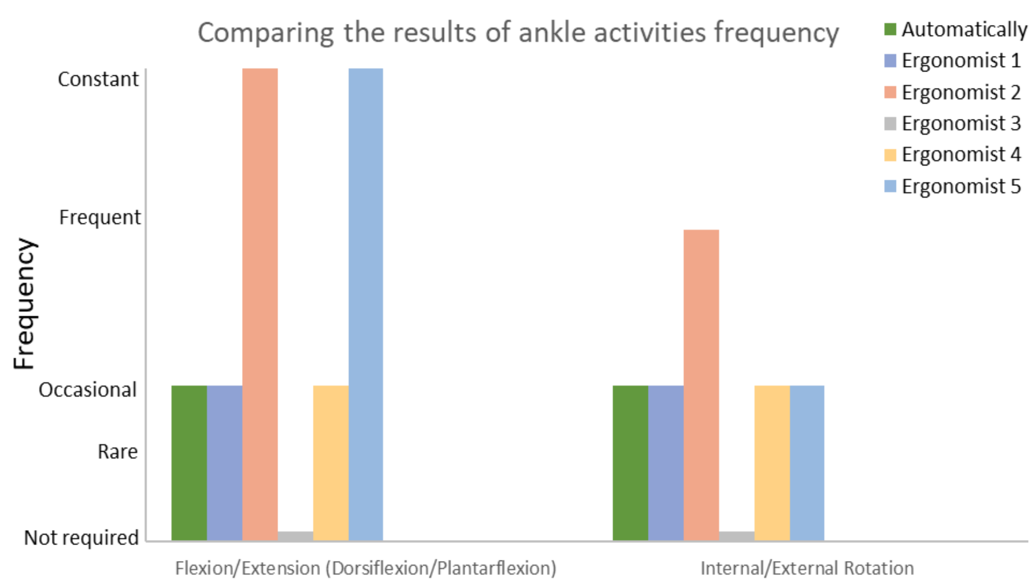


Figure 44: Comparison of the frequency of ankle activities between the automated framework and five ergonomists.

4.4. Results of the Case Study

This section shows the results of two different methods of implementing the PDA form for the on-site experiment at the construction site. Table 32 shows the frequency of activities in percentage and range definition for the case study, for manual handling tasks. Table 33 gives this information for positional tasks.

Table 32: Comparing the frequency of activities for the case study (% and range), for manual handling tasks

Manual handling tasks	Frequency per shift (percentage)		Frequency per shift (N-R-O-F-C)	
	AI model	**Ergonomist 1**	**AI model**	**Ergonomist 1**
Lifting				
Low-level	12.56	4.00	O	R
Knee level	18.76	0.00	O	N
Waist level	3.22	2.30	R	R
Shoulder level	11.29	0.00	O	N
Above-shoulder	0.26	0.00	N	N
Carry				
Front	13.16	0.00	O	N
Side	2.52	4.00	R	R
Side, right hand	1.06	1.00	R	R
Side, left hand	1.96	3.00	R	R
On shoulder	0.10	0.00	N	N
Pushing/pulling				
Stationary pushing	0.06	0.00	N	N
Stationary pulling	40.07	0.00	F	N
Dynamic pushing	0.00	0.00	N	N
Dynamic pulling	4.00	0.00	R	N

Table 33: Comparing the frequency of activities for the case study (% and range), for positional tasks

Positional tasks	Frequency of workday/shift		Frequency per shift (N-R-O-F-C)	
	AI model	**Ergonomist 1**	**AI model**	**Ergonomist 1**
Mobility				
Sitting/driving	1.02	0.00	N	N
Standing	21.61	14.30	O	O
Walking	17.82	4.10	O	R
Climbing – stairs	1.56	1.70	R	R
Climbing – ladders	0.14	0.00	N	N
Climbing – stools, etc.	1.68	0.00	N	N
Crouching	0.00	0.00	N	N
Squatting	46.66	1.20	F	N
Kneeling	0.00	0.00	N	N
Crawling	0.00	0.00	N	N
Back				
Forward bending	61.75	58.20	F	F
Trunk rotation	2.74	7.00	R	O

Backward bending	0.08	9.30	N	O
Shoulder				
Below shoulder level reaching	35.42	30.80	F	O
Forward shoulder level reaching	48.84	30.80	F	O
Above-shoulder level reaching	40.81	53.10	F	F
Sideway shoulder reaching	16.18	0.00	O	N
Behind shoulder reaching	0.20	0.00	N	N
Neck				
Forward bending	20.62	81.50	O	C
Backward bending	4.19	0.00	R	N
Twist/tilt	56.71	2.30	F	R
Elbow				
Flexion/extension	95.71	84.00	C	C
Wrist				
Flexion/extension	80.54	64.00	C	F
Bending (ulnar/radial deviation)	84.94	18.90	C	O
Rotation (supination/ pronation)	23.49	18.90	O	O
Ankle				
Flexion/extension (dorsiflexion/plantarflexion)	1.56	57.10	N	F
Internal/external rotation	40.03	0.00	F	N

Chapter 5 – Discussion

5.1 Discussion of Laboratory Experiment

The following paragraphs compare the frequency of activities in percentage terms using the three methodologies utilized:

In most activities, the results related to the time study method are significantly higher than the two other methods. These differences could be related to the low precision of the method in measuring the frequency of activities. In this way, observers monitored the video related to the worker for whole minutes and checked marks every minute into the printed time study spreadsheet to record the worker's motion. The total number of checkmarks equals minutes of the activity's time, although the action may be done less than 1 minute per checkmark (e.g. doing low-level lifting only for 20 seconds instead of a whole 1 minute). In addition, the high amount of standard deviation for different activities shows high variability in observers' results. So, the collected results by this method are unreliable for comparing with two other used methods in this research.

The first ergonomist who participated in this research calculated the percentage of each frequency that allowed comparing with the proposed framework results. In low and knee-level lifting activities, there are some differences between the percentage results of the automated framework and the ergonomist's method. These differences are because of human bias, human errors in level detection, and different definitions of the activities. However, the results of knee-level activity are in the same frequency range definition. Moreover, the percentage results in waist, shoulder and above shoulder level lifting are approximately the same. Although, the above shoulder level activity results are in different frequency range definitions.

The results from the two methods are approximately similar in front carrying activity. However, the results in other kinds of carrying activities show less than 2 percent error in the proposed algorithm that needs to be considered as not required activity.

The results in stationary and dynamic pushing activities again show less than 2 percent error in the proposed algorithm that needs to be considered as not required activity. In stationary and dynamic pulling activities, the results show higher errors in the algorithm. The reason is the research's limitation related to not using force sensors to accurately determine muscle loads and the direction of forces to identify these activities.

There are different situations in the results of mobility activities' frequency. In sitting, the results of the two methods are nearly identical. Conversely, the percentage results in standing and walking have some distinctions because of human bias and different definitions of the activities. Although, they are in the same frequency range definitions. In squatting activity, knee flexion is determinant because different definitions for knee joint angle cause different results. The proposed framework considers knee flexion greater than 30 degrees as squatting based on REBA. The activity frequency for this definition equalled 44.7 percent, although if the algorithm changes the knee flexion to 40 degrees, the result will be 22.11, similar to the ergonomist's result. So, it means that the ergonomist considered 40 degrees as squatting. Also, the result in climbing stairs and stools activity shows less than 2 percent error in the proposed algorithm that needs to be considered as not required activity. Moreover, the results from the two methods in other mobility activities equal zero.

The frequency percentage results in the below shoulder level reaching and the above shoulder level reaching have a little difference between the two methods used. Although, they are in the same frequency range definitions. The reasons are the same as the lifting activities: human bias, human errors in level detection, and different definitions of the activities. Conversely, the forward shoulder level reaching results are approximately the same and in the same frequency range definitions. In addition, the result in sideway shoulder reaching activity shows less than 2 percent error in the proposed algorithm that needs to be considered as not required activity. Also, behind-shoulder reaching activity results from the two methods equal zero.

Generally, the algorithm results are more accurate than the ergonomist method in the activities related to each segment movement, such as back, neck, elbow, wrist, and ankle. Because in the manual method, measuring the joint angles is challenging, and there are human errors. However, in the automated framework, the sensors detect the angles accurately.

In activities related to the trunk, the frequency for forwarding bending and rotation are nearly identical in the two methods. Although, the forwarding bending results are in different frequency range definitions. Conversely, realizing the trunk extension in backward bending when the participant was sitting on a chair was difficult because of human errors. So, in this activity, the result of the proposed framework is more reliable.

In activities related to the neck, the frequency of the forward bending, twisting, and tilting differ in the two methods. Although, twisting results are in the same frequency range definitions. In these activities, T8_Head flexion, T8_Head axial bending, and T8_Head lateral bending are determinants because different definitions for these angles cause different results. Based on REBA, the proposed framework considers T8_Head flexion greater than 20 degrees as neck forward bending. The activity frequency for this definition equalled 43.78 percent, although if the algorithm changes the joint angle to 40 degrees, the result will be 13.13, near the ergonomist's result. As well as that, the proposed framework considers T8_Head axial bending and T8_Head lateral bending greater than 20 degrees as neck twisting and tilting based on REBA. The activity frequency for this definition equalled 32.79 percent, although if the algorithm changes the joint angle to 30 degrees, the result will be 14.88, near the ergonomist's result. The results show that the ergonomist considered 40 degrees as neck forward bending and 30 degrees as neck twisting and tilting. In addition, the result in neck backward bending activity shows less than 2 percent error in the proposed algorithm that needs to be considered as not required activity.

In the elbow activity, the frequencies for elbow flexion differ in the two methods. The proposed framework considers elbow flexion, which is determinant, greater than 20 degrees as elbow flexion based on REBA. The activity frequency for this definition equalled 86.13 percent, although if the algorithm changes the joint angle to 45 degrees, the result will be 27.27, near the ergonomist's result. It means the ergonomist considered 45 degrees as elbow flexion.

In activities related to the wrist, the frequency of flexion/extension and bending differ in the two methods. In these activities, wrist flexion/extension and wrist ulnar/radial deviation are determinants because different definitions for these angles cause different results. The proposed framework considers wrist flexion greater than 15 degrees and wrist extension less than -15 degrees as wrist flexion/extension based on REBA. The activity frequency for this definition equalled 82.40 percent, although if the algorithm changes the joint angles to 30 and -30 degrees, the result will be 31.55, near the ergonomist's result. As well as that, the proposed framework considers wrist radial deviation greater than 10 degrees and wrist ulnar deviation less than -15 degrees as wrist bending (Lind et al., 2020). The activity frequency for this definition equalled 90.52 percent, although if the algorithm changes the wrist radial deviation to 30 degrees, the result will be 25.95, near the ergonomist's result. It means the ergonomist considered 30 degrees as wrist radial deviation. Moreover, realizing the wrist rotation during the work was difficult because of human errors in joint angle detection. So, in this activity, the result of the proposed framework is more reliable. It should be emphasized that video recording may not be appropriate when employees are highly mobile since the viewing angle of a video camera is restricted. Additionally, certain stations may have insufficient working space, resulting in a difficult camera setup. So, in this activity, the result of the proposed framework is more reliable.

In activities related to the ankle, the frequency for flexion/extension and rotation is nearly identical in the two methods, with a few differences because of human errors in joint angle detection and different definitions of the activities. Also, they are in the same frequency range definitions.

In addition, five ergonomists' findings indicate that each has a unique approach to determining the frequency of activities. The first ergonomist who participated in this research calculated each frequency's percentage and range definition, but the next four ergonomists measured only the range definition of each frequency. The results show that they have distinct meanings for each action that cause different outcomes. So, there is no consistency in the ergonomists' results in some activities such as standing, walking, trunk forward and backward bending, neck forward bending, elbow and wrist and ankle flexion because of subjective data-collection techniques. Eventually, the results show a progression in detecting frequency results from observers to ergonomists and the proposed framework.

5.2 Discussion of Case Study

The following paragraphs compare the frequency of activities in percentage terms and the range definition between the results of the proposed framework and the first ergonomist:

The first ergonomist who participated in this research calculated the percentage of each frequency that allowed comparing with the proposed framework results. In low and knee-level lifting activities, there are some differences between the percentage results of the automated framework and the ergonomist's method. These differences are because of human bias, human errors in level detection, and different definitions of the activities. Conversely, the percentage results in waist level lifting are approximately the same and in the same frequency range definitions. In addition, detecting the shoulder level lifting activity during the work was difficult for the ergonomist because that part was done at 4.2 m above the earth on a scaffold, and the station had insufficient working space, resulting in a difficult camera setup. It shows that video recording may not be appropriate when a video camera's viewing angles and levels are restricted. So, the proposed framework's result is more reliable in this activity. Moreover, the above shoulder lifting activity results show less than 2 percent error in the proposed algorithm that needs to be considered as not required activity.

The results from the two methods are approximately similar in side carrying activity. Conversely, the front carrying activity results show that the ergonomist did not consider bringing mortar from the pallet as front carrying; however, it was measured in the proposed algorithm.

The stationary and dynamic pushing activities results show zero percent in both the proposed algorithm and ergonomist. In stationary and dynamic pulling activities, the results show some errors in the algorithm results. The reason is the research's limitation related to not using force sensors to accurately determine muscle loads and the direction of forces to identify these activities.

There are different situations in the results of mobility activities' frequency. In standing and climbing stairs, the results of the two methods are nearly identical and in the same frequency range definitions. Conversely, the percentage results in walking have some distinctions because of human bias and different definitions of the activities. In squatting activity, knee flexion is determinant because different definitions for knee joint angle cause different results. The proposed framework considers knee flexion greater than 30 degrees as squatting based on REBA. The activity frequency for this definition equalled 46.66 percent, although if the algorithm changes the knee flexion to 70 degrees, the result will be 1.42, near the ergonomist's result. So, it means that the ergonomist considered 70 degrees as squatting. However, the ergonomist considered 40 degrees as squatting in the laboratory experiment. It shows no consistency in the ergonomist results because of subjective techniques for data collection. Also, the results in sitting and other climbings activity show less than 2 percent error in the proposed algorithm that needs to be considered as not required activity. Moreover, the results from the two methods in other mobility activities equal zero.

The frequency percentage results in the below shoulder level reaching have a little difference between the two methods used because of the same reasons for the lifting activities: human bias, human errors in level detection, and different definitions of the activities. Their results are in the different frequency range definitions because the percentages are around 33%, which is the boundary of the two range definitions. In addition, detecting the forward shoulder level, above shoulder level, and sideway shoulder reaching during the work was difficult for the ergonomist because working 4.2 m above the earth on a scaffold resulted in a complex camera setup. It shows that video recording may not be appropriate when a video camera's viewing angles and levels are restricted. The results show that the ergonomist considered some of the forward shoulder level reaching as the above shoulder level reaching. So, the proposed framework's result is more reliable in this activity. Moreover, behind-shoulder reaching activity shows less than 2 percent error in the proposed framework, which must be considered as not required activity.

In activities related to the trunk, the frequencies for forwarding bending are nearly identical in the two methods. Conversely, the results of the backward bending show some differences because of human bias and different activity definitions. Also, the proposed framework considers L5S1 Axial Bending greater than 10 degrees as trunk rotation. The activity frequency for this definition equalled 2.74 percent, although if the algorithm changes the joint angle to 8 degrees, the result will be 7.39, near the ergonomist's result. The results show that the ergonomist considered 8 degrees as trunk rotation. So, in these activities, the result of the proposed framework is more reliable.

In activities related to the neck, the frequency of the forward bending, twisting, and tilting differ in the two methods. In these activities, T8_Head flexion, T8_Head axial bending, and T8_Head lateral bending are determinants because different definitions for these angles cause different results. Based on

REBA, the proposed framework considers T8_Head flexion greater than 20 degrees as neck forward bending. The activity frequency for this definition equalled 20.62 percent, although if the algorithm changes the joint angle to 0 degrees, the result will be 52.16. The results show that the ergonomist considered the frequency of neck forward bending higher than the actual condition because of considering all trunk forward bending situations as neck forward bending; however, It did not occur continuously in that situation. Moreover, realizing the neck twisting, tilting, and backward bending during the work was difficult because of human errors in joint angle detection. So, in this activity, the result of the proposed framework is more reliable. It should be emphasized that video recording may not be appropriate when employees are highly mobile since the viewing angle of a video camera is restricted. Additionally, certain stations may have insufficient working space, resulting in a difficult camera setup. So, in these activities, the result of the proposed framework is more reliable.

In the elbow activity, the frequencies for elbow flexion are nearly identical and in the same frequency range definitions in the two methods.

In activities related to the wrist, the frequency of flexion/extension and bending differ in the two methods. In these activities, wrist flexion/extension and wrist ulnar/radial deviation are determinants because different definitions for these angles cause different results. The proposed framework considers wrist flexion greater than 15 degrees and wrist extension less than -15 degrees as wrist flexion/extension based on REBA. The activity frequency for this definition equalled 80.54 percent, although if the algorithm changes the joint angles to 20 and -20 degrees, the result will be 64.86, near the ergonomist's result. Also, the proposed framework considers wrist radial deviation greater than 10 degrees and wrist ulnar deviation less than -15 degrees as wrist bending (Lind et al., 2020). The activity frequency for this definition equalled 84.94 percent, although if the algorithm changes the wrist radial deviation to 40 degrees and ulnar wrist deviation to -40 degrees, the result will be 14.98, near the ergonomist's result. It means the ergonomist considered 40 and -40 degrees as wrist radial/ulnar deviation. However, the ergonomist considered 30 degrees as wrist radial/ulnar deviation in the laboratory experiment. It shows no consistency in the ergonomist results because of subjective techniques for data collection. Conversely, the frequencies for wrist rotation are nearly identical and in the same frequency range definitions in the two methods.

In activities related to the ankle, the frequency of flexion/extension has some differences between the two methods. Ankle dorsiflexion/plantarflexion are determinants in this activity because different definitions for these angles cause different results. Based on REBA, the proposed framework considers ankle dorsiflexion greater than 15 degrees and ankle plantarflexion less than -15 degrees as ankle flexion/extension. The activity frequency for this definition equalled 1.56 percent, although if the algorithm changes the joint angles to 8 and -8 degrees, the result will be 58.71, near the ergonomist's result. It means the ergonomist considered 8 and -8 degrees as ankle flexion/extension. Moreover, realizing the ankle internal/external rotation during the work was difficult because of human joint-angle detection errors. So, in this activity, the result of the proposed framework is more reliable.

Chapter 6 – Conclusions

6.1 Thesis Summary

Construction zone workers are often exposed to awkward body postures and repeated motions that contribute to WMSDs that cause projects or manufacturing lines to be delayed proportionately. Thus, a critical component of construction projects is worker productivity and the factors that influence it, such as ergonomics. Implementing ergonomics and connecting employees to their assigned jobs will drop worker injuries, increase productivity, and decrease project costs. So, authentic ergonomic assessment techniques enable the evaluation of worker safety in modular construction to identify and eliminate ergonomic risks associated with WMSDs.

This study focuses on PDA as a systematic method for analyzing the working conditions associated with physical demand. It helps the health and safety department understand the construction activities and plant operation for each job and production line to identify possible ergonomic hazards for employees. Typically, ergonomists collect data manually to complete the forms connected with the PDA approach, which entails observing various jobs and talking with workers about the physical demands of a particular profession on specific body parts. This study aims to establish a direct observation approach for determining the physical demands of a job. This technique may address concerns about the accuracy of PDAs, the time necessary to develop a PDA form, and the related high expenses. Thus, a framework is proposed for PDA and filling the related forms on construction sites by utilizing the Xsens MVN Awinda, which includes 17 wireless motion trackers as a MOCAP to gather joint angles and body segment positions during manual handling and operational tasks. In the next stage, a rule-based expert system as an artificial intelligence technique was used to convert the collected data to various manual handling and positional tasks, identify their frequency and automatically fill posture-based PDA forms.

Eventually, the results demonstrate the development of a posture-based PDA form that enables users to obtain precise information about the physical demands of a particular job for various purposes, including ergonomic risk assessment, recruiting and training, job matching, and modified tasks for injured workers. Also, by incorporating lean construction 4.0 into this process, the automated PDA filling system is established to eliminate wastes connected with costs and person-hours in subjective data collecting and solve the issues related to inaccurate PDA.

