USING WEARABLE SENSORS TO EVALUATE MATERIAL HANDLING OPERATOR'S FATIGUE IN REPETITIVE ACTIVITIES: A DESIGN OF EXPERIMENTS APPROACH

by

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DEDICATION

I dedicate my research work to my family, professors and many friends. A special feeling of gratitude to my parents whose words of encouragement and push for tenacity ring in my ears.

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LIST OF ABBREVIATIONS

Abbreviation	Description
MMH	Manual Material Handling
MoCap	Motion Capture
NIOSH	National Institute for Occupational Safety and Health

ABSTRACT

Manual Material Handling is one the major causes which contributes to a large percentage of musculoskeletal disorders. In a manufacturing environment, associates lift loads repeatedly which leads to physical fatigue. Human fatigue not only leads to critical injuries, but also lowers productivity in a work environment which has an impact on the entire supply chain process. Hence, physical fatigue is a challenging safety issue in a manufacturing environment. In this research, a Lifting fundamental skill move mimicking a manufacturing environment is physically simulated with the use of Hexoskin sensors and a motion capture framework. The motion capture framework consists of multiple high version cameras, a workstation to perform the experiment, Hexoskin sensors, and a processor that collects a catalog of Bio-MoCap data on a time-series. The main goals of the study are to 1) determine the correlation of the physiological variables with the subjects RPE level of the Lifting skill move on the Borg's scale, and 2) predict the level with respect to the task. In this study, we use statistical analysis and regression techniques to determine the relationship of the bio-factors with fatigue. A separate regression model is built to predict fatigue with respect to heart rate and time function. Results show the statistical significance of the bio-factors in the process of getting fatigued. A multi-objective optimization method is used for posture prediction and analysis with consideration of fatigue effect and its application case. This research has potential to contribute in the field of manual material handling and can help in efficiently planning workforce with the available resource.

1. INTRODUCTION

In manual material handling, fundamental skill moves are basic activities that are performed by a material handler in a repetitive basis; these activities include lifting, putting down, pushing, pulling, carrying or moving [1]. The fundamental skill moves are derived from the basic day to day operations performed by operators in a manufacturing environment. An effective fundamental skill move, through repetition, optimizes the operator’s motions necessary to carry on a task, and reduces any risks of injuries if performed within the natural constraints of body postures and ranges of motion. Hence, performing fundamental skill moves in a safe and effective manner can help in training the operator, standardizing their work, eliminating waste in the operator’s motion, and improving their health and safety [2]. Some of the challenges faced by manual material handling are:

- **Over Exertion:** Over exertion causes 28% of all reported injuries, the bulk of which are due to moving, handling and/or lifting of something within a work environment. Lifting heavy goods beyond the operators capacity can be one of the main reason of physical fatigue [3].
- **Performing Repetitive motions:** Manual material handling exposes workers to energy consuming, repetitive activities for long duration times which leads to physical fatigue. The operators are generally not trained for efficient ways of material handling. According to the U.S Department of Labor Bureau (2016), the top five injuries include – encountering harmful objects, over exertion, slip and falls, repetitive motion and contact with harmful substances [3].
- **Accidents due to falling objects:** Manual material handling requires picking and

placing of loads which are generally placed at different heights. The loads that are stored at a higher level are of higher risk as it may cause severe injuries due to falling. The operator can collide with objects in a material handling environment. due to poor lighting or uncleaned aisles [4].

- **Time and Cost:** During manual material handling, bad moves or postures can lead to physical fatigue. There are different types of injuries an operator experiences such as cuts, crushed finger and toes, contusions, and fractures. Due to physical fatigue in a workplace, there could be loss in the operator's efficiency. Fatigue in a workplace also leads to a shortage in manpower [5].

Subjective evaluations, such as self-report questionnaires and interviews, estimate fatigue in the operators as a function of length of time-on-task, workplace, and timing of rest breaks [6]. Mamman *et al*. [4], for instance, propose an approach to monitor and detect physical fatigue using wearables such as heart rate monitors, Inertial Measuring Unit (IMU's), Electromyography (EMG's), and Electroencephalography (EEG's). The sensors collect the cardiovascular data of the subject performing the experiment for data analysis. A few factors used in the model are the fitness-for-duty test, sleeping habits of the operators, intrusive monitoring of the brain activity, and the change in muscle movement. Results show the fatigue level of every operator who have performed the experiment. The paper does not work towards improving or being able to predict fatigue. There is very low emphasis on how to use the sensory data from multiple sensors and successfully evaluate risk. [4].

Lee *et al*. [7] propose a control approach with a goal to reduce muscle fatigue of a human. The overloading torque is analyzed at various joints of the human and an optimization technique is followed to reduce the torque at every joint. A statistical model and center of pressure is calculated to estimate the force on the joints. An optimization technique is used to reduce the force and the center of pressure on the human. Some of the constraints used in the optimization model are the human stability, task constraints, and ergonomics. Results show an optimal value of torque generated on the joints. The author detects and optimizes human physical fatigue; however, the paper does not work on the causes and impact of fatigue. There is no study of the behavior of bio-factors which is a critical part in the human getting fatigued [7].

1.1 Research Objective

Most of the research papers focuses on detecting fatigue of a human operator. These papers don't address the impact each motion has on fatigue. There is very low emphasis on the human bio-factors and ways it impacts physical fatigue of an operator. Earlier research mostly focusses on human fatigue detection, and not talking about fatigue prediction. There are two main research objectives to address the gaps.

1) This thesis will fill the gaps by extending research on the significance of bio-factors in manual material handling and the impact it has on physical fatigue.

Justification:

Previous literature shows very low emphasis on the human respiratory system's responses to material handling and physical fatigue. When an experiment commences, the respiratory system varies with time and intensity. It is studied that; heart rate increases with respect to time and intensity of the activity. Other respiratory factors such as breathing rate and VO2 max (maximum rate of oxygen consumption measured during incremental exercise) also show an increasing trend if the activity intensity is high and the duration is short [8]. It is clear that the trend and significance of bio-factors can change according to different tasks.

In this study, the literature review was conducted using main keywords such as; 1) manual material handling 2) physical fatigue 3) industry 4.0 4) bio-factors and fatigue 5) NIOSH 6) fundamental skill moves 7) working capacity of male and female. Around 40-50 records were found relevant to this study out of which 9 records were key papers. The literature survey is interpreted in the next chapter. We used many engineering and technology research databases for this study. Some of the main research databases used were 1) IEE Xplore, 2) Engineering Village-2, 3) Compendex, 4) Science Direct, 5) NIOSH, and 6) Google scholar. There is no study done in observing the correlations between different bio-factors and physical fatigue. There is no record found which predicts physical fatigue in a manual material handling environment.

Proposed methods:

The objective of the research is to determine the significance of the bio-factor based on information extracted from the wearable Hexoskin sensor. A lifting fundamental skill move is performed by different subjects in a bio-motion capture framework to build a catalog of datasets containing the bio-factor data and time information. The Borgs data (i.e. a measurement of rated perceived exertion or RPE) is recorded for every subject performing the task until the subject is fatigued. Once the data is collected and pre-processed, a multiple regression analysis is performed for both the “Male-only” and “Female-only” datasets. The goal of the regression model is to study the statistical significance of the bio-factors with respect to fatigue.

2) The second objective of this study is to build a data-driven model to predict fatigue with respect to the heart rate and the time taken by the subject performing the Lifting experiment.

Justification:

In manual material handling, fatigue can be an important factor in the loss of time and revenue. The entire supply chain is affected due to physical fatigue in a material handling environment. Fatigue in a workplace also leads to a shortage in workforce making it unclear whom to assign next to accomplish the task. High labor and medical costs add to the challenges [5]. Previous literature focusses largely on detecting and estimating the level of fatigue physical fatigue. This research will contribute to building a data-driven regression model which can potentially predict fatigue with respect to time and the task. This research objective would potentially help in planning workforce and assignment of tasks effectively.

Proposed methods:

A potential approach to model fatigue development is to use Regression techniques to fit the function *f*. Based on the experiment and the bio-factor information collected, we perform an additional Multiple Linear Regression for both male and female datasets. The goal of the second regression is to determine $Y_{borgs} = f(X)$, where X is a vector containing the features x (i.e. seconds, heart rate, minute ventilation, activity, breathing rate, interval, and distance). The actual Borg's Scale values are used in the data-driven regression technique. If the models are accurate in predictions, we can determine whether a worker is physically fatigued or not.

In the predictive model, the heart rate and time information are taken as the dependent variable and the Borgs data is taken as the independent variable. The Borg's scale is a relative scale which matches how hard it is to work with numbers from 6 to 20. The scale starts with "no feeling of exertion", which rates a 6, and ends with "very hard" which rates a 20 [4]. We split 80% of the number of datasets into a training set and the rest 20% as the test set. We run the regression model on the training set (80% of the total number of datasets for male and female) and fit the function Y_{borgs} on the test set (20% of the total number of datasets for male and female). The r^2 is computed for the training set and test to make comparisons for validation.

1.2 Hypothesis Testing

Null hypothesis (H_0) = The data of the bio-factors do not correlate with the subject's Rate of Perceived Exertion level.

Alternative hypothesis (H_a) = *The data of the bio-factors correlate with the subject's Rate of Perceived Exertion level.*

1.3 Summary of Proposed Experiments

The testing and analysis of these hypothesis will generate the insight needed to answer the following questions:

1) When will the worker reach the fatigue level with respect to the task?
2) What is the impact on fatigue level with respect to actions performed?
3) At what time, one should assign an alternate worker for the task in case the human reaches fatigue level?

This research paper will 1) develop a physical simulation, 2) integrate datasets to generate a catalog of BioMoCap datasets, and 3) analyze the datasets to detect presence or build-up of fatigue.

The dataset is created by performing physical simulation on Leg Lifting which is one among the following fundamental skill moves [9].

Table 1 provides a summary of data which has been defined by [4] to estimate fatigue. The table shows the factors used by [10] to create a model of fatigue. The table also shows the data collected by the Hexoskin sensors.

Table 1: Hexoskin Sensors

Hexoskin Sensor	**Functions**
Cardiac Sensors	ECG, Heart Rate, Quality (30-220 BPM, 1Hz), QRS event detection, RR intervals
Breathing Sensors	Breathing Rate, Tidal Volume, Minute Ventilation, Inspiration and Expiration Events
Movement Sensors	Acceleration, Activity Level, Step Counting, Cadence, Energy Expenditure

Datasets are created for the leg lifting fundamental skill move simulation. The following responses is collected by using Hexoskin devices.

Response:

- **Breathing rate:** Tells us the rate at which the human performing the task is breathing. The unit is respirations per minute (RPM) [4].
- **Heart rate:** Tells us the heart rate of the person performing the task. The unit is beats per minute (BPM) [4].
- **Minute Ventilation:** Measures the amount of air moving in and out of the lungs. The unit is Liters per minute (L/min).

- **Activity**: Tells us the intensity, steps and pace of the activity the human is performing. The unit is Grams (g).

The following factors will be varied in the experiment in order to test the impact each skill move has on the Borg's scale.

Factors:

- **Interval**: the rate of interval between lifts. The unit is seconds [11].
- **Gender:** Determines the gender of the person who is performing the experiment [4].
- **Height:** Determines the height of the person performing the experiment. The unit is ft in [4].
- **Distance from shelf to ground:** the distance from ground level to the shelf in which the load is to be placed. The unit is cm [12].

1.4 Data Dictionary

- **Breathing rate:** Tells us the rate at which the human performing the task is breathing. The unit is respirations per minute (RPM) [4].
- **Heart rate:** Tells us the heart rate of the person performing the task. The unit is beats per minute (BPM) [4].
- **Minute Ventilation:** Measures the amount of air moving in and out of the lungs. The unit is Liters per minute (L/min).
- **Activity**: Tells us the intensity, steps and pace of the activity the human is performing. The unit is Grams (g).
- **Distance**: Tells us the Lifting distance between ground level to shelf level. The unit is Centimeters (cm). [12]

- **Interval**: Tells us the intervals between lifting the load. The unit is Seconds. [11]
- **Borgs:** The Borg's scale is a relative scale which matches how hard it is to work with numbers from 6 to 20. The scale starts with "no feeling of exertion", which rates a 6, and ends with "very hard" which rates a 20 [4].

