ANALYSIS OF REPETITIVE MOTION IN MANUAL MATERIAL HANDLING SYSTEMS USING A DIGITAL TWIN FRAMEWORK

by

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DEDICATION

I would like to dedicate this research work to my family, professors, and friends for their endless encouragement, support and love.

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LIST OF ABBREVIATIONS

Abbreviation	**Description**
MMH	Manual Material Handling
MoCap	Motion Capture
DTW	Dynamic Time Warping
QCC	Quality Control Chart
LCL	Lower Control Limit
UCL	Upper Control Limit
NIOSH	National Institute for Occupational Safety and Health

ABSTRACT

Manual material handling accounts for more than 122,000 workplace injuries at U.S. One of the major reasons for injuries in the workplace is due to accidents caused by improper execution of the material handling fundamental moves. This may lead to serious musculoskeletal disorders. Research has been carried out to analyze the musculoskeletal disorders, but there are only very few related to manual material handling. This research proposes a methodology to analyze the quality of motion during lifting task performed in the manual material handling environment. The methodology consists of a motion capture environment, a system of sensors, a processor that collects time series data, and a data analysis module. Using motion capture cameras, data is collected on a variety of human subjects performing manual lifting task related to a material handling activity. The parameters for lifting experiment are obtained from the Snook's table. The collected data are analyzed through Dynamic Time Warping (DTW) technique which will compare the similarities between two motion sequences. At the end, the quality of the motion is analyzed through quality control charts which will provide the behavior of each motion. This research has potential impact for contribution in the manual material handling industry. Using the latest developments in motion capture technology and data analytics, the analysis of the quality of motion will enable an industry to modify the human motion operations that are injurious to the operator and also help eliminate the non-value-added motions from the operations.

I. INTRODUCTION

According to the U.S. Department of Commerce and Bureau of Labor Statistics, material handling and logistics is one of the fastest growing industries in America [1]. In fact, the material handling and logistics equipment and system consumes more than $156 billion per year and employs more than 700,000 workers [1]. Materials handling is the art and science of moving, packaging, and storing of substances in any form. It is also providing the right amount of the right material, in the right condition, at the right place, in the right position, in the right sequence, and for the right cost, by the right methods [2] [3]. We described the challenges and opportunities for the manual material handling industry.

<u>Challenges:</u>

The main challenges faced by the manual material handling are:

- **Repetitive motion and workplace conditions cause injuries in operators:** Manual material handling (MMH) still accounts for more than 122,000 workplace injuries in recent years. According to the U.S. Department of Labor Bureau of Labor Statistics (2016), the top five types of injuries include – encountering harmful objects (36.7%), overexertion (9.7%), slips and falls (19%), repetitive motion (5.7%), and contact with harmful substances/chemicals (5.2%) [4]. As manufacturers strive to reduce the "takt" times of their manufacturing processes, they design jobs that require higher operator pace, but overlooks occupational safety and ergonomics. Hence, they look out for suitable technology that could solve the problem.

- **Moving heavy objects:** Loading and unloading of goods and materials are the sources of injuries among the workers. An average working hour for a material handler is eight hours. Continuous lifting and moving of objects can result in fatigue, sore muscles, which leads to wrong postures. A repetitive wrong motion for profuse number of times can lead to musculoskeletal disorders.
- **Accidental of falling objects:** The objects that are stored above head level will cause less to severe injury to the operator. Accidental colliding of foot onto heavy objects cause tripping and less to severe injury. This is due to poor lighting, obstructed view, uneven walking surfaces, etc. [5]
- **Labor Costs:** In manual material handling industry, hundreds and thousands of tons of materials are handled every day. This requires use of large amount of workforce in order to perform these tasks. These tasks are performed by well-trained operators who knows the techniques for handling the heavy equipment in a manufacturing plant. But the problem is there is a shortage in skilled labor force to perform manual material handling operations, and therefore the industry faces the challenge of workforce shortage. High labor wages due to low availability of labor and medical costs adds to the challenges.

Opportunities:

Industry 4.0 penetration is creating several opportunities for growth that will impact the manual material handling industry:

- **Connectivity:** Smart material handling systems are designed to create an ergonomic environment for the operators. Here, the system is constructed in a way that products, workstations and systems are made by improving communication between units in the system to establish more adaptable control of assembly flow and system performance [6].

- **Advances in sensor technologies to track operator's health:** There are lots of technological advancements, like bio suit, which helps in tracking the motion of an operator, heart rate, respiratory rate that can be used for further analysis for the detection of factors like fatigue.
- **Design of real time ergonomic evaluation tools:** To evaluate the risk factors involved in the work-related musculoskeletal disorders, different methods and tools have been developed. Postural analysis tools were introduced to assess the workers movement in a manual assembly process. RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment) are used to assess the workers to operate within the secure limit [7]. A Human Motion Simulation (HUMOSIM) framework is developed to control human figure models and analysis of simulated tasks. This framework consists of hierarchical set of algorithms and motion modules that controls movements like walking, carrying, moving, etc. [8]. Terrestrial magnetism and acceleration sensors are incorporated to develop a system that monitors worker's motion in factory [9]. Image based operator motion monitoring system is developed based on the Direct Linear Transformation (DLT) method, which detects an operator's position during human-robot cooperation assembly process and protects not only the operator, but also predict the operator's intention according to his position [10].
- **Development of human assistance and collaborative robots:** In different manufacturing industries, the handling of material is a high resource consuming

task. The conventional manually guided handling system lack an intuitive and may lead to physical injuries and fatigue. The development of modular flexible collaborative robots with an intelligent power system that can work with people also in a direct physical contact, combining human intelligence and skills, and can address the safety issues that have been considered as paramount importance [11].

- **Training using virtual- and augmented- reality:** The use of virtual reality (VR) and augmented reality (AR) are now widely regarded as a promising platform for industrial maintenance and assembly tasks training [12]. Head-worn (AR HWD) technologies such as smart glasses may become an everyday tool in the workplace, allowing workers to perform hands-free tasks while viewing real-time information related to a task within their visual field of view [13].

<u>Fundamental skill moves – The Toyota Way</u>

Fundamental skill moves are the basic day-to-day operations performed by a manufacturer operator. Toyota uses the Fundamental Skill Training to train their new employees to become familiar with and comply with standardized work by practicing the fundamental skill moves with the real equipment and machines. In manual material handling, fundamental skill moves include lots of repetitive motions like lifting, pushing, carrying, etc. Similar to the Toyota's fundamental training, it helps in standardizing the material handler's movement and prevent injuries that occur due to wrong postures. In fact, it is Toyota's second basic concept of making the best use of labor environment and excellent workers through eliminating waste movements by workers and consideration for worker's safety. In Toyota, operations involving danger, injurious to health, operations requiring hard physical labor, and monotonous repetitive operations have been mechanized, automated, and unmanned [14]. Therefore, following the Toyota way, the fundamental skill moves are studied to create an ergonomic environment for the operator. These fundamental skill moves have been documented in detail in [15] and [16]. In this thesis, a data analysis method will be proposed to study the fundamental skill moves of manual material handling with the objective of maximizing the operator's safety and ergonomic conditions in the workplace.

1.1 Problem Statement

Motion Capture (MoCap) is a process to track and capture the real-time human motion into 3D coordinates. MoCap technology plays an important role in optimizing the workers' movement in manual material handling. Recording the worker's motion and posture are critical in order to determine the risk of musculoskeletal injuries in the workplace.

A marker-free and calibration-free ergonomic evaluation of potential musculoskeletal disorders was proposed by Plantard et.al using Microsoft Kinect to evaluate RULA ergonomic assessment in real work condition using occlusion-resistant Kinect skeleton data correction [17]. A different approach to assess real time work-related musculoskeletal disorders for repetitive efforts was developed by Peppoloni et al. [18] by using a novel wearable wireless system to assess the muscular efforts and postures of the human upper limb based on RULA and Strain Index (SI). Patrizi et al. [19] compared both low-cost marker-less and high-end marker-based motion capture systems to investigate practical working activities involving object lifting and displacement. There are also datasets available to document motion capture data for a few manual material handling systems. Carnegie Mellon's CMU Graphics Lab Motion

Capture Database and University of Pennsylvania's SIG Center for Computer Graphics Multi Modal Motion Capture Library has several datasets regarding the movement of hands, lower back, upper back, fingers, among others.

All these papers and databases indicate that there are several resources available on how to perform motion capture studies. However, there is a lack of methodologies available to use the MoCap data to perform motion and time analytics and characterize the time and standard deviation of the fundamental skill moves.

1.2 Research Objective

The objective of this paper is to develop a methodology to analyze manual material handling operations by using motion capture data. The material handling operation will be segmented into fundamental skill moves. The methodology uses the MoCap data to analyze a fundamental move by individually segmenting each motion. Each marker on the segmented motion is then analyzed using dynamic time warping methodology to obtain the motion statistics, thus predicting the quality of the motion. Control charts are specified in order to inspect and control the quality of the move.

Research Hypothesis

It is hypothesized that: "breaking the manual material handling tasks by fundamental skill moves will help predict the quality of the motion."

The hypothesis will be tested by performing motion capture experiment with different factor levels. With the help of the data collected through these experiments, individual motions are analyzed through data analysis and statistical process control methods.

II. LITERATURE REVIEW

Sunwook et al. (2014) propose a three-classification algorithm to classify the manual material handling tasks. The authors use an unsupervised clustering system to explore hidden structures in the dataset, then they perform feature extraction and data reduction to characterize a time series of the system. The result provides an effective, field-based exposure assessment measure using wearable technology, which provides both numerical and contextual information about a job. The result also provides guidelines on selecting input data sets for the manual material handling tasks [20].

A maximum acceptable weight limit for a manual material handling task was developed by Stover H. Snook (1978). The author discusses that the variables like weight, distance, and frequency of the task, the size and weight of the object, worker's sex, age and physique, and the effects of heat stress are investigated. The subjects performed fundamental tasks like lifting, pushing, pulling, etc. From the data obtained by performing these tasks, a table was designed for each fundamental skill move, and for both male and female. The table presents the maximum acceptable weight limits for 10, 25, 50, 75, and 90% of the working population. The result indicates that by designing the job to fit the worker can reduce up to one-third of industrial back injuries [16].

A framework was proposed by Mendez et al. (2018) to obtain and analyze real time data related to dynamic and natural motion of individuals in a manufacturing environment that involve human labor. The study uses motion capture system to analyze various complex motions performed by the human subjects. The collected data were then analyzed through dynamic time warping technique for a comparative analysis of the motion. The result obtained is used to identify optimal activity motions [21].

An image-based operator monitoring was developed by Duan et al. (2009) to study operator's motions in real time. The authors use Direct Linear Transformation to obtain 3-D data from detected 2-D data. The operator's motions were detected by IP cameras with the help of color marks attached to the operator's body. To accurately predict the position of the 3-D data, the authors develop a cost efficient kinematic human body simulator. The converted joint-angle data of the operator is fed to the simulator to successfully regenerate the operator's motions in real time. Finally, the authors successfully develop a system to assist the operator in the assembly process effectively. The system monitors and optimizes the operator's motions in an assembly process and can be used to predict the collision between the operator and robot during the human-robot cooperation assembly process [10].

Sempena et al. (2011) used exemplar-based sequential single layered approach using Dynamic Time Warping (DTW) to recognize basic human motions such as clapping, waving, punching, etc. Dynamic Time Warping technique is used because of its robustness and is very efficient in time-series similarity measure. The authors use depth camera to track human motion and to identify human joints in 3-D real world coordinate system. The orientation of each body part's joints is used to build feature vector along time series that is constant to human body size. The 3-D rotation is represented by quaternion system in order to avoid singularities so that an accurate representation of rotational transformation is obtained. Kinect camera is used to perform motion capture for six motions including clap, punch, smash, wave, run, and kick action. The result obtained for the six actions is then compared and found that upper part generated actions are recognizable, whereas it is difficult to recognize lower part actions [22].

Sunwook et al. (2013) study the capabilities of the commercially available inertial motion capture (IMC) system in quantifying physical exposure during various simulated manual material handling tasks. The authors use optical motion capture (OMC) system and inertial motion capture system to capture whole body kinematics while performing five specific MMH tasks. The IMC performance is compared with OMC system to quantify physical exposure and the results were obtained in terms of joint angles, joint angular velocities, and joint moments. The results obtained from many comparative measures of physical exposures has a significant change in performance over time. Though the changes seemed to be relatively small, the performance of the IMC is rather stable over the period. Also, the accuracy of kinematics recorded by the IMC system varied considerably and generally consistent with the movement across different MMH tasks [23].

Four basic approaches were used to study the occupational health problems that arise due to overexertion by Chaffin DB (1979). The four approaches utilized are: 1) epidemiological studies of job and worker attributes to identify the cause of musculoskeletal accidents both individually and in combination, 2) psychophysical studies to determine the volitional tolerance of workers to the stress mitigated by manual material handling activities, 3) biomechanical studies on common exertions on the musculoskeletal system during manual material handling activities, 4) physiological studies to assess the strain imposed on the cardiovascular system during repeated load handling activities. From the result of these approaches, the author summarizes that more substantial controls are needed to lessen the economic burden and human suffering associated with manual material handling activities in industry [24].

