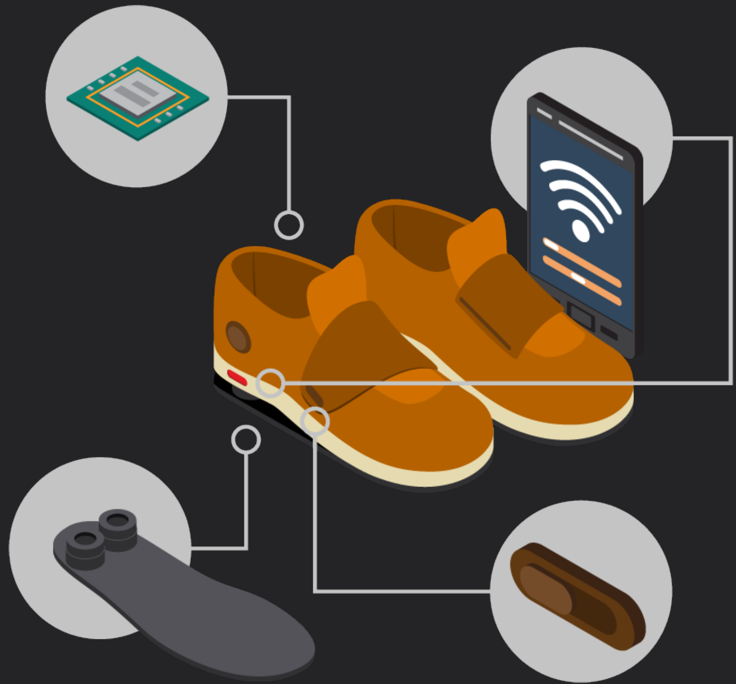

Smart safety shoe of the future: Detecting risks of low back pain

Master Thesis

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List of abbreviations

AI - Artificial Intelligence
AGI - Artificial General Intelligence
ANN - Artificial Neural Networks
DT - Decision Tree
EU-OSHA - European Agency for Safety and Health at Work
FBD - Free Body Diagram
FSR - Force Sensitive Resistor
GRF - Ground Reaction Force
IMU - Inertial Measurement Unit
IoT - Internet of Things
IPD - Integrated Product Design
KNN - K Nearest Neighbours
LBP - Low Back Pain
MCU - Microcontroller Unit
MEMS - Micro-electro-mechanical systems
ML - Machine Learning
NIOSH - National Institute for Occupational Safety and Health
OWAS - Ovako Working posture Assessment System
PCB - Printed Circuit Board
PLA - Polylactic Acid
PPD - Plantar Pressure Distribution
RTC - Real Time Clock
SPD - Strategic Product Design
SVM - Support Vector Machines
TPU - Thermoplastic polyurethane
WMSD - Work-related Musculoskeletal Disorders

Abstract

The warehousing sector is among the top when it comes to the risk of developing work-related musculoskeletal disorders (WMSDs), in particular low back pain (LBP). In this sector, LBP is a prevalent issue, due to the nature of the job of lifting and moving (heavy) objects around. The issue has significant implications for the workers' health, in terms of quality of life. Companies and society feel the consequences in terms of financial costs. This issue could be tackled by introducing smart technology in the form of a smart safety shoe. The concept has been developed by a strategic product design student and the strategic direction has been determined. This project explores the concept further and validates the idea of smart safety shoes to reduce the risk of LBP during manual handling, through technological means.

To understand the problem of LBP in context, extensive literature research was conducted on ergonomics. Understanding what causes it and the current methods to reduce the risks. Further, looking into the possibility of detecting causes through technology. The research results were used to build a prototype for validation of the concept.

The causality of LBP is not easy to point out, as multiple factors (physical, psychosocial, and individual) play a role in its development. Research does conclude that physical factors play a major role, which is related to heavy lifting, repetitiveness, and awkward postures. Manual handling can be performed safely as long as the weight is below 23 kg and correct postures are adopted. Though not all workers adhere to correct posture, and it is hard to track through observational methods.

Postures can be tracked or detected through plantar pressure distribution (PPD), by using pressure sensors. These sensors can be placed within safety shoes and will collect PPD data of workers. The PPD data shows certain patterns and have characteristics that can be linked to different postures. The data can be analysed using machine learning, to automate the process and could be able to give feedback to the user when a risky posture is adopted.

A pressure insole has been prototyped with the conducted research to collect PPD data of different postures (stoop lifting, lifting above shoulder height, and asymmetrical lifting). The collected data were manually analysed to understand how patterns may look like. A machine learning model was made, using a tree algorithm, to analyse the data as well. It can classify all the measured static postures with 100% accuracy. Dynamic lifting data were not analysed by the model yet as it needs additional data preparation. At this point, the concept needs more development to analyse dynamic data and to implement the hardware in the safety shoes.

Based on the results, the core components of the concept have been proven to work and able to detect different postures with great accuracy. The idea of a smart safety shoe that can detect and warn the worker of potential injury is not far-fetched.

This project is the first step in the development of the concept. Due to the complexity of the issue and required knowledge, additional research is needed for the continuation of the project. The posture database has to be set up, improving the machine learning model for dynamic lifting data, hardware design and a live feedback system. With these developments, a smart safety shoe could be brought to market that could improve workers' lives and save additional costs for companies.

Table of Contents

1. Introduction

In the Netherlands, 560.000 people work in construction and 443.000 in warehousing as of 2019 (CBS, 2019). These sectors are unfortunately at the top of the ranking list for the risk of developing work-related musculoskeletal disorders (WMSDs) (NEA, 2019). According to a report from the NEA (2019), 18.7% of the 2170 employees in construction and 10.8% of the 2772 people in warehousing responded in the survey that they suffer from low back pain (LBP) in 2018. Making it a total of 29.5% within these two sectors. These disorders could lead to increased costs for employees, employers, and society (EU-OSHA, 2019). Absence due to pain or discomfort could cost 5800 euros on average per employee per year. In 2019 there were around 178.000 workers absent from work due to LBP (TNO, 2020). The costs could lead to hundreds of millions of euros yearly. The problem size and consequences of LBP alone show reason to develop a novel smart safety shoe that could help reducing or even preventing the risk of LBP. Improving the overall safety of these working environments and reducing the costs significantly.

Allshoes is a company that specializes in safety shoes that are used in all kinds of working sectors. The thriving sectors for these shoes are warehousing, construction, and transport. Due to the nature of these jobs, handling heavy objects and interacting with heavy machinery, the shoes protect the feet of the workers from dangers such as falling objects and slipping. Currently, safety shoes only play a passive role in the safety of workers. Allshoes has envisioned that equipping shoes with proactive capabilities can introduce a competitive advantage. Deploying proactivity to help combat WMSDs could be an excellent opportunity. To give the shoes proactive capabilities, a new shoe has to be designed and developed using smart technology that could detect and collect data about increased risk or high-risk situations. Allshoes aim to develop an innovative proactive smart safety shoe that will protect the workers from (short term) dangers and prevent (long term) musculoskeletal disorders.

This project is the follow-up project to an earlier smart shoe project for Allshoes. The strategic direction of this project has been executed by a Strategic Product Design (SPD) master student, and an initial smart shoe concept has been developed. The focus of the SPD student was to explore and find opportunities for the future of safety shoes and found that giving the current safety shoes proactive capabilities could improve the overall safety in warehousing and construction. The focus on these sectors comes from Allshoes, as these are the major clients of the company. These capabilities have been explored by looking at electronics and artificial intelligence. The final concept is a smart safety shoe equipped with sensors and machine learning to proactively assess situations to reduce the risk of low back pain.

It is often thought that LBP is caused by poor posture, but it comes from a combination of factors (Roffey et al., 2010). It could arise from (unsafe) manual handling alone in some cases but often combined with several factors such as heavy loads or frequent lifting in a short time that contribute to its development (Descatha et al., 2020; Parreira et al., 2018; Swain et al., 2020). Finding the exact cause of LBP due to manual handling is difficult since several factors play a role.

Preventive measures are provided by regulatory agencies such as European Agency for Safety and Health at Work (EU-OSHA). They provide guidelines and programs to prevent WMSDs but are often generic and do not consider the specific work settings (Antwi-Afari et al., 2017). The measures do not have much effect in reducing or preventing injuries. Largely due to the individual need to learn and understand the different measures (Driessen et al., 2010). Current methods of assessing risks are done manually through observational methods, such as NIOSH and Ovako Working posture Assessment System (OWAS), which takes a lot of time and effort (D. Wang et al., 2015).

There are several studies (Antwi-Afari, Li, Seo, et al., 2018; Eskofier et al., 2017; Huang et al., 2007; Kim et al., 2019; Ren et al., 2020; Shu et al., 2010; X. Wang et al., 2013; Yu et al., 2018) that have been exploring and experimenting with making shoes smart by equipping it with sensors to gain insights on gait, posture, detecting activities using machine learning (ML), and assessing risks of WMSDs. Eskofier et al. (2017), Huang et al. (2007), and Kim et al. (2019) looked into the use of IMUs in shoes for gait analysis and found that it yields accurate assessment without the boundaries of a lab. Shu et al. (2010) and X. Wang et al. (2013) looked into making foot plantar pressure analysis practical by using force-sensitive resistors in shoes and obtained stable analysis results from experiments in both static and dynamic loads. Antwi-Afari, Li, Seo, et al. (2018) and Ren et al. (2020) examined the accuracy of activity classification by machine learning through plantar pressure information and achieved an average of 80% accuracy (detects/classifies the activity correctly such as running or falling). Yu et al. (2018) conducted research estimating the physical workload of construction workers using plantar pressure information. This information has been combined with a smartphone camera, which is run through an app with an advanced deep learning algorithm to extract skeleton data from workers, to assess risk factors of WMSDs. They found that this assessment method gives accurate results in finding WMSDs. These studies show promising practical uses and possibilities, though most of the studies are conducted in a controlled (lab) environment and focuses on gait and fall detection. At this moment there no smart shoes or soles available for warehousing and construction. Only a few studies have conducted research using smart shoes in warehousing, as mentioned before. This may be a good indication of an opportunity in the market but could also mean that the available technology is not mature yet or simply does not exist. To assess whether it is possible to develop a safety shoe that is capable of assessing the risk of LBP during work, additional research concerning ergonomics, sensors and smart data processing is needed.

This leads to the following research question of the thesis:

“Can equipping safety shoes with sensors and smart data processing help reducing the risk of LBP, and eliminate the need for deploying labour-intensive observation methods for that purpose?”

Ergonomics is important to determine the causal effects of working postures concerning the risk of developing LBP (Swain et al., 2020). While sensors can acquire data about the user, such as the amount of load force on the body and possibly different postures. Acquired data can be analysed manually but would be time-consuming. Instead, smart data processing (artificial intelligence and/or machine learning) will be used in analysing the data. The exact method will be determined based on the acquired data.

The aforementioned research components are needed to develop a novel smart safety shoe and to test whether it can help to reduce the risk of LBP. Later, smart safety shoes will be developed further to reduce WMSDs in general, as LBP is only a part of musculoskeletal disorders caused by work. The results from a built functional prototype and conducted user tests will reveal the feasibility, desirability, and viability of a new smart safety shoe. The target audience for this project will be the workers in warehousing as Allshoes has its own warehouse. This makes it possible to conduct tests during development and later utilize the product at its own location when the product launches.

Reader’s guide

The introduction already shed some light on what research areas has been conducted. The following chapter will go into detail on what the project exactly is. First, discussing the problem which has been formed into an assignment based on the project brief and the taken approach.

Chapter three will go into literature research conducted on ergonomics. It explains in more detail what LBP is and how it can be viewed to reduce the risks.

Chapter four explores technology, mainly readily available technology as the aim is to build a prototype. It goes over possible hardware that can be used and what smart data processing is that will be used.

Chapter five is the section where the prototyping design is discussed. The prototype has been built and tested and showing a bit of the process. Further in this section, the prototype has been tested and the results are discussed.

Chapter six is a chapter that discusses the roadmap that Allshoes could follow as the project still needs further development.

Chapter seven will answer the research question and ends with the conclusion of this project.

Chapter eight consists of several recommendations, based on results and a built prototype. These recommendations are mostly (design) aspects that have been considered but due to time or complexity not implemented during the project.

Chapter nine will end with a personal reflection on this project.

2. Project

An overview of the project and the approach is presented here. Describing the problem and the impact of the problem within the target group. Further, briefly explaining the initial assignment provided by the company and the setting of the scope.

2.1 Problem Analysis

In the Netherlands, the occurrence of WMSDs, in particular low back pain, is most common in the warehousing and construction sectors (NEA, 2019). Common causes for WMSDs are awkward working posture, lifting too heavy objects, or standing for too long (EU-OSHA, 2007). WMSDs may affect general health, the quality of life is deteriorating as pain or discomfort might be experienced, even during rest and sleep. It may reduce productivity at work, slowing down due to pain or trying to avoid discomfort. Ultimately, it can result in absenteeism from work (EU-OSHA, 2019). All these consequences lead to increased cost for the workers themselves (medical expenses), enterprises (loss in production and Ziektewet) and society (insurance premium).

To tackle the issue, the root causes have to be identified and addressed to prevent employees from developing WMSD injuries (Humantech, 2017). Finding the cause may be difficult, as it may have started at an early age and reflected when an employee started working. It may be a badly designed working place, difficult to reach tools or manual heavy loads lifting for example. In a study conducted by NIOSH (1997), it was found that three primary risk factors could lead to WMSDs, high force, awkward working posture, and extended duration or high frequency (repeated movements). Additionally, psychosocial factors, such as stress and job dissatisfaction, may influence the development of WMSDs (Menzel, 2007).

A possible way to find where the problem originates is by observing and analysing how the employee works. Assessing individual workers through ergonomic observation-based methods, such as the NIOSH method where 15-minute sampling per task is recommended (Middlesworth, 2020), to collect the physical ergonomic data may be time-consuming (D. Wang et al., 2015). Observation-based methods “rely heavily on the observer’s experience and judgement, and the interrater reliability of this assessment is questionable” (Umer et al., 2017).

A more accurate ergonomics assessment can be done through special setups, using sensors (IMUs) and/or cameras. However, the setup could affect the workers at their jobs and tasks. The setup requires multiple sensors to be placed on the body which may feel intrusive and could cause annoyance (Yu et al., 2018). Through habituation, this problem may go away after using it several times (e.g., as workers are getting used to it) (Nasiopoulos et al., 2014), but adds another piece of equipment that could be forgotten to wear.

Current methods to prevent risks of WMSDs are done through regulations, safety rules, and equipment (EU-OSHA, 2020). Another measure to reduce the risk is by training employees through programs. Learning to assess risks and to perform different manual handling safely. Still, the occurrence exists due to some barriers to successful implementation. Yazdani & Wells (2018) reviewed 88 articles to identify common challenges to implementing and sustaining WMSD prevention programs. They identified eleven barriers to successful implementation:

1. Insufficient time
2. Insufficient resources
3. Insufficient communication
4. No management support, commitment, and participation
5. Insufficient knowledge and training
6. High resistance to changes
7. Changing work environment
8. Scope of activities
9. Lack of trust, stableness, or loss of authority
10. In efficient processes
11. Challenge of implementing controls

Participatory ergonomics programs should be the most effective at reducing the incidence of WMSDs by actively involving employees in the process of developing a safer work environment (Burgess-Limerick, 2018; Vink et al., 2006). From another study conducted by Driessen et al. (2010), it seems that the participatory ergonomics programs are not effective in preventing WMSDs among large groups of employees. The success rate may increase if the program is combined with active continuous involvement of workers and giving them individualized feedback.

To sum up, WMSDs have a significant impact on employees, employers, and society due to the increased costs and loss of quality of life. Finding the origins of WMSDs is not easy, it can be done by manually observing workers in the working environment, but it is a rather time-consuming process. Technology can be used to make it easier but may interfere with work or feel intrusive for the employees. Instead, preventive measures have been created and regulated by safety agencies such as EU-OSHA. However, training does not have much effect on reducing the risks. The success rate may go up with individualized feedback.

2.2 Assignment

The objective of this graduation project is to design and test to reveal the feasibility, viability, and usability of a connected smart shoe concept in warehousing and construction. This follow-up project aims to develop the concept into a prototype.

The goal for the company is to develop a smart safety shoe of the future, aimed at preventing musculoskeletal issues, monitored, and analysed by smart data processing to proactively reduce the risk of LBP and finally WMSDs in general.

Within the time scope of the thesis, the aim is to create a proof of concept that is capable of detecting causes of LBP by collecting data for analysis and proofing its reliability and usability. The target group will be limited to warehousing and construction as these are the biggest client groups of Allshoes (Arts, 2020).

From the problem analysis, the main research question has been formulated. The question is already orientated towards a possible solution to the problem; this would not fit in a traditional research thesis. Though, the thesis aims to make a proof of concept based on the assignment provided by the company.

Main research question

Can equipping safety shoes with sensors and smart data processing help reducing the risk of LBP, and eliminate the need for deploying labour-intensive observation methods for that purpose?

To answer the main research question in a complete and substantiated manner, additional research sub-questions are formulated and divided into three sections for a better overview. The ergonomics section looks into the causal effects of (wrong) manual handling within the target group, as lifting is the primary performed action. Further, looking into how currently the WMSD risks are assessed. The technology exploration section will look into electronics to acquire data for risk assessment and how this data could be processed using smart data processing. Also, analyse whether the data correlates to real-world postures and tasks (manual handling). The smart data processing section looks into the possibilities of artificial intelligence and machine learning to analyse the acquired data automatically.

Sub-research questions

Ergonomics

- What are the causes of low back pain in warehousing and construction?
    - What are the correct and safe manual handling techniques in warehousing and construction?
    - Which causes can potentially be detected by using smart safety shoe?
- How are WMSD risks currently assessed and prevented?
- To what extent is biomechanics needed to analyse WMSD risks?

Electronics and Data

- Which manual assessment aspects have to be considered when using sensors in order to acquire data about manual handling forms?
    - Which sensors can used to detect how someone walks, how they stand and how they perform manual handling?
    - Which sensors are inexpensive and able to fit in safety shoe?
- Will the collected sensor data correlate to postures and handling?

Smart Data Processing

- Can smart data processing find causes or patterns that lead to (the increased risks of) MSDs?
- Can machine learning be used to characterize how patterns in the collected data of manual handling and postures relate to LBP?

2.3 Design Approach

In this graduation project, two approaches have been used. In the analysis stage, it was mainly literature research to understand the fundamentals of the problem and finding causality. The research also helped me to become knowledgeable of what is already out there in terms of state-of-the-art.

The second approach is prototyping design, where the design process is done through making ideas or concepts that relate to the design goal. This can also be seen as the Agile methodology which is used in software development. Prototype design helps with quickly making tangible results and iterating based on found problems in the prototype.

The built prototype will be used to conduct tests for collecting data which is needed to validate the feasibility of this project.

3. Research Analysis

To design and develop a novel product, research is needed to see what the problem exactly is and how it can be solved. This section presents the analysis of underlying theoretical fundamentals and state-of-the-art based on literature review.

3.1 Ergonomics

This section will look into the ergonomics in warehousing and construction, in particular manual handling. For lifting or moving objects, guidelines are provided by health and safety agencies which will be used as a reference for correct manual handling. Even with these guidelines in place, people get injured occasionally. Van den Berg (2020) looked into this matter and found three causes that still leads to injuries:

- Safety culture of the company
- The design of the
    - o Task
    - o Environment
    - o Tools
    - o Instructions
- Individual capabilities
    - o Health and fatigue
    - o Risk perception
    - o Knowledge

All three causes should be approached to prevent future risks of LBP. Starting small at the individual level could lead to a change on a bigger scale, companies safety culture. Redesigning tasks and environment can be done when it is known where the problems occur.

3.1.1 Musculoskeletal Disorders in Warehousing and Construction

''Musculoskeletal disorders (MSDs) are impairments of bodily structures such as muscles, joints, tendons, ligaments, nerves, cartilage, bones, and the localised blood circulation system. If MSDs are caused or aggravated primarily by work and by the effects of the immediate environment in which work is carried out, they are known as work-related MSDs'' (EU-OSHA, 2019).

Based on the description above, it can be concluded that many injuries and disorders could fall under MSDs. Not all of them are prevalent in the target group. Narrowing it down to the most common ones will help with analysing the cause.

Among construction workers, the most common WMSDs are carpal tunnel syndrome, tendonitis, trigger finger, tennis elbow, and LBP (D. Wang et al., 2015). In warehousing, there are similar common disorders, which includes LBP, neck pain and upper-limb disorders (HSE, 2007). Employees that suffer from WMSDs can have reduced work-ability and there is an increased chance that symptoms become worse. In some serious cases, it may even lead to permanent disability (Albers & Estill, 2007). In both sectors, LBP is the most common injury that results in absenteeism from work. In both sectors, comparable manual handlings are performed, leading to similar injuries. Though the variety of tasks performed in construction is much higher, which will not be included in this graduation project due to the focus on manual handling. This will be considered in future further development of the smart safety shoe.

The focus shall be on LBP as this affects the majority of the people that suffer from a musculoskeletal disorder.

This is the definition of LBP:
"Low back pain (LBP) is defined as pain and discomfort, localised below the costal margin and above the inferior gluteal folds, with or without leg pain." (Burton et al., 2006).

This is below the lowest rib and above the lowest part of the butt, see Diagram 1. It can be further categorised into non-specific LBP, which is also known as common LBP. It can be defined as LBP not associated with recognisable, known specific pathology (e.g. tumour, infection). Acute LBP can be defined as LBP that persisted for less than six weeks; sub-acute LBP for between six and twelve weeks; chronic LBP for twelve weeks or more (Burton et al., 2006). From the definitions, it is clear that LBP is a condition that is not easy to find the cause. The causality of LBP will be discussed in the following chapter.

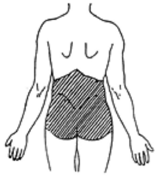


Diagram 1 - LBP area (MATSUDAIRA et al., 2015)

3.1.2 Causes of Low Back Pain

“Although low back pain is still largely idiopathic, research has identified over one hundred risk factors for the condition. Of these risk factors, manual material handling tasks are perhaps the most widely explored within the biomechanical literature, as these tasks have been associated with high mechanical stresses on the lower back” (Cole & Grimshaw, 2003).

The causality of LBP remains a major research topic in the field of ergonomics and biomechanics. This will be utilised, through literature research, as a basis to develop a novel smart safety shoe. More recent studies found that manual lifting is the most demanding handling technique as workers are exposed to high force stresses and awkward body postures (Basahel, 2015; D. Wang et al., 2015). The result of high spinal compression, due to lifting, is what may cause LBP (Basahel, (2015); Parreira et al., (2018). Limiting the lifting force may lead to reduced risks of LBP.
Several factors may contribute to the cause of LBP, physical, psychosocial, and individual (EU-OSHA, 2007). The factors may act alone, but generally in combination with heavy lifting, performance pressure (stress) and low job satisfaction. It is important to take the different factors into account, as they may contribute to the development of LBP (Menzel, 2007). A list below is provided by EU-OSHA (2007), showing the variety of factors contributing to the development of WMSDs in general. There is no specific list provided for LBP, though the factors may still be relevant.

Physical and biomechanical factors (EU-OSHA, 2007):

- Application of force, e.g., lifting, carrying, pulling, pushing
- Repetition of movements
- Awkward and static postures, e.g., with hands above shoulder height, or long standing and sitting
- Vibration
- Environment temperature (Cold or high heat)
- Poor lighting conditions, e.g., could lead to errors and accidents
- High noise levels, e.g., causing the body to tense up (muscle fatigue)

Organisational and psychosocial factors:

- Demanding work, lack of control over the tasks performed, and low levels of autonomy
- Unsatisfactory job level
- Repetitive work at a high pace
- Low or no support from colleagues, supervisors, and managers

Individual factors:

- Medical history
- Physical fitness
- Age
- Smoking
- Obesity

Currently, the causality of LBP is determined by analysing the work tasks and work environment of employee (Descatha et al., 2020). Due to the multifactorial nature of LBP, it is difficult to determine the aetiology. To find the cause, it is needed to take a holistic approach. Considering occupational and nonoccupational influences. The diagram below shows an overview of how different factors linked to contributing to the risk of MSDs.

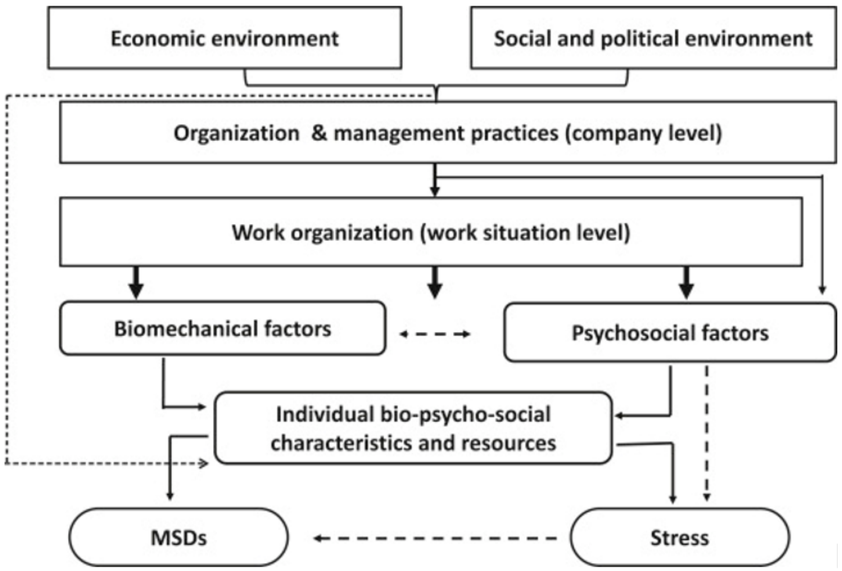


Diagram 2 - Schematic overview for assessing MSDs (Roquelaure, 2016)

Smart safety shoes may analyse or determine the risks of LBP by following the diagram. Physical (biomechanical) factors may be detected by sensors equipped in a smart safety shoe. Psychosocial factors could be considered by acquiring data through surveys from a possible smartphone app. Individual factors could be provided by linking the safety shoes to individual profiles (individualized smart safety shoes). These are some possibilities of accounting for different factors; more possibilities will be discussed in a later chapter. The diagram is a good starting point but does not consider the different weight of the factors. Biomechanical stress may contribute more to LBP than psychological stress. This should be determined in co-operation with an ergonomics expert.

3.1.3 Preventive Measures

Health and safety agencies around the world provide preventive guidance and measures against risks of WMSDs. From the problem definition section, it is clear why the WMSDs need to be tackled. It decreases the quality of life and the huge costs that entail. In the case of warehousing and construction, manual handling is ergonomically the most hazardous (Basahel, 2015). Over the years, the health and safety agencies developed guidelines for manual handling techniques to minimize risks. The different aspects of manual handling shall not be covered extensively as it has been covered in the previous thesis by Van den Berg (2020). A brief review of the aspects will be presented here. The purpose of the review is to see whether the different aspects can be translated for (data) analysis purposes. For example, looking at how posture can be read by sensors. The additional biomechanical analysis will be done to understand the lifting techniques more in-depth. This analysis will be used as the basis for distinguishing different aspects of manual handling in the sensor data analysis.

It is important to know what the correct handling techniques are, to distinguish them from the incorrect ones for the smart shoe. Van den Berg (2020) found five different aspects of manual handling: posture, weight load, duration and frequency, acts, and environment. The analysis is based on guidelines and recommendations provided by HSE (2007, 2016a, 2016b, 2018), Arboportaal (2020), EU-OSHA (2006). When all of these aspects are considered while performing manual handling, the risks should be minimal. The aforementioned aspects may also be used as a form of objective manual handling assessment.

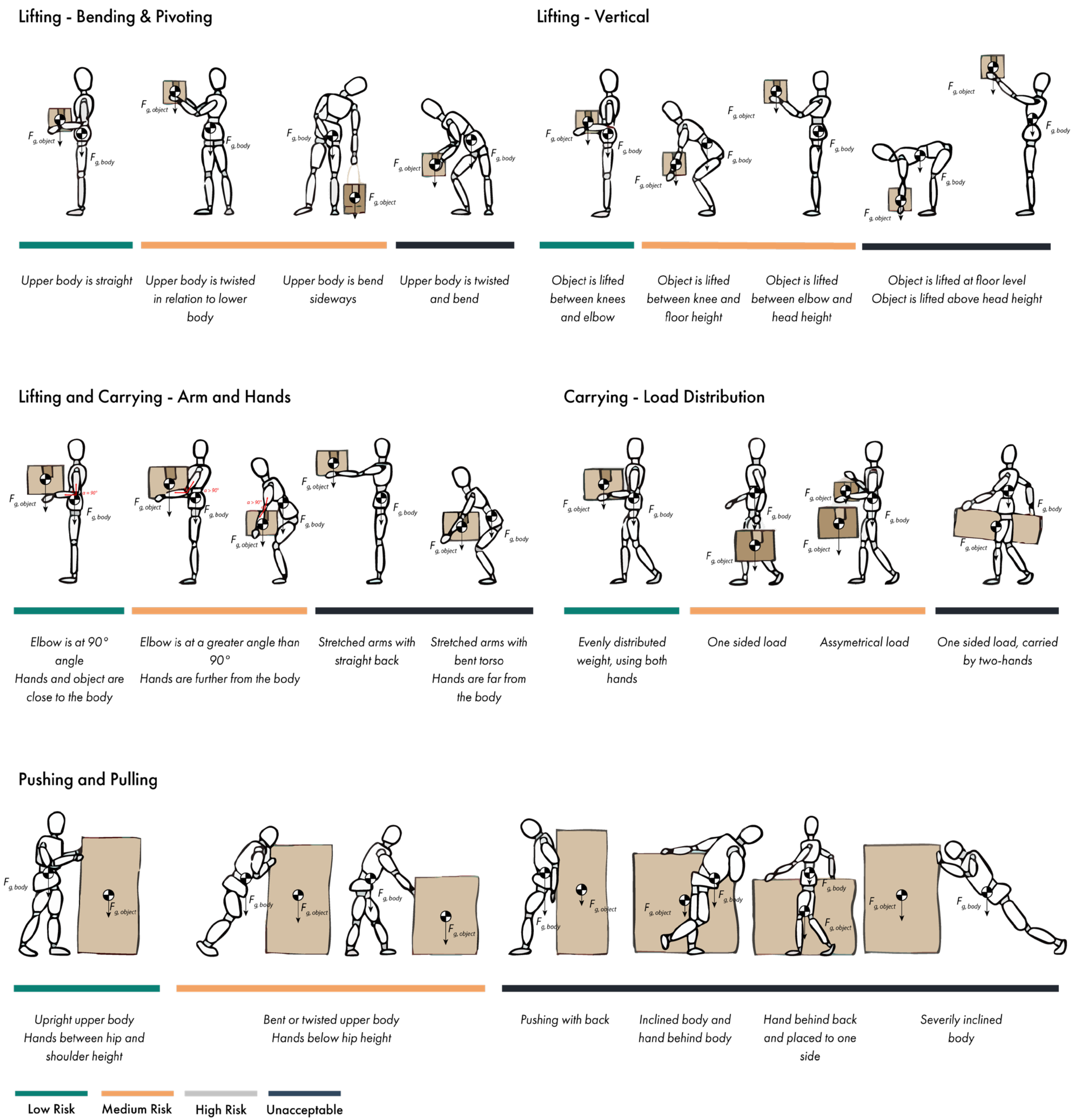


Figure 1 - Manual handling technique for lifting, carrying, pulling, and pushing, original visuals by HSE (2016a, 2016b and 2018).

Posture

Posture relates to body posture or stance during lifting, carrying, pushing, and pulling of loads. Figure 1 shows the correct and incorrect handling techniques. A proper or correct posture will reduce the risk of injuries as loads will be distributed more evenly over the body. The list below shows recommendations that may be detected by using sensors.

- Body Postures
  - Bending and twisting the back is considered harmful and should be avoided
    - To avoid a bend back while lifting objects, bend the knees and keep back straight
  - Pivoting the body should be done from the feet, not the hips
  - Reaching for objects should be minimal
- Load location relative to body (Centre of Mass of Object)
  - Keep loads as close to the body as possible
  - Carry heavy loads between knee and shoulder height (power zone)
  - Push and pull loads between elbow and shoulder height
  - Plantar pressure should be evenly distributed when lifting

Weight load limits

The weight of an object is crucial in manual handling. Figure 2 shows the weight limits when using equipment and other handling techniques. If an object is heavy, muscle fatigue will occur sooner (D. Wang et al., 2015). Fatigue may lead to improper handling, which could result in injury.

- Maximum recommended handled weight is 23 kg, without tools (NIOSH, 2007)
- Maximum weight can deviate based on load position in relation to body (also Figure 2) and alternate techniques (e.g., rolling and dragging)

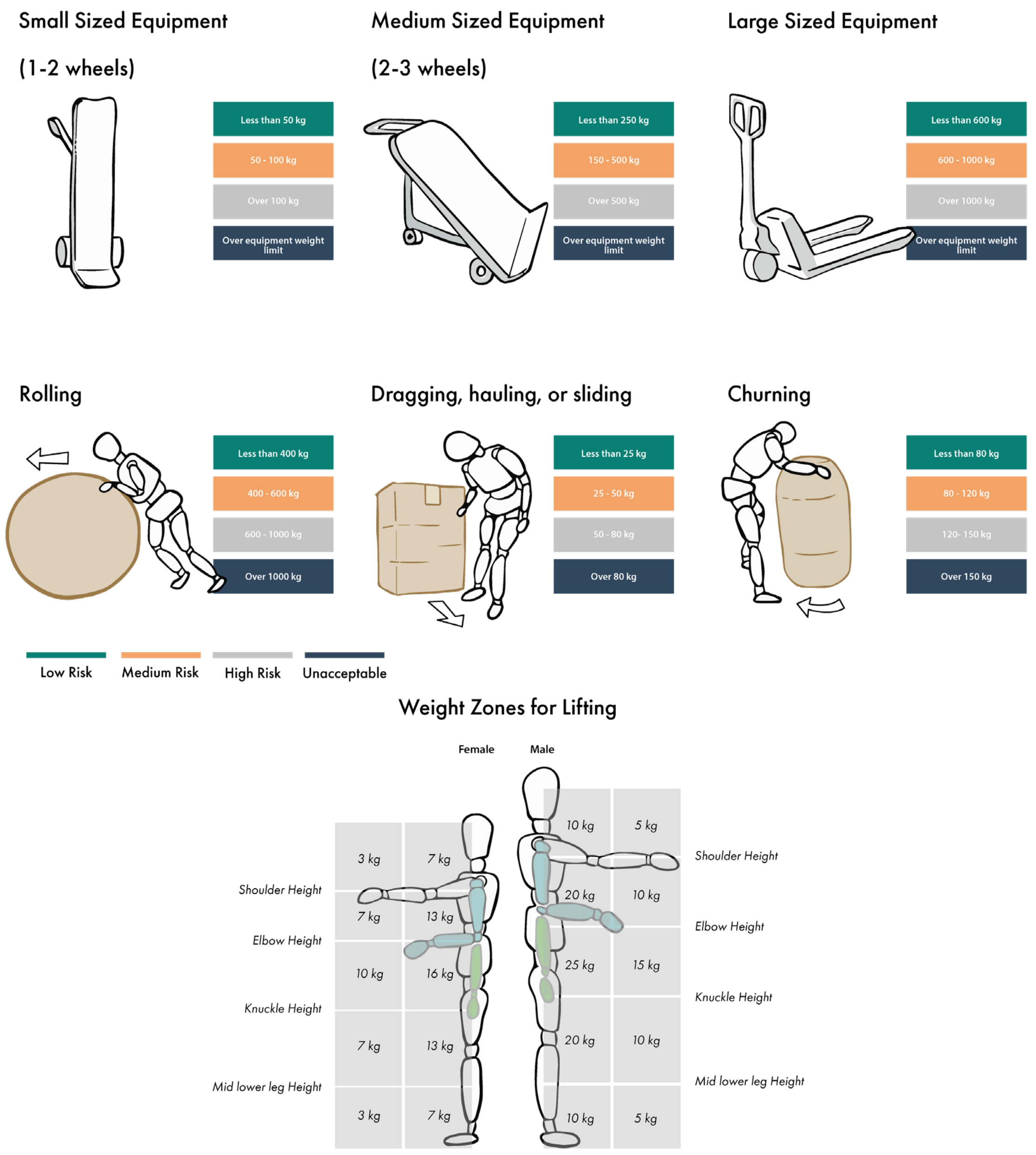


Figure 2 - Maximum weight loads, original visuals by HSE (2016a, 2016b).

Duration and frequency

The time length of manual handling task, how often a task is performed and distance plays a role as well. With increased weight or duration, the body will be put under more stress. Depending on the weight and whether the equipment is used, different durations and frequencies are advised. Figure 3 shows carrying and lifting recommendations based on frequency and weight. The green area shows that frequent lifting, up to 720 times per hour, a load under 10 kg poses a low risk. For carrying, this number is lower, up to 300 times per hour, but at a higher load limit of 15 kg. The frequency drops when the load increases (HSE, 2018).

- Tasks should be performed for a certain time period
    - Heavier objects should be handled for a short duration

Distance

- Carrying should be limited to 4 meters distance (low risk)
    - Up to 10 meters is allowed, though with significant increased risk
    - More than 10 meters is unacceptable
- Pulling and pushing with wheels should be limited to 10 meters distance
    - Up to 30 meters is allowed, though with significant increased risk
    - More than 30 meters is unacceptable
- Pulling and pushing without wheels should be limited to 2 meters distance
    - Up to 10 meters is allowed, though with significant increased risk
    - More than 10 meters is unacceptable

Acts

Certain actions may increase risks, aside from the mentioned unsafe handlings before. The acts are visualised in Figure 4. These acts may occur incidentally, for example catching a falling object. It happens instinctively and differs per person. Still, these acts should be avoided, when possible.

- Always look up and ahead to avoid tripping or colliding
- Always use tools and equipment when available
- Avoid manual handling with obstructed view
- Always handle with controlled movement
- Never try to catch falling objects, in particular heavy or large objects

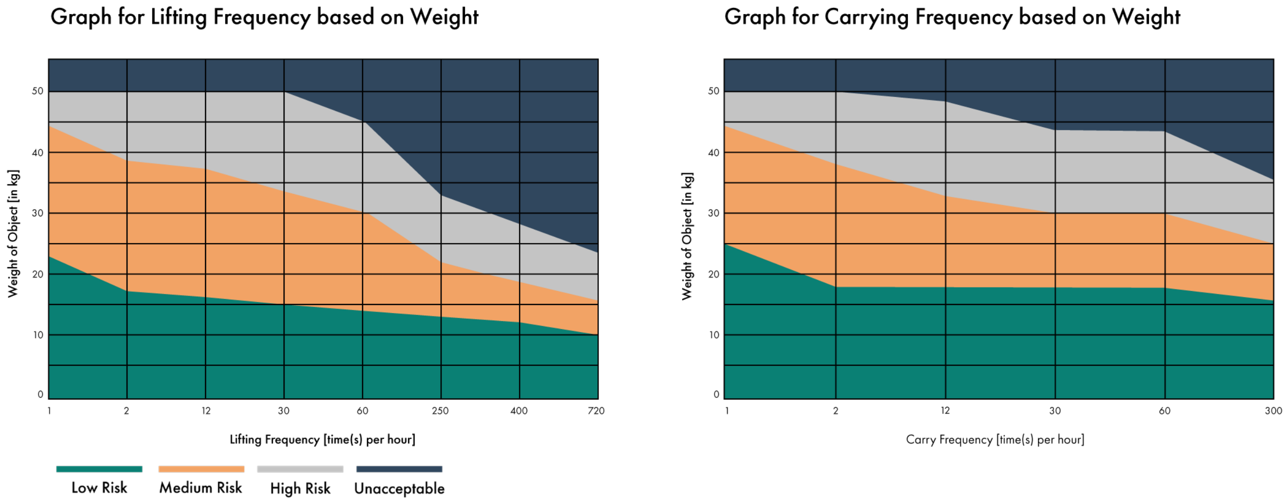


Figure 3 – Maximum weight loads based on frequency and duration, original visuals by HSE (2018).

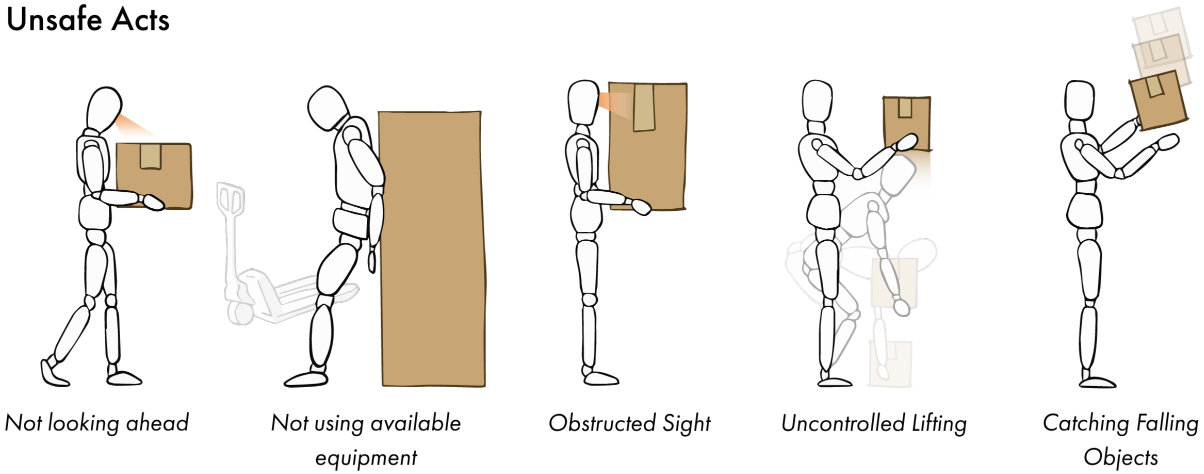


Figure 4 – Unsafe acts during manual handling.

Environment

The last factor is the work surrounding, including physical factors and psychosocial factors, as it may directly affect manual handling.

This relates to:

- Available surrounding space
- Floor surface, e.g., rough/grip, unstable, unevenness
- Object characteristics, e.g., form, size, and available grip
- Obstacles on walking path
- Environment condition, e.g., ambient temperature, humidity, noise, and lighting
- Work demand and pattern (repetitiveness)
- Condition of equipment and tools

Top five riskiest lifting postures

During literature research, a list of the riskiest lifting postures could not be found. Though, this information is needed to reduce the number of possible postures for the testing phase. To acquire this information an email has been sent to J. Metselaar (EHS Manager at Bunzl) (15 March, 2021) asking for a list of the most dangerous lifting postures that he has documented related to Bunzl's warehousing and replied with the following list:

1. Reaching towards objects in racks with an awkward posture
2. Lifting material above shoulder height
3. (Fast) Picking of medium weight objects with one hand to the side
4. Repeatedly moving objects (with some speed)
5. Stoop lifting

According to J. Metselaar, the weight limit seldom gets exceeded during work as people follow this rule. When heavier loads have to be handled, dedicated

WMSD Risk Assessment Methods

Several methods exist to assess risks in a working environment. Each method has its focus area such as the upper body, limbs, and whole body. Reviewing some methods may help to determine how the risks are assessed currently. It can be used as a reference and creating an assessment overview for smart data processing (Sasikumar & Binoosh, 2018).

Here is a list of methods made by Roman-Liu (2014), reviewing them to create new methods that could cover multiple assessment methods. Creating an overview of different methods and categorised them into specific focus areas.

- Key Item Method - KIM
- Revised NIOSH lifting equation
- Ovako Working Posture Analysis System - OWAS
- Postural Loading on the Upper Body Assessment - LUBA
- Occupational Repetitive Actions - OCRA
- Strain Index - SI
- Upper Limb Risk Assessment - ULRA
- Procedure in Standard EN 1005-4:2005
- Rapid Upper Limb Assessment - RULA
- Rapid Entire Body Assessment - REBA

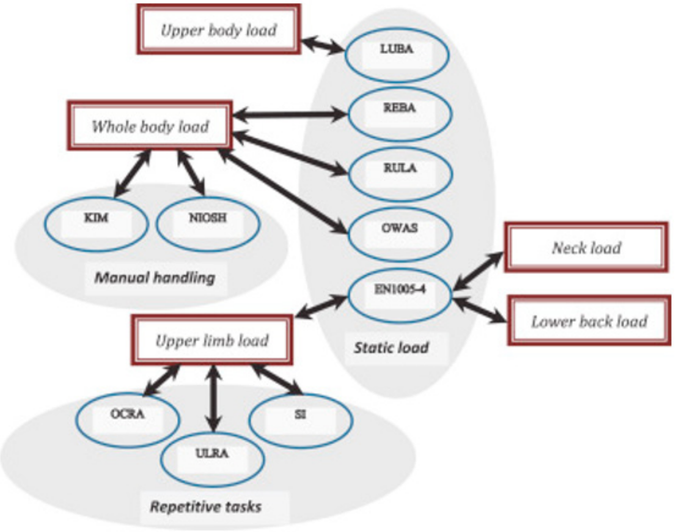


Diagram 2 - Categorised assessment methods (Roman-Liu, 2014).

For assessing manual handling, one could use KIM (Key Item Method), the revised NIOSH lifting equation and OWAS (Ovako Working Posture Analysis System) as they are dedicated for load assessment during manual handling (Roman-Liu, 2014). NIOSH lifting equation may be the most suitable method for assessing manual handling, as it is developed for reducing lifting injuries, especially LBP (Caris, 2020). It looks into load weight, duration and lifting distance, to assess the performed lift. OWAS analyses the working posture to determine the musculoskeletal injury risk but does not consider the load as much as NIOSH (Karhu et al., 1977). KIM analyses load on the body based on frequency, weight and posture, to assess the risk of workloads (BAuA, n.d.).

Gait Analysis

Analysis of the gait (human locomotion) can be used to assess how workers walk as it analyses walking patterns (Whittle, 2007). Walking patterns may reveal if someone is experiencing discomfort or pain (Eskofier et al., 2017; Tasch et al., 2008). This could serve as additional indicators to assessing risks. In the detecting the factors section, some factors are detected using gait analysis, using an inertial measurement unit (IMU) (Kim et al., 2019). Below is a list of factors that are captured through gait analysis.

Factors and parameters (Mazumder & Vashista, 2017):

- Step length
- Stride length
- Angle of the foot
- Angle of the hips
- Speed
- Cadence

There are several measurement methods for gait analysis, which are listed below:

Spatial and temporal

- Timer and floor markings
- Walking on pressure plate
- Laser range (distance) sensors, few cm above ground
- Inertial measurement sensors

Kinematics

- Chronophotography
- Video
- Passive marker systems
- Active marker systems
- MEMS inertial sensors

In a study by Kim et al. (2019) found that novel IMUs are capable of detecting gait events within a small range of error. For heel-strike and toe-off detection there was an error of 0.03 seconds and other detections were within the range of 0-0.01 seconds. This study shows that IMU could be utilised in gait analysis without the limitations of more traditional methods that are used in laboratories.

Ergonomics Conclusion

The causality of LBP has been a research topic for years, yet there is no clear cause. There might not be a clear cut due to how multifactorial the issue is. Studies do agree on the fact that high forces and awkward body postures have a significantly increased risk of developing LBP. Though in warehousing, manual handling cannot be avoided as these actions have to be performed due to the variety in dimensions of the objects. However, manual handling can be performed safely. Health and safety agencies have developed guidelines and instructions. There are six factors to safe manual handling: posture, weight load limits, duration, frequency, acts, and environment. When all of these factors are considered, the manual handling task can be performed safely. The riskiest lifting postures people adopt in warehousing are: reaching towards objects in racks, lifting above shoulder height, asymmetric lifting, repeatedly moving objects (with some speed), and stoop lifting. Currently, the risk of LBP can be assessed through NIOSH lifting equation, OWAS and KIM as it assesses the load on the body. The physical factors of manual handling could be detected using electronics, such as pressure sensors and IMUs. Gait analysis could be a good addition to LBP risk analysis as it can detect when something is wrong with the worker.

3.1.3 Allshoes Warehouse

Allshoes has its warehouse for the distribution of shoes and foot accessories in Alkmaar. The warehouse ships orders to businesses, retailers and directly to consumers, which results in orders as small as one to two pairs of shoes or as big as bulk orders of hundreds of shoes. For this to work properly, the warehouse has been designed to allow this kind of workflow, the scaffolding can be seen in Figure 5. At the lowest level the single products are easily accessible for order pickers, at the second level individual boxes are stored and at the top level, the products are stored in bulk or pallets.