1.5 Organization of Thesis

The organization of the thesis research is as follows. Chapter 2 is an extended version of previous research work and literature. We discuss in detail about material handling and how physical fatigue is studied. Research gaps are identified in this section and explains how the thesis research addresses the literature gaps. Then, we present our methodology for model development and evaluation in Chapter 3. We provide our results and discuss their statistical significance. Finally, Chapter 4 offers our conclusions and our opinions about future research directions.

2. LITERATURE REVIEW

2.1 Preamble

Chapter 2 describes the literature review of past published work in material handling and the study of human fatigue. Previous studies focus on detecting and estimating fatigue level by descriptive, predictive, and prescriptive methods. Fatigue detection models are built to prevent the loss of critical injuries and maximize productivity in the workplace. In earlier research, the fatigue models use human bio-metric data, which is collected using wearable sensors. The literature survey discusses the research gaps and uncertainty in the study of human fatigue models which aims to reduce injuries and increase productivity in a workplace. As was discussed earlier, this thesis has two main objectives.

- This paper will fill the gaps by extending research on the significance of bio-factors in manual material handling and the impact it has on physical fatigue.
- The second objective of this study is to build a data-driven model to predict fatigue with respect to the heart rate and the time taken by the subject performing the Lifting experiment.

In this chapter, we will be providing the literature survey on previous work done in the study of human fatigue due to material handling. The literature will also emphasize on the use of wearable sensors and biometrics in the study of human fatigue.

2.2 Relevant Research

Seo *et al.* [13] propose a simulation-based framework to study about the physical demands and muscle fatigue. A discrete event simulation evaluates how factors such as: sleep hours, taking voluntary rests, Gender, and Body Mass Index (BMI) affects time and cost performance of the planned operation. Results prove that the workers' excessive physical demands result in an excessive loss of time and increase in cost for the respective operation. Based on the results obtained, the author concludes that operators should be given work according to their physical capacity.

Calzavara *et al*. [6] propose fatigue level real-time monitoring for an order-picking operation, and they compare this method to traditional methods such as self-report, questionnaires, direct measure of EMG, and energy expenditure. The aim of the paper is to evaluate the data obtained from devices which are used in an order picking task to detect fatigue. The author uses data for several variables such as, distance to be covered by the operator, experience of the operator, the measurement of the heart rate, duration of the activity, the value of energy expenditure and measurement of muscular fatigue in the analysis. Statistical data analysis techniques are used to evaluate the quality of fatigue detection, and comparisons are made between the traditional methods and the method which can be applied in a picking context. Results show that the fatigue detection has the highest statistical significance in the heart rate monitoring device. The author concludes that the data obtained by the devices in an order picking context has higher significance than the traditional method of measuring fatigue.

Maman *et al*. [4] use of wearable sensors to detect and quantify physical fatigue in three different simulated manual tasks, which contains elements of assembly, supply/pickup/insertion and manual material handling. In this experiment, the author makes use of the Borgs scale to measure the level of fatigue while performing the tasks. The Borg's scale is "a relative scale which matches how hard it is to work with numbers from 6 to 20". The scale starts with "no feeling of exertion", which rates a 6, and ends with "very hard" which rates a 20. Factors such as handedness, gender, age, height and, weight of the subjects are considered in the model. The authors use a penalized logistic regression and multiple linear regression to correlate physical fatigue with sensory data such as: - wrist acceleration, hip acceleration, wrist jerk, torso jerk, ankle jerk and ankle acceleration and heart rate. Results show that wrist acceleration, torso jerk, hip acceleration, heart rate, wrist jerk, and ankle jerk have a positive relationship, whereas torso acceleration, hip acceleration, and hip jerk had a negative relationship. The author concludes by estimating the level of fatigue with Borgs scale for every participant and shows us the relationship between fatigue and the sensory data collected.

Liu *et al.* [14] propose an electro-encephalogram (E.E.G) based evaluation for mental fatigue. The authors design an experiment to classify four levels of fatigue from relaxation level to high difficulty level. The experiment is conducted with seven male participants from 21 years-26 years. The E.E.G data is collected from the participants using a 14 Channel Emotiv device which is mounted on their head. The authors use machine learning techniques to match the E.E.G data with the respective level of fatigue. The subjects are then asked to fill a fatigue Checklist Individual Strength (CIS) questionnaire with points for every question. The CIS questionnaire are "a set of questions regarding the subjective feeling of fatigue, concentration, motivation, and the physical activity". Higher points in the CIS questionnaire indicate higher level of fatigue.

Results show a 93.45 percent accuracy using six statistical features with Linear Support Vector Machine method. The authors conclude by making comparisons between the machine learning fatigue detection model and fatigue questionnaire which has 82% accuracy.

Avital *et al.* [15] propose a simulation-based optimization methodology to study a a manual material handling task. In this optimization problem, the objective is to maximize workers productivity and have good ergonomic conditions. The workplace and work are simulated using a modelling and analytical software. The best design of the workplace and work are found by using an optimization algorithm. Results show an increase in productivity by 105% compared to methods used in previous studies.

Idrees and Farooq [16] conduct a study based on energy of detail wavelet coefficient for muscle fatigue detection in the upper limb. Seven subjects participate in three trials each using three channels related to biceps, bronchi, flexor carpii radial muscles respectively. Findings from the experiment show that the energy of detail coefficient of the 3^{rd}, 4^{th} and the 5^{th} level of wavelet decomposition increases as the muscle fatigue level increases. Results show that the 3^{rd} level of wavelet decomposition had the maximum value of energy followed by the 4^{th} and the 5^{th} level respectively. Fatigue is detected among subjects when the average final energy value is five times the initial value for 15.6-62.5 Hz range.

Xi Peng *et. al* [17] propose a deep neural network-based framework to capture full body three-dimensional poses of subjects performing a lifting task. An inverse algorithm calculates L5/S1 joint kinetic motion using the 3-D body pose and the subject's anthropometric. The lifting data is collected from 12 subjects to calculate the kinetic force and moment at L5/S1 joint using sensors. Results are validated against a marker-based motion capture (MoCap) system as reference. The author concludes that the proposed method provides a reliable tool for assessment of the lower back joint kinetics during lifting.

Kodama *et al.* [18] develop a worker-wear assistance suit to reduce arm muscle fatigue for repetitive motion involving shoulders. A lifting experiment is conducted using six subjects who are 22-26 years old. The aim of the experiment is to measure the muscle activities of the six subjects wearing the suits. The authors perform a mathematical simulation in order to determine the feasibility and functionality of the layout. The simulation model determines the statistical significance of the torques of the elbow and shoulder joints using the suits. Results show 45% improvement in shoulder and arm muscle injuries.

Sibarani *et al.* [19] analyze the different lifting and moving activities with an aim to optimize energy spent in material handling. Experiments are conducted where the subjects carry and transport a load weighing 15 kgs between two locations. The study aims at finding an efficient method to determine the optimal amount of energy to carry and transport the 15-kg load. The workload is assessed using the method of cardiovascular strain load where labor type, age and fitness level are significant factors that affect the cardiovascular load. The authors use statistical techniques to determine the significance between the workload and energy spent while doing the task. Results show that there are high correlations between energy spent while doing the task and the workload. The subject who did not experience fatigue received a percentage strain below 30%. The authors conclude that the subjects with appropriate posture while lifting loads conserves more energy and suffers less injuries. However, the reason behind the subjects getting fatigued remain unanswered.

Carolyn *et al.* [20] evaluate the performance of manual material handling operations in a moving environment. The authors analyze how the task performance, posture control and lower limb muscle changes with respect to the material handling task. The tasks which are examined are 1) lifting operations 2) mental arithmetic task and 3) visual processing task. Results show that the visual tracking task has a negative impact by motion while the arithmetic task performance are unaffected. It was also found that the postural control remained unaffected by the presence of motions in the tasks. Lifting is the only task where the postural control is negatively affected as the participants engaged in lower limb muscle activation.

Kamarudin *et al.* [21] measure and analyze the muscle contraction of the muscle during lifting tasks in manual material handling. Different factors like height, load of the material, angle of twisting and lifting frequency are considered. In this experiment, 14 subjects performed the lifting operation task with different loads ranging from 10 kgs-24kgs. The experiment is done with lifting height positions of 70 cm and 130 cm, performed at a rate of 1-6 lifts per minute. Fatigue levels of the subjects are measured through an assessment where the authors evaluate whether the subject has reached the fatigue level. The Electromyogram (EMG) system is used to record the movement of the biceps and triceps. The sensory data collected by the system is used to analyze the contraction movement of the muscle. The authors use statistical analysis to determine the relationship between muscle contraction and weight of the load. An additional model is built to determine the correlation between fatigue and muscle contraction. Results show statistical significance between muscle contraction and the weight of the load, but at the same time, it shows no statistical significance between fatigue and muscle contraction. The authors conclude that this approach effectively determines the weight load limit that can be lifted by the subject during the lifting task.

Singh and Kumar [22] investigate the effect of the operator's lumbosacral bending movement in a steel rolling mill. The experiment is conducted with different load weights and horizontal location of the load. The authors aim to evaluate the strain on the L5/S1 joint while performing the bending movement in the lifting task. The authors make use of Design of Experiments (DOE) and Analysis of Variance (ANOVA) to determine the level of importance of the parameters on bending moment at L5/S1 joint. Results show a reduction in the bending moment at L5/S1 after utilizing a lifting device which reduces injuries by 22%-38%. The resulting model is also capable of predicting bending moment at L5/S1 to a reasonable accuracy. The research reduces fatigue by using a lifting device while carrying heavy loads. The study predicts the bending moment at L5/S1 joint.

Aziz and Nicholas [23] assess the effect of visual feedback techniques to enhance the performance of humans in a virtual environment while carrying out manual lifting operations. The study aims to reduce back injuries by allowing the users to monitor their own back conditions while performing the lifting task in an augmented reality (AR) environment. Lifting experiments are conducted to analyze and evaluate the effectiveness of the feedback on performance. In this study, several variables such as time, percentage of harmful lifts, and response time are used to evaluate fatigue. Results show that the combined visual feedback technique was able to detect bad moves and help the operator track fatigue based on the errors made while lifting. The authors conclude that the visual feedback can be a potential way to avoid injuries and improve productivity in a manufacturing industry.

Murugappan *et al.* [24] analyze the lifting task performed in a manufacturing industry which involves different body postures like squat lifting, and stoop lifting. The humans performing the lifting task tend to use improper body postures and have an effect to human lower-back region over extended period. The authors propose a mathematical model to represent the lower extremity of human body during lifting operations. A two-dimensional space kinematics open chain approach is used to build the mathematical model to analyze the extremity on the human body while performing the lifting task. The moments of the human body are captured using a motion capture system. The torque acting on every joint of the body is measured and the effect it has on the lower back region is analyzed and determined. The authors conclude that this method helps to lower the number of back injuries in a material handling environment.

Bonato *et al.* [25] made a comparison study of the localized muscle fatigue in back muscles vs dynamic contractions. The Surface Electromyography data is recorded as it is very effective in quantifying paraspinal muscle impairments. In this paper, back impairment classification is based on muscle fatigue derived from the Surface Electromyography signals. The authors present a mathematical procedure to measure localized muscle fatigue during dynamic contractions. The authors plot contour plots of the TF distribution derived from two SEMG signals. The plots show different levels on the contour that indicate relative magnitude of fatigue. The results show that the dynamic contractions of paraspinal muscles are more fatigued when compared to static contractions of paraspinal muscles.