W Monroe Keyserling (2000) presents a review of laboratory studies and biomechanical models of work factors associated with increased risk of upper extremity musculoskeletal disorders. The relationship between selected work parameters (e.g., forces exerted during hand-intensive work, wrist postures, shoulder postures, repeated exertions, use of gloves) and selected strain responses of body tissue (e.g., electromyographic activity of muscles, intracarpal tunnel pressure, compression of tendons and nerves) were examined through biomechanical studies. Also, through psychophysical studies, the relationship between selected work parameters and perceived discomfort as well as the relationship between selected work parameters and performance levels that can be achieved without incurring excessive fatigue were examined. Through these studies, an insight on how people react and respond to specific physical risk factors were studied [25].

Ann E. Barr and Mary F. Barbe (2002) discuss the scope of upper extremity work-related musculoskeletal disorders, relationship between repetition-force and work-related musculoskeletal disorders, cellular indicators of injury, and animal model of repetitive movement disorders. The authors propose a conceptual framework for the development of work-related musculoskeletal disorders in general. The authors also use animal models of upper extremity WMSDs to study the response of injured tissues to therapeutic interventions which contributes to physical therapy practice in occupational healthcare settings. The resultant model enhances the ability to predict risk and to manage WMSDs in humans [26].

A range of methods have been developed by G. C. David (2005) for the assessment of exposure to risk factors for work-related musculoskeletal disorders. The author put forth various methods to assess the WMSDs, most for the assessment of the upper regions of the body such as the back, neck, shoulder, arms, and the wrists. The author categorizes the methods under three: 1) self-reports from the workers, 2) observational methods involving simpler techniques and advanced techniques developed for the assessment of postural variation for highly dynamic activities, 3) direct measurements using sensors attached to the subject for the measurement of exposure variables at work. The results suggest that the use of method varies depending upon the application and the objectives of the study, and in more general, observation based assessments appear to be best matched to the needs of occupational safety and practitioners who has limited time and resource to establish the basis for prevention [27].

Another work-related musculoskeletal disorder was studied by da Costa et al. (2010) to evaluate evidence available for the many suggested work-related musculoskeletal disorder risk factors. The authors designed and conducted a systematic review on available WMSDs literature compared to the different assessment methods carried out by G. C. David (2005). The authors use a different selection criteria and definitions for the classification of the levels of evidence. The level of evidence was classified as strong evidence risk factors, reasonable evidence risk factors, insufficient evidence risk factors of their causal relationship with different types of WMSD. The review was also performed for each body part and their risk factors leading to MSD. The results conclude that risk factors with at least reasonable evidence leading to WMSDs include heavy physical work, smoking, high body mass index, etc., and the most commonly reported biomechanical risk factors include excessive repetition, awkward postures, and heavy lifting [28].

Shrawan Kumar (2001) propose four theories based on scientific evidence in literature about precipitation of musculoskeletal injuries in the workplace. 1) Multivariate interaction theory to assess how different factors determine the final outcome (pain behavior), 2) Differential fatigue theory for unbalanced and asymmetric occupational activities, 3) Cumulative load theory recommends a threshold range of load and repetition product beyond which injury precipitates since materials have limited life, 4) Overexertion theory implies that physical efforts exceeding the tolerance limit precipitates occupational musculoskeletal injury. The result suggests that although these theories explain the immediate mechanism of precipitation of injuries, they all operate simultaneously and interact to modulate injuries to varying degrees in different cases [29].

An epidemiologic capture – recapture methodology was used by Morse et al. (2005) to study the trends in musculoskeletal disorder. The authors utilize musculoskeletal disorders data from workers' compensation and physician reporting data in Connecticut for seven years (1995 – 2001) to perform capture – recapture analysis. The analysis was used to estimate the number of unreported and total MSD cases. The results of the capture – recapture estimates are compared with the Bureau of Labor Statistics survey that is done in concert with OSHA and the method provide an improved surveillance method for monitoring temporal trends in injury rates. The results of the study found evidence of extensive under-reporting of work-related upper-extremity MSD, with less than 10% reported to workers compensation in different years [30].

Wu et al. (2005) propose a definition of a joint coordination system (JCS) for the shoulder, elbow, wrist, and hand. The authors create a standard for the local axis system in each articulating segment or bone for each joint. These axes are used to standardize the joint coordination system and motion for the constituent joints. The result suggests that these standards can be used by researchers to relate the marker or other coordinate systems to the defined anatomic system through digitization, calibration movements, or population based anatomical relationships [31].

Boocock et al. (2019) aim to determine the ability of the handler to modify lumbosacral posture in response to real-time external feedback during repetitive lifting task and to determine the behavioral adaptations adopted to comply with feedback and the potential consequences for the risk of injury. Thirty-six participants were selected to perform repetitive lifting tasks. The participants were divided into two groups where one group received real-time feedback on lumbar posture using inertial sensors and the other group with a non-biofeedback. From the result, the author summarize that the biofeedback group adopted less lumbosacral flexion when compared to the non-biofeedback group resulting in a significant reduction in lumbosacral passive resistance forces [32].

Robin Burgess – Limerick and Bruce Abernethy (1997) present the use of a postural index to define the postures adopted at the start of lifting. The authors provide a quantitative and empirically grounded definition of lifting posture that is robust in the changes in task parameters. Seventy-One untrained participants were selected to perform manual lifting task with ten reflective markers attached to the participants. From the data obtained, ANOVA and MANOVA were used to obtain means and standard deviation for extreme conditions and statistics describing effect of load mass and starting height on posture adopted at the start of the lift. The result provides that postural index permits lifting posture to be defined independently of absolute joint position [33].

Vincent M. Ciriello (2001) investigate the effects of vertical distance and the box size on maximum acceptable weights (MAW) of lifting and lowering, the effects of height on maximum acceptable weights of lowering, and the effect of a four component combination task on maximum acceptable weight. The methodology involves use of eight male industrial workers as subjects, performing 27 variations of lifting, lowering, pushing, pulling, and carrying. The selected subjects were analyzed through a psychophysical methodology. The result concludes that MAWs of lowering were not significantly affected by distance of lowering, height of lowering, or the box size except for the 25cm lowering task. Also, the result suggests that MAWs of lifting large boxes were not significantly affected by distance of lift and MAWs of lowering were not significantly different from lifting [34].

Wagner et al. (2007) aim to quantify the differences between a static and dynamic analysis of a materials handling task using the AnyBody modeling system to include the effects of motion. The authors analyze a three-dimensional lifting task performed by the human subjects using the AnyBody human modeling system and motion capture data. The data obtained are used to create a manikin which replicates the actual movement of the human subject with accurate scaling using AnyBody. The model is assessed for the analysis of an asymmetric lifting task. From the result, comparisons between low back moments, compression and shear forces for dynamic and static analyses were analyzed [35].

A hand force (HF) estimation method based on an ambulatory measurement system was evaluated by Faber et al. (2018) using inertial motion capture (IMC) and instrumented force shoes (FSs). Sixteen subjects performed lifting and carrying experiment and the 3D full body kinematics were measured using optical motion capture and inertial motion capture, and 3D ground reaction forces were measured using force plates and force shoes. The root mean square differences were calculated between the estimated hand forces to the reference hand force. The result shows that estimating hand forces using an ambulatory measurement system resulted in hand force estimation error of 10-27N, which is regarded acceptable for the assessment of spinal loading during manual lifting [36].

A laboratory-based study was conducted by Azevedo et al. (2014) to analyze manual material handling tasks on the construction site with obstacle clearance and to understand the contribution of these tasks to accident occurrence. Eight healthy volunteer construction workers were selected for the experiment. The subjects had reflective markers placed bilaterally on the skin. The experiment was performed on a treadmill with subjects performing with and without load. ANOVA test was conducted using the data collected from the experiment. The result from the test suggests that the obstacle clearance pattern changes with load weight but no influence was observed on the load handling strategy. Thus, the authors conclude that manual material handling contributes to the occurrence of falls during obstacle clearance and the need of intervention measures in order to prevent falls in construction sites [37].

Yeung et al. (2002) investigated symptoms in musculoskeletal that are prevalent in different and multiple body regions among manual material handling workers and whether a simple index is associated with musculoskeletal outcomes in single and multiple body regions. The authors conduct a structured questionnaire and interviews with a study population consisted of 217 male workers with varied levels of manual lifting experience. A statistical analysis was performed based on the data collected from the interview and the prevalence percent for musculoskeletal symptoms in different and multiple body regions were analyzed. From the result, it was inferred that lower back symptoms were the most frequent among manual material handling workers, followed by shoulders, upper back, hips-upper legs, and neck [38].

Zhou et al. (2015) investigated the effects of a laterally slanted ground on trunk biomechanical responses during sudden loading events. The research consists of thirteen healthy male subjects to perform the task. The experiment was designed with two independent variables which are slanted ground angle with three different angle conditions (0, 15, 30) and mass of load. The motion of the subjects was tracked through an eight-camera 3D optical motion tracking system and a surface electromyography (EMG) system was used to record EMG activities. From the data, multivariate analyses of variance (MANOVAs) were performed to test the main and interaction results and the variables that were found significant in MANOVA were further analyzed using univariate ANOVAs. From the result, it was concluded that, one will experience larger increase of L5/S1 joint compression force when standing on laterally slanted ground while sudden loading which indicate a high risk of low back injury [39].

Bortolini et al. (2018) present a motion analysis system (MAS) for human body digitalization and analysis during the execution of manufacturing/assembly tasks in industrial workstation. The authors develop a hardware system adopting commercial

MOCAP devices and extending their applicability to the industrial sector for the dynamic assessment of work content. The MAS architecture consists of Wi-Fi network and four depth cameras to perform the MOCAP operations. The research consists of seven subjects who will perform a specific set of predetermined identical activities for a particular duration. The result consists of position vector of all the operator joints over time. The position vector (X, Y, Z) provides a dynamic representation of all the movements executed by the operator. From the result, the authors suggest how MAS is a valuable hardware/software architecture to assess a manual manufacturing/assembly workstation highlighting the productive and ergonomic aspects of possible improvements [40].

Marc J. Dysart and Jeffrey C. Woldstad (1996) present three separate models to predict the human postures while performing static sagittal lifting tasks. The authors use a common inverse-kinematics characterization to mathematically represent feasible postures but explore three different criteria functions for selecting a final posture. The first criterion assumes that subjects choose a posture which requires minimum overall effort. The second criterion assumes that subjects minimize local effort or fatigue. The third criterion assumes that subjects choose the posture with greater stability. To compare the actual postures, sixteen healthy subjects performed isometric sagittal lifts at each designated hand positions. The postures predicted by the three models were then compared with the postures assumed by the subject. From the result, it was inferred that the total torque criterion (first criterion) was, on the average, the most accurate [41].

The effects of the magnitude of the load handled and movement speed on lumbar vertebral kinematics during two-handed sagittal symmetric lifting tasks was investigated by Zhang et al. (2003). The research includes ten subjects who will perform the lifting experiment from the floor to a shelf. The motion of the subject was analyzed by placing reflective markers on participants' surface bony landmarks corresponding to the major joints and seven spinous processes (C7, T7, and L2-S1). The three-dimensional coordinate data were acquired for markers at C7, T7, L2-S1. The center of rotation (COR) locations and segmental movement profiles for L2-S1 were analyzed. From the result, the authors suggest that, 1) the COR locations and vertebral angular displacement does not affect speed or load variation, 2) a faster speed tends to shorten the time to complete the acceleration for all the lumbar vertebrae, 3) the shape of the angular profiles on a normalized scale but significantly influenced by the torso extension speed variation during lifting motions [42].

Marras et al. (1993) assess the contribution of three-dimensional dynamic trunk motions to the risk of low back disorder during occupational lifting in repetitive manual material handling. The authors develop a lumbar motion monitor (LMM) to document the three-dimensional components of trunk motion in the work environment. The data collected through the LMM signals were processed to determine position, velocity, acceleration of the trunk as a function of time in the sagittal, frontal, and transverse planes of the body. From the data, three types of analyses were made, 1) to determine the variation of trunk motion and workplace measures from cycle-to-cycle within a job, 2) the relationship of each trunk motion and workplace variable, 3) to predict the probability of high-risk group membership through multiple logistic regression. From the result, it was observed that the model could be used as a quantitative, objective measure to design the workplace to minimize the risk of low back disorder in repetitive MMH [43].

The differences between the kinematics and kinetics of repetitive lifting in two groups of handlers of different ages were investigated by Boocock et al. (2015). Two groups of younger and older adults performed a prolonged repetitive lifting task. A nine-camera motion analysis system with retro-reflective markers attached to the subjects was used to track the position and movement of body segments. An eight-segment biomechanical model was built to measure the postural kinematics and kinetics throughout the lifting task. The surface electromyography was used to record muscle activity of the lower erector spinae (LES) and upper erector spinae (UES). The authors perform statistical analysis using one-way repeated measures ANOVA to investigate differences in median frequency intercepts of UES and LES, back muscle strength, and maximum lumbosacral flexion pre-and post-lifting tasks. From the result, it was inferred that older participants appeared to control the harmful effects of fatigue associated with repetitive lifting [44].

