Know your limits.

Predicting lift capacity using time series spine kinematics for a military manual handling task.

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1. Abstract

In Australia, 41% of industry injury claims are due to manual handling tasks, costing $14.58 billion annually. In the Australian Army, 78% of physically demanding tasks are considered manual handling, which increases the risk of musculoskeletal injury. Of injuries in active service personnel for the Australian Army, 22% occurred in the trunk [3, 4] with manual handling recognised as the cause for 5% of all injuries [3, 4]. This has led to the need for an exoskeleton system that can support, move and adapt to repetitive, fatiguing tasks. The predecessor to this exoskeleton system is the development of an assist-as-needed control algorithm that will predict when personnel are lifting above their maximum acceptable weight of lift (MAWL), which is indicative of an increased injury risk. This algorithm could also be deployed on a simpler stand-alone wearable device that could assist personnel in reducing risk factors associated with injury due to manual handling tasks, through providing visual or auditory feedback.

Laboratory experiments using biomechanical task analysis based on military manual handling protocols were performed with a sample size of 32 participants. Inertial measurement units (IMUs) were used in a six-segment spine model for data collection. The normalised (for time) kinematic output of the IMUs for participants during lift-to-platform tasks were analysed for the relationship between changes in spine kinematics and increasing external load. Statistical parametric mapping was performed to determine significance in the IMU variables. Additionally, polynomial correlation of discrete features were analysed for use as predictive factors of external loading above a participant's capability which resulted in poor correlation.

Machine learning was performed due to its ability to find trends and features in data that may not be apparent via statistical inference. Supervised machine learning algorithms capable of classifying multivariate time series data were compared. The Random Convolutional Kernels (ROCKET) algorithm had the highest accuracy for its ability to classify a high risk (at or above MAWL) or low risk (below MAWL) lift, with a 10-fold cross validation mean accuracy of 91.2 ± 2.7%. A moderate f1-score was

maintained through dimensionality reduction of the spine segments and data frames per feature. Reducing the spine segments to one (middle lower thoracic) and data frames to half (50) resulted in a f1-score of 86%.

This research contributes an accurate novel predictive model that uses machine learning to classify spine kinematics from IMUs into high and low risk lifts, based on MAWL. In future work, the novel predictive model developed in this thesis will contribute to the development of a stand-alone device providing user-feedback. The model will also be part of an assist-as-needed control system for the development of an active exoskeleton that could provide augmentation to Defence personnel during manual handling. These devices aim to reduce injuries caused by lifting above an individual's capacity.

2. Declaration

"I, Jasmine Kerina Proud, declare that the PhD thesis entitled *Know your limits. Predicting lift capacity using time series spine kinematics for a military manual handling task* is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

"I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures. All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee (HRE18-231)".

Signature [redacted] 17th July 2022

3. Dedication

For my children, my husband, my family, my friends

and everyone that knew I would make it, even when I doubted.

4. Acknowledgements

What a journey! It is hard to describe the mental roller-coaster that is trying to complete a PhD. There are the highs of discovery and the lows of frustration, but the love of learning never diminished. However, I may take a nap for a few days once this is complete.

Firstly, I need to acknowledge the tireless support of my husband, Russell. You have sacrificed so much to realise my ambitions even if I did not say it at the time, I recognise that without you, this would not have been possible. For my children Elliot and Astrid, through every minute I spent away from you, know that you were in my thoughts. I wanted you to be proud of your mum and know that whatever the setbacks, love, support and a sprinkle of tenacity will get you through. You will always have my love and support. I love you all to the edge of the universe.

For all of my wonderful family and friends, thanks for all the childcare, coffee, food, chats and endless support. I will forever appreciate all the offers to read my thesis. You are the people that shaped me.

Of course, there are my supervisors. I had such a great team behind me, your knowledge and encouragement helped create this. Thank you to Prof. Rezaul Begg, A/Prof. Daniel Lai, Dr. Kurt Mudie and Dr. Alessandro Garofolini. I may not have seen you in person for a few years but knew you were only a Zoom call away.

Thank you to Dr. Alessandro Garofolini for all your knowledge and support during the human trials, especially while I was extremely pregnant and Dr. Arezou Soltani for your assistance with machine learning modelling.

Okay, this is becoming like an Oscars speech that has gone too long, I hear the music playing me out, I will close off by saying, Enjoy!