6.2 Overall Conclusion

This research proposed a new framework that uses innovative ideas to make automation in the industry's PDA field. In conclusion, by using this framework, some positive results will happen:

1) Reduce the ergonomist's subjective judgements and biases in evaluating PDA based on their different definitions of activities.
2) Establish a consistent strategy for collecting data on physical demands compared to ergonomists, who employ various data collection techniques with different results and inconsistencies.
3) Eliminate human errors related to detecting joint angles and body segment positions.
4) Provide the PDA for each job more accurately than other methods.
5) Assist ergonomists in spending more time on workstation design rather than data collecting to improve worker health and safety by reducing ergonomic risks and potential injuries.
6) Increase project productivity through ergonomic techniques and mitigating delays caused by WMSDs.

6.3 Contributions

Contributions from this research consist of:

6.3.1 Academic Contributions

- Using MOCAP and AI-based algorithm to obtain postures, joint angles, and body segment positions to define different activities.
- Using the definitions and a rule-based expert system to develop an automated PDA filling system.

- Developing a new posture-based PDA form.

6.3.2 Industry Contributions

- Reducing wastes associated with costs and person-hours for data collection and PDA form completion.
- Using the proposed framework will aid in the ergonomic design of a workstation or a manufacturing plant's production line. Also, instead of collecting data, ergonomists will concentrate their time on physical ergonomic interventions, such as improving the workplace's equipment and surroundings, reducing employees' exposure to ergonomic risks and enhancing worker health and safety.
- Helping workplace organizations and health care specialists to identify and modify occupations or activities as a customized, effective, and efficient return-to-work program to accommodate disabled or injured workers and assist them in returning to their prior positions.
- Identifying the most demanding activities to avoid assigning them to inexperienced or weak employees and matching jobs to specific persons within the worker's working capacity to increase practicality, efficiency, agility, operational effectiveness, and productivity.
- Analyzing the physical demands of alternate work methods and developing modified tasks or tactics to prioritize safety risks, mitigate ergonomic risks and prevent workplace accidents.
- Utilizing the framework may proactively reduce workers' insurance claims and injury reports and lower the industry's workers' compensation costs.
- Preparing a specific job demands documentation for training, recruiting, therapists to develop suitable treatment objectives, health care practitioners, and workers' compensation boards.

6.4 Recommendations for Further Research

The proposed framework also contains some limitations that should be addressed in future work. First, it should be noted that this research focuses only on body movements such as joint angles and body segment positions. In the future, it is preferable to include force sensors into the framework to determine muscle loads and the direction of forces to identify specific activities such as pushing and pulling accurately.

The second limitation is related to monitoring finger joint angles during work. This research did not use Xsens gloves to detect this motion. Thus, other investigators may include this section into the framework to increase the accuracy of identifying activities that require holding an object by hand, such as lifting, reaching, and carrying.

The other constraint is linked to the battery capacity of the IMU sensors employed in this investigation. According to the device's instructions, the batteries have roughly six hours of charge capacity. This condition means that if data collection requires a longer time, there will be a delay in obtaining data while the batteries charge, or it will need to acquire more sensors as a backup. Another restriction is linked to noise data generated by unexpected actions, such as stretching, which cannot be eliminated.

The other limitation is the number of collaborated ergonomists. Other researchers can work with a higher number of expert ergonomists to have a better comparison with their results.

A recommendation for further research to implement this process is to gather a large amount of data through experiments and use machine learning to label each movement separately. This data can be used to train large classifiers, like neural networks. Indeed, there is no need to set rules when utilizing neural networks since they extract rules automatically based on the person's stance as determined by sensors. For example, reaching and gripping an object can be done in various ways that cannot be distinguished using simple rules. However, it can become feasible by using the power of neural networks as feature extractors and classifiers.

Additionally, by incorporating vision-based systems such as depth cameras into this framework, it will be able to recognize items, which will improve the algorithm in recognizing activities that involve gripping or holding particular objects.

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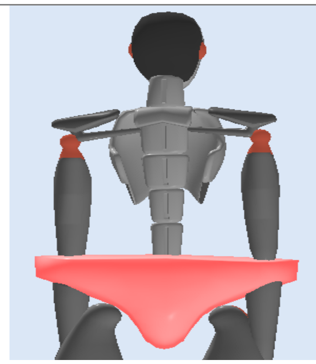
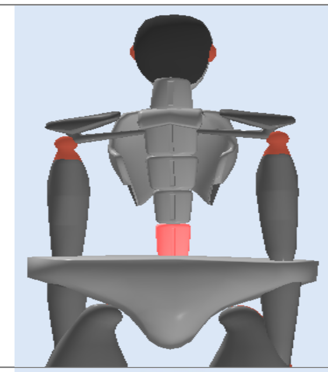
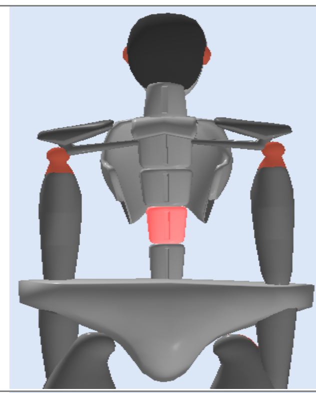
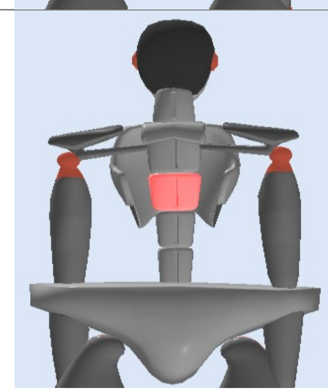
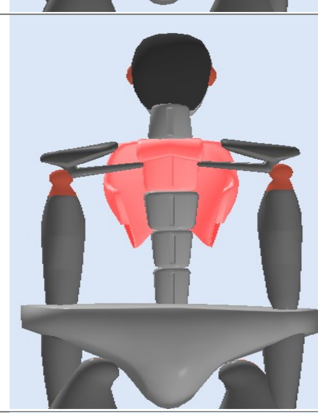
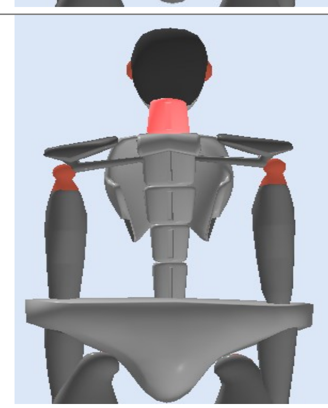
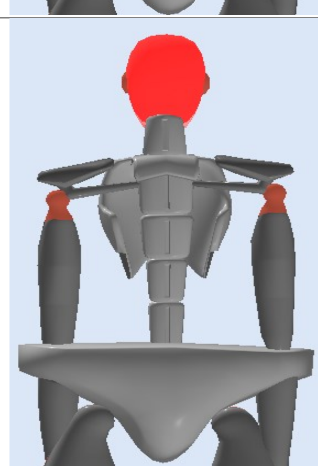
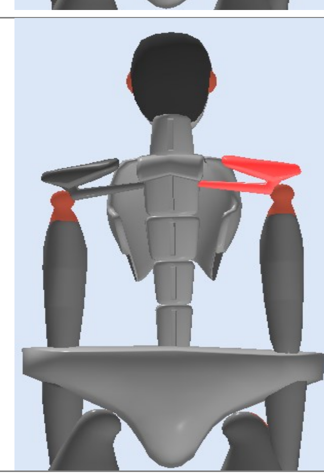
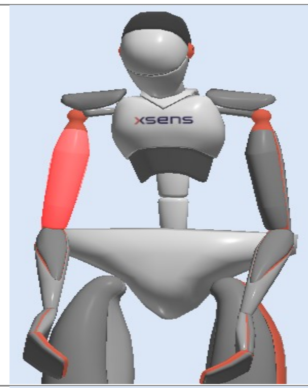
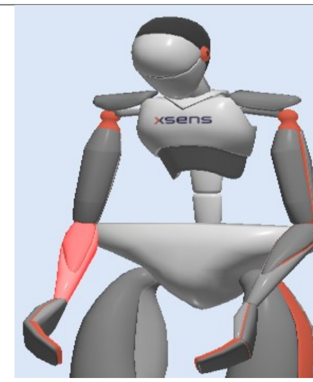
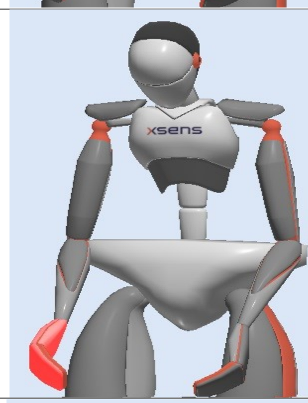
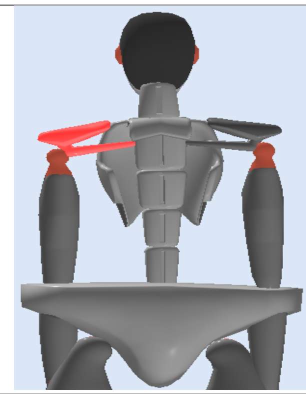
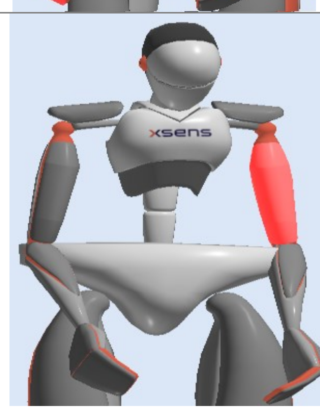
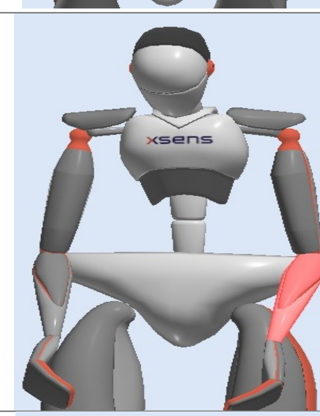
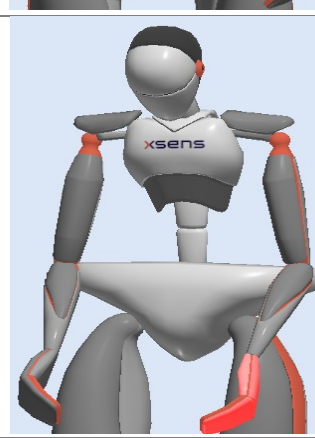
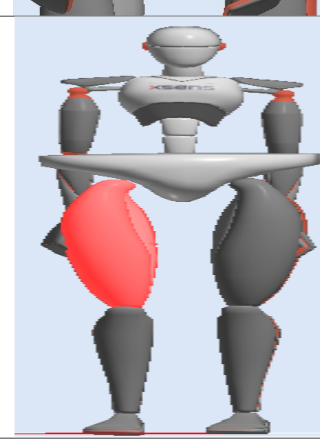
Appendix A

Schematic drawing of body segments, joints, and ergonomic joint angles

Table A-1: Schematic drawing of body segments

Body segment	Schematic drawing	Body segment	Schematic drawing
Pelvis		L5	
L3		T12	
T8		Neck	
Head		Right Shoulde r	

Right Upper Arm		Right Forearm	
Right Hand		Left Shoulder	
Left Upper Arm		Left Forearm	
Left Hand		Right Upper Leg	

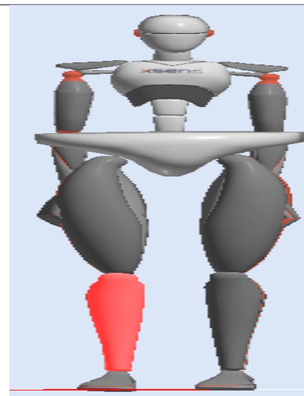
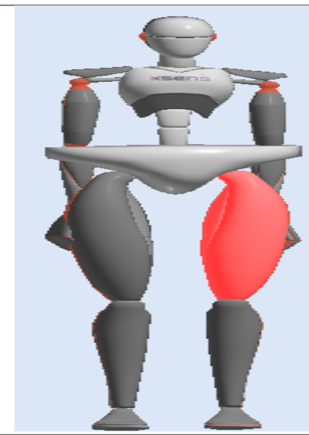
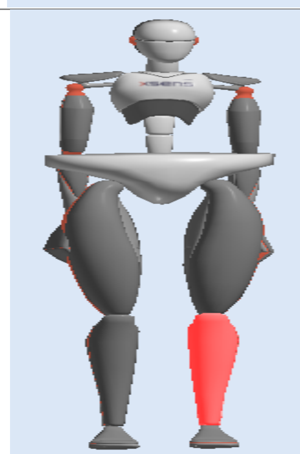
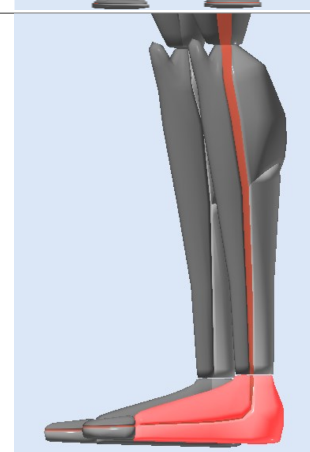
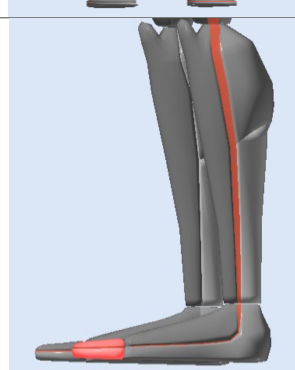
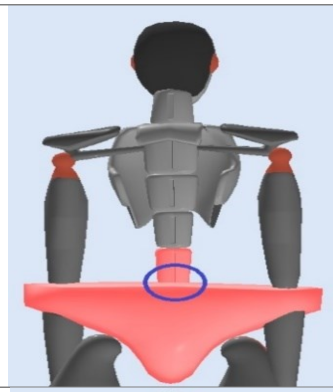
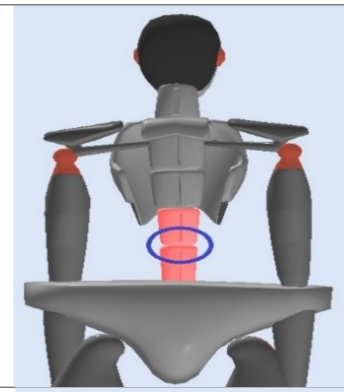
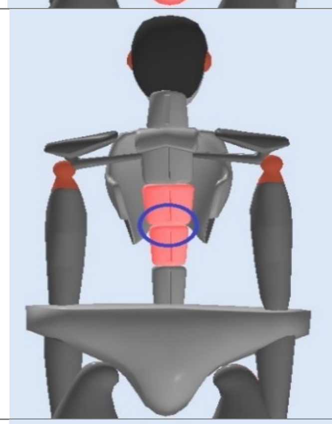
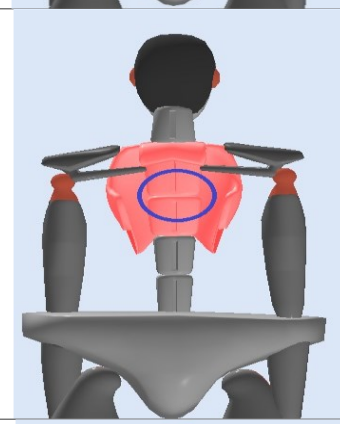
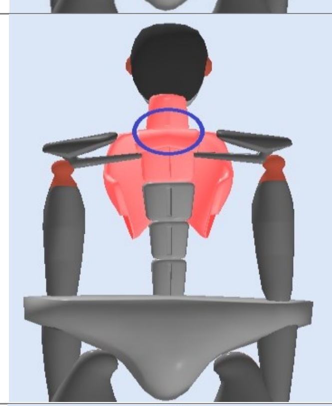
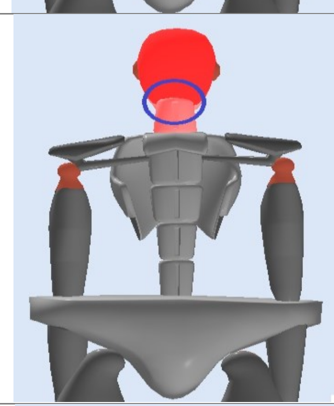
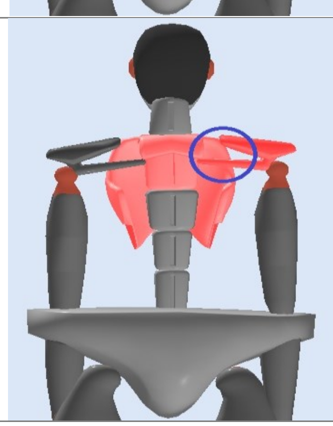
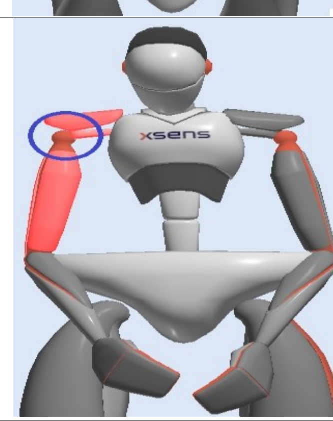
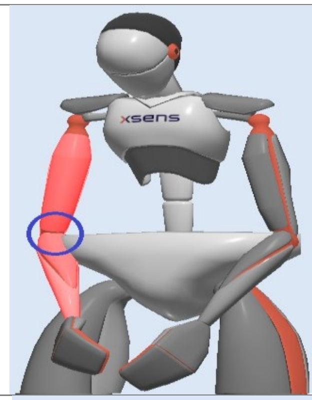
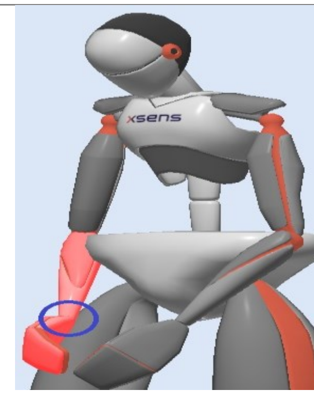
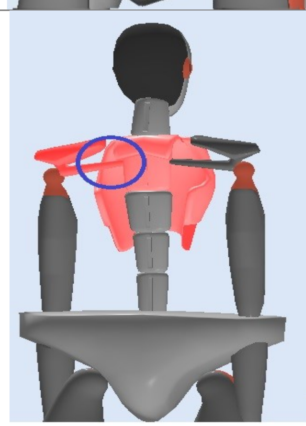
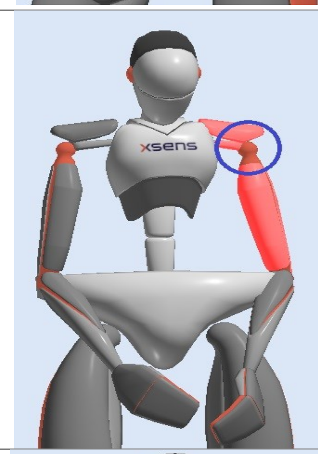
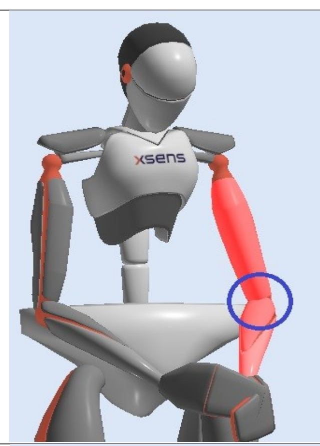
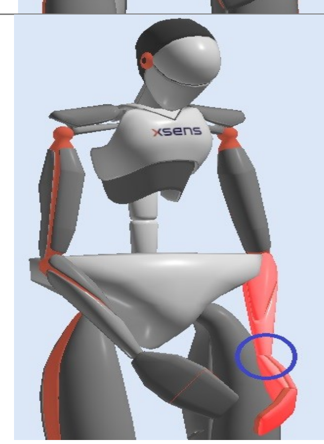
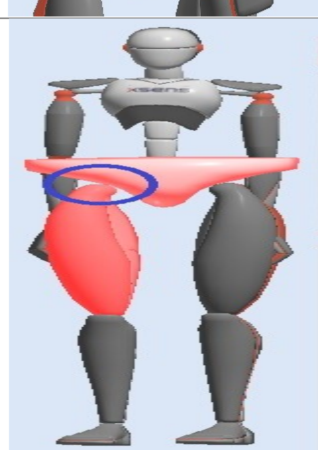
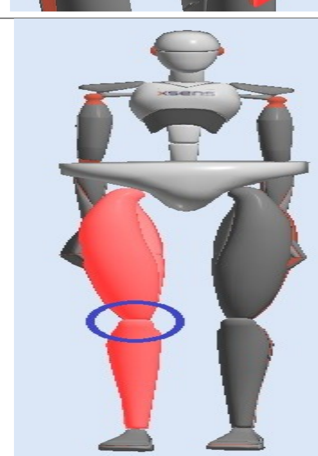
Right Lower Leg		Right Foot	
Right Toe		Left Upper Leg	
Left Lower Leg		Left Foot	
Left Toe			