The warehouse is planned in such a way that the most popular products are the closest to the packing table. This reduces the distance that has to be walked to pick more common orders. Less popular products are placed further away as they will be picked less often. Boxes with shoes are placed on the ground and chest level for workers to pick up products easier, products on the ground are elevated to avoid stooping, see Figure 6. Pallets of the same products are placed in the scaffolding above for easy refilling of the section when the product runs out.

All orders are picked by using a cart, to group different products per order, see Figure 7. Multiple orders can be picked this way, without walking back and forth to the packing table. Orders are packed up to approximately 20 kg per box. When there is a bulk order from a bigger business or retailer, a whole pallet could be prepared. This could consist of different brands and sizes or a single brand and size. These pallets are moved by forklift trucks, see Figure 8.

The height of the scaffolding for order picking is a little over two meters, though most products are around my shoulder height, as seen in Figure 9. There are products placed higher and could be inconvenient, as seen in Figure 10. This could lead to awkward postures, trying to pick order above shoulder or even head height. My length is 180 cm and the products at the top were barely reachable.


Figure 5 – Storage scaffolding at Allshoes distribution center in Alkmaar.

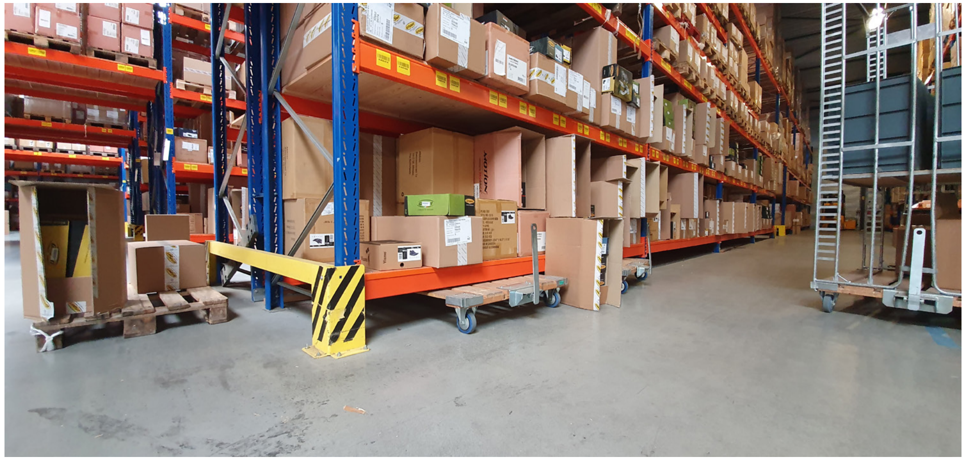


Figure 6 – Elevated scaffolding to avoid stoop lifting.

Figure 7 – Electric picking car.

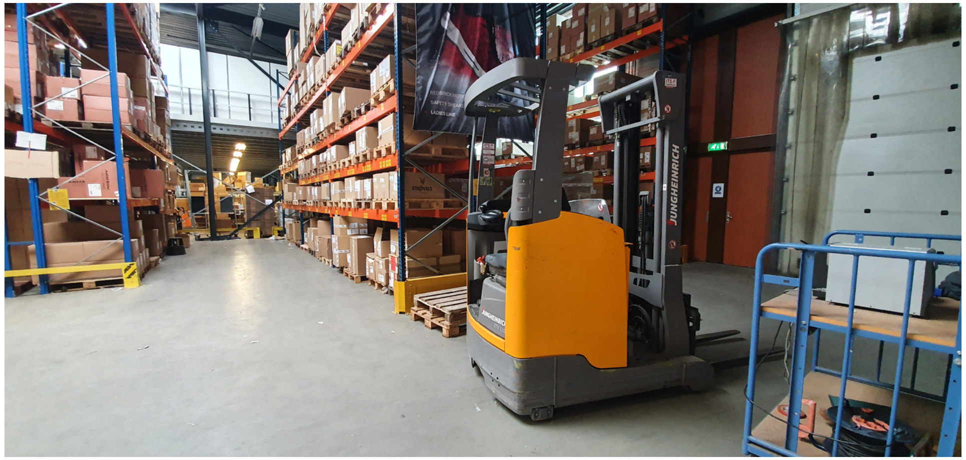


Figure 8 – Forklift.

Figure 9 – Picking a product, around shoulder height.

Figure 10 – Picking product, above shoulder height.

3.2 Biomechanics and Lifting

"Biomechanics is the study of the structure and function of biological systems by means of the methods of mechanics." (Hatze, 1974)

To understand how one's musculoskeletal system works or behaves when lifting, biomechanics becomes important (Garg & Kapellusch, 2009). It can be used to investigate causes of work injuries and finding the maximum reaching distances, for example. Biomechanical calculations can also help with assessing whether a task is too strenuous for the body.

3.2.1 Biomechanical Analysis

By analysing how forces act on the body, it can be estimated how much stress is put on the musculoskeletal system (Beck, 2020). For example, calculating the amount of strain, compression and shear stress, on the spinal discs in the low back region when the person is lifting an object of 10 kg.

To estimate the amount of compression on ones back, the following information is needed:

- Height and weight of the person
- Bending degree
- Weight of the load object

Here is an example given by Beck (2020):

''Using this case as an example, we might have a situation with a caregiver who weighs 80 kilos, is 186 cm tall, and bend 45 degrees forward, lifting a patient's legs, weighing 10 kilos, at a reaching distance of 30 cm.
This case will result in a strain on the caregiver corresponding to approx. 255 kg on the disc in the lumbar region (or the weight of an adult male lion). If we further take into account, that the caregiver is often not just standing still, but is lifting and moving the patient's legs, the load must be multiplied by 3, and the adult male lion turns into a large rhino equivalent to 765 kilos!''

The example above is a rough calculation using a static biomechanical model. A static model is a simplified form of a complex phenomenon, for example, lifting an object from floor level up to a shoulder level rack. To simplify this phenomenon, it will be reduced to the point of a non-moving world, where everything is static and frozen in time. It helps with comprehending the situation, how the forces are applied and how it affects the whole body. It may be used for designing manual lifting guides or assessment models, such as the NIOSH lifting model. The downside of static models is that some important factors are not considered, in particular inertial forces. It makes some situations look safe, but in reality, they are not (Parida & Ray, 2015).

Figure 11 shows a simplified calculation and shows that a 20 kg box would result in an exerted force of 5493.6 N by the back muscles. The compression and shear force on the spine can be calculated if the angle is known. If 45 degree is taken, there would 3884.6 N compression force which is comparable to 395.9 kg.

$$M = F * L$$
$$F = m * g$$

$$F_{g,\,object} = 20\ [kg] * 9.81 [m/s^2] = 196.2\ [N]$$
$$F_{g,\,body} = 40\ [kg] * 9.81 [m/s^2] = 392.4\ [N]$$

$$\Sigma M = 0 = F_{back} * L_{back} = - F_{g,\,body} * L_{body} - F_{g,\,object} * L_{object}$$
$$\Sigma M = 0 = F_{back} * 0.05 = - 392.4 * 0.6 - 196.2 * 0.2$$

$$F_{back} = 5493.6\ [N]$$
$$F_{comp} = \cos(\alpha) * F_{back}$$
$$F_{shear} = \sin(\alpha) * F_{back}$$

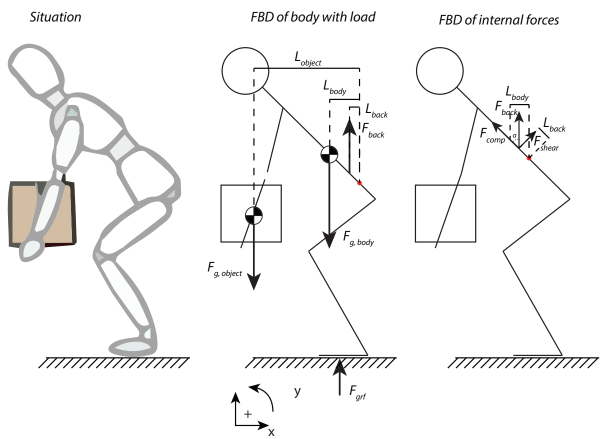


Figure 11 – Biomechanical calculation of lifting a 20 kg box.

Dynamic biomechanical analysis is complex, due to the inclusion of inertial forces of the load and body segments. The amount of these forces should not be underestimated during dynamic movements as it can increase the stress on the body significantly. In addition to the forces from the load and body weight, effects of motion dynamics along with acceleration and velocity are included in the model. There are two types of complexity introduced in the model. The first type is how motion must be described in the kinematic form, direction of movement, speed (velocity) and acceleration over time. The second type is the inertial forces that are created during movement, which can slow down or speed up the movement (Parida & Ray, 2015). Dynamic models will not be considered due to their complex nature, involving more aspects such as the direction of force and time. A biomechanical expert or engineer might be needed to make correct models for analysis, which would not fit within the time frame and scope of the thesis.

Figure 12 – Dynamical Analysis of an athlete

Ground Reaction Force

Estimating the exact force on the spine may be difficult and not the goal of this project. Though, it is still important to understand the basics of biomechanics for developing the new smart shoe. To make use of biomechanics for the project, ground reaction force (GRF) might be rather helpful. Looking at how forces are applied to the feet may reveal how forces are applied to the body. The feet will always interact with the ground with everything that is manually handled, revealing the total force in a static model. Karatsidis et al. (2016) state that “ground reaction forces (GRF) and moments are important measures used as input in biomechanical analysis to estimate joint kinetics, which often is used to infer information for many musculoskeletal diseases”. GRF is measured using force platforms as illustrated in Figure 13. The measured forces may help with the prediction of increased risk of LBP. Analysing possible highest GRF location(s) could be an indication of how a worker is manual handling or whether the load is too heavy.

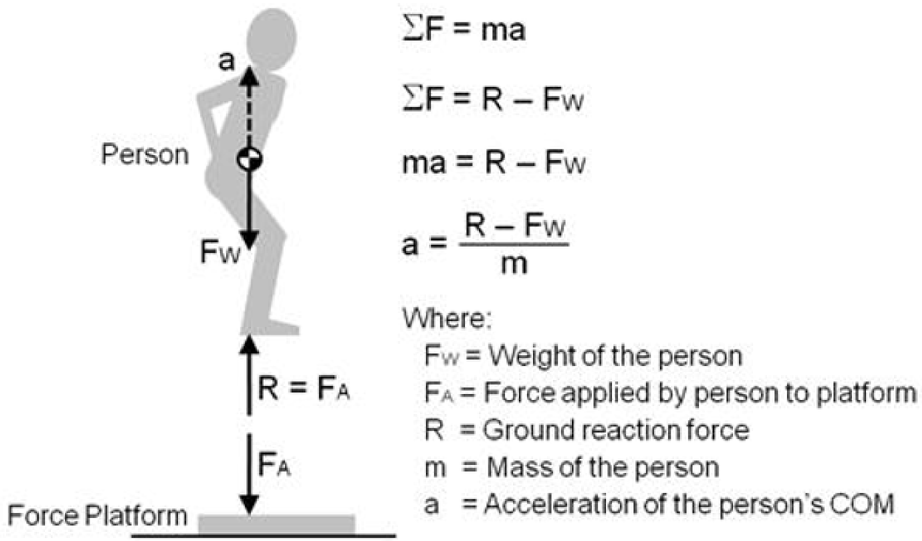


Figure 13 – Measuring GRF (G. Smith, n.d.).

There are several studies done on feet analysis involving GRF by using pressure sensors (Castro et al., 2013; Fong et al., 2008; Jung et al., (2014). Fong et al., (2008) conducted a study in estimating GRF with pressure sensing insoles, comparing it to a complete GRF analysis using a force plate, and found that the results of both devices were rather comparable. Jung et al. (2014) also came to the same conclusion but using estimation models to estimate GRF using insole pressure mat data as input. Castro et al. (2013) compared GRF (using force plates) and plantar pressures (using in-shoe pressure system) between occasional loaded (wearing a backpack) and unloaded gait and found that occasional load increases pressure in midfoot and toes area. The studies show that pressure sensors are capable of estimating the GRF without the location constraint (use force plates in a lab) and can provide more detailed information about characteristics of forces acting on the body (Castro et al, 2013). Pressure sensors proofed to be useful in several studies when it comes to plantar pressure analysis. It shall be used as the basis for assessing LBP risks. Though, currently, there is no paper or study available that has looked into the use of plantar pressure in manual lifting recognition.

Correct Lifting according to Biomechanics

It is often thought that squat lifting (Figure 14c) is the best method to lift vertically, while stoop lifting (Figure 14a) is considered harmful. From studies conducted by Burgess-Limerick (2003) and Van Dieën et al. (1999), it was found that squat lifting is not much better than stoop lifting, from a biomechanical point of view. Van Dieën et al. (1999) reviewed 27 biomechanical studies involving lifting and found no support in advocating squat lifting. Additionally, it was found that the net moments and compression forces may cause LBP. Bending during stoop lifting remains below injury levels making it safe to perform. Dreischarf et al. (2016) found that squat lifting even resulted in 4% higher resultant loads than stoop lifting, using a modified strain gauge attached to the lumbar. A more recent study conducted by Ausavanonkulporn et al., (2019) also found, through musculoskeletal modelling using AnyBody Technology software, that there is no significant difference in compressive and resultant force among squat and stoop lifting. Instead of teaching the perfect single lifting technique, Burgess-Limerick (2003) and Steffens et al., (2016) proposes to educate workers on general lifting techniques and assisting them in finding their appropriate postures and patterns of movement. The main takeaway of these studies is, keep loads as low as possible, avoid extreme lumbar vertebral flexion (extreme stoop lifting at 60°), trunk (upper body) rotation and lateral flexion to reduce the risk of LBP. These four points will be mainly considered in the assessment as they may have the most influence on LBP.

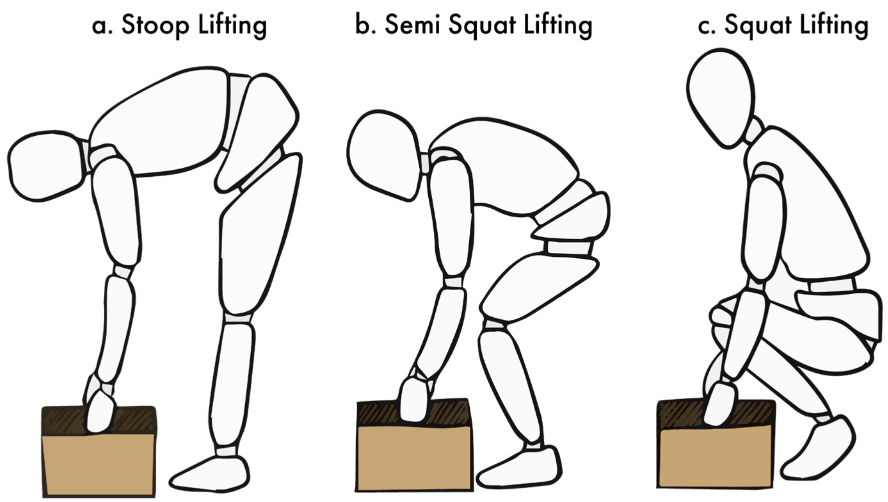


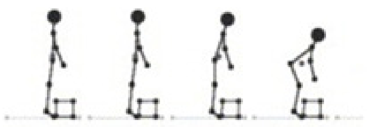
Figure 14 – Lifting Techniques.

Lifting Phases

During a manual lift, there are several phases that a worker goes through. In these phases, different forces are applied over the body (Matt Maines & Reiser, 2006). This information is useful, as it can be used as determinants for assessing how much is being lifted and possibly determining lift technique.

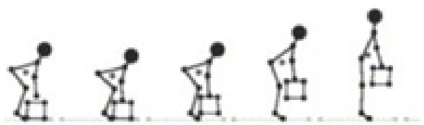
There are five steps involved in lifting an object, lowering the body to the object to lift, lifting the object, bringing the object close to the centre of mass (CoM) of the body, carry to the destination and lower the object. Matt Maines & Reiser (2006) conducted a study in load asymmetries during a lift, by measuring GRF in both feet separately using one force plate per foot. Figure 15 shows the created force graph over time. The GRF on the test person is 833 N and lifts an object of 17 kg. The total force is found by adding up the force of left and right feet. The beginning and end of the graph show a steady line, indicating that the test person is standing stable. If there are strong fluctuations of GRF, this may indicate strong jerks during a lift which is considered a risk of LBP (Xu et al., 2008).

1. Initial – Unweighted Phase



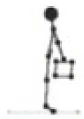
There is no additional load on the body. Force changes due to acceleration in direction of gravity.

2. The lift – Weighted Phase



Force increases to more than the weight of body and object. Caused by increased force to counter gravity and inertial forces.

3. Final – Unweighted Phase



Body and load are in a balanced state with a neutral spine, showing total weight.

4. Carrying – Weighted Phase
5. Additionally Lowering

Figure 15 shows the changes in force when the worker is going through the first three lifting phases. The fourth and fifth phase was not measured by Matt Maines & Reiser (2006). This information might be needed for lifting pattern recognition.

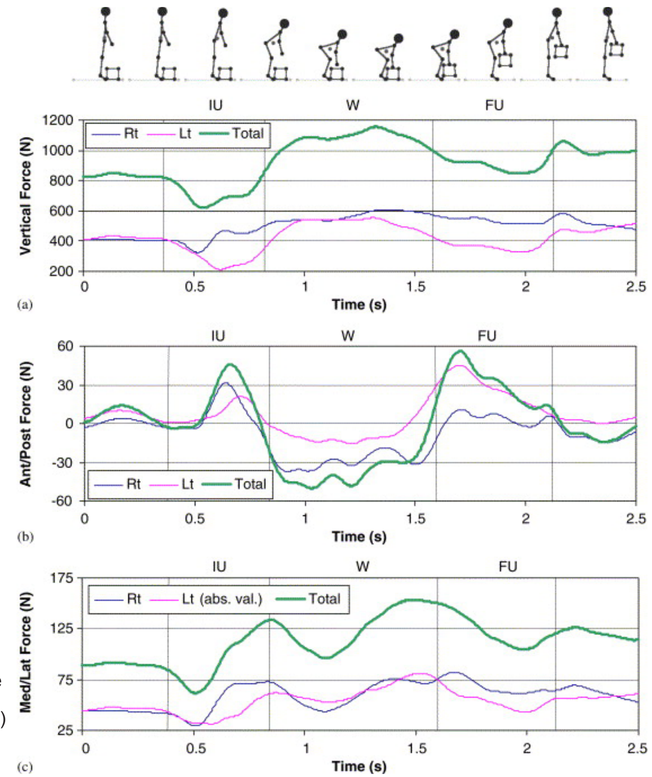


Figure 15 – Lifting phases and the GRF (Matt Maines & Reiser, 2006)

Detecting the different phases may hold valuable information due to the dynamic load's information. In a static analysis, one would only see data at a specific time point. At that time point, the peak loads may not be as high as in dynamic analysis. Figure 16 shows that the anterior is a positive force and the posterior a negative force. In Figure 15, the peak load in phase 2 is more than 1100 N, 100 N more than phase 3. In some cases, the additional 100 N may increase the risk of LBP, due to exceeding the maximum recommended load of 3400 N (Waters et al., 1993).

The lifting phases may have recognizable patterns which could be used in lifting pattern recognition. In Figure 15b and c, it is shown how forces are distributed in anterior-posterior and lateral-medial directions. In Figure 15b the force peaks at -45 N between 1 and 1.5 s, meaning the peak load was on the posterior side. This indicates that the forces were placed on the heel of the feet to counterbalance, by leaning the trunk backwards.

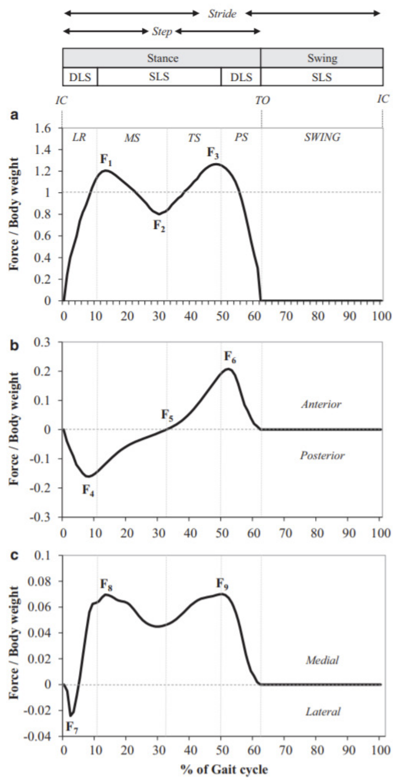


Figure 16 – Interpreting graphs (Chockalingam et al., 2016)

Biomechanics Conclusion

Understanding biomechanics is necessary to comprehend the physical causality of LBP. The studies conducted over the years uncover more and more factors that may lead to the problem. For this project, the found literature can be used as a basis to develop the design. Using GRF as the assessment measurement for risk of LBP. GRF can be measured using pressure sensors placed at the feet, giving possible insights into lifting behaviour. Stoop lifting is not more dangerous than squat lifting. Instead, heavy loads, extreme stoop lifting, rotating with the trunk or lateral flexing with the trunk do have an increased risk of LBP. The goal will be to detect these four points to reduce the risk. To analyse these points, the GRF of lifting phases will be captured. Looking at total force, peak force, force distribution and patterns.

3.2.2 Detecting Physical Factors

To reduce the risk of LBP, awkward postures and lifting heavy loads have to be avoided. Ideally, this would be done by predicting them before they happen. Before the prediction of dangers is possible, there need to be (theoretical) reference models that understand which postures are good and bad. In this section, the current state-of-the-art will be reviewed.

Antwi-Afari, Li, Yu, et al. (2018) conducted a study to automatically detect and classify awkward working postures using insole with pressure sensors to measure and map plantar pressure distribution (PPD). This study shows how different postures may be revealed through PPD data, as seen in Figure 17. The PPD profiles are distinctive from each posture. To detect the different postures automatically, Antwi-Afari, Li, Yu, et al. (2018) used supervised machine learning to classify them. They have used four supervised machine learning classifier models to compare reliability: artificial neural network (ANN), decision tree (DT), k-nearest neighbour (k-NN), and support vector machine (SVM). SVM classifier has performed the best and had an accuracy of 99.7%.

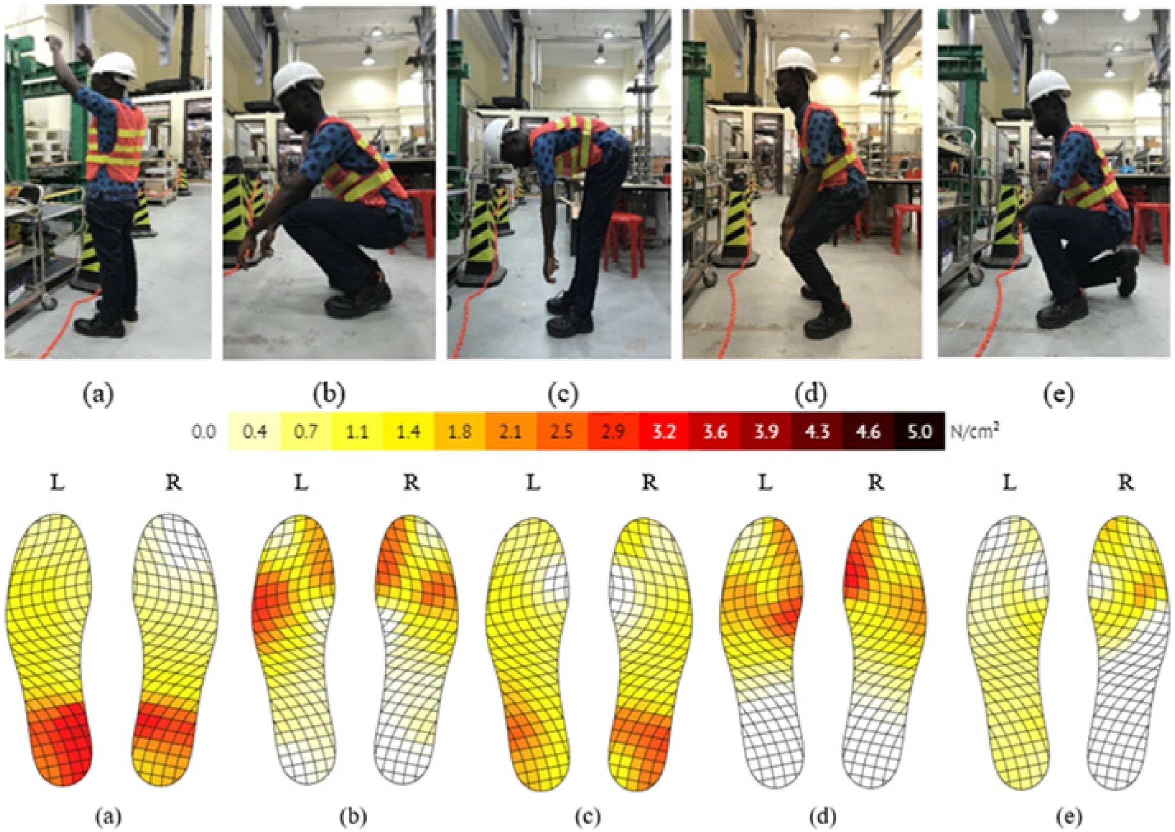


Figure 17 - Postures and plantar pressure distribution profiles (Antwi-Afari, Li, Yu, Kong, 2018)

For an accurate GRF measurement, the sensor layout has to cover most of the foot. Shu et al. (2010) proposed the following layout, shown in Figure 17, as these foot areas support the majority of the body weight and are used for balancing the body. “The sole of foot can be divided into 15 areas, as heel (area 1–3), midfoot (area 4–5), metatarsal (area 6–10), and toe (area 11–15)” (Shu et al., 2010). Instead of fully equipping insoles with fifteen sensors, which could increase complexity, Shu et al. (2010) tested a setup with only six sensors per foot and found rather good results which clearly shows changes in plantar pressure. This layout has been used to simplify the system and reduce the overall cost. The sensors were placed in the metatarsal area and the heel as these places show the most forces. Wang et al. (2016) conducted research looking into different pressure sensor layouts and tested every layout shown in Figure 19. The results were compared to a Tekscan 3000E, a pressure insole with 4 cells/cm2, and found that 7C (7 sensors) had the best performance. Ciniglio et al. (2021) tested the fifteen sensor layout in different applications from weightlifting to gait analysis and found that the setup can be considered adequate in both sport and clinical fields, where precise information is needed. Fewer sensors may be used, but there should not be empty areas due to possible loss of information. Instead, Ciniglio et al. (2021) suggest using larger pressure sensors to cover more area of the foot which is done in their sensor layout, see Figure 20.

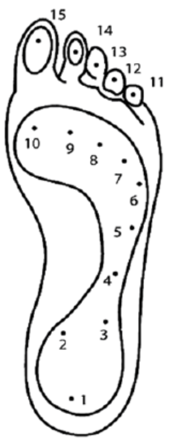


Figure 18 - Pressure Sensor Location (Shu et al., 2010).

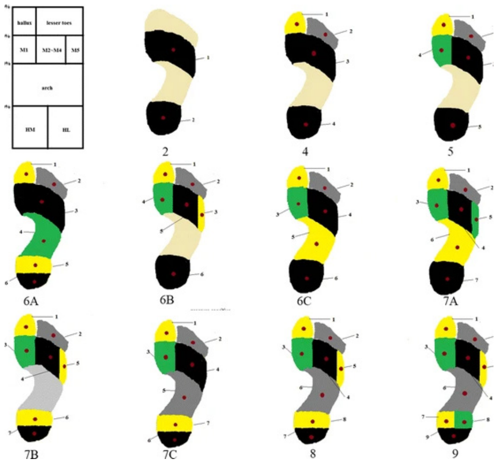


Figure 19 - Variants of pressure sensor layouts (Wang et al., 2016)

Detecting Physical Factors Conclusion

The risk of LBP could be reduced if heavy lifting and awkward postures are avoided. By analysing how workers are lifting over the day, could reveal potential dangers. There is a study that looked into recognizing awkward manual handling postures, using ML to detect them. The study revealed that posture recognition is possible and has the potential to be utilized in practice. To acquire a good GRF measurement, the whole foot needs to be measured. This can be done by equipping an insole with 15 sensors that cover the whole body weight. This number of sensors is useful for precise measurements. Fewer sensors can yield good results as well, but at the cost of precision. Additionally, the system becomes less complex and more cost-effective.

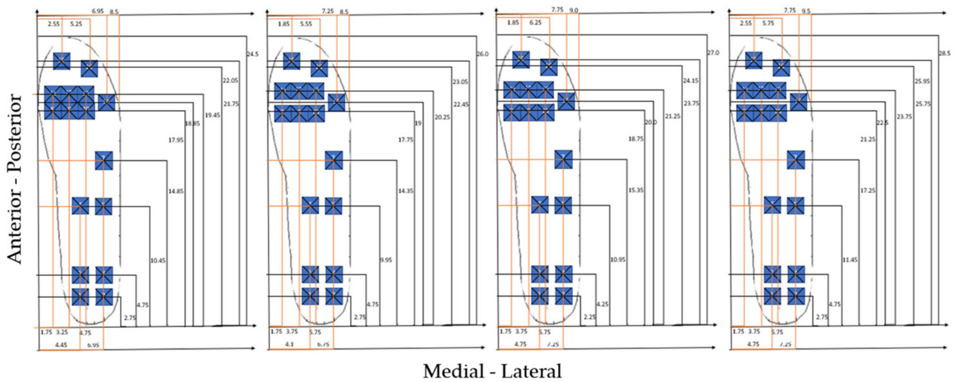


Figure 20 - Pressure sensor layout for different shoe sizes (Ciniglio et al., 2021)

Conclusion

Low back pain has no clear causality as the issue is a multifactorial one. It may be caused due to physical strain, psychological issues or a combination. Studies have found that high forces and awkward body postures are the main contributors to the occurrence of LBP. To reduce the risk, five factors have to be considered for safe manual handling: posture, weight load limits, duration and frequency, acts, and environment. The riskiest lifting postures people adopt are: reaching towards objects in racks, lifting above shoulder height, asymmetric lifting, repeatedly moving objects and stoop lifting.

Assessment of safe manual handling is done through observational methods such as NIOSH and OWAS which looks at load on the body. This could be supported by utilizing technology, which is currently done by implementing pressure sensors and IMUs in shoes. A pressure sensor will be able to measure the total load on the body and IMUs can be used for gait analysis.

Biomechanics can help understand how the physical world works, how loads are distributed over our body and how much strain it puts on certain areas. Analysing the whole body would be difficult. Instead, looking at our feet could be the solution. There is always force on the feet, which is also known as ground reaction force. This force can be detected and measured during everything people do from walking to lifting objects. The most important GRFs to note will be heavy loads, extreme stoop lifting, rotating with the trunk or lateral flexing with the trunk which all lead to a high risk of LBP.

To be able to detect these GRFs, pressure sensors are needed. The data from the pressure sensors could reveal patterns specific patterns for every lifting posture. The layout of the sensors is an important factor to achieve precise results. It is found that 6 and 7 sensor layouts do perform rather well but at the cost of some precision.

4. Technology Exploration

This section presents the exploration of existing technological possibilities. Looking into electronic components that are needed to capture data and smart data processing to analyse it.

4.1 Electronics and Data

This section shall look into electronics that could be used in the smart shoe. Instead of assessing through manual observational methods, the smart shoe will do the assessing with the data from sensors. These sensors will analyse the physical factors mentioned Detecting Physical Factors chapter. The data acquired can be used to assess the risk of LBP per individual.

The key element in this research is the accuracy and reliability. Due to the experience level of the experts, the assessment of risks is reliable. Though, as humans have different experiences and ways of thinking, there is always a level of subjectivity. This may influence the assessment to some extent. Electronics or sensors do not have a bias, the output data is objective. Meaning that there is no room for interpretation or guessing. This brings an additional level of reliability as one level of subjectivity is taken away. Though, the correctness of the sensors setup may influence reliability. The electronics have a few tasks: sensing physical quantity (pressure or force), converting data into information (smart data processing), store historical data, detect changes in data compared to historical data, predict new data and warning the worker. This has been visualised in Figure 21.

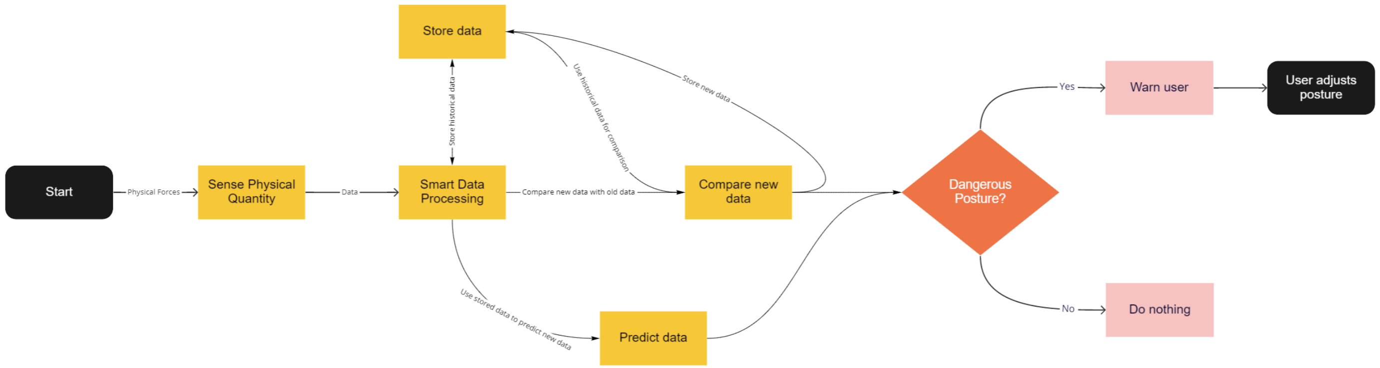


Figure 21 – Data flow diagram

Sensing Physical Quantity

The main functionality of the shoe is to measure the GRF and this will be done by pressure sensors. Additionally, gait analysis could assist the assessment of an individual by monitoring their mobility, for example, walking distance with a load. By adding an IMU, the acceleration and angle of the feet can be measured.

The following factors could be detected using these two sensors:

- Walking pattern (gait (Whittle, 2007))
  - o Step length
  - o Stride length
  - o Cadence (steps/min)
  - o Step width
  - o Gait speed (walking speed)
  - o Foot angle
- Force distribution while standing
- Force distribution while lifting
- Normal posture (based on force distribution)
- Lifting pattern
- Posture during lifting (based on force distribution)

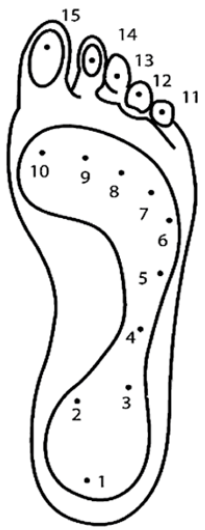


Figure 22 – Pressure Sensor Location and Distribution (Shu et al., 2010)

There is a variety of pressure sensors currently on the market, but only a few are cost-effective or available off-the-shelf. Abdul Razak et al. (2012) conducted a study reviewing off-the-shelf pressure sensors and applications of such pressure sensors in other publications. They found that off-the-shelf components work well in analysing plantar pressure distribution as they are designed following several key requirements: spatial resolution, sampling frequency, accuracy, sensitivity, and calibration. The study also made a list of requirements for the implementation of pressure sensors in smart shoes.

Implementation Requirements in Smart Shoes (Abdul Razak et al., 2012)

1. Very mobile
    a. Light and small
2. Limited cabling
    a. Wireless is ideal, for comfort, safety, and natural gait
3. Shoe and sensor placement
    a. Ideally 15 sensors to cover most of the body weight, see Figure 22).
4. Low cost
5. Low power consumption

With the requirements listed above, force-sensitive resistors (FSRs), Figure 23, are the most cost-effective and readily available sensor. The sensor can measure the amount of force that is applied to the sensor by measuring the amount of resistance (Interlink Electronics, Inc., n.d.). Another existing smart insole product uses the same sensor, see Figure 24.

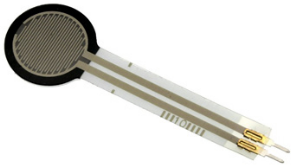


Figure 23 – FSR made by Interlink Electronics Inc.

Figure 24 – NURVV Run Insoles (NURVV, 2021)

An inertial measurement unit (IMU) is an electronic device that can measure specific forces, angular rate, and orientation of the body (Iosa et al., 2016). This is done by using a combination of an accelerometer and gyroscope. In Figure 25 the IMU, LSM6DS3, is the black unit in the middle and measures at 2.5 x 3 x 0.83 mm. The LSM6DSM is currently the best IMU, for gyroscope and accelerometer, according to Winer (2021) due to its price, accuracy, and lower power consumption. The size makes it ideal to integrate it into the smart shoe.

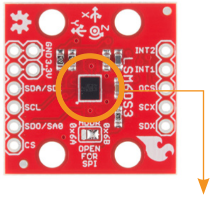


Figure 25 – IMU LSM6DS3 Breakout (Sparkfun, n.d.)

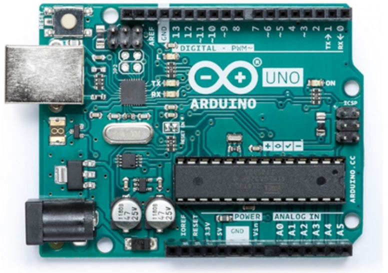


Figure 26 – Arduino Uno (Arduino, n.d.)

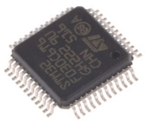


Figure 27 – Arm Cortex M0 Microcontroller Unit

Processing Data

The sensors have to be controlled by a microcontroller, an Arduino would be the most fitting for prototyping due to its ease of use, readily available software, and community support. For the initial setup, an Arduino Uno is used as it is compact enough and is highly compatible with additions like Arduino Shields.

A microcontroller unit (MCU) is a small computer that is designed for embedded applications (Fan et al., 2019). The actual MCU on the Arduino Uno is the black rectangular chip, see Figure 26. By connecting the sensors to the chip, it will process all of the receiving data. Depending on how it is programmed, it can save the data or even do something based on the received information.

To integrate into the safety shoe, the size of the MCU should be smaller than the one used in Arduino. An Arm Cortex-M series, see Figure 27, would be the fittest for the project. It has been utilised in microcontrollers such as STM32, which is aimed towards data processing by smart software (STMicroelectronics, n.d.). It makes the ideal option due to its low power consumption, the small size of 7.2 x 7.2 x 1.45 mm, low price, and existing support by major manufacturers.

Storing Data

For building the prototype, to capture the first dataset, an Adafruit Data Logging Shield will be used. It is almost plug-and-play and sits flush on the microcontroller, see Figure 28. It also has a built-in Real-Time Clock (RTC) to track the time in the real world, which is useful for manual pattern recognition. The data will be saved on the SD card and will be analysed manually.

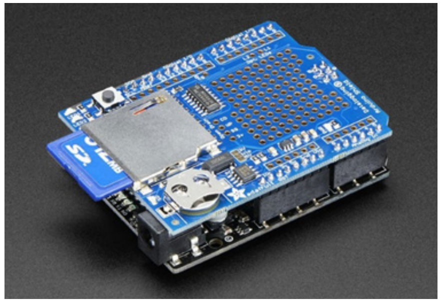


Figure 28 - Adafruit Data Logging shield for Arduino (Adafruit, 2013)

Detecting

In Detecting Physical Factors chapter, it was explored how different factors could be detected. The data that is collected by the setup, will be logged in a .csv format file. This file can be opened in Excel on the computer to be analysed. To be able to comprehend the captured data, some data processing will be needed to make it more visual. Below is a list of what kind of data will be captured.

For the posture of the body
- Looking at PPD and the location of pressure in newton

Weight load of the objected
- Estimate total and peak loads from PPD in newton

Duration and frequency of handling
- Time length of load and unload in time ranges
- Frequency of load and unload in a number
- Distance tracking in meters

Acts
- Tripping data in degrees angle
- Abrupt loads (catching falling objects) in newton related to time

Environment
- Repetitiveness (same loads over sustained time period) in a number
- Environment condition data through smart technology (connected sensors)

Warning

The worker could be warned through a vibration motor. Sounds would be hard to hear in warehouses due to machines. Lights placed on the shoe could be missed when lifting, as people do not look at their feet continuously.

Testing Setup

For the test setup, the components mentioned above will be used. An Arduino Uno will be the microcontroller, FSRs are the pressure sensors, Adafruit Datalogger Shield with an SD card is the module to collect the data. Additionally, a 16-channel analogue multiplexer will be used to be able to connect fifteen FSRs to the Arduino Uno, which has only five analogue inputs.

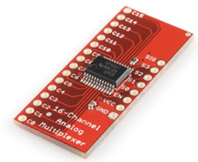


Figure 29 - SparkFun Analog/Digital MUX Breakout (SparkFun, 2015)

Publications on FSR usage

The pressure sensors that will be used in the pressure insole have been discussed. Interlink Electronics FSR 402 sensors will be used due to readily availability and cost-effectiveness. The same sensors have been tested and used in studies conducted by Dyer & Bamberg (2011) and Howell et al. (2013). Dyer & Bamberg (2011) compared the performance of an instrumented insole with a force plate, the instrumented insole was a custom-built insole using the FSR 402 sensors, as seen in Figure 30. The sensors were individually calibrated up to 30lb. (13.6 kg) and the results revealed that the FSR are rather capable as seen in Figure 31, where the centre of plantar pressure is compared between the two systems. FSR sensors may not be as accurate as a force plate, but due to their portability, making it a great solution for analysis outside labs and even in daily lives (Dyer & Bamberg, 2011). Howell et al. (2013) conducted research on kinetic gait using a custom-built insole, equipped with Interlink FSR (individually calibrated) see Figure 32, and comparing it to clinical motion analysis laboratory equipment. This equipment includes infrared motion sensors and force plates. In Figure 33 the results from the lab equipment and the custom-built insole are compared, the results from both systems do not deviate much. According to Howell et al. (2013), the results deviate less than 10% from each other.

The accuracy of the Interlink FSRs can be improved by calibrating them individually (Florez & Velasquez, 2010). As mentioned before, Dyer & Bamberg (2011) and Howell et al. (2013) used calibrated sensors in their setup, which both did by using a loadcell as a reference, which can measure the absolute weight (in kg/lbs). By stacking the loadcell and the FSR on each other, as shown in Figure 34 and applying force on them both, the loadcell will measure the weight and send it to the computer. The computer will link the weight to the voltage value measured by the FSR, this process is done through a custom computer script.
Though, due to my limited access to an accurate loadcell and lack of experience in using one, no calibrated pressure sensors will be used in the prototypes. This will lead to less accurate results but will most likely only affect the maximum force measurements as the studies above focused on calibrating the force values.

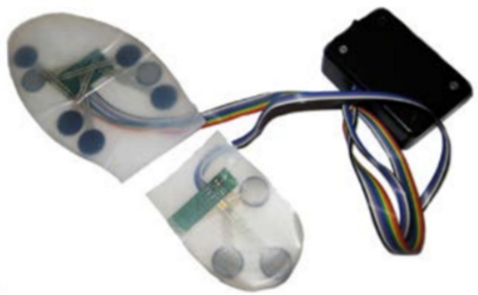


Figure 30 - Custom-built pressure insole (Dyer & Bamberg, 2011).

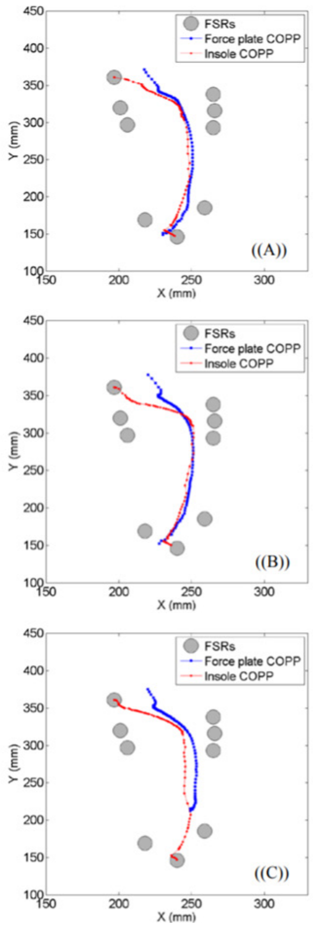


Figure 31 - Centre of plantar pressure compared (Dyer & Bamberg, 2011).

Figure 32 - Custom-built pressure insole (Howell et al., 2013).

Figure 34 - Calibration of sensors using a loadcell in a vice (Dyer & Bamberg, 2011).

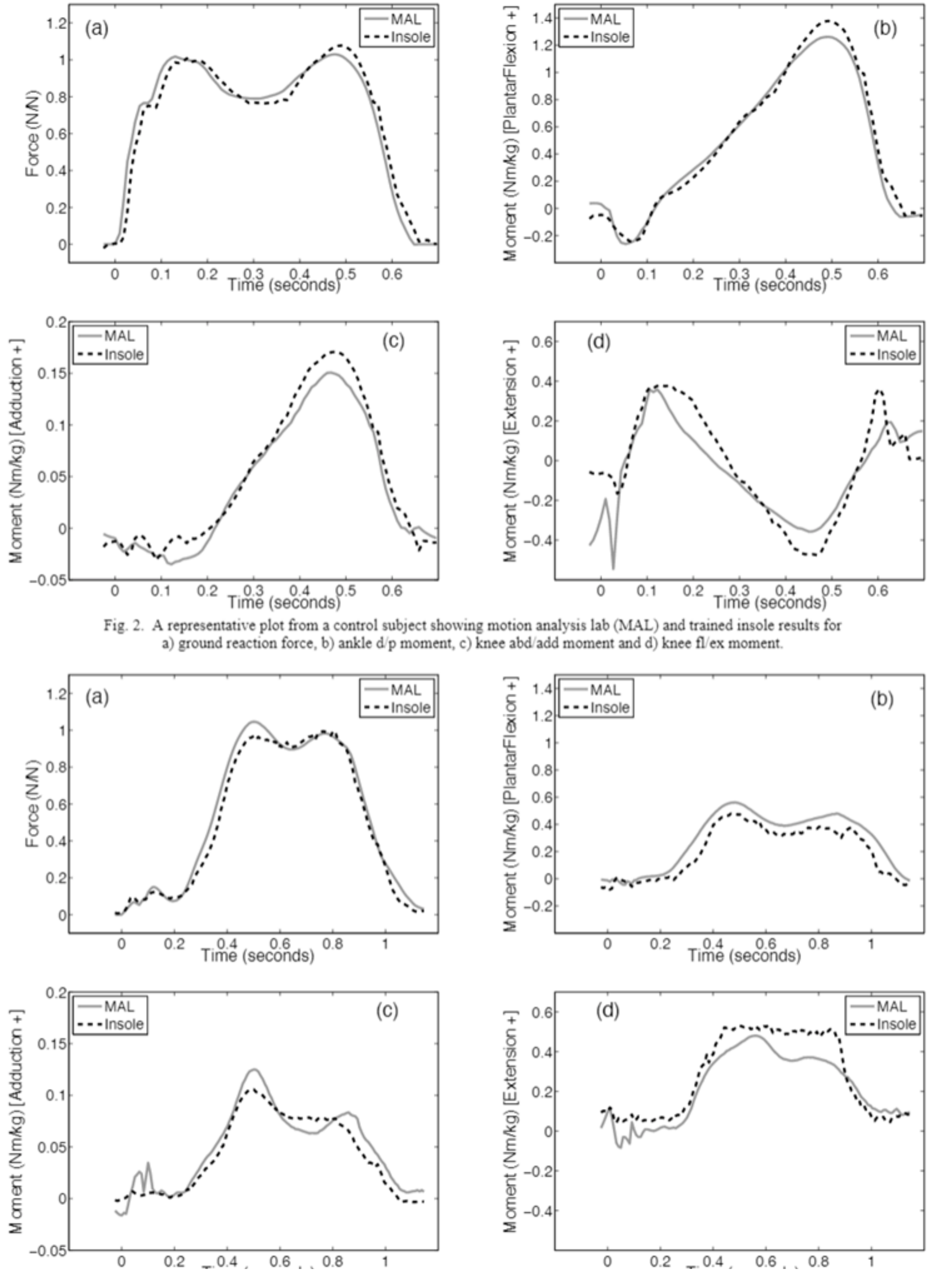


Figure 33 - Comparison of measurements between custom-built insole and lab equipment (Howell et al., 2013).