Raut et al. (2017) analyzed the posture of the workers during manual material handling tasks 3D motion capture and machine learning technique. Eight subjects were made to perform squatting and stooping action in front of Kinect. The authors analyze the posture while lifting by Body Mask tracing with KinectV2 videos using DFW and AdaBoost. A modified dynamic time warping (DTW) on frames, known as the dynamic frame warping (DFW) was used to analyze the least distance between the two sequence and Euclidean distance to extract the features. The classification of stoop and squat motion was performed using AdaBoost algorithm. From the result, it is observed that DFW algorithm along with AdaBoost gives 85% accuracy and this method can be used to analyze workplaces with MMH operations [45].

Switonski et al. (2012) proposed a gait identification method based on the nearest neighbor classification technique with motion similarity assessment using dynamic time warping. The authors use kinematic motion data represented by the joint rotations coded by Euler angle and unit quaternions. The motion capture data for analysis were obtained from the laboratory and the 3D coordinates of the gathered data were reconstructed. Based on the data, dynamic time warping is used to assess the whole motion similarity. The percent of correctly classified motion were obtained using the nearest neighbor classifier with motion similarity measure corresponding to the cost of determined path by DTW transform. From the result, it is inferred that the classification with all joints has accuracy over 91 percent [46].

Giorgino (2009) discusses a variety of algorithm and constraints for the DTW technique used in R. The R-software's "dtw" package provides a comprehensive solution for the computation and visualization of DTW alignments. The author also provides discussions on how the user can customize the classic constraints of the algorithm like local slope, endpoints, windowing, and how create plots of the alignment results [47].

III. METHODOLOGY

3.1 Dynamic Time Warping

DTW is a well-known technique to find an optimal alignment between two given (time-dependent) sequences under certain restrictions [48]. The explanation behind using DTW is, for given two time series, to stretch or compress them locally in order to make them resemble as close as possible. Thus, the optimal alignment $\emptyset$ is given by [47]

$$\boldsymbol{D}(\boldsymbol{X},\boldsymbol{Y}) = \min_{\emptyset} \boldsymbol{d}_{\emptyset}\,(\boldsymbol{X},\boldsymbol{Y})$$

where:
X, Y = warped time series
$\emptyset$ = optimal alignment

In the DTW matrix, each vector is compared against all the other vector to find the minimum warping point. Using the Dynamic Time Warping (DTW) algorithm, the data is analyzed to predict the time and standard deviation of the motion. At the end, a quality chart is created to analyze the behavior of the motion.

3.2 Quality Control Chart

The quality control chart is generally used to analyze how a process changes over time. It is one of the primary tools used in the analyze and control steps of DMAIC. In control charts, when dealing with the quality characteristic, it is usually necessary to monitor both the mean value of the quality characteristic and its variability [49].

The formulas for constructing quality chart are as follows

UCL = $\overline{x}_D + 3S_D$

Center Line = $\overline{x}_D$

LCL = $\overline{x}_D - 3S_D$

where:
$\bar{x}_D$ = Average Distance
S_D = Standard Deviation

A control chart has central average line, an upper control limit line, and a lower control limit line. Depending upon the quality characteristics, various control charts like x-bar, R chart, S chart are used.

3.3 Model Design and Implementation

A motion capture dataset containing a series of motion has been studied. These datasets are created from a guide of movements, which are executed in increasing complexity. The complexity has been defined from the number of changes in directions in a continuous movement.

Multivariate time series and dtw algorithm

A multivariate time series analysis is used to model and explain the interactions and co-movements among a group of time series variables. The analysis involves examining three or more variables. In this research, the motions are 3-dimensional which varies over time; hence, it is a multivariate time series. When dealing with the multivariate time series, the actual time series value only enters the dtw algorithm through their cross-distance matrix, given as:

$$\boldsymbol{d(i,j) = f(x_i, y_j) \geq 0}$$

where:
$d(i, j)$ = cross-distance matrix
x_i, y_j = any pair of elements
f = local distance function

From the equation, the choice for the local distance function influences how strongly the alignment will avoid the mismatching regions. There are a variety of dissimilarity functions f available, e.g., the Euclidean distance, the squared Euclidean distance, Manhattan, and many others. Among them, the Euclidean distance is the commonly used [50].

To analyze the multivariate time series, the dtw is provided with two matrices X_{ic} and Y_{jc}, where i and j are time indices given by, $i = 1 \ldots N$ and $j = 1 \ldots M$, arranged in rows, whereas the multivariate dimensions, $c = 1 \ldots C$ are arranged in columns. The dtw assumes an Euclidean local distance by default, i.e.,

$$\boldsymbol{d(i,j)^2 = \sum_{c=1}^{C} (X_{ic} - Y_{jc})^2}$$

where:

$d(i, j)$ = cross-distance matrix

X_{ic}, Y_{jc} = two matrices

c = multivariate dimensions

The dynamic time warping gives an optimal alignment between the given time-dependent sequences. It pairs the points of the n-dimensional space and compares them to each other, and the one that has the minimum distance with a similar warping curve gives an optimal alignment.

3.4 Model Development, Verification, and Validation

A model is developed based on an experiment which has complex motions with number of changes in direction during continuous movement.

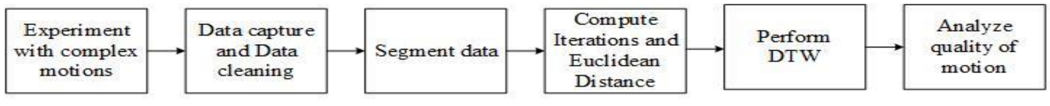


Figure 1: Model Process Flow

3.4.1 Data Capture and Data Cleaning

The data obtained from the motion capture are saved in .C3D format. This standard binary file format is a public domain which is used to record synchronized 3D and analog data and is mostly supported by all major 3D motion capture system. The captured 3D data will be analyzed, cleaned, and subjected to segmentation.

3.4.2 Segmentation Process

The motions are segmented into each individual motion in order to analyze multiple repetitions and to align its corresponding time series. Successful analysis of multiple repetitions depends on identifying those movements. The segmentation of time series data for each movement depends on identification of initial and the destination markers. The alignment of the time series depends on the segmentation of movements. The captured 3D data are segmented using R Studio software.

The data obtained through segmentation consists of a repeating group of time series for each frame. The time series consists of point coordinates (spatial data) along a predefined path with identified start and stop locations. For each subject, a continuum of multiple repetitions of data is collected. The multiple repetitions in the data set can be identified by the index. This index denotes the unique iteration for each segmented movement that can be analyzed.

The identification of segments requires identifying the start and end points for each segment. These are denoted as OUT and IN events. The OUT events signify the beginning of a segment and the IN event signifies the end of a segment. The proper sequence will be OUT-to-IN, IN-to-OUT which signifies time within the sphere of proximity. The OUT and IN points are captured by a distinct change in direction within a specified origination area and a distinct change in direction occurring within the destination area. Thus, a specific motion can be measured from the distinct change in direction [21].

Once the origination and destination points are identified, the segments are checked for proper event patterns and the out of sequence events are removed. At the end, the segment files are generated and are defined by the first and last fixed-point identifiers.

The segments are generated based on the IN and OUT event of the fixed marker that comes within the radius and, each motion segments represents an individual motion captured during the experiment. It is noted that the maximum number of segmentations can be obtained with minimum event point radius value. The R statistical software is used for the data analysis. The segmented data will contain the 3d-coordinates and index for each frame which will act as the iteration.

3.4.3 Computing Dynamic Time Warping Distance

From the data obtained through segmentation, the Euclidean distances for each iteration for the selected markers are computed based on the Euclidean distance equation discussed earlier. Each iteration and its corresponding Euclidean distance correspond to a vector which will form the matrix vector (*m.v*) given as,

$$d(m.v) = \begin{bmatrix} V_1 & \cdots & V_n \\ \vdots & \ddots & \vdots \\ V_n & \cdots & \end{bmatrix}$$

where:

$\boldsymbol{V_1} \ldots \boldsymbol{V_n}$ = Motion Vector

n = Iteration

The motion vector compares them to each other to form the dtw matrix *d(m.v).* In this case, the vector V_1 is compared with all the other vectors to form a dtw matrix. Using the dtw technique, the degree of similarity between the movements can be determined. In general, the R statistical software allows to perform time series calculations using DTW method and Euclidean Distance. For this research, DTW method was used as it allows many-to-one point comparisons, whereas the Euclidean Distance allow only point-to-point distance comparison. From the behavior of the motion pattern, the quality of the motion can be determined.

3.4.4 Analyze quality of motion

The quality of motion can be determined by generating a quality control chart (qcc) as discussed in Chapter 3.2. The qcc chart is generated from the motion vectors obtained through DTW technique. This chart provides information on the motions with good and bad runs with respect to their iteration. A motion is said to be bad if the point in the qcc chart lies outside the control limits. A bad motion occurs whenever the operator deviates from the regular motion. The deviation is captured in the control chart whenever there is a huge variation in the distance between the fixed and the destination markers i.e., when the fixed marker on the operator goes beyond the fixed radius point. These variations are captured in the qcc chart as points beyond the control limits. The respective iterations of the beyond value points are cross-checked with the respective frame on the Qualisys Track Manager software to determine the wrong motion. Once the bad moves are verified, the data for the respective beyond limit points are removed from the qcc chart. This process is repeated until all the iterations lie within the control limits.

3.4.5 Test for special causes

The test for special causes are used to analyze whether the plotted points are randomly distributed within the control limits and to identify specific patterns and trends in the data. Each test detects specific pattern which gives a different aspect of process reliability.

There are eight tests available with the control chart. These are,

Test 1: One point more than 3-sigma from center line – Identifies subgroups that are unusual compared to other subgroups.

Test 2: Nine points in a row on the same side of the center line – Identifies shifts in the process centering or variation.

Test 3: Six points in a row, all increasing or all decreasing – This test detects trends that consistently increase or decrease in value.

Test 4: Fourteen points in a row, alternating up and down – This test detects systematic variation.

Test 5: Two out of three points more than 2-sigma from the center line (same side) – This test detects small shifts in the process.

Test 6: Four out of five points more than 1-sigma from center line (same side) – This test detects small shift in the process.

Test 7: Fifteen points in a row within 1-sigma of center line (either side) – This test detects a pattern of variation that is sometimes mistaken as evidence of good control.

Test 8: Eight points in a row more than 1-sigma from center line (either side) – This test detects a mixture pattern.

IV. EXPERIMENT

4.1 Fundamental skill moves

Ten fundamental skill moves related to manual material handling are shown in Table 1. There are five factors that affects these fundamental skill moves: 1) weight of the material; 2) position of the load; 3) rate of work, 4) duration of task, and 5) grip capability. The NIOSH Work Practices Guide provides recommendation and directions on performing these fundamental skill moves to be ergonomically safe. The methodology proposed in this research will be tested only in lifting. Lifting is one of the most effort-intensive moves and the primary cause for back injuries [51].

Table 1:Basic fundamental skill moves for manual material handling with NIOSH guidelines for performing the skill moves

<table>
<tr><th>Fundamental Skill Moves</th><th>Guide for performing the skill moves</th></tr>
<tr><td>Back Lifting</td><td rowspan="2">i. Lifting should be smooth, with no sudden acceleration effects.
ii. Objects to be lifted should be of moderate width, with a hand separation of less than 75cm.
iii. Lifting postures should be unrestricted, with no bracing of the torso.
iv. Couplings should be good. Handholds should be secure and the shoe-floor slippage potential low.
v. Temperatures should be favorable to lifting. [15]</td></tr>
<tr><td>Leg Lifting</td></tr>
<tr><td>Pulling (shoulder height)</td><td rowspan="2">i. Lifting should be smooth, with no sudden acceleration effects.
ii. Push/pull force capability is related to shoe/floor friction, with greater friction allowing subjects to achieve more leaning forward or backward to create the desired push or pull force.
iii. Persons with large reach and high body weight can achieve high push/pull force capability if also provided with high-traction surfaces and enough space to lean appropriately.</td></tr>
<tr><td>Pulling (elbow height)</td></tr>
</table>

Table 1: Continued.

Pushing (shoulder height)	iv. Push/pull capability is highest when the point of application of force is between shoulder and hip heights. [52]
Pushing (elbow height)	

Data collection method

The data collection is based on a Mocap master capture plan, which is based on the Snook's table for the design of manual handling tasks [16]. The table provides data for maximum acceptable weight of lift for male and female for various parameters. Based on these parameters, the experiment is performed to obtain the motion capture data.