Table A-2: Schematic drawing of joints

Joints	Schematic drawing	Joints	Schematic drawing
J L5S1		J L4L3	
J L1T12		J T9T8	
J T1C7		J C1Head	
J T4 Right Shoulder		J Right Shoulder	

J Right Elbow		J Right Wrist	
J T4Left Shoulder		J Left Shoulder	
J Left Elbow		J Left Wrist	
J Right Hip		J Right Knee	

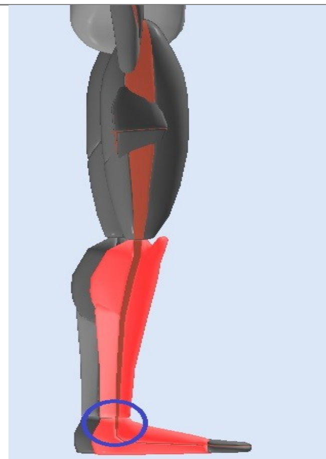
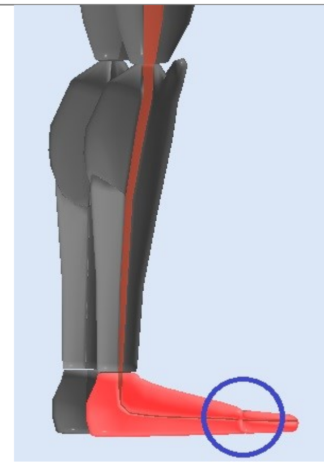
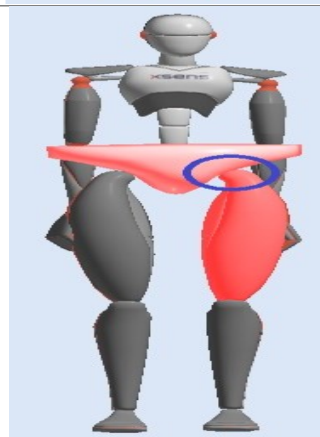
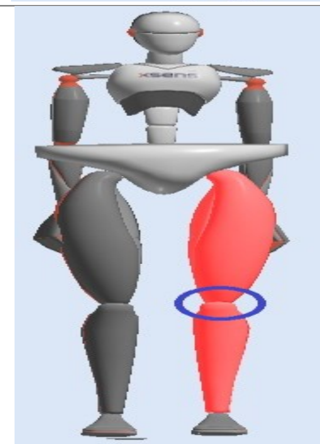
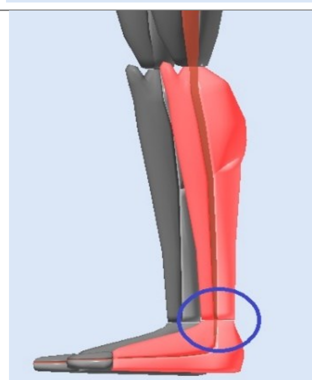
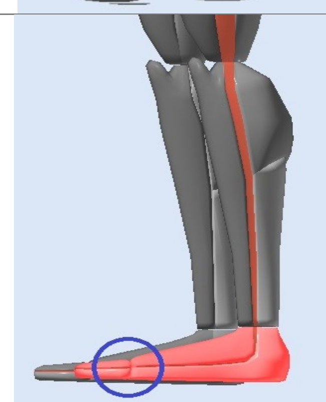
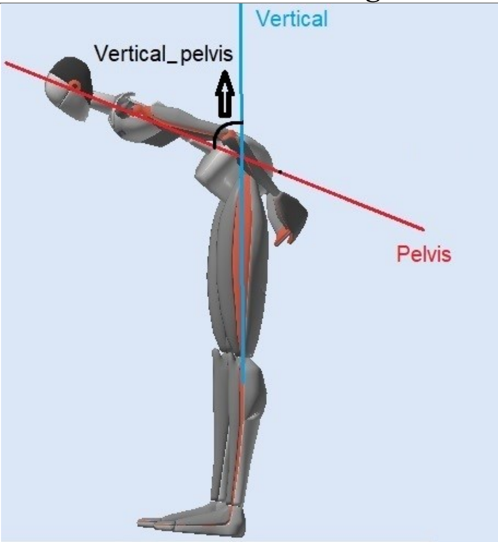
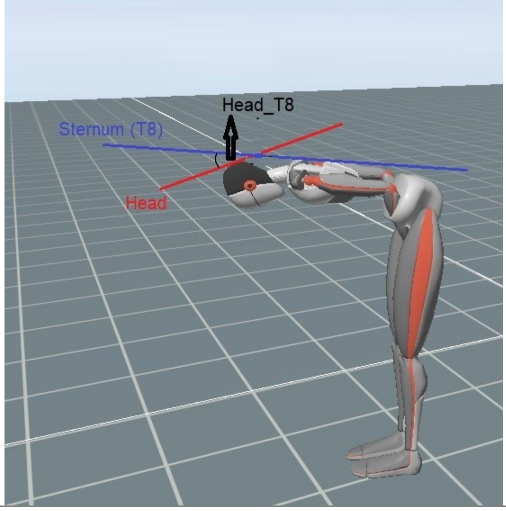
J Right Ankle		J Right Ball Foot	
J Left Hip		J Left Knee	
J Left Ankle		J Left Ball Foot	

Table A-3: Schematic drawing of ergonomic joint angles

Joints	Schematic drawing
Vertical_Pelvis	
T8_Head	

Appendix B

Definitions and figures for forty-one activities

Lifting

Raising an object to a higher level includes upward pushing or applying an upward force to maintain a static position. As a starting point, determine the object's vertical height in centimetres. When a participant begins lifting from the floor to the hand level, this distance measures how far it has to go. Consider recording minimum and maximum values if the object's starting height is variable. Then, measure the object's vertical endpoint in inches to determine the last resting place's exact length and measure it up to the height of the person's hands from the ground (OHCOW., 1998). In this area, any dynamic lifting to the left (L), right (R), or sagittal (straight-S) planes by employing the left (L), right (R), or Both (B) hands is described. Additionally, each lift will have a "Horizontal Front" value. A "Horizontal Right/Left" value will also be assigned to one-handed or asymmetrical lifts (OHCOW., 1998).

1. Low-Level Lifting

The level of hands should be lower than the knee level in this position.

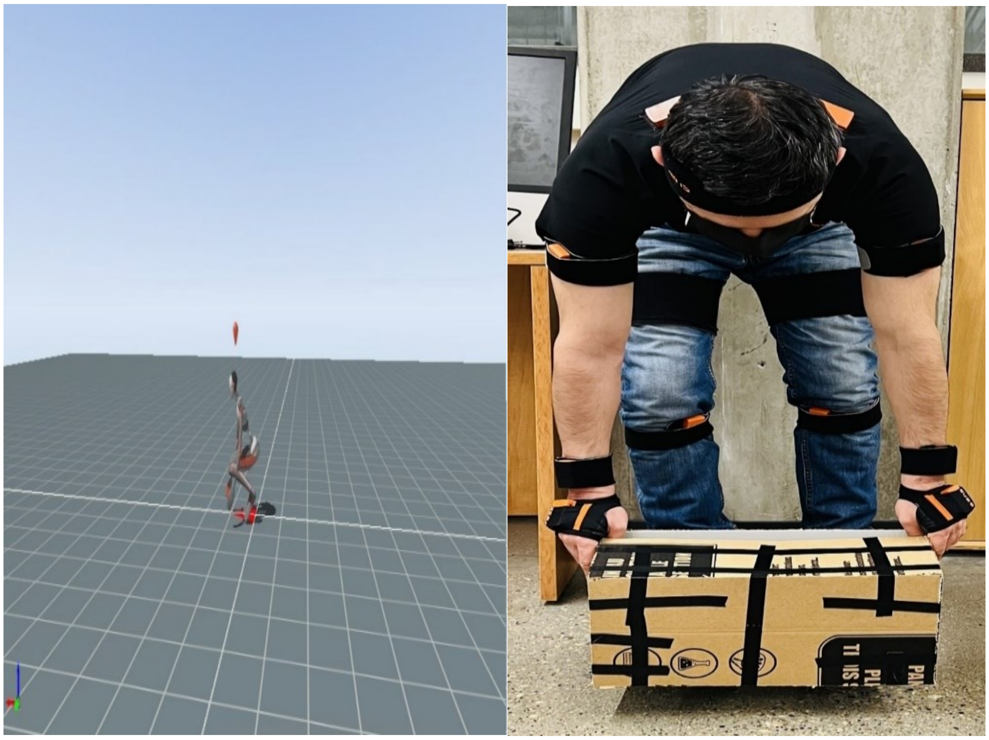


Figure B-1: Low-level lifting

2. Knee Level Lifting

The level of hands should be between the knee height and the middle of the hip.

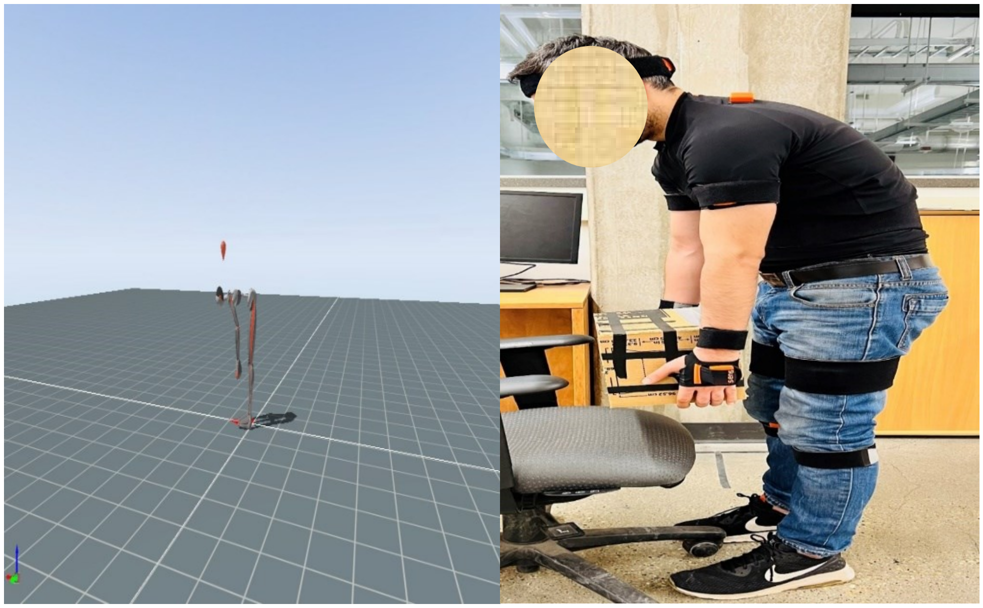


Figure B-2: Knee-level lifting

3. Waist Level Lifting

The level of hands should be between the middle of the hip and the middle of the back.

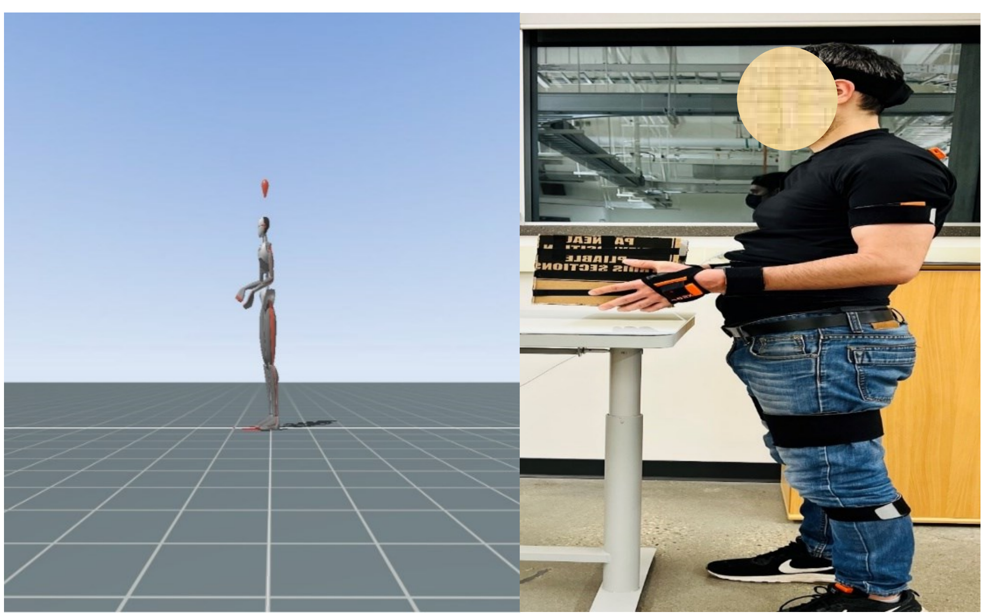


Figure B-3: Waist-level lifting

4. Shoulder Level Lifting

The level of hands should be between the middle of the back and the shoulder level plus 10 centimetres.

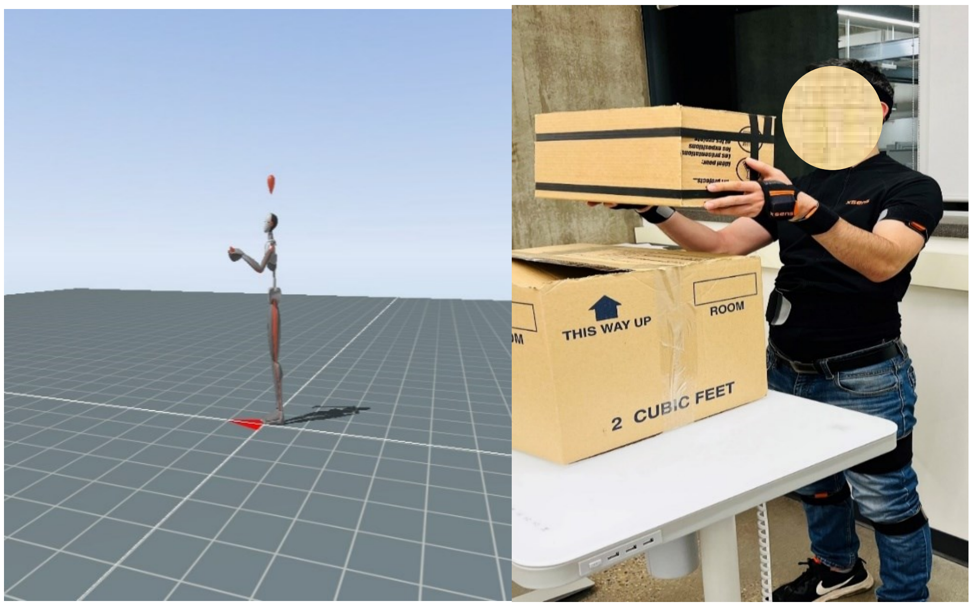


Figure B-4: Shoulder-level lifting

5. Above Shoulder Lifting

The level of hands should be equal and above the shoulder level plus 10 centimetres.

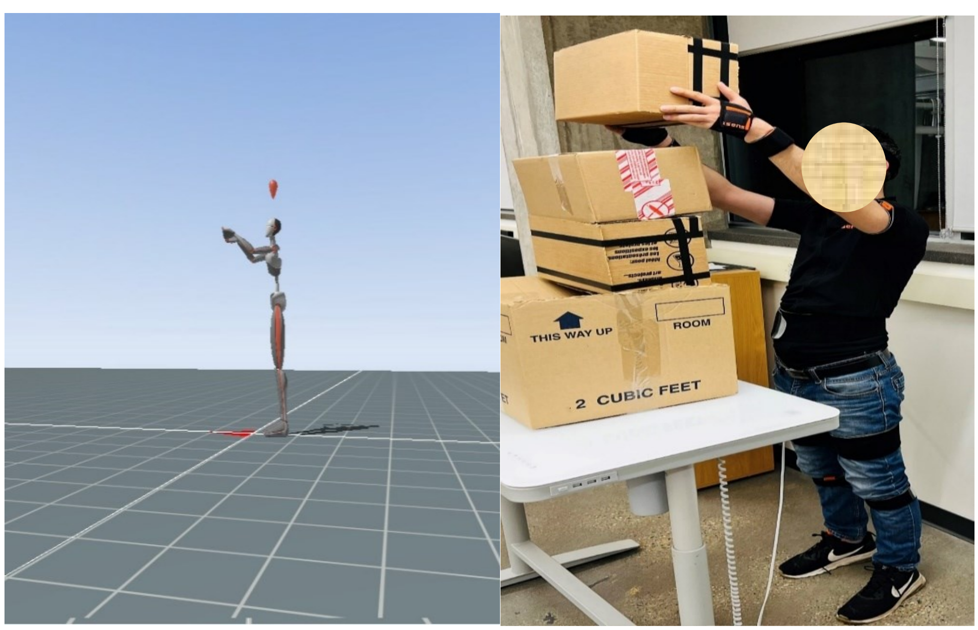


Figure B-5: Above shoulder-level lifting

Carrying

Carrying an object, frequently in the hands, arms, or over the shoulder, is determined by the distance in centimetres between the item's beginning and resting points. Additionally, detect the object's level: below the shoulder, the shoulder level, or above the shoulder (OHCOW., 1998).

6. Front Carry

The hands' position should be in front of the body.