Conclusion

Electronic components come in all forms and sizes. There is a wide variety in quality and purpose. To find which components could be used for making the prototype, a list has been made that shows how the relevant data can be captured and analysed. Sensing physical quantity (pressure or force), converting data into information (smart data processing), store historical data, detect changes in data compared to historical data, predict new data and warning the worker.

The decisions are made based on availability, price and familiarity. Which is mainly due to the time constraint. All the components have decent performance and are small enough to be able to fit into the shoes. For sensors, the FSR 402 has been chosen. For data conversion, an Arduino Uno will be used. Storing of data will be done on an SD card. The user will be warned through a vibration motor.

Force-sensitive resistors have been chosen as the pressure sensors, as these are well known and relatively easy to use. Specifically FSR 402 by Interlink, these have been tested by several studies and found that they are decent enough for most measurements but need calibration.

4.2 Smart Data Processing

This section looks into how smart data processing could aid in analysing and reducing the risk of WMSDs. Artificial intelligence or machine learning can analyse vast amounts of data. There is no need for (continuous) supervision, and it can be done continuously. Analysis of data may also be done more thoroughly or find patterns that otherwise would have been missed.

Types of Smart Data Processing

There are many types and models of AI, used for different purposes. Generally, they are categorised into two groups, Narrow AI, and Artificial General Intelligence (AGI). Narrow AI is only able to execute tasks in a limited context but do it very well. AGI is capable of doing a variety of things, often seen as robots with human-like intelligence in movies. True AGI has yet to be achieved. Machine learning falls under narrow AI, using learning model to achieve intelligence.

Several interesting AI models are available for data analysis and risk assessment. For this project rule-based AI (expert system) and machine learning may be most useful. Though, choosing should be done based on the volume, velocity, and variety (three V's in big data) (Rajput, 2020) and what will be done with the data (J. Vroon, personal communication, February 23, 2021).

Outcomes of an expert system are based on rules that are coded by people. The model utilizes the rule of if-then coding statements and consists of two major components, a set of rules and a set of facts (Smith, 2020) This system is deterministic, making decisions based on set rules.
Machine learning can make its own set of rules that are based on data outcomes. The model could continuously evolve, develop, and adapt based on new data. A fixed model could also be used, which is offline pre-trained and will not evolve and develop further. It takes a probabilistic approach. The machine learning system is much more scalable compared to rule-based AI. Though, much more data is required to learn.

For analysing data from sensors the following methods can be used (W.F. van der Vegte, feedback, 5 March, 2021):

- Regression
- Classification
- Clustering
- Affinity analysis
- Sequential pattern mining
- Time-series forecasting
- Anomaly detection

Regression analysis is a process to infer the relationship between a dependent (data) variable and independent (data) variables. "In this analysis, it is often attempted to find the best decision function which can satisfactorily explain the variation of the target parameter based on the input variables." (Gholami & Fakhari, 2017). It is often used for predicting and forecasting values, based on historical data.

Classification identifies and groups data that have something in common. These groups or classes are pre-determined. New data will be identified looking for similarities and will be put in these groups with similar properties or features (ScienceDirect, n.d.).

Clustering, groups objects or data in groups based on similarities or how closely they are associated. It is an unsupervised learning algorithm (Qualtrics, 2021). This differs from classification where it specifically looks for a certain similarity that fits a specific group. Clustering can be used to group data with an unknown amount of clusters.

Affinity analysis looks for meaningful correlations between different data points based on their co-occurrence in a data set (Saygın, 2021). It searches for all frequent attributes and generates association rules based on predefined criteria, which will be used to identify frequent itemsets (set of items that occur together, "data pairs").

Sequential pattern mining looks for relevant patterns between known data and new data that is sent in a sequence. By identifying the data on frequently occurring patterns and comparing sequences for similarities, it can create an efficient database (Mabroukeh & Ezeife, 2010).

Time-series is a series of data points in time order, it could be indexed, listed or graphed. This can be analysed for forecasting, by looking at patterns that occurred at certain time points (Shmueli & Jr, 2016). Data from time series can also be aggregated (e.g., averages per hour or per day) to apply regression or classification (W.F. van der Vegte, feedback, 3 May, 2021).

Anomaly detection, also outlier detection looks for data points that differ significantly from the majority of the data (Zimek & Schubert, 2017). It may be used to find changes in data that does not seem normal.

For every problem, there is a different approach to analyse the data. It all depends on how the data is captured, in what form and what the goal is with the data.

Literature research may be useful to find what kind of algorithms or models are used, but may not apply to this project. Their use case may be different and with different goals in mind. The literature research will be used only for orientation purposes, as to what could be used for similar goals.

Di Noia et al. (2019) deployed machine learning on data regarding worker and workplace to predict occupational disease risks. They found that using supervised cluster-based algorithms, k- nearest neighbours (KNN) and support vector machines (SVM), could help in risk assessment and forecasting risks. The study also advised using a clustering-based classifier for a grey box approach.

A study by Sasikumar and Binoosh (2018) uses machine learning to find a correlation between postural, psychological, and work-related factors that may lead to the occurrence of MSDs. “The Random Forest algorithm or Naïve Bayes Classifier model developed based on these factors could be used to accurately predict the risk of musculoskeletal disorders among computer professionals at any instance of time, during their work.” (Sasikumar and Binoosh, 2018).

A study conducted Antwi-Afari, Li, Yu, et al. (2018), which has been discussed in 2.3.3, uses supervised machine learning, specifically: artificial neural network (ANN), decision tree (DT), KNN, and SVM. All of these models were able to identify different lifting postures with great accuracy, 90% on average.

Conclusion

Smart data processing has its roots in mathematics and statistics. It all looks like magic but is nothing more than algorithms that continuously calculate the input data and show outcomes in the forms of data tables or graphs. There are several automated processes in the field of AI, one is a model that has been pre-defined by rules, expert system. Second is machine learning which has two methods of learning (making models), with the help of people or supervised and unsupervised.

To understand what is needed for the envisioned goal, the methods or types of problems have to understand. It is an extensive list that has different approaches and goals. Choosing a method depends on the generated or acquired data and the goal in mind.

From literature research, it is found that for every problem, there are more specific models that can be used. Though, these models may or may not work for this project and should only be used as reference. Machine learning can detect patterns in lifting postures that could give more insights into which postures could lead to WMSDs.

5. Design

This section presents the design process of the technology that will be implemented in safety shoes. Discussing how the pressure insole is made and tested. The results have been analysed and interpreted.

5.1 Design Vision

"Design a novel safety shoe for warehousing that can acquire plantar pressure distribution data and automatically warn workers for dangerous lifting postures while performing manual handling techniques."

The vision is based on the conducted literature research, strategic direction of Van den Berg (2020) and the company's wishes. From the research, it was found that PPD could be used to detect different postures and find potential causes of LBP. In the first horizon, as shown in Figure 35 (Van den Berg, 2020), a fairly basic prototype was envisioned that could analyse postures and warn the wearer in case of danger. Lastly, the company would like to see a novel safety shoe that has a proactive role in preventing work-related risks and dangers.

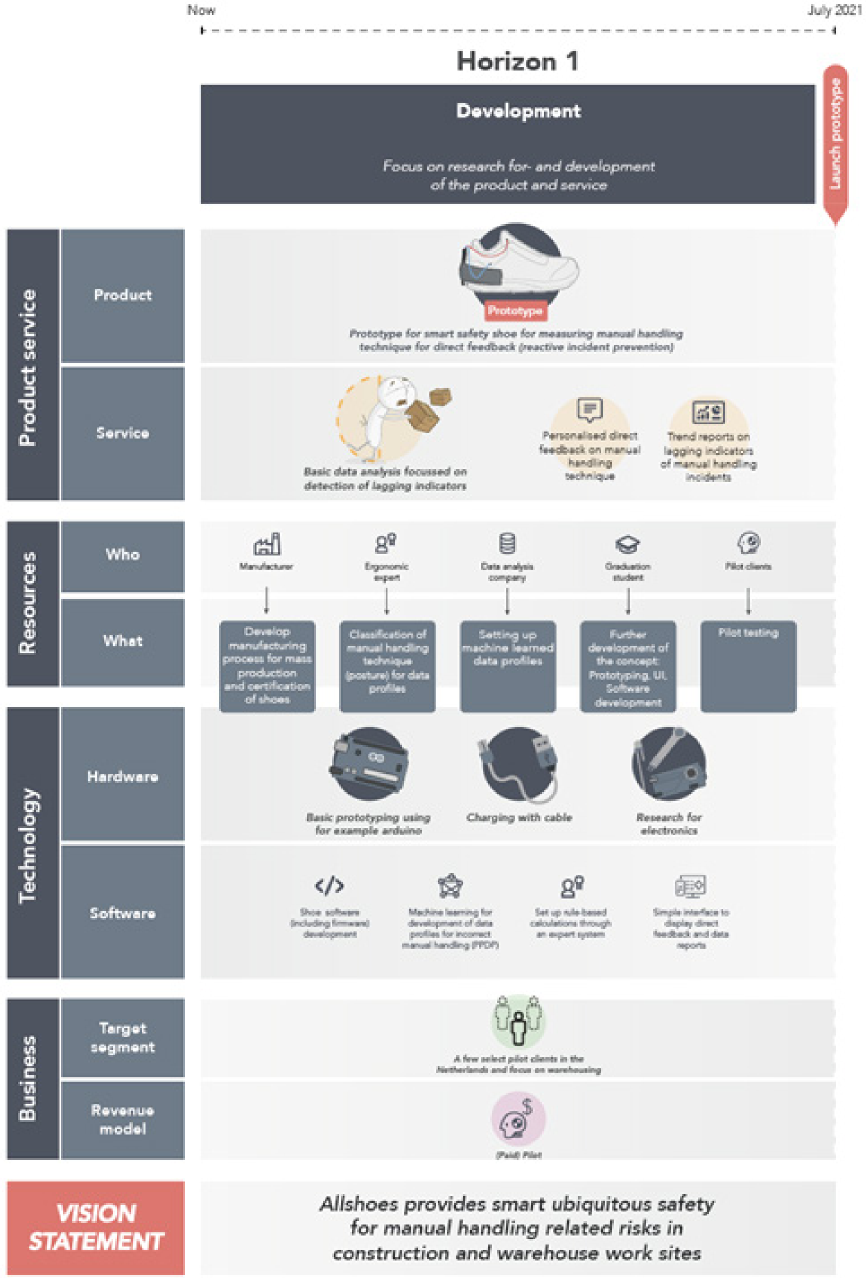


Figure 35 - Strategic First Horizon (Van den Berg, 2020).

5.2 Design Scope

To limit the range of possibilities for the design of the novel smart shoe, a design scope has been set. The envisioned smart safety shoes consist of several elements, divided into smart (technology) and shoe, as shown in Figure 36 below. The shoe group will not have the focus on the design process due to the risk of breaking the certification and lack of specific knowledge in this field. Still, all the elements have to consider due to adding new components in the shoe which will affect safety, comfort, and aesthetics. By adding components, the internal structure of the shoe design will be affected, for example, increased stiffness which may lead to less comfort. The focus will be on the smart group as this will give the safety shoe the ability to gain a proactive role in preventing injuries. The most important aspect is the data collecting and processing part, which could be seen as the brain of the product. Data will be collected through sensors, processed by an MCU which also will give an alert when needed.

Design Goal

The defined scope above shows all the elements that will be focused on but does not show the end goal that could be achieved within the given time frame. In order to work towards something, a tangible goal has to be set. The goal is to make a working prototype of a smart safety shoe that is able to collect PPD data and an analysis system that is able to analyse the data to detect different lifting postures. It should be at a level that a worker could wear the prototype and work for a day. The data could be analysed after the working day through the analysis system to see what kind of postures were adopted during the day.

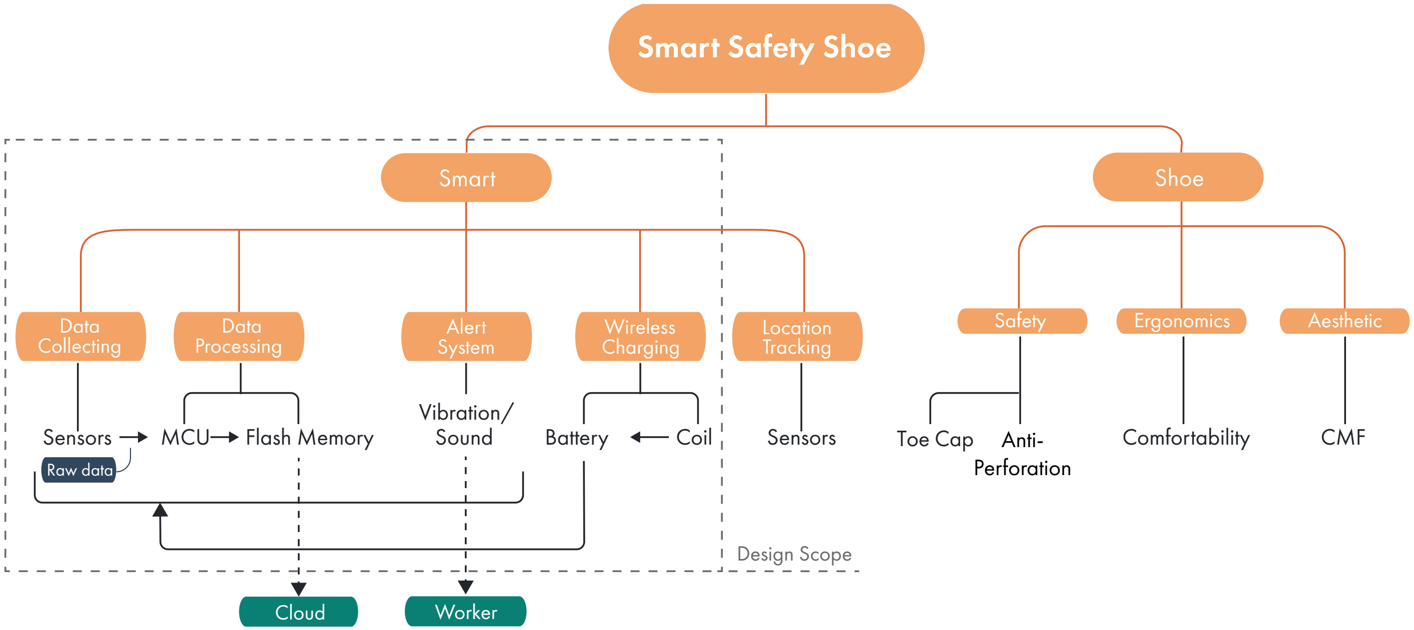


Figure 36 - Design scope of the project.

5.3 Function Analysis

This is a flowchart to create an overview of how the envisioned product would function, Figure 37. The orange shows what the user does, the green is a function of the product and dark blue is direct feedback from the product to the user. At the start, the user will take the shoe and put it on, as these actions cannot be done by the shoe itself. As the shoe is put on, the shoe will start calibrating the sensors to the body weight. A signal will be given when the calibration is done. The user will start to work, and their feet are always protected while wearing them till the shoes are taken off. Shoes will provide protection against falling objects, sharp objects that may pierce through the sole, give the feet support and avoid slippage. During work, manual handling tasks will be performed by the user. When the shoe detects a dangerous posture, it will start vibrating to warn the user. Once the posture has been corrected to a safe one, the vibration will stop. At the end of a workday, the user will take off the shoes and put them on a charging dock where it will automatically start charging the shoes. While it is on the dock, the captured data will be downloaded to the dock and transferred to a local server of the company. This data will be analysed locally for direct insights for the employees and it gives the managers insights on injuries within the company as a whole. Further, this data will be sent to a data analysis company for further macro analysis (city-wide or even countrywide) and this could be sold to manual handling training companies for further improving their education. This model has been made by Van den Berg (2020) and the visual of this model can be found in Appendix A.

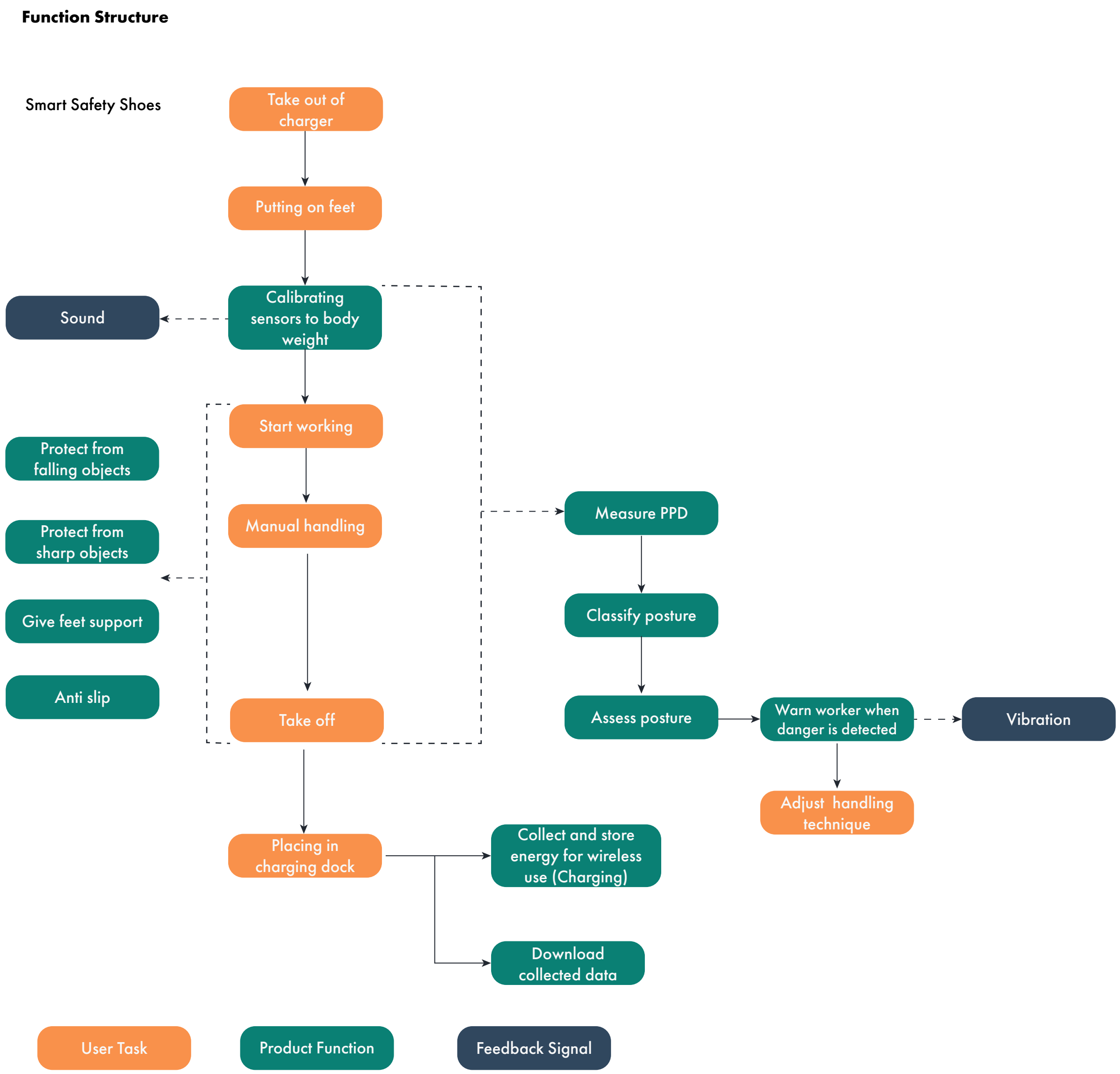


Figure 37 - Function analysis diagram

5.4 Prototyping of critical functionality

Prototyped pressure insole

To see what kind of lifting postures are taken during manual handling, PPD data will be utilised for this purpose. Capturing the PPD for posture analysis has been reviewed in 3.2.2, where Antwi-Afari, Li, Yu, et al., (2018) used in-shoe pressure sole to measure the PPD and classify different lifting postures based on the data. A similar approach will be taken to capture PPD data in the safety shoes. Due to safety certification of safety shoes, no aftermarket parts, such as a personal insole, may not be used in a certified shoe during work. Unless they are re-certified as a new combination, e.g., same safety shoe with a personal aftermarket orthopaedic insole (F. de Bruyn, personal communication, 22 February, 2021). For that reason, a custom pressure insole will be designed and tested. This pressure insole will be included in the novel safety shoe during manufacturing to avoid additional (re)certification. During a co-creation session on placement possibilities of components in the shoe with Floris de Bruyn, the in-house designer at Allshoes, it was found that stitching the pressure insole in the shoe on top of the Kevlar (anti-perforation) layer would be a good option, components placement will be discussed more in detail later. Stitching it will prevent the pressure insole from moving back and forth in the shoe, which would otherwise affect the measurements from day-to-day usage and making the data comparison more difficult.

For the design process of the pressure insole a trial-and-error approach has been used. Several prototypes have been made and tested to make improvements. As this approach works better personally than continuously making conceptual designs on paper. Ideas and concepts become more tangibility when they are made. Detailed process of prototyping is discussed in Appendix B. Every prototype has been made with a purpose in mind, such as testing the layout and capturing PPD data.

Insole for testing

The prototypes have been made based on three goals, first was too test and understand hardware and writing the software code. Second was to make the sensor layout that would cover the foot but with a smaller amount of sensors. Final prototype has been made for collecting PPD data for posture analysis purposes, software from the first prototype and the layout from the second.

The pressure insole has been made out of 3D printed TPU (thermoplastic polyurethane) layer to hold the sensors in place and the other layer is the pressure-zone layer, see Figure 39. TPU is an elastic material that can compress under load (Treatstock, n.d.-b). It will also help to distribute the force more evenly over the sensor, when placed on uneven surfaces.

The sensor layout is based on the layouts from the literature, discussed in 3.2.2, which covers the majority of the foot. To improve the amount of GRF that sensors can sense, a pressure zone system was made inspired by a paper that redirected all the force to the sensors by placing the sensors on the cleats on a pair of football shoes. This is explained in detail in Appendix B. Instead of placing the sensors externally, the “cleats” are placed in a layer that is placed on top of the sensors, the system has been visualised in Figure 38.

After testing with this new pressure sole, it was found that the TPU pressure zone-layer did not work as intended due to the flexibility of the material. To fix this issue, a stiffer material is needed. A 3D printed PLA (polylactic acid) layer was made and placed on top of the sensor layer, as shown in Figure 40 where the PLA layer is between the fingers. PLA is a common and low-cost bio plastic material with decently tough mechanical properties (Treatstock, n.d.-a). This setup has been tested by standing on the two custom made pressure insoles and performing several lifting postures. The test has been done with and without the PLA layer, to see how much impact the layer has on the accuracy of the measurements. In depth testing of the insoles with results will be discussed in a dedicated section.

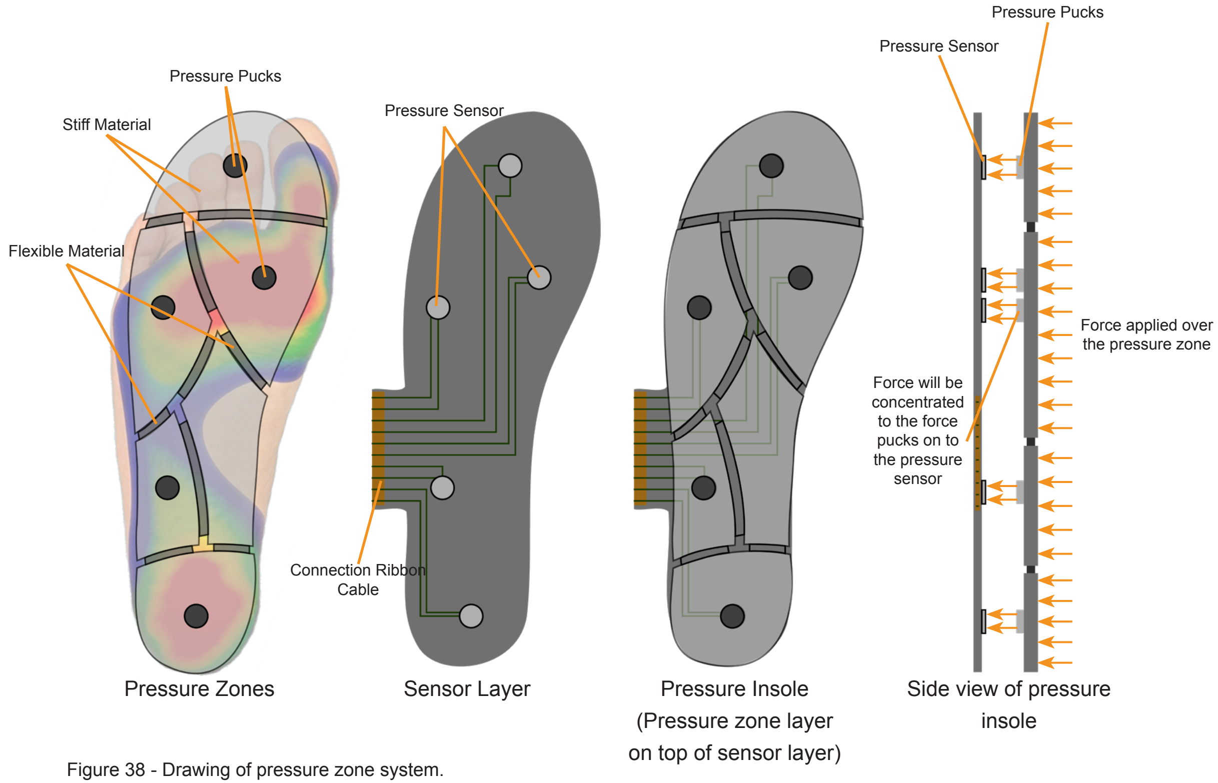


Figure 38 - Drawing of pressure zone system.

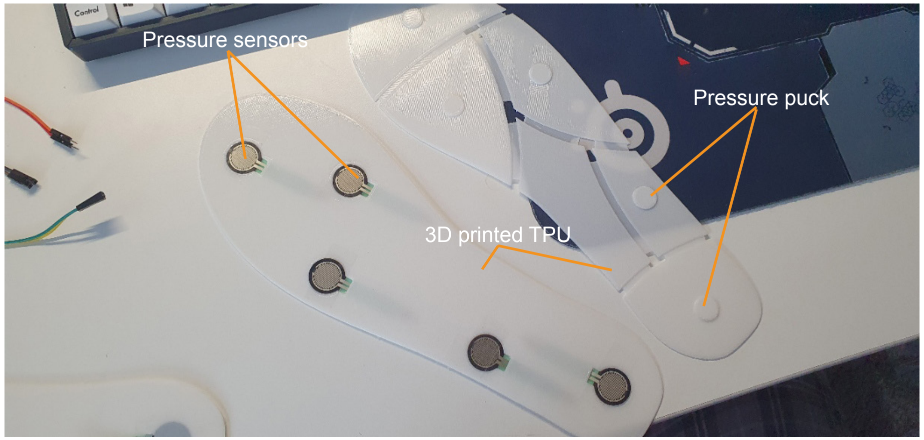


Figure 39 - 3D printed TPU pressure sole

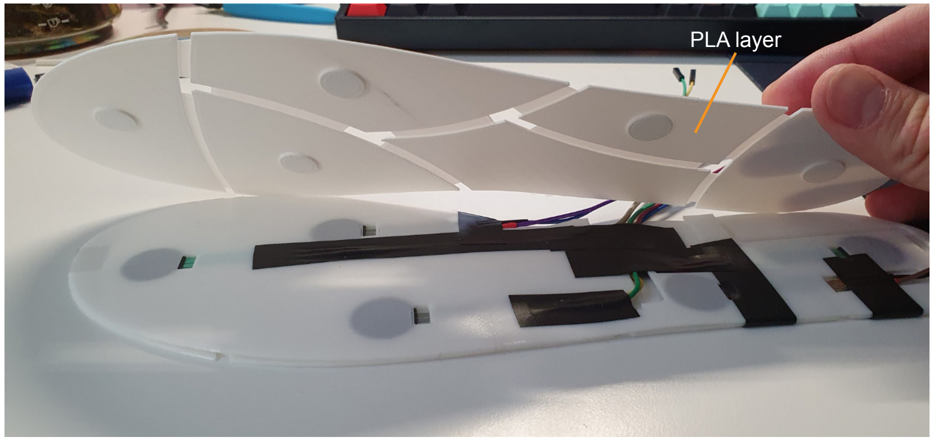


Figure 40 - 3D printed PLA pressure-zone layer.

5.5 Plantar Pressure Distribution Assessment

With the made pressure insole, it will be used to collect PPD data from different postures. This will later be analysed to see whether patterns can be found.

5.5.1 Theoretical plantar pressure data analysis

First, theoretical analysis on different manual lifting will be performed to create an overview of possible points of attention, patterns, and load locations. This analysis is based on static biomechanical analysis and the study conducted by Antwi-Afari, Li, Yu, et al. (2018), using insole pressure sensors to map plantar pressure distribution.

The common dangerous lifting techniques have been analysed based on how they may be detected in PPD data and have been visualised in pressure heat maps. Figure 41 shows how an ideal PPD map would look like, where the load is held close to the body. The PPD map shows that the pressure is evenly distributed over the whole feet and some higher at the metatarsal and heel.

Actual pressure data will be captured by two pressure insoles, equipped with force-sensitive resistors (FSRs), as shown previously. Sensors are connected to a microprocessor (Arduino) and the data will be stored on an SD card.

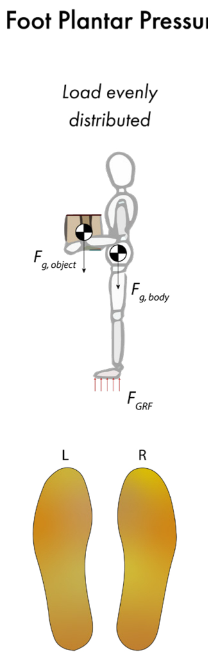


Figure 41 – Ideal PPD with evenly distributed pressure

Posture and load

As mentioned in problem analysis and also found in biomechanics literature research, awkward postures and heavy loads may be the key contributors to LBP. The focus on the detection of risks will be on these two key factors. Different scenarios of possible PPD profiles have been visualised.

Detecting Load

The amount of load could be measured by adding all the measured forces together. If this number approaches or exceeds the recommended force of 3400 N (on top of the workers own weight force), action should be taken.

- Load distribution, Figure 42.
  - Ideal: Left and right foot should have equal PPD and under 3400 N
  - Hazard Indication:
    1. Total load higher than 3400 N (on top of workers weight)
    2. Peak pressures over 3400 N
    3. Increased pressure on one side

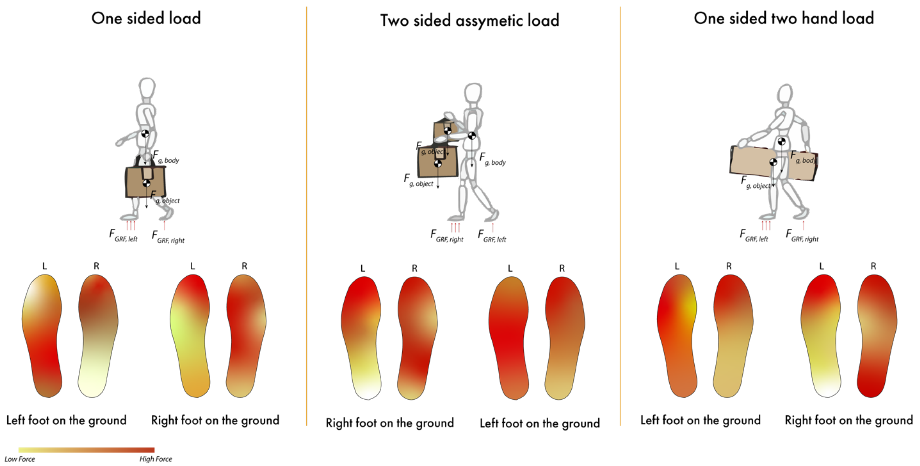


Figure 42 – Unequally distributed weight

Detecting Awkward Postures

There are many posture variations of how a worker could lift, covering them all would be difficult due to the variety in combinations. Instead, the most hazardous key elements will be included in the analysis. It includes twisting of trunk, lateral (sideways) movement of the trunk, load balance, reaching and lifting form. Different lifting forms (stoop, semi-squat, and squat) may not have different risks but may reveal increased risk or damage in long term, which has not been studied in the literature (Marras et al., 2006). For that reason, the lifting forms are included for collecting long term analysis.

- Twisting and pivoting the trunk, Figure 43.
  - Ideal: Left and right foot should have equal PPD
  - Hazard Indication: PPD change over time in a gradual and/or rotating manner
    1. When twisting the back, the load could shift gradually (rotational) from equilibrium to one side (incorrect handling)
    2. When pivoting from hips, the load could shift abruptly from equilibrium to one side (incorrect handling)

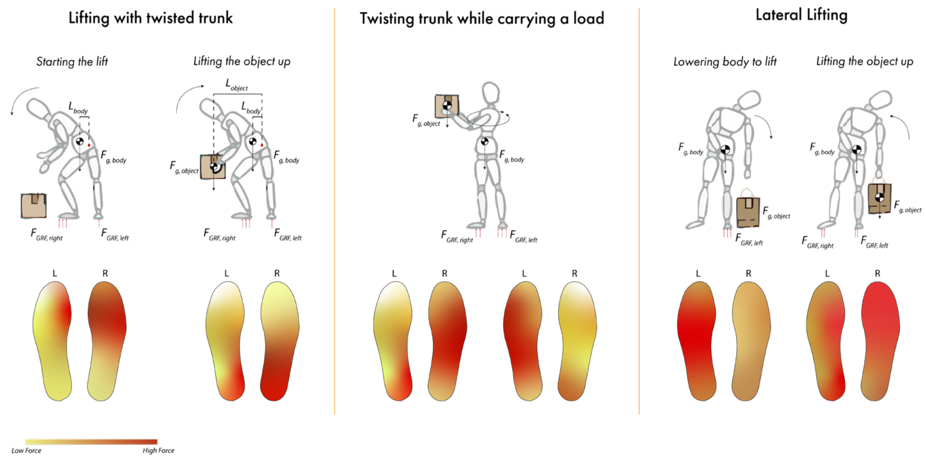


Figure 43 – Twisting and Bending of Trunk

- Lifting postures, Figure 44.
  - Ideal: Equal PPD over whole both feet, no severe pressure peaks
  - Starting Lift
    1. Squat Lift: Middle and heel feet area have the highest pressure
    2. Semi-squat Lift: Middle and heel feet area have the highest pressure
    3. Stoop Lift: Middle and toe feet area have the highest pressure
  - Lifting
    1. Squat Lift: Pressure shift towards middle and fore feet due change of center of mass
    2. Semi-squat Lift: PPD remains similar, increase PPD due to load and inertial forces
    3. Stoop Lift: Middle and heel feet area due to counter balancing load of object
  - Hazard Indication:
    1. High peak pressures at toe or heel area, unbalanced lifting

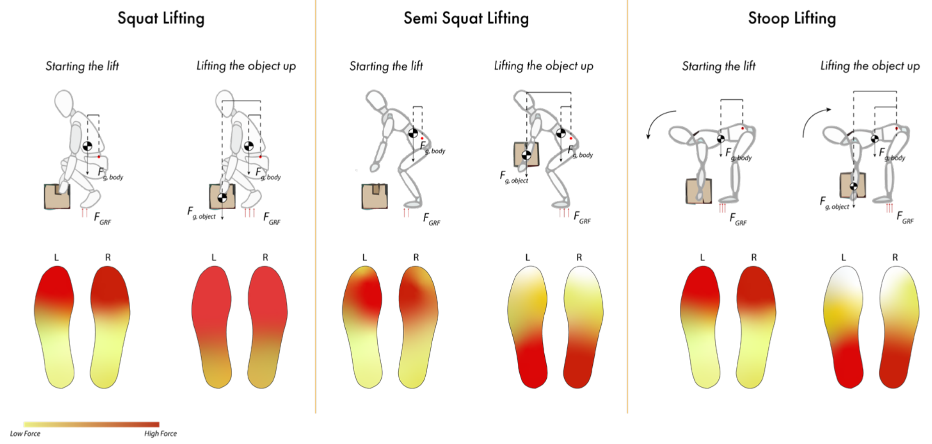
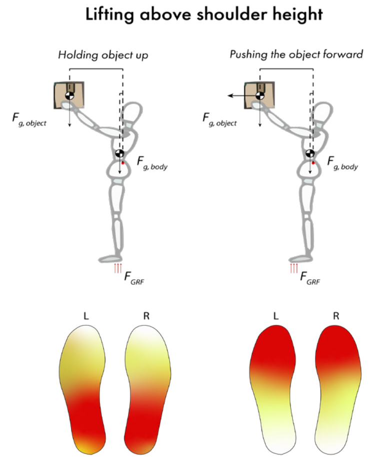


Figure 44 – Lifting Postures.

- Reaching for objects or lifting above shoulder level, Figure 45.
  - Ideal: Equal distribution of PPD over both feet (Objects are lifted between knee and should height)
  - Hazard Indication:
    1. Pressure peaks in both shoes at the toe area (reaching for object or pushing object in a high rack)



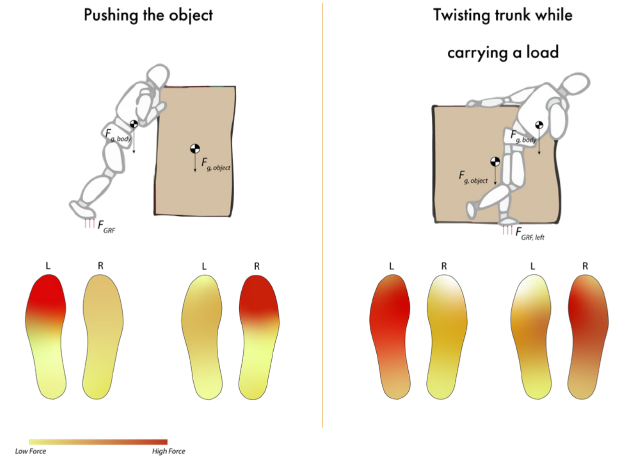


Figure 45 – Reaching for or with objects

Figure 46 – Pushing and Pulling Detection

- Pushing and pulling loads , Figure 46.
  - Ideal: Equal distribution of PPD over the foot during pushing or pulling
  - Hazard Indication:
    1. High pressure at toe area

Duration and Frequency

The amount of time manual handling takes and how often this is done may contribute to LBP (Nourollahi et al., 2018; Stobbe et al., 1988). The duration of manual handling could be tracked, and the frequency could be counted by analysing the lifting phases. Distance could reveal how far the worker is walking with an object.

- Duration
  - The start time minus the end time of increased load, indicating a lift and carry, would reveal the total duration of a manual handling
- Frequency
  - Counting how often a load starts and ends can reveal the frequency of manual handling
- Distance
  - Handling distance may be interesting to analyse, which could be done by using an IMU (inertial measurement unit)

Acts

Acts may be difficult to detect due to the unpredictability, there are no leading indicators for these factors. It may still be interesting to collect occurrence data for the improvement of the workspace.

- Tripping (due to not looking ahead or the obstructed view) could be detected through an IMU and PPD
  - An IMU has a gyroscope, which could detect when an employee is not standing anymore, PPD could confirm when there is low pressure detected
- Catching falling objects could be detected through plantar pressure map, an abrupt increase in load may indicate catching something

Environment

Physical surrounding is difficult to detect due to the diversity of factors, for example obstacles on the walking path and available surrounding space.

- Repetitiveness or pace could be detected similarly to frequency factor
- Danger area of slipping and tripping could be pinpointed by using a localization sensor or triangulating via existing WiFi/Bluetooth
- Environment condition could be sent to the shoe via other connected products (sensing temperature, humidity, and noise)

Psychosocial Factors

Repetitive physical stress loading may lead to fatigue and psychological stress from work may aggravate the risk of LBP further (Yip, 2001). Workers may not be able to focus on their work. They are more prone to errors and may result in injuries. Due to the individual character of this factor, it is difficult to find out the cause.

Current risk assessment methods do not consider psychosocial factors, or rather limited. Mental wellbeing can be measured by asking the workers. A way of gathering psychosocial factor data could be through frequent short surveys. For example, in an app that is connected to the smart shoe, though desirability has yet to be reviewed. Though, this will remain as a possibility for future development as the current goal is to be able to detect the physical factors of LBP.

5.5.2 Pilot Static PPD Measurements

The first PPD assessment has been conducted by performing static (lifting) postures, as this is based on the theory in the research section. The focus will be on three particular lifting postures: lifting above shoulder height, stoop lifting and asymmetric lifting. These postures resulted in most injuries at Bunzl (J. Metselaar, email, 15 March, 2021). For the capturing of the data, the insoles were placed on the floor with Kevlar layers beneath the insoles, to reduce the dampening effect of the carpet as shown in Figure 47. Four static postures have been performed and measured, standing upright, holding arms above shoulder height, stoop lift and asymmetrical lift, see Figure 48. The second set of measurements can be found in Appendix C.

Capture data from the assessment has been analysed by cleaning the data first, removing dynamic data points and thereafter plotted in graphs. It has been considered to visualise the data into pressure heatmaps as in Figure 49, but due to limited experience and knowledge about this process, it has not been pursued. Additionally, a pressure heatmap would be only useful for manual analysis by humans as it makes it visually easier to understand. In the final product, these data points will be analysed by a computer, making the heatmaps obsolete.

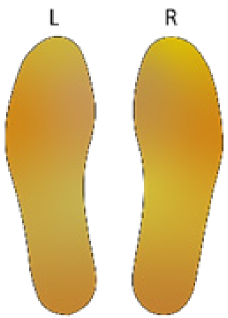


Figure 49 - Heat map of plantar pressure distribution

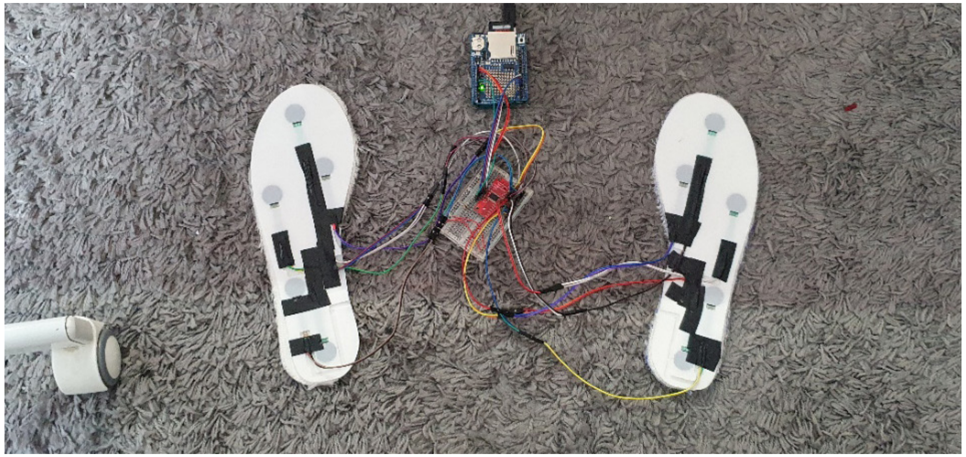


Figure 47 - Testing setup with pressure insoles connected to the Arduino.

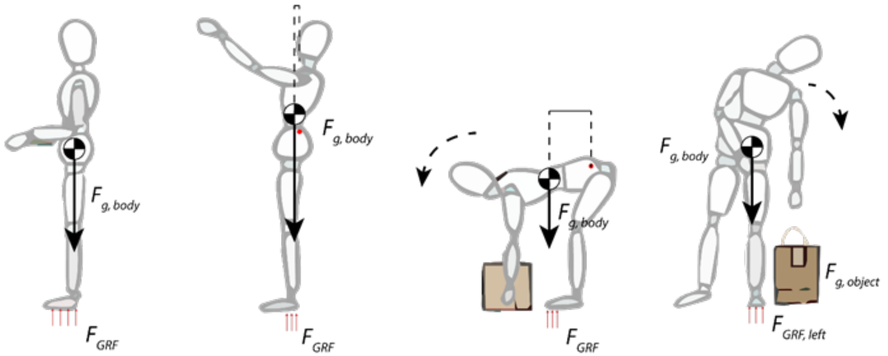
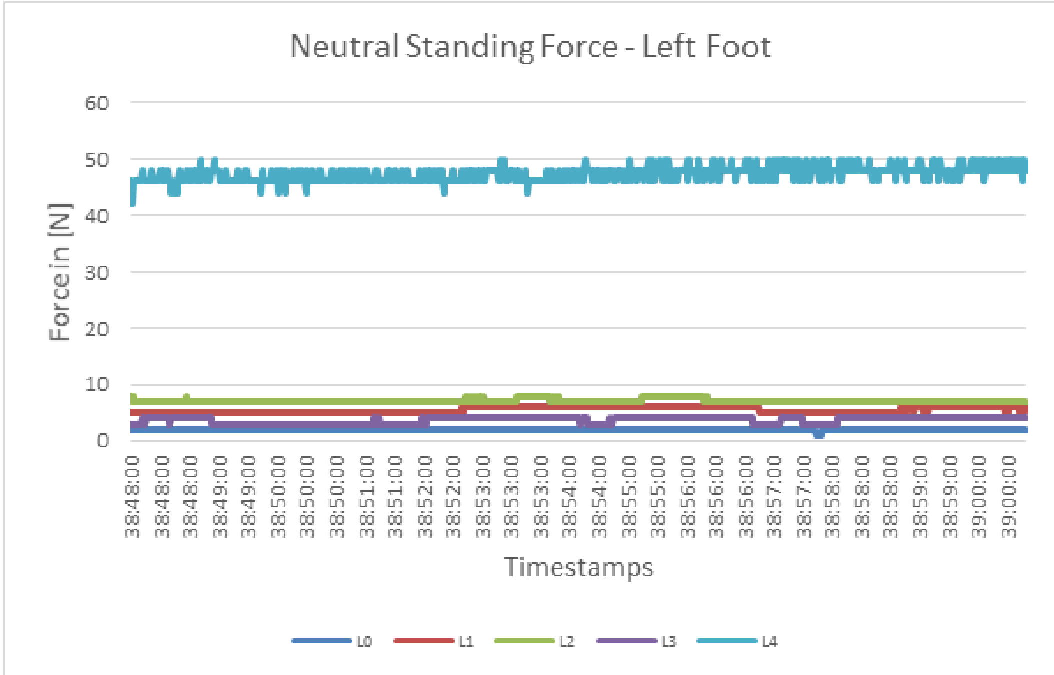


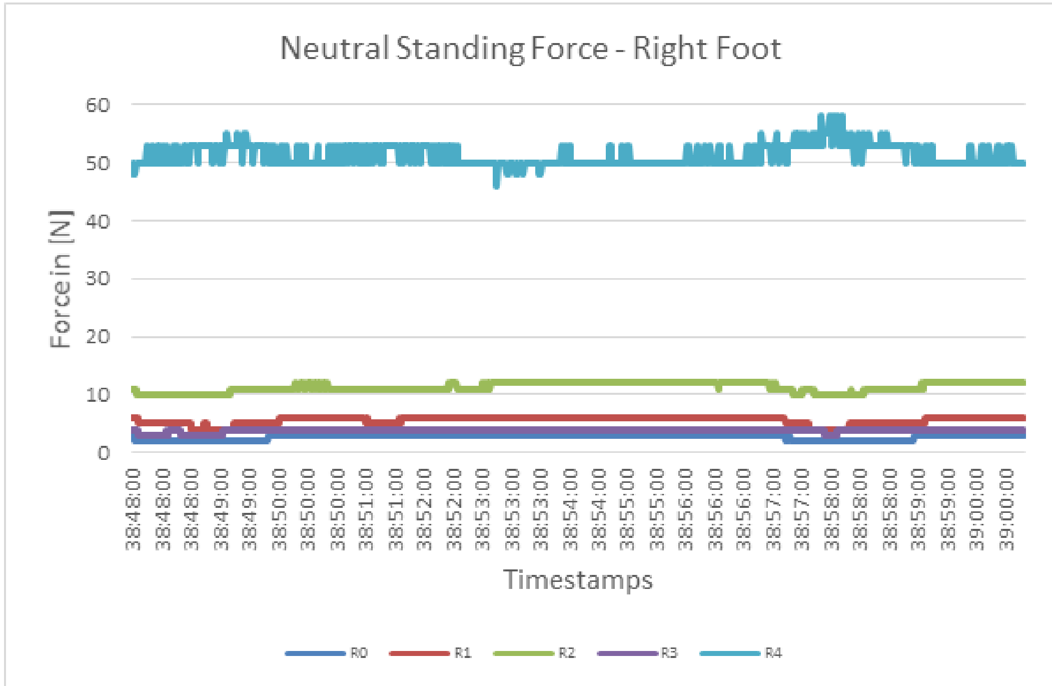
Figure 48 - Four performed static postures: Neutral standing, arms above shoulder height, stoop lift, asymmetric lift.