Sparto *et al.* [26] analyze the adaptation to fatigue during a repetitive lifting operation in a manufacturing industry. Twelve subjects participated in the experiment of performing repetitive lifting task until exhaustion. A load weight which is 25% of the subjects inertial lifting capacity is lifted and lowered at a maximal lifting rate from mid tibia to waist height. The motion capture (MoCap) data is captured by a video system and is stored in a database. The authors make use of statistical techniques to determine the changes in the kinematic stability of the subject at every stage of the task. It is observed that knee and hip range of motion are significantly decreased, while peak and trunk flexion increased at the end of the lifting task. The subject's postural stability decreases and tend to extend their knee, hip and spine earlier in the lifting phase which caused fatigue.

Terada and Hanawa [27] determine the relationship between fatigue and foot pressure while walking. The center of pressure (COP) is studied as a metric to detect fatigue. Walking experiments are conducted to collect the gait data of the subject. The center of pressure is analyzed, and changes are observed. The authors use a Pedar-in-shoe pressure system to measure the pressure distributions. The Pedar insole is 1.9 mm thick and has up to 99 sensors. The authors use statistical regression technique to find the relationship between COP and fatigue. Results show the fatigue level by continuously measuring the foot pressure data of the subject.

Chopra *et al.* [28] create a system by detecting bad posture by using sensors and a wearable device. The wearable device is designed in the form of a belt and helps detect postures of the human operator while manually handling materials. The belt is also designed to detect areas of stress and provides time information of the subject. The goal of the study is to detect correct and incorrect postures. The incorrect posture is detected by calculating the angle of tilting with the help of an accelerometer. The belt sends a warning signal if a bad posture is detected. This study can be used to reduce fatigue and back injuries in workplaces.

Yee *et al.* [29] use two different Mechanomyography sensors to make comparisons and detect the muscle fatigue during muscle contraction. The two Mechanomyography based sensors used in this study are vibromyography sensor and muscle contraction sensor. The subjects with back injuries participated in the experiment to perform knee extension for the strength and fatigue test. The data is collected from each of the MMG-based sensors for data analysis. Regression and time series analysis are used to determine the effects and correlations between the MMG sensor readings and fatigue. Results show that the data of sensors correlated with the measured output torque to identify the linearity of sensor signals with output. The sensors with coefficient of correlation nearest to one is considered more reliable in muscle activity and fatigue detection. The authors conclude that the muscle contraction sensor is better in detecting and measuring muscle movement activity for the subject, whereas the vibromyography sensor is better for detecting and measuring muscle fatigue.

Rong *et al.* [30] use a time frequency method to detect muscle fatigue. An experiment is performed by ten subjects to record the Surface Electromyography (EMG) signals on the right upper limb. In the initial phase of analysis, the EMG signals are analyzed in a time-frequency method since the signals are non-stationary and non-linear. The authors use a neural network system to recognize the state of the muscle based on the

EMG signals. The model accuracy is then computed statistically. The test findings show that the first sample has the highest accuracy with 81.5%, whereas, the other six samples has around 75% accuracy. However, the number of training sets are not enough to classify the testing sets correctly and can be potentially improved in the future.

Kim and Nussbaum [31] propose a three-classification algorithm to classify manual material handling tasks. Manual material handling tasks are performed by 10 volunteers between 19 to 29 years old. The experiment is performed in 6 different ways (i.e. carry and walk, asymmetric lifting, lifting from knuckle height, pushing, pulling, and placing). In this study, the authors use three mathematical classifiers namely: - 1) linear discriminant analysis (LDA), 2) K-nearest neighbors (KNN), and 3) multilayer feedforward neural network to classify the manual material handling tasks. The use of classifiers helps in identifying and distinguishing patterns in the datasets. The results show that the algorithms classify the MMH tasks with a statistical significance of eighty percentage. The authors conclude that LDA and KNN classifiers are effective choices, however classifiers like the Bayesian decision-making, support vector machines, and Markov models can be explored for higher statistical accuracy.

Ciriello [12] analyze 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. Experiments are conducted with eight male industrial workers as subjects. The subjects perform 27 variations of lifting, lowering, pushing, pulling, and carrying. The selected subjects are analyzed through a psychophysical methodology. The results show that MAWs of lowering are not significantly affected by distance of lowering, height of lowering, or the box size except for the 25cm lowering task. The results also show that MAWs of lifting large boxes are not significantly affected by distance of lift and MAWs of lowering are not significantly different from lifting.

Snook *et al.* [11] perform experiments to study and assess the effects of different factors such as size, distance, height and frequency on material handling tasks. The first experiment is conducted to evaluate the frequencies. Ten male industrial workers performed 51 variations of lifting, lowering, pushing, pulling and carrying operations. The frequencies varied from 5 seconds to once in 8 hours. The second experiment is conducted to investigate object size, distance of lift and height of push/pull. Lifting task is performed at high frequencies once in 9 seconds and 14 seconds depending on the lifting height. Results show that the lower frequency task has forces which are lower compared to the ones in the previous studies and the maximum acceptable weight and forces for female workers are significantly lower, but proportional with the maximum acceptable weights and forces for male and female workers.

Strimpakos *et al.* [32] study the correlations between electromyography (EMG) and Borgs scale assessment of the neck muscles. In the experiment, thirty-three volunteers performed an isometric contraction test from a standing position with neck movements. The authors estimate fatigue by employing the Borg's scale. Intra class correlations coefficient, standard error of measurement, smallest detectable difference indices and correlation coefficient are calculated for the analysis. Results show that the normalized median frequency slope has low repeatability for the muscles of each movement. Initial median frequency had moderate to good reliability and small error. The authors conclude that the Borgs scale assessment is more reliable than the EMG results.

Zulkifle *et al.* [33] aim to predict a body exhaustion threshold based on the electrocardiogram feature using artificial neural network. An Electrocardiogram device is used in the experiment with an electrode connected to the upper thorax. The fatigue level is determined using the Borgs scale. The Borgs scale and time to exhaustion are used as the target data and the sensory ECG data provides specific information for the input. Results show that exhaustion is highly correlated with the ECG data, and r^2 is 91 percentage. The highest fatigue threshold prediction contributed to 89.3 percentage to the model. The authors conclude that this method is promising for the prediction of exhaustion threshold in order to replace the qualitative with quantitative measure.

Li and Liu [34] conduct a study on manual material handling tasks performed on floors under three frequency levels. The aim of the study is to determine the maximum acceptable weight of handling (MAWH) for an operator. Lifting experiments are performed by eight male subjects from 22 years to 26 years. Sensors are used to record the bio-factors such as heart rate, maximum rate of oxygen consumed (VO_2) and rate of perceived exertion (RPE). The rate of perceived exertion (RPE) is collected for every subject based on the Borgs scale. The authors conduct an analysis of variance test for all the bio-factors including the RPE. Results show that the MAWH was significantly affected by time frequency. The frequency of three per minute had significantly higher MAWH than the other two frequencies. Heart Rate and VO_2 was statistically significant at a 0.05 level of significance. However, the effects of frequency on the rate of perceived exertion is significantly low.

Surang *et al.* [35] focus on physiological indicators related to accumulated fatigue and heat stress. Biomechanical factors such as heart rate, body temperature, and sweating rate of soldiers during training period are recorded. A wristwatch device is used to record the body temperature and heart rate of the subject performing the experiment. A time series analysis is performed to observe the trend of the sensory data. Results show an increasing trend of the moving average of the heart rate for three participants and the others have a stable trend. The skin temperature showed an increasing trend for one subject. However, the other two subjects had a decreasing trend of skin temperature. The authors perform a regression to determine the correlations between skin temperature and fatigue, and results showed very low significance. The authors conclude that the resting heart rate can be used to as a sign for accumulated fatigue while there is no trend on the skin temperature.

2.3 Summary

Most of the previous research papers focuses on detecting fatigue of a human who's doing the task. The authors measure the amount of fatigue on critical joints in the human body. Various papers study manual material handling in a manufacturing industry and optimize bad lifting postures. The published literatures don't talk about the impact a task has on fatigue. In other words, it only detects when the human has attained fatigue.

The studies by Snook focus on factors such as size, distance, height and frequency on material handling tasks. The maximum acceptable weight for both genders is studied. These papers also design intervals between lifts which is very essential in this thesis.

This research will fill the gaps in the literature of manual material handling by finding out how much the lifting fundamental skill move impacts the Borg's scale. The Borg's scale is a relative scale which matches how hard it is to work with numbers from

6 to 20. The scale starts with “no feeling of exertion”, which rates a 6, and ends with “very hard” which rates a 20 [4]. This research primarily focuses on the significance of the human bio-factors while performing the task. The study aims to build a predictive model for male and female subjects with respect to their heart rate and time. The study will help us to determine the fatigue level of the human operator at different time frames.

Table 2 shown below is a literature review matrix summarizing previous studies in fatigue-related problems. Based on the literature survey, the fatigue related problems are listed below along with the methods followed in the respective research. The table shows the research gaps based on the literature survey.

Table 2: Key Literature and Gaps

Problem	Descriptive Methods	Predictive Methods	Prescriptive Methods
Fatigue Estimation	Calzavara M et al. (2017)	-	Kim et al. (2018)
Fatigue detection using Smart Sensors	Pollock K et al. (2011) Maman et al. (2017)	-	Sanjay Sood et al. (2016)
Optimization of bad moves in material handling using smart sensors	Mendez et al. (2018)	-	-
Optimization of Fatigue	Strimpakos et. al	-	Sibarani J et al.
Study of bio-factors and fatigue	Li and Liu (2018)	-	Decho Surang (2019)
Study of acceptable loads & frequency for humans	Ciriello (2003) Sunwook et al. (2014)	-	Snook (1978)
Fatigue prediction & study of bio factors using wearables	This work	This work	-

3. USING WEARABLE SENSORS TO EVALUATE MATERIAL HANDLING OPERATOR'S FATIGUE IN REPETITIVE ACTIVITIES: A DESIGN OF EXPERIMENTS APPROACH

3.1 Introduction

The material handling industry employs over 700,000 workers [3]. Material handling operators lift loads repeatedly over a long period of time, which leads to physical fatigue. Physical fatigue is defined as a reduction of force which is generated when a human performs muscular activities [13]. Physical fatigue often occurs due to the need to travel from one location to the other, and the need to carry heavy loads to a certain height on the rack or shelf [6].

Physical fatigue of an operator could lead to order picking inefficiency and longer picking times [6]. Physical fatigue can also result in injuries and long-term health effects, such as chronic fatigue syndrome and reduced immune [4]. Manual material handling, in general, causes 28% of all reported injuries, the bulk of which are due to moving, handling and/or lifting of something within a work environment [3]. The operator could stop working several weeks, and in some cases lead to permanent disabilities. According to the United States Department of labor, it has been estimated that employers compensate $1 billion dollar every week due to workplace injuries [3].

In this study, the fundamental skill move is studied since it is one of the most intense moves and one of the most common in a material handling environment [9]. According to NIOSH, lifting fundamental skill move is defined as an act of grasping an object/load, and vertically moving the object without mechanical assistance [2]. Lifting postures often change after repetitively performing the pick and place task. Lifting can also lead to bracing of torso when the lifting posture is unrestricted. The operators frequently fail to follow the NIOSH safety guidelines after performing repetitive lifts thereby leading to critical injuries.