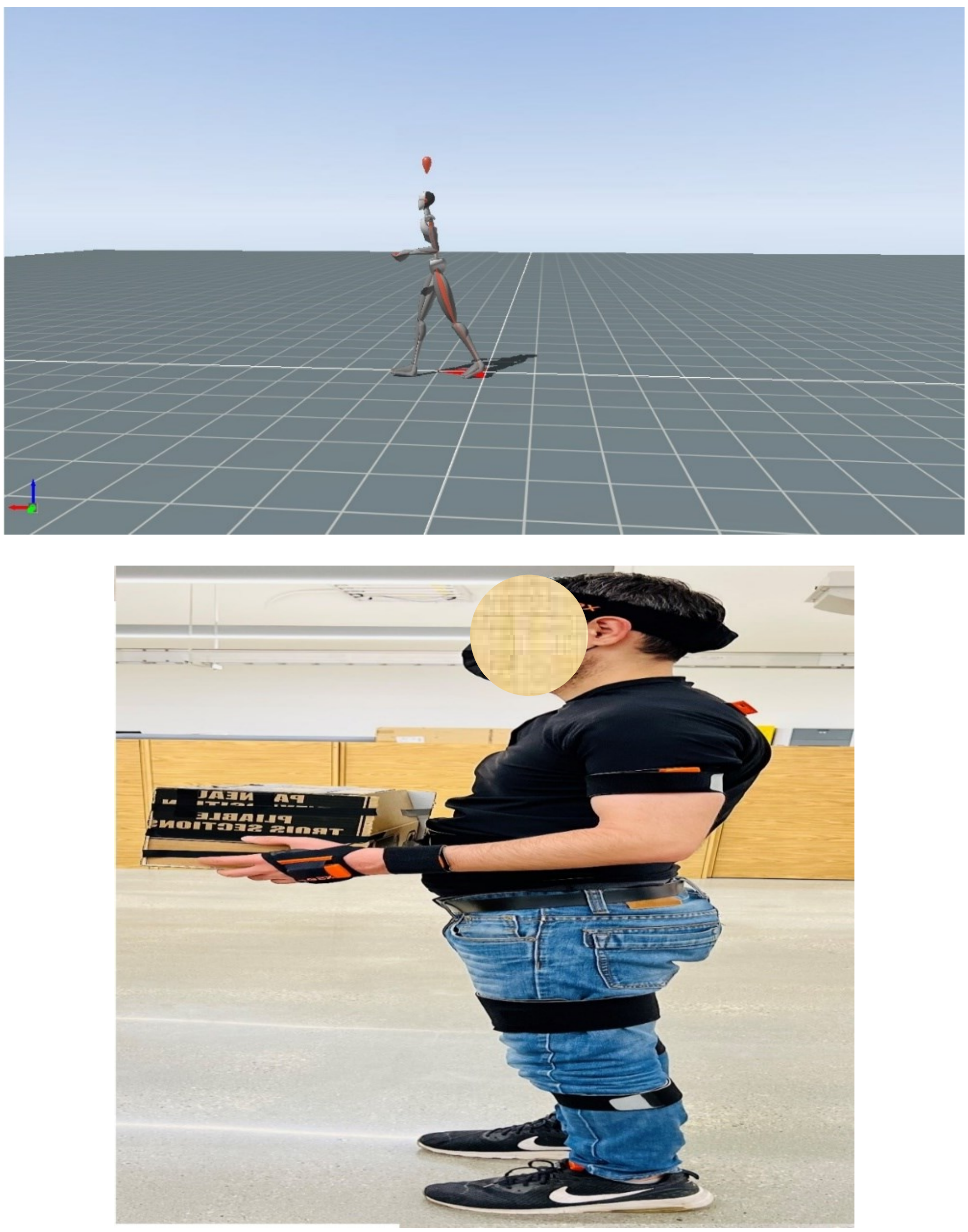


Figure B-6: Front carry

7. Side Carry

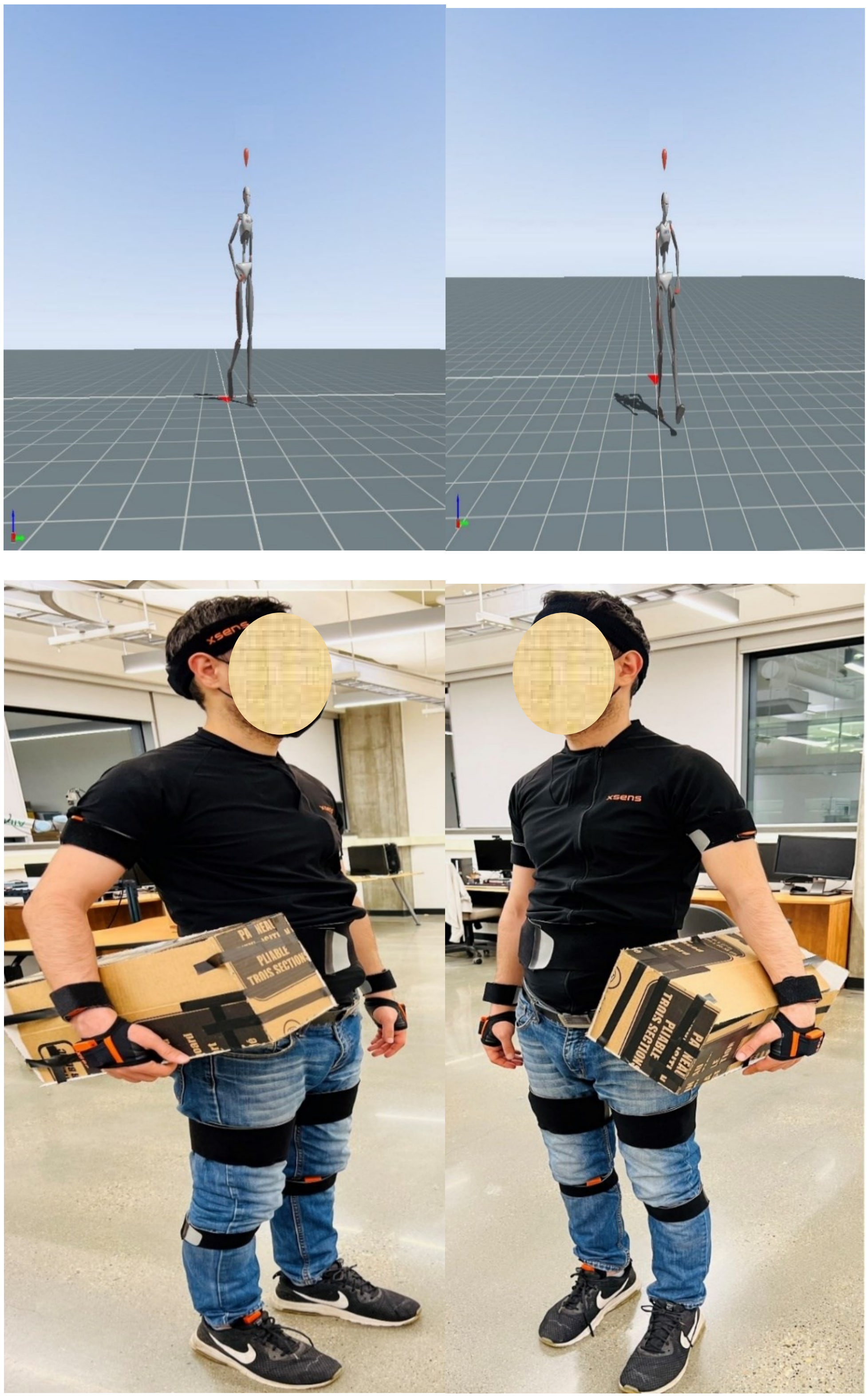


Figure B-7: Side carry

8. Side Carry-Right Hand

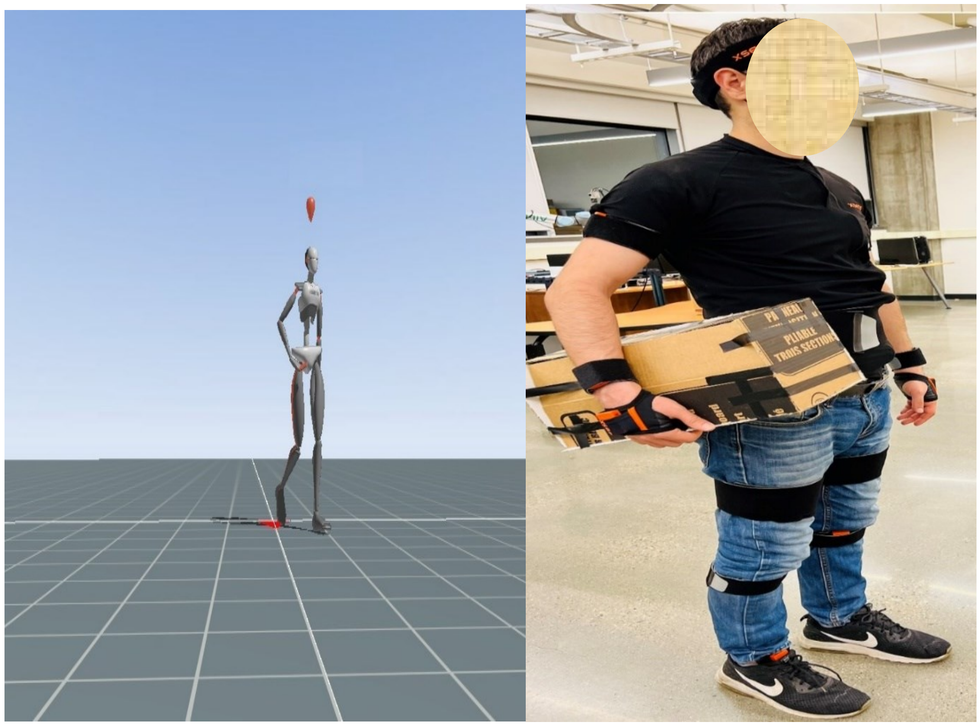


Figure B-8: Side carry-Right hand

9. Side Carry-Left Hand

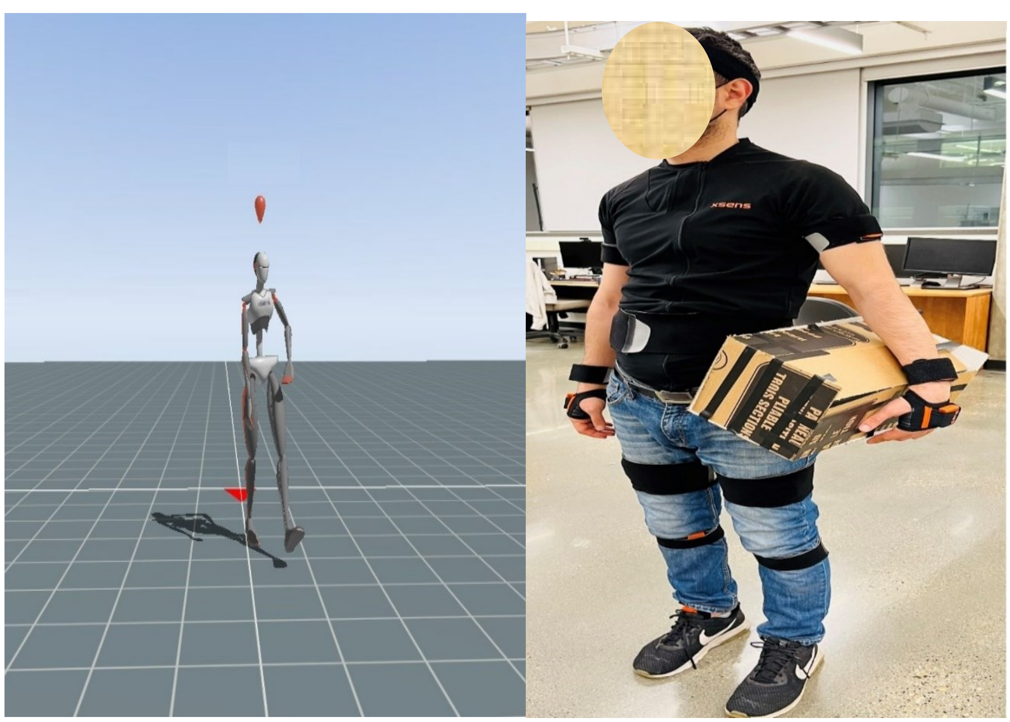


Figure B-9: Side carry-Left hand

10. Carry on Shoulder

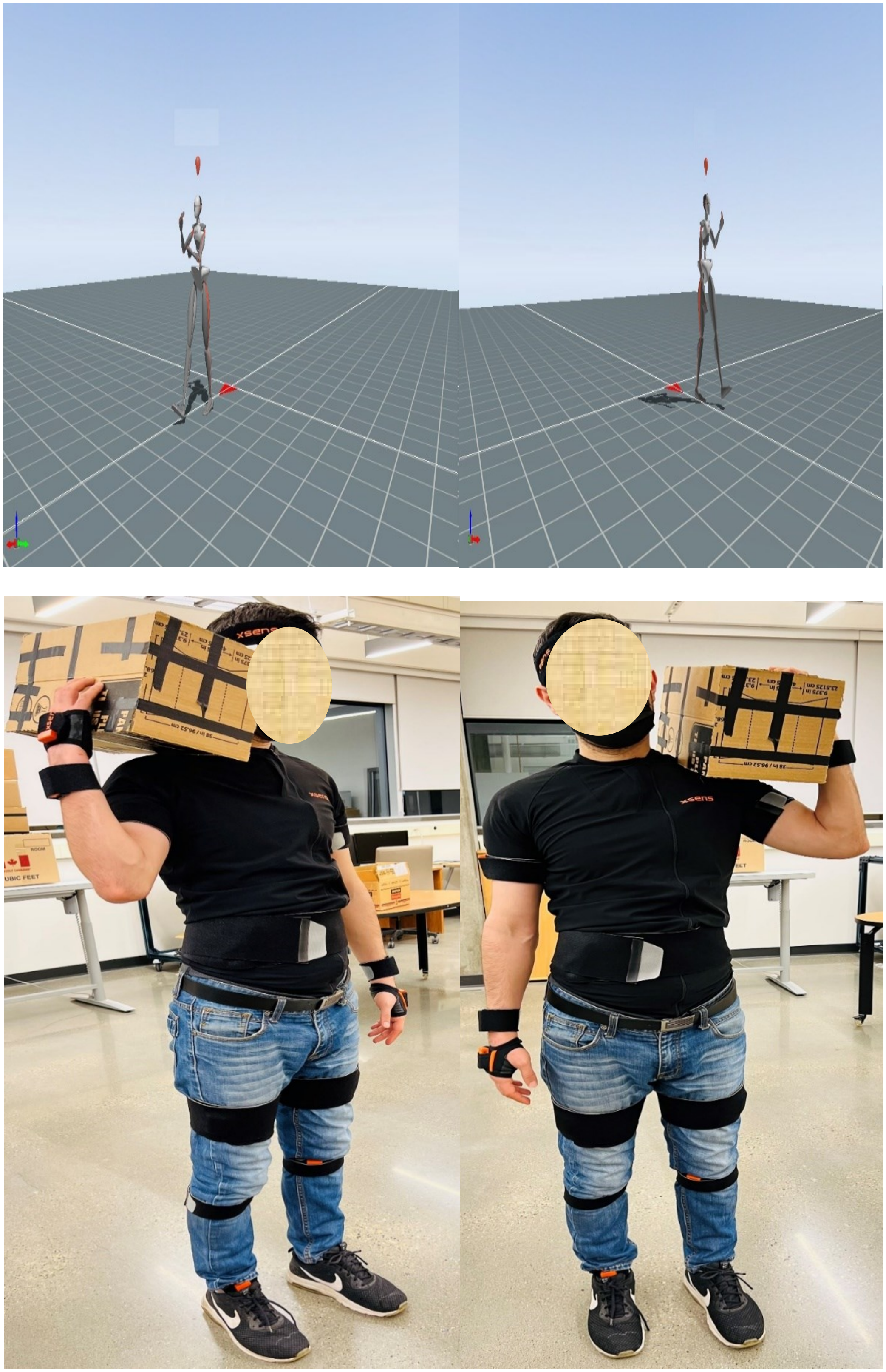


Figure B-10: Carry on shoulder

11. Static Pushing

Exerting force to maintain a static position for an item using the Left hand (L), the Right hand (R), or Both hands (B) (OHCOW., 1998).

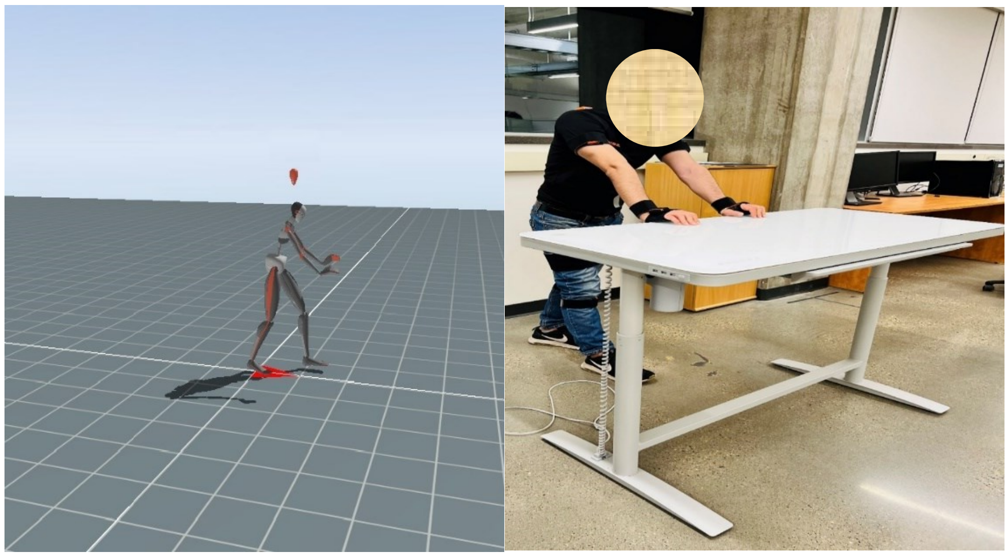


Figure B-11: Static pushing

12. Static Pulling

Exerting force to maintain a static position for an item using the Left hand (L), the Right hand (R), or Both hands (B) (OHCOW., 1998).

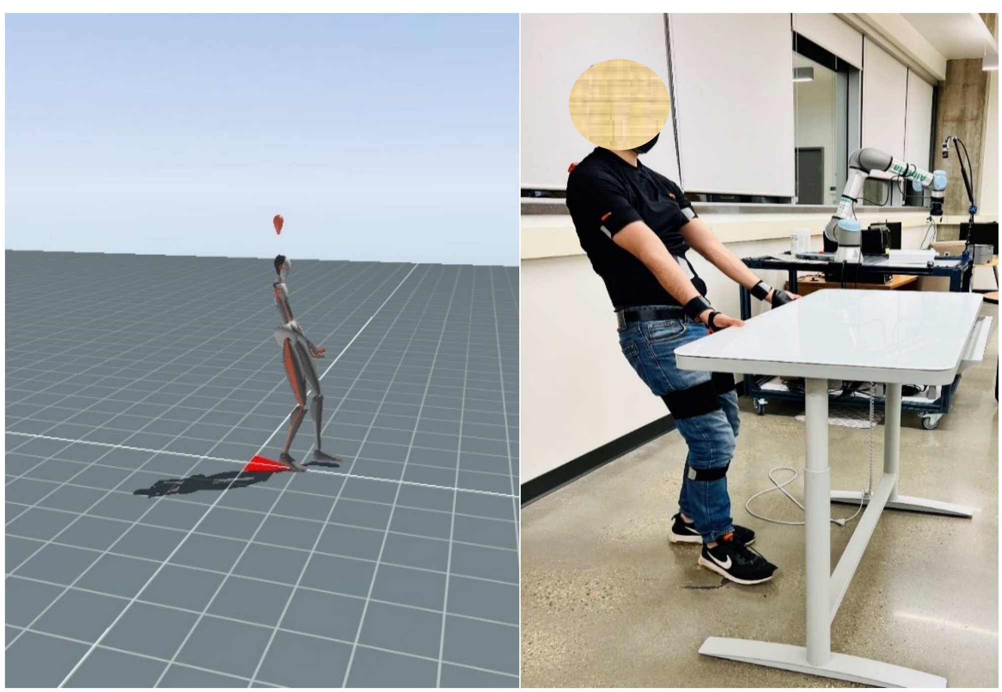


Figure B-12: Static pulling

13. Dynamic Pushing

An action that causes an item to move away from the force exerted upon it with the Left hand (L), Right hand (R), or Both hands (B). (OHCOW., 1998).

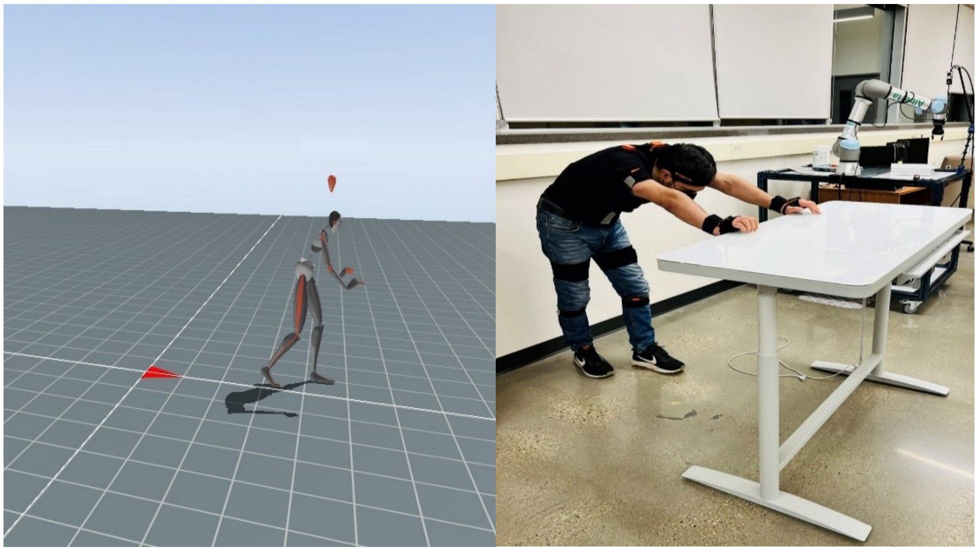


Figure B-13: Dynamic pushing

14. Dynamic Pulling

An action that causes an item to move toward a force exerted upon it with the Left hand (L), Right hand (R), or Both hands (B) (OHCOW., 1998).

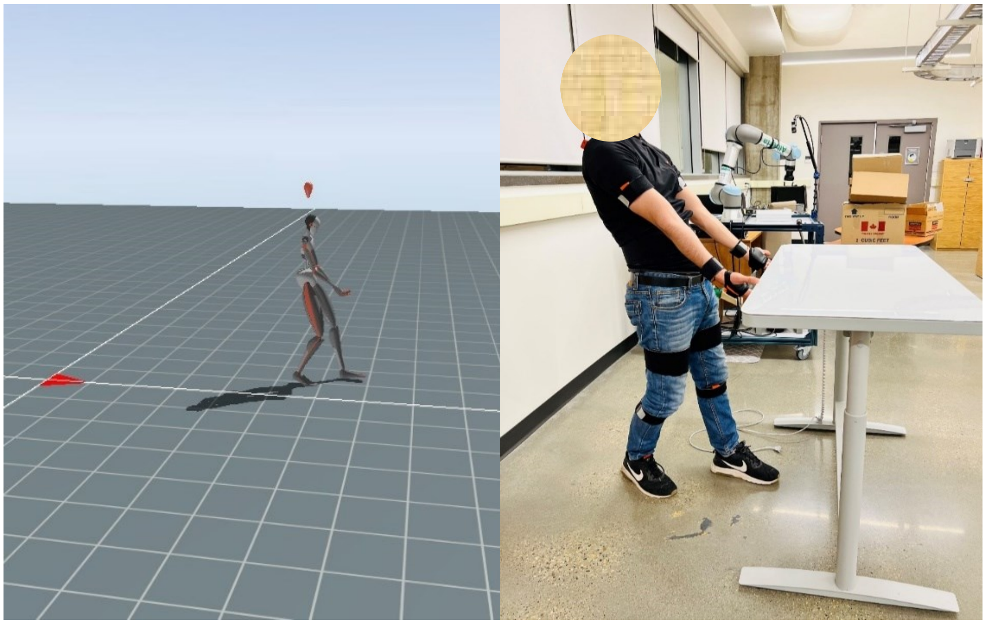


Figure B-14: Dynamic pulling

15. Sitting

Remain seated position.