For manual analysis of static postures, the graphs have been studied in depth. The procedure for the analysis is as follows: The graphs have been studied by looking at the highest GRFs and holding the pressure map layout next to them, see Figure 51, to know where the specific GRFs are located. These high GRF areas indicate where the person has been putting the most of their weight on their feet. The biomechanics theory from the Research section has been used to explain what the high GRF areas mean and/or how it can be translated to postures.

Graph 1 and Graph 2 shows the measurements done by standing on the pressure insole with body weight and without the PLA layer. The graphs can be read by looking at the sensor layout in Figure 51, sensors are colour coded for easier reading. From the graphs above, it can be seen that the most weight has been put on the heel area, sensors L4/R4, and some in the middle foot area, sensors L2/R2. The high force in the heel area comes from the body weight, as seen in Figure 50, the centre of mass is perpendicular to the heel of the foot. There is some force in the middle feet, which is caused by the balancing act of the body, using the middle feet to increase the surface area.



Graph 1 - Force graph of the left foot with no additional load in Newton.



Graph 2 - Force graph of the right foot with no additional load in Newton.

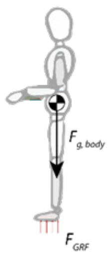


Figure 50 - Plantar pressure distribution with no load

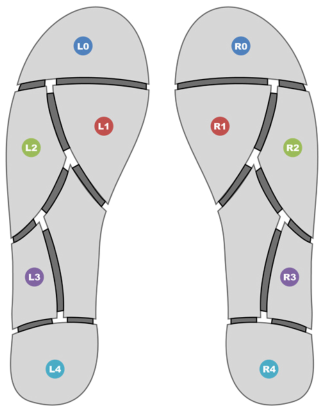


Figure 51 - Colour coded sensors related to the graphs, five sensors layout.

Graph 3 shows the total force of all sensors summed up. The average total force is 140 N, which is 14.3 kg (140 [N] / 9.81 [m/s2] = 14.27 [kg]). It does not match my absolute weight of 90 kg. This is caused by the force range and accuracy of the sensors and also the loss of force as mentioned earlier in 5.4 Prototype Two.

Additionally, during the analysis of the lifting postures, it was found that the sensors in the toe area could not measure the forces well. Some other sensors, such as L2/R2 and L3/R3 also had difficulties. The graphs of the posture analysis can be found in Appendix B. This issue is caused by the incorrect positioning of the sensors. With the results from this pilot analysis, a prototype version four was made, which included an additional sensor in the toe area on the big toe spot and some sensors have been moved to better spots, see Figure 52, at the big toe and new spots. The new sensor locations are based on Figure 53, which have been proposed and tested by Ciniglio et al. (2021).

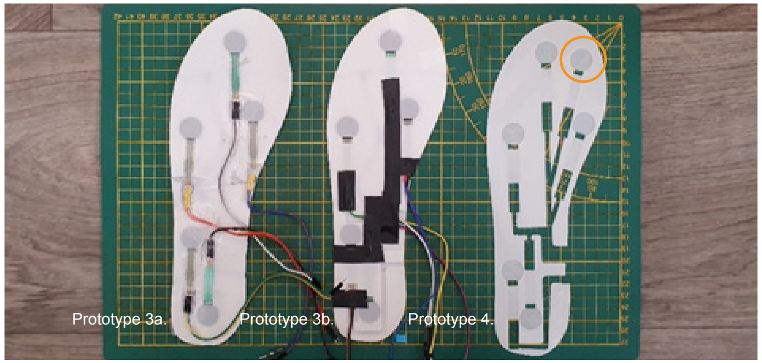
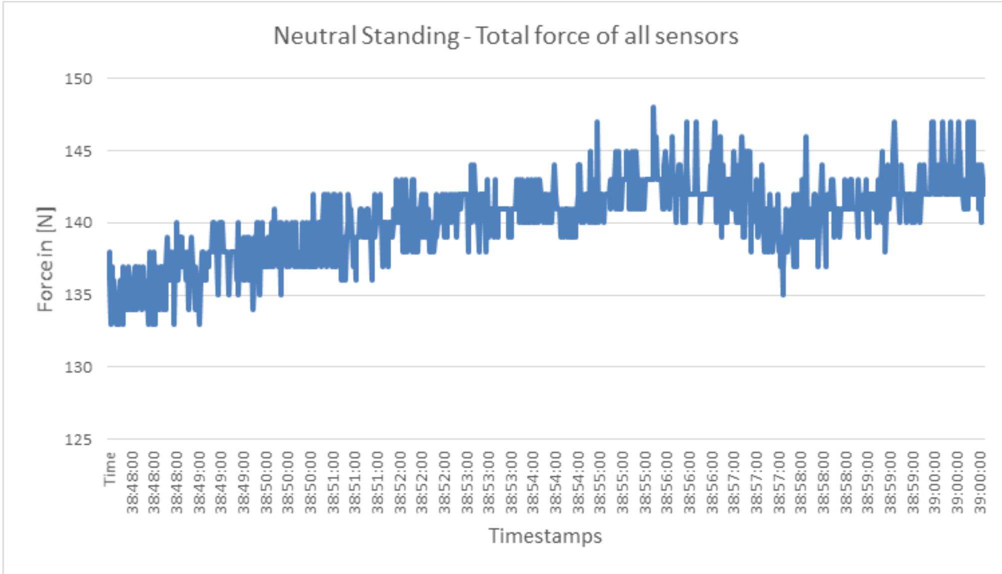


Figure 52 - Iterations of pressure sole prototypes, prototype 3a, 3b and 4.



Graph 3 - Force graph of all sensors of both feet.

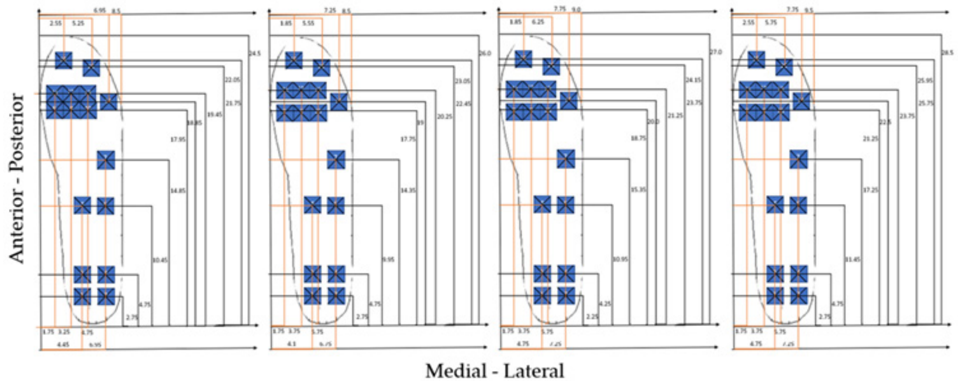


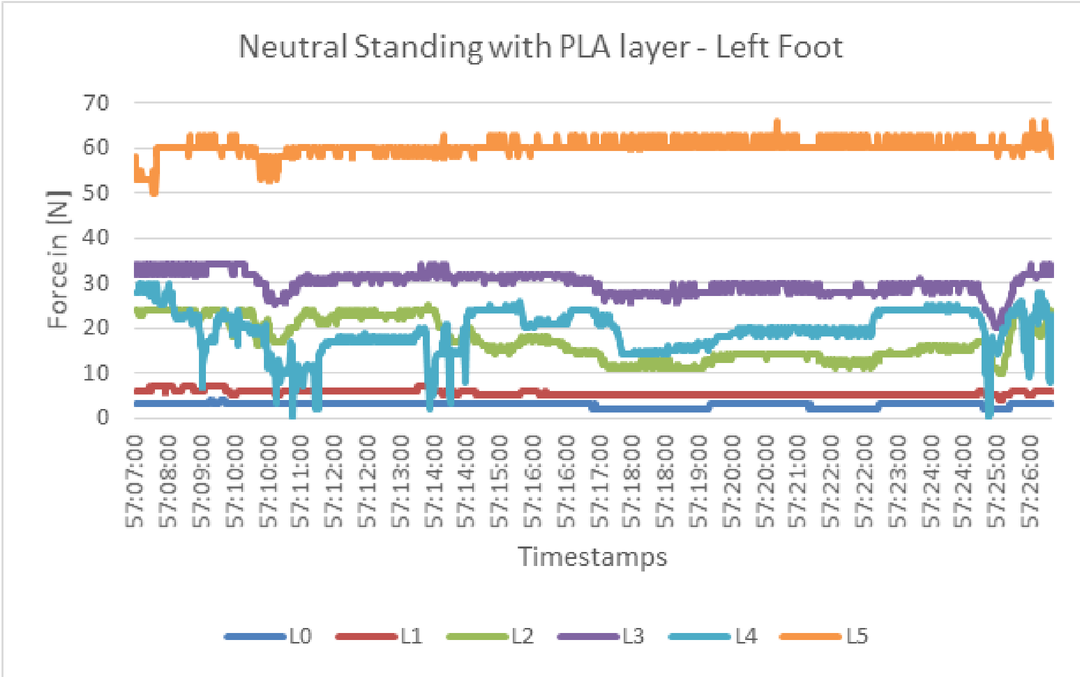
Figure 53 – Pressure sensor layout for different shoe sizes (Ciniglio et al., 2021)

5.5.3 Static PPD Measurements

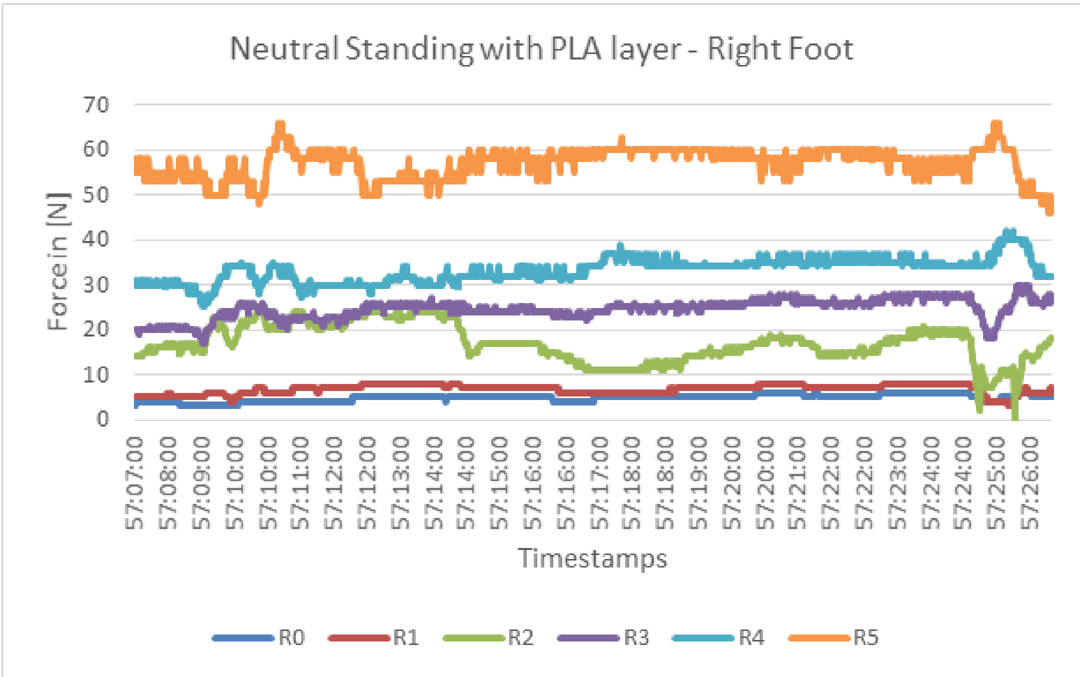
Standing up right

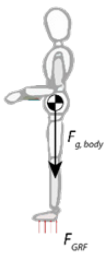
With the fourth iteration of the pressure insole prototype, the measurements became significantly better. The amount of force is higher on each of the sensors due to the better placement of sensors and the reduced loss of force with the stiff PLA pressure-zone plate. The results are analysed and discussed below in more detail. The second set of measurements can be found in Appendix D.

As the layout has changed, Figure 54 shows where each sensor is located, each colour in Graph 4 and Graph 5 corresponds to the colours in the new layout. In the new graphs, it can be seen that all the values are higher than previous Graph 1 and Graph 2, even though the body weight did not change. This improvement makes the posture analysis more reliable as the values are more distinct from each other. In Graph 4 and Graph 5 a pattern can be recognised for standing upright. L5/R5 shows the highest force, followed by R4 in Graph 5. Graph 4 shows that L3 is the second-highest after L5. This may be caused by incorrect placement of the foot or due to balancing of the body. L2/R2 and L3/R3 are similar in force due to the location of the sensors, at the metatarsal. L0/R0 and L1/R1 show little force.



Graph 4 - Force graph of the left foot with PLA pressure-zone layer, no additional load, in Newton.





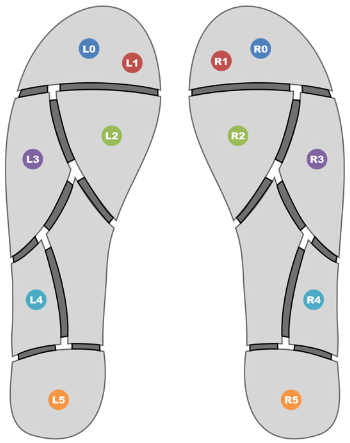


Figure 54 - Colour coded sensor map on the insole, six-sensor layout.

Graph 5 - Force graph of the right foot with PLA pressure-zone layer, no additional load, in Newton.

The average total force of all the sensors combined with the new pressure sole is 278 N, which is 28.3 kg. This is an improvement of 98.6% relative to the previous pressure sole, which only measured a total of 140 N. Still, it is only around a third of my weight of 90 kg.

Comparing to the theory

These measurements are compared to the lifting phases that are presented in 3.2.1 to see if it shows similar results. The forces of the lifting phases, shown in Figure 55, are measured during a dynamic stoop lift situation. The start is a static situation as the person is standing on top of the pressure plates. This moment can be compared with the graphs above. The total force in one foot slightly differs from the other foot while standing, which can be seen in Graph 7 as well. Around 0.12 seconds in the Ant/Post Force graph, in Figure 55, it can be seen that there is an increased force towards the posterior. This is similar in Graph 4 and Graph 5 where L4/R4 and L5/R5 has the highest forces, meaning that when standing there is more force at the heel area.

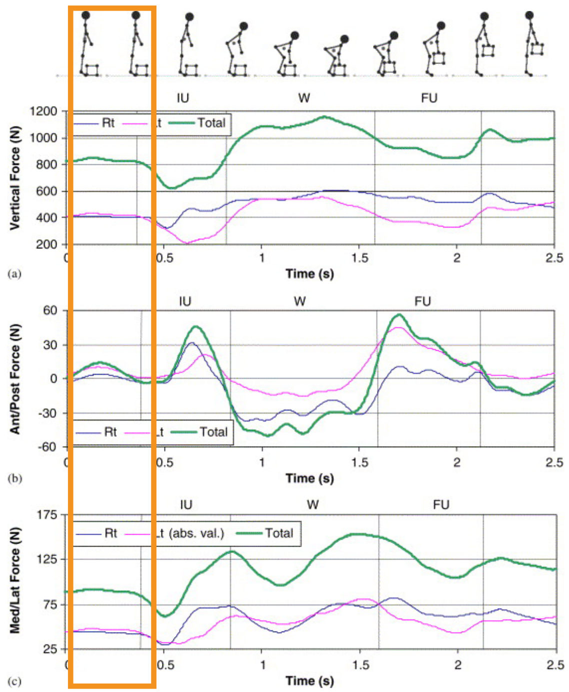
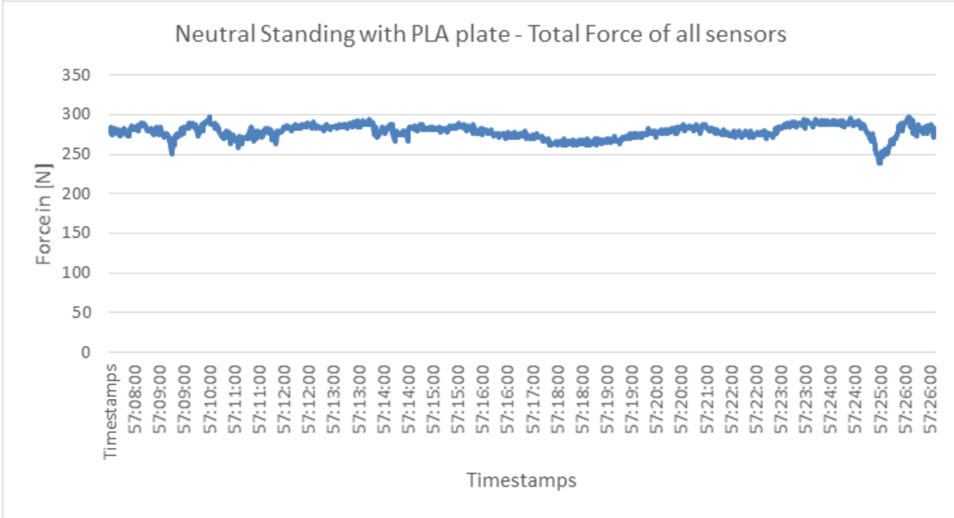
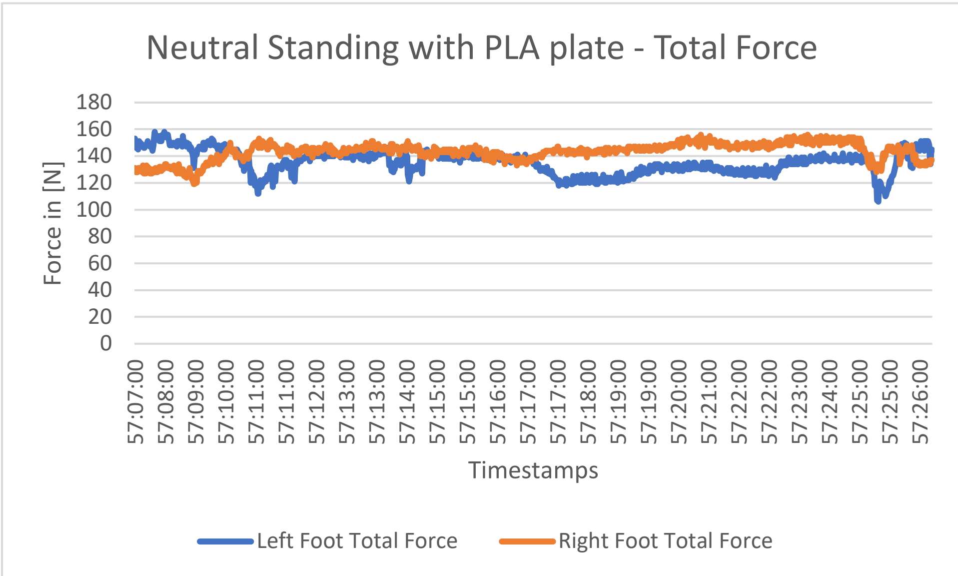


Figure 55 - Lifting phases and the GRF (Matt Maines & Reiser, 2006)



Graph 6 - Force graph of both feet with PLA pressure-zone layer.



Graph 7 - Total force per foot

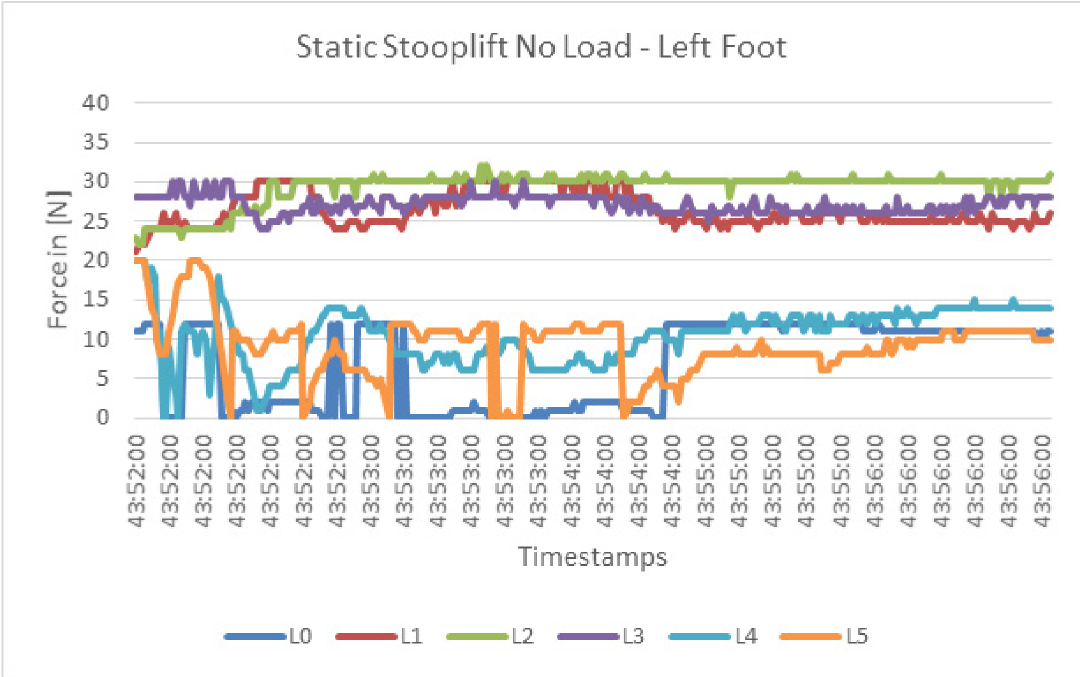
Stoop Lift

The static posture of stoop lifting has been analysed in two situations, without any external load and with a 10 kg load. As for the first situation, the person will stoop down to pick up an object.

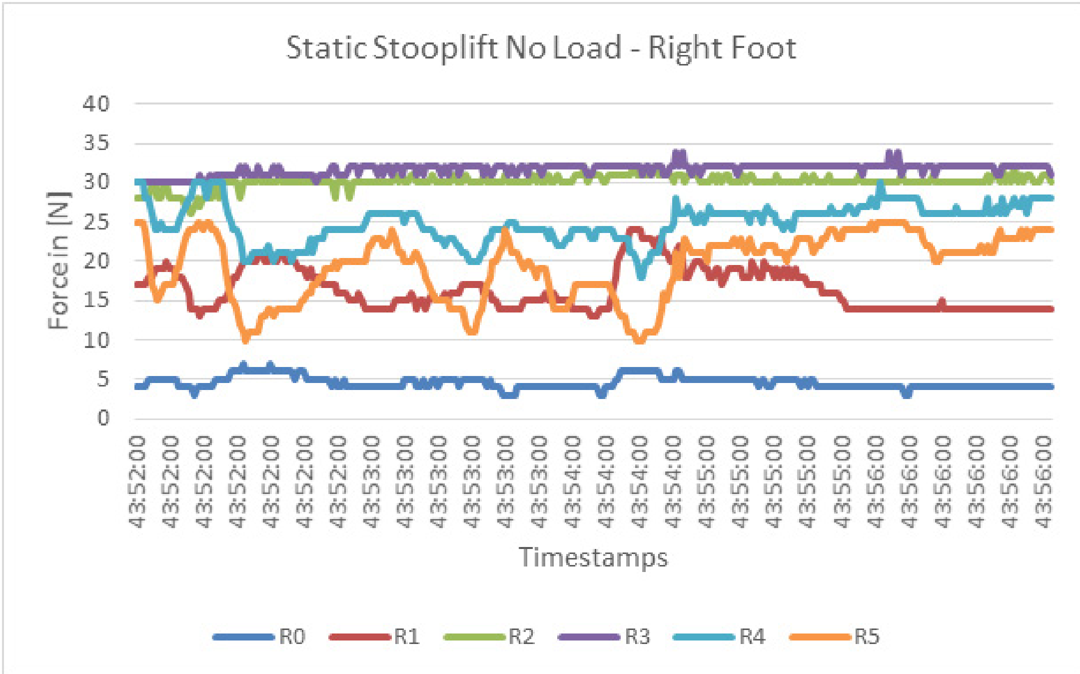
Graph 8 and Graph 9 show the highest forces in L1, L2/R2 and L3/R3, as the centre of mass of the body is perpendicular to the middle foot area. The force values of the other sensors in the right foot do not match or show similarities to the left foot sensor values. This is most likely due to foot placement on the pressure insole. The heel area fluctuates in the amount of force to balance the body. Otherwise, the person would fall forward.

Recognisable patterns:

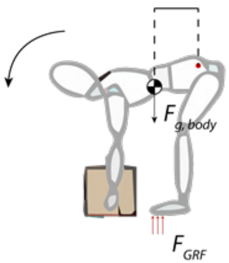
- L1(/R1*), L2/R2 and L3/R3 show highest constant force
- L4/R4 and L5/R5 show balance adjustment forces over time

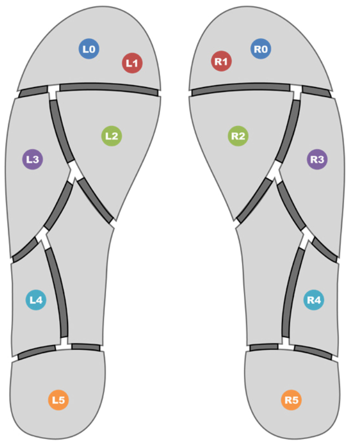


Graph 8 - Force graph of left foot, no load, in Newton.



Graph 9 - Force graph of left foot, no load, in Newton.





Comparing to the theory

Comparison between a dynamic measurement and a static measurement is not fully representative due to non-existing inertial forces in a static measurement. It can still provide useful insights nonetheless. Later, a dynamic measurement will be compared with the literature research.

In Figure 56, between 1 and 1.5 seconds in the Ant/Post Force graph, it can be seen that the force is in on the anterior side, meaning towards the toe area of the feet. This can be seen in Graph 8 and Graph 9 where the highest forces are in L1/R1, L2/R2 and L3/R3. Ant/Post Force graph in Figure 56 also shows a slightly higher force in one foot compared to the other. This has been measured as well during the test as seen in Graph 11.

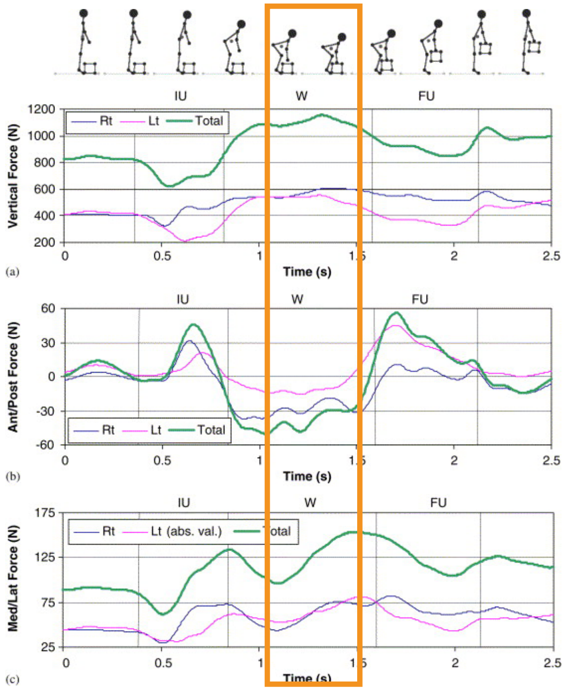
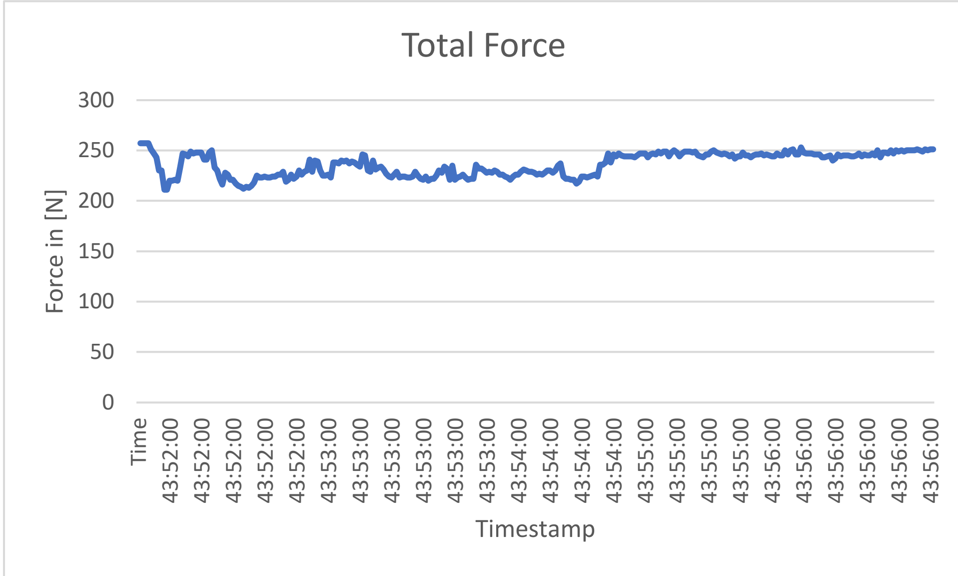
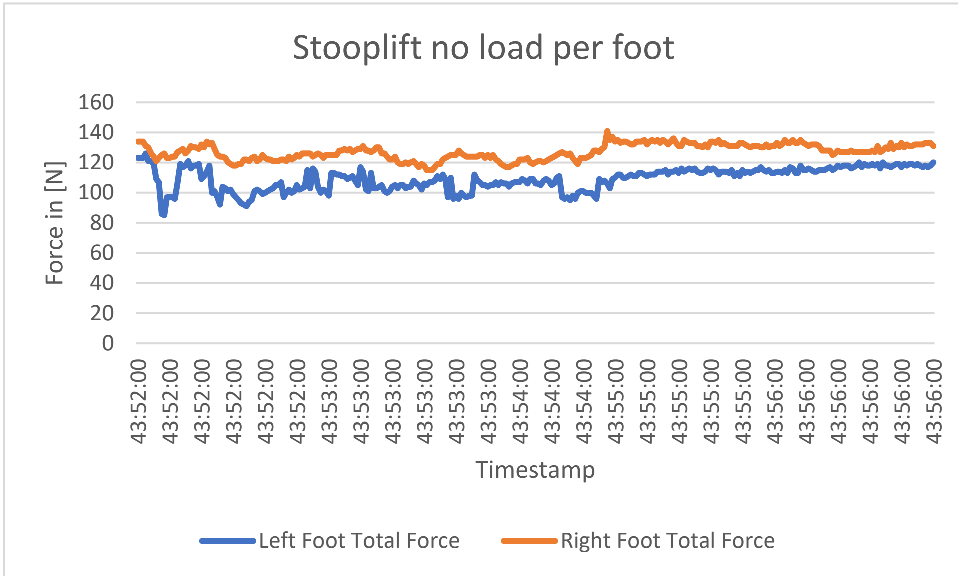


Figure 56 - Lifting phases and the GRF (Matt Maines & Reiser, 2006)



Graph 10 - Force graph of both feet while stoop lifting



Graph 11 - Total force per foot

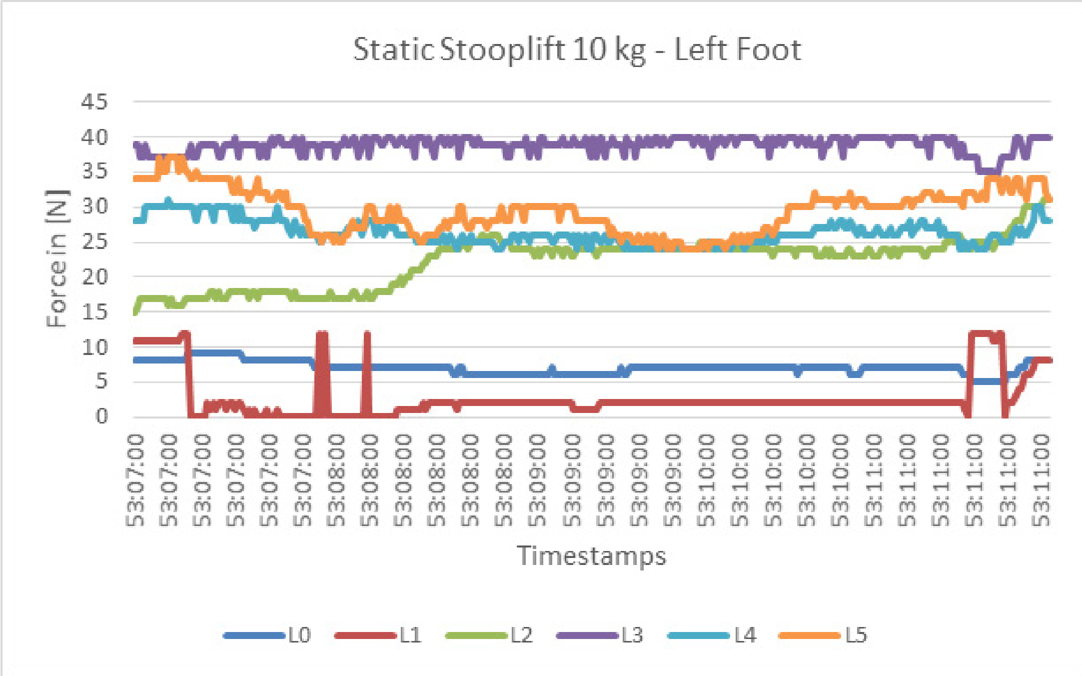
Stoop Lift 10 kg

The second situation is where the worker would lift a load of 10 kg while stooped.

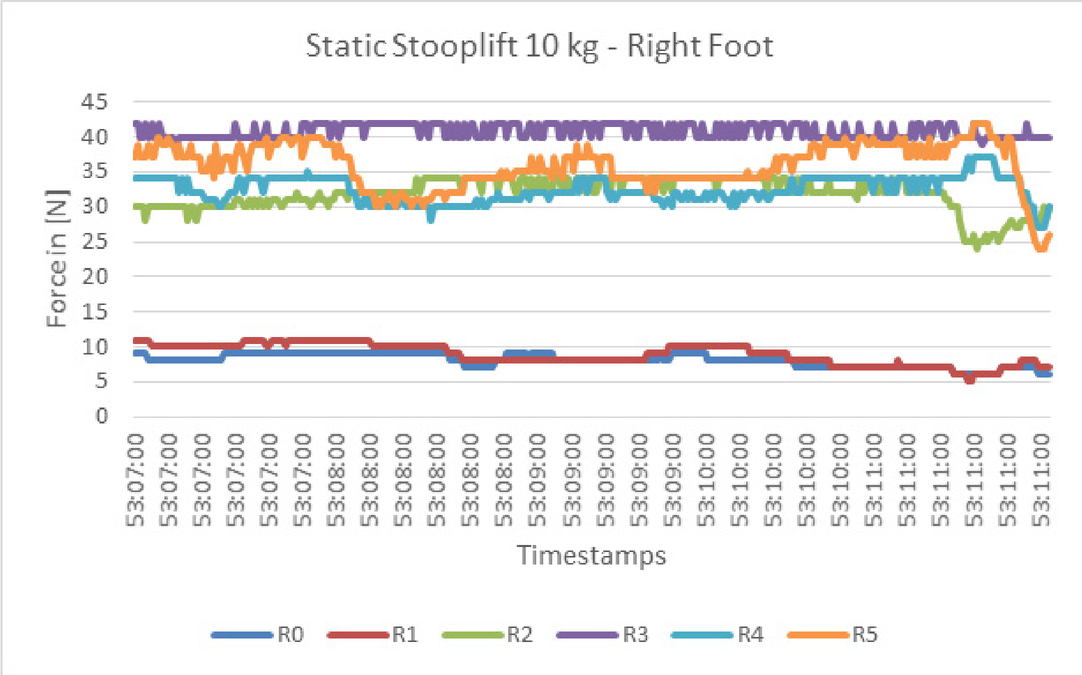
Graph 12 and Graph 13 show the highest amount of force is in L3/R3 followed by L5/R5, L4/R4 and L2/R2. To maintain the balance of lifting a 10 kg load, the body has to lean backwards putting some of the load towards the heel area. With the load in the front, most of the force will be in the middle foot area.

Recognisable patterns:

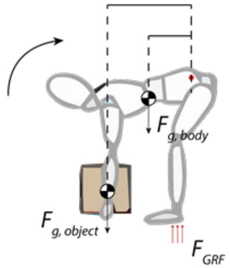
- L3/R3 show highest constant force
- Followed by L5/R5, L4/R4 and L2/R2, which all show around an equal amount of force
- L0/R0 and L1/R1 show little force

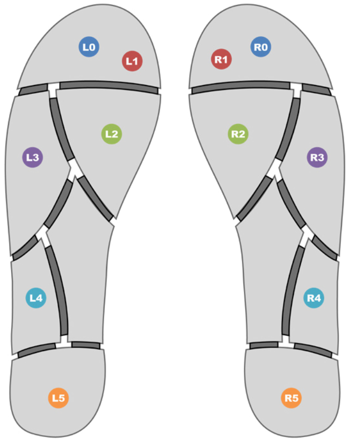


Graph 12 - Force graph of left foot, load of 10 kg, in Newton.



Graph 13 - Force graph of left foot, load of 10 kg, in Newton.





Comparing to the theory

During the lift of a load in a stooped posture, the amount of force increases in the posterior side, see Figure 57 in the Ant/Post Force graph. This can be seen in Graph 12 and Graph 13 by looking at L2/R2, L3/R3, L4/R4 and L5/R5. During the test measurement, the box was held a few centimetres above the ground.

The difference between left and right foot force is bigger than standing or starting the stoop lift. This can be seen in both Figure 57 and Graph 15.

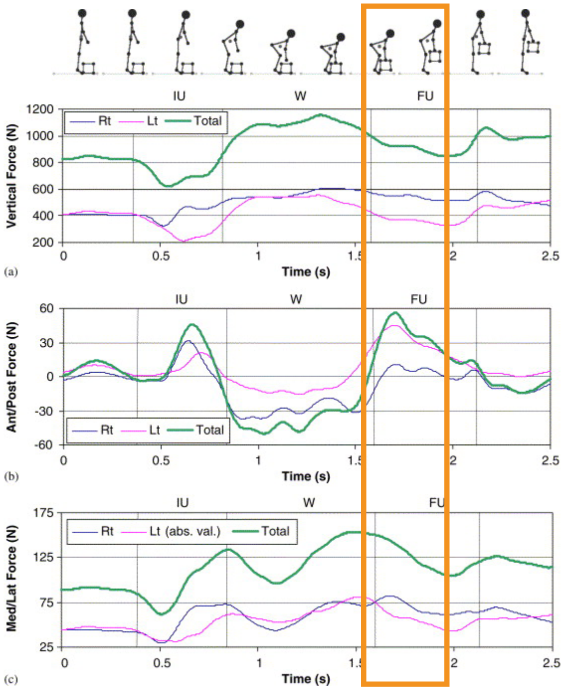
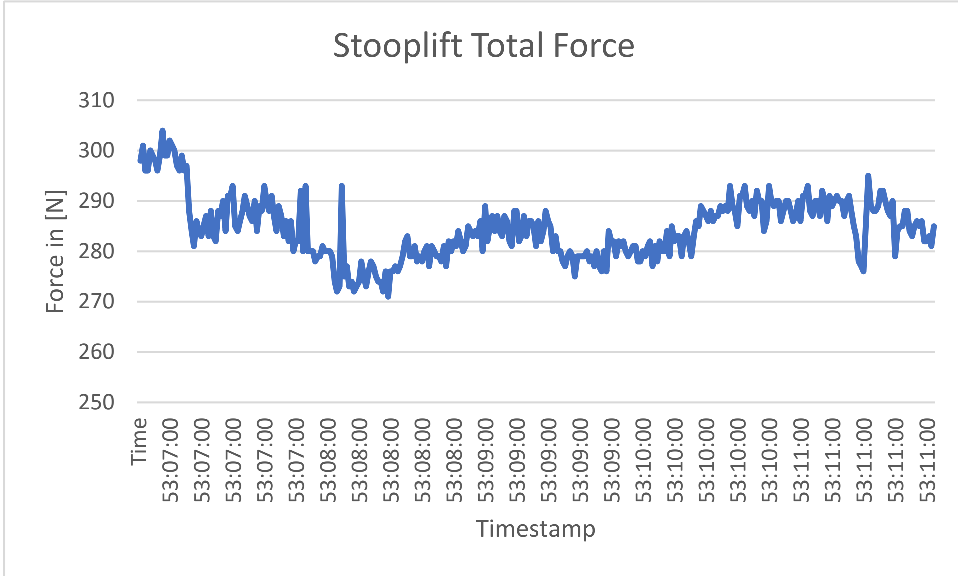
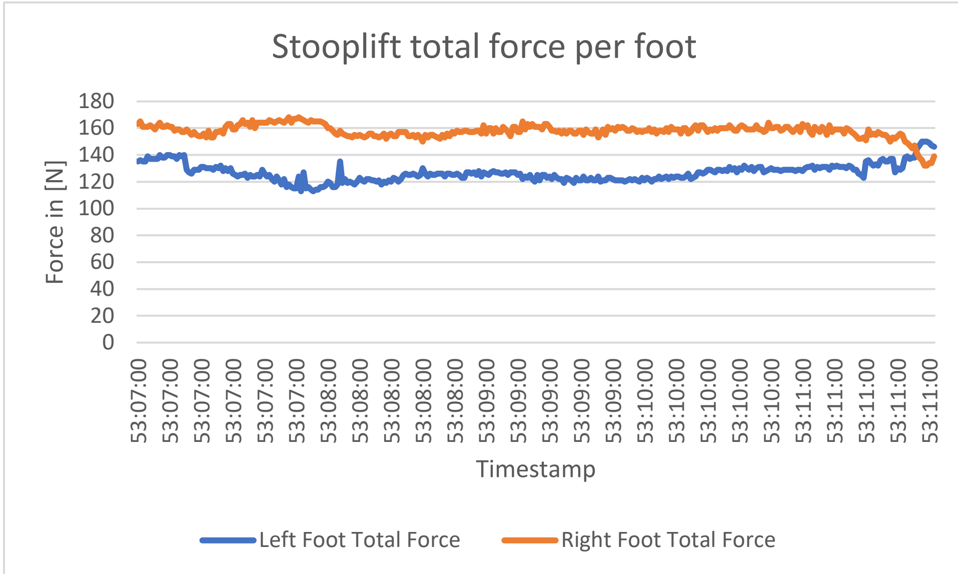


Figure 57 - Lifting phases and the GRF (Matt Maines & Reiser, 2006)



Graph 14 - Force graph of both feet while stoop lifting



Graph 15 - Force graph of both feet while stoop lifting

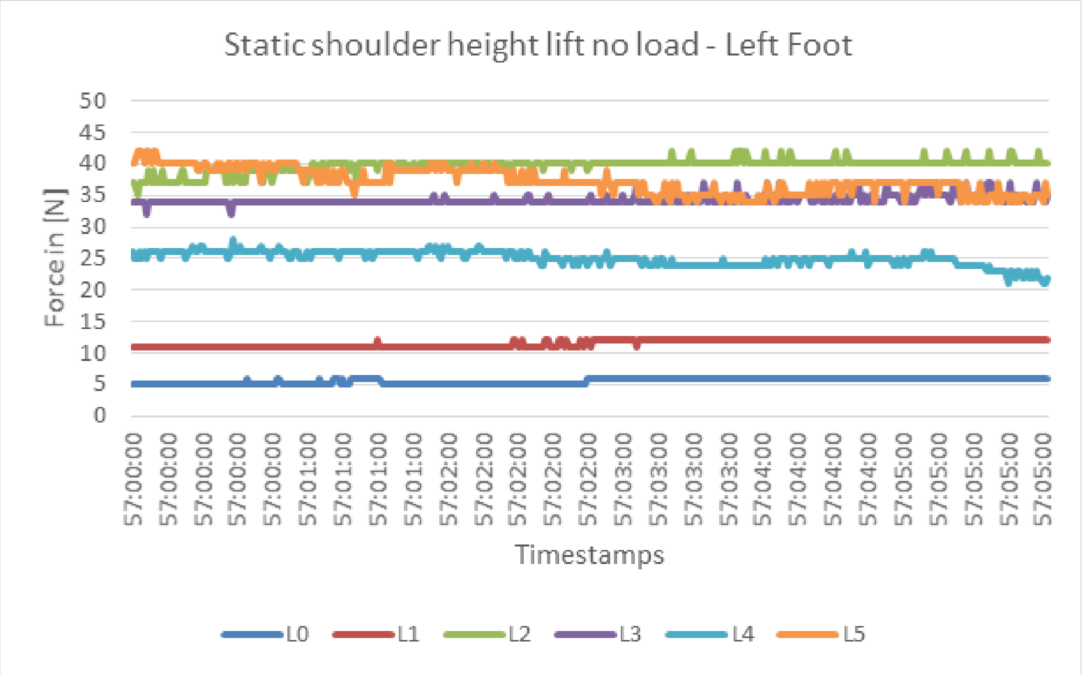
Shoulder Height Lifting

The static posture of having arms above shoulder height has been analysed in two situations, without load and with a load of 10 kg. In the first situation, it can be seen as a posture that could be used to reach for an object in a rack.

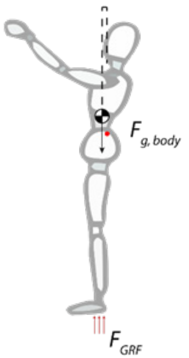
Graph 16 and Graph 17 shows high forces in the metatarsal area (L2/R2 and L3/R3) and heel area (L4/R4 and L5/R5). This happens due to the centre of mass of the body that moves forward as the arms create a moment arm. The toe area also increases in force, to balance the body, as it is used to create more surface area for the feet.

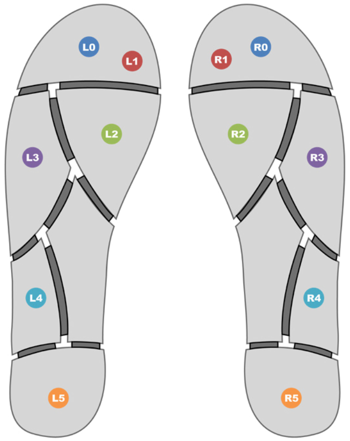
Recognisable patterns:

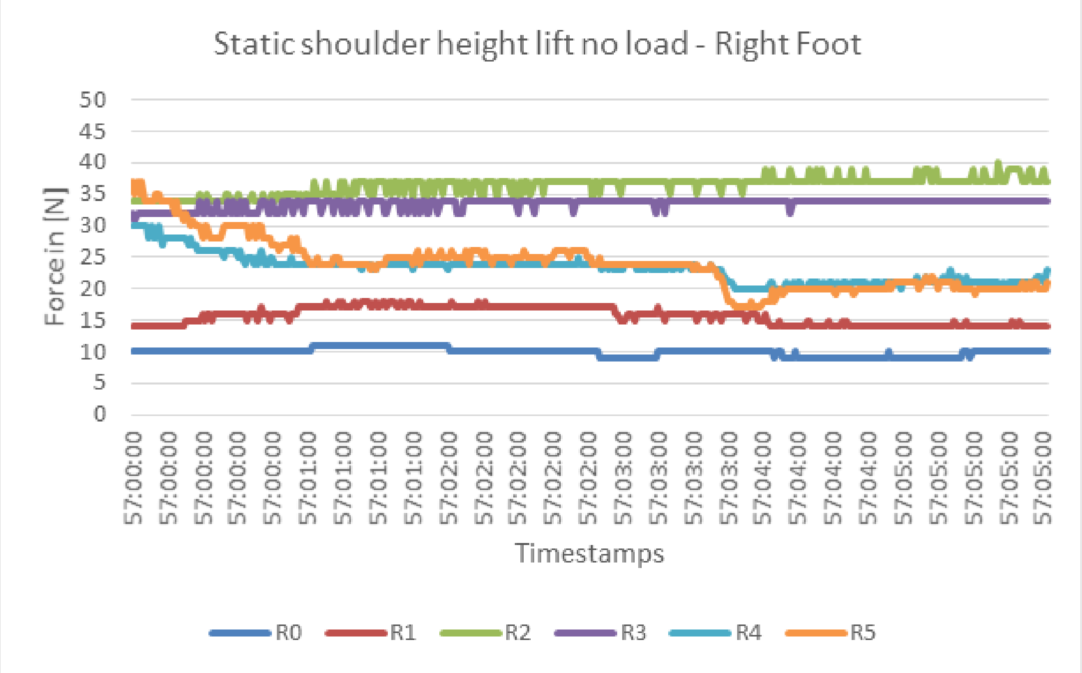
- L2/R2 and L3/R3 shows the highest force
- Followed by L4/R4 and L5/R5
- L0/R0 and L1/R1 has a small increase in force



Graph 16 - Force graph of left foot, no load, in Newton.