The aim of modelling human fatigue is to provide quantitative information on the factors causing fatigue or risk associated in a workplace. Fatigue modelling is highly important as it provides evidence and helps in optimizing the problem thereby improving the workers efficiency and reducing work-place injuries. Some of the key factors that causes work-place injuries are manual material handling, sleep pattern, bad ergonomics, and not following the OSHA standards. Seo *et al.* [13] propose a simulation-based framework to study about the physical demands and muscle fatigue. A discrete event simulation evaluates how factors such as sleep hours, taking voluntary rests, gender, and the body mass index (BMI) affects time and cost performance of the planned operation. Simulation-based results show that the operators' physical demands result in a loss of time and increase in cost for the respective material handling operation. Sparto *et al.* [26] analyze human muscle fatigue during a repetitive lifting operation in the manufacturing industry. The authors make use of a statistical technique to determine changes in the kinematic stability of subjects at every stage of the task. Results of the statistical model show that a decrease of knee and hip range of motion concurrently with an increase of in peak and trunk flexion range of motion. Maman *et al.* [4] attempt to examine the use of wearable sensors to detect physical fatigue in a simulated task, and estimate the fatigue level over time. Three experimental tasks are conducted with eight participants; the sensory data are recorded for each participant. The tasks are related to assembly, supply, pick up and insertion and manual material handling. Once the task is performed, fatigue data is collected with the use of Borgs scale. The author makes use of a penalized logistic regression to correlate physical fatigue and the level of estimation. The resulting model for fatigue detection and fatigue development are similar in terms of the features selected and their performance in training and testing.

Calzavara *et al*. [6] propose fatigue level real-time monitoring for an order-picking operation, and they compare this method to traditional methods such as self-report, questionnaires, direct measure of EMG, and energy expenditure. The aim of the paper is to evaluate the data obtained from devices which are used in an order picking task to detect fatigue. The author uses data for several variables such as distance to be covered by the operator, experience of the operator, the measurement of the heart rate, duration of the activity, the value of energy expenditure and measurement of muscular fatigue in the analysis. Statistical data analysis techniques are used to evaluate the quality of fatigue detection, and comparisons are made between the traditional methods and the method which can be applied in a picking context. Results show that the fatigue detection has the highest statistical significance in the heart rate monitoring device. The author concludes that the data obtained by the devices in an order picking context has higher significance than the traditional method of measuring fatigue.

Strimpakos *et al.* [32] study the correlations between electromyography (EMG) and Borgs scale assessment of the neck muscles. In the experiment, thirty-three volunteers performed an isometric contraction test from a standing position with neck movements. The authors estimate fatigue by employing the Borg's scale. Intra class correlations coefficient, standard error of measurement, smallest detectable difference indices and correlation coefficient are calculated for the analysis. Results show that the normalized median frequency slope has low repeatability for the muscles of each movement. Initial median frequency had moderate to good reliability and small error. The authors conclude that the Borgs scale assessment is more reliable than the EMG results.

Mendez *et al.* [36] propose a Motion Capture framework to study the repetitive motions of humans in a manufacturing environment. The authors make use of motion capture cameras, markers which are attached to the operator's body, and sensors to collect data on subjects performing the task. The sensory data is analyzed using machine learning techniques like, regressions, time series, and classifications techniques. Results identify the bad motions and the most optimal motions of the subjects.

Kim and Nussbaum [31] propose a three-classification algorithm to classify manual material handling tasks. Manual material handling tasks are performed by 10 volunteers between 19 to 29 years old. The experiment is performed in 6 different ways (i.e. carry and walk, asymmetric lifting, lifting from knuckle height, pushing, pulling, and placing). In this study, the authors use three mathematical classifiers namely: - 1) linear discriminant analysis (LDA), 2) K-nearest neighbors (KNN), and 3) multilayer feedforward neural network to classify the manual material handling tasks. The use of classifiers helps in identifying and distinguishing patterns in the datasets. The results show that the algorithms classify the MMH tasks with a statistical significance of eighty percentage. The authors conclude that LDA and KNN classifiers are effective choices, however classifiers like the Bayesian decision-making, support vector machines, and Markov models can be explored for higher statistical accuracy.

Snook *et al.* [11] perform experiments to study and assess the effects of different factors such as size, distance, height and frequency on material handling tasks. The first experiment is conducted to evaluate the frequencies. Ten male industrial workers performed 51 variations of lifting, lowering, pushing, pulling and carrying operations. The frequencies varied from 5 seconds to once in 8 hours. The second experiment is conducted to investigate object size, distance of lift and height of push/pull. Lifting task is performed at high frequencies once in 9 seconds and 14 seconds depending on the lifting height. Results show that the lower frequency task has forces which are lower compared to the ones in the previous studies and the maximum acceptable weight and forces for female workers are significantly lower, but proportional with the maximum acceptable weights and forces for male and female workers.

Ciriello [12] analyze 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. Experiments are conducted with eight male industrial workers as subjects. The subjects perform 27 variations of lifting, lowering, pushing, pulling, and carrying. The selected subjects are analyzed through a psychophysical methodology. The results show that MAWs are unaffected by lowering distance, height, or the box size, except for the 25cm lowering task. The results show that MAW values between lifting and lowering are not significantly different from lifting.

Li and Liu [34] conduct a study on manual material handling tasks performed on floors under three frequency levels. The aim of the study is to determine an operator's maximum acceptable weight of handling (MAWH). Lifting experiments are performed by eight male subjects from 22 years to 26 years. Sensors are used to record the bio-factors such as heart rate, maximum rate of oxygen consumed (VO_2) and rate of perceived exertion (RPE). The rate of perceived exertion (RPE) is collected for every subject based on the Borgs scale. The authors conduct an analysis of variance test for all the bio-factors. Results show that the MAWH was significantly affected by time frequency. The frequency of three per minute had significantly higher MAWH than the other two frequencies. Heart Rate and VO_2 are statistically significant at a 0.05 level of significance. However, the effects of frequency on the rate of perceived exertion is significantly low.

Physical fatigue is a prevalent issue in a material handling environment. It is important to know the operator’s capacity and predict the time of fatigue based on the task to plan and allocate work in manufacturing unit. Our review of the published literature has identified a lack of research for predicting fatigue, particularly as a function of physiological factors. This study aims to build a statistical design of experiments approach to build a metamodel for predicting operator’s fatigue for a lifting task. The model predicts rated perceived exertion with respect to several time series related to physiological factors, such as breathing rate, heart rate, minute ventilation, and activity. In our unique approach to the execution of the factorial experimental design, state-of-the-art physiological wearable devices are mounted in operators to collect large scale datasets of the response. The novelty of this research is in the applications of the meta model as part of a large-scale digital twin framework to monitor the operator’s performance and health in real time as a lifting activity is carried out in a production setting.

The rest of the thesis is organized as follows: Chapter 3.2 gives us a brief background of the research where we discuss about the use of a digital twin technology in this research, and the potential ways it can be helpful to optimize material handling operations. Chapter 3.3 discusses about the methodology followed to prove our hypothesis and gain additional insights about physiological factors and the impact it has on fatigue. In this chapter, we discuss about the lifting experiment, participants recruited, and the system configurations designed in a motion capture framework. Chapter 3.5 discusses about the design of experiments, where an experiment based on factors specified in the lifting experiments is designed from the Hazard Analysis Tool. We provide the factors and factor levels considered in this research. Chapter 3.6 and 3.7 present the development of the male and female model. We provide the statistical results obtained for the models and make conclusions. Finally, Chapter 4 offers conclusions of the research and our opinions about future research directions.

3.2 Background

In this research, we use a digital twin approach with an aim to optimize a material handling task for operators. A digital twin is defined as “a virtual representation that interacts with a physical object throughout its lifecycle and provides intelligence for evaluation, optimization, and prediction of processes” [37]. A digital twin bridges the gap between a physical system and its digital representation with the ability to exchange information between each other [38]. A digital twin is widely used in industry 4.0 with the combination of technological devices. Automated industries or industry 4.0 optimize operations by collecting real-time data directly from the production line and help in eliminating the underlying process and identifying the bottle necks [38]. To the best of our knowledge, the digital twin technology is not widely used in industry, where there are significant opportunities to optimize manual material handling operations, particularly to assist in reducing the operator’s fatigue [39]. In this study, we develop a digital twin technology with a combination of high-performance motion capture cameras and wearables featuring physiological sensors. The digital twin framework collects real-time data to optimize the material handling task. The technology helps in modelling fatigue and standardizing the operation. We analyze the digital twin in a monitor for discrepancies and can make necessary changes in the process. There is a wide scope in using augmented reality to communicate with human operator in real-time [40].

Our digital twin is structured into four modules. The first module is the data collection module where we obtain range of motion and exertion data from motion capture cameras and sensors to characterize the digital twin project. The data is integrated and stored in a cloud-based database for further analysis. The next module is the data pre-processing module where we clean the datasets for bad sensory readings and errors. In the data analysis module, we develop statistical models to predict fatigue and determine the significance level of the operator's physiological factors with respect to fatigue. The statistical models aim to optimize the material handling operation and improve the overall productivity of the operator. Figure 1 shows us the module framework of proposed operator centric Industry 4.0 environment [39].

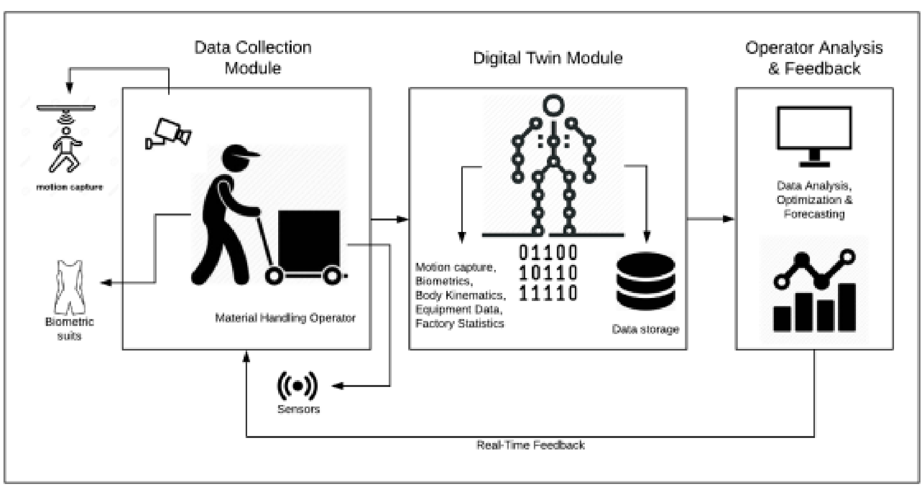

Figure 1: Industry 4.0 - Module Framework

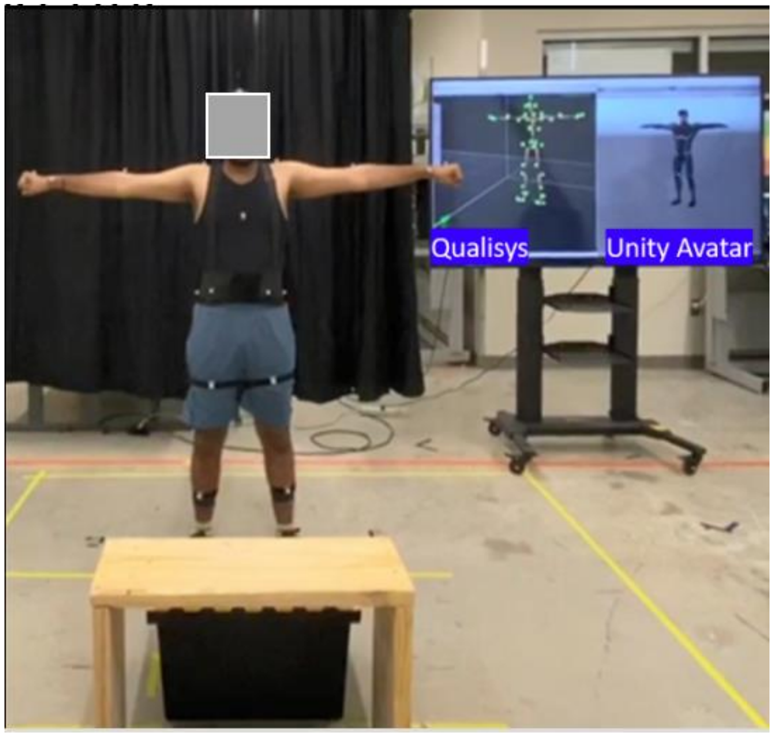

Figure 2: Real-time Digital Twin system

The use of a digital twin technology for a human operator can be a significant contribution to reduce workforce in manufacturing industries. The digital twin can help in optimizing repetitive motions and reduce the operator's fatigue. Many companies use a digital twin to reduce the cycle time and increase throughput of the respective operation. A digital twin along with a combination of statistical, mathematical and simulation techniques can generate insights on the behavior of the operator's physiological data in a material handling environment.