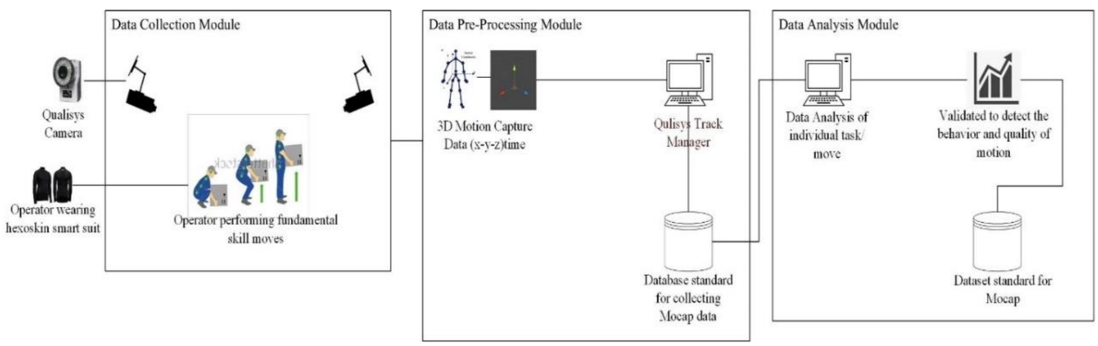


Figure 2:MOCAP Framework

Data collection module

The data collection module consists of fleet of nine Qualisys infrared cameras, which captures the operator's motions. The Oqus 510 (5+ series) and Miqus M3 cameras are used with capture rate of 10000 frames per second. The physical attributes of the operator like height, reach distance, age, etc. are taken into consideration. The experiment space is calibrated for all the nine cameras to capture within the designated bounding box. The operator will then perform the fundamental skill move for each factor levels.

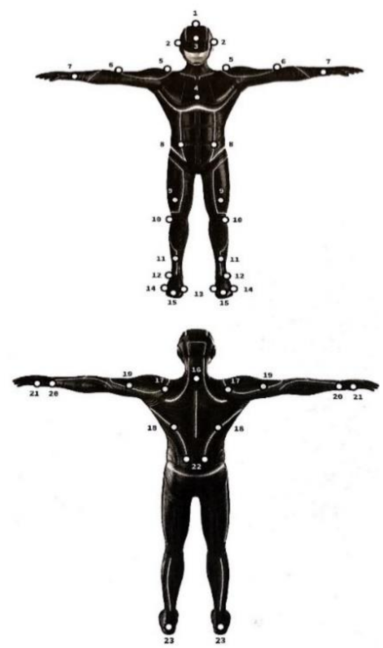


Figure 3: Position of markers (front & back)

The camera captures each move of the operator with the help of markers attached to different positions on the operator’s body (see Fig.1 for a map of sensor locations). The cameras will be synchronized and placed at different angles. Each camera captures the operator’s movement from various angles, thus improving the motion capture accuracy. Qualisys Track Manager (QTM) is then used to convert the captured data into real-time 3d coordinates.

Data pre-processing module

The data collection module produces a dataset containing the 3d coordinates of the markers attached to different positions in the human body. In the data pre-processing stage, the captured motion data are transferred to the Qualisys Track Manager [53] to generate a real-time 3D coordinate as a function of time. Each body part of the generated 3d human model are assigned a name for easy identification during the time of analysis. The obtained data are then cleaned and stored in a database which will later act as a standard for analyzing the Mocap data.

Data Analysis Module

From the data stored in the database from the pre-processing stage, each skill move/ motion data obtained is chosen individually for analysis.

The motion capture data obtained from the fundamental skill move are used to derive segments of motion for the particular skill task. The segmenting of motion helps in analyzing each individual motion from the task and gives the number of iterations. Using the 3d coordinates, the Euclidean distance for each iteration are obtained. The Euclidean distance is given as:

$$\boldsymbol{D} = \sqrt{(\boldsymbol{x_2} - \boldsymbol{x_1})^2 + (\boldsymbol{y_2} - \boldsymbol{y_1})^2 + (\boldsymbol{z_2} - \boldsymbol{z_1})^2}$$

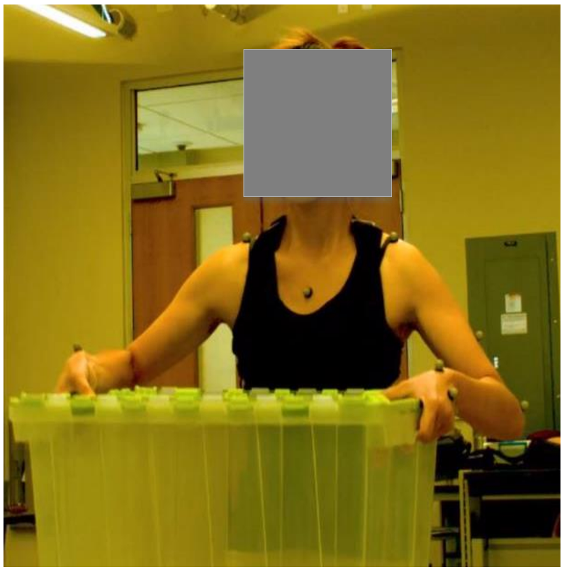
where:
x, y, z = 3d-coordinates
D = Euclidean Distance

Once the Euclidean distance is computed, a vector of motion is created for the Euclidean distance of each iteration. This vector of motion is used as an input to the Dynamic Time Warping (DTW) algorithm, as it is explained below. Vector X is the time series representing the first segment in the series of repetitive motions, which is taken as a baseline move in the analysis. Vector Y is the time series for the segment to be analyzed by the algorithm. Note that each segment is analyzed one at a time.

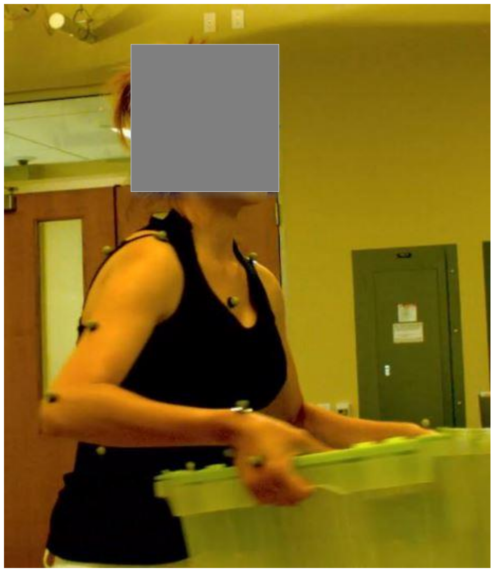
Performing the Lifting task

A lifting experiment is designed to analyze the behavior of the motion along the time series. The experiment is based on the number of factors and factor levels, which are discussed later in the design of experiments section. Two types of lifting motions are performed for a detailed analysis of the quality of the motion.

1. Normal lifting task with respect to the different factors and factor levels.
2. Normal lifting task with respect to the different factors and factor levels, but with an induced intentional wrong motion to further analyze the quality of the motion.



Normal lifting task



Lifting task with intentional wrong motion

Figure 4: Normal lift vs Wrong lift

4.2 Design of Experiments

Based on the Mocap master capture plan, a 2^2 factorial is created for 50% of the population with respect to their factor levels.

Table 2: Factors and Levels

Factor	Levels	Number of levels
Gender	Male, Female	2
Interval	9 seconds, 14 seconds	2

Based on the interval, the amount of weight (kg) to be lifted and the vertical distance (cm) are determined. The detailed experimental plan is built based on the following factors

Table 3: MoCap experiment plan

Subject	Gender: Male and Female
	Height: Short, Medium, and Tall (Based on medium equal to 1st standard deviation of human height for male and female)
Experiment	Range: Floor-to-Knuckle; Knuckle-to-Shoulder; Shoulder-to-Arm length
	% industry: % of industry capability
	Height: Vertical height in centimeters
	Weight: Amount of weight moved in kilograms.
	Interval: Cycle time for the experiment is seconds.

Based on the percentage of industrial population, the maximum weight limit is determined. The weight to be lifted also varies depending upon the gender. Based on the factors and factor levels, the data from the following experimental plan will be analyzed.

Table 4: Mocap Leg Lift Master Capture Plan

Subject	Experiment					
Gender	Height	Range	% Industry	Weight (kg)	Height (cm)	Interval (sec)
Female	Short	Floor- Knuckle	50	15	25	9
Female	Short	Floor- Knuckle	50	13	51	9
Female	Short	Floor- Knuckle	50	12	76	9
Female	Short	Floor- Knuckle	50	16	25	14
Female	Short	Floor- Knuckle	50	14	51	14
Female	Short	Floor- Knuckle	50	13	76	14
Male	Medium	Floor- Knuckle	50	24	25	9
Male	Medium	Floor- Knuckle	50	20	51	9
Male	Medium	Floor- Knuckle	50	19	76	9
Male	Medium	Floor- Knuckle	50	28	25	14
Male	Medium	Floor- Knuckle	50	24	51	14
Male	Medium	Floor- Knuckle	50	22	76	14

The selection of the factors and factor levels are based on the Hazard Analysis Tool generally called as the Snook Tables. The tables are based on controlled experiments using psychophysical evaluation, and can be used to determine the acceptable weight limits for activities like pull, push, and carry for male and female. Based on the percentage of industry population that can perform these tasks for an interval of time, the weights are determined.

The guidelines for lifting based on the Snook Table are:

- Select width of object (outward from body) in the table close to that encountered in the task
- Select closest distance of lift.
- Select the lifting range (floor-to-knuckle, knuckle-to-shoulder, shoulder-to-arm reach).
- Select the gender of the worker.

- Find closest weight in the table corresponding to width, distance, range, gender, and interval.
- Select the corresponding percent of population who can perform the task without stress.

Based on the input from Snook Table, the floor-to-knuckle range was selected. This range was selected particularly for the positional set up of the destination markers. The experiment is designed based on the 50% of the industry population that can lift the weight from floor-to-knuckle height at different intervals. The interval between each lift determines the weight to be carried which varies for male and female.

V. RESULTS

In this chapter, the results of the development model, verification model, and validation model will be discussed. Initially, a base model is developed from the existing data set with complex motion (not lifting task) to study the quality of the motion. In the verification model, the lifting experiment is performed with the 2^2 factorial. From the data set, dynamic time warping is performed, and a quality control chart is built to analyze the quality of the motion. The third phase is the validation model, which has the lifting task performed with the induced intentional wrong motion.

5.1 Model Development: Computing the quality of the motion

As discussed from the previous chapter, a base model is built for a repetitive right-arm movement, for a right-handed person. The analysis for the development model involves the movements of the markers attached to the right elbow (one marker), right wrist (one marker), and right shoulder (one marker). The objective of building a base model is to analyze how statistical process control methods can be used to evaluate the behavior of the motion along the time series for an operator.

The data analysis is performed using the dynamic time warping technique and the quality of the motion can be analyzed through generating a quality control chart (qcc). The qcc chart performs the statistical quality control for the dtw matrix *d(m.v).* The qcc.groups function was used to group dtw data to use as input to the qcc function. This function uses the observed data values and the sample indicators for the data values to return a matrix of suitable dimensions [54].

5.1.1 Computing the quality of the motion for elbow

An x-bar chart has been plotted to study the behavior of the motion along the time series. The x –bar chart is used since it gives the means of a continuous process variable. At the y-axis, the group summary statistics gives the dynamic time warping distances obtained from the motion vector matrix. The x-axis is the iterations of motions obtained from segmentation. Through segmentation, a total of 58 iterations were obtained each representing the breakdown of motions performed. While building the qcc chart, these iterations are grouped to a sample size of three, which gives a total of 19 groups along the x-axis.

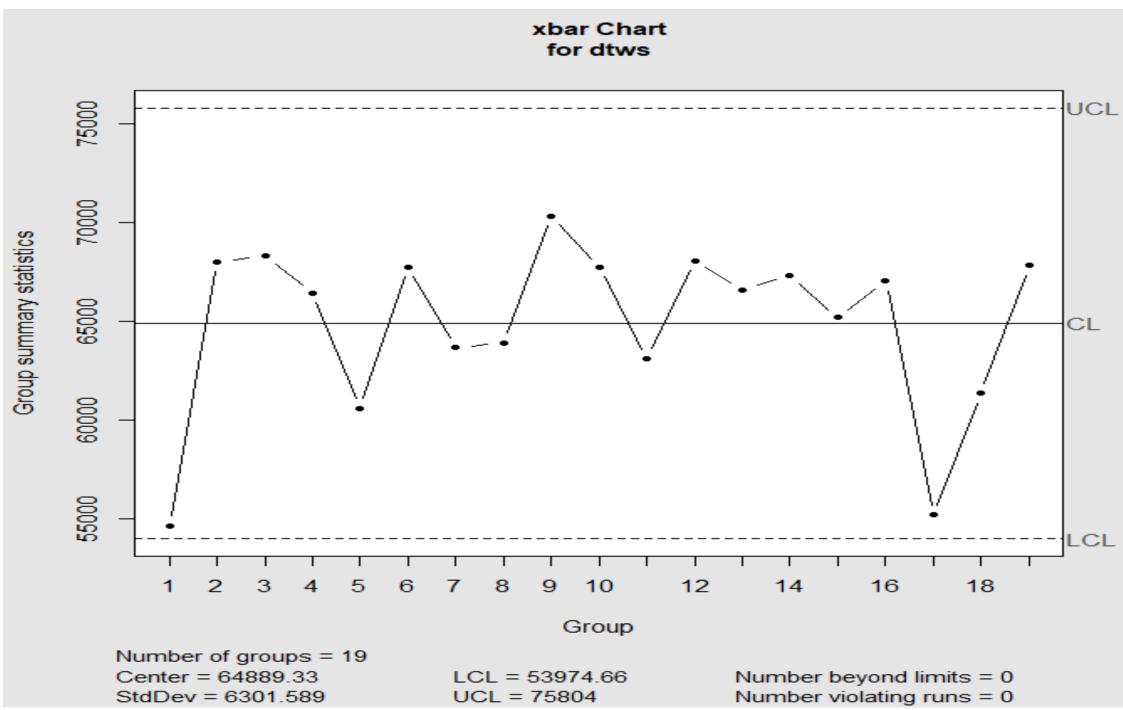


Figure 5: qcc plot for Elbow

The data obtained through x-bar chart are inferred in the table below.