Graph 17 - Force graph of right foot, no load, in Newton.

Shoulder Height Lifting 10 kg

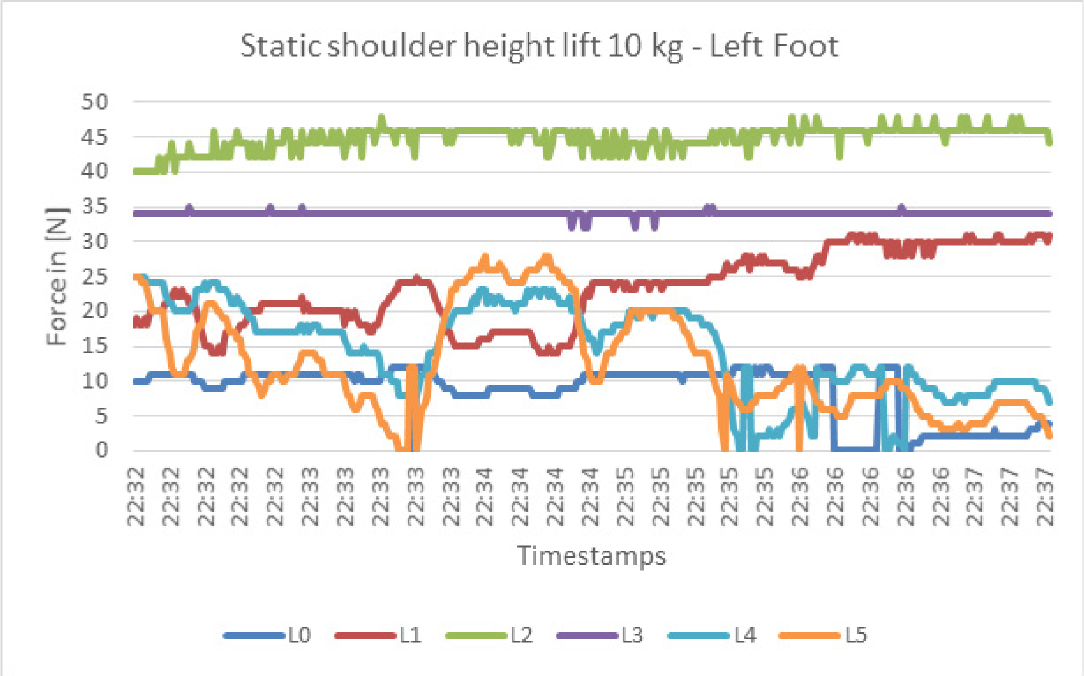
The second situation is lifting an object of 10 kg above shoulder height, to put it in a rack for example.

Graph 18 and Graph 19 do not show (relative) straight static force lines due to micro-adjustments of the body to maintain balance. Especially with a load far from the body and above shoulder height, creating a big moment arm. The highest forces are in L2/R2 and L3/R3 as this would be perpendicular to the middle feet when the load of the object and the load of the body would be combined and averaged.

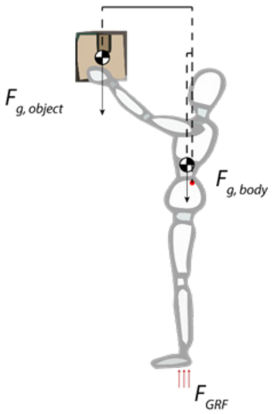
L1/R1 sensors show increased force, meaning the big toes are trying to maintain the load that is in front of the body. L4/R4 and L5/R5 are fluctuating in forces to maintain the balance of the body and object, otherwise, the person would fall forward.

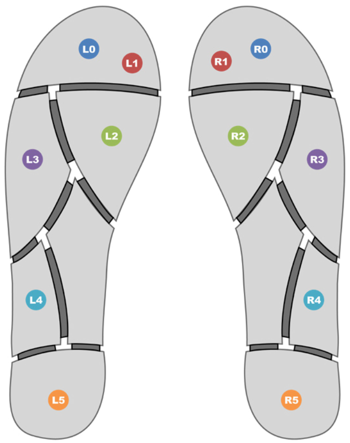
Recognisable patterns:

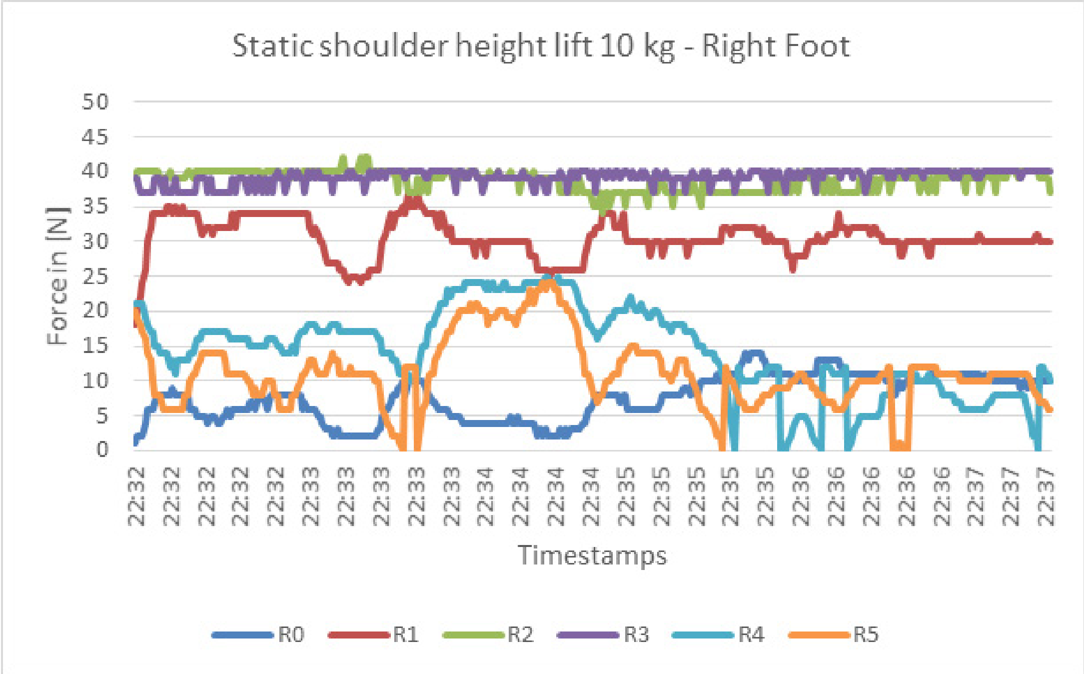
- L2/R2 and L3/R3 show highest constant force
- L0/R0, L1/R1, L4/R4 and L5/R5 show balance adjustment forces over time



Graph 18 - Force graph of left foot, load of 10 kg, in Newton.







Graph 19 - Force graph of right foot, load of 10 kg, in Newton.

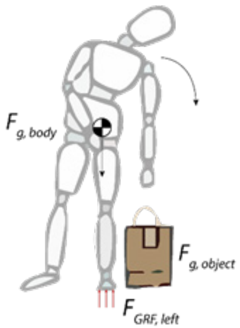
Asymmetric Lifting

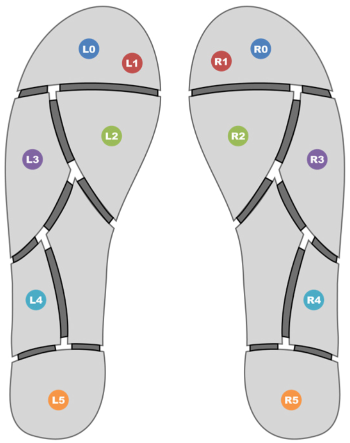
Two situations have been analysed for asymmetric lifting, first without an external load and second with a load of 10 kg. The first situation could be a case where someone bends sideways down to pick up a load.

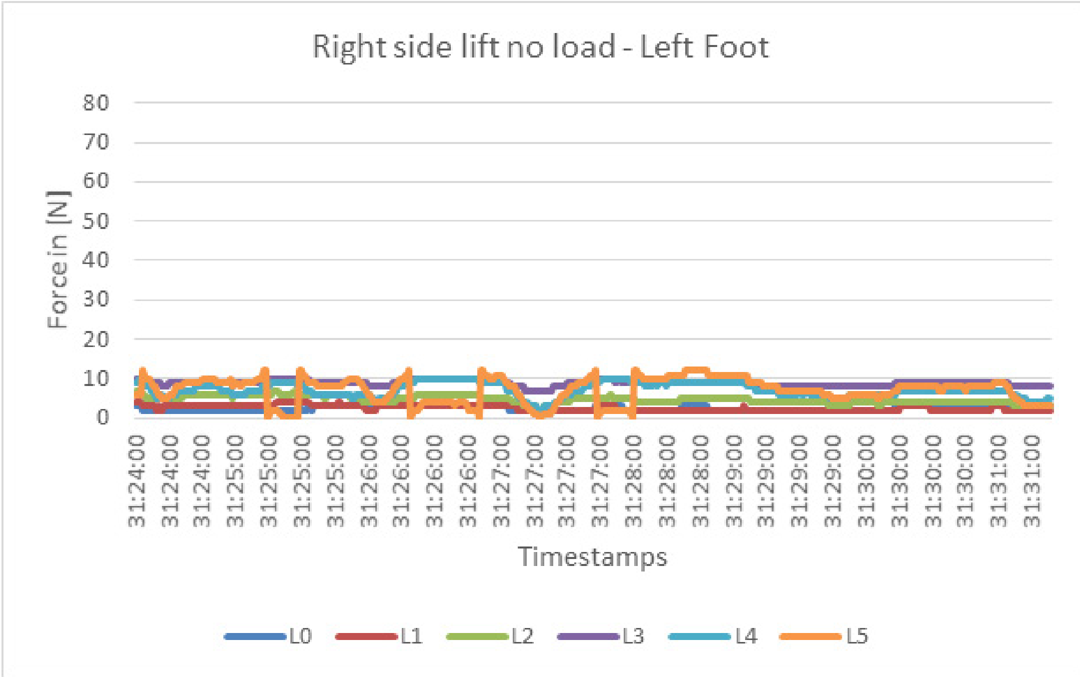
Graph 20 shows little to no forces, while Graph 21 shows high forces. This indicates that the worker is standing asymmetrically. The notable sensors are R3 and R4 as these are on the right side of the shoe, here are the higher forces meaning that the person is leaning to the right on the right foot. R5 is the highest due to the increased body weight on one foot and R2 is used to maintain the balance of the body.

Recognisable patterns:

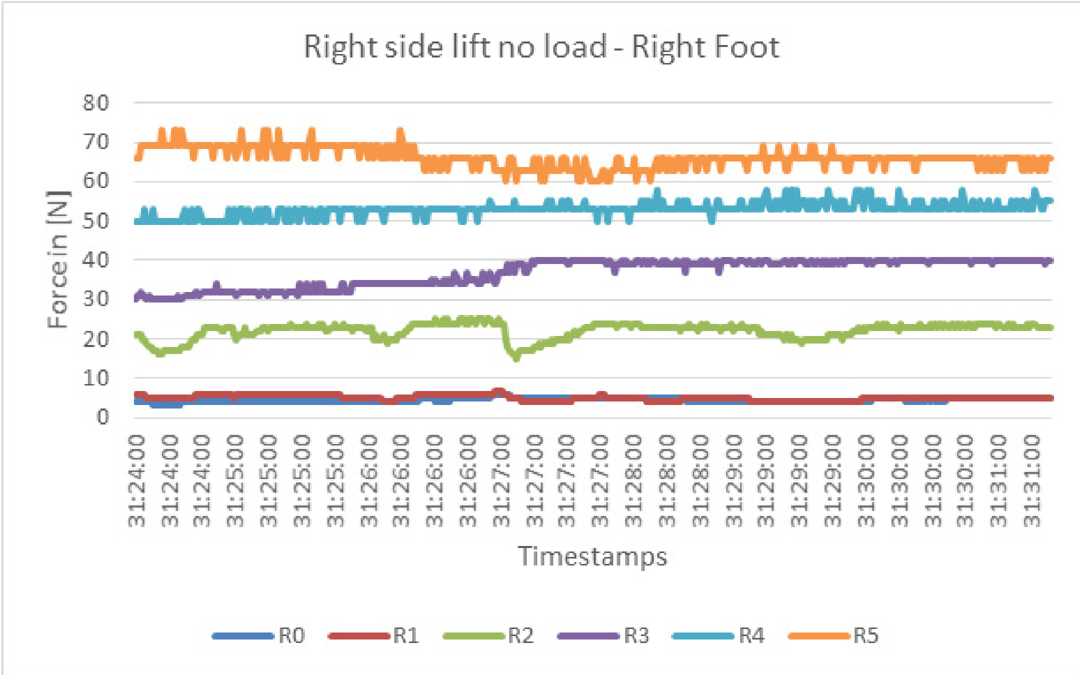
- Low force in left foot
- R3 and R4 > R2
- Highest force in R5







Graph 20 - Force graph of left foot, no load, in Newton.



Graph 21 - Force graph of right foot, no load, in Newton.

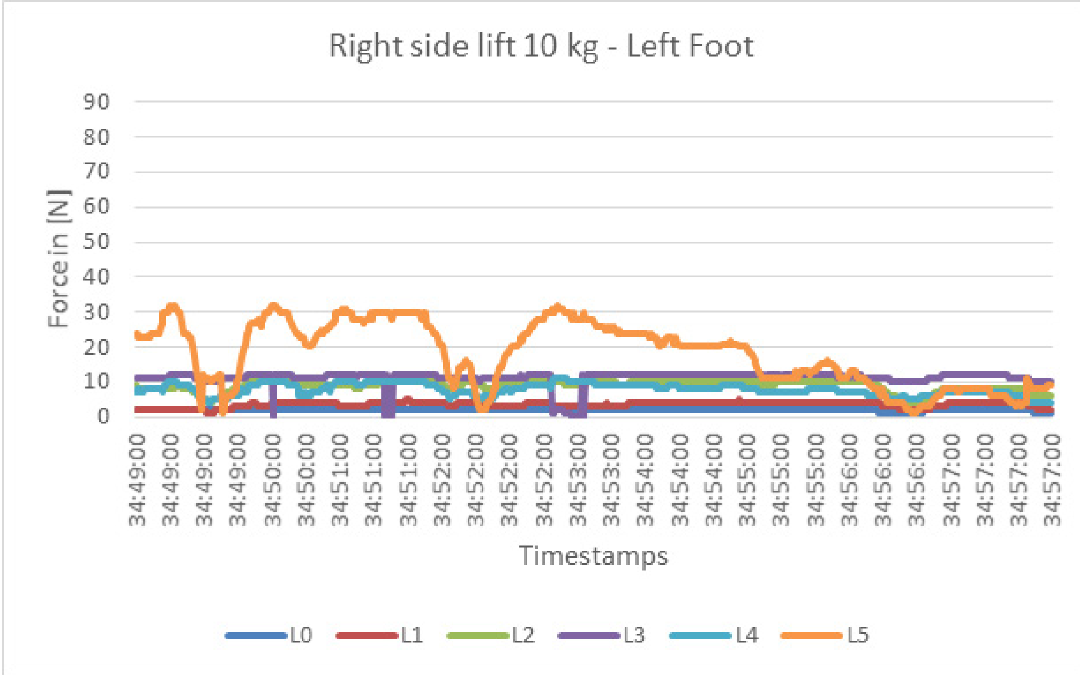
Asymmetric Lifting 10 kg

The second situation is where the worker would lift a load of 10 kg while stooped.

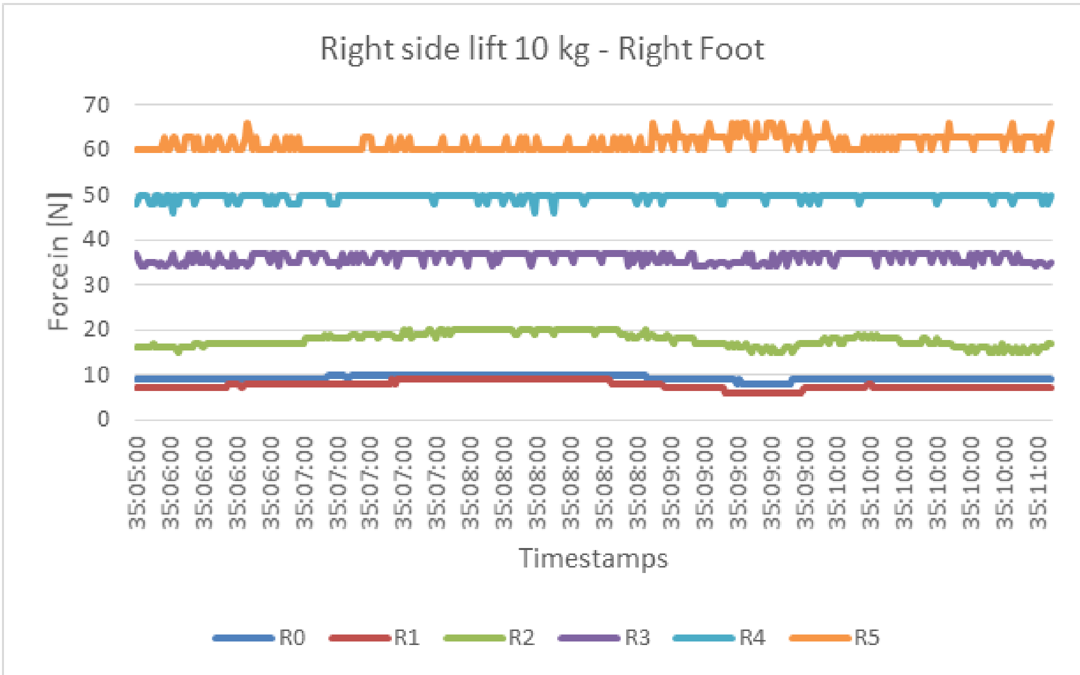
Graph 22 and Graph 23 look similar to asymmetric lifting without any load. The major difference is the force in L5, as seen in Graph 17. This force occurs due to the balancing of the body as there is an additional load of 10 kg. The body tries to counterbalance using its weight.

Recognisable patterns:

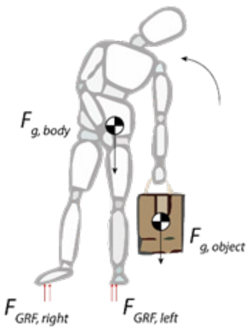
- Force in L5
- Low force in the rest of the left foot
- R3 and R4 > R2
- Highest force in R5

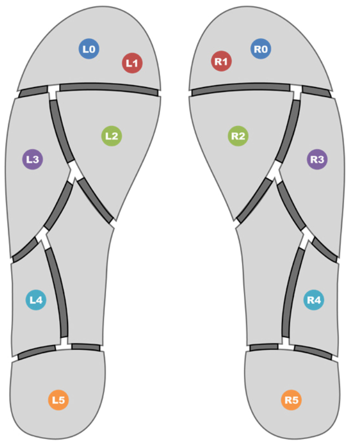


Graph 22 - Force graph of left foot, load of 10 kg, in Newton.



Graph 23 - Force graph of right foot, load of 10 kg, in Newton.





5.5.4 Dynamic PPD Measurements

Stoop lift

Analysing dynamic lifting is more difficult as there are more forces on the body due to motion. As mentioned before, the dynamic measurement will be compared to the theory discussed in 3.2.1.

The performed dynamic lift is the same as visualised in Figure 58. Graph 26 can be compared with the vertical force graph in Figure 58. The graphs are not similar due to sensor sensitivity and/or placement. From dotted line 1 in Graph 24, 25, and 26, to line 2 the force should increase in the total force graph. This is the case in Figure 58, from 0.6 seconds to 1 second. At the dotted line 3 the amount of total force increases, which is comparable to Figure 58 at 2.1 seconds.

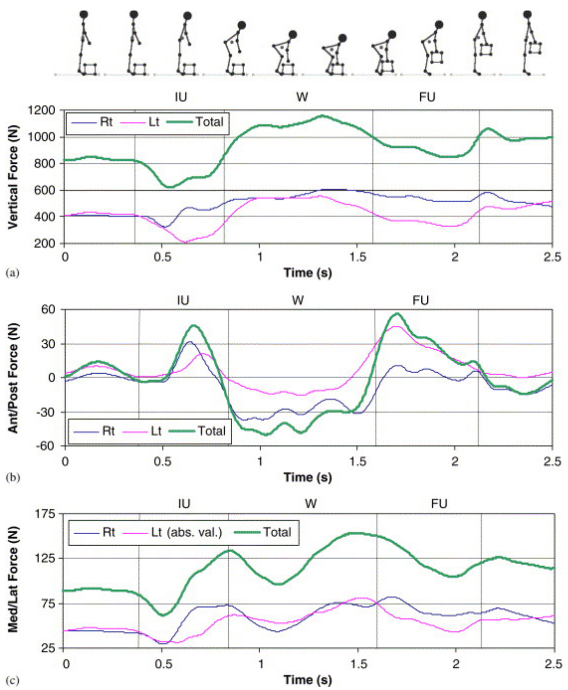
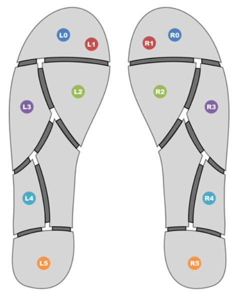
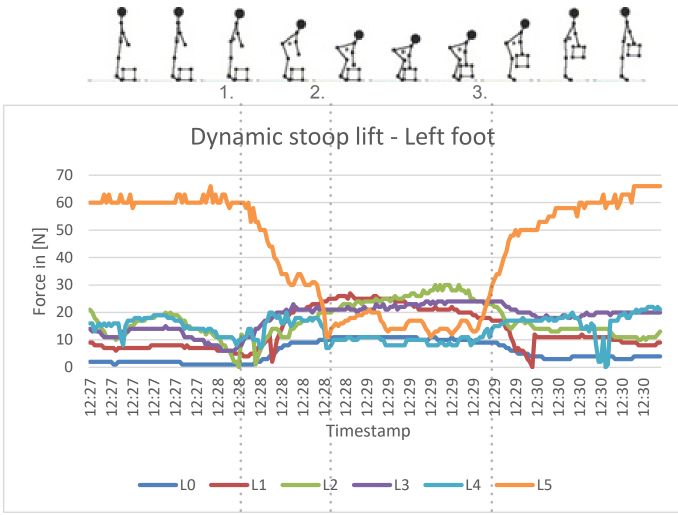
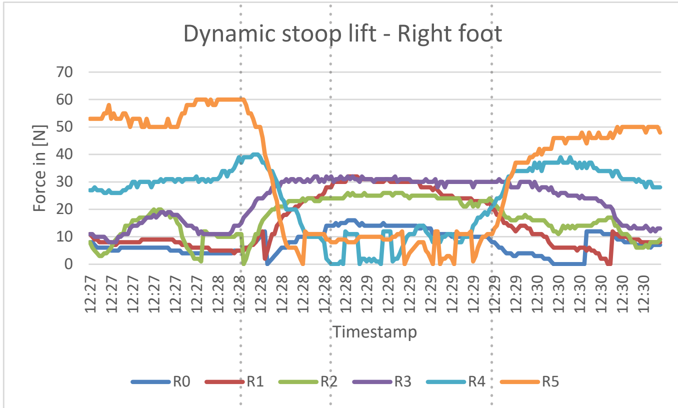


Figure 58 - Lifting phases and the GRF (Matt Maines & Reiser, 2006)

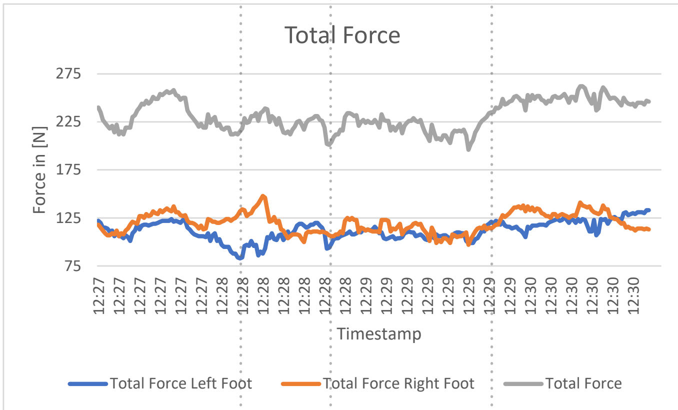




Graph 24 - Force graph of right foot



Graph 25 - Force graph of left foot



Graph 26 - Force graph of the total and per foot

Graph 24 and 25 can be compared to the ant/post force graph in Figure 58. At 0.6 second there is an increase of force in the posterior. This can be seen as a high force in L4/R4 and L5/R5 in Graph 24 and 25. At 0.7 seconds the force drops to the anterior which can be seen as a drop-in force in L4/R4 and L5/R5 and an increase in L0/R0, L1/R1, L2/R2 and L3/R3.

These results show that the prototype is capable of measuring dynamic lifting. Though the placement of sensors needs to be improved or the sensors have to be calibrated, to achieve higher accuracy of measurement values. Additionally, the used sensors are not sufficiently sensitive, as they can not measure an increase in force due to acceleration. The current prototype is capable of capturing the location of the peak GRF, in either anterior or posterior.

Comparing static measurements to dynamic measurements is not an equal comparison. Though, it helps with understanding where to look for unique characteristics in terms of peak forces per sensor or zones (e.g., toe area or heel area). Smaller details such as distinctive force amount per sensor are less obvious, as some performed lifts have a similar force distribution pattern, such as stoop lifting and lifting above shoulders. With a closer look at each sensor, differences or patterns can be found. Smaller details and characteristics can be found by using smart data processing, which will be discussed in the next section.

Conclusion

The three lifting postures, lifting above shoulder height, stoop lifting and asymmetric lifting, all have recognisable patterns when analysed from a static point. This shows that it is rather viable to distinguish different lifting postures from each other. There is a second set of all the static postures, which included in Appendix C. There are some differences relative to the first analysed set. This has been caused by how the participant stood on the insoles and how the body lifts loads after some effort as muscle fatigue could change how someone lifts.

The static stoop lift measurement has been compared to the dynamic stoop lift measurement from the literature research. This may not be a direct comparison, but it can help with confirming how patterns will look like. For instance, starting to stoop lift the force peaks in the toe area, while lifting the load will increase the force in the heel area. This was found from a biomechanical perspective and confirmed by comparing it to the literature.

Additionally, a dynamic stoop lift measurement has been performed and compared to the literature. The measurement of the prototype does reveal similar results. Though, due to differences in used hardware, the prototype does not yield equally accurate values. This may be improved by using better pressure sensors or by calibrating them individually. Nonetheless, the current prototype is capable of measuring dynamic lifts.

Instead of manually analysing the lifting data, smart data processing will be used to see if it can detect different lifting postures.

5.5.5 Machine Learning

To automate this analysis process, machine learning will be utilised. The same data sets that have been used for manual analysis, will also be used in the machine learning process. The model will be set up in Orange, which is an open-source machine learning and data visualisation software.

The model has been set up in Orange by Wilfred van der Vegte, with the use of a classification tree algorithm. Before the data set is imported into the program, it has to be cleaned up first, removing irrelevant data or that has errors. Second, the data points need to have labels for the algorithm to learn the specific postures. The different postures were manually labelled in Excel sheets. The data has been imported into Orange where different steps are performed to filter out fluctuations and smoothing the values using moving averages.

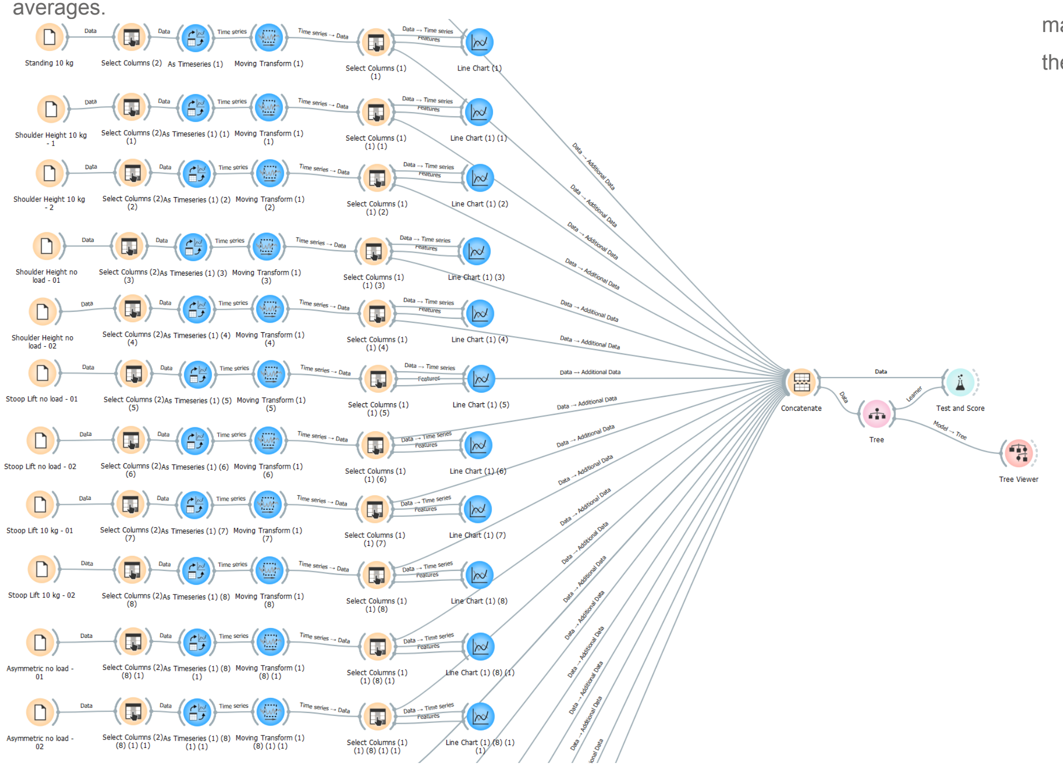


Figure 59 – Data learning model in Orange using Tree algorithm.

In Figure 59 each widget, shown as a circle, performs a certain step or process to make the data readable for the algorithm. The settings of each Orange widget can be found in Appendix E.
The first widget in Figure 59 imports the data set of a specific posture. Next, the columns from the data set will be selected, irrelevant columns can be ignored. As the data is measured over time, the order of the data points is important, the widget As Timeseries has been used to maintain this order of data. The captured data has some short-term fluctuations, the blue line in Figure 60, this has been smoothed out using Moving Transform, with moving average setting. The result is the red line in Figure 60. A transformation of a whole data set can be found in Appendix F.
The transformed data will be selected for the continuation of the process. All the processed data sets will be Concatenated or linked into one data set.
This set will be used by the Tree algorithm as training data to make a model. The model will be validated to see how accurate it can classify data, this is done by using the Test and Score widget. Figure 61 shows that the model has an accuracy of 99.7%, which means that the model can classify data with little error. The test is performed by withholding 20% of the data set for learning. After making the model, the 20% unused data will be used to test the model, by letting the model classify these test data points, which has a known label.

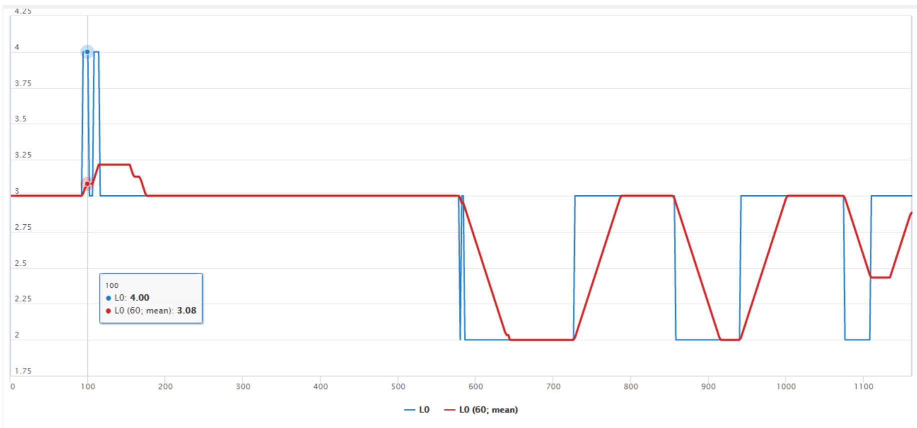


Figure 60 – Graph with original data and transformed to moving average.

The model is visualised using the Tree Viewer widget, it is a resulting decision tree, as shown in Figure 62. This visualisation shows how the model works if new data is introduced to the model. For prediction, in the case of the project, it is detection, it will go through the decision tree to classify the new data points. For example, if the value of L0 is bigger than 0 it will go to Neutral_Standing_NoLoad. If the value R2 is bigger than 23.7167, then it will go to Shoulder_Height_NoLoad. If R3 is bigger than 34.1333, go to Stooplift_10kg. If L1 is smaller than 14, classify the data point as Stooplift_10kg. This process of if-then will be performed till it reaches the end of the decision tree to classify each data entry.

Looking at the end of the decision tree, it can be seen that every posture can be classified with 100% certainty. Meaning that every posture has unique patterns and that the model is reliable in identifying each posture with certainty.

Though, this model is based on data sets from one person. It is possible that this model may not work for other people due to differences in weight and length. Further development and steps to take will be discussed in the recommendation section.

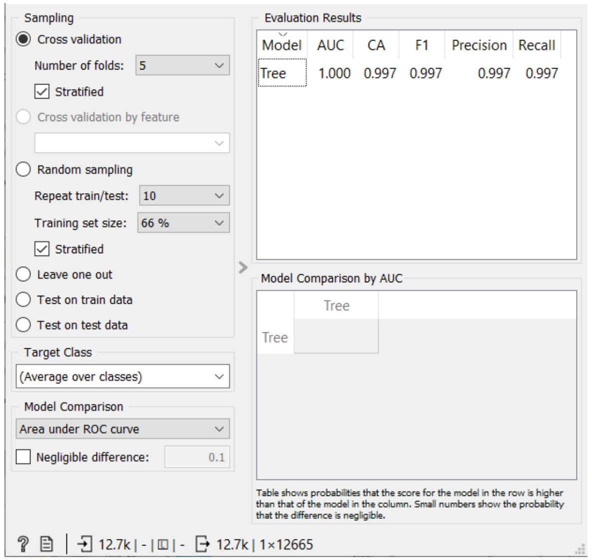


Figure 61 – Result of tested model.

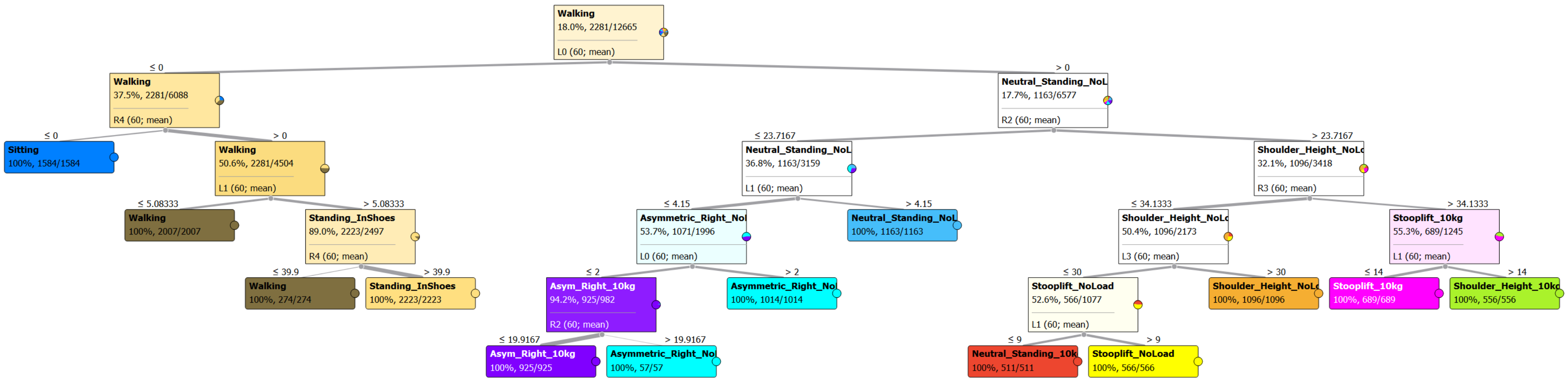


Figure 62 – Postures classified by machine learning.

Machine learning is capable of analysing static postures with no problems, as it can distinguish the postures with 100% accuracy. What has not been analysed yet is dynamic posture data. This has been measured but due to the time constraint, this has not been processed using machine learning. Labelling of this data is much more difficult due to the sheer amount of data. Additionally, the methodology for taking videos alongside measuring the lifting was not done synchronously as there was some deviation in time. This makes analysis rather difficult and less reliable.

At this point, it shows that machine learning can be trained using a (relative) simple tree algorithm. The model that came out, has close to no errors in classifying data. During a meeting with Van der Vegte, it was discussed that alternative algorithms may be used that could lead to different models, which may or may not perform better (W.F. van der Vegte, personal communication, 2 June, 2021). Alternative algorithms have not been tried as these are more complex such as neural networks. The development of ML should be explored further as currently, the data set is only from one person. If the data set grows in a variety of individuals and postures, another algorithm may be needed.

5.6 Design considerations

During ideation and prototyping, several (potential) bottlenecks were found that could have an impact on the realization of the smart safety shoe. These concerns have to be taken into account in the future design process. Some have been left out during this project, as the focus was to create a prototype with the critical functionality to see if the idea is feasible. This chapter shall discuss what has been considered and potential focus points.

Here is a list of aspects that directly influences the performance of the smart safety shoe:

- Sensor performance (accuracy, drift and longevity) (reliability aspect)
- Sizing of hardware (comfort aspect)
- Smart data processing (smart aspect)
- Variety of postures (machine training aspect)
- Assessment system
- Connectivity (IoT) and data storage (network aspect)

This list is ranked in functionality priority. The first and most important aspect is the sensors and the sensor layout as these components do all the measuring during the use of smart shoes. They have to reliable and sufficiently accurate to measure the amount of force applied to the ground. The prototype works relatively well with the Interlink sensors. Though, the reliability aspect has not been fulfilled yet. Alternative sensors could be explored such as the FSRs from Tekscan. This will be discussed further in detail in the recommendation section.

The second aspect is the comfortability of the safety shoe, which is related to component placement within the shoe. Comfortability might be affected by placing rigid and stiff electronics in the shoes. Almost every part of a shoe is flexible to some degree and by introducing stiff components, this flexibility will be decreased. This aspect has to be explored in more detail as the users of the safety shoes have to wear them every day during work. A close collaboration between the hardware developer and the shoe manufacturer is needed to succeed. Comfortability has been explored to some extent but not further elaborated due to the client's wish to let this be explored and executed by the shoe manufacturer. Some ideas can be found in Appendix G.
Comfortability sits just higher than smart data processing, as the workers are required to wear safety shoes during the whole working day. If the smart safety shoes are less comfortable than regular safety shoes, workers will be less inclined to wear them. It does not make smart data processing less important. This is the whole smart aspect of the idea, the software that could assess postures without the need for a human. The smart data processing model has to be based on the data from the sensors. That is the reason why the priority lies with the sensors.

Many variables could influence how a person lifts. Age, fitness, experience, length, weight and more could all contribute to how someone lifts. At this stage, only one person has been measured and the model is trained based on that data. If another person would be measured, this data could strongly deviate and the model would not be able to classify the postures correctly. An extensive database with a variety of postures is needed to train the model that would be able to classify postures from a wide range of people.

Next to the posture detection model, an assessment system or model is needed to give feedback to the user. This aspect has not been looked into during the project. There are only some ideas on how this could be set up. For instance, some postures have an increased risk of injury, these could be red-flagged every time the model detects it. It might not be dangerous if it is done once or twice. If it is done systematically, the model could give the user a warning. Further, aspects such as age or fitness could reduce the risk somewhat, making the threshold higher before it warns the user. This could be seen as a point system as injuries may come from cumulative small strains throughout the day.

Lastly, the connectivity of the product is an aspect that has to be considered. Currently, the decision has not been made yet, whether the data will be continuously transmitted to a local network or stored in the shoe itself. The consideration between the two is the power consumption. It requires some electricity when data is continuously transmitted, which could lead to a depleted battery before the end of the working day. The benefit of continuous data is live data analysis and insights. On the other hand, people could have privacy concerns. From this point of view, it might be best to opt for storing the data in the shoe and transmit the data at the end of the day. This yields lower power consumption and fewer privacy concerns.

6. Roadmap

Next steps

Currently, the project has only shown that the idea is feasible. Without using high-end pressure sensors, the core principle of the smart safety shoe has been tested and proven that works. Not as accurate as desired, but this should be easily be improved with better sensors or calibrating the current ones.

From here on, there are several paths available to continue the project. This roadmap has been set up together with J. Arts to give the roadmap a more realistic outlook. The decisions are based on the novelty and complexity of the idea combined with the desired launch date. Naturally, the timeline is a gross estimation as unexpected delays are inevitable.

To be able to launch the product, a variety of parties have to be involved to realize the idea. Allshoes is a safety shoe distributor and does not have the in-house resources for designing and testing the hardware or software. The major party that is already involved is AMF, a shoe producer located in Portugal who has the capabilities of adapting manufacturing to new shoe designs. Though, from a meeting with the producer, it was found that they do not have experience with working with electronics.

Electronics and software still have to develop further. Additionally, a larger ergonomic database is required to encompass different people. It is preferred to proceed with the project with TU Delft. They have the capabilities to develop hardware, software and setting up the database. It has been suggested by the staff team to proceed with postdoctoral researchers, as they have more experience in developing such novel products. Two or more may be needed to develop the idea further due to the complexity of the problem that is trying to be solved. Ideally, one researcher should be a hardware and software expert, second the other should be an ergonomics expert, and the third an AI and/or ML expert. This way, the electronics can be designed with the required software. The database should set up by the ergonomics researcher. Lastly, the AI/ML expert will be able to make models based on the captured data. This stage could be seen as research and development.

The TU Delft team may be able to develop a state-of-the-art product, based on extensive scientific research. It is estimated that the team would need roughly nine months to execute the research. AMF should be involved from the beginning as they will be the party that will do the production. Additionally, they will be providing insights on safety shoe knowledge regarding comfortability and possibilities of placing components. They will also be making samples of shoe designs to fit the hardware. TU Delft will be developing a working prototype, database and ML model. At this point, the commercial viability has to be reviewed by Allshoes, to see if it is worth pursuing in terms of profit.

It might be a good idea to focus on a user group or use case. Currently, the focus was on warehouse workers who have to pick orders the whole day. Most products that are picked are not too heavy or awkwardly sized. There is a potential client/party that is greatly interested in this project due to common LBP injury occurrence. This party delivers gas cylinders that are heavy and often awkwardly sized as they are cylinders. This kind of target group would greatly benefit from the smart shoes, to see when they are lifting incorrectly. Instead of building a posture database that is all-encompassing, taking months to set up, it will be reduced to a more specific set of postures.

For commercial development of the hardware and software, a commercial party in IoT will be involved. They have more experience in commercializing hardware with IoT solutions. The hardware design from TU Delft should be considered, with some production changes. They would also be developing the network infrastructure for data, software for the users (front end and back end) and hardware design for production. Close cooperation with AMF would be needed as the hardware has to be placed within the shoes during production. Several iterations may be needed before the production can start.

Allshoes should start a marketing campaign before production starts, to create some awareness around the product. As it is a novel product, people may not understand what the product is for or what value it could bring them. This development and production stage would roughly take another nine months. Which totals 18 months to reach launch. A comprehensive roadmap with time estimations, tasks, and goals can be found in Appendix H.

7. Conclusion

This project is to design and validate the theoretical feasibility of a smart safety shoe of the future. To reduce WMSDs in warehousing due to manual handling. Through research, it was found that LBP was the most common WMSD, which has a significant impact on the life of the workers, companies, and society as a whole. Traditional (observational) methods could help people on the work floor but this would cost too much time and money. Technology would be a better fit to aid workers in their daily work. Therefore, the main research question was formulated:

Can equipping safety shoes with sensors and smart data processing help reduce the risk of LBP, and eliminate the need for deploying labour-intensive observation methods for that purpose?

To answer the question, extensive literature research was conducted to understand the causality of LBP, correct manual handling, the basis of biomechanics, and current technological standing. This formed the foundation of the project that led to the prototypes with critical components. The prototypes were used to conduct tests to measure forces during manual handling.

Research has shown that the causality of LBP is not easy to point. A combination of different factors contributes to it. Though, the physical factor is the most prominent in the cause. By looking at how a worker is performing manual handling, the risk could be assessed. The way how a worker is performing a lift can be seen through ground reaction forces, without the need for complex biomechanical calculations.

Technology has progressed far, components can be easily fit in shoes. Placing pressure sensors in the sole of a shoe, the ground reaction force can be measured. With the aid of machine learning, data can be analysed without the continuous involvement of people. The GRF is analysed by an ML model to classify the postures. The model can identify static postures with 100% accuracy. An assessment model has not been set up due to time constraint, though risky postures are identified with little error.

From the research and the conducted tests, it is found that equipping safety shoes with sensors and smart data processing, ML, can detect risky postures that would lead to injuries without the need for labour-intensive observation methods. Even though the prototype is not at the level desired, it is capable of fulfilling the intended goal. With further development, Allshoes would be able to bring a novel product to market that could help lots of people and prevent future work injuries.

Discussion and limitations

The smart safety shoe could potentially be a great beneficial product that could help millions of people in many sectors. It is proven that it is possible, even with a rough prototype using sensors that are not fully capable off-the-shelf. Reducing or preventing LBP (or WMSDs down the road), is much more complex than initially thought. There is still a long way ahead before the product can be launched. Some of the considerations will be discussed in this section.

Complexity of the issue
At the beginning of the project, the complexity of LBP was overlooked. Once the research started, the complexity became apparent. Knowledge from prior projects or simply logical thinking is not sufficient. In-depth knowledge was required for this project as the causality of LBP is not as simple as just lifting something wrong. The conducted research during the project barely scraped the top layer of the required knowledge. To develop the product to the desired level that could assess lifting postures without the interference of people, real experts are required in the field of ergonomics, AI/ML and electronics.

Ergonomics
Build a database to cover all the data about postures will be quite the challenge. This database will be needed to cover a large percentage of the population. The challenge lies in how every human has its unique characteristics, from different walking patterns to lifting postures. One way would be building an enormous database or another way would be trusting the smart data processing to make the correct decision. As mentioned before in the roadmap, a good start would be starting by focusing on one target audience and collect data in smaller phases.

Smart data processing
Machine learning (or AI) needs much more development as it currently can only detect static postures. Dynamic postures are much more complex due to how fast the posture values/data changes over time. Additionally, inertial forces could make posture data less predictable due to balancing of the body for example. This could lead to false positives or wrong classifications. It is a major challenge that has to be tackled from the beginning of development as AI/ML is the brain of the product.

Furthermore, the currently used algorithm may not be fit for dynamic lifting data. The complexity of making decisions by the model increases as the amount of postures increases. A more complex algorithm could be a better fit. This has to be explored further in-depth.

Electronics
The components that have been used for prototyping are not chosen based on best performance or value. All the components are chosen based on ease of use and readily available. Which has to lead to big components that would never fit inside a shoe. From technology exploration and my knowledge, some components could achieve similar results with maybe even better performance with a much smaller footprint. Though, these components are not easy to work with normal home equipment. Special tools are required. For that reason, hardware design should be handled by an electronics expert. Further, some safety regulations should be adhered to, avoiding shorting for example.

Limitations
As mentioned before, this is not a simple project to execute. There are too many aspects to be covered by only one student at a time. To successfully execute this project, a bigger team is required to work on different aspects simultaneously. This led to the expected limitation of time, every aspect has been covered to some extent but not to the level as desired.

Further, product desirability has not been explored extensively, it is only known that one company within the Bunzl group has a great interest in the product. This is already a good sign for the adoption of the product. Though, it is not known to what extent, in terms of expectations.