3.3 Methodology

3.3.1 Physical simulation activity

A material-handling-based physical simulation mimics a manufacturing pick and place task in an assembly process. In the experiment, a group of participants performs a leg-lifting fundamental skill move; see Figure 3. The experiment is performed in the Bio-MoCap framework, which consists of a total of nine Qualisys Oqus 510 cameras, and one Opus 210c video camera positioned so that at least three of them covers all motion markers on the subject. While performing the lifting task, participants wear a Hexoskin sensor to collect physiological data (i.e., respiratory rate, heart rate, minute ventilation, and intensity of activity) with respect to time. The experiment is based on the number of factors and factors levels that are discussed in the Section 3.5. The Hexoskin sensor records data at the rate of 256 frames per second. The data collected is then stored in Bio-MoCap database for further analysis. Below are the physiological factors which are recorded and stored:

- **Breathing rate:** rate at which the human performing the task is breathing. The unit is respirations per minute (RPM) [4].
- **Heart rate:** heart rate of the person performing the task. The unit is beats per minute (BPM) [4].
- **Minute Ventilation:** amount of air moving in and out of the lungs. The unit is Liters per minute (L/min).
- **Activity**: intensity, steps and pace of the activity the human is performing. The unit is Grams (g).

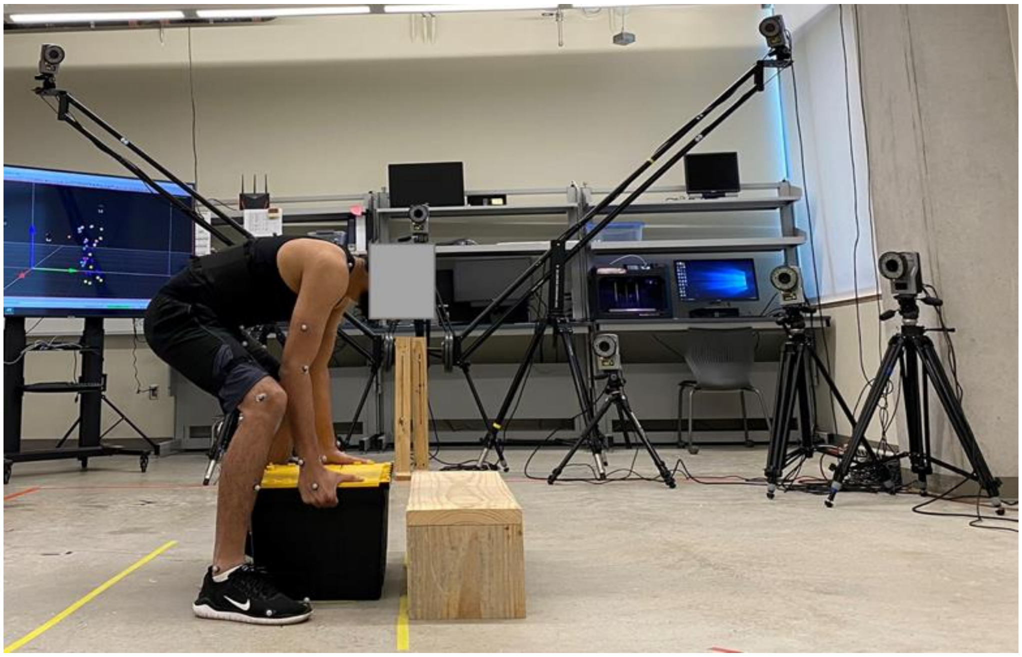

Figure 3: Lifting task in a MoCap environment

The experiment also collects the rate of perceived exertion using the widely known Borg's scale. More specifically, the Borg's scale is a measure of the rate of perceived exertion ranging from 6 to 20. The scale starts with "no feeling of exertion", which rates a 6, and ends with "very hard" which rates a 20 [41]. The Borg's scale data is collected every 60 seconds until the subject is fatigued from the lifting operations. The data is recorded manually by asking the subject an estimate of his or her RPE. The subject is presented during the experiment a color-coded chart with brief descriptors of what clues to look for in regard to fatigue and physical body performance in each particular scale.

3.4 Participants

In this study, eleven subjects (7 males, 4 females) were recruited over a period of two months (approx.). All the subjects performing the task are university research assistants between 18-27 years of age. Subjects recruited are mainly graduates and undergraduates from Texas State University. The subjects wear the Hexoskin suit and place the markers around their body according to the system protocol. Once the subject is equipped with the Hexoskin suit and markers, the cameras are simulated and made sure it captures every marker on the subject's body. In this experiment, we do not assign a warm-up time since 2-3 subjects are made to perform the task per day, and on an alternate basis if needed. Hence, there is a resting opportunity once the subject completes the task. Subjects perform the lifting experiment where an object is leg lifted from the ground level and placed on the shelf level to complete one repetition. The measurement of the object used in the experiment are 21 inches length, 15 inches width, and 12 inches height. The ground level is considered as the start position and the shelf level as the end position. The experiment is designed for time intervals of 9 seconds and 14 seconds between each repetition. There is no opportunity for rest between repetitions, and the subject should complete each repetition in the assigned interval for some repetitions after the subject reaches the 15-level in the Borg's scale. Once the experiment is performed, the sensor is detached and sent for a data transfer process. The time for performing each combination ranges between 5 minutes to 30 minutes depending on the respective participant. The data was collected on Thursdays and Fridays for 2-3 hours for 2 months (approx.). The experimental procedures are approved by the Institutional Review Board, a committee established to review and approve applications for research projects involving human subjects.

3.5 Design of Experiments

We design an experiment specified in Table 3 based on factors specified in the lifting experiments in the Hazard Analysis Tool [42] aiming to build a predictive metamodel and optimize the material handling task. Snook developed a series of tables for evaluating the design of manual handling tasks. These tables present maximum acceptable weights for the male and female genders to 10, 25, 50, 75 and 90% industry population. The factors considered in this experiment are interval, gender, height, and distance. The interval factor levels considered are 9 seconds (low) and 14 seconds (high) and the distance factor levels are 51 cm (low) and 76cm (high). We consider two factor levels for the height of the subject: 5’2”-5’11” classified as medium, and height above 5’11” classified as tall. We design the factors for 50% of the population with respect to their factor levels. Based on the gender, interval, and distance, the weight-lifting capacity is determined for each combination of the factorial experiment. The boxes to be lifted during the experiment were prepared prior to the start of the experiment according to the maximum lifting capacity specified for each combination. We consider 50% industry population to avoid bias. The full factorial experiment consists of 20 combinations.

Table 3: Training and validation parameters

Factors	Name	Levels	Number of levels
A	Intervals	Low, High	2
B	Gender	Male, Female	2
C	Height	Medium, High	2
D	Distance	Low, High	2

The regression models are built separately for the male and female datasets. There are many differences between the male and female physiology as per the American Physiological Society Education Committee. It is scientifically proven that the genders have differences in the physiology of cardiovascular, musculoskeletal, and immune systems [43]. This research shows that males have more muscle mass, more bone mass, and a lower percentage of body fat in a person. Based on the physiological factors, two separate regression models are created for males and females. The statistical summary is analyzed for the male and female models separately to gain insights [43].

Figure 4 [44] shows a cube plot with different factors designed in this experiment along with their factor levels. Each corner of the cube shows the different levels in their respect side.

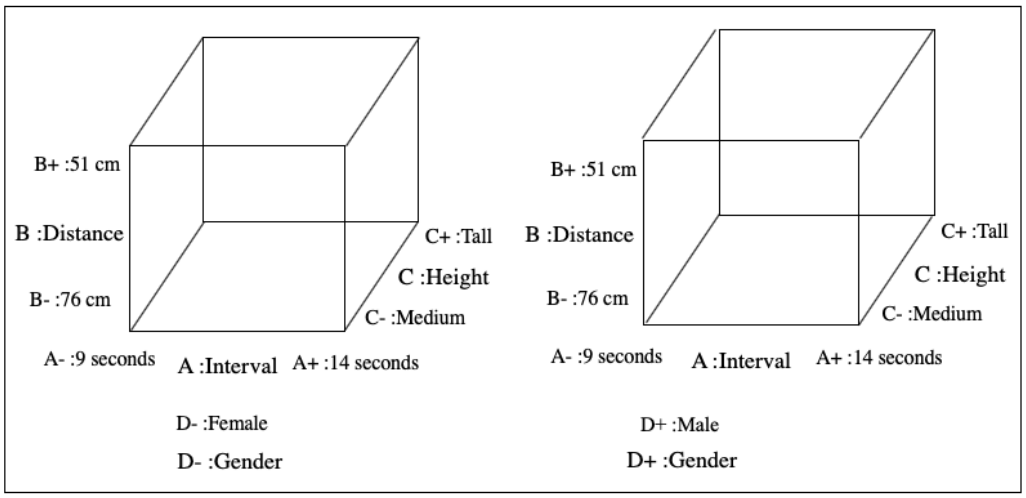

Figure 4: Cube Plot - Factors and factor levels

3.6 Model Development

The dataset generated from the experiment is segregated into a training dataset and a test dataset. In the training phase, 80% of the number of datasets are trained, and in the validation phase, rest of the 20% of the sample size are tested. The split of the training set and test set for male and female datasets are shown in Table 4 and Table 5. A higher percentage of the dataset is trained and we fit the regression model to the data. If the split of the training set is too small, then the parameters might have a higher variance. On the other hand, if the test set is too small, the model performance or validation might be unreliable. If the sample size is too large, the split size of the training set can be reduced if the method is computationally intensive. A recommended starting point is 80-

20, however it all depends on the size of the data used in the model [45]. Hence, based on the sample size used in this thesis, we use the 80-20 split.

We aim to find the respective coefficients of the independent variables (β_0, β_1, β_2) and the value of constant. The mathematical equation for multiple regression is shown below.

$$\mathbf{Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p} \qquad \textbf{(1)}$$

where,

Y_i = dependent variable

x = independent variables

β_0 = y-intercept

β_p = slope coefficients

It is made sure that the training set contains a uniform proportion of data for both male and female modes to increase modeling accuracy. We then apply the estimated model on the test set which consists of data that is independent from the data used to fit the model.

Table 4: Split percentage for male data

Male	**Training set**	**Test set**	**Total**
Number of datasets	10	3	13
Number of datapoints	113	37	150

Table 5: Split percentage for female data

Female	**Training set**	**Test set**	**Total**
Number of datasets	5	2	7
Number of datapoints	56	15	71

We build multiple linear regression models for both the male and female datasets considering a significance level of α=0.05 in this study. The main goal of conducting the analysis is to determine the significance level of the independent variables on the dependent variable. The results also determine if the null hypothesis is rejected or true.

3.7 Results and Discussion

In this chapter, the computation and development of the statistical models are explained. The Borgs score is coded as the independent variable (Y_i). The corresponding section discusses the statistical results for the male model and the female model.

3.7.1 Male model

In the preliminary phase of analysis, we visualize a correlation plot as shown in Figure 5. The correlation plot shows the correlation level between the bio-factors, variables and Borgs on a scale from -1 to 1. We can observe that the correlation plot gives us significance levels when the variables interact with each other. The correlation plot summarizes our dataset and identifies patterns during interactions. For instance; heartrate and seconds correlate with the Borgs score. They also show high correlation when interacted with each other. The plot is also used as a diagnostic to our regression models for an additional insight. The correlation plot for male is shown below.