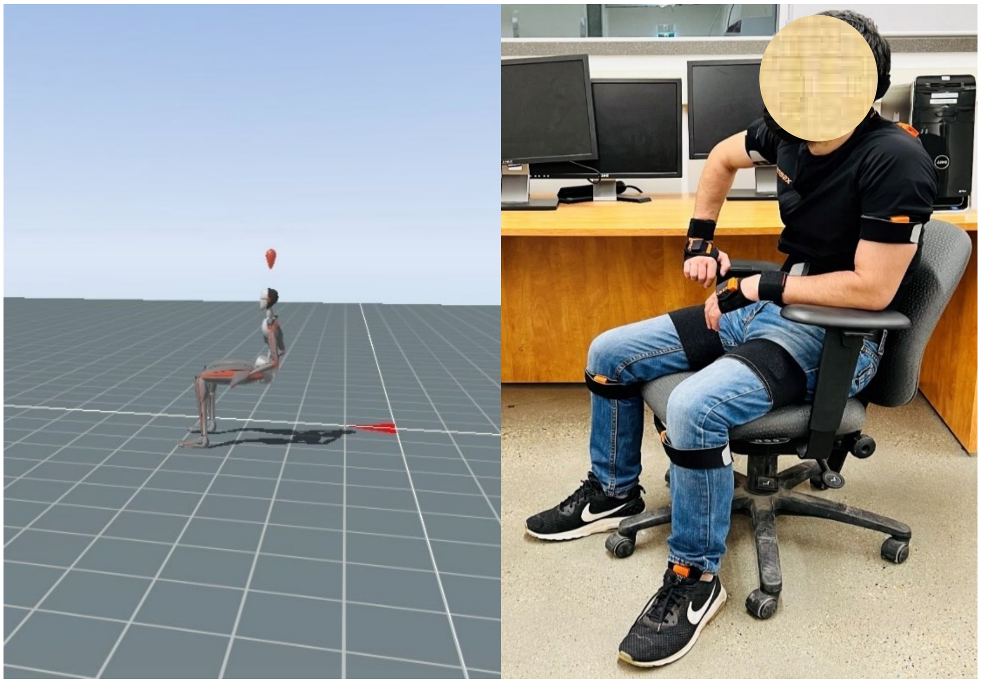


Figure B-15: Sitting position

16. Standing

Remain erect on feet without moving more than 5 (cm).

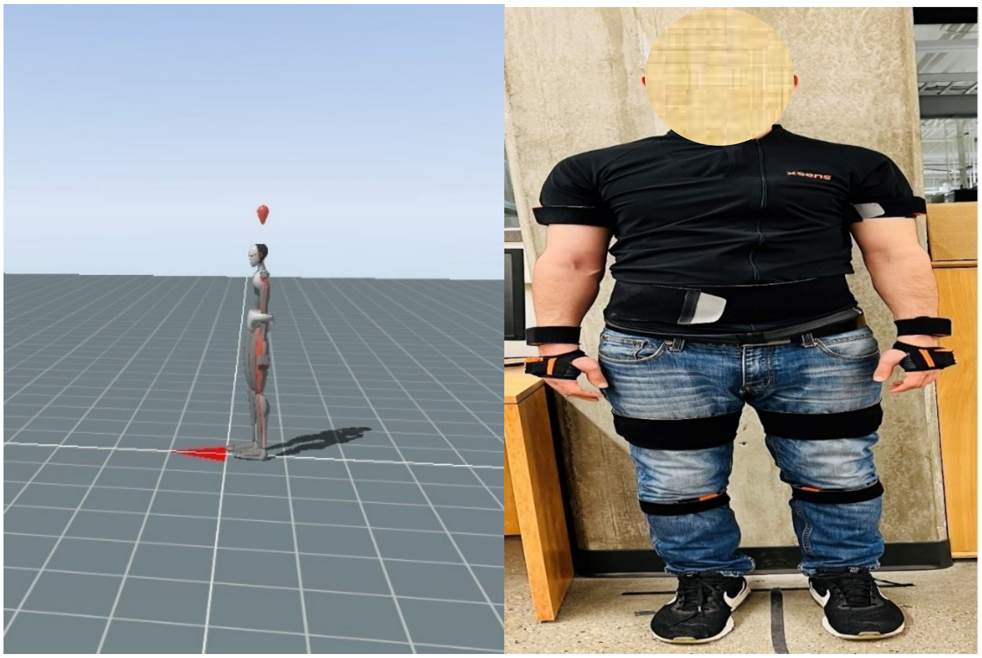


Figure B-16: Standing position

17. Walking

Moving on feet more than 5 (cm).

Figure B-17: Walking position

Climbing

Ascending or descending ladders, stairs, stools, and similar structures use feet and legs or hands and arms (OHCOW., 1998).

18. Climbing-Stairs

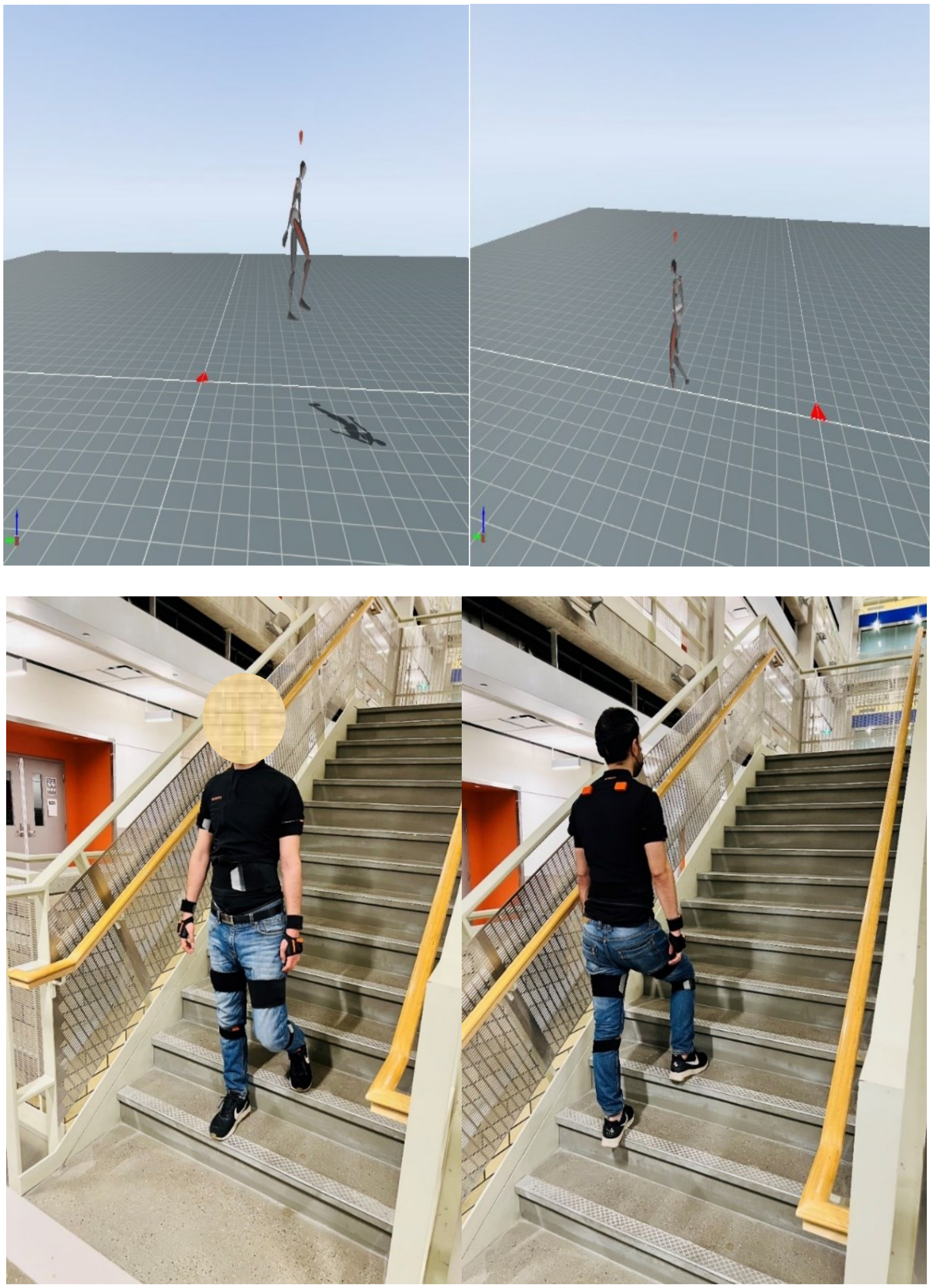


Figure B-18: Climbing stairs

19. Climbing-Ladders

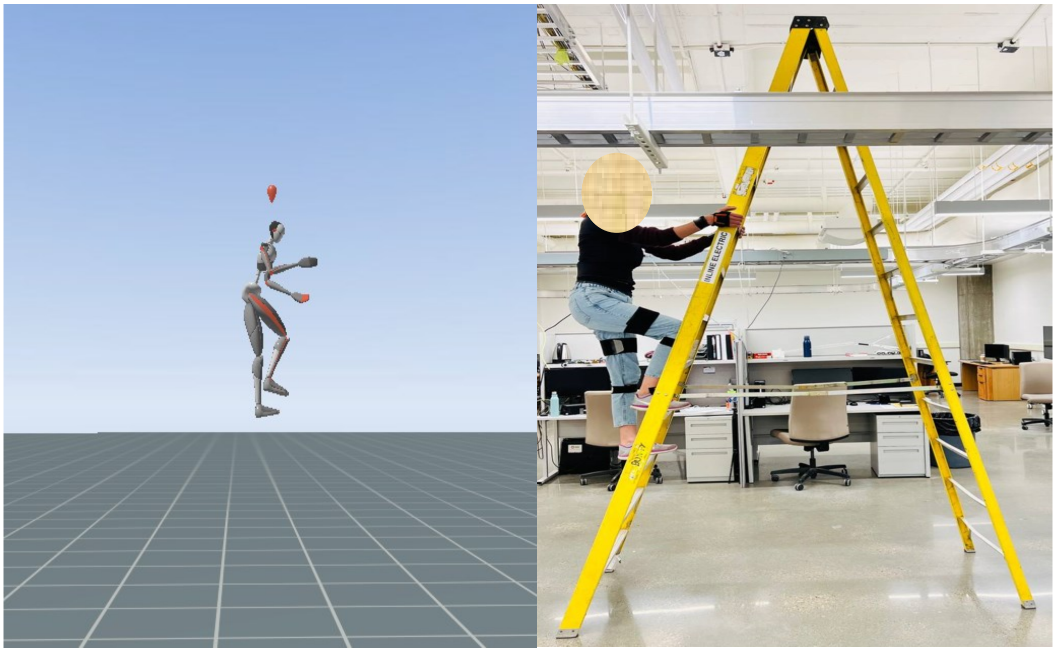


Figure B-19: Climbing ladder

20. Climbing Stools and Similar Structures

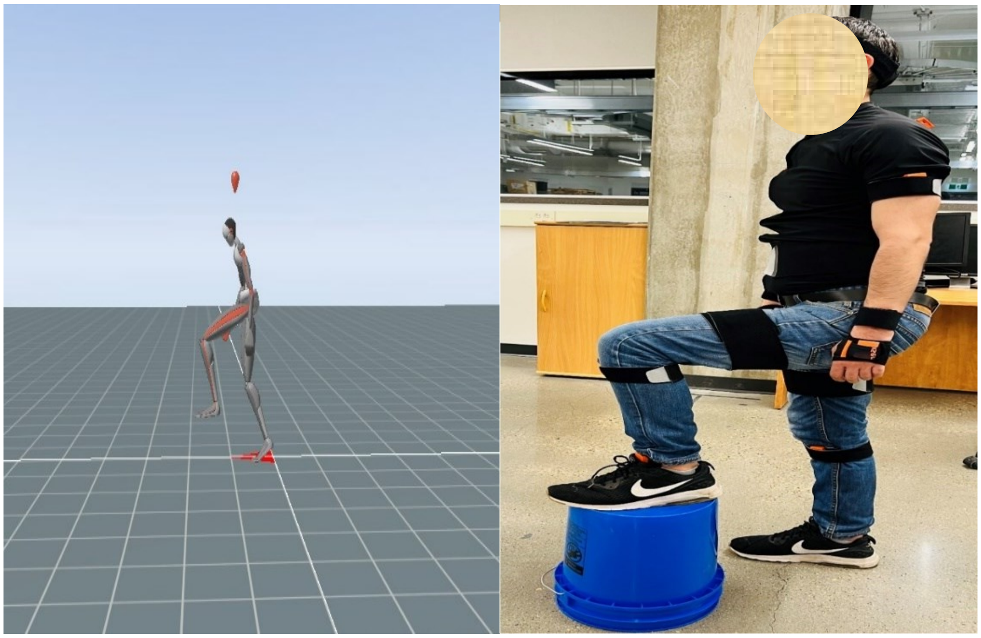


Figure B-20: Climbing stools and similar structures

21. Crouching

Bend the body forward and downward with the legs and spine (OHCOW., 1998).

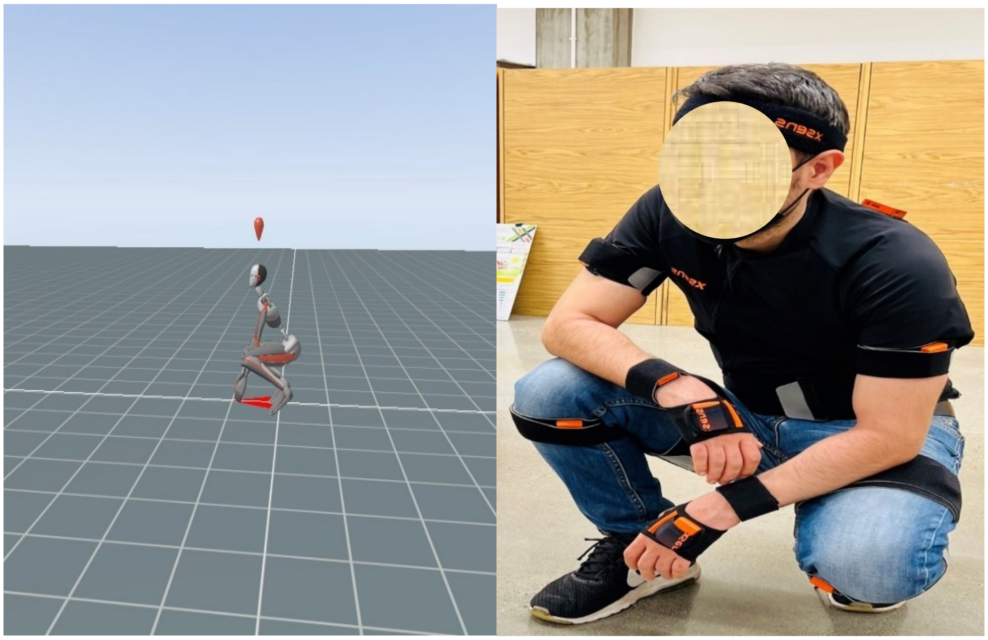


Figure B-21: Crouching position

22. Squatting

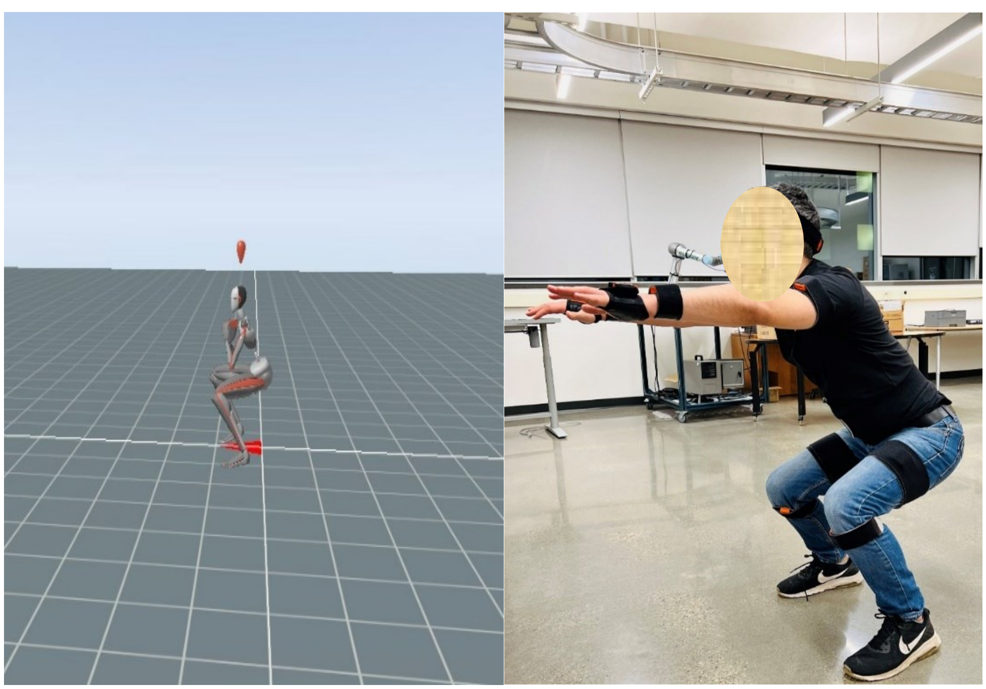


Figure B-22: Squatting position

23. Kneeling

Bring one or both legs to rest on the knees by bending them at the knees. Additionally, a knee bent, the other straight should be noted as kneeling (OHCOW., 1998).

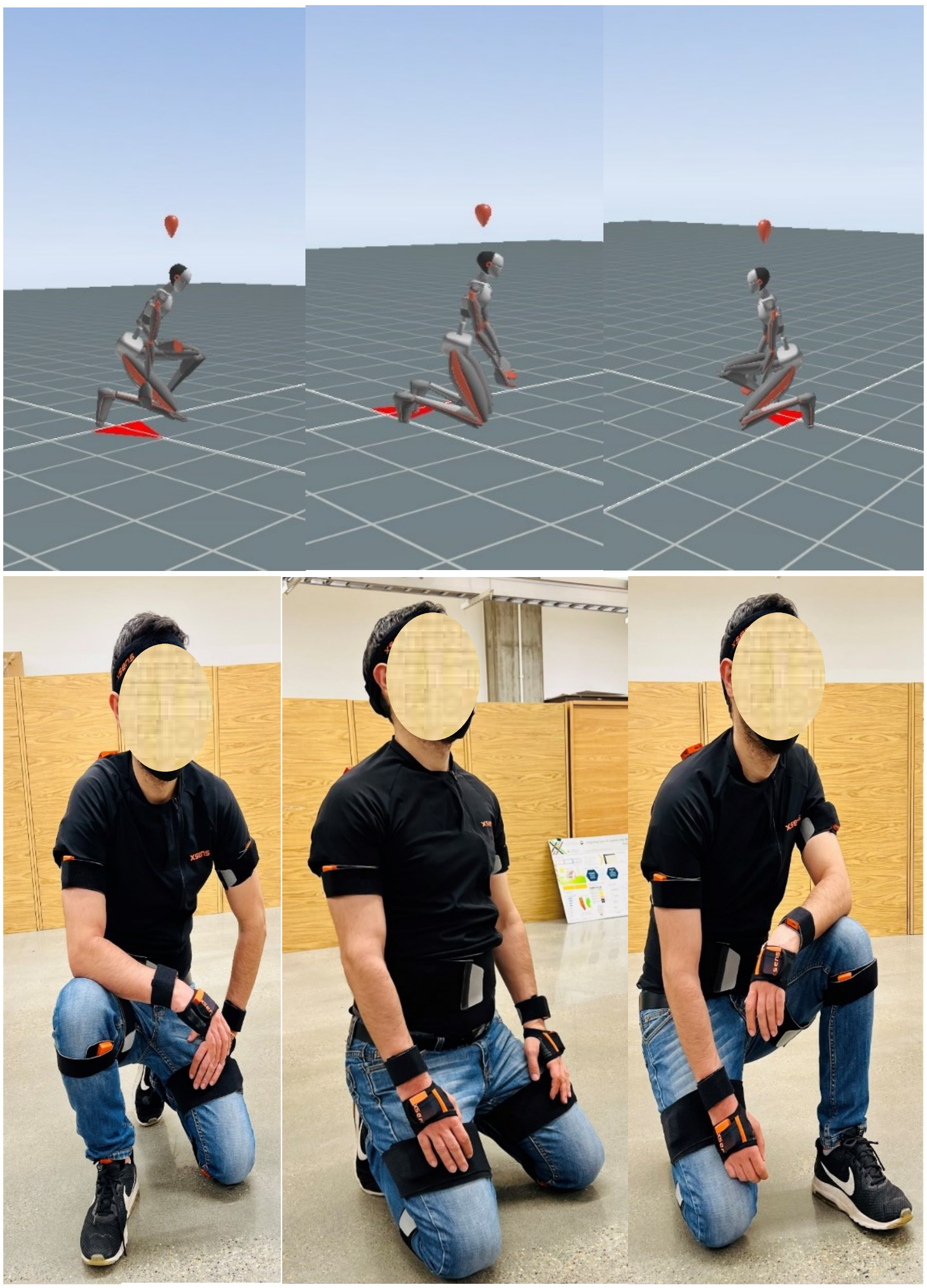


Figure B-23: Kneeling positions

24. Crawling

On hands and knees, moving around.