Lastly, the long term reliability of electronics components has not been investigated. There are technical specifications on the pressure sensors, but in reality, they may differ. The sensors may not be fit for eight hour-long loads, every day. They could lose accuracy over weeks or months. How much this decrease is unknown and it should be tested by using a machine setup that could put a load on the shoes with sensors for a set amount of time and unload after.

8. Recommendation

There are a lot more possibilities for this project in which direction it can go. This section shall discuss what it is recommended to explore further to develop the project. Of course, it has been discussed in the roadmap what potential following steps may be. Though, it does not go into detail which will be discussed here.

Sensors

The current sensors from Interlink are easy to implement and cost-effective, but it has accuracy and resolution limitations in its uncalibrated form. From literature research, it shows that these sensors are capable of measuring GRF with good accuracy after calibration. Though, this process is time-consuming and will increase the cost per sensor. Alternatively, better sensors may be used such as Tekscan's, but has a much higher price. To make an informed decision on this aspect, both options should be explored in more detail regarding performance and total pricing. For example, if the performance of the sensors from Interlink can perform similarly to Tekscan after calibration. With only an increase in the price of 100%, it would still be more cost-effective than its competitor.

Sensor layout

To cover the majority of the foot, the sensors have to placed at spots where the most force is applied while standing or walking. The used layout for prototyping is based on literature research but still with some guesswork and by looking at my own feet. There is no perfect sensor layout as humans have unique feet sizes and forms. Ciniglio et al. (2021) has looked into sensor layout based on shoe sizes. The study did not test every layout to see whether it fitted the shoe size, but something similar should be explored. More sensors could yield higher accuracy but with an increased cost. Lower sensors could be bare essential pattern recognition, but with a lower cost.

Shoe material

The outer sole of the shoe has some influence on the measurements of the pressure sensors. During the project, it has not been tested in-depth to see to what extent. It was noticed during the static and dynamic measurements. This cannot be entirely be eliminated as the shoes has to be flexible for comfortability. Instead, the software should compensate for the small inaccuracy. This should be tested in a lab environment using a universal testing machine. The machine can put an amount of known force on top of the sensor while in a shoe. This could be done for a variety of forces to see how it behaves based on the applied force. From this data, a formula could be formulated and should be added to the code for compensation.

Lacing tightness

There is a concern that lacing the shoes too tight or too loose, could affect how the sensors measure the force. If it is too tight, the sensors will always sense a higher force than they should be. If it is too loose, the measurements might not register. This concern could be solved with a calibration process when the shoes are put on. The shoes could give a signal when it reaches the optimal force tightness. A force range is desired as people have their preference.

Feedback system

When potential danger to injury is detected, warning feedback will be given to the worker. It has been suggested to use a LED light, but it may not work or increase danger even more. Workers will not look at their feet while working, the warning will go unnoticed. When employees are looking at their feet, they might not notice what is happening in front of them. Vibration as a warning is better, which is inaudible and can be felt. The placement of the component is crucial, it should be at a spot that could always feel it. From the comfortability experiment, it was found that this is the inside of the foot, the area between the heel and ankle. Further experimenting is required.

Target audience

In the roadmap section, it has been discussed that the focus could be put on a use case such as the gas cylinder company. The solution that has to be developed will be more tangible than making something that could cover everything, but only does half the job e.g., (incorrect detection or false positives). Instead of making a detection model that could detect everything, specific models can be made per working sector. This results in higher detection accuracy and models can be made in several phases.

Weight Calibration

The sensors in the smart shoes have to be calibrated every day to have a good baseline or reference point for long term data analysis. It also has to accommodate people with different weights. Calibration functionality can built-in the software, it measures the force of the user while standing and uses this as offset values.

9. Reflection

This was a challenging but rather fulfilling project, knowing that the idea has the potential to help protect people from daily potential injuries. All the subjects that are relevant to this project were not new to me, but the basic knowledge was simply not sufficient. The need to dive deep into the theory was unexpected. Of course, a research phase is needed to get a better understanding of the problem and get knowledgeable on what is out there already. Though, research became more and more complex the deeper it went. Instead of finding answers, only more questions arose. Contacting an expert in the field would have helped a lot. Giving clear directions where to look or at least have a discussion about certain subjects. This would have saved lots of research hours.

The second difficulty is understanding some scientific papers, as terminology can be an issue. It felt like learning a whole new course for the project, aside from working on the project itself. My understanding of ergonomics and AI/ML grew a lot and putting it to practice in the project. Maybe it would have been better if a list of assumptions was made before and conduct research based on the list. This would create a better overview of what I already knew and what has to be looked deeper into.

Working closely with an actual client is new for me. Usually, there is only a contact moment with the client every two weeks or once per month. Having contact every week and even two times per week is great for decision making. Though, at times it felt like it took away a bit of designer freedom. Thinking of multiple options or directions. There might have been a good option on a path that was decided not to take. In the end, it did work out well, making much faster decisions.

TU Delft is where everyone learns to concept design. This approach is understandable, as concept designing takes less time, effort and especially low cost. Though, it does not work for me very well. Getting stuck on a limited amount of ideas that may or may not work. Instead, trying to make concepts through prototyping works much more efficiently for me. It brings an idea to life, adding dimension to ideas. Working on essential elements first and working down to the details. From the beginning of the project, it was expected to build prototypes for testing purposes and investigating the feasibility of the idea.

Looking back at the process, the prototyping phase started just a bit too early. The ideation phase was cut too short and certain elements, in general, were considered. For future projects, I need to find a better balance between these two phases. A longer ideation phase would help with building better prototypes. Every approach has its advantages and disadvantages.

Planning for this project went considerably well, it helped a lot when I planned goals per week. At some points in time, it looked like I didn’t adhere to the planning anymore. Either falling behind or doing work that is needed later. Though, looking back at the planning as a whole, the tasks that were done were always as planned. When I was falling behind, it was often that there wasn’t sufficient time planned for that task. During the project, I’ve learned a lot about planning from Jan Arts, the company mentor. Planning in the bigger picture, the why’s, is much more important than planning every task, the how’s. Also, trying to plan tasks in parallel helps a lot, instead of chronologically.

Overall, it was a great but challenging project to do. Gained lots of new knowledge and experience, improving myself as a technical designer. It was great to work at a company like Allshoes, timelines move much faster and results have to made on weekly basis. Also, bringing something new and innovative to the table, is not easy. Especially, as there is not much else to compare it to. Sometimes you have to be the first to start something new, to innovate a market. This is what I want to keep doing as a designer.

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Appendices

Appendix A - Proposed revenue model (Van den Berg, 2020)

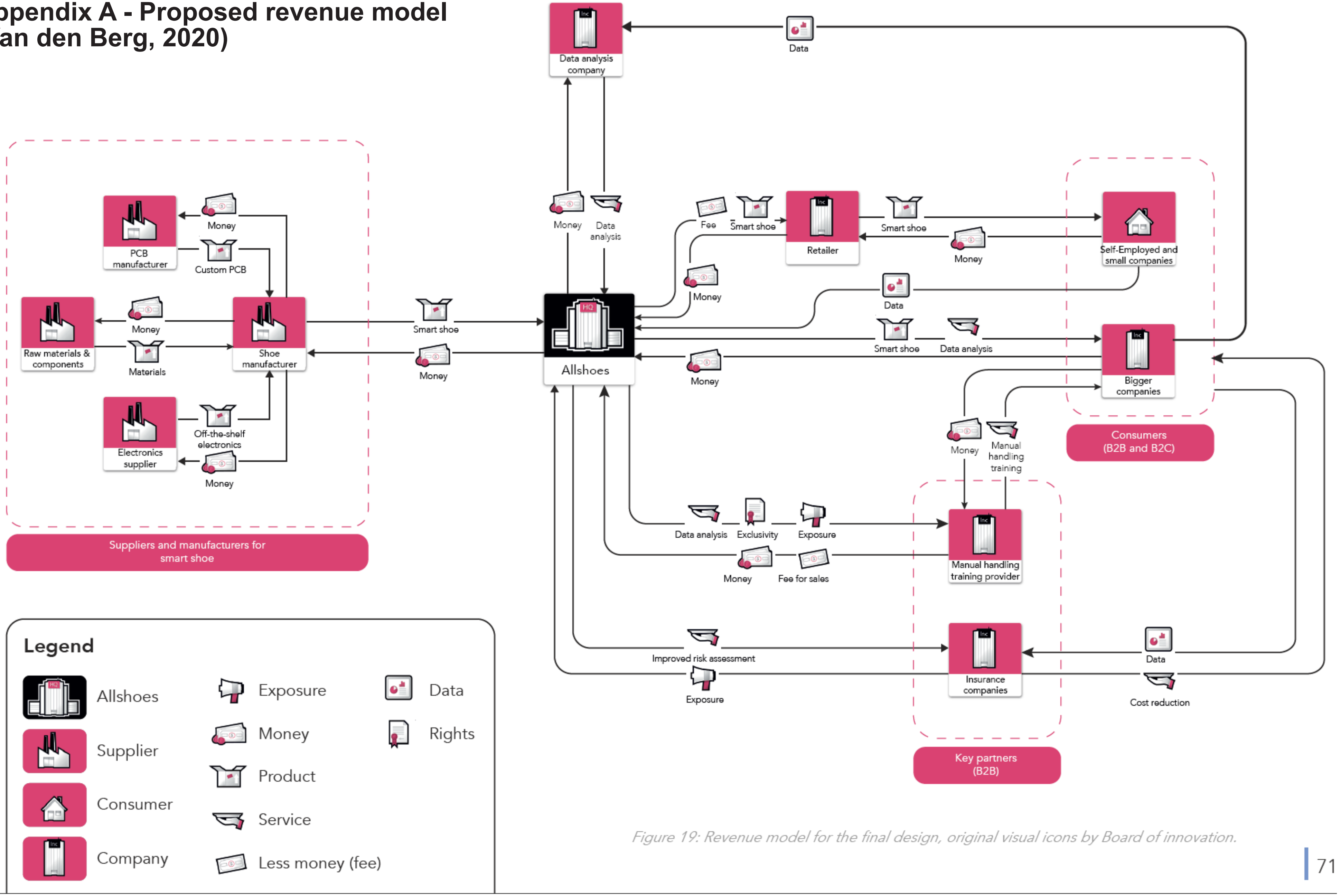


Figure 19: Revenue model for the final design, original visual icons by Board of innovation.

Appendix B - Prototyping Stage 1 and 2

Prototype One – Testing hardware & writing code

This is the first prototype where the electronics and the software have been tested. It has been made to get to know the hardware better and know their capabilities, as documented values may not always apply to every situation. Further, the focus was on writing the Arduino code for controlling the sensors and logging the data. From personal experience, writing and debugging code can take some time and effort, especially resolving bugs.

The first pressure insole has been made using cardboard for a quick test. It follows the sensor layout as provided by Shu et al. (2010) in Figure 1, as it covers all the foot pressure areas as shown in Figure 2. The first prototype uses fourteen sensors instead of fifteen due to size and wiring difficulties, see Figure 3 and Figure 4. It does cover all the pressure areas on the foot. In the first tryouts, it was found that the sensor layout works but not optimally as some sensors did not show any value while standing on it. This may be caused by the anatomy of the foot, as some areas do not exert any force while standing. No real tests have been conducted using the first prototype as that was not the main purpose of this prototype.

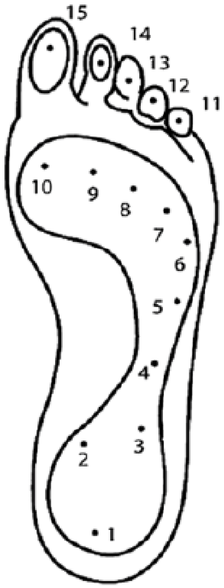


Figure 1 - Pressure Sensor Location (Shu et al., 2010).

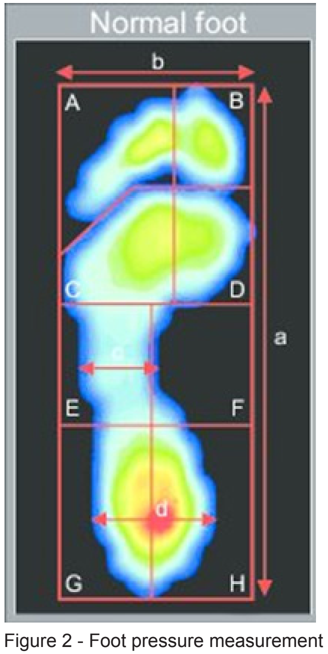


Figure 2 - Foot pressure measurement image (Son et al., 2015).

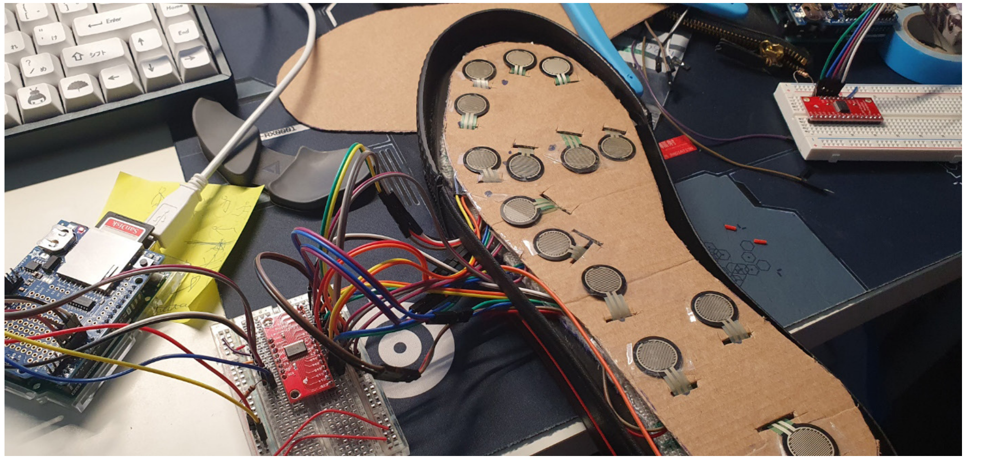


Figure 3 - Cardboard pressure sole.

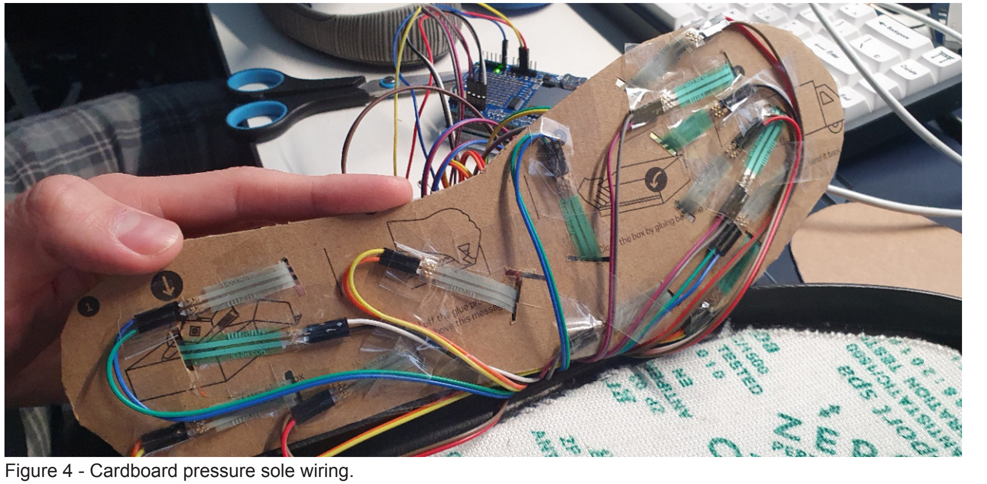


Figure 4 - Cardboard pressure sole wiring.

Prototype Two – Designing a new pressure insole

The second prototype was to reduce the number of pressure sensors needed as this is a requirement of Allshoes to reduce the price of the (final) product. To reduce the number of sensors without losing accuracy, a new design has to be made. The new design has been inspired by a paper by Muzaffar and Elfadel (2020), where they put pressure sensors on the cleats of soccer shoes, which would result in full GRF measurements. This comes from the same problem, where a portion of the force "disappears" through areas without any sensors, visualised in Figure 5a. Instead, measure the GRF by standing on a "solid" plate and placing pressure sensors beneath the plate. The sensors should interact with the ground giving the full GRF of the body, visualised in Figure 5b. This idea has experimented with a proof of concept, shown in Figure 6. The measurements were four times better than the existing state-of-the-art, according to Muzaffar and Elfadel (2020).

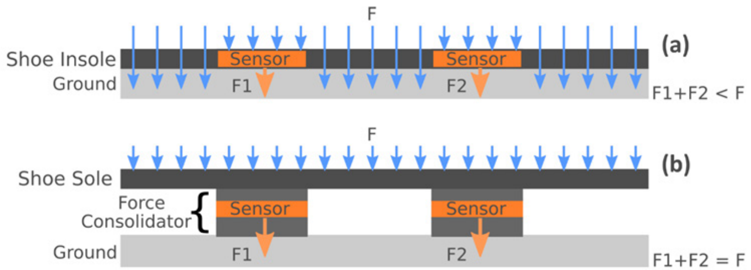


Figure 5 - (a) Sensors placed in insole (b) "Sandwiched sensor force consolidators" (Muzaffar & Elfadel, 2020).

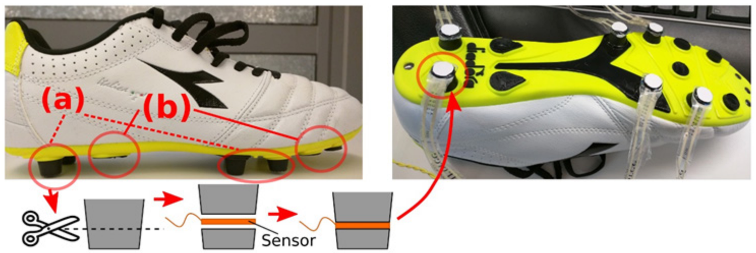


Figure 6 - Proof of concept (Muzaffar & Elfadel, 2020).

This idea solves the issue of needing an insole fully equipped with sensors. On safety shoes, it would not be possible to place sensors on the outside of the sole, nor good for the longevity of the sensors. Instead, this study serves as an inspiration to create a new insole that could measure the full GRF with fewer sensors by concentrating the force to the available sensors.

The first sole in the figure shows the foot zones that have been created. These zones are based on how the sole can be divided into several zones, which Shu et al. (2010) have described in Prototype One section. Zone 1 is the toe area. Zone 2 and 3 is the metatarsal area, split in two to be able to measure whether the person is more standing to the left or right which will be useful during measurement. Zone 4 is the middle foot area and zone 5 is the heel area. The area next to zone 4 has been left empty as this is the arch of the foot, which should not show any force in a healthy foot. The dimensions of zones are based on the pressure map of a healthy foot, as seen in Figure 36 as the zone-layer is laid over on top of the foot and tries to cover the most high-pressure areas. The second figure is the sensor layer, where the sensors are embedded in a flexible PCB and the third figure shows the two layers on top of each other. The final figure shows a side view of the two layers, where the flexible "pucks" will be placed on top of the sensors.

Each zone will be made out of stiffer material, for the force to go to transfer to the sensors. The connection parts between the zones will be made out of flexible material such as silicone or rubber, to have individual flexibility per zone.

Pressure sensors are placed in the middle point of these areas from a mechanical perspective.

If some of the force is applied to the outer brims of the zones, the sensor would still be able to measure it.

This idea has been made and tested using cardboard, see Figure 7 and Figure 8, and showed similar results as the first prototype with fourteen pressure sensors. Even with the use of cardboard and tape, the results were better than expected. Though, the results were not captured and documented, because the first and second prototype was used to get familiar with the hardware and creating a new sensor layout with fewer sensors.

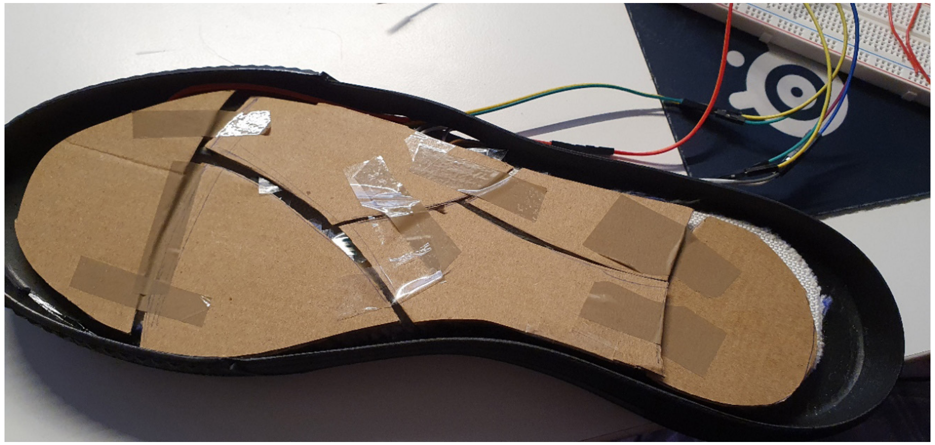


Figure 7 - Cardboard pressure sole with zones.

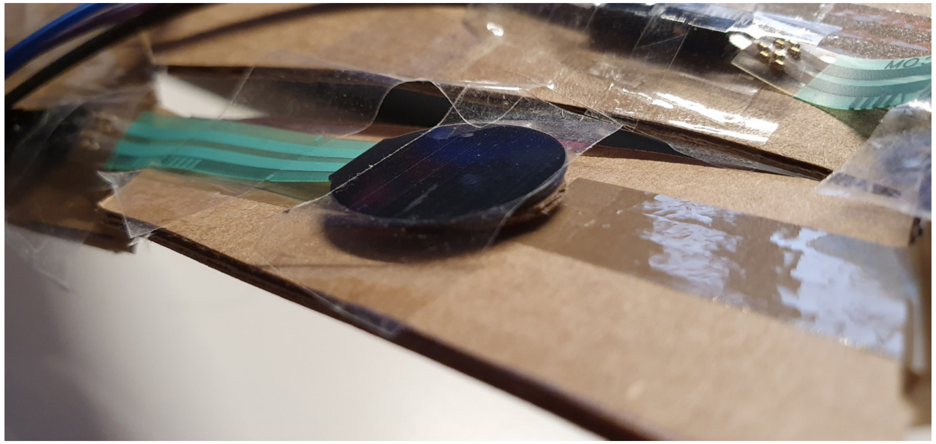
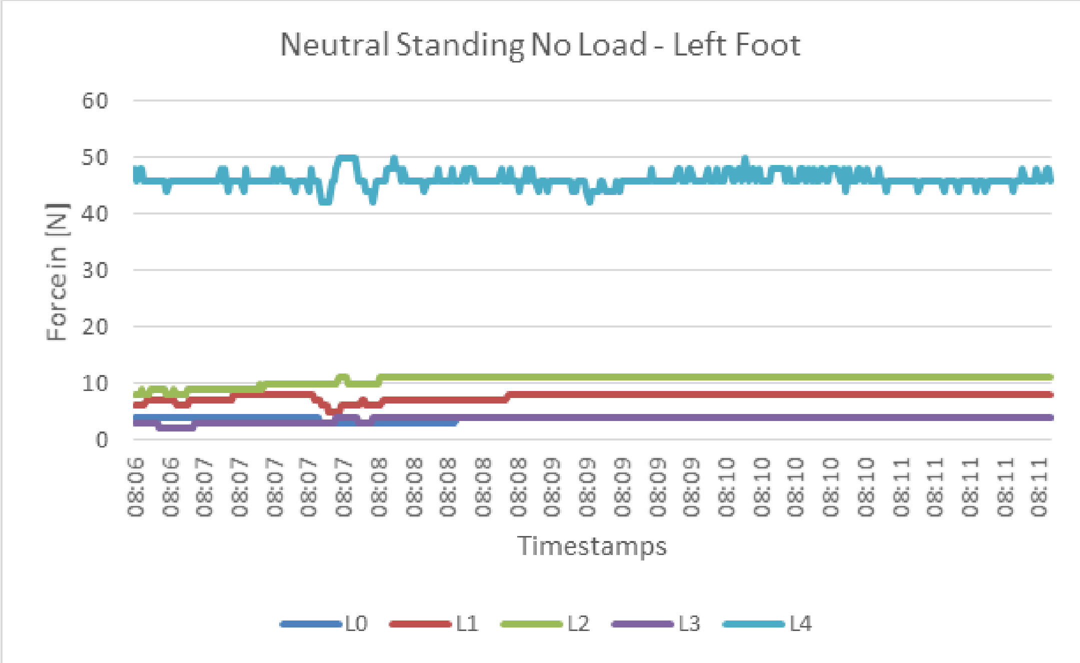
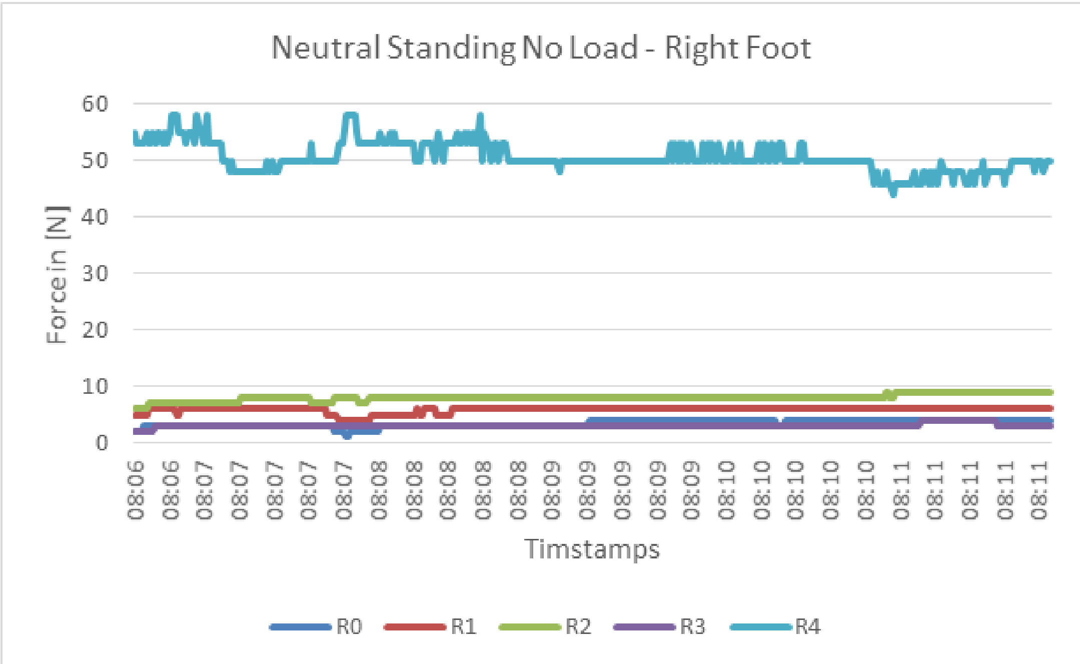


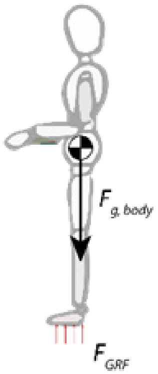
Figure 8 - Sensors elevated with a cardboard puck.

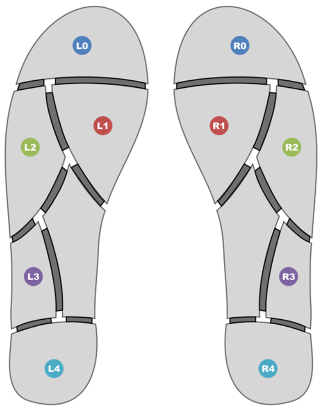
Appendix C - Results of pilot test with 5-sensor layout

Standing up right - no load

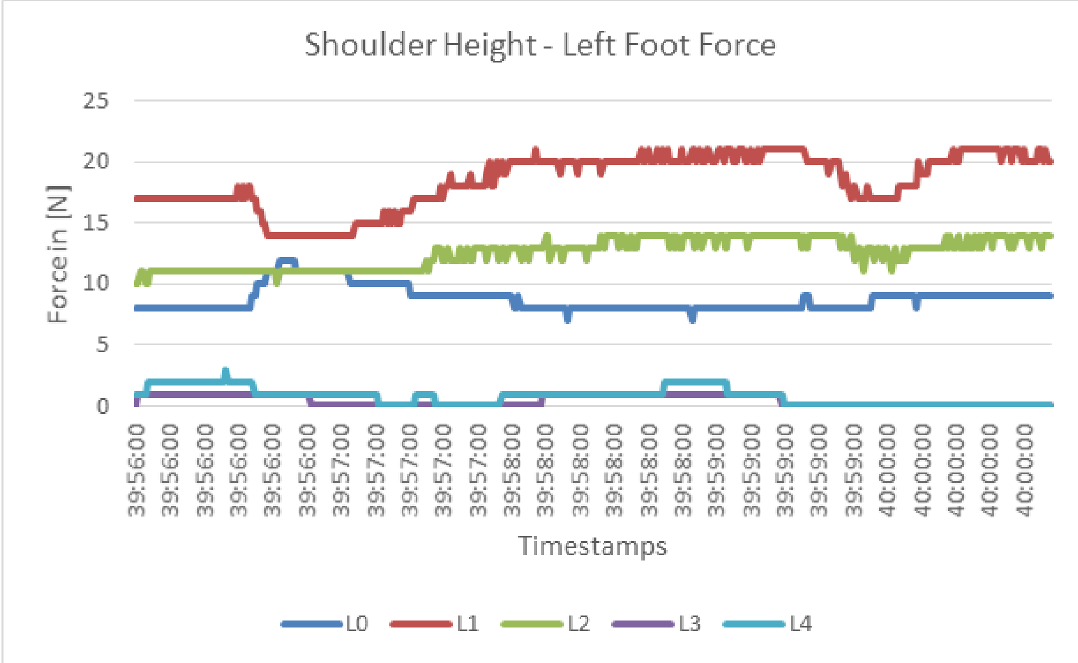


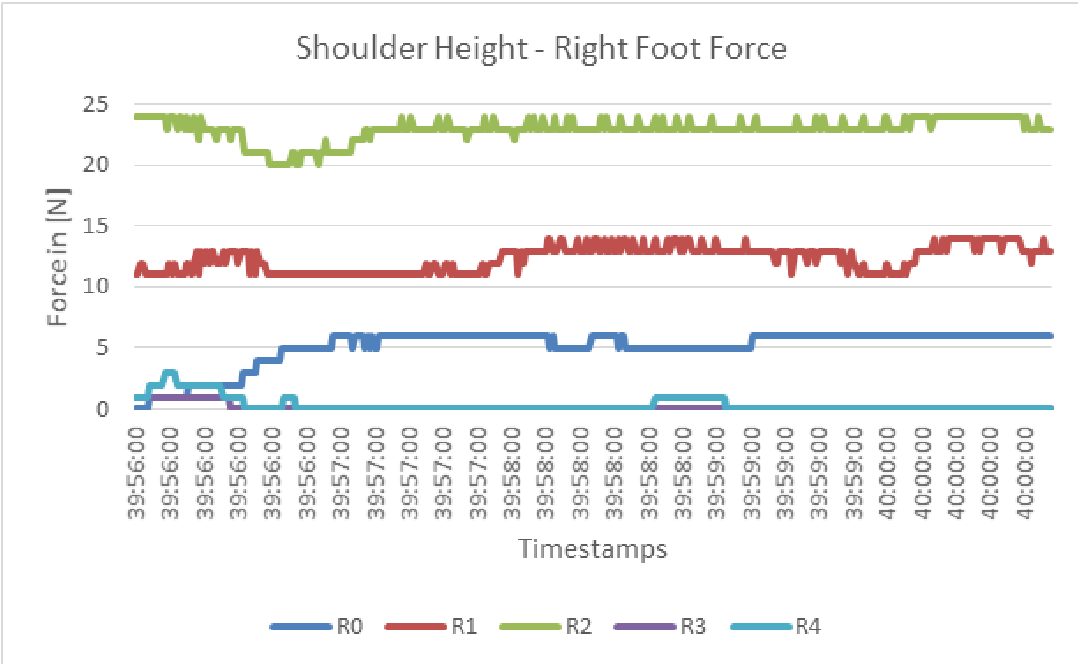


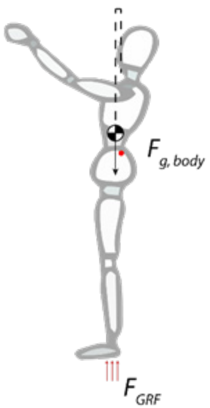


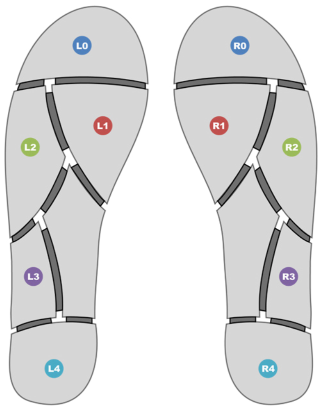


Lifting Shoulder Height Lifting - No load

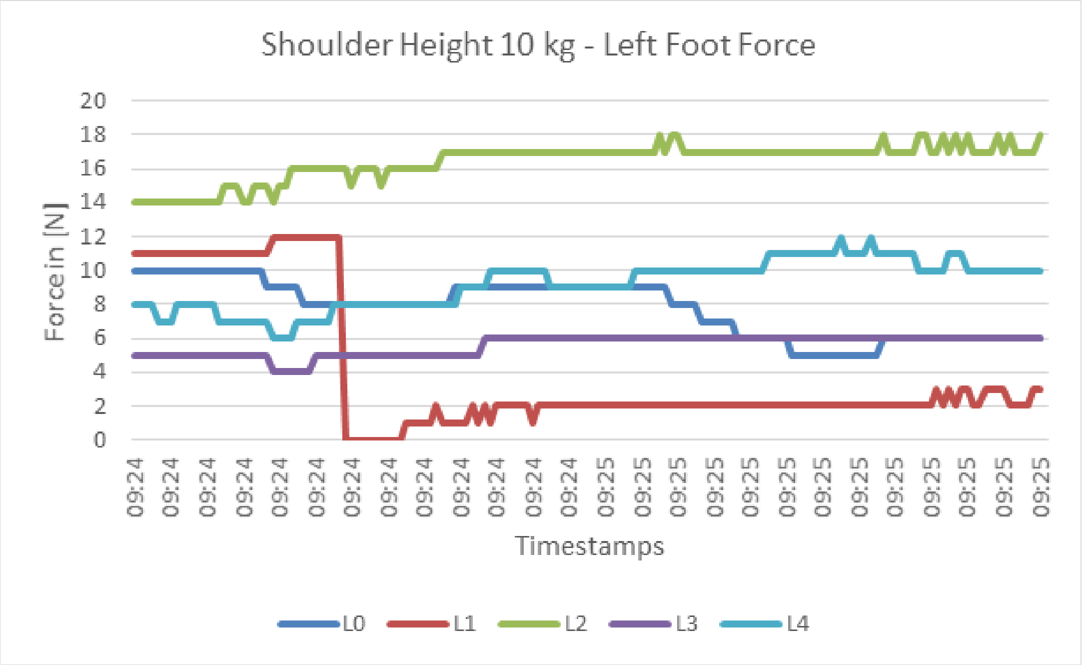


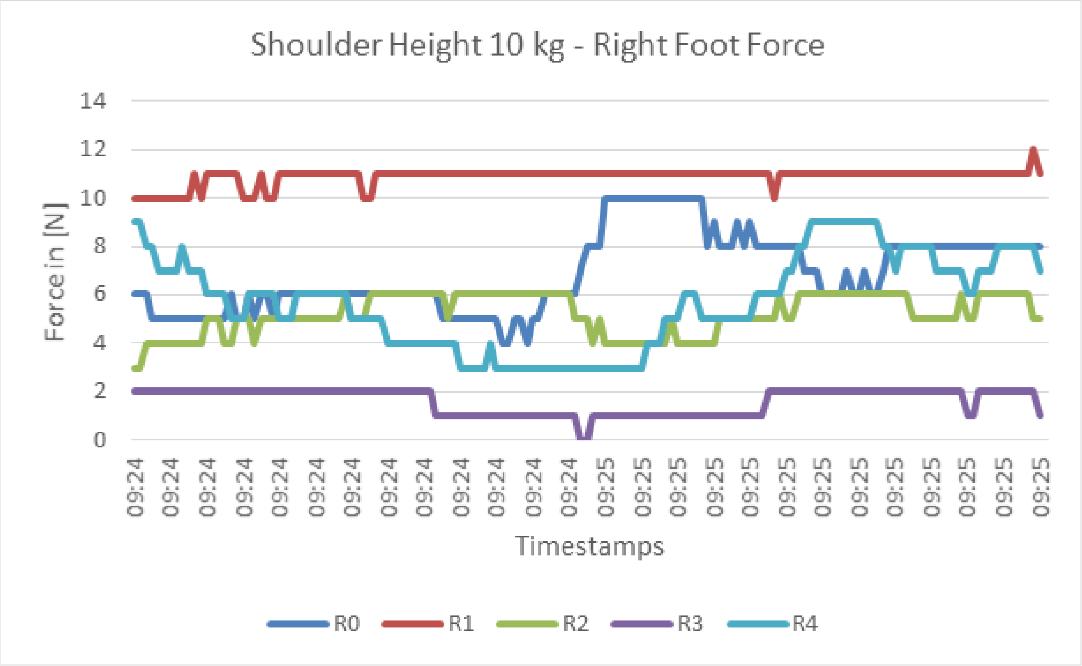


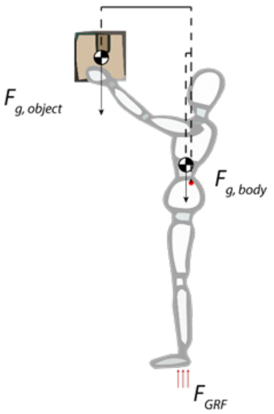


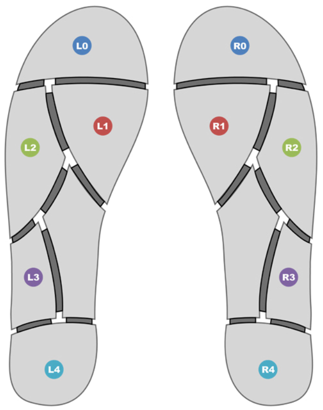


Shoulder Height Lifting - 10 kg

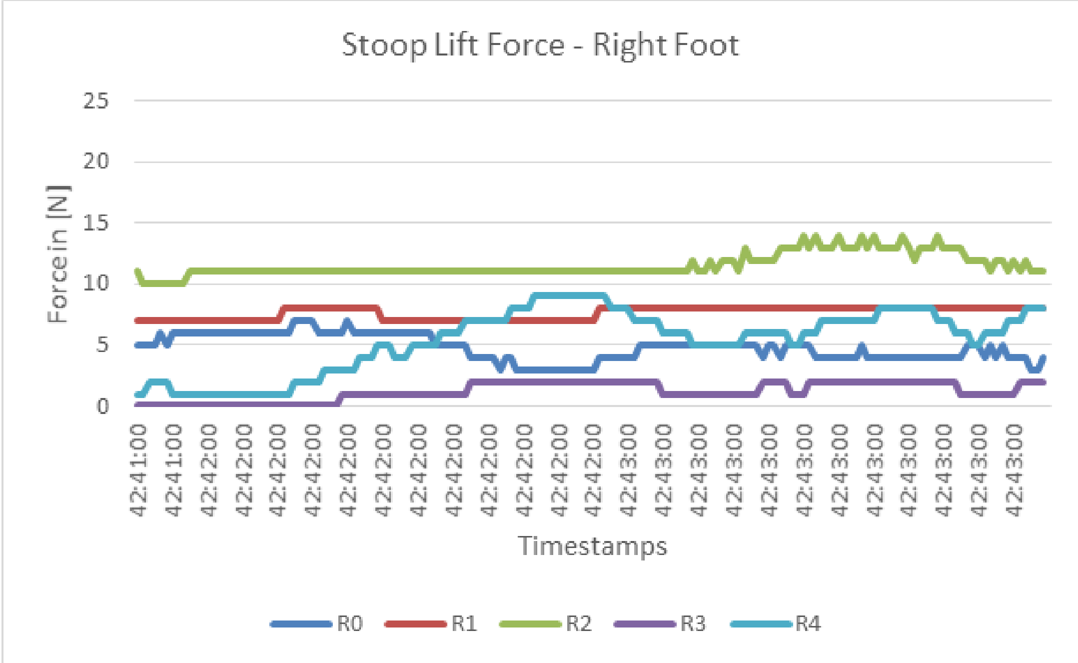


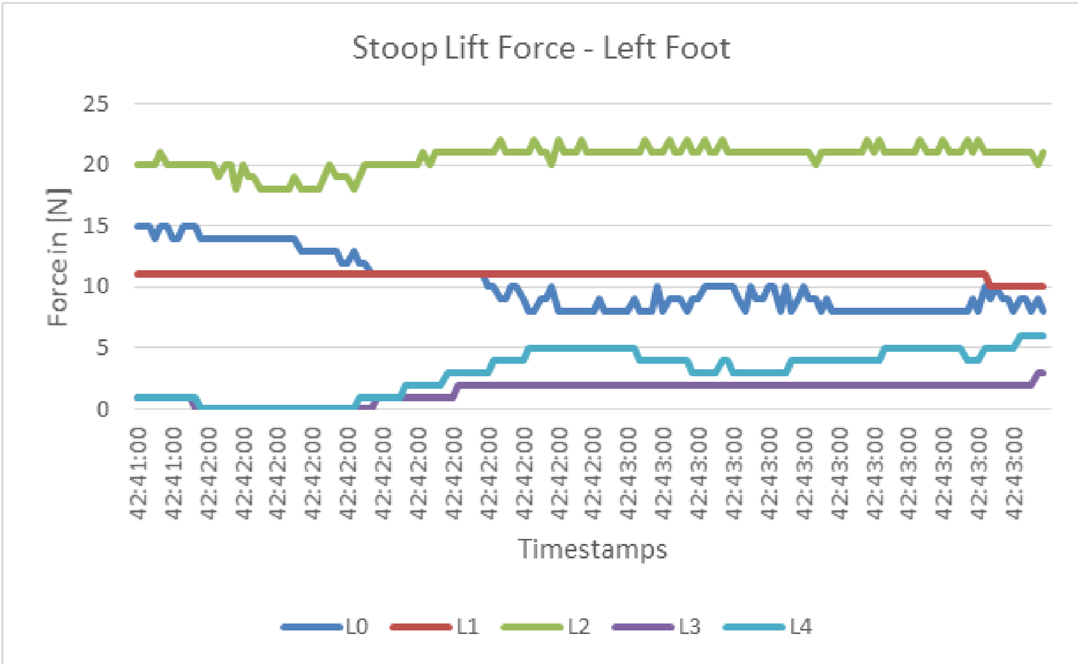


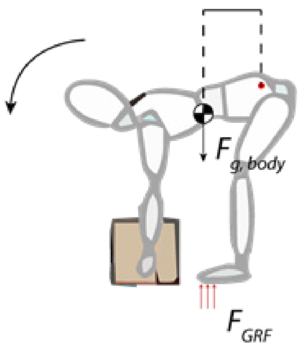


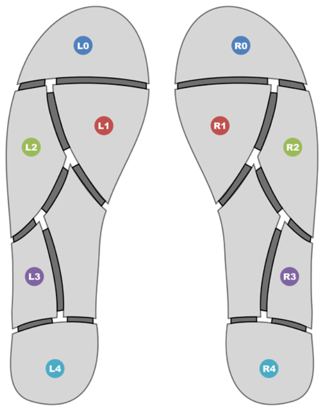


Stoop Lift - No load

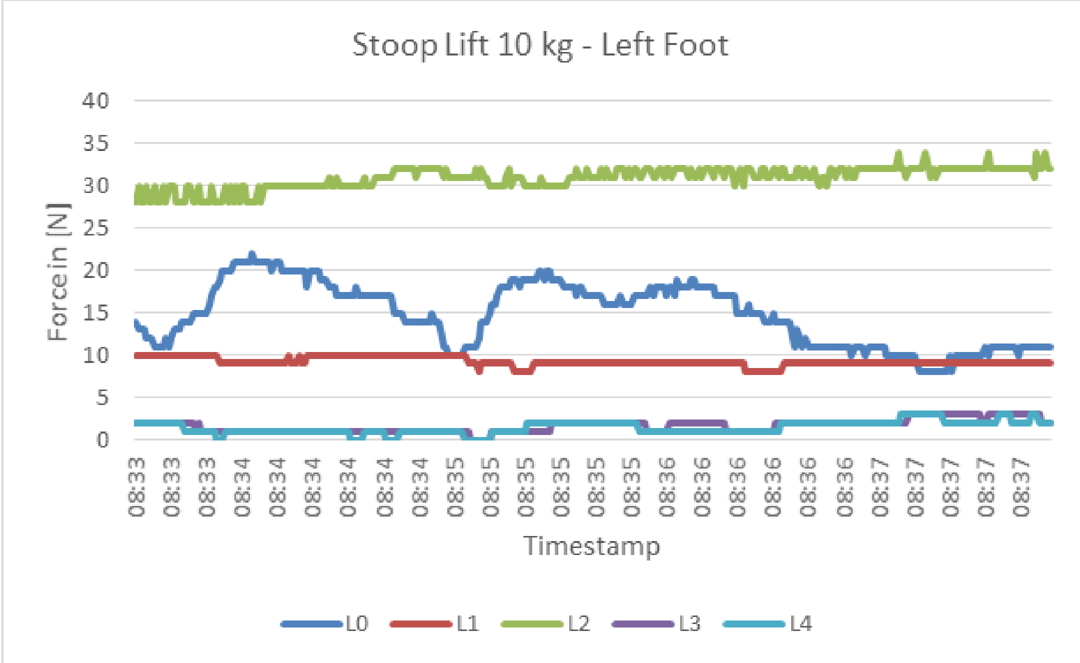


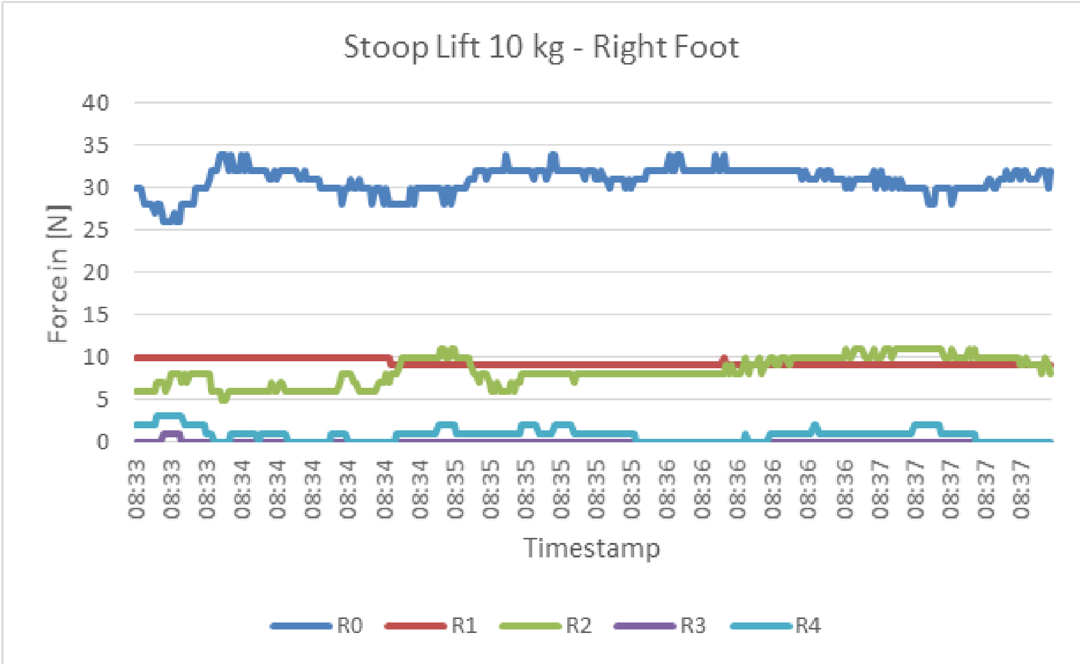


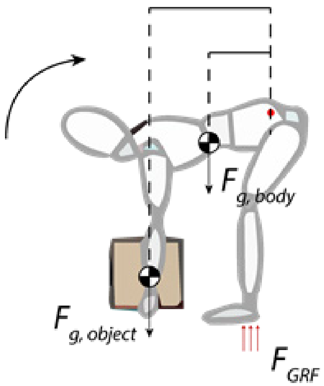


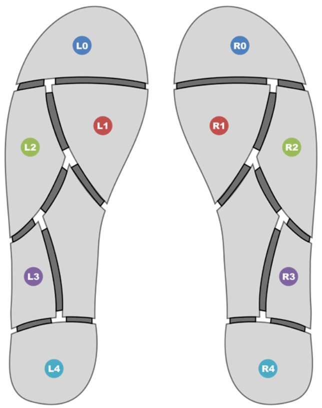


Stoop Lift - 10 kg



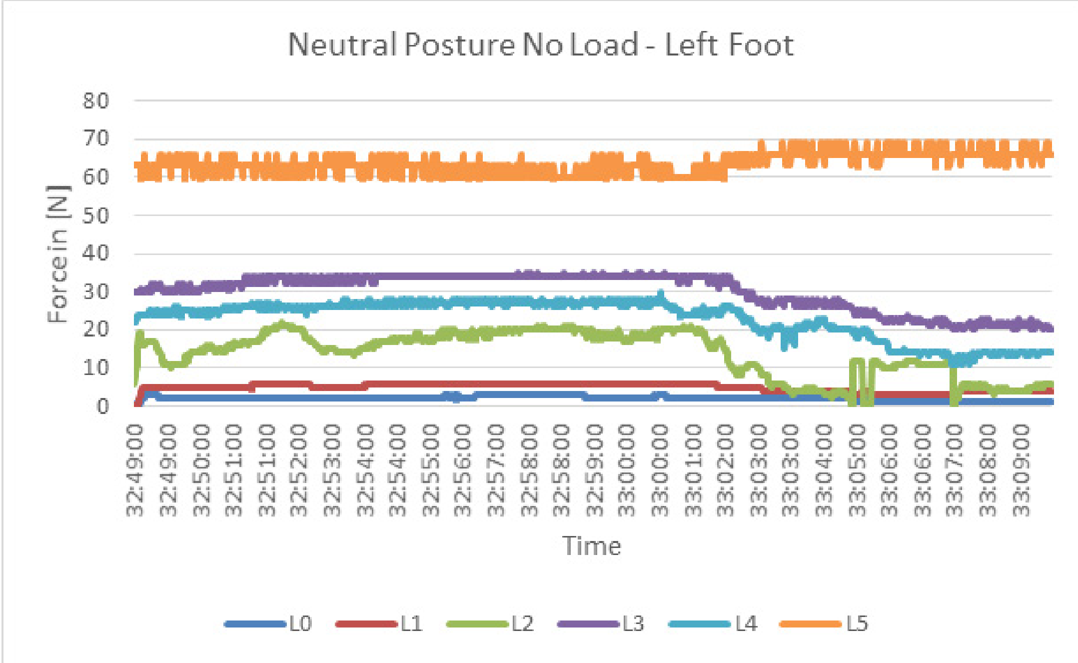


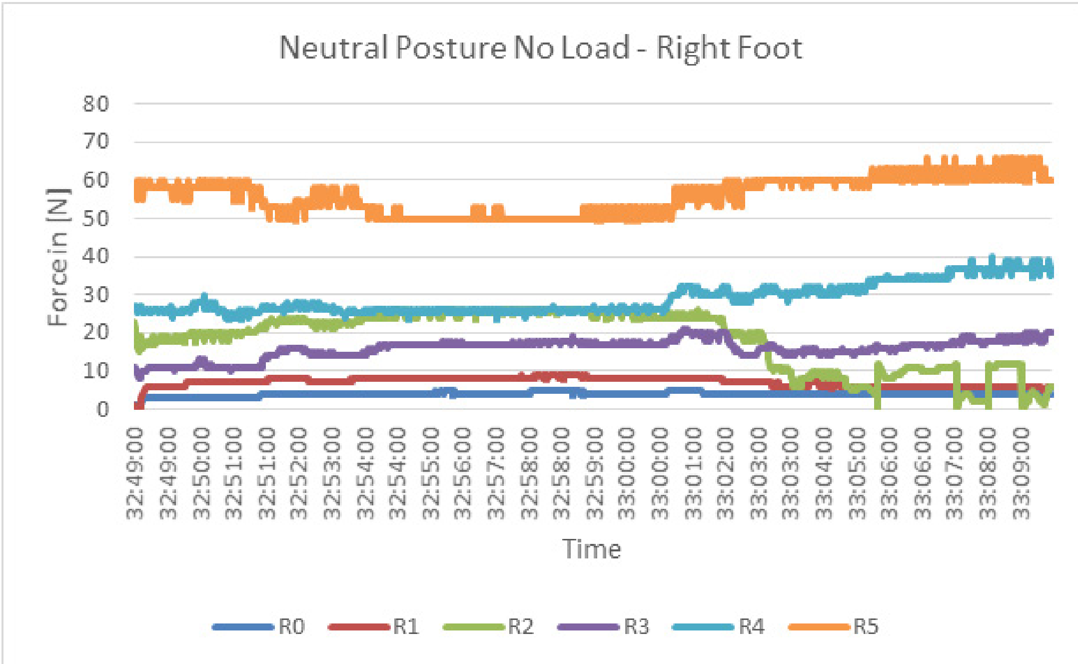


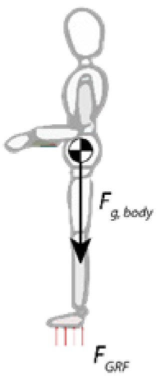


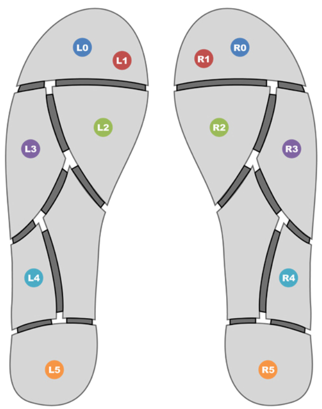
Appendix D - Results of 6-sensor layout test