Figure 5: Correlation plot - Male

Preliminary Model I

We build regression models in the preliminary phase to study about the trends of the data collected. This study helps us to determine if the factors and variables are fit for building a robust regression model. We check for variables which are collinear, since the presence of multicollinearities leads to instability in the model. In the preliminary phase, we use interactions to determine if there is an impact on the regression model. We include the study of data by interpolating the Borgs score in the regression model. Based on the regression models calculated in the preliminary phase, we develop to build a robust regression model in the final analysis.

We calculate a multiple regression analysis to predict the Borgs score based on the subject's physiological variables (heartrate, breathing rate, activity, minute ventilation) and factors (intervals, distance) with a considered significance level of $\alpha=0.05$. We use 2-way interactions between factors and variables as the independent variable and the Borgs score as the dependent variable. In the preliminary models, we perform the analysis with a different combination of training set and test set compared to the final male model. The different use of sample is to experiment and identify different patterns from the results, which would help us build a robust regression model. In this model, we interpolate the Borgs score since the data is collected every 60 seconds and has missing data points. Hence, the sample size of the model is 7790 datapoints. We split the data as 80% of the total sample size and validate 20% of the sample size.

From the regression results, we can infer that activity does not show correlations with the Borgs score. The interactions between seconds and interval do not show correlations. The statistical summary shows all other variables and their interactions significant. The R^2 statistic was found to be 80.82% for the training phase and 77.37% for the validation phase. The difference in the R^2 in the training phase and the validation phase is very less, which seems to be unreliable. Since the dataset is interpolated, it can be argued that the significance is the product of a sample size that is large but also unrealistic. We have interpolated data for almost 90 percent of the sample size and hence, can be fake data. This information can be misleading, and we conclude that interpolation in this case is unrealistic.

Based on the above results, we do no use interpolation for the Borgs score since it makes the data unrealistic. We build a separate multiple regression model with all the factors and variables of the male subjects to predict Borgs.

Preliminary Model II

A multiple regression analysis is calculated to predict the Borgs score based on the subject's physiological variables (heartrate, breathing rate, activity, minute ventilation) and factors (intervals, distance) with a considered significance level of α=0.05. In this model, we do not use interpolation since the results was unreliable due to the sample size.

It is estimated that seconds and heart rate have high correlation with the Borgs score. The distance factor shows high multicollinearity in the model and therefore shows no stats in the summary. The regression model shows that minute ventilation, activity, breathing rate, and interval are not significant. We obtain a R-squared value of 64 percent for the male training set. We use the Variance Inflation Function (VIF) in R to detect for multicollinearities in the model. We perform the VIF in R since the regression model becomes unstable with the presence of multicollinearity. As a rule of thumb, the VIF value exceeding 5 or 10 indicates multicollinearity. In this study, we consider a more conservative VIF value of 5. The heart rate VIF value was found to be 7.5 which exceeds the considered limit. Therefore, we can conclude that the regression model is unstable and do not compute the equation of the model.

From the preliminary phase of analysis, we develop the modelling phase and build two multiple linear regression models. We found that heart rate and time accounts for a high R-squared percentage. Hence, we build a predictive model eliminating all the other variables keeping in heart rate and time. In the subsection, we present the regression models for the final analysis.

Model I

We conducted a multiple regression analysis on the Borgs score for the male model's training set. The heartrate and time data are the independent variables. The purpose of using the heartrate and time data is to build a predictive model. In the analysis, the Borgs score is rescaled from 60 to 200 for better data visualization. We do not factor the other variables in the predictive model since our preliminary analysis show that the R^2 statistic is low when the other variables are taken into consideration. Instead, we aim to build a separate regression model with the other variables to determine their significance levels on the Borgs score.

The statistical results as shown in Table 6 indicate that the heartrate and time have high significance with respect to the Borgs score. The regression results estimated for the predictive model shows (t(6.43), p(3.29e-09)) seconds and (t(14.13), p(2e-16)) heart rate are significant and have correlations with fatigue as shown in Table 6. The estimated regression equation for the male training set is shown in Equation 2.

$$Y_{borgs} = -36.75 + 0.03 \text{ seconds} + 1.28 \text{ heartrate} \quad (2)$$

We obtained a R-squared value of 84.93 percent in the training phase. The results indicate a positive slope, and an increase in fatigue when the heartrate and time factors are increased from low to high level. From the Equation 2, we can interpret that, for every additional BPM of heartrate, the expected Borgs score level increases by 1.28 on average, holding all other variables as constant. As mentioned earlier the Borgs score is scaled from 60 to 200. Similarly, we can infer that for every additional second, the expected fatigue level increases by 0.03 on average, holding all other variables as constant. The model did not show the presence of multicollinearity. The statistical summary is shown in Table 6.

Table 6: Statistical summary - Male model I

Variables	**Coefficients**	**Std-error**	**t-value**	**P-value**
Seconds	0.03	0.004	6.43	3.29e-09
Heart rate	1.28	0.09	14.13	2e-16
Intercept	-36.75	9.57	-3.83	0.0002

Residual std error: 14.72 on 110 degrees of freedom
Multiple R-squared: 0.8493
F-statistic: 310 on 2 and 110 DF, **p-value**: < 2.2e-16

The male test set prediction of the Borgs score is visualized in Figure 6. The plot consists of the actual Borgs score, predicted Borgs score, and their confidence level. The Borgs score is scaled from 60 to 200 for better visualization. From the analysis, we can conclude that the male subject's heart rate and the time performing the task correlate with fatigue and satisfy our significance level.

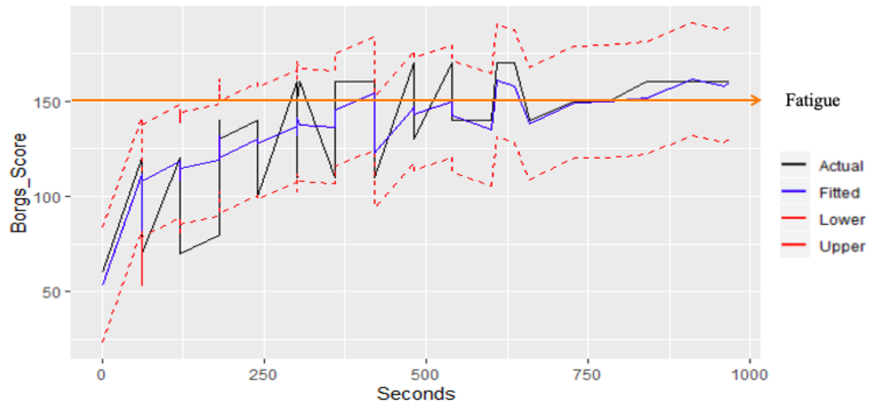

Figure 6: Fatigue with respect to time - Male

In the validation phase, the training set's regressor is used for the test set data. The R^2 statistic is computed to get a more realistic assessment of the goodness of fit of the model. The R-squared value for the test set sample was 72 percent. From the statistical results, we can conclude that the model has 72 percent prediction accuracy of fatigue.

The model shows an increasing trend of Borgs with respect to time. The plot shows the visualizations for the male test set data which consists of 20% of the male sample size. Thus, we observe a wave like trend which increases overall with time and does not increase constantly. The model shows that the male subjects get fatigued after 6 minutes of lifting (approx.).

Model II

Now, we build a separate regression model for the male subjects with an aim to determine the statistical significance of the other variables and to check if they correlate with fatigue. Since it was estimated that the preliminary model was unstable due to multicollinearity, we eliminate heart rate and distance from the regression model. Similar to Equation 2, we build a regression model on the Borgs score for male on a significance level of α=0.05. In this model, we factor in seconds, breathing rate, minute ventilation, interval, and activity. The result obtained shows that the multiple regression equation is significant and has correlations between the bio-factors and Borgs. The obtained regression equation for the male training set is shown in Equation 3.

$$\mathbf{Y_{borgs} = 68.76 + 0.075\ seconds - 15.3\ interval + 1.145\ breathing\ rate + 25.33\ activity + 0.0004\ minute\ ventilation \quad (3)}$$

The regression results estimated for the predictive model shows (t(12.43), p(<2e-16)) seconds, (t(-3.615), p(0.0004)) interval, and (t(4.12), p(7.13e-05)) are significant and have correlations with fatigue as shown in Table 7. From the regression results, we found that the variables in Equation 3 have high correlation except for minute ventilation and activity. We obtained a R-squared value of 73 percent in the training phase. From Equation 3, we can interpret that, for every additional second, the expected fatigue level increases by 0.075 on average. Similarly, for every additional RPM of breathing rate, the expected fatigue level increases by 1.145 on average. The interval between repetitions shows a negative slope with fatigue. There is an increase in fatigue when intervals are decreased from low to high level. It can be interpreted that, for every second decreased in interval, the expected fatigue level increases by 15.3 on average. The interpretation is with respect to the rescaled Borgs score. We can infer from the statistics that breathing rate, seconds, and interval correlate with fatigue. The variables minute ventilation and activity do not correlate with fatigue based on the considered significance level in the hypothesis. The statistical summary for the regression model is shown in Table 7.

Table 7: Statistical summary – Male model II

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.075	6.08e-03	12.43	2e-16
Intervals	-15.3	4.23e+00	-3.61	0.0004
Breathing rate	1.145	2.77e-01	4.12	7.3e-05
Activity	25.33	16.17	1.566	0.12
Minute Ventilation	0.0004	0.0003	1.473	0.14
Intercept	68.76	5.58e+00	12.32	2e-16

Residual std error: 19.83 on 107 degrees of freedom
Multiple R-squared: 0.73
F-statistic: 59.08 on 5 and 107 DF, **p-value**: < 2.2e-16

Minute ventilation and activity have a significance level of 0.14 and 0.12 respectively. Activity and minute ventilation do not satisfy the considered level of significance and are eliminated. Therefore, we can conclude that activity and minute ventilation are not correlated with the Borgs score. The new estimated regression equation with the significant variables is shown in Equation 4.

$$\mathbf{Y_{borgs} = 68.76 + 0.075\ seconds - 15.3\ interval + 1.145\ breathing\ rate} \quad (4)$$

In the validation phase, the training set's regressor is used for the test set data. The R^2 statistic is computed to get a more realistic assessment of the goodness of fit of the model. The R-squared value for the test set sample was 64.91 percent. From the statistical results, we can conclude that the model has 64.91 percent prediction accuracy of fatigue.

Inference – Male model

We consider the heartrate and time data with respect to the Borgs score to build a fatigue predictive model. Based on the preliminary model, we do not include activity, minute ventilation, breathing rate, interval and distance in the predictive model since it affects the R-squared value. From the analysis, we can conclude that fatigue is correlated with the male's heartrate and time and shows a R^2 statistic of 72 percent. Table 7 shows that interval, seconds, and breathing rate satisfy the significance level. Minute ventilation, and activity of the male subjects does not satisfy the significance level considered in this hypothesis. Hence, we can conclude that minute ventilation and activity do not correlate with Borgs score. We can conclude that Equation 2 has a higher R-squared value when compared to Equation 4.

3.7.2 Female model

We follow the similar methods for the female model. In the preliminary phase of analysis, we visualize a correlation plot as shown in Figure 7. The plot shows the correlation level between the bio-factors, variables and Borgs on a scale from -1 to 1. The correlation plot gives us insights on the correlation levels when the variables interact with each other. For instance; we find that seconds and heartrate show high significance. Similarly, the plot shows correlations between seconds and intervals. The correlation plot for female is shown below.