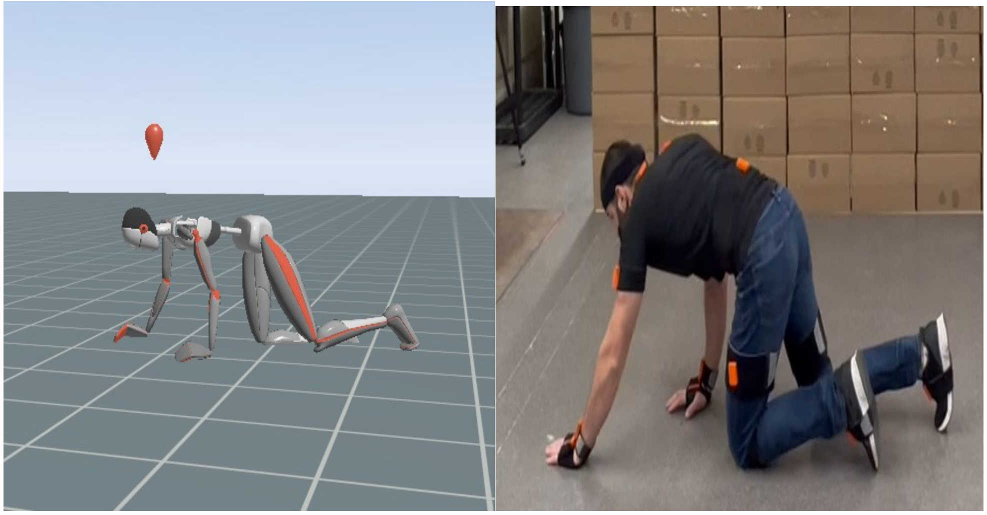


Figure B-24: Crawling positions

25. Trunk Forward Bending

Bending the spine at the waist to move the body forward and downward, equivalent to 20 degrees, involves all lower extremity and back muscles (OHCOW., 1998).

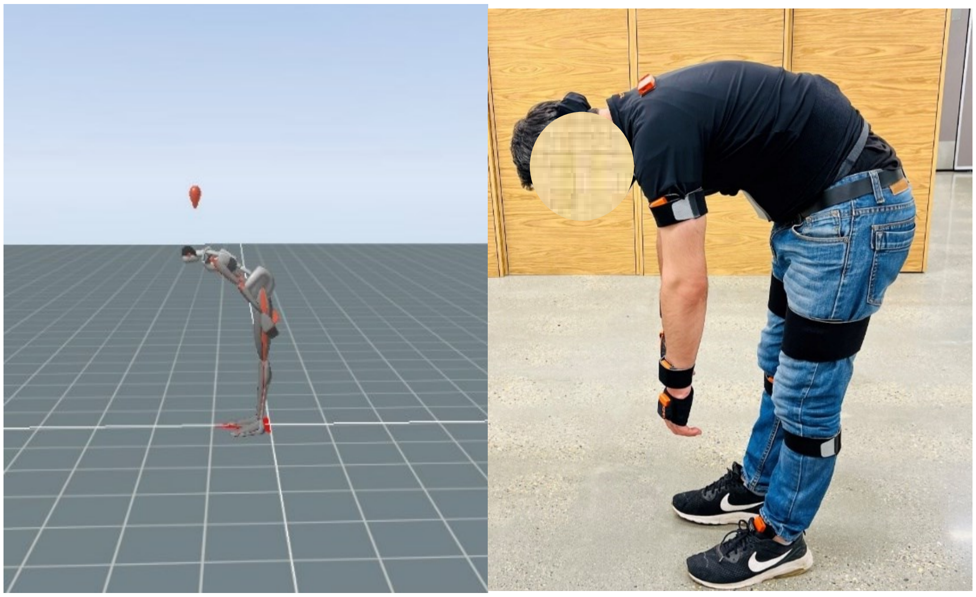


Figure B-25: Trunk forward bending

26. Trunk Rotation

Twist the upper body (trunk) more than 10 degrees to the sides at the waist (OHCOW., 1998).

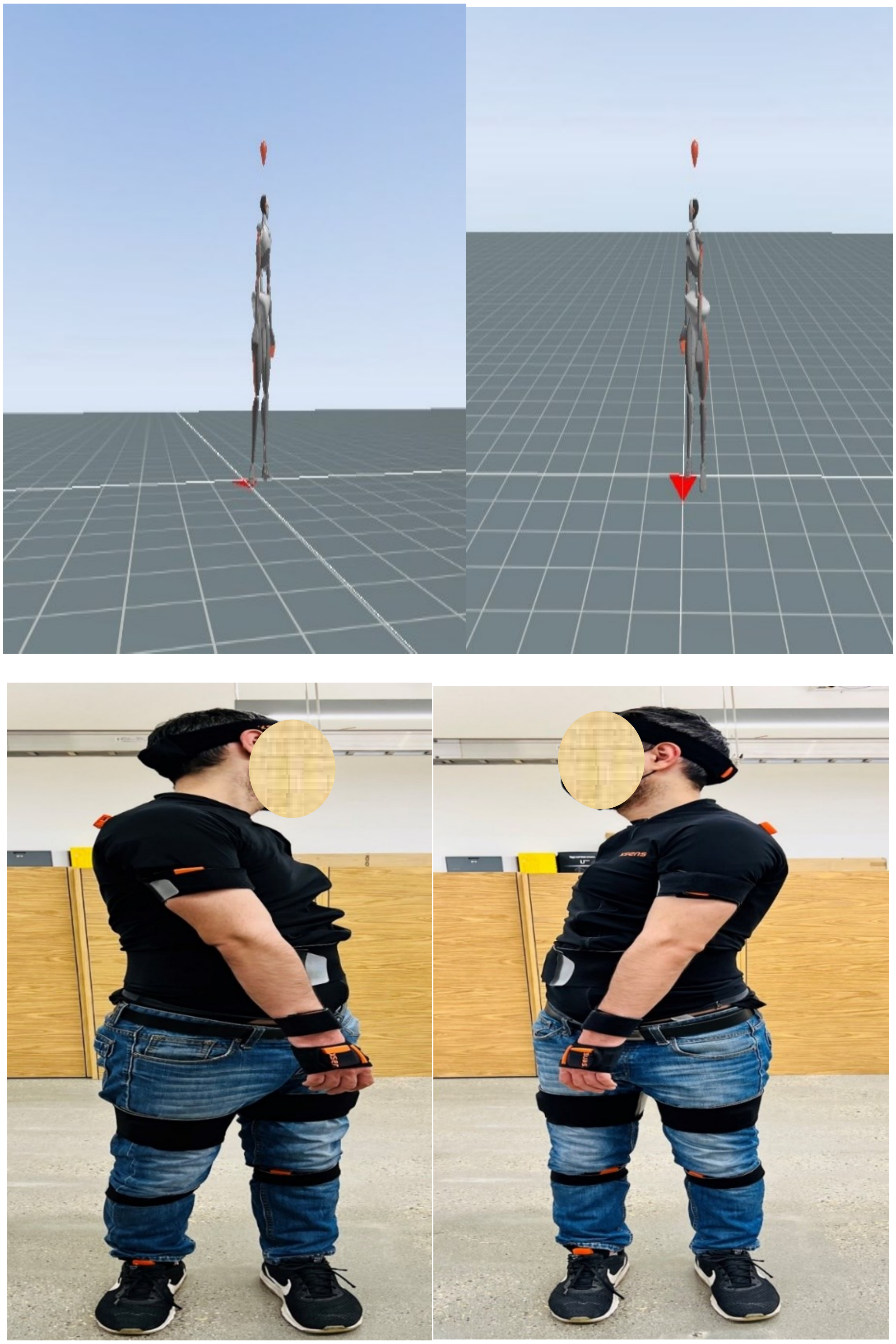


Figure B-26: Trunk rotation

27. Trunk Backward Bending

Bend the body backward by bending the spine at the waist equivalent to or more than 20 degrees, involving all lower extremity and back muscles (OHCOW., 1998).

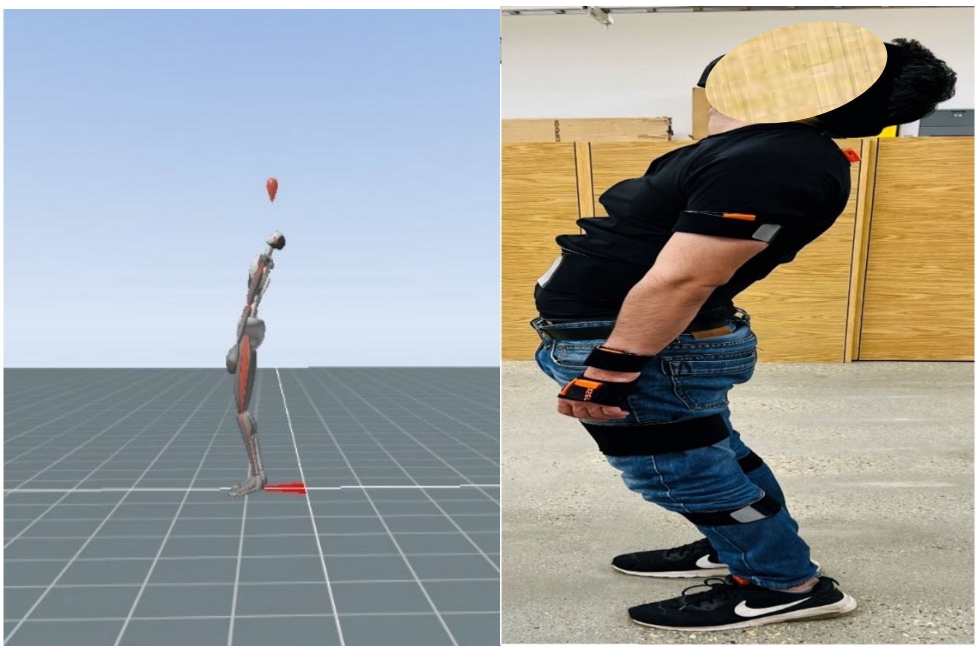


Figure B-27: Trunk backward bending

Reaching

Extending arms and hands in different directions, such as right, left, front, or back, from the neutral position of the arms. Horizontal reach lengths should be measured on a plane parallel to the floor for right, left, forward, and backward. Additionally, record the reach's lowest and maximum vertical height ranges in cm beginning from the floor and ending with the position of the hands. Also, determine which hand was employed, Left (L), Right R), or Both (B) (OHCOW., 1998).

28. Below Shoulder Level Reaching

The distance front is used to track forward reaches, and the level of hands should be less than the middle level of the trunk.

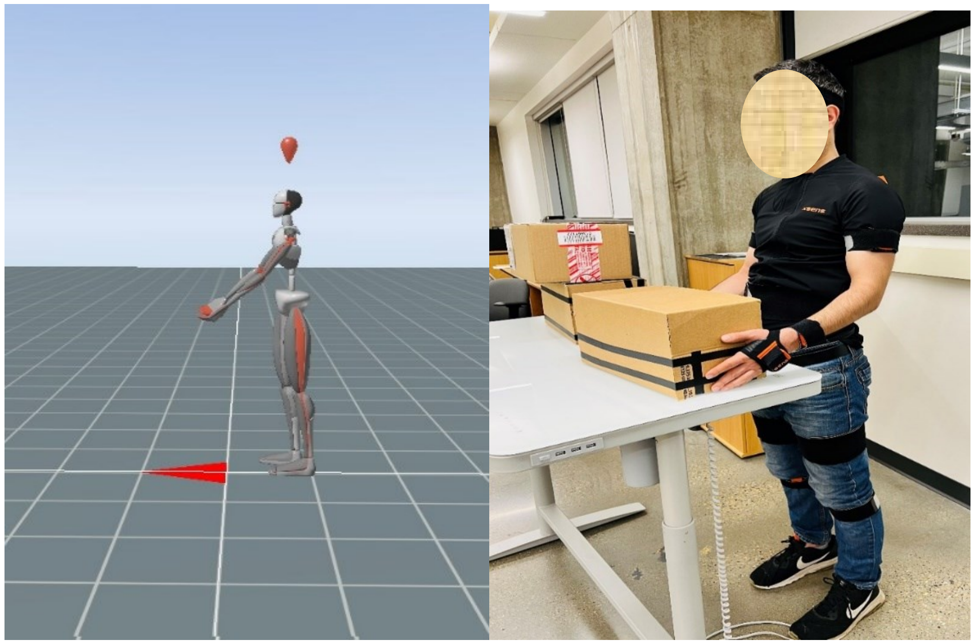


Figure B-28: Below shoulder level reaching

29. Forward Shoulder Level Reaching

The distance front is used to track forward reaches, and the level of hands should be between the middle level of the trunk and the shoulder level plus 10 (cm).

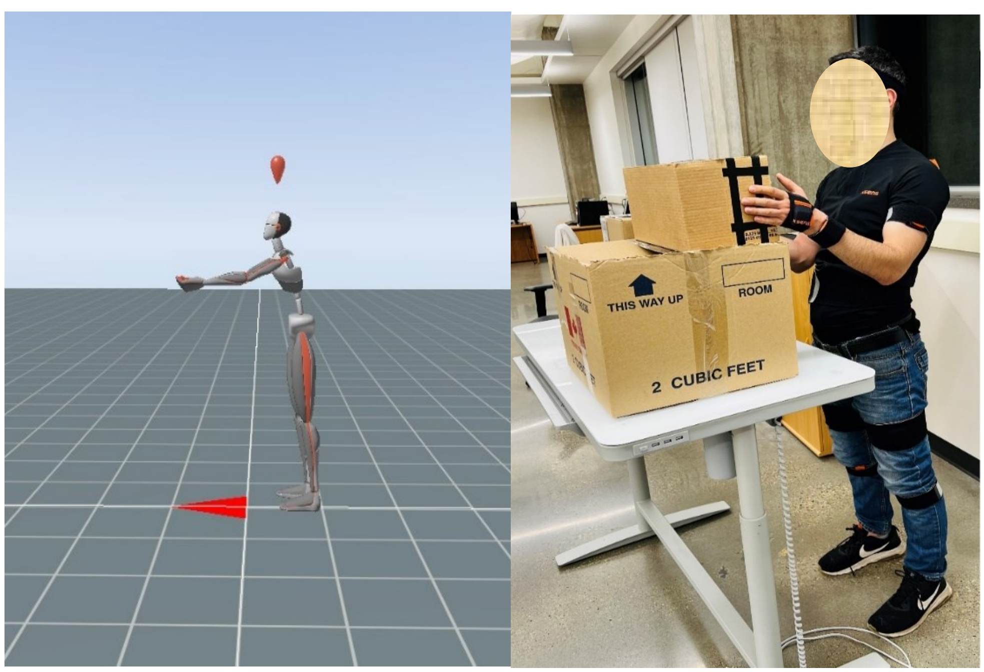


Figure B-29: Forward shoulder level reaching

30. Above Shoulder Level Reaching

The distance front is used to track forward reaches, and the level of hands should be equal and more than the shoulder level plus 10 (cm).

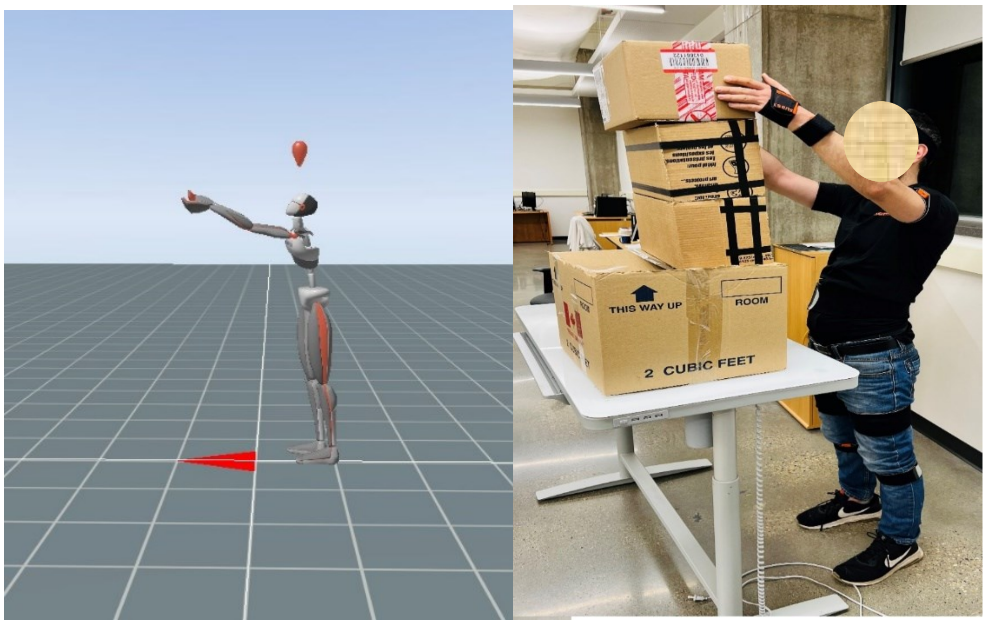


Figure B-30: Above shoulder level reaching

31. Sideway Shoulder Reaching

When reaches occur to the side of the body, record the distance right or left.