Standing upright - No load

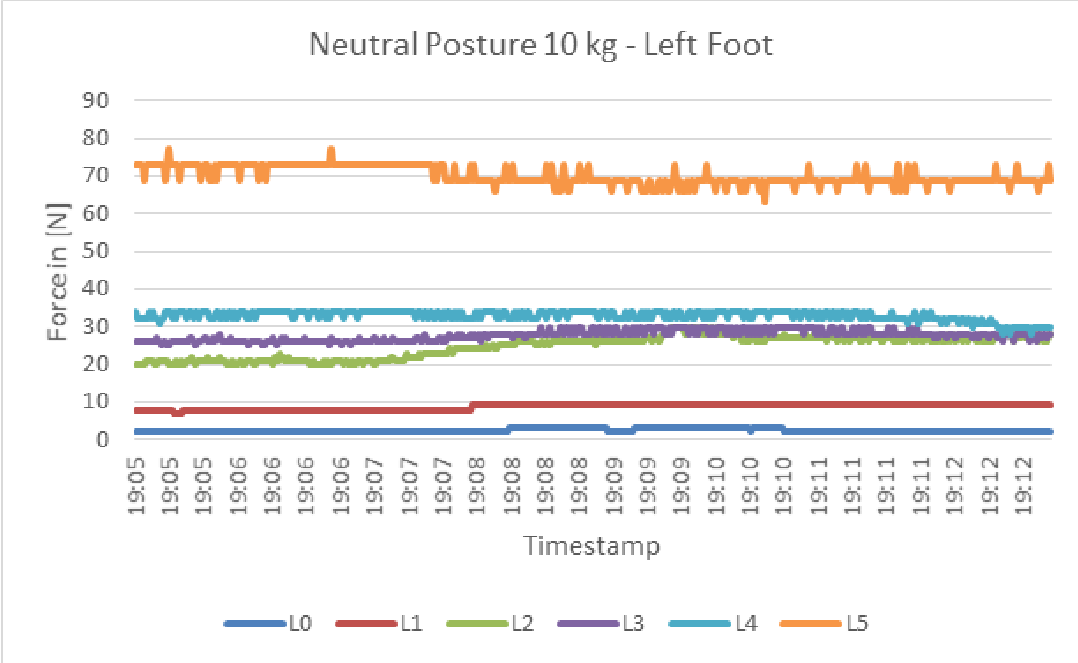


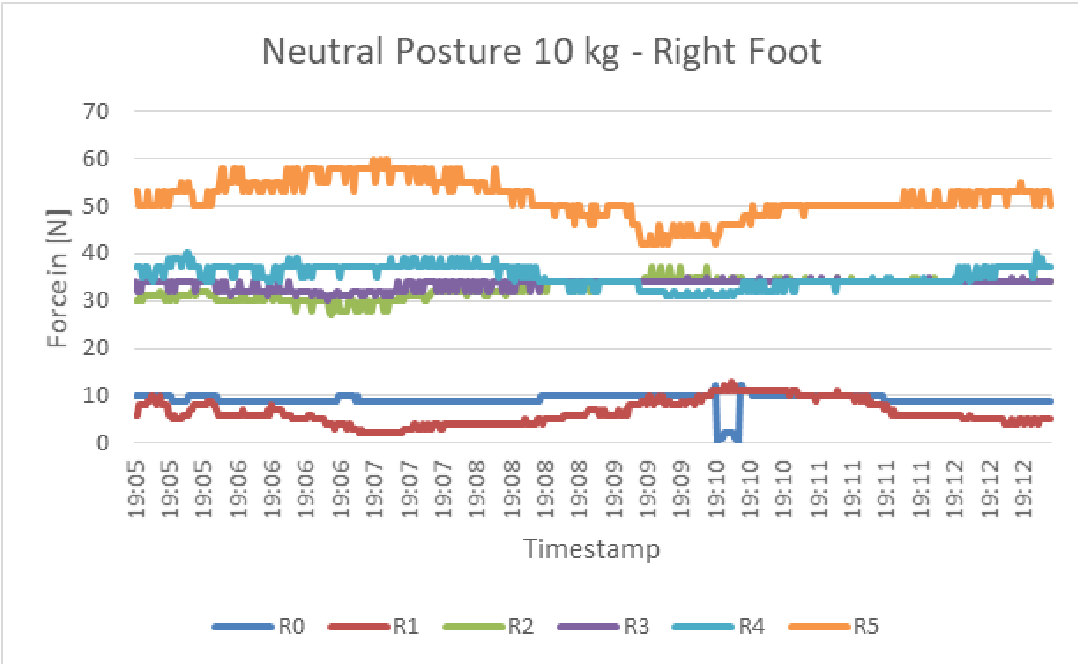


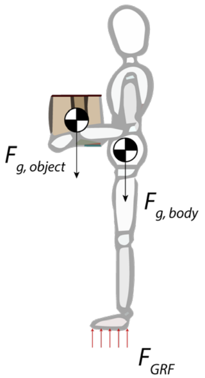


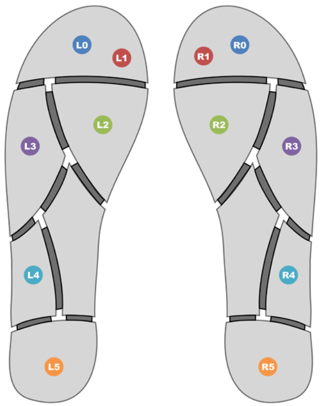


Standing up right - 10 kg

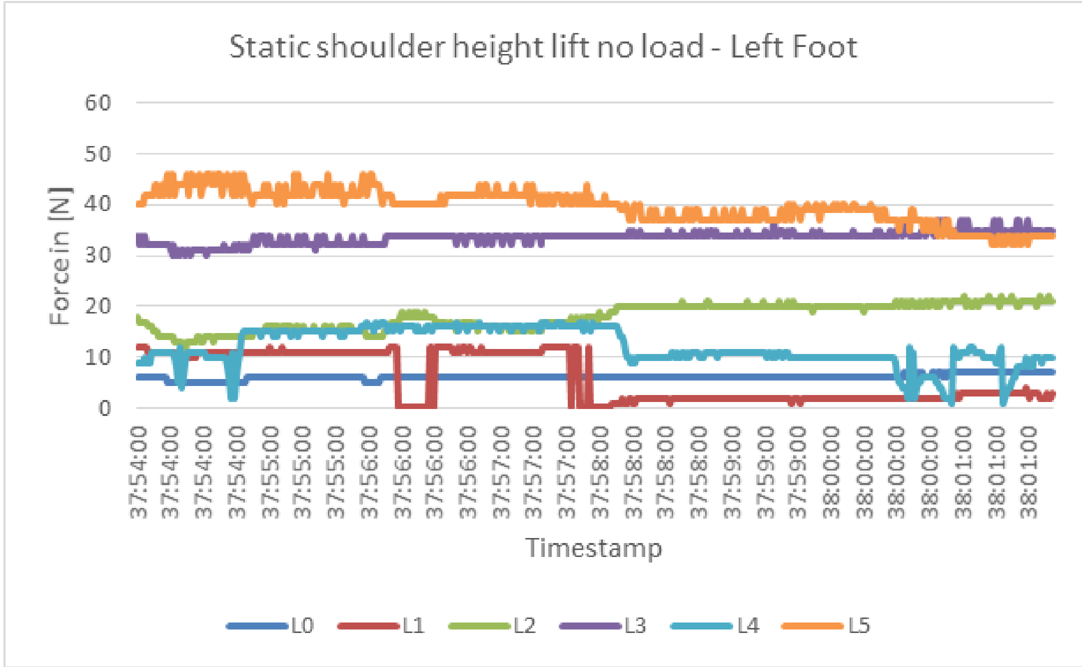


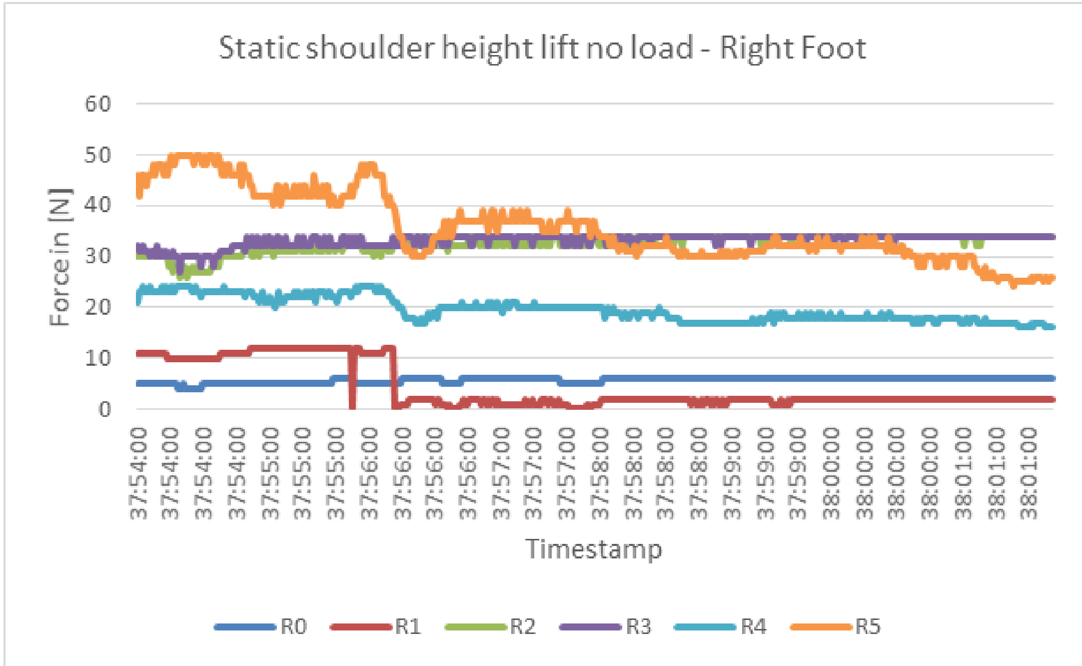


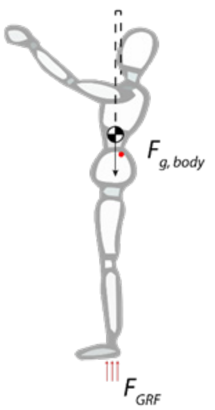


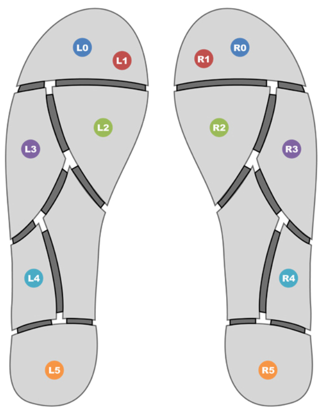


Shoulder Height Lift - No load

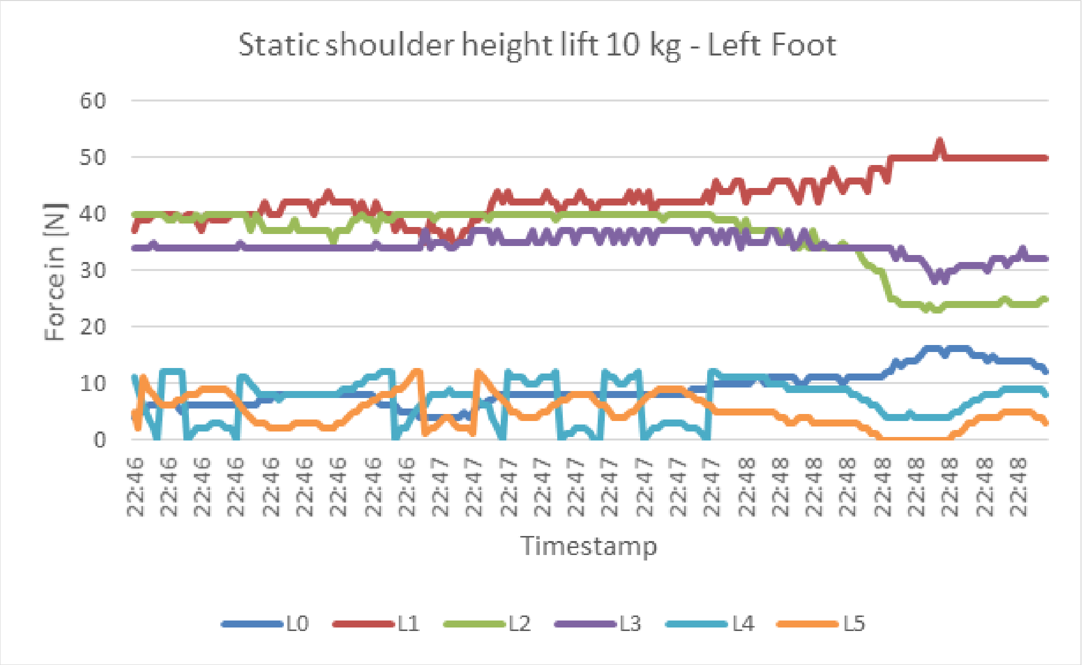


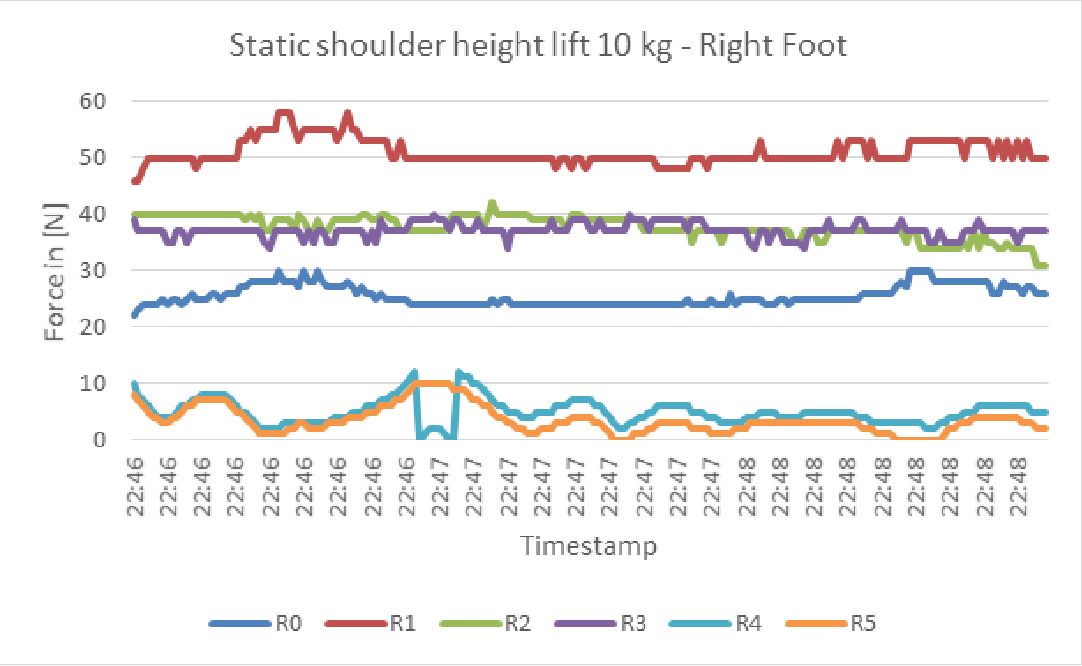


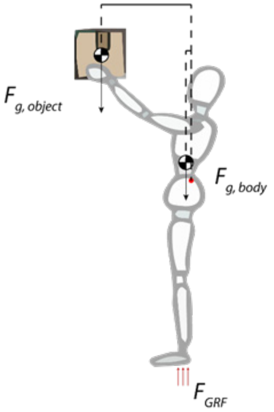


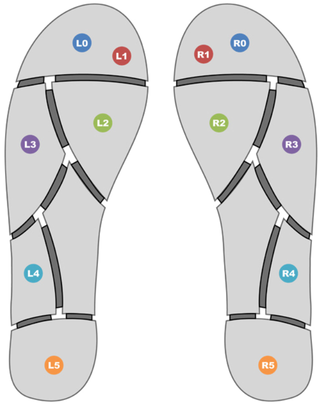


Shoulder Height Lift - 10 kg

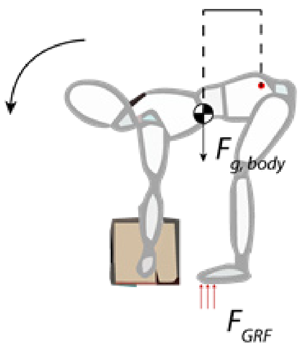


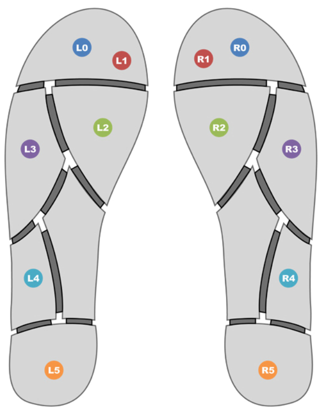


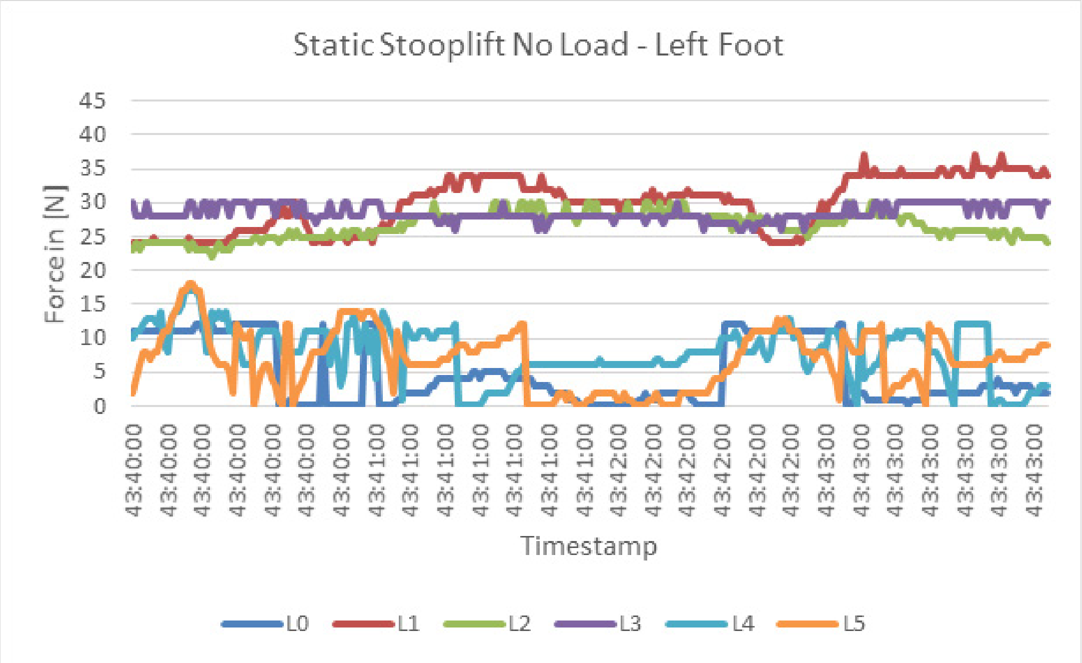


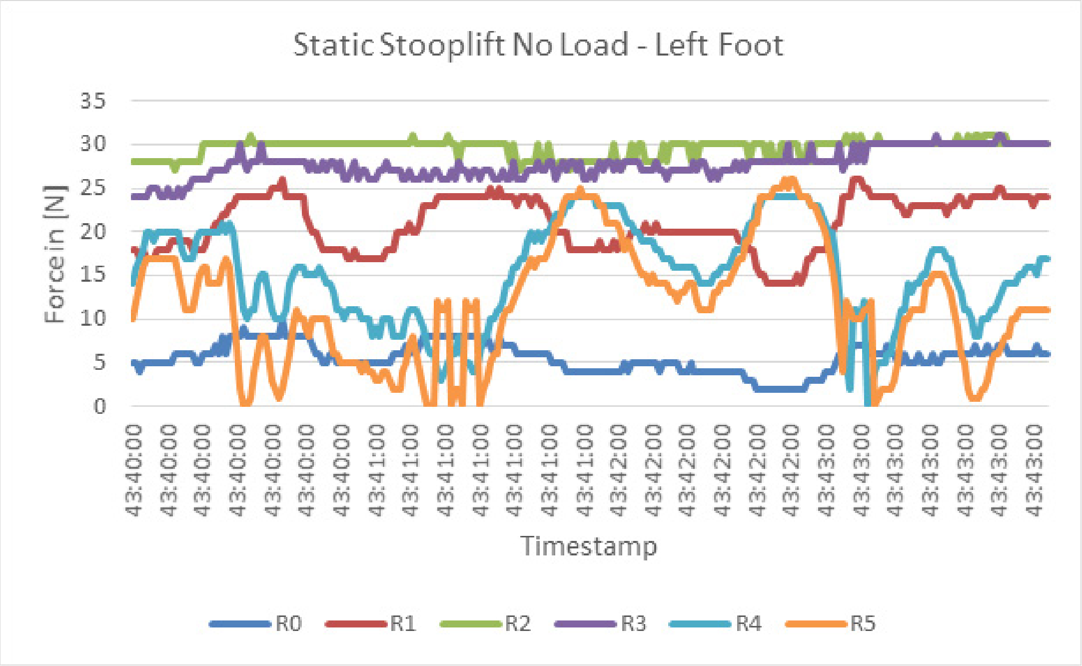


Stoop Lift - No load

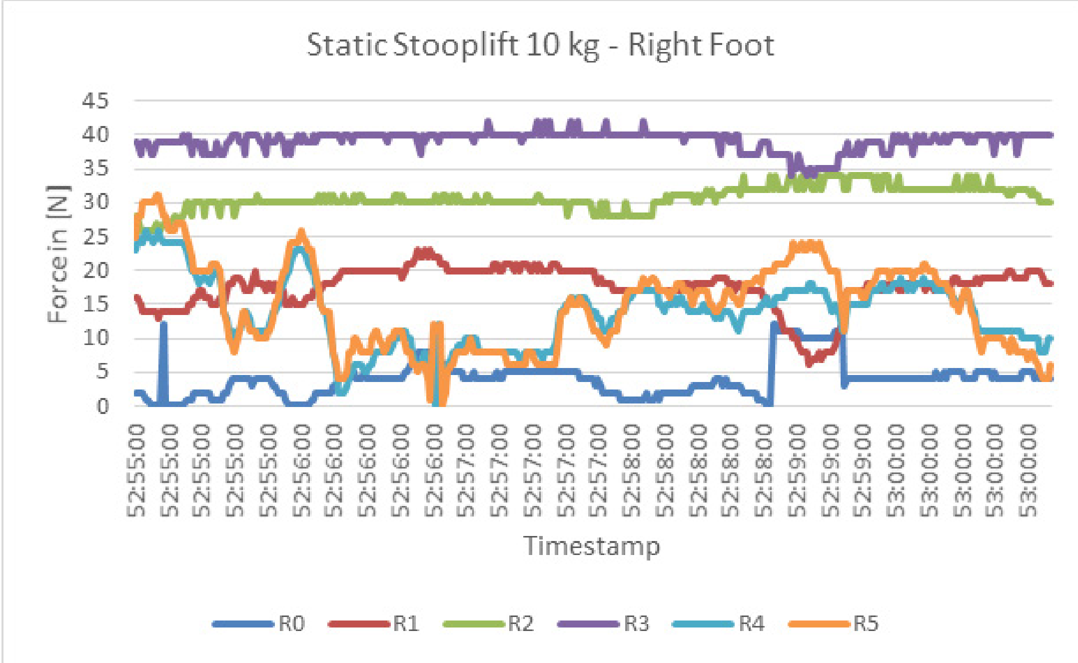


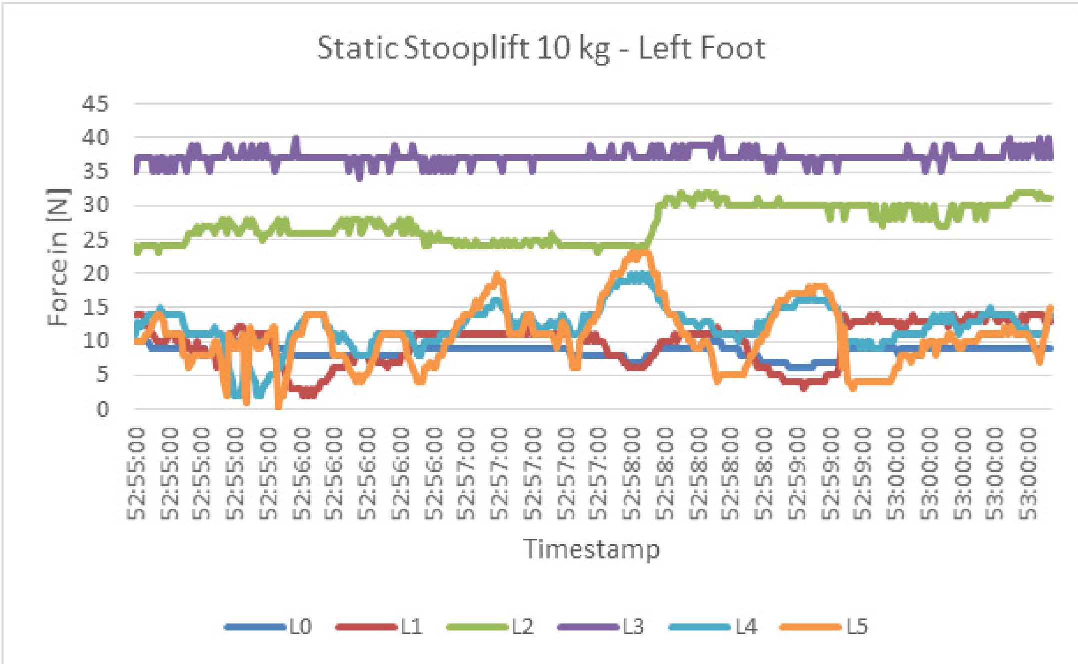


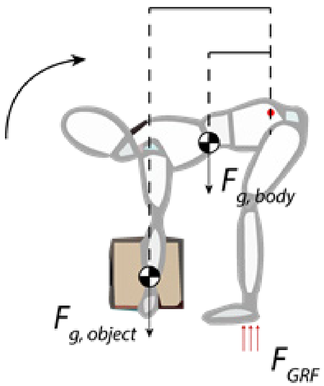


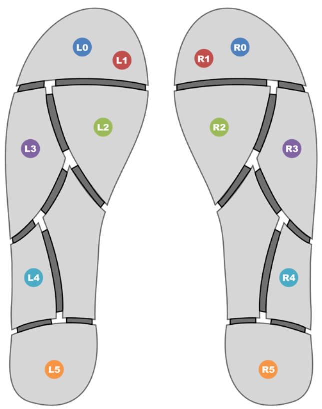


Stoop Lift - 10 kg

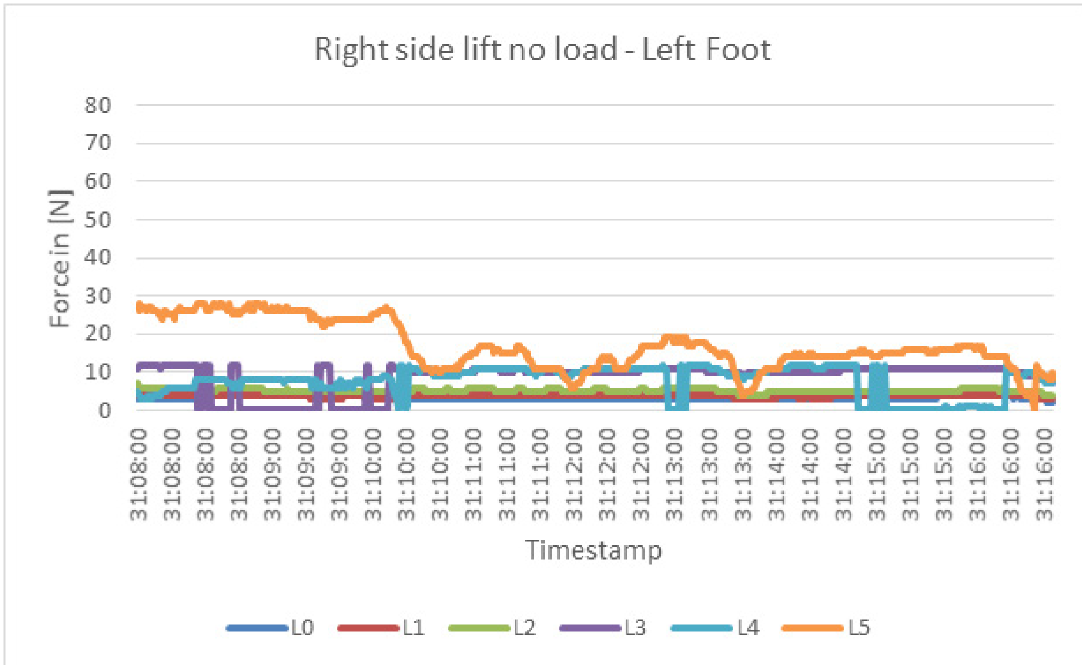


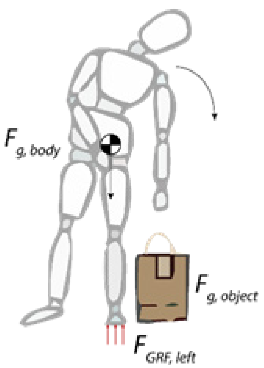


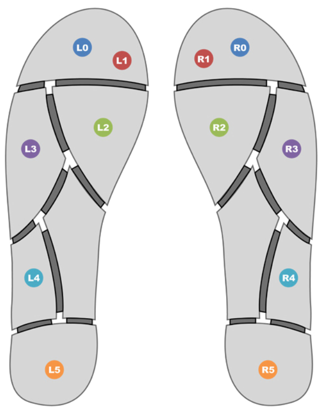




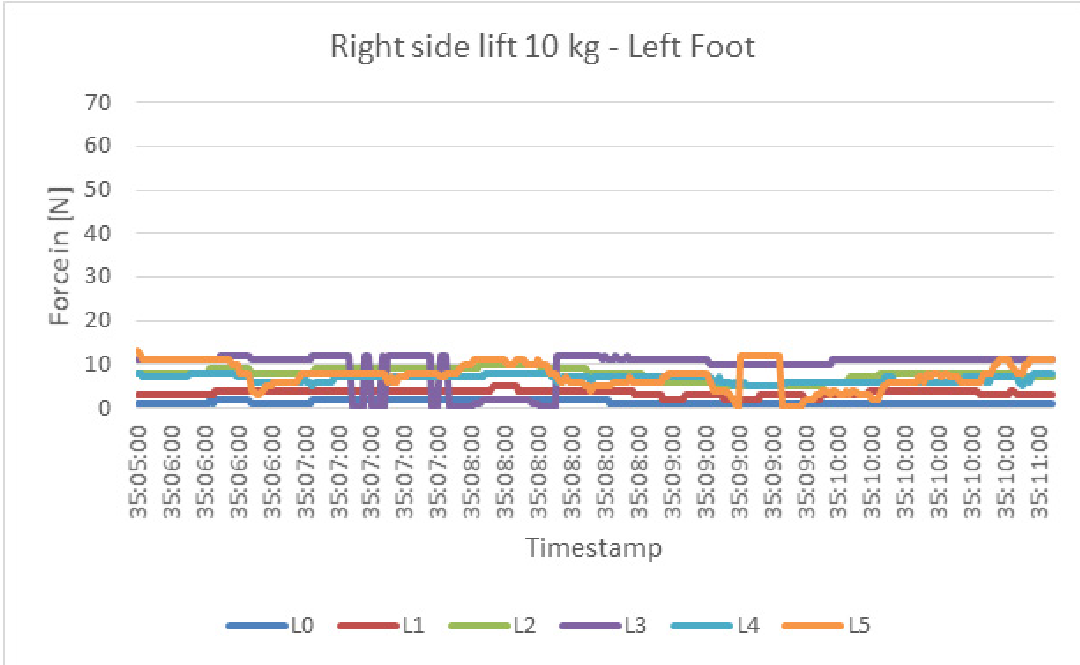
Asymmetric Lift - No load

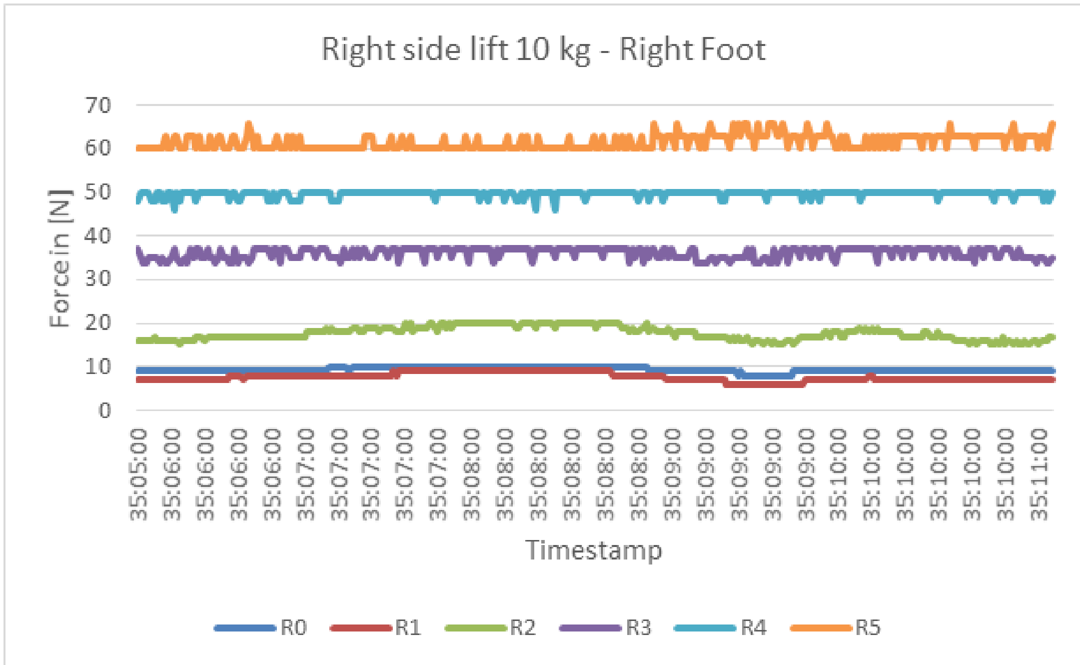


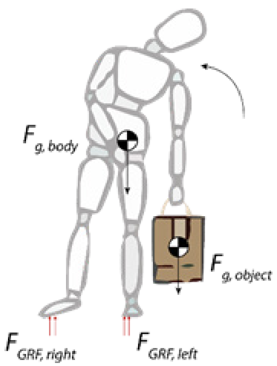


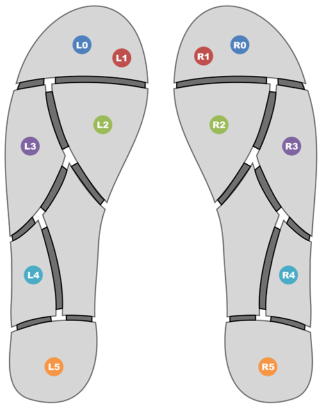


Asymmetric Lift - 10 kg



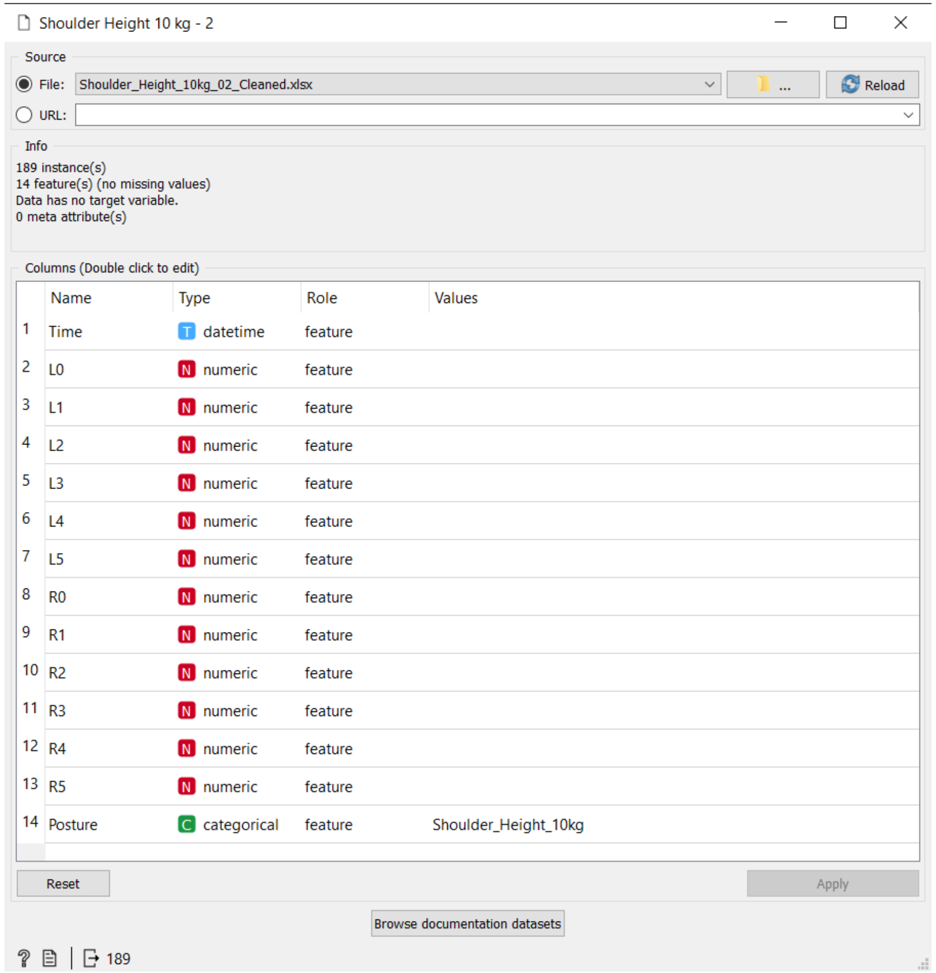




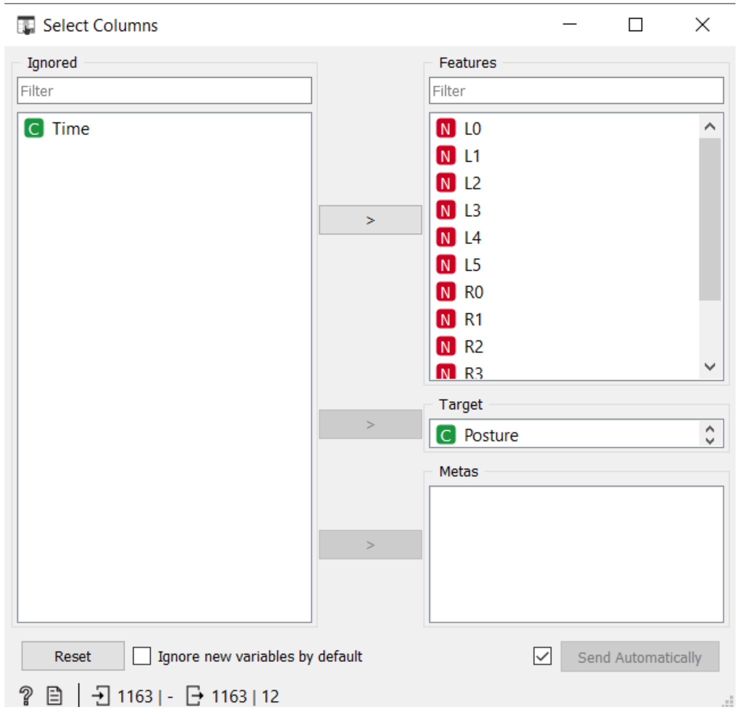


Appendix E - ML in Orange Settings

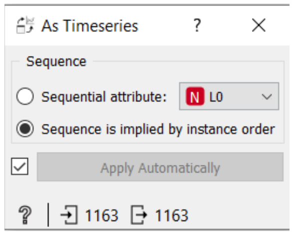
Imported data



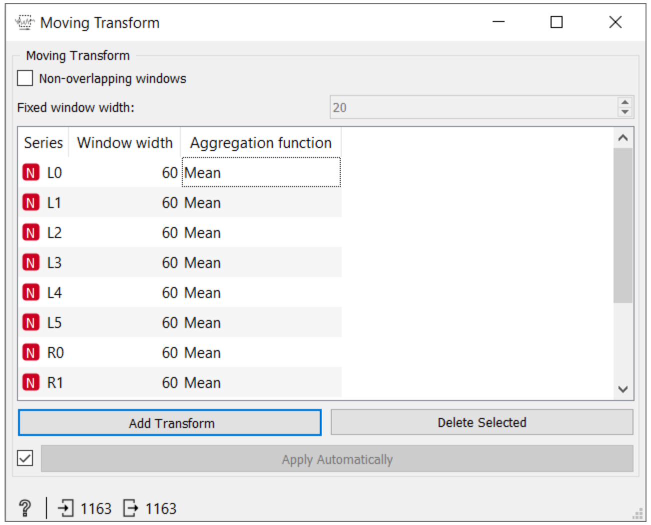
Selected columns



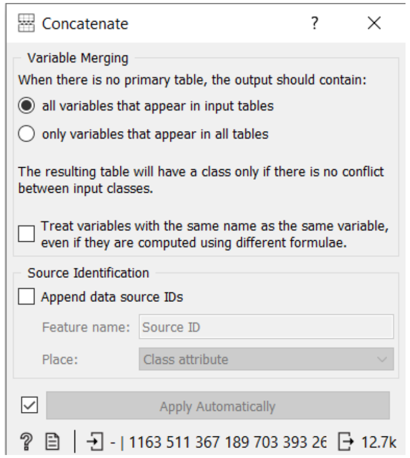
Timeseries in sequence as in the set



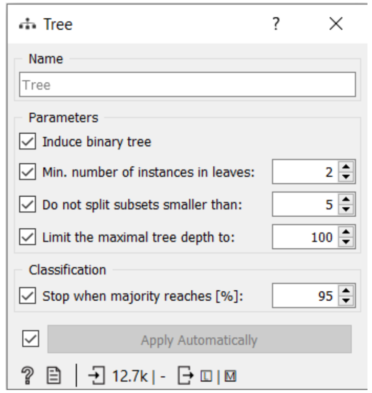
Moving transform for transforming the data into moving averages