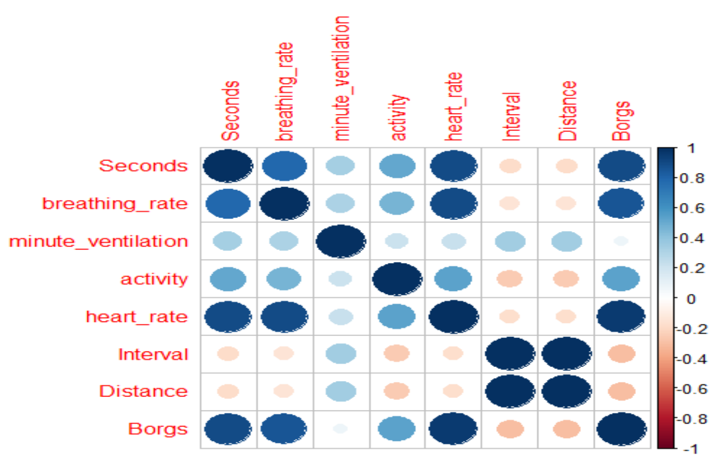

Figure 7: Correlation plot - Female data

Preliminary Model I

In the preliminary phase of modelling for the female dataset, a multiple regression analysis is calculated to predict the Borgs score based on the subject's physiological variables (heartrate, breathing rate, activity, minute ventilation) and factors (intervals, distance). We use 2-way interactions between factors and variables as the independent variable and the Borgs score as the dependent variable. In the preliminary models, we perform the analysis with a different sample set compared to the final female model. The different use of sample is to experiment and identify different patterns from the results, which would help us build a robust regression model. We interpolate the Borgs score since the data is collected every 60 seconds and has missing data points. Hence, the sample size of the model is 2440 datapoints. We split the data as 80% of the total sample size and validate 20% of the sample size.

From the regression results, distance show high multicollinearity with the variables it interacts with and by itself. The R^2 statistic was found to be 96% for the training phase and 93% for the validation phase. The difference in the R^2 in the training phase and the validation phase is very less, which seems to be unreliable. Since the dataset is interpolated, it can be argued that the significance is the product of a sample size that is large but also unrealistic. We can also conclude that the model is unstable due to the presence of collinearity.

Preliminary Model II

It is estimated that seconds, heart rate, breathing rate and intervals have high correlation with the Borgs score. The distance factor shows high multicollinearity in the model and therefore shows no stats in the summary. The regression model shows that minute ventilation and activity are not significant. We obtain a R-squared value of 81 percent for the male training set. We use the Variance Inflation Function (VIF) in R to detect for multicollinearities in the model. As mentioned earlier, we perform the VIF in R since the regression model becomes unstable with the presence of multicollinearity. The heart rate VIF value was found to be 17.5 which exceeds the considered limit.

Based on the insights, we develop the model and build two multiple linear regression models for the female. From the preliminary phase of analysis, we found that heart rate and time accounts for a high R-squared percentage similar to the male model. Hence, we build a predictive model eliminating all the other variables keeping in heart rate and time. We use the VIF to check for the presence of multicollinearity.

Model I

We conducted a multiple regression analysis on the Borgs score for the female model's training set. The heartrate and time data are the independent variables. The purpose of using the heartrate and time data is to build a predictive model. We do not factor the other variables in the predictive model since our preliminary analysis for the female dataset shows that the R^2 statistic is low when the other variables are taken into consideration. Instead, we aim to build a separate regression model with the other variables to determine their significance levels on the Borgs score. In the analysis, the Borgs score is rescaled from 60 to 200 for better data visualization.

The statistical results as shown in Table 8 indicate that the heartrate and time have high significance with respect to the Borgs score. The regression results estimated for the predictive model shows (t(4.19), p(0.0001)) seconds and (t(9.2), p(1.43e-12)) heart rate are significant and have correlations with fatigue as shown in Table 8. The estimated regression equation for the male training set is shown in Equation 5.

$$\mathbf{Y_{borgs} = -18.67 + 0.04\ seconds + 1.07\ heartrate} \quad \mathbf{(5)}$$

The variables in the regression equation satisfy the considered significance level. We obtained a R-squared value of 95 percent in the training phase. The results indicate a positive slope, and an increase in fatigue when the heartrate and time factors are increased from low to high level. From Equation 5, we can interpret that, for every additional BPM of heartrate, the expected fatigue level increases by 1.07 on average, holding all other variables as constant. Similarly, we can infer that for every additional second, the expected fatigue level increases by 0.04 on average, holding all other variables as constant. The model did not show the presence of multicollinearity. The statistical summary is shown in Table 8.

Table 8: Statistical summary – Female model I

Variables	**Coefficients**	**Std-error**	**t-value**	**P-value**
Seconds	0.04	0.01	4.19	0.0001
Heart rate	1.07	0.117	9.2	1.43e-12
Intercept	-18.67	10.72	-1.74	0.087

Residual std error: 8.35 on 53 degrees of freedom
Multiple R-squared: 0.95
F-statistic: 512.7 on 2 and 53 DF, **p-value**: < 2.2e-16

In the validation phase, the training set's regressor is used for the test set data. The R-squared value for the test set sample was 86 percent. From the statistical results, we can conclude that the model has 86 percent prediction accuracy of fatigue. The female test set prediction of the Borgs score is visualized in Figure 8. The plot consists of the actual Borgs score, predicted Borgs score, and their confidence level. The Borgs score is scaled from 60 to 200 for better visualization. From the analysis, we can conclude that the female subject's heart rate and the time performing the task correlate with fatigue and satisfy our significance level.

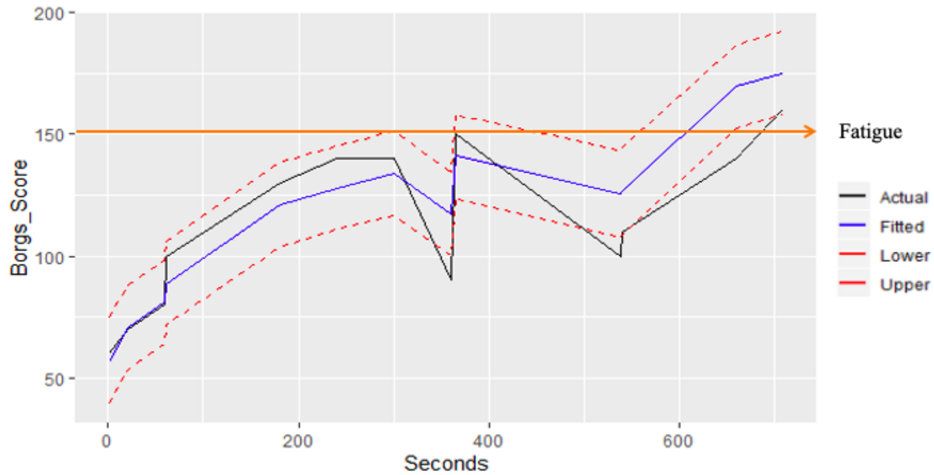

Figure 8: Fatigue with respect to time - Female

The model shows an increasing trend of Borgs with respect to time. The plot shows the visualizations for the female test set data which consists of 20% of the female sample size. The model shows that the female subjects get fatigued after 7-8 minutes of lifting (approx.).

Model II

Now, we build a separate regression model for the female subjects with an aim to determine the statistical significance of the other variables and to check if they correlate with fatigue. Since it was estimated that the preliminary model showed multicollinearity for heart rate and distance, we eliminate heart rate and distance from the regression model. We build a regression model on the Borgs score for female on a significance level of α=0.05. In this model, we factor in seconds, breathing rate, minute ventilation, interval, and activity. The estimated regression equation for the male training set is shown in Equation 6.

$$\mathbf{Y_{borgs} = 53.31 + 0.11\ seconds - 16.4\ interval + 0.8\ breathing\ rate + 22.15\ activity + 0.0002\ minute\ ventilation} \quad \mathbf{(6)}$$

The regression results estimated for the predictive model shows (t(10.05), p(1.35e-13)) seconds, (t(-3.48), p(0.001)) interval, and (t(2.72), p(0.008)) breathing rate are significant and have correlations with fatigue as shown in Table 9. From the regression results, we found that the variables in Equation 6 have high correlations except for minute ventilation and activity. We obtained a R-squared value of 92 percent in the training phase. From Equation 6, we can interpret that, for every additional second, the expected fatigue level increases by 0.11 on average. Similarly, for every additional RPM of breathing rate, the expected fatigue level increases by 0.8 on average. The interval between repetitions shows a negative slope with fatigue. There is an increase in fatigue when intervals are decreased from low to high level. It can be interpreted that, for every second decreased in interval, the expected fatigue level increases by 16.4 on average. Minute ventilation and activity have a significance level of 0.12 and 0.18 respectively. As discussed earlier, we do not consider activity and minute ventilation since it does not satisfy the considered level of significance. The statistical summary for the regression model is shown in Table 9.

Table 9: Statistical summary – Female model II

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.11	0.01	10.05	1.35e-13
Intervals	-16.4	4.72	-3.48	0.001
Breathing rate	0.8	0.29	2.72	0.008
Activity	22.15	16.32	1.35	0.12
Minute Ventilation	0.0002	0.0001	1.55	0.18
Intercept	53.31	5.70	9.341	1.52e-12
Residual std error: 10.95 on 50 degrees of freedom **Multiple R-squared:** 0.92 **F-statistic**: 115.6 on 5 and 50 DF, **p-value**: < 2.2e-16				

Minute ventilation and activity have a significance level of 0.18 and 0.12 respectively. Activity and minute ventilation do not satisfy the considered level of significance and are eliminated. Therefore, we can conclude that activity and minute ventilation are not correlated with the Borgs score. The new estimated regression equation with the significant variables is shown below.

$$\mathbf{Y_{borgs} = 53.31 + 0.11\ seconds - 16.4\ interval + 0.8\ breathing\ rate} \quad \mathbf{(7)}$$

In the validation phase, the training set's regressor is used for the test set data. The R^2 statistic is computed to get a more realistic assessment of the goodness of fit of the model. The R-squared value for the test set sample was 79 percent. From the statistical results, we can conclude that the model has 79 percent prediction accuracy of fatigue.

Inference – Female model

We consider the heartrate and time data with respect to the Borgs score to build a fatigue predictive model. We do not include activity, minute ventilation, breathing rate, interval and distance in the predictive model since it has lower significance levels compared to the heartrate and time. Equation 5 suggests that fatigue is correlated with the female's heartrate and time and shows a R^2 statistic of 86 percent. Table 9 shows that interval, seconds, and breathing rate satisfy the significance level. Minute ventilation, and activity of the female subjects do not satisfy the significance level considered in this hypothesis. Hence, we can conclude that minute ventilation and activity do not correlate with Borgs score. Seconds, intervals, and breathing rate show correlations with the Borgs score. We can conclude that Equation 5 has a R-squared value when compared to Equation 7.

From the statistical results for the female model, we can conclude that it is comparable to the male model. The female model has a higher prediction accuracy of fatigue compared to the male model. The models show similar margin of error and has a negative constant. Both the female and the male models show that heartrate has high significance on Borgs. The trends show that the male subjects get fatigued after 6 minutes of lifting and the female subjects get fatigued after 7-9 minutes of lifting. The difference in the weight designed and the physiological factors of the genders can be reasons behind the difference in the fatigue time. From the male and female models, we estimate comparable coefficients of variables and comparable statistical summary. The male and female models show that activity and minute ventilation are the only two factors which are not significant. On the other hand, seconds, breathing rate, and intervals show significance with respect to fatigue. As mentioned earlier, the distance and heartrate factor show high multicollinearity when included in the second model for males and females.

3.8 Conclusion of Results

This research uses a MoCap framework and physiological data of subjects with an aim to analyze human fatigue and optimize material handling operations in manufacturing industries. We use statistical techniques to build predictive model for the male and female subjects performing a lifting task. Our goal is also to determine the important correlations between the physiological data and human fatigue. The heartrate and time frame data are factored in to predict fatigue using a regression algorithm. Based on the DOE parameters, the statistical results show that the male model predicts fatigue with 72% accuracy, and the female model predicts fatigue with an 86% accuracy. On a general note, we find the physiological variables heartrate, and breathing rate highly significant and correlated with human fatigue. Based on the model, we also find the factors seconds, and interval highly significant and correlated with fatigue. The results show that the subject gets fatigued as time, heartrate, breathing rate increases and the interval decreases. The physiological variables activity and minute ventilation did not satisfy the level of significance considered in this model. However, we could conclude by saying that activity and minute ventilation are considerably significant with respect to fatigue. Finally, the fatigue plot for the male and female proves that fatigue increases with time of the task, and heartrate is an essential physiological variable with respect to fatigue. Based on the results, we provide answers to the following questions in section 1.