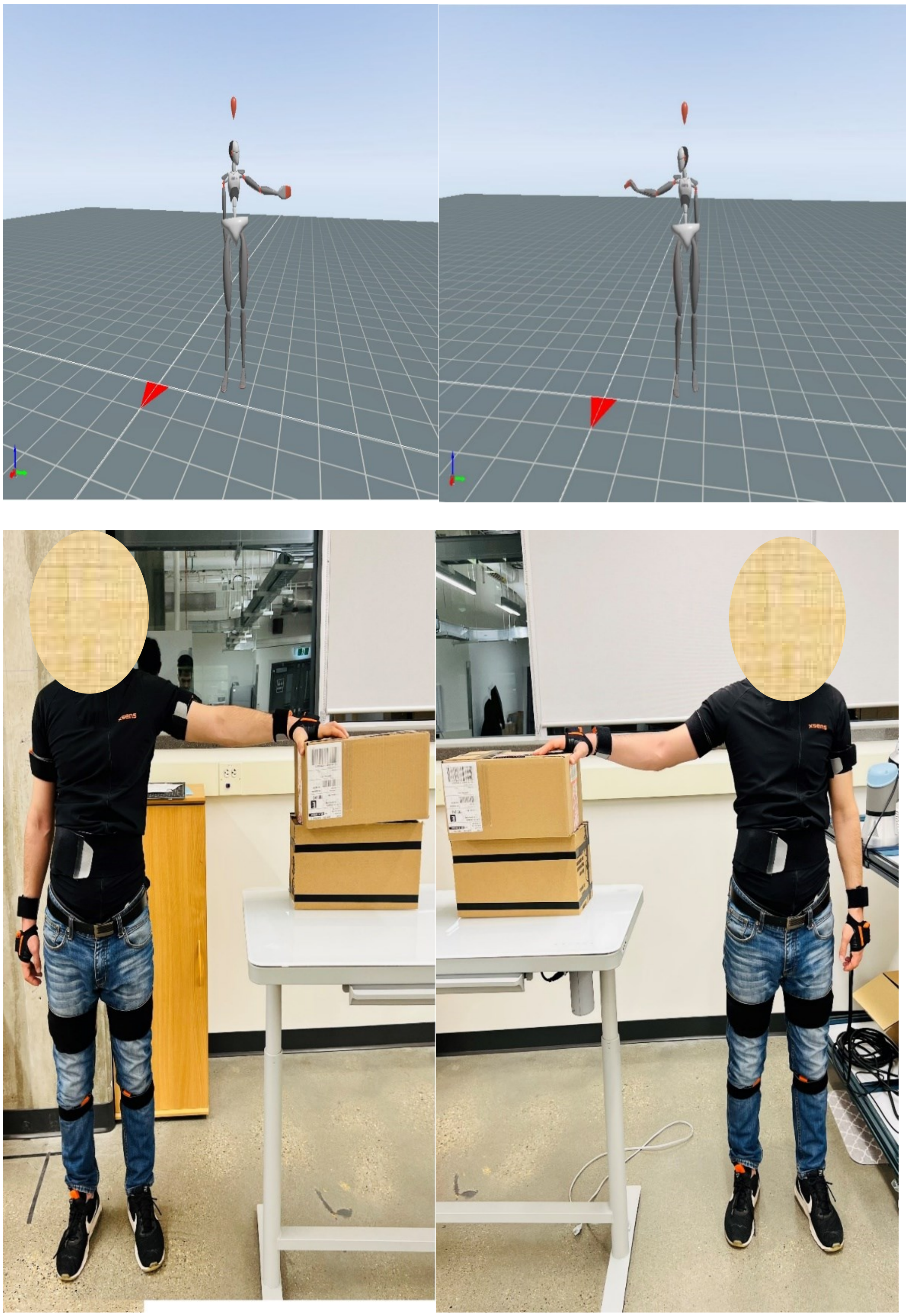


Figure B-31: Sideway shoulder reaching

32. Behind Shoulder Reaching

When reaches occur to the back of the body, record the distance in the back.