Table 5: Statistics for elbow

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Elbow	64889.33	6301.589	53974.66	75804	0	0

It is inferred from Table 5, that the average distance obtained from the dtw calculation is 64889.33 and a standard deviation of 6301.589. As discussed earlier, the quality control chart has 3-sigmas to use for computing control limits. From the graph that there are no groups whose mean value violates both the upper control limit and lower control limit which might act as a benchmark to identify the optimal motion for elbow movements. It is also inferred from the graph that from iteration 12 to iteration 16, there are four consecutive points on the same side above the control limit. According to the test for special causes discussed in Chapter 3, the control chart follows rule 6, which means that there is a small shift in the process is detected.

5.1.2 Computing the quality of the motion for wrist and shoulder

Similar to the elbow, a qcc plot is also generated for the right shoulder and right wrist. The summary of the data obtained for the respective markers are listed in Table below.

Table 6: Summary of Statistics

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Shoulder	17070.79	2046.477	13526.18	20615.39	0	0
Right Wrist	111128.2	10325.55	93243.85	129012.6	1	2

It is inferred from Table 6; the right shoulder follows the same pattern as right elbow with no violating runs and beyond limit points. In the case of right wrist, it is observed that there are two groups with violating runs and one group which is beyond limit. The point that is beyond the control limit infers that there are certain motions which are irregular and need to be investigated further.

5.1.3 Interpretation of LCL and UCL for all markers

The behavior of the chosen marker joints can be analyzed through the study of LCL and UCL.

Table 7: Interpretation of markers

Marker	UCL	LCL	Difference in LCL and UCL
Shoulder	20615.39	13526.18	7089.21
Elbow	75804	53974.66	21829.34
Wrist	129012.6	93243.85	35768.75

From Table 7, it is understood that the difference between UCL and LCL for elbow and wrist are significantly higher compared to the shoulder. Thus, it is inferred that the elbow and wrist perceive more movements compared to the shoulder, which is almost stationary or with less movement. Through this, further study can be made for the parts of the body with frequent motions.

5.2 Model Verification: Computing the quality of the motion

In the model verification phase, the quality of motion for an actual lifting task is analyzed. The lifting task is carried out with the help of guidelines for lifting from the Snook's table. For the model verification, the data set of a female subject carrying 14 kilograms at 14 seconds interval is selected for analysis. After dtw is performed, the qcc chart is built for computing the motion behavior.

5.2.1 Computing the quality of the motion for right elbow

Similar to the development model, an x-bar chart was generated from the dtw distance matrix to analyze the motion quality. The y-axis carries the dtw distance and the x-axis carries the number of iterations in groups.

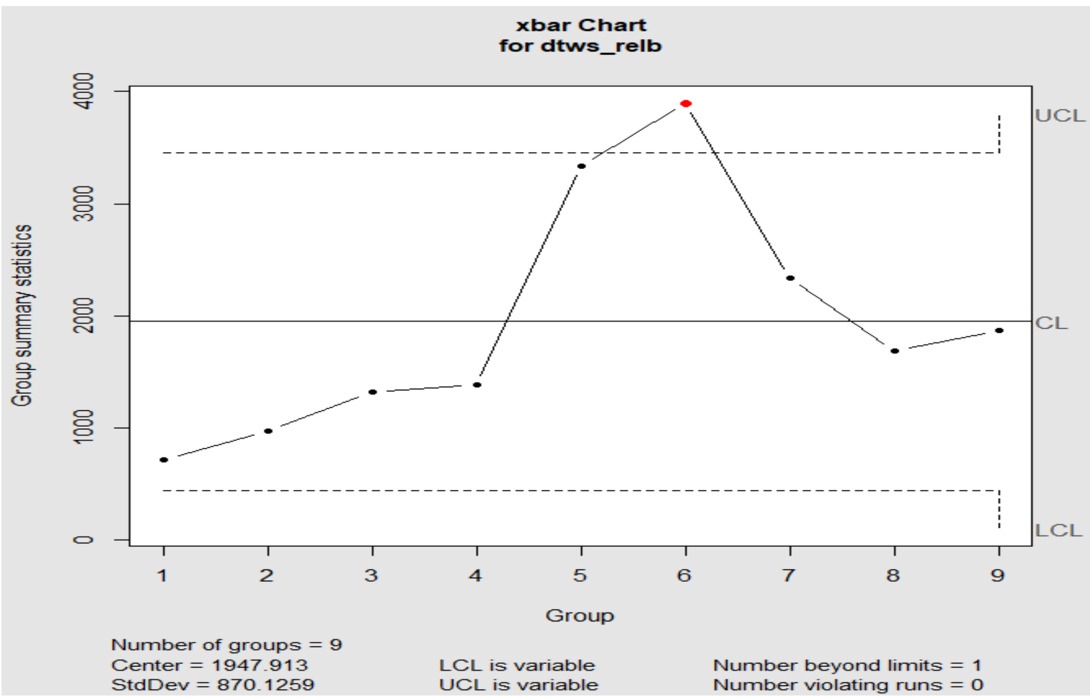


Figure 6: qcc plot for right elbow

It is inferred from the x-bar chart that the groups from 1 to 4 follows an increasing trend along the time series. This follows the rule 6 of the test for special causes which implies that there is a small shift in the process is detected. The chart has one group that lies beyond the upper control limit. The data obtained from the x-bar chart are given in the table below

Table 8: Summary of statistics for right elbow

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Elbow	1947.913	870.1259	440.8105	3455.015	1	0

From Table 8, the average dtw distance calculated is 1947.913. By default, the qcc chart take 3-sigmas to use for computing control limits. The point that is beyond the control limit is further investigated by comparing the motion data (c3d file) to their respective iterations and frame number. In this experiment, it should be noted that we take the radius in 100mm, so even a small deviation from the normal motion, for example as low as 3cms, will be very sensitive in the system. By eliminating the point beyond the limit and recomputing the qc chart, the following chart is obtained:

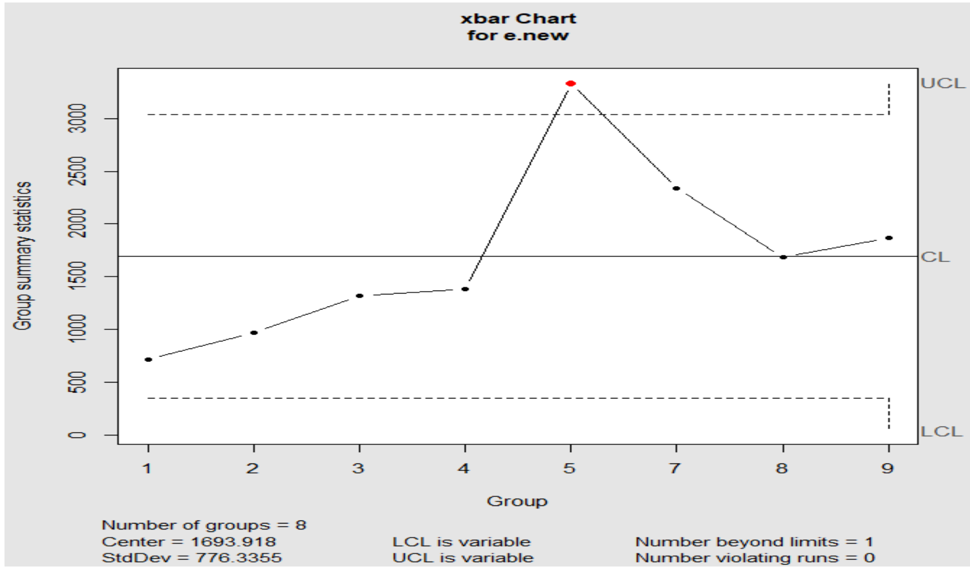


Figure 7: qcc plot of right elbow after recomputing

The new data obtained after recomputing the points are

Table 9: Summary of statistics of right elbow after recomputing

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Elbow after recomputing	1693.918	776.3355	349.2653	3038.57	1	0

From the x-bar chart after recomputing, the average dtw distance now is 1639.918. Also, the UCL and the LCL is recalculated again based on the new group size. Even after recomputing, there is still a group that lies beyond the upper control limit. Therefore, the particular group is investigated further to determine the cause of the irregularity. Recomputing of the qcc is performed until all the points lie between the control limits.

By recomputing the qcc once again to eliminate the point beyond the limit, the following plot is obtained.

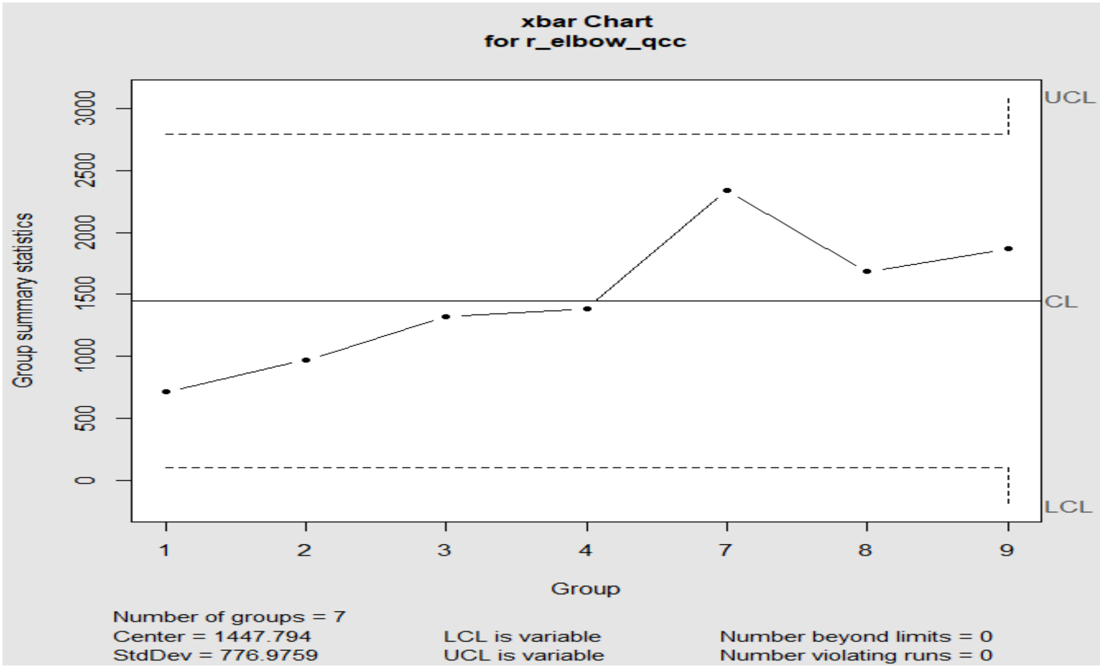


Figure 8: qcc plot of right elbow after final computing

The data obtained after recomputing the qcc are shown in Table 10

Table 10: Summary of Statistics of right elbow after final computing

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Elbow after recomputing	1447.794	776.9759	102.0318	2793.555	0	0

The x-bar chart recomputed again has the average dtw distance of 1447.794. The control limits were also recalculated based on the new group size. From Fig.8, the recomputed qc chart with no violating runs and beyond limits are obtained. This gives a series of motions performed with no irregular or wrong movements.

5.2.2 Computing the quality of the motion for different markers

Similar to the right elbow, a qcc plot is also generated for the right wrist, left elbow, and left wrist. The summary of the statistics obtained for each marker are given in Table 11.

Table 11: Summary of statistics for different markers

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Left Elbow	3877.735	1557.675	1179.763	6575.707	6	0
Right Wrist	1259.891	727.8929	-0.8560632	2520.639	1	0
Left Wrist	1907.069	785.6106	546.3511	3267.786	2	0

From Table 11, all the markers that were analyzed has points beyond the control limits. Similar to the analysis performed for the right elbow, further investigation was performed on the points that were beyond control limits.

Recomputing the beyond limits

All the markers were investigated for the possible cause for the beyond limit points by manually cross-verifying the 3d motion with their respective iteration and frame. The recomputed summary of the statistics generated by the x-bar chart is given in Table 12.

Table 12: Summary of statistics of different markers after recomputing

Marker (recomputed)	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Left Elbow	598.0153	92.20051	438.3194	757.7113	0	0
Right Wrist	1033.501	651.4396	-94.8251	2161.828	0	0
Left Wrist	925.2046	594.5034	-104.5055	1954.915	0	0

5.3 Model Validation: Computing the quality of the motion

In this model, the lifting task is validated by manually inducing an irregular motion in between the normal lifting experiment. For the validation, an experimental data set of a female subject carrying 13 kilograms at 9 seconds interval is analyzed. The wrong motion is induced randomly between the usual lifting task as shown in Fig 4. For validation, the subject's right elbow is chosen for the analysis.