1) When will the worker reach the fatigue level with respect to the lifting task?

   As discussed earlier, it is highly important to efficiently plan workforce in a material handling environment. In a manufacturing industry, the entire process in an assembly line may come to a halt when the operator experiences physical fatigue. Supervisors are unaware of each operator's capacity for performing the respective task, and hence, planning workforce becomes complicated. The results from the thesis addresses this issue by building a model which can predict the operator's fatigue based on a lifting task. From Equation 2 and Equation 5, we can estimate the time of fatigue with the Borgs score (RPE) and heartrate information. Borg considers an RPE score of 150 (rescaled value) as the subject's fatigue level. By using Borgs value and heartrate information in the equations, the time of fatigue can be estimated for males and females. Using the regression equations (4) and (5), the supervisors can efficiently plan workforce as he has an estimate of when the operator reaches fatigue level.

2) What is the correlation between fatigue level and the activity performed?

   There is a need to determine the correlation between fatigue level and the task performed in material handling. A material handling environment includes different tasks like lifting, walking with loads, pushing, and pulling. A solution to the question would help the supervisor gain insights if he needs skilled or unskilled operators to perform the task based on the difficulty. For instance, if there is correlation between fatigue and the task, the supervisor may assign skilled operators to perform the operation. The thesis results help in answering the above question. The statistical models for male and female show that there is high correlation between fatigue level (Borgs score) and the lifting task. Figure 6 and Figure 8 show that the Borgs score has a positive relation with time. The plots show an increasing trend of the Borgs score with time. Hence, we can conclude that the lifting task may need skilled labors.

3) At what time, one should assign an alternate worker for the task in case the human reaches fatigue level?

   The solution to this question may help the supervisor to assign the next operator for the task without wastage of time. When the Borgs is 150, it is considered that the operator is fatigued. The fatigue predictive models for male and female (Model I) can give the time of fatigue information depending on the subjects. With the "time of fatigue" information, one can calculate the time he needs an alternate operator to complete the task.

4. CONCLUSION

In this research, a manual material handling environment was set up in a MoCap framework. A manufacturing pick and place task in an assembly process is simulated using a digital twin project. The goal of this study is to optimize a lifting operation and researching about human fatigue. We use wearable sensors to build a catalog of datasets considering multiple factors and factor levels as discussed in chapter 3. In this study, statistical and analytical techniques were used to determine two key facts: -

1) To determine the significant Bio-factor variables which correlate with the subject's rate of perceived exertion level.
2) To predict the Borg's score with respect to time and the task performed by the subject.

The Bio-MoCap environment was designed with the help of NIOSH equations and the use of fundamental skill moves. The leg lifting experiment was designed based on metrics from the Snook's table. The data collected is stored and segregated in separate databases respectively. The datasets are cleaned and pre-processed for further analysis. A multiple linear regression model for the male and female genders are built separately to determine the statistical significance level of variables and predict fatigue with respect to time and task performed.

The validation phase is performed an aim to compare the R-squared values between the training set data and the test set data. The regression algorithm is applied to the training set prior to the validation phase. The predictions of fatigue were found to be 72 percent for males and 86 percent for females. The predictive model can be used in material handling industries to plan workforce efficiently and save time.

The fatigue plots help analyze the predicted Borgs data and the actual Borgs data for all the subjects who performed the task. The plots prove that the subjects get fatigued with respect to time as we observe an increasing trend. We can infer that heartrate and breathing rate are highly corelated with fatigue. It can be concluded that there are correlations between fatigue and the Bio-factors, and the system can predict fatigue with respect to time.

This study emphasizes the importance of industry 4.0 and the use of digital twin technology in material handling and fatigue modeling. The proposed model can be used in manufacturing industries where manual material handling is a major operation in their process. The manufacturing industries can use the model with an aim to reduce fatigue of operators and plan their workforce efficiently. As discussed earlier, based on the metrics and damages caused due to fatigue, the model can be used by manufacturing industries to save money and reduce fatigue by optimizing material handling operations.

4.1 Challenges

There were two challenges faced in this study,

1) The resource was limited in this study since the experiment was conducted in a university environment, thereby making the sample size more considerate.
2) In this study, time was a significant constraint in the analysis.

4.2 Limitations

1) The sample size used in the experiment is minimal.
2) The subjects who participated in the experiment are not completely trained, and hence the predictions might not be very accurate for a bigger sample size with a mix of skilled labors and unskilled labors.
3) The number of factors considered while performing the experiment are very limited. More accurate predictions may have been generated if a greater number of factors were considered.
4) While performing the experiment, the Borg's data is recorded manually. The process can be more efficient if this can be automated.
5) Since this thesis was performed in a university environment, the age group of participants recruited for the activity range from 20-27 years old. In a manufacturing industry, the age group of operators generally range between 20-50 years old with different skill level. The age factor causes a difference in their skill level and performance. Hence, the age group of the participants considered in the model is a limitation to address the problem.

4.3 Future Work

In this research, a Bio motion capture (Bio-MoCap) framework is used to analyze the human Bio-factors while performing the lifting fundamental skill move. The future work of this research can concentrate on adding more factors like: - 1) Handedness, 2) Grip/No Grip 3) Skilled/Unskilled subject 4) Electrodermal Activity, etc. The future researcher can focus on collecting more data, thereby increasing the sample size.

The future researcher can work on an Artificial Intelligence technology, where the AI model can not only predict fatigue, but can tell us the human recovery time. A potential approach would be to collect the subject's rest time data. The researcher can use the Borg's scale to capture the time, the subject recovers back to "no exertion" (6 on the scale) once he completes the lifting task. The human recovery time can be factored in an AI model to train the system.

APPENDIX SECTION

Male

Preliminary model 1

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.22	0.009	25.36	<2e-16
Breathing rate	-1.98	0.2777	-7.14	9.6e-13
Minute Ventilation	-2.5e-03	2.688e-04	-8.81	3.91e-16
Activity	10.85	15.16	0.71	0.47
Heartrate	0.35	0.052	6.70	2.16e-11
Interval	-9.07	2.32	-3.899	9.73e-05
Distance	-21.37	2.087	-11.103	<2e-16
Seconds*Breathing rate	-3.97e-04	1.39e-04	-2.85	0.042
Seconds*Minute Ventilation	-2.5e-06	1.40e-07	-17.98	<2e-16
Seconds*Activity	8.01e-03	5.99e-03	1.33	0.181
Seconds*Heartrate	-8.3e-04	7.43e-05	-11.1	<2e-16
Seconds*Intervals	-1.69e-04	1.13e-03	-0.14	0.88
Seconds*Distance	7.091e-03	8.92e-04	7.94	2.24e-15
Breath rate*Min Ventilation	5.35e-05	3.7e-06	14.277	<2e-16
Breathing rate*Activity	-.242	2.72e-01	-0.889	0.374
Breathing rate*Heartrate	0.01	2.59e-03	6.05	1.51e-09
Breathing rate*Intervals	5.53e-01	3.83e-02	14.43	<2e-16
Breathing rate*Distance	0.67	0.033	20.25	<2e-16
Minute Ventilation*Activity	5.47e-04	3.26e-04	1.707	0.087
Min Ventilation*Heartrate	1.65e-05	2.60e-06	6.36	2.07e-10
Minute Ventilation*Interval	-4.07e-04	4.80e-05	-8.46	<2e-16
Minute Ventilation*Distance	-4.26e-04	3.80e-05	-10.97	<2e-16
Activity*Heartrate	0.16	0.146	-1.10	0.2711
Activity*Interval	5.002	2.09	2.388	0.01
Activity*Distance	3.198	1.86	1.7	0.08
Heartrate*Interval	0.049	0.024	2.02	0.04
Heartrate*Distance	0.123	0.09	6.19	6.29e-10
Interval*Distance	-5.670	0.3	-18.32	<2e-16
Intercept	42.10	5.04	8.34	<2e-16

Residual std error: 14.57 on 6973 degrees of freedom
Multiple R-squared: 0.8005
F-statistic: 999 on 28 and 6973 DF, **p-value**: < 2.2e-16

Preliminary Model II

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.06	0.0093	6.431	5.5e-0.8
Heart rate	0.08	0.0014	5.63	9.12e-07
Minute Ventilation	5.69E-05	0.00002	0.555	0.581
Activity	8.11	9.404	0.863	0.393
Breathing rate	0.03	0.241	0.162	0.872
Distance	NA	NA	NA	NA
Interval	2.24	3.10	0.7	0.691
Intercept	2.841	9.85	0.288	0.774

Residual std error: 16.72 on 107 degrees of freedom
Multiple R-squared: 0.6493
F-statistic: 119.2 on 7 and 107 DF, **p-value**: < 2.2e-16

Female

Preliminary Model I

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.335	0.015	22.304	<2e-16
Breathing rate	0.44	0.33	1.33	0.18
Minute Ventilation	-5.47e-04	9.64e-05	-5.679	1.56e-08
Activity	-59.49	20.59	-2.89	0.003
Heartrate	0.31	0.108	2.87	0.0004
Interval	-8.549	3.835	-2.29	0.02
Distance	NA	NA	NA	NA
Seconds*Breathing rate	-9.8e-04	3.83e-04	-2.55	0.01
Seconds*Minute Ventilation	-9.7e-07	9.665e-08	-10.124	<2e-16
Seconds*Activity	-8.77e-03	0.07	-0.489	0.62
Seconds*Heartrate	-9.83e-04	7.69e-05	-12.71	<2e-16
Seconds*Intervals	-5.06e-04	0.005	-0.101	0.91
Seconds*Distance	NA	NA	NA	NA
Breath rate*Min Ventilation	5.23e-07	1.097e-06	0.477	0.633
Breathing rate*Activity	0.299	0.40	0.747	0.45
Breathing rate*Heartrate	0.002	0.004	0.636	0.52
Breathing rate*Intervals	-2.89e-01	6.74e-02	-4.197	2.82e-05
Breathing rate*Distance	NA	NA	NA	NA
Minute Ventilation*Activity	2.58e-04	8.267e-05	3.12	0.018
Min Ventilation*Heartrate	4.20e-06	9.924e-07	4.234	2.40e-05
Minute Ventilation*Interval	8.45e-05	1.68e-05	5.099	3.75e-07
Minute Ventilation*Distance	NA	NA	NA	NA

Activity*Heartrate	0.16	0.146	-1.10	0.2711
Activity*Interval	5.002	2.09	2.388	0.01
Activity*Distance	NA	NA	NA	NA
Heartrate*Interval	0.206	0.045	4.520	6.57e-07
Heartrate*Distance	NA	NA	NA	NA
Interval*Distance	NA	NA	NA	NA
Intercept	42.10	5.04	8.34	<2e-16

Residual std error: 0.177 on 107 degrees of freedom
Multiple R-squared: 0.94
F-statistic: 1584 on 21 and 1930 DF, **p-value**: < 2.2e-16

Preliminary Model II

Variables	Coefficients	Std-error	t-value	P-value
Seconds	0.0431	0.004	8.94	1.58e-14
Heart rate	1.29	0.11	11.914	<2e-16
Minute Ventilation	-0.0004	0.0002	-3.673	0.379
Activity	-4.07	1.09	-3.72	0.710
Breathing rate	0.9	1.87e-01	5.332	0.0056
Distance	NA	NA	NA	NA
Interval	-3.39	2.78	-4.29	3.9e-05
Intercept	-3.511	9.42	-3.7	0.0031

Residual std error: 6.72 on 48 degrees of freedom
Multiple R-squared: 0.812
F-statistic: 289.2 on 6 and 48 DF, **p-value**: < 2.2e-16

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