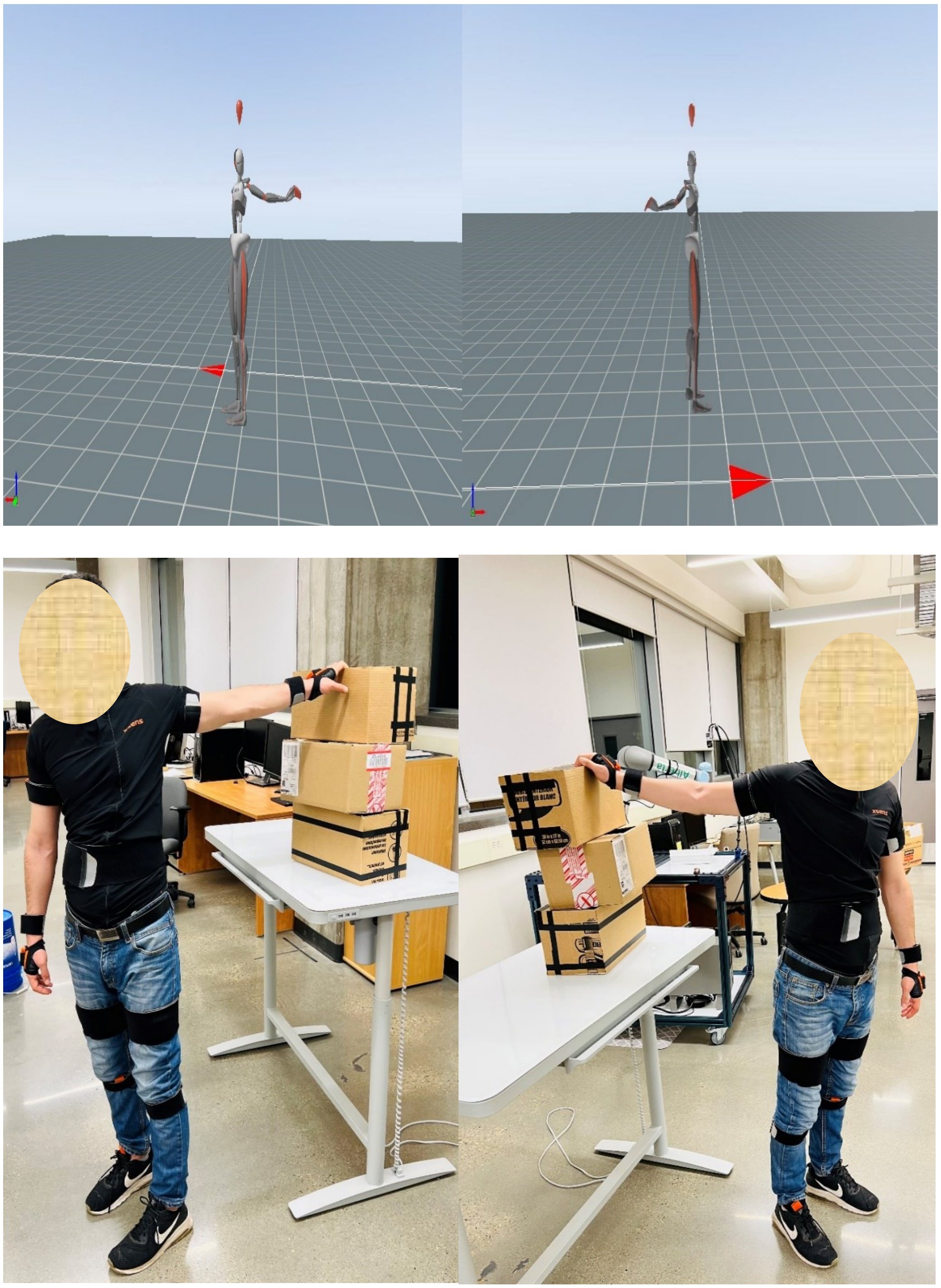


Figure B-32: Behind shoulder reaching

33. Neck Forward Bending

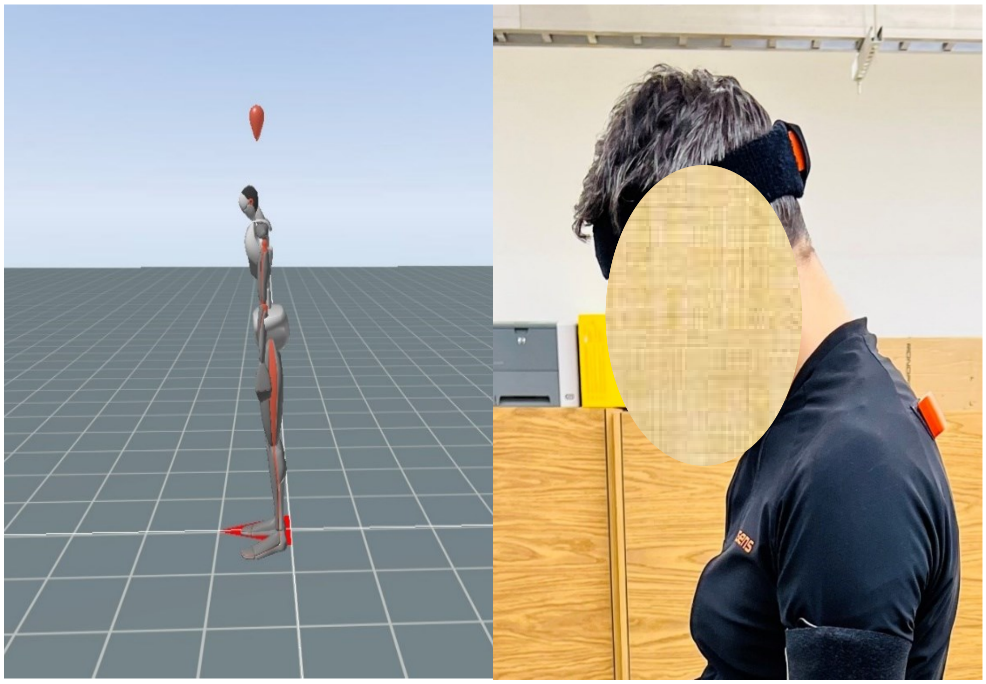


Figure B-33: Neck forward bending

34. Neck Backward Bending

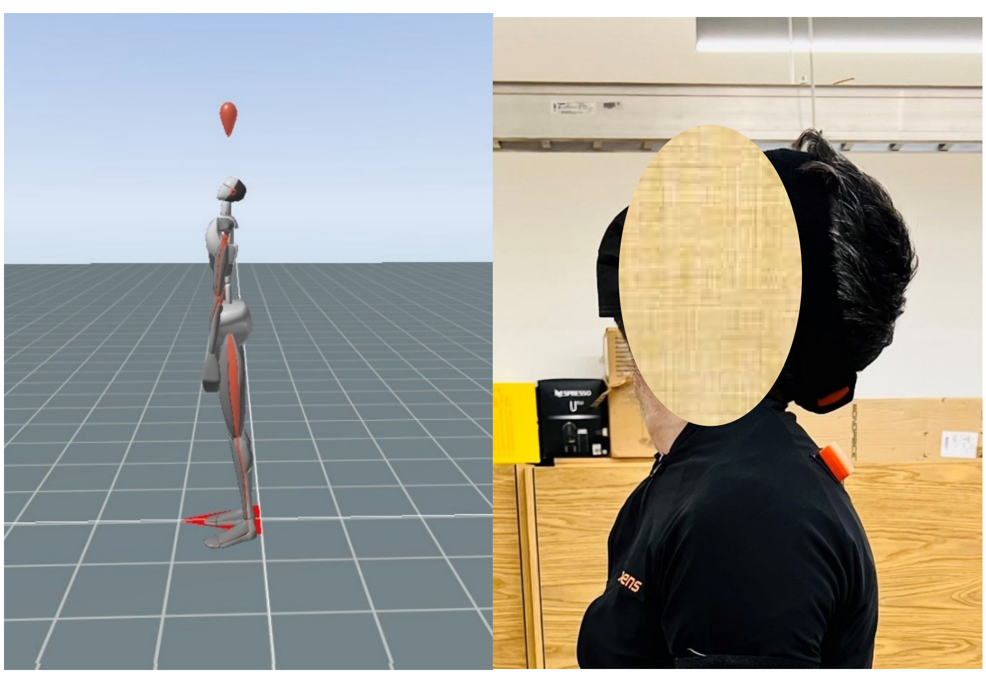


Figure B-34: Neck backward bending

35. Neck Twist/Tilt

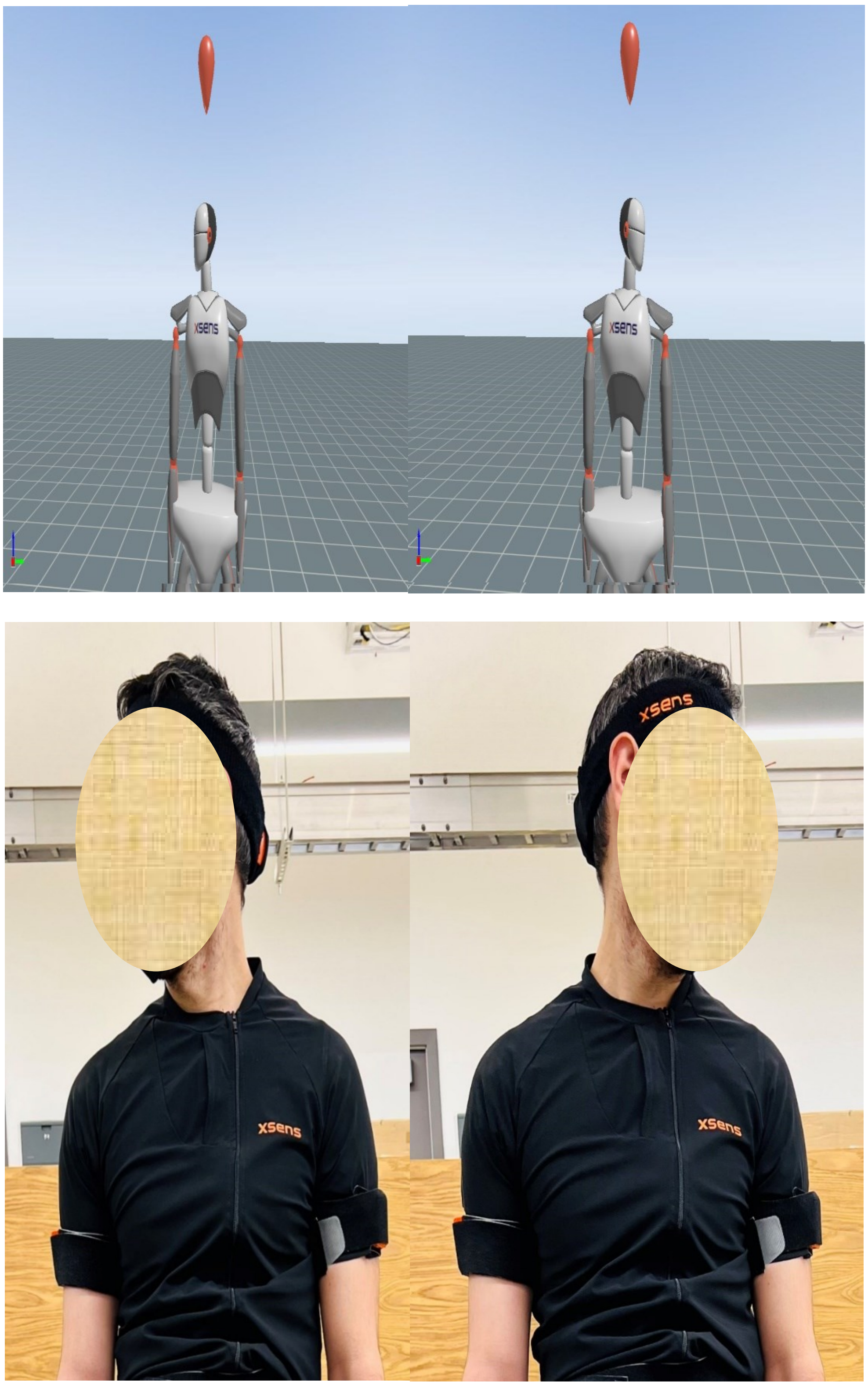


Figure B-35: Neck twist

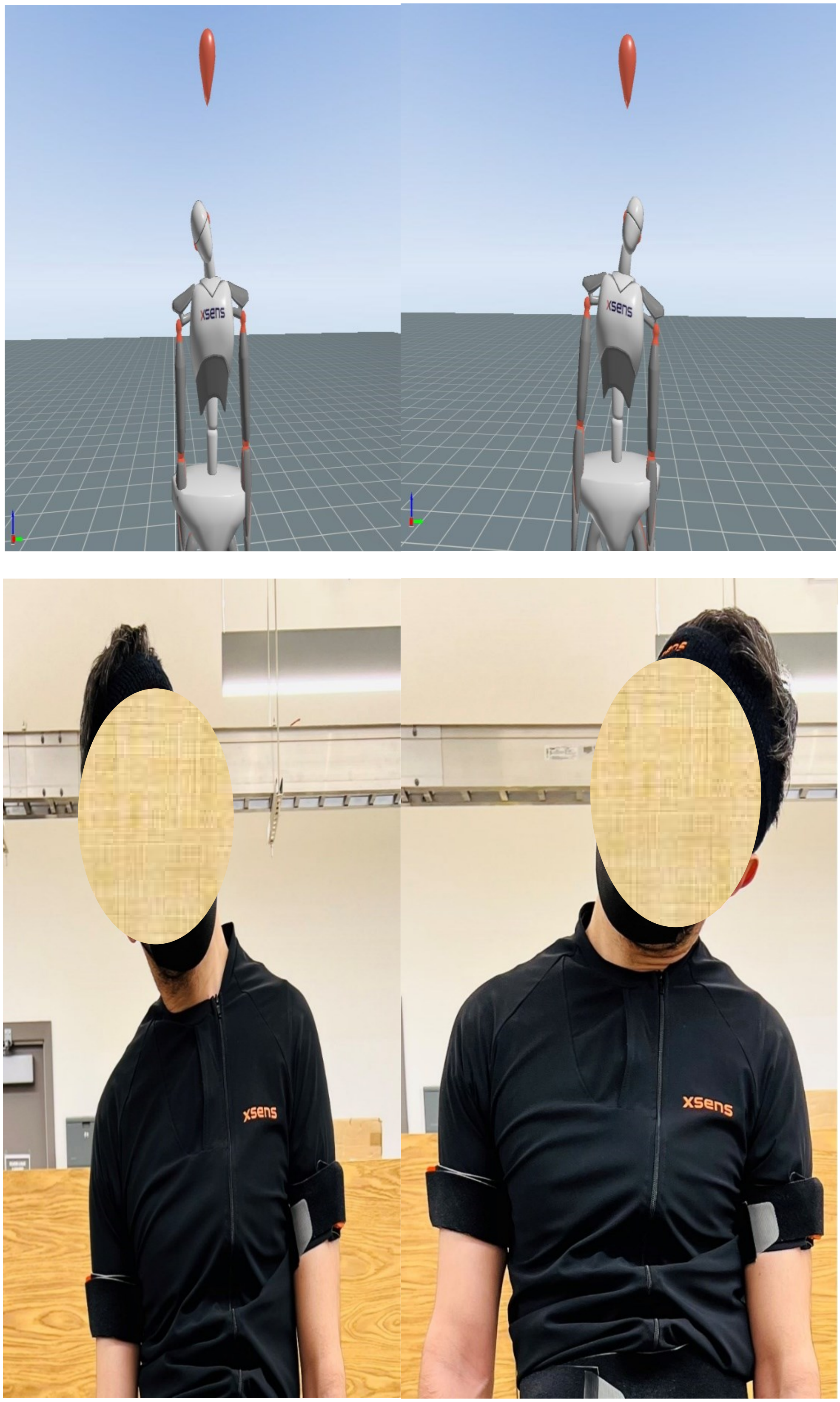


Figure B-36: Neck tilt

36. Elbow Flexion/Extension

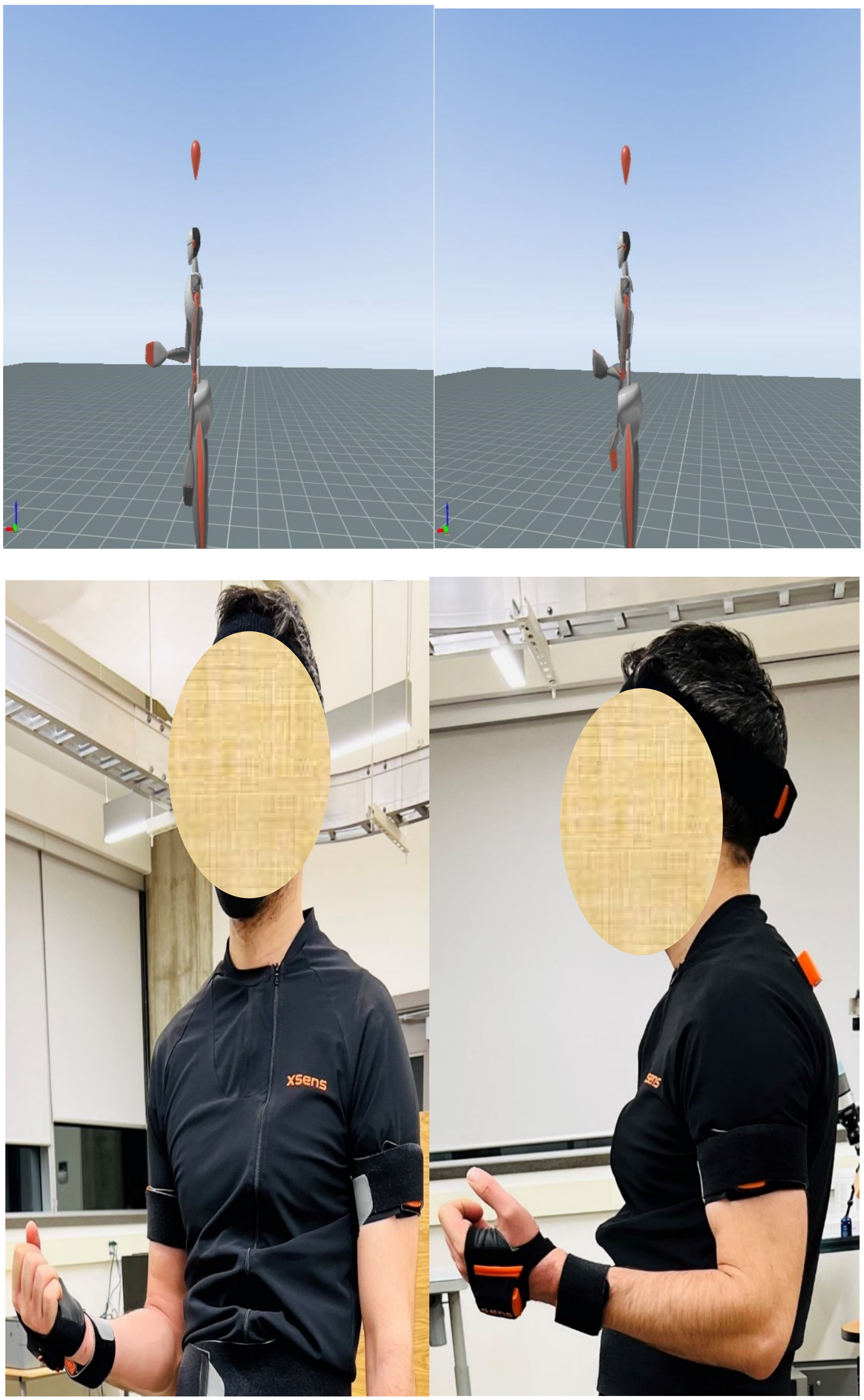


Figure B-37: Elbow flexion and extension

37. Wrist Flexion/Extension

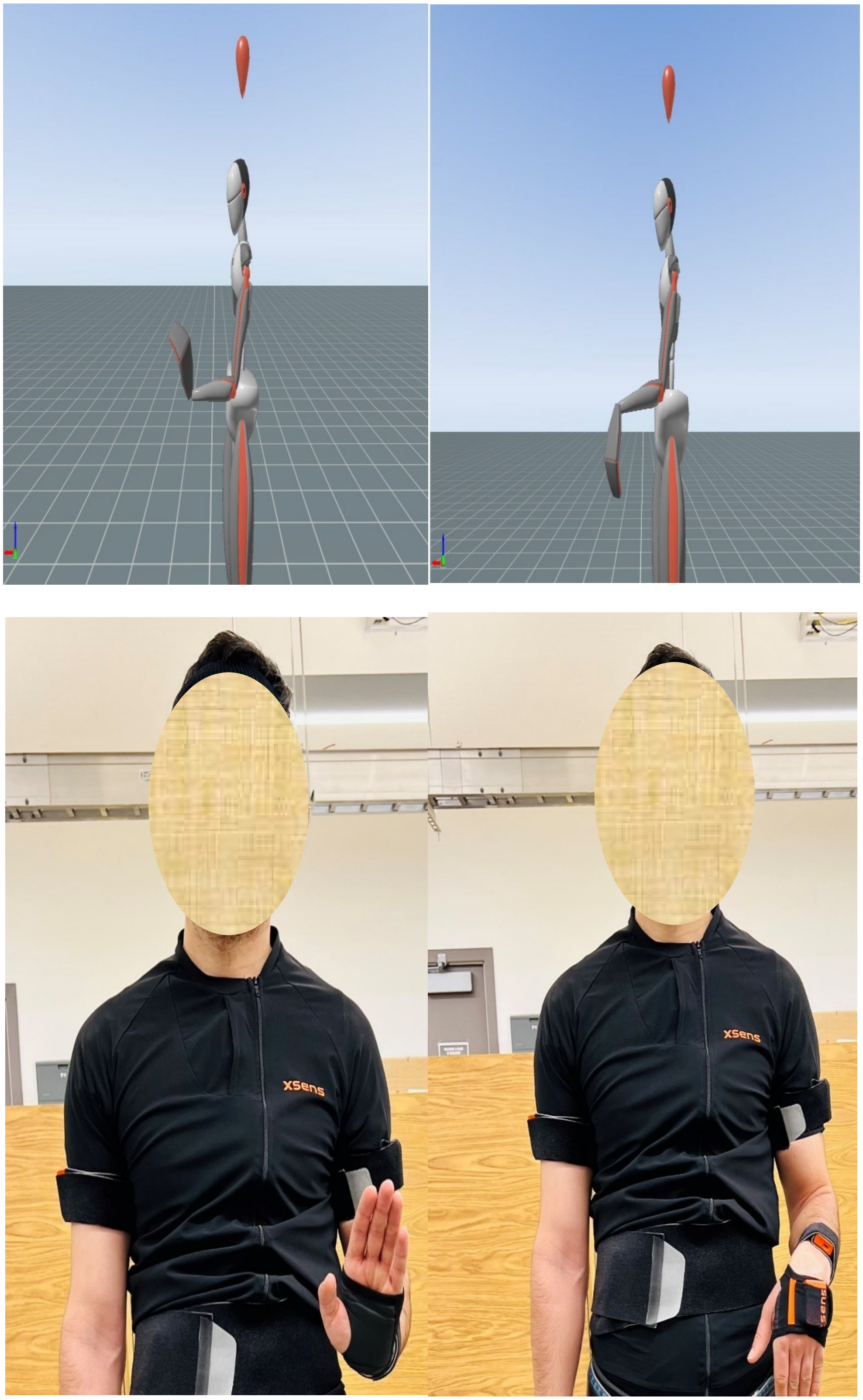


Figure B-38: Wrist flexion and extension

38. Wrist Bending

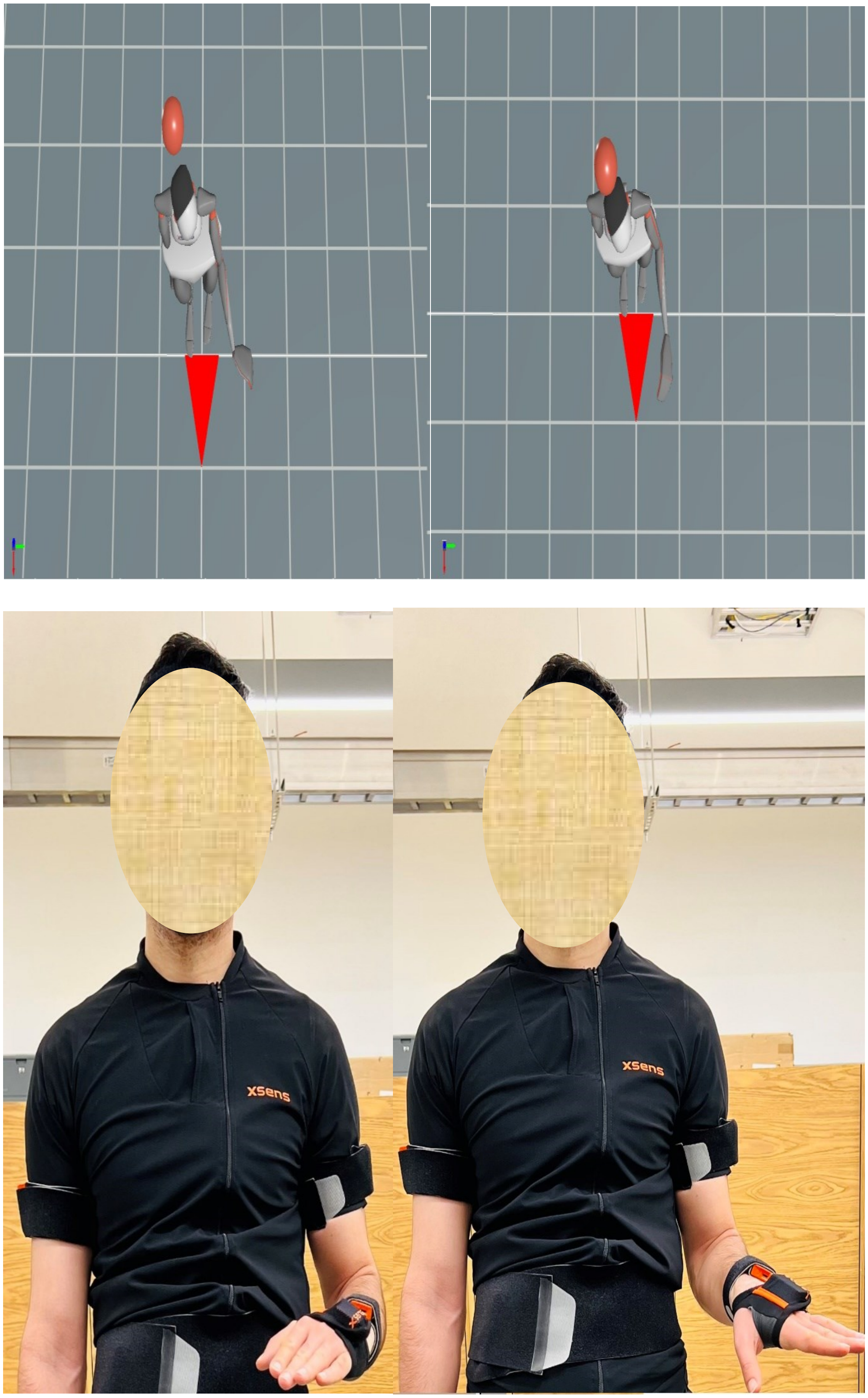


Figure B-39: Wrist flexion and extension

39. Wrist Rotation

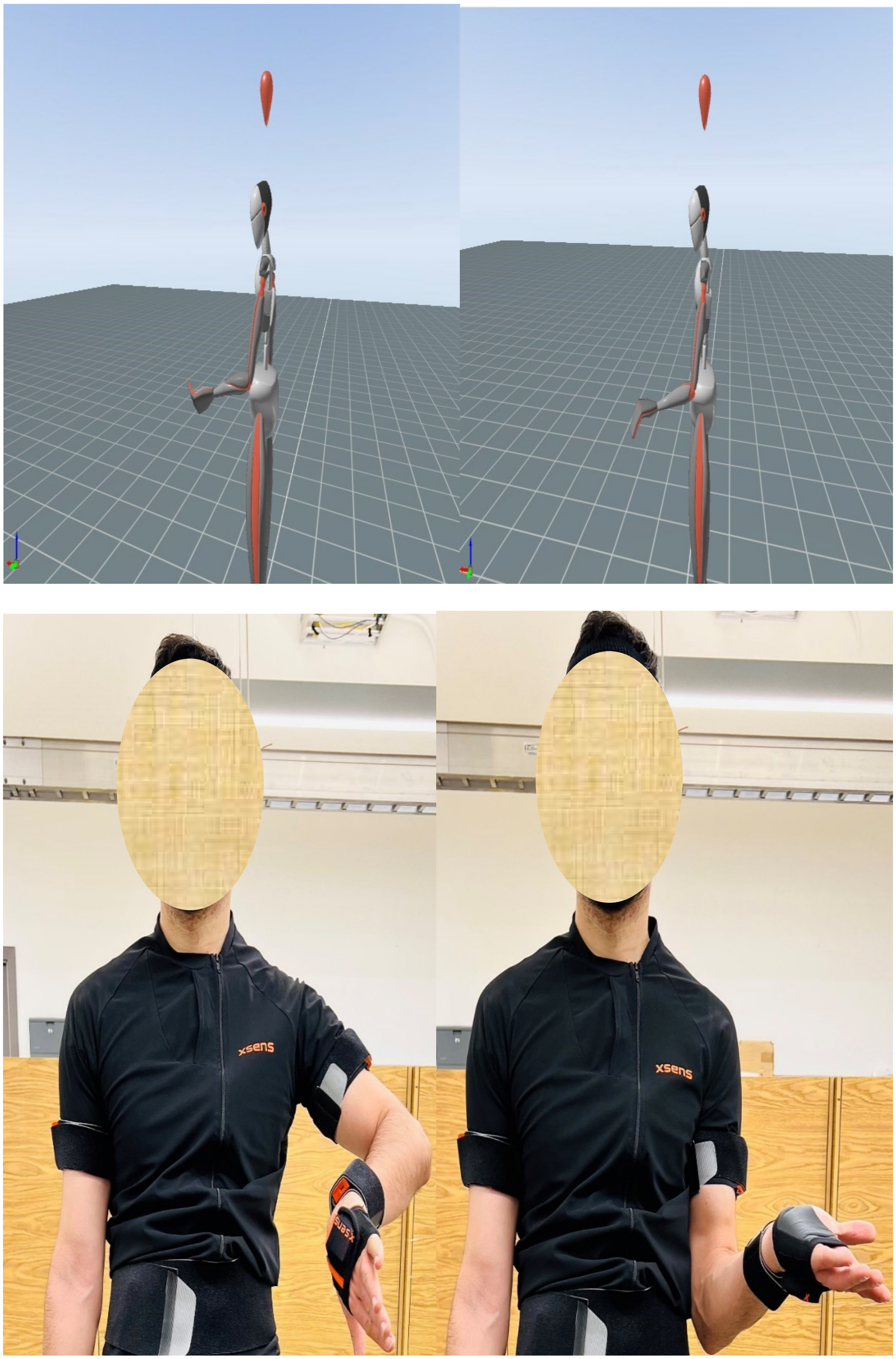


Figure B-40: Wrist rotation

40. Ankle Flexion/Extension

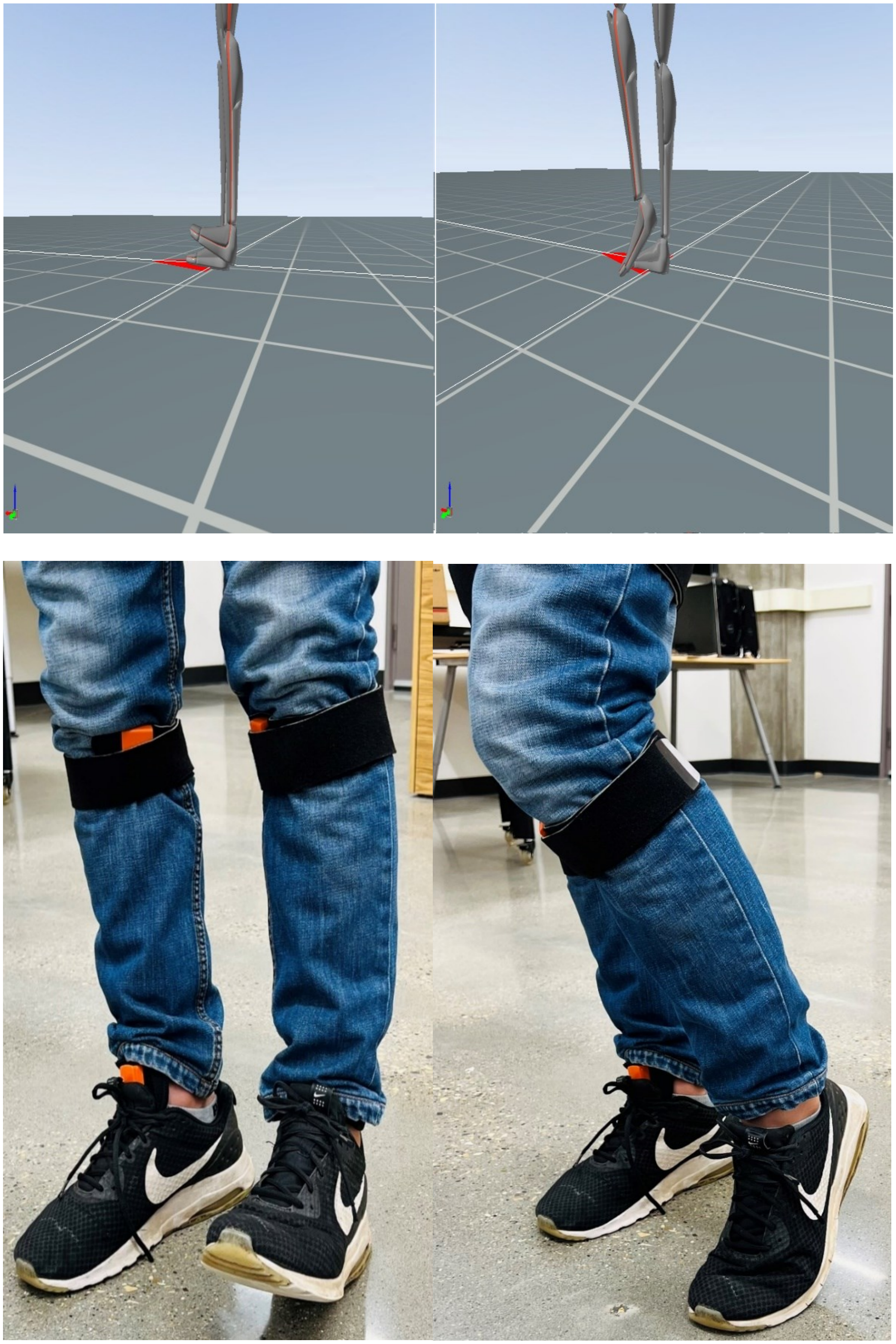


Figure B-41: Ankle flexion and extension

41. Ankle Rotation

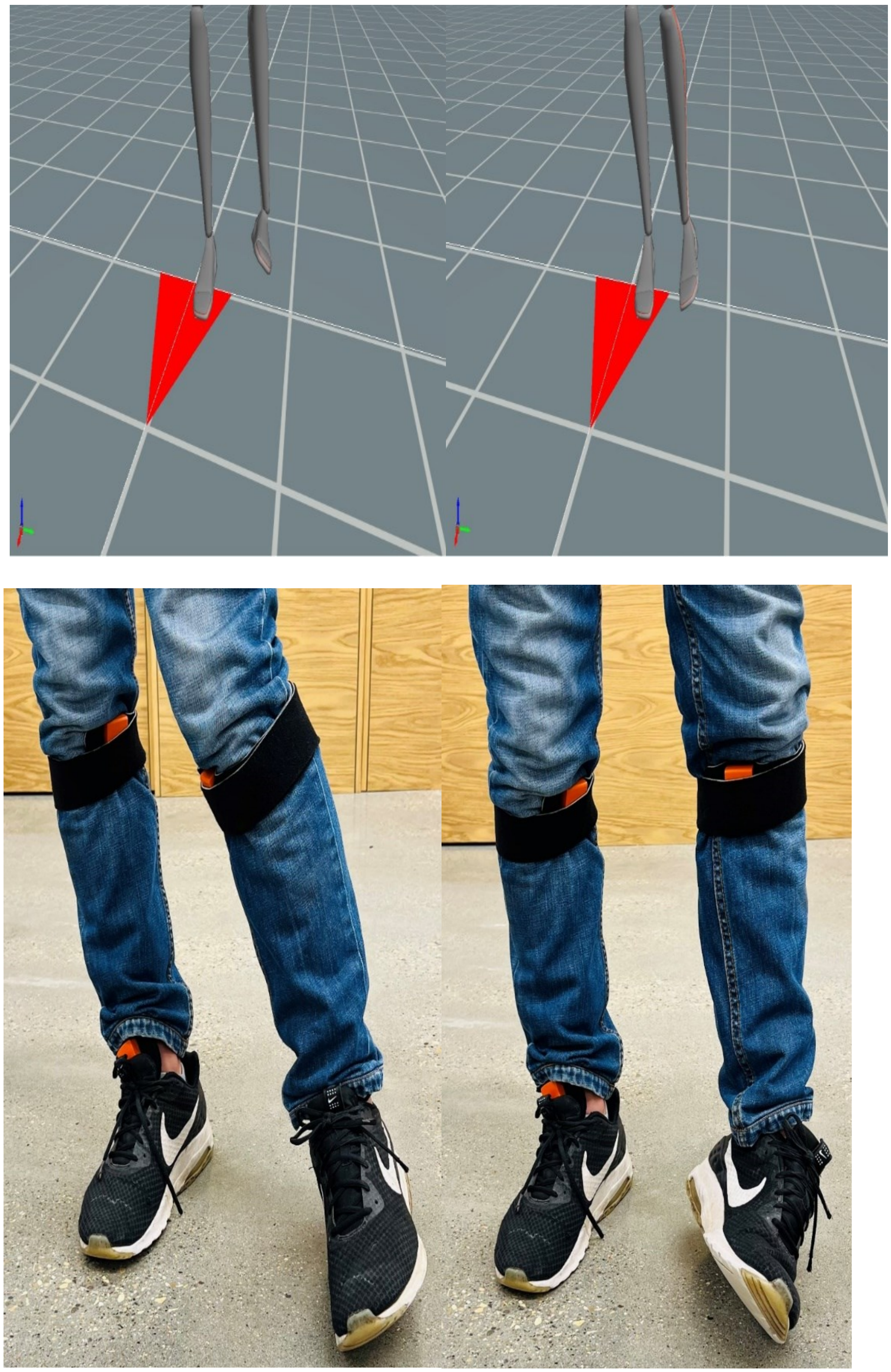


Figure B-42: Ankle rotation