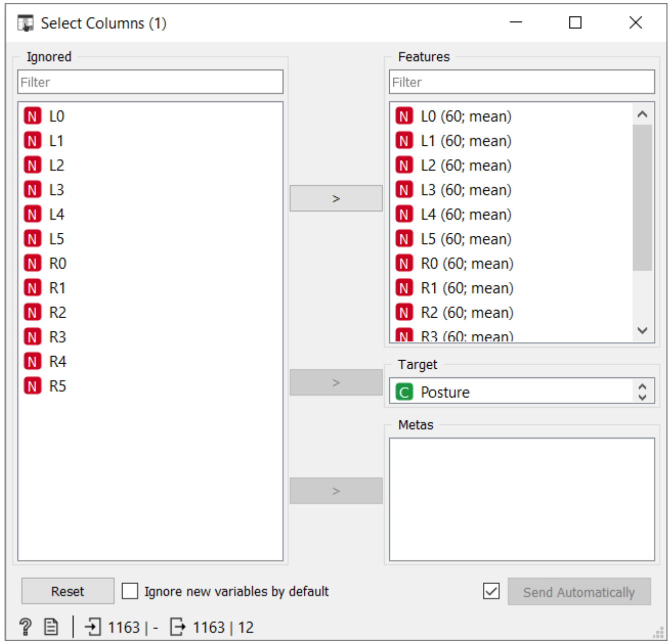
Concatenate the data



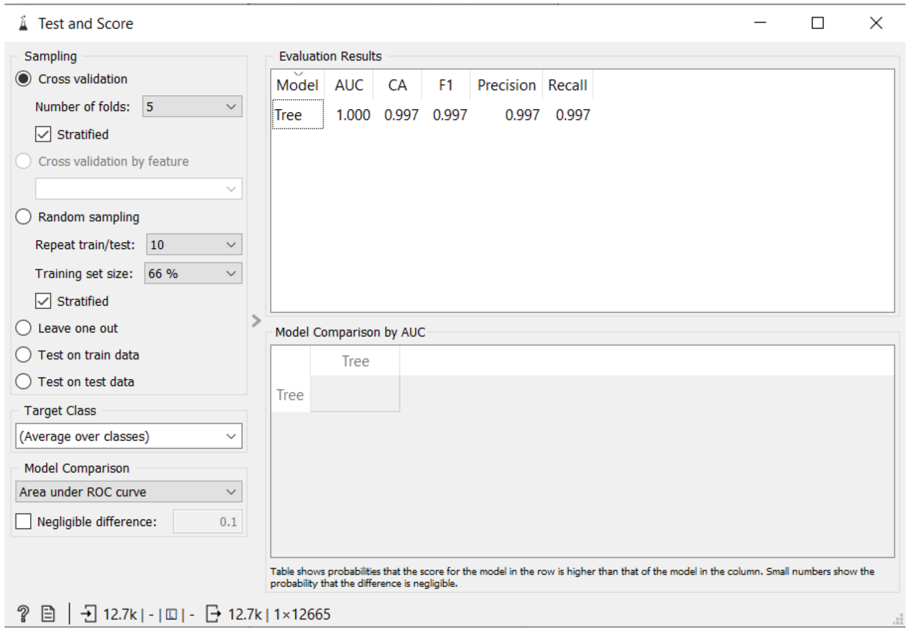
Settings for the tree algorithm



After transforming the data, select the transformed data

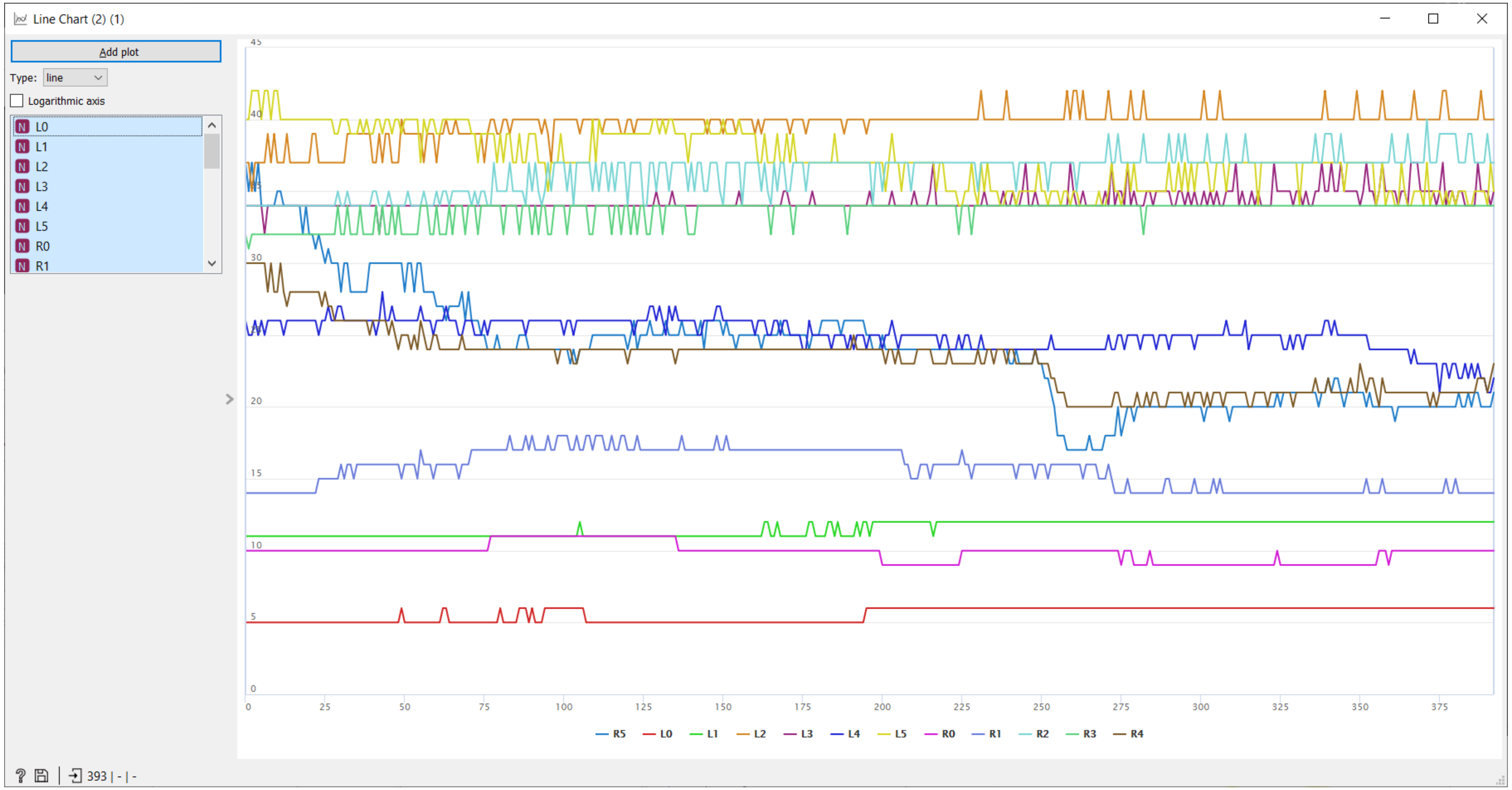


Test the tree model with a 5-fold cross validation

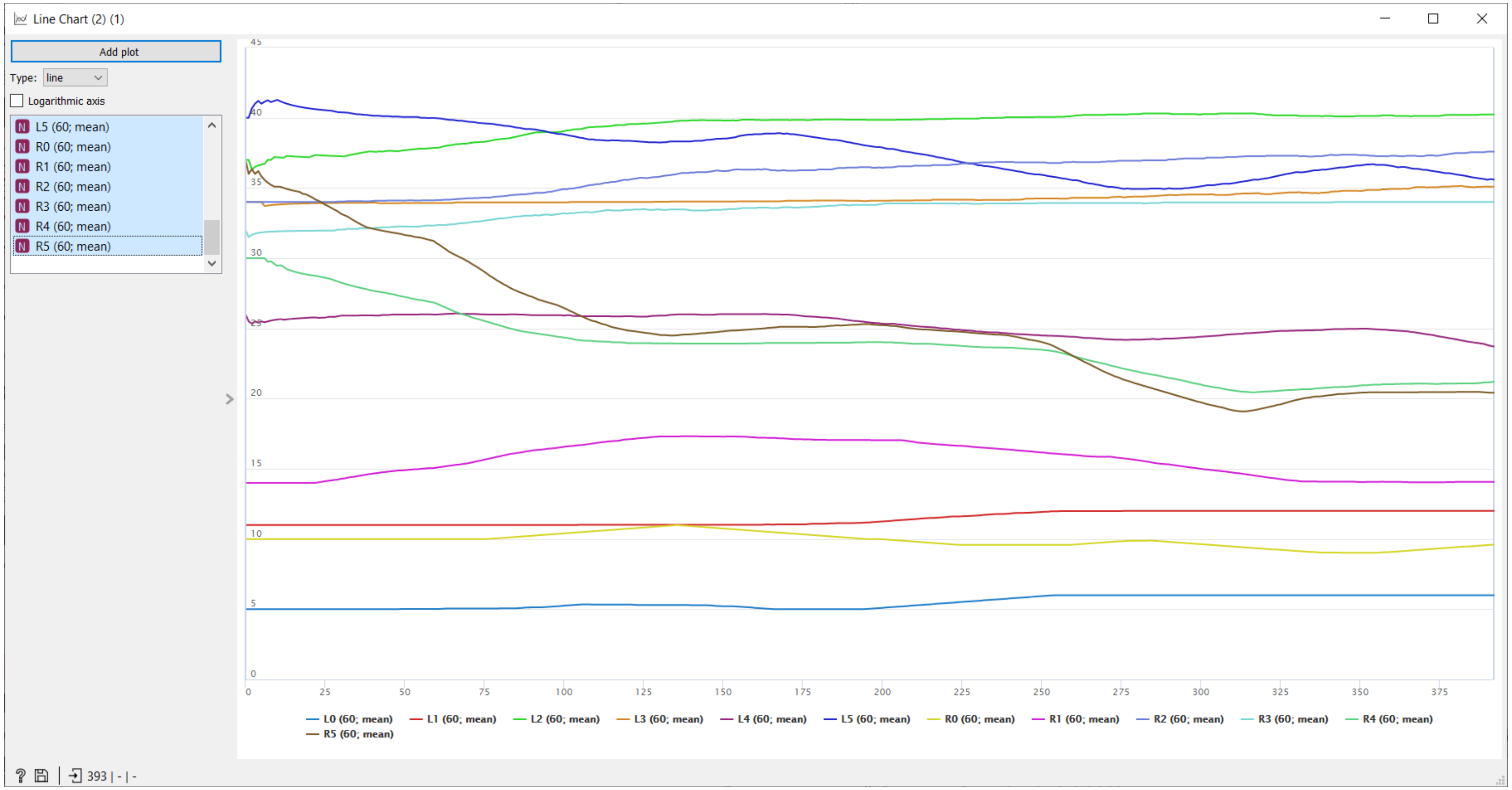


Appendix F - Moving Averages

Data graph before moving average transform



Data graph after moving average transform



Locations

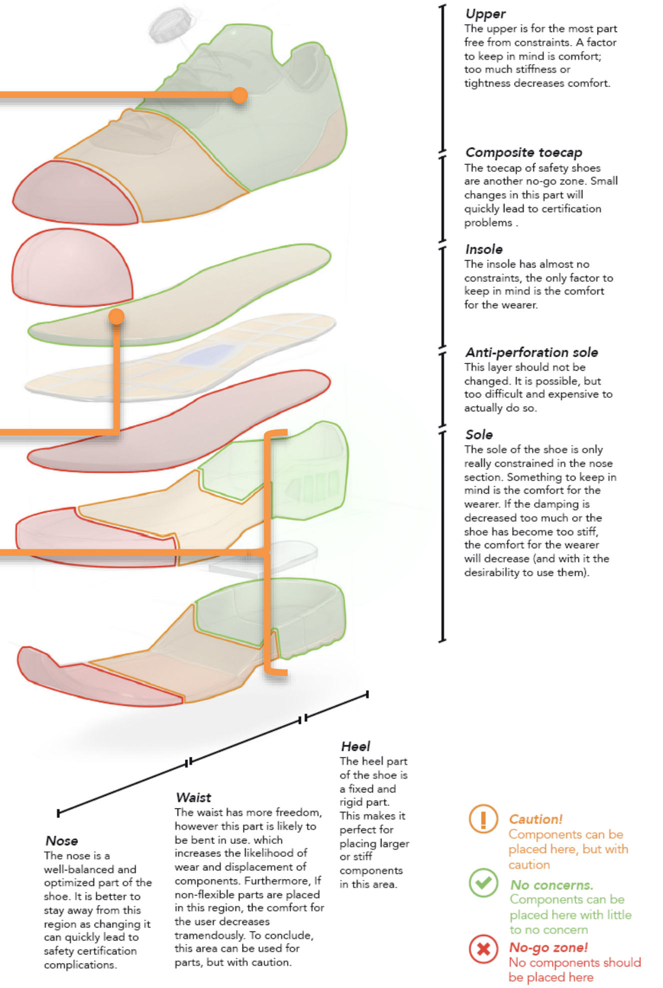
Spots to place components

Where would it fit?

Heel of the upper
+ Does not affect safety
- Comfort might be affected due to increased stiffness

Insole
+ Does not affect safety
- Comfort might be affected due to hard components
- Rather thin

Heel of the sole
+ Rigid area, great place for stiff components
- Safety hazard due to puncturing (can be solved with additional anti perforation layer)
- May affect comfort by adding rigid components



Source: Van den Berg (2020)

Considerations

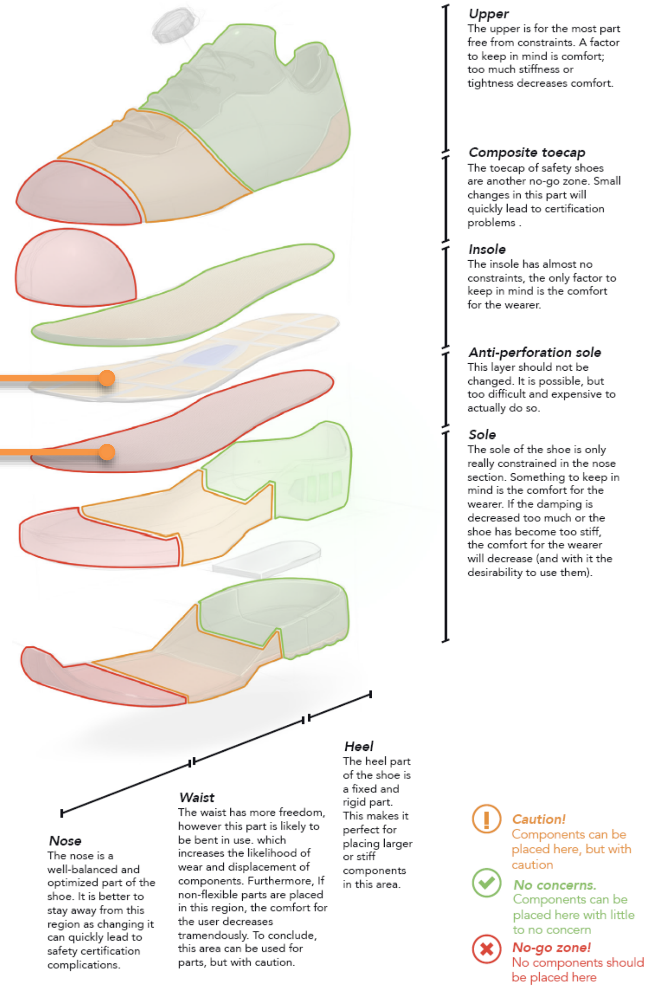
Possible locations for components

PPD sensors

- PPD Sensors above anti-perforation sole
- Stitch PPD Sensors onto anti-perforation sole

Consider

- Space for flat cable
- Margin for stitching
- ESD / Anti-static (Certification)



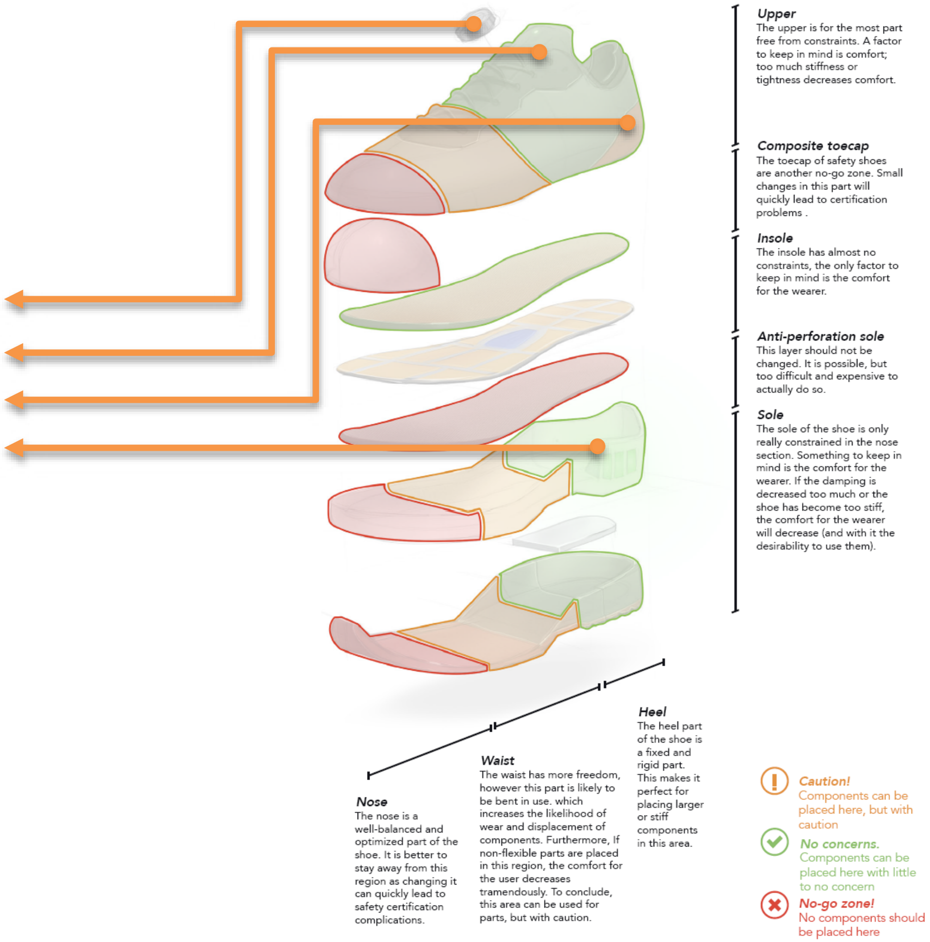
Source: Van den Berg (2020)

Considerations

Possible locations for components

Controller

- Integrate in BOA button
- Tongue of the shoe
- Heel of upper (side or back)
- Heel of sole (using two anti-perforation layers)



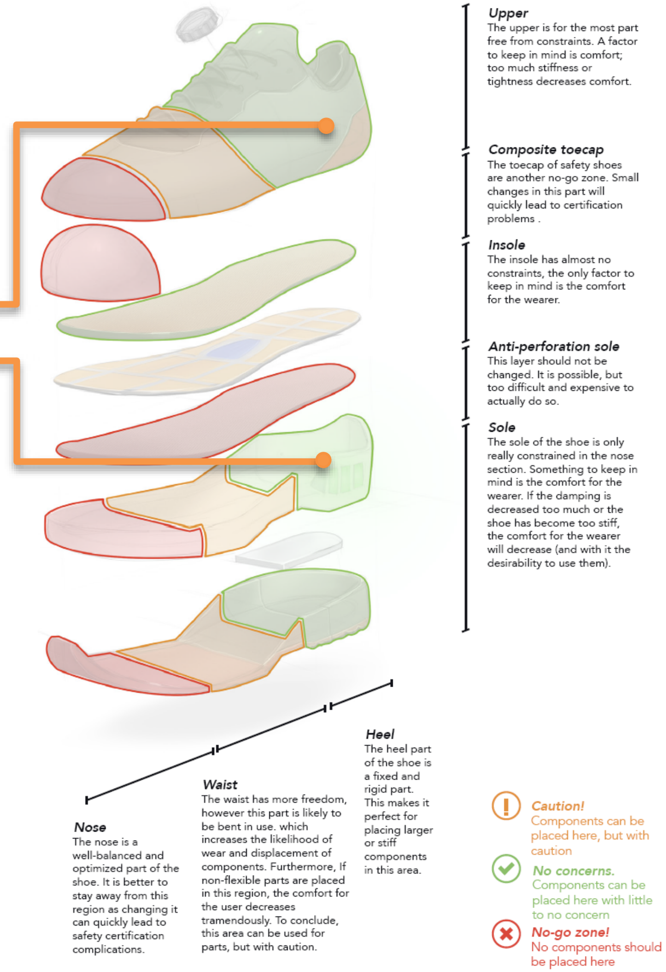
Source: Van den Berg (2020)

Considerations

Possible locations for components

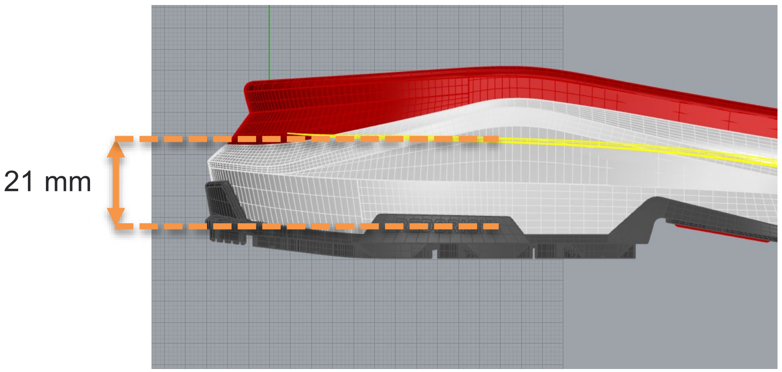
Battery

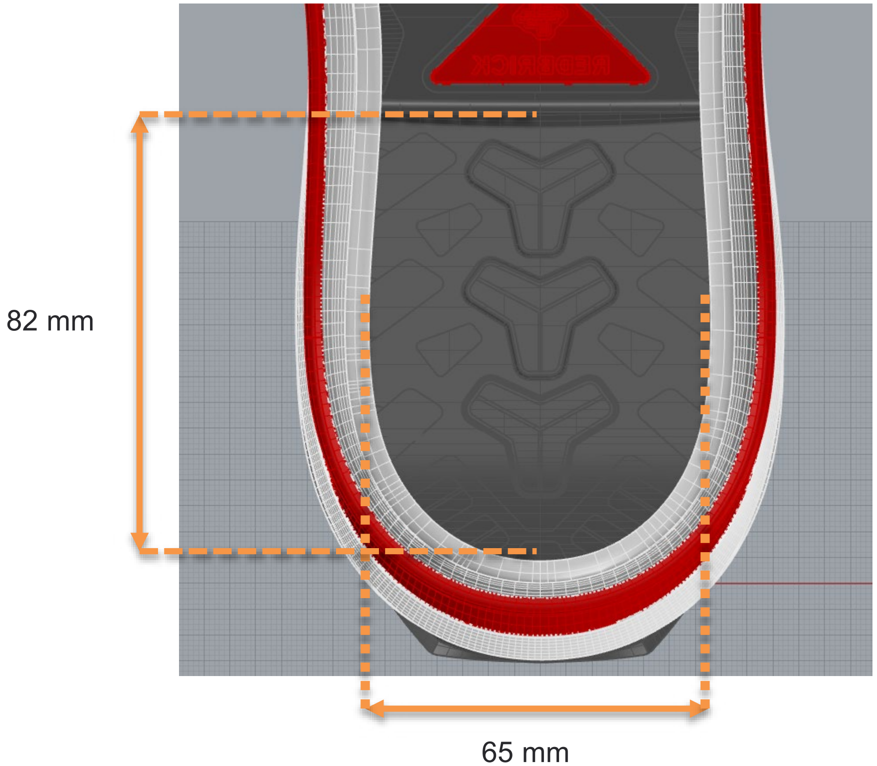
- Heel of upper (side)
- Heel of sole (using two anti-perforation layers)



Source: Van den Berg (2020)

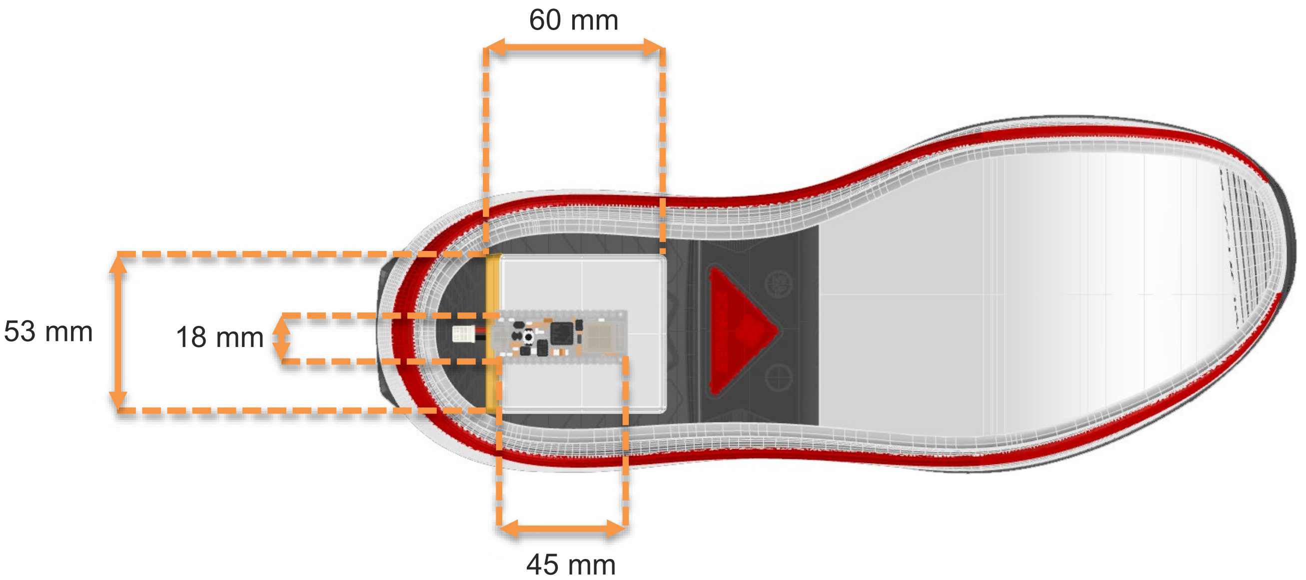
Sole heel dimensions



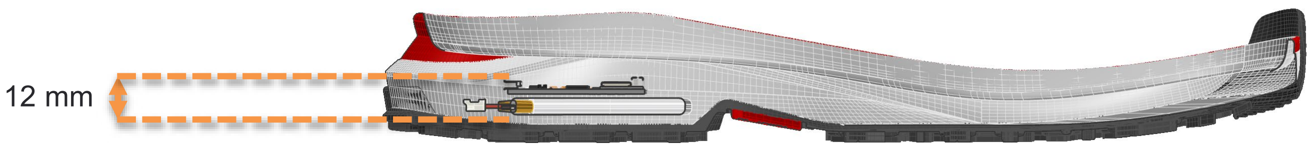


Configuration

Fitting in the sole of the shoe



Total of 82 mm x 65 mm



Total of 21 mm

Configuration

Fitting in the upper of the shoe

Side of the upper
- Adding “pouches” for electronics

Appendix H - Roadmap

Roadmap Allshoes											
Goal	**Developing novel smart safety shoes for prevention of musculoskeletal disorders**										
				2020				**2021**			
Pillar	**Strategies**	**Workflows**	**Resposible**		**June**	**July**	**August**	**September**	**October**	**November**	**December**
Research for opportunities and possibilities	Research current market and look for opportunities	Strategy exploration	TU Delft - SPD Graduation student	Delivered a thesis with strategic opportunities and directions							
	Research idea and test for plausibility	Feasibility exploration	TU Delft - IPD Graduation student		Researched feasibility and made first prototypes for testing feasibility						
	Research for development of database and hardware	Ergonomic data base	TU Delft - Postdoc			Arrange agreement	Determine necessary ergonomic data; Prepare lab for ergonomics measurements	Collect ergnomic data from a variety of people; Build lifting posture database	Structuring the collected data in database		Use prototype to collect ergonomic data
		Hardware design							Design and develop hardware setup	Prototype hardware setup and test	Improve hardware design
		Smart data processing model						Develop an AI/ML model for data processing	Training/testing the model with collected data	Improving the model	Using the model on data from prototype
	Research business model feasibility	Business model	Allshoes			Make business model to see if the idea is worth pursuing					Review business plan based on potential hardware costs
Development	Development of hardware on commercial scale	Hardware development	IoT hardware specialist								
	Developing data acquisition infrastructure and processing	Smart data processing development									
	Developing the software for data and user interface	Software development									
	Supporting on development and design of smart safety shoe	Shoe design development	AMF / Allshoes						Assissting in making prototype, sharing knowledge on safety shoes		
Production	Production of the safety shoes	Shoe production	AMF								
	Hardware production and assissting in implementing of hardware in shoes	Electronics hardware production	IoT hardware specialist								
	Setting up IoT infrastructure for routing data to local data storage	IoT infrastructure	IoT specialist								
Launch	Marketing of the product through different channels	Marketing	Allshoes								

2022				2023			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Analysing and correlating reference (lab) data with prototype data							
New prototype and technical documentation							
Improve the model further							
Cooperation with TU Delft	Adopting hardware design and improving; Building hardware prototype	Hardware design drawings for production					
	Adopting models; Improving models	Developing infrastructure for data; GDPR					
	Software backend development		Software frontend development				
	Sharing knowledge on safety shoes; placement of components	Creating prototypes/sample models for testing purposes; Prepare certification process					
		Make production plans and adapt	Run production; Produce first samples				
			Order and assess quality				
			Optimisation of data through different networks				
Make marketing plan	Execute marketing plan			Launch product			

DESIGN FOR our future

TUDelft

IDE Master Graduation

Project team, Procedural checks and personal Project brief

This document contains the agreements made between student and supervisory team about the student's IDE Master Graduation Project. This document can also include the involvement of an external organisation, however, it does not cover any legal employment relationship that the student and the client (might) agree upon. Next to that, this document facilitates the required procedural checks. In this document:

- The student defines the team, what he/she is going to do/deliver and how that will come about.
- SSC E&SA (Shared Service Center, Education & Student Affairs) reports on the student's registration and study progress.
- IDE's Board of Examiners confirms if the student is allowed to start the Graduation Project.

USE ADOBE ACROBAT READER TO OPEN, EDIT AND SAVE THIS DOCUMENT

Download again and reopen in case you tried other software, such as Preview (Mac) or a webbrowser.

STUDENT DATA & MASTER PROGRAMME

Save this form according the format "IDE Master Graduation Project Brief_familyname_firstname_studentnumber_dd-mm-yyyy". Complete all blue parts of the form and include the approved Project Brief in your Graduation Report as Appendix 1 !

family name: Zhang

initials: Y.X. given name: Yi Xiang

student number: 4378776

street & no.:

zipcode & city:

country: Netherlands

phone:

email:

Your master programme (only select the options that apply to you):

IDE master(s): ★ IPD ◯ DfI ◯ SPD

2nd non-IDE master:

individual programme: - - (give date of approval)

honours programme: ◯ Honours Programme Master

specialisation / annotation: ◯ Medisign

◯ Tech. in Sustainable Design

◯ Entrepeneurship

SUPERVISORY TEAM **

Fill in the required data for the supervisory team members. Please check the instructions on the right !

** chair: W.F. van der Vegte dept. / section: IoT

** mentor: A.H. Jellema dept. / section: AED

2nd mentor: J. Arts

organisation: Allshoes

city: Amsterdam country: The Netherlands

comments (optional):

Chair should request the IDE Board of Examiners for approval of a non-IDE mentor, including a motivation letter and c.v..

Second mentor only applies in case the assignment is hosted by an external organisation.

Ensure a heterogeneous team. In case you wish to include two team members from the same section, please explain why.

APPROVAL PROJECT BRIEF

To be filled in by the chair of the supervisory team.

chair W.F. van der Vegte date - - signature

CHECK STUDY PROGRESS

To be filled in by the SSC E&SA (Shared Service Center, Education & Student Affairs), after approval of the project brief by the Chair.
The study progress will be checked for a 2nd time just before the green light meeting.

Master electives no. of EC accumulated in total: ______ EC

Of which, taking the conditional requirements into account, can be part of the exam programme ______ EC

List of electives obtained before the third semester without approval of the BoE ______

YES all 1st year master courses passed

NO missing 1st year master courses are:

name ______ date - - signature ______

FORMAL APPROVAL GRADUATION PROJECT

To be filled in by the Board of Examiners of IDE TU Delft. Please check the supervisory team and study the parts of the brief marked **.
Next, please assess, (dis)approve and sign this Project Brief, by using the criteria below.

- Does the project fit within the (MSc)-programme of the student (taking into account, if described, the activities done next to the obligatory MSc specific courses)?
- Is the level of the project challenging enough for a MSc IDE graduating student?
- Is the project expected to be doable within 100 working days/20 weeks ?
- Does the composition of the supervisory team comply with the regulations and fit the assignment ?

Content: APPROVED NOT APPROVED

Procedure: APPROVED NOT APPROVED

comments

name ______ date - - signature ______

Initials & Name Y.X. Zhang Student number 4378776

Title of Project Smart Safety Shoe of the Future

Smart Safety Shoe of the Future

project title

Please state the title of your graduation project (above) and the start date and end date (below). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.

start date 11 - 12 - 2020 | 17 - 05 - 2021 end date

INTRODUCTION **

Please describe, the context of your project, and address the main stakeholders (interests) within this context in a concise yet complete manner. Who are involved, what do they value and how do they currently operate within the given context? What are the main opportunities and limitations you are currently aware of (cultural- and social norms, resources (time, money,...), technology, ...).

Allshoes is a company that specializes in safety shoes that is used in all kinds of working sectors. The main thriving sectors for these shoes are logistics, construction and transport. Due to the nature of these jobs, handling heavy objects and interacting with heavy machinery, the shoes will protect the feet of the workers from most dangers. Though, still many injuries happen everyday. To get a better insight on the underlying problem, a new shoe should be designed using smart technology that could collect this data. The aim of Allshoes is to design an innovative shoe that will protect the workers from (short term) dangers and prevent (long term) musculoskeletal disorders.

This project is the follow-up to an earlier Smart Shoe project for Allshoes, which was done by an SPD student. From the prior project, it was concluded that the shoe of the future will use artificial intelligence and machine learning to prevent musculoskeletal problems. The data will be acquired by implementing sensors into insoles or integrate them in the shoe. Figure 1 illustrates the imagined system.

Since the solution is still in an early concept stage, there is a lot of room for adjustment and development. The product is aimed at a target group that work in a highly dynamic work environment, where anything could happen. The employers might be the most interested in smart shoes, as they could use the data to improve the work environment for their employees. They could get insights in what kind of injuries happen often and where it happens. To prevent future problems they could make boxes lighter or require the employees to use machinery instead.

The employees may not be that interested in such a shoe, if it does not bring them any comfort for example. Possibly, to make it more interesting for them, could be direct advice (via smartphone) based on the collected data. One could think of posture improvement or show the time spent standing or walking. Tracking personal physical data is already possible using smart watches and smart shoes.

Allshoes wishes to use AI as it could put them in a pioneering position within the shoe industry. From an initial quick search on Google, there are no smart working shoes as of this moment. Smart shoes are now mostly aimed at sports to track the performance of athletes. One example could be found, where body tracking technology has been trialled in a work environment, see figure 2. This was Ford Valencia Engine Assembly with collaboration with the Instituto Biomecánica de Valencia (IBV). Using motion sensors on several places on the body and motion cameras, it captured all the movement data. The focus of the research was to improve posture of the workers. The need for such product or technology does exist, but the real benefits and use has yet to be recognized.

The main challenge lies in the viability of the product. Will the needed data be captured and to what extent is it usable? Are the necessary electronics available and affordable? Will the data correlate to the body movements? In the research done by Ford and IBV, they required lots of equipment which is undesirable in day to day working environment. Implementing all the necessary components in the shoes could resolve this issue.

One possible limitation for the project will be adoption of such product. People do not like the feeling of being observed all the time. People do also not recognize the need or benefit of these products directly. Another one is the time limitation of the project for obtaining sufficient data to analyze trends and patterns. Also the reliability of the data could pose an issue; will it be sufficiently consistent to uncover meaningful patterns?

space available for images / figures on next page

introduction (continued): space for images

image / figure 1: Smart Shoe Data - Visualization and Integration

image / figure 2: Ford Valencia - Body Tracking Setup (Ford, 2018)

PROBLEM DEFINITION **

Limit and define the scope and solution space of your project to one that is manageable within one Master Graduation Project of 30 EC (= 20 full time weeks or 100 working days) and clearly indicate what issue(s) should be addressed in this project.

In many working sectors, (longterm) physical problems occur due to different reasons. Couple of reasons could be wrong working posture, lifting too heavy objects or standing for too long. As all humans are unique, it is hard to determine the cause per person. Tracking the workers to collect the physical ergonomic data is time consuming.

Currently, collecting data about ergonomics is often done in a short period during work. Not all the problems occur during this snapshot, the crucial moment or event could be missed. Secondly, a special setup is needed, which can influence the workers at their tasks.

Designing a new smart safety shoe could help analyzing potential problems and maybe even prevent them. Without needing a special setup, the workers can continue working as usual

The scope will be aimed at the feasibility of smart shoe, to be proven by research and testing. Research will be focused on the correlation between sensor data and ergonomic assessment. Exploring the practicality of artificial intelligence to analyze data and to present it in a meaningful manner.
Testing will comprise of building prototypes and product testing. This will proof the usability and reliability of such product.

The integration of technology in a shoe will be the secondary goal of the project. The materials in the shoe might not interact with the components as intended. Repairability of the product should also be taken into consideration.

ASSIGNMENT **

State in 2 or 3 sentences what you are going to research, design, create and / or generate, that will solve (part of) the issue(s) pointed out in "problem definition". Then illustrate this assignment by indicating what kind of solution you expect and / or aim to deliver, for instance: a product, a product-service combination, a strategy illustrated through product or product-service combination ideas, ... In case of a Specialisation and/or Annotation, make sure the assignment reflects this/these.

Design the smart safety shoe of the future aimed at preventing musculoskeletal issues, monitored and analyzed by AI to detect early symptoms. Creating a proof of concept will reveal the potential and usability of the product.

The goal is to create and design a product that is capable of generating insightful data that can be used to prevent musculoskeletal problems. Breaking down the assignment into sub-assignments:
- Research bio-mechanics to establish a baseline of good ergonomics related to shoes.
- Proof that a smart shoe is a product that can detect and prevent musculoskeletal issues.
- Explore opportunities with AI to automate the process of analyzing large amount of data without the need for continuous involvement of health professionals.

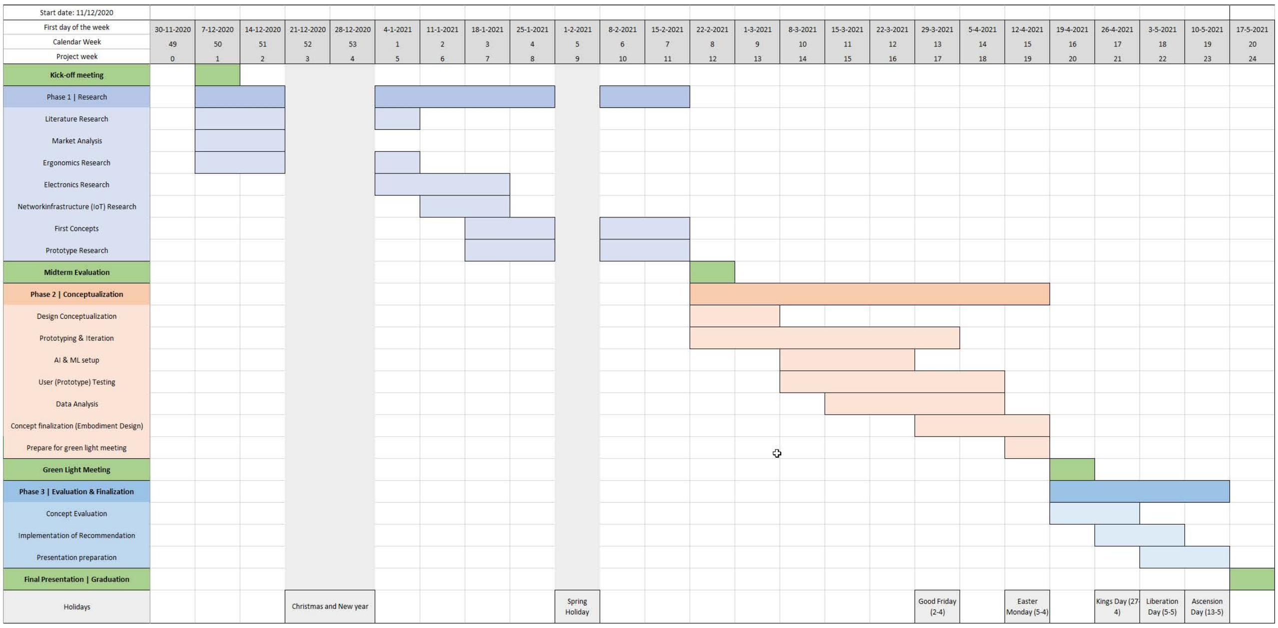
To show the potential and usability of a new smart shoe as a proof of concept has to be created and tested. The smart shoe will be equipped with sensors capable of collecting a variety of data. This data could be analyzed locally or in a cloud server with AI. The users could be recommended to do things differently, based on the found issues.

Embodiment design of the product will be the secondary assignment, which is a responsibility of an IPD design student. The consideration of the different technical aspects is part of the challenge to create and design a smart shoe of the future.

PLANNING AND APPROACH **

Include a Gantt Chart (replace the example below - more examples can be found in Manual 2) that shows the different phases of your project, deliverables you have in mind, meetings, and how you plan to spend your time. Please note that all activities should fit within the given net time of 30 EC = 20 full time weeks or 100 working days, and your planning should include a kick-off meeting, mid-term meeting, green light meeting and graduation ceremony. Illustrate your Gantt Chart by, for instance, explaining your approach, and please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any, for instance because of holidays or parallel activities.

start date 11 - 12 - 2020 17 - 5 - 2021 end date



The approach for this project will mainly be hands on prototyping design. With a foundation on research, done in the early phase to have a reference point and general understanding of the smart technology products. As there is no prototype yet, (user) research will be done with built prototypes, to gain the necessary data and insights. It will be an iterative process between building and researching, following an agile approach .

In the first phase, the research will be the foundation of the project. The intended result of this phase will be a report or overview of necessary components that correlate with each other. Based on bio-mechanics and ergonomics knowledge, the sensors will be selected. In this phase the first concepts will be made. Testing prototypes will be build to see if the components will work as imagined and to collect the first data to analyze.

In phase two, the concept design will be developed further. The actual prototype will be built during this phase to test with people and acquire data. The data is needed to correlate the ergonomic knowledge to the data. Consequently, with this data, AI can be trained to detect patterns and trends. The (final) concept will be developed in this phase as well.

Initials & Name Y.X. Zhang Student number 4378776

Title of Project Smart Safety Shoe of the Future

MOTIVATION AND PERSONAL AMBITIONS

Explain why you set up this project, what competences you want to prove and learn. For example: acquired competences from your MSc programme, the elective semester, extra-curricular activities (etc.) and point out the competences you have yet developed. Optionally, describe which personal learning ambitions you explicitly want to address in this project, on top of the learning objectives of the Graduation Project, such as: in depth knowledge a on specific subject, broadening your competences or experimenting with a specific tool and/or methodology, ... Stick to no more than five ambitions.

This project was chosen because I like to design functional and technical products. Often with cutting edge technology. The following points explains what my ambitions and interests are as a designer.

1. Technical & Embodiment Design
My personal interest has always been with technical subjects; engineering, state-of-the-art technology and production for example. Making a (concept)product really working, is what drives me as a designer. If you design through prototyping, the design process is in my opinion much quicker and more tangible. Often, new technology is accessible and comprehensible for some people. My ambition is to make new technology accessible, to make their lives easier and/or better. With this project, I will be able to do this. With the help of embodiment design experience, I will be able to implement new technology into new products.

2. Electronics
Designing with electronics is something I like to do and a skill that not many designers have. Having knowledge of this is a huge benefit when one is trying to develop a working (test)prototype. It helps with designing more feasible concepts. Especially in a world where electronics can be found in almost any product.

3. AI
Artificial Intelligence is being used in more and more products and services. It is inevitable that it becomes more used in products, as it is able to perform tasks that humans find tedious or simply not doable. Understanding the capabilities of AI is future proofing yourself as designer. I've read a lot about AI, but never really used it in practice. With this project I will get the opportunity to do so.
AI has potential in this project, as it can monitor and analyze data at any given moment. If one only has to analyze data points from a few people, that is doable by hand. However, if the number of people increases to a few hundreds or thousands and the amount of sensors increases then it would be hard to process the data by hand. AI could be a good automated helping hand for data processing and analysis.

4. IoT
During my electives, I've learned to use IoT technology, making a hub and connecting different sensors to it. The hub was able to collect and share the data to a cloud. The cloud represented the data in a meaningful manner to humans. Though, I've mainly learned the theory and basics of the technology, I wish to use it during this project. This knowledge will be useful to design and create a product with the desired usefulness.

5. Prototyping
I do not mind to get my hand dirty to build something. It helps me to come up with better feasible ideas. It is also easier to communicate your ideas through a physical product. There are countless possibilities, but they might not always work. So, building it, show immediately if it works or not. For this project, it will be valuable to create as many prototypes as achievable.

FINAL COMMENTS

In case your project brief needs final comments, please add any information you think is relevant.

Appendix J - Graduation Opportunity

Graduation Opportunity

Develop the Smart Safety Shoe of the Future!

Part 2

SMART SAFETY SHOE

Our story

The Netherlands excels at logistics, construction and transport. These industries are growing fast! A huge number of people work in these sectors. Working in warehouses, on constructions sites or with heavy equipment involves risks. Safety shoes are required in many workplaces and 1.5 million pairs of safety shoes are sold in The Netherlands each year, with Allshoes Safety Footwear as market leader. With own brands such as Redbrick and Mr. Miles and exclusive distribution rights for Grisport and Vismo, our company owes its success to our courageous decision to introduce revolutionary safety footwear that reflects the latest fashion and sports trends into a conventional market.

Our aim

Despite many measures to prevent accidents at work, 60 people are killed and 2,300 seriously injured every year. Safety shoes only protect the feet and only provide protection when an incident occurs. In other words, safety shoes currently play a static role. To help prevent manual handling injuries, such as back problems, we want to contribute in proactive incident prevention. Our goal? To create a "smart" safety shoe that detects and alerts the wearer to danger in high-risk situations. In cooperation with TU Delft and a SPD graduation student, research was conducted regarding this topic. A strategic concept has already been developed in which a smart safety shoe measures the leading and lagging indicators with regard to manual handling. This shoe can then give feedback by sending the measured data to relevant parties in order to eliminate the causes of manual handling incidents. It was strongly suggested that machine learning and/or AI offer predictive capabilities with strong potential, but concrete deployment of these technologies needs further elaboration.

Your task? Make the concept of "smart shoe" concrete.

On behalf of Allshoes Safety Footwear, we challenge you to further develop the smart safety shoe that will reduce the number of injuries caused by manual handling. It is your task to follow up on the current strategic concept; build tangible prototypes, test them and finally end up with an innovative smart safety shoe with the aim of bringing it to the market. You will continue to develop the current idea including the technology behind it.

Who are we looking for?

Are you the one who wants to bring the smart safety shoe to life and who wants to drive change with us? Then you are the person we are looking for! We are looking for an IPD graduation student who is able to develop an idea into a tangible prototype. You are willing to explore the potential of machine learning, AI, IoT and related cutting-edge technologies, and meaningfully incorporate these into your design. You do not hesitate to ask for information or assistance: during the project our colleagues will be there to offer helpful insights and advice.

What do we offer?

You can make use of a great workplace at the heart of safety-shoe land in our brand-new office in Amsterdam. However, it is also possible to work remotely. You will have access to our large network of manufacturers to gain all the information needed. There will be a budget available for you to develop your idea into a prototype. Our organization is informal and we have short lines of communication. You will receive an internship allowance and your travel expenses will be reimbursed.

Will you be the one to develop the Smart Safety Shoe?

If you're interested, please contact Jan.Arts@allshoes.eu

Wilfred van der Vegte from the Knowledge & Intelligence Design section is the envisaged chair for this graduation project. He can offer support on machine learning and related technologies. He also chaired the foregoing SPD assignment and is available for additional info: w.f.vandervegte@tudelft.nl

Allshoes
safety footwear