5.3.1 Computing the quality of the motion for right elbow

From the raw data, the data is segmented with respect to start and end frame and their respective iterations are computed. Once the dynamic time warping is performed from the segmented data, the qcc plot is generated.

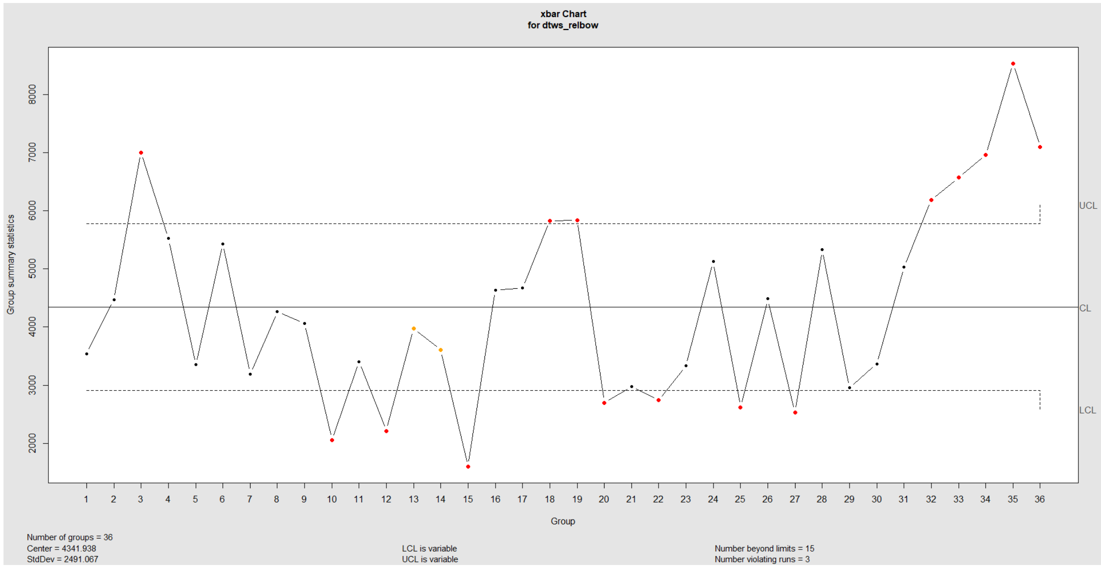


Figure 9: qcc plot for right elbow with induced wrong motion

From the x-bar chart, it is inferred that there are lot of groups lie beyond the control limits. By investigating the points beyond the control limits, it is concluded that those points represent the induced wrong motions between the experiments. It is observed from the iteration 32 to iteration 36, that the process follows the universally recognized test, rule 1, which detects the out of control points. Thus, the system can detect whenever a wrong motion is performed by the operator.

Table 13: Summary of statistics for right elbow with induced wrong motion

Marker	Center	Std.Dev	LCL	UCL	Number of beyond limits	Number of violating runs
Right Elbow	4341.938	2491.067	2903.72	5780.156	15	3

From Table 13, it is observed that the average dtw distance obtained is 4341.938. From the analysis result, the points lying beyond the control limits not only define the wrongly induced motions but also the other irregular movement of the subject during the experiment. From the validation model, two important key points are learned:

1. The system can detect the irregular motions of the subject performed during a manual lifting task.
    - From the analysis of the control chart, the points that are between the control limits are generally considered as good motions. These good moves are further analyzed through the trend followed by the iterations along the time series. By applying special causes test, the good motions are further investigated for the change in variability along the time series. This further improves the motion of the operator.
2. By detecting the wrong motions, the risk of injuries occurring during manual material handling task can be prevented.
    - It has been proved from the research results, that the system can detect bad motions whenever an operator deviates from the regular lifting. The bad moves are further investigated to find the degree of injury it can cause to an operator. This will help in building a standardized work instruction which will prevent the operator from performing those motions, thus preventing related injuries.

5.4 Managerial Implications

This empirical research on using motion capture technique to build a framework and analyze the quality of motion of an operator performing manual material handling task contribute to the safety of the workers in a manual material handling industry. Since this is a thinly researched area, especially in the field of manual material handling, the findings from this research are expected to be fruitful, both for management perspective as well as for industry. Following are the managerial implications of this study:

Opportunities:

1. This research offers and test a conceptual model of a manual lifting task related to manual material handling environment. It provides a framework to researchers, industry personnel to explore the factors causing injuries to the operator while performing the manual material handling task that are significance in the MMH and manufacturing industry.
2. This research contributes by developing a reliable process to analyze irregular motions performed by the operator during manual lifting of heavy objects and thus offers researchers and industry personnel a research tool that can be used for future research.
3. The research highlights the importance of certain demographic factors like age, gender, height, and other factors including weight of the object, height of the table, interval between each lift and the impact of these factors in identifying the acceptable manual material handling tasks that can be performed by an operator in the MMH environment.

Challenges:

1. It was observed from the research that it was difficult to train an inexperienced subject to perform the manual material handling task, hence further standard instructions are needed to perform the manual material handling tasks.
2. The cost of the experiment equipment was found to be costlier. Also, the experiment conducted for the research needed a lot of space requirements.

3. Since the research was based on a specific sample size, it might have suffered from certain limitations. The results may have been more generalizable had a bigger sample been taken.

VI. CONCLUSION AND FUTURE WORK

In this research, a manual material handling framework was developed to assess the manual lifting tasks in a MMH environment. The dynamic time warping technique, as discussed in Chapter 3, was used to assess the similarities between the motions performed during the manual lifting task. To further analyze the quality of the motion, a quality control chart was built to study the behavior of the motion along the time series.

The motion capture framework consists of three modules:

- Data Collection Module
- Data Pre-Processing Module
- Data Analysis Module

The data collection module was based on the Snook's table for the maximum acceptable weight limit for men and women. The experiment is configured based on the Snook's table. Through data pre-processing module, the collected motion capture data is converted into 3d-coordinates. The data is cleaned and further used for analysis. At the data analysis module, the collected 3d-coordinate data is subjected to segmentation to identify each motion and its iteration. The segmented data is used to perform dynamic time warping to obtain the motion vector for each iteration. Further, quality control chart is used to analyze the quality of the motion.

The framework for analysis is built by performing data analysis on a test data, which is the development model, as discussed in Chapter 5. A model was developed from an existing data set to study the quality of the motion using the quality control chart. From the base model, further analysis for the manual lifting task was developed.

A verification model was built from the dataset obtained by performing manual lifting task. Since the distance between the placement of the markers and sensors are very minimal, even with a small deviation in motion gives a large variation, which can be inferred from the quality control chart. By further investigating the outer limit points and eliminating them, the motions that are relatively close to each other can be obtained from the control chart.

In the validation model, it is important to verify if the algorithm detects any irregular motion. In order to verify, an intentional wrong motion was induced in a usual lifting task. The motion that was performed intentionally with wrong motion should be detected by the system and indicate in the quality control chart. After the analysis, the qc chart provided the plot with all the intentional wrong motion beyond the control limit, thus validating the algorithm used.

Limitations

- Though the proposed framework can identify irregular motions in an operator, we cannot conclude that the good motions are the optimal motions since the experiments are performed by students who do not have an experience in the manual material handling environment.
- The proposed framework is currently only capable of providing a benchmark for what we call as an optimal motion, but not declaring that the obtained good motions are the optimal motion.
- The experiments are limited by the number of cameras that has been used. The position of the camera used for the experiment may even miss out a

certain movements of body parts when the subject performed the lifting task.

- The experiments are also limited by the sample size of the subject used. The results obtained are experiments conducted for female of certain height and age. More accurate representation of the results may have been generated if a bigger sample size has been taken.

Future Work

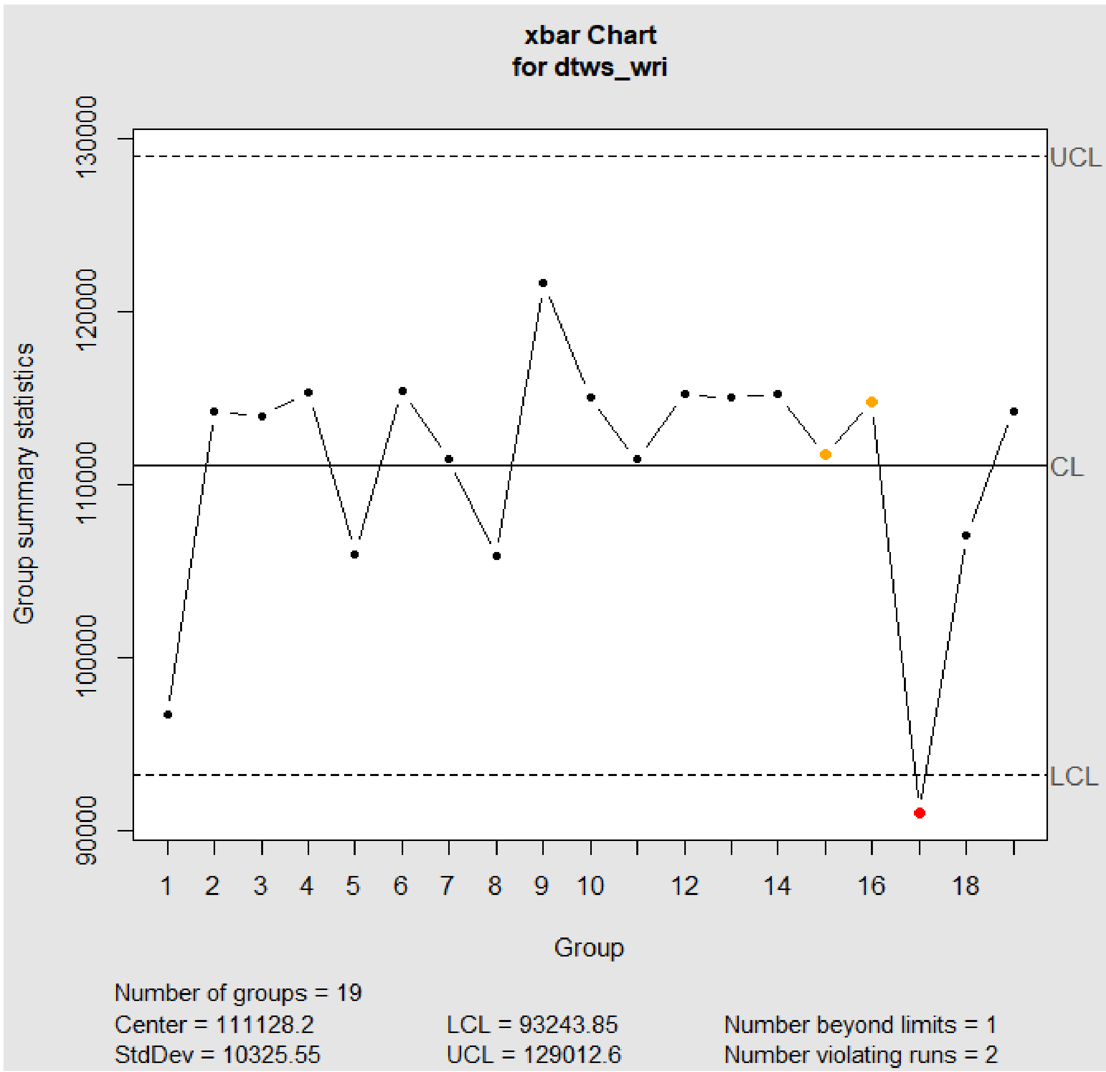
This research provides a framework to analyze the fundamental skill moves in a manual material handling industry. The future research will be performed with the help of the experienced manual material handling operators. From the data obtained, an optimal motion for performing a manual material handling task will be identified. This research has not taken consideration of any biometric data of the subject like heart rate, respiratory rate, etc. With the help of a biometric suit, the data for heart rate, respiratory rate, acceleration can also be calculated which will give a wide range of scope for further improvements in the operator's motion. The future research can also make use of augmented reality to analyze the operator's motion with few cameras from which various metrics of the subject can be obtained and used for analysis.

The results of the research will help in analyze the operator's fatigue, energy expenditure, and many other ergonomic factors as well depending on the interest of the future researchers. The results of the research can be combined with digital twin technology to bridge the physical and virtual environment and allows analysis of data virtually beforehand. Also, with the advancement in augmented reality in manual material handling industry, the operator can physically monitor the heart rate, respiratory rate, and many biometric factors in real time while performing the operation. As mentioned before, the results will help future researchers to further develop the methodologies through various IoT systems that will improve the quality of the manual material handling environment.

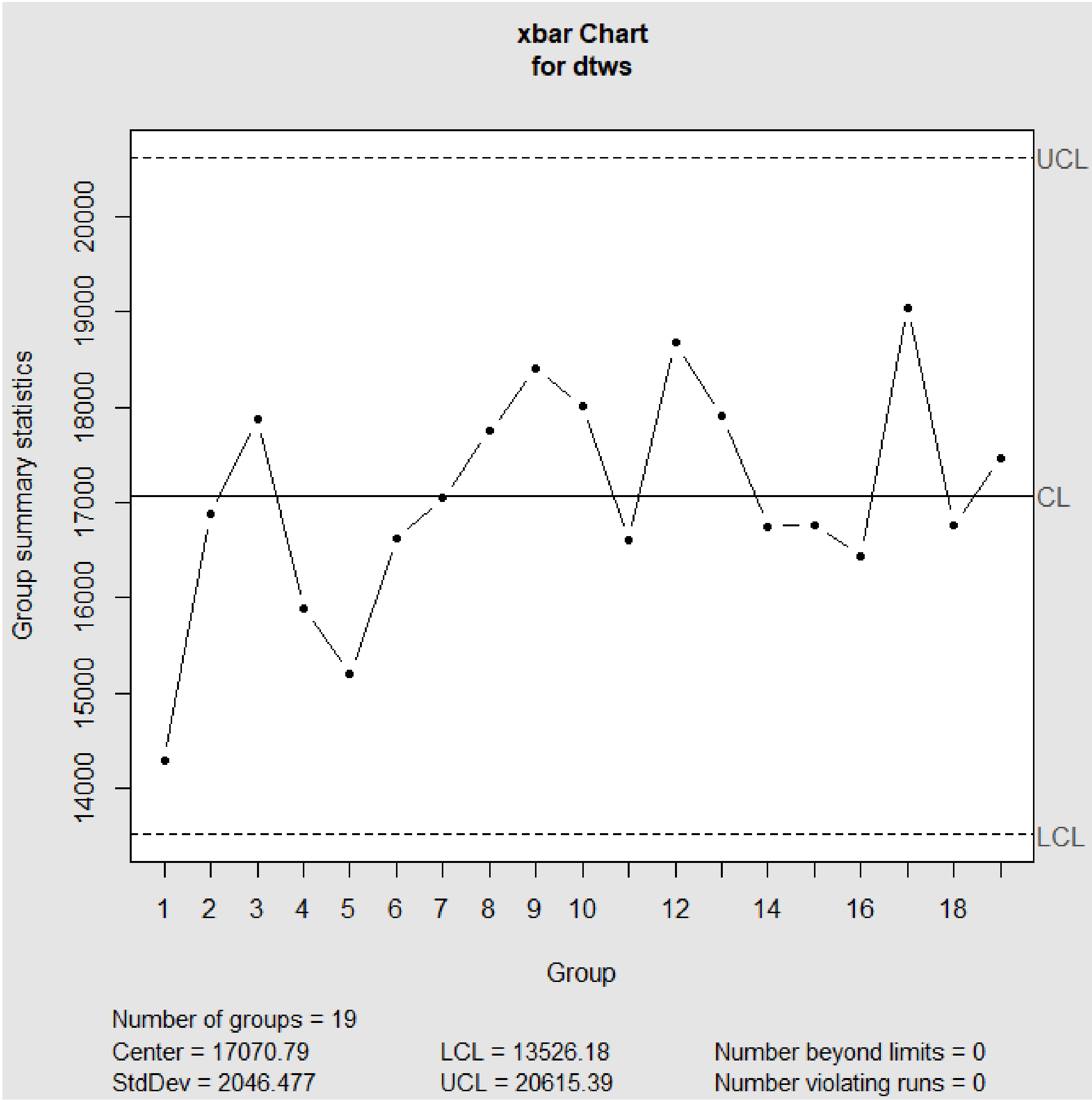
APPENDIX SECTION

Quality Control Chart for model development phase

Qcc plot for Right Wrist

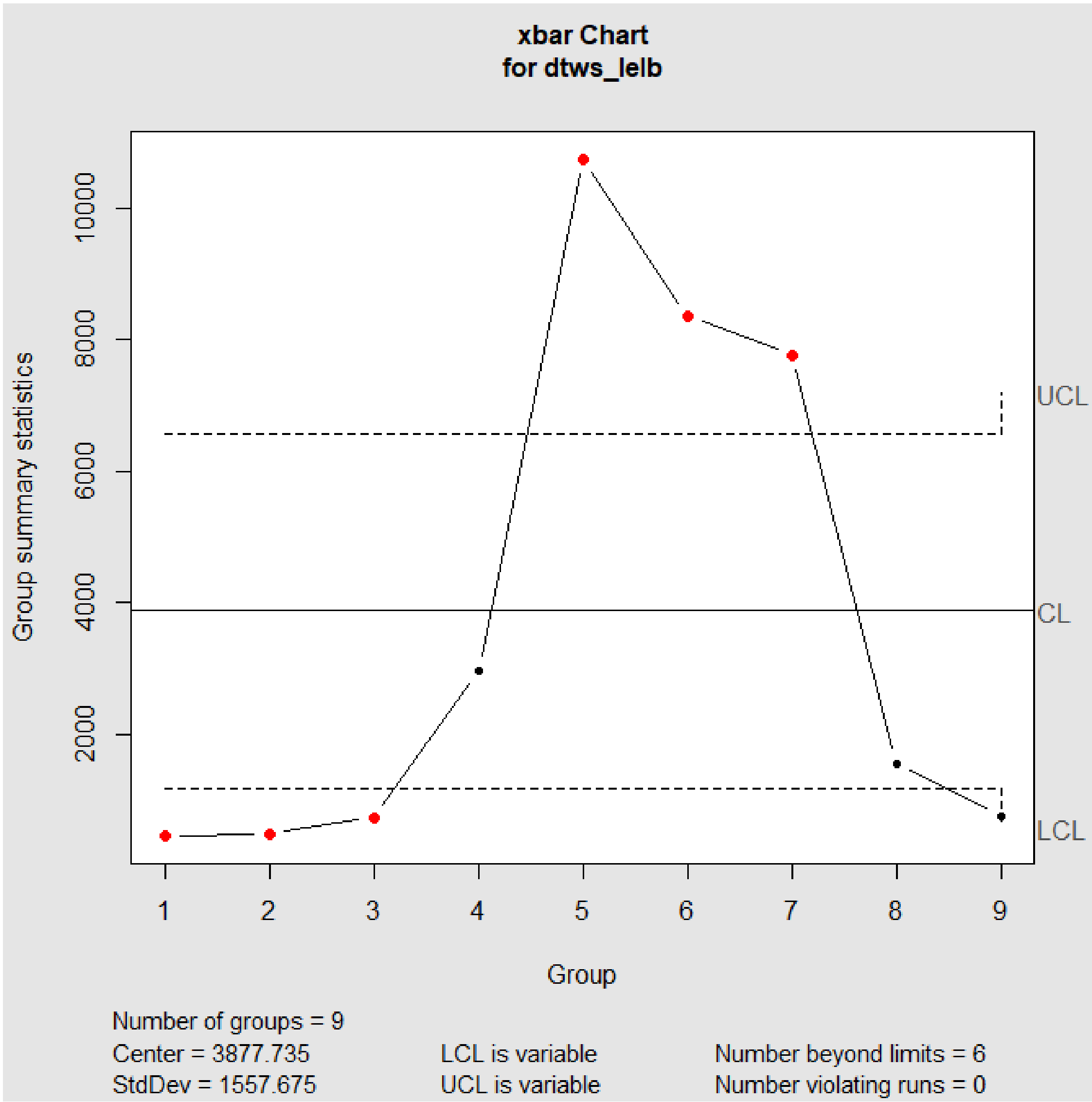


Qcc plot for Right Shoulder

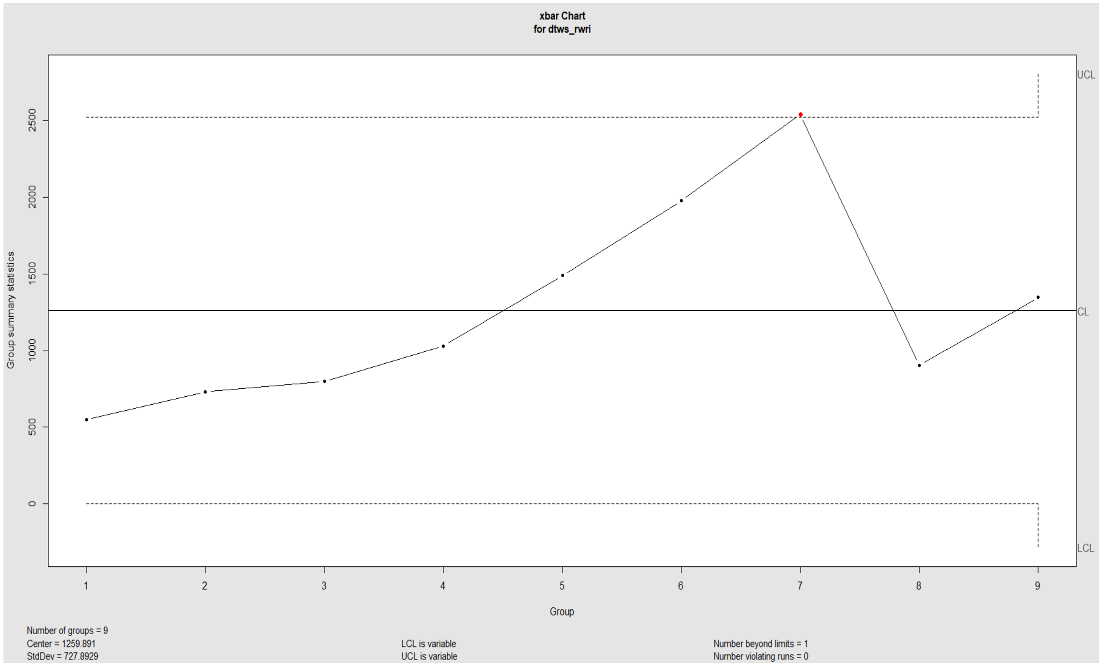


Quality Control Chart for verification phase

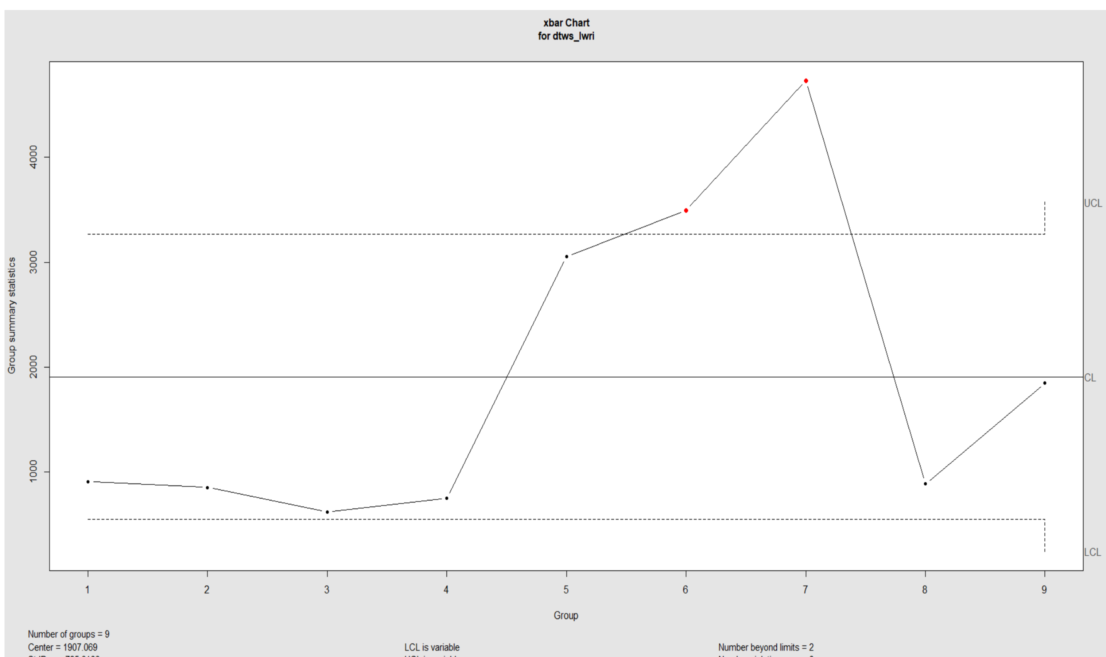
Qcc plot for left elbow



Qcc plot for right wrist



Qcc plot for left wrist



Snook's table for maximum acceptable weight limits for males

Maximum Acceptable Weight of Lift for Males (kg)

Width	Distance	Percent	Floor level to knuckle height One lift every								Knuckle height to shoulder height One lift every								Shoulder height to arm reach One lift every							
			5	9	14	1	2	5	30	8	5	9	14	1	2	5	30	8	5	9	14	1	2	5	30	8
			s			min				h	s			min				h	s			min				h
		90	*6*	7	9	11	13	14	14	17	8	10	12	13	14	14	16	17	6	8	9	10	10	11	12	13
		75	*9*	11	13	16	19	20	21	24	10	14	16	18	18	19	21	23	8	10	12	14	14	14	16	17
	76	50	*12*	*15*	17	22	25	27	28	32	13	17	20	22	23	24	26	29	10	13	15	17	17	18	20	22
		25	*15*	*18*	*21*	28	31	34	35	41	16	*21*	*24*	27	27	28	32	35	11	16	18	21	21	22	24	27
		10	*18*	*22*	*25*	33	37	40	41	48	*19*	*24*	*28*	31	32	33	37	40	*14*	18	21	24	24	25	28	31
		90	6	8	9	12	13	15	15	17	8	11	13	15	15	16	18	19	6	8	9	12	12	12	14	15
		75	*9*	11	13	17	19	21	22	25	11	15	17	20	20	21	23	25	8	11	12	15	15	16	18	20
75	51	50	*13*	15	18	23	26	28	29	34	14	19	21	25	25	26	29	32	10	14	16	19	20	20	23	25
		25	*16*	*19*	22	29	33	35	36	42	*17*	*23*	26	30	31	32	36	39	13	17	19	23	24	25	27	30
		10	*19*	*22*	*26*	34	38	42	43	50	*20*	*26*	*30*	35	36	37	41	45	*15*	19	22	27	27	29	32	35
		90	8	9	11	13	15	16	17	20	10	13	15	18	18	19	21	23	7	10	11	14	14	14	16	18
		75	*11*	13	15	19	22	24	24	28	13	17	20	23	24	25	27	30	10	13	15	18	18	19	21	23
	25	50	*15*	18	21	26	29	32	33	38	17	22	25	30	30	31	35	38	12	16	19	23	23	24	27	29
		25	*18*	*22*	26	33	37	40	41	48	*20*	*27*	*30*	36	36	38	42	46	15	20	22	28	28	29	32	35
		10	*22*	*26*	*31*	38	44	47	49	57	*23*	*31*	*35*	42	42	44	49	53	*17*	*23*	26	32	32	34	38	41
		90	7	8	10	13	15	16	17	20	8	10	12	13	14	14	16	17	7	9	10	12	12	13	14	16
		75	*10*	12	14	19	22	24	24	28	10	14	16	18	18	19	21	23	9	11	13	16	16	17	19	21
	76	50	*14*	*16*	19	26	29	32	33	38	13	17	20	22	23	24	26	29	11	15	17	20	21	21	24	26
		25	*17*	*20*	*24*	33	37	40	41	48	16	21	24	27	27	28	32	35	13	18	20	25	25	26	29	31
		10	*20*	*24*	*28*	38	43	47	48	57	*19*	*24*	*28*	31	32	33	37	40	*15*	*21*	23	28	29	30	33	36
		90	7	9	10	14	16	17	18	20	8	11	13	15	15	16	18	19	7	9	11	14	14	14	16	18
		75	10	13	15	20	23	25	25	30	11	15	17	20	20	21	23	25	9	12	14	18	18	19	21	23
49	51	50	*14*	17	20	27	30	33	34	40	14	19	21	25	25	26	29	32	12	15	18	23	23	24	27	29
		25	*18*	*21*	25	34	38	42	43	50	17	23	26	30	31	32	36	39	14	19	21	28	28	29	32	35
		10	*21*	*25*	*29*	40	45	49	50	59	*20*	*26*	*30*	35	36	37	41	45	*16*	*22*	25	32	32	34	37	41
		90	8	10	12	16	18	19	20	23	10	13	15	18	18	19	21	23	9	11	12	16	16	17	19	21
		75	12	15	17	23	26	28	29	33	13	17	20	23	24	25	27	30	11	14	16	21	21	22	25	27
	25	50	*16*	20	23	30	34	37	38	45	17	22	25	30	30	31	35	38	14	18	21	27	27	28	32	35
		25	*21*	*25*	29	38	43	47	48	56	*20*	*27*	30	36	36	38	42	46	16	22	25	33	33	34	38	42
		10	*24*	*29*	*34*	45	51	56	57	67	*23*	*31*	*35*	42	42	44	49	53	*19*	*25*	*29*	38	38	40	44	48
		90	8	10	11	15	17	19	19	23	8	11	13	15	15	16	18	19	8	10	12	14	14	15	16	18
		75	*12*	14	17	22	25	28	28	33	11	15	17	20	20	21	23	25	10	14	16	18	19	19	24	24
	76	50	*16*	*19*	22	30	34	37	38	44	14	19	21	25	25	26	29	32	13	17	20	23	24	25	27	30
		25	*20*	*24*	*28*	37	42	47	47	55	17	*23*	26	30	31	32	36	39	*16*	*21*	24	28	29	30	33	36
		10	*24*	*29*	*33*	44	50	54	56	65	*20*	*26*	*30*	35	36	37	41	45	*18*	*24*	*28*	33	33	34	38	42
		90	9	10	12	16	18	20	20	24	9	12	14	17	17	18	20	22	8	11	13	16	16	17	18	20
		75	*12*	15	18	23	26	28	29	34	12	16	18	22	23	23	26	29	11	14	17	21	21	22	24	26
34	51	50	*17*	20	24	31	35	38	39	46	15	20	23	28	29	30	33	36	14	18	21	26	27	28	31	34
		25	*21*	*25*	*30*	39	44	48	49	57	18	24	27	34	35	36	40	44	*17*	22	25	32	32	33	37	41
		10	*25*	*30*	*35*	46	52	57	58	68	*21*	*28*	*32*	40	40	42	46	51	*19*	*26*	*29*	37	37	39	43	47
		90	10	12	14	18	20	22	23	27	11	14	16	20	20	21	23	26	10	13	15	19	19	19	22	24
		75	*15*	18	21	26	30	32	33	38	14	18	21	26	27	28	31	34	13	17	20	24	25	26	29	31
	25	50	*20*	24	28	35	40	43	44	52	18	23	27	33	34	35	39	43	16	22	25	31	31	33	36	40
		25	*26*	*30*	*35*	44	50	54	55	65	*21*	*28*	32	40	41	42	47	52	*20*	*26*	*30*	37	38	39	44	46
		10	*29*	*35*	*41*	52	59	64	66	76	*25*	*33*	*37*	47	47	49	55	60	*23*	*30*	*35*	43	44	45	51	55

Note:
1. Width is dimension away from body in cm

2. Distance is vertical lift in cm

3. Percent pertains to industrial population

4. Italicized values exceed 8 hr physiological criteria

Snook, S. H. and Ciriello, V. M., The design of manual handling tasks: revised tables of maximum acceptable weights and forces, *Ergonomics*, 34, 9, 1991

Snook's table for maximum acceptable weight limits for female

Maximum Acceptable Weight of Lift for Females (kg)

Width	Distance	Percent	Floor level to knuckle height, One lift every: 5 s	9 s	14 s	1 min	2 min	5 min	30 min	8 h	Knuckle height to shoulder height, One lift every: 5 s	9 s	14 s	1 min	2 min	5 min	30 min	8 h	Shoulder height to arm reach, One lift every: 5 s	9 s	14 s	1 min	2 min	5 min	30 min	8 h
		90	*5*	6	7	7	8	8	9	12	5	6	7	9	9	9	10	12	4	5	5	6	7	7	7	8
		75	*7*	8	9	9	10	10	11	14	6	7	8	10	11	11	12	14	5	6	6	7	8	8	8	10
	76	50	*8*	10	10	11	12	12	13	17	7	8	9	11	12	12	13	16	6	7	7	8	9	9	10	11
		25	*9*	*11*	12	13	14	14	15	21	*8*	9	10	13	14	14	15	18	7	7	8	9	10	10	11	13
		10	*11*	*13*	*14*	14	15	16	17	23	*9*	10	11	14	15	15	17	20	7	8	9	10	11	11	12	14
		90	*6*	7	8	8	9	9	10	14	6	7	8	9	10	10	11	13	5	6	7	7	7	7	8	9
		75	*7*	*9*	9	10	11	11	13	17	7	8	9	11	12	12	13	15	6	7	8	8	9	9	9	11
75	51	50	*9*	*10*	11	12	13	14	15	21	*9*	9	11	13	14	14	15	17	7	8	9	9	10	10	11	13
		25	*10*	*12*	*13*	15	16	16	18	24	*10*	11	12	14	16	16	17	20	8	9	10	10	11	11	12	14
		10	*11*	*14*	*15*	17	18	18	20	27	*11*	12	14	16	17	17	19	22	*9*	10	11	12	13	13	14	16
		90	*6*	8	8	9	9	9	11	14	6	7	8	10	11	11	12	14	5	6	7	8	8	8	9	10
		75	*8*	10	11	11	12	12	13	18	7	8	9	12	13	13	14	17	6	7	8	9	9	9	10	12
	25	50	*10*	*12*	13	13	14	14	16	21	9	10	11	14	15	15	16	19	7	8	9	10	11	11	12	14
		25	*11*	*14*	15	15	16	17	19	25	10	11	12	16	17	17	19	22	8	9	10	12	12	12	14	16
		10	*13*	*16*	*17*	17	19	19	21	29	*11*	12	14	18	19	19	21	24	9	10	11	13	14	14	15	17
		90	5	6	7	8	8	8	9	13	5	6	7	9	9	9	10	12	4	5	5	7	7	7	8	9
		75	*7*	8	9	10	10	10	12	16	6	7	8	10	11	11	12	14	5	6	6	8	8	8	9	11
	76	50	*8*	10	10	12	12	13	14	19	7	8	9	11	12	12	13	16	6	7	7	9	10	10	11	12
		25	*9*	11	12	14	15	15	17	22	*8*	9	10	13	14	14	15	18	7	7	8	10	11	11	12	14
		10	*11*	*13*	14	15	17	17	19	25	*9*	10	11	14	15	15	17	20	7	8	9	11	12	12	13	15
		90	*6*	7	8	9	10	10	11	15	6	7	8	9	10	10	11	13	5	6	7	7	8	8	9	10
		75	*7*	9	9	11	12	12	14	18	7	8	9	11	12	12	13	15	6	7	8	9	9	9	10	12
49	51	50	*9*	10	11	13	15	15	16	22	*9*	9	11	13	14	14	15	17	7	8	9	10	11	11	12	14
		25	*10*	*12*	13	16	17	17	19	26	*10*	11	12	14	16	16	17	20	8	9	10	11	12	12	13	15
		10	*11*	*14*	15	18	19	20	22	30	*11*	12	14	16	17	17	19	22	*9*	10	11	13	14	14	15	17
		90	6	8	8	9	10	10	11	15	6	7	8	10	11	11	12	14	5	6	7	8	9	9	10	11
		75	*8*	10	11	12	12	13	14	19	7	8	9	12	13	13	14	17	6	7	8	9	10	10	11	13
	25	50	*10*	12	13	14	15	15	17	23	9	10	11	14	15	15	16	19	7	8	9	11	12	12	13	15
		25	*11*	14	15	16	18	18	20	27	10	11	12	16	17	17	19	22	8	9	10	12	13	13	15	17
		10	*13*	*16*	17	19	20	21	23	31	*11*	12	14	18	19	19	21	24	9	10	11	14	15	15	16	19
		90	*7*	8	9	9	10	10	11	15	6	7	8	9	10	10	11	13	5	6	7	8	9	9	10	11
		75	*8*	10	11	12	13	13	14	19	7	8	9	11	12	12	13	15	6	7	8	9	10	10	11	13
	76	50	*10*	*12*	13	14	15	16	17	23	*9*	9	11	13	14	14	15	17	7	8	9	11	12	12	13	15
		25	*12*	*14*	15	17	18	18	20	27	*10*	11	12	14	16	16	17	20	8	9	10	12	13	13	15	17
		10	*13*	*16*	*18*	19	20	21	23	31	*11*	12	13	16	17	17	19	22	*9*	10	11	14	15	15	16	19
		90	*7*	9	9	11	12	12	13	18	8	8	9	10	11	11	12	14	7	7	8	9	10	10	11	12
		75	*9*	*11*	12	14	15	15	16	22	9	10	11	12	13	13	14	17	8	8	9	11	11	11	12	14
34	51	50	*11*	*13*	*14*	16	18	18	20	27	*10*	11	13	14	15	15	17	19	*9*	10	11	12	13	13	14	17
		25	*13*	*15*	*17*	19	21	21	24	32	*12*	13	14	16	17	17	19	22	*10*	11	12	14	15	15	16	19
		10	*14*	*18*	*19*	22	24	24	27	36	*13*	14	16	18	19	19	21	24	*11*	*12*	14	15	16	16	18	21
		90	*8*	10	11	11	12	12	14	19	8	8	9	12	12	12	14	16	7	7	8	10	11	11	12	14
		75	*10*	12	13	14	15	15	17	23	9	10	11	13	14	14	16	18	8	8	9	12	12	12	14	16
	25	50	*12*	*15*	16	17	18	19	21	28	10	11	13	16	17	17	18	21	9	10	11	13	14	14	16	18
		25	*14*	*17*	*19*	20	22	22	24	33	12	13	14	18	19	19	21	24	10	11	12	15	16	16	18	21
		10	*16*	*20*	*21*	23	25	25	28	38	*13*	14	16	19	21	21	23	27	*11*	12	14	17	18	18	20	23

Note:
1. Width is dimension away from body in cm
2. Distance is vertical lift in cm
3. Percent pertains to industrial population
4. Italicized values exceed 8 hr physiological criteria

Snook, S. H. and Ciriello, V. M., The design of manual handling tasks: revised tables of maximum acceptable weights and forces, *Ergonomics*, 34, 9, 1991

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