Cheers, Jas

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1. **Proud, J. K.,** Lai, D. T. H., Mudie, K. L., Carstairs, G. L., Billing, D. C., Garofolini, A., & Begg, R. K. (2022). Exoskeleton Application to Military Manual Handling Tasks. Human Factors, 64(3), 527–554. https://doi.org/10.1177/0018720820957467
2. Zaroug, A., **Proud, J. K.,** Lai, D. T., Mudie, K., Billing, D., & Begg, R. (2019). Overview of Computational Intelligence (CI) techniques for powered exoskeletons. *Computational intelligence in sensor networks*, 353-383. https://doi.org/10.1007/978-3-662-57277-1_15

Chapter 1. Introduction

1. Project Funding and external collaboration

This work was jointly funded by the Defence Science and Technology Group of the Department of Defence (Australia) and Victoria University through the Program in Assistive Technology Innovation (PATI). The group's research aims were to research the design and development of assistive devices that could aid Australian Infantry soldiers to carry out loaded manual handling tasks. Thus, the research in this thesis falls within the PATI's research focus by looking at Australian Defence Force manual handling tasks and how exoskeletons can play a part in the augmentation of soldier carrying out these tasks.

Due to access limitations to Australian Infantry soldiers, experimental participants were recruited from the civilian population. The age (mean age 29.5 ± 5.6 years) and sex (66% Male & 34% Female) of the civilian population was recruited to reflect that of the Australian Defence Force (median age 31 years for males and 29 years for females with 81% of the population Male and 19% Female) [5].

2. Problem Statement

Back injuries are a real problem in manual handling (MH) industries around the world, they are painful, effecting personnel's quality of life and their ability to perform workplace tasks [6]. They are expensive to companies, reducing productivity and adding costs for rehabilitation, retraining and loss of hours [6]. There is such a large body of research around the topic of back injuries, their many possible causes, procedures for preventing them, equipment interventions to reduce the risk of them, and still, they are extremely prevalent across all industries, especially with the Defence Force [7].

Manual handling injuries are of particular concern in physically demanding Defence Force occupations. Musculoskeletal injuries make up 20% of the most common disorders supported for Australian Defence personnel returning from active service [8]. Studies looking into the prevalence of injuries in active service for the Australian Army found that between 21.2% and 22.8% of injuries occurred in the trunk [3, 4]. Load carriage attributed to 20.7% of injuries (e.g., marching, patrolling, physical training, manual handling) [4] with manual handling recognised as the cause for 5% of injuries [3, 4]. Prevention methods for load carriage injuries can include training, practice, education and wearable interventions.

When exploring some of the wearable interventions that have been introduced in literature (e.g., back braces, exoskeletons, posture garments, lifting devices), there did not seem to be a solution that took a person's ability to perform a task into consideration. Many of these devices were always providing assistance, where perhaps it was not needed. A back brace is always providing intra-abdominal pressure, this is not needed when walking through the warehouse. The exoskeleton can lift loads of 20 kg, but if the wearer is lifting 1 kg boxes, lifting for them could result in a reduction of strength and stamina.

The benefit of an exoskeleton is that they can be turned off while still being worn and this can be automated via its control system [9]. The use of exoskeletons could be a solution to manual handling back injuries by providing augmentation and supported motion to the wearer, but it is important to consider that taking away all loading off the musculoskeletal system can cause more injuries in the long term [10]. It is vital that any intervention does not reduce the ability of the wearer over time, only assisting when there is a need, such as when the wearer is performing a dangerous motion. Dangerous motions are those that include hyperflexion or hyperextension, such as when lifting from the floor or above shoulder height [11, 12], performing tasks when fatigued and trying to lift more than an individual is capable of lifting [13].

A measure used by the Australian Defence Force of the limit of a person's ability to lift is known as maximum lift capacity (MLC) whereas, a measure of a person's limit to continue lifting safely is known as the maximum acceptable weight of lift (MAWL) [13]. Across seven strength-based lifting tasks the MAWL was determined to be 84 ± 8% of MLC [13]. Matching a person's capability to the physical demands of their job has been shown to reduce the occurrence of injury [14], therefore limiting external loads to below 84% of a person's MLC may reduce injury risk.

Understanding the effect that increased loads have on the spine and using this understanding to predict when a person has reached their capability limits could provide a way to reduce these costly injuries. Prediction can be achieved through machine learning algorithms. Machine learning (ML) classification algorithms have the ability to learn from past observations and make predictions on which class a new observation belongs to without needing to be explicitly trained for any new data [15].

The use of a ML algorithm for prediction means that assistive devices would have the ability to augment movement without reducing the physical ability of the wearer. This can be achieved by only providing assistance when a threshold has been reached, such as MAWL, through assist-as-needed activation of the intervention, such as an exoskeleton.

3. Theoretical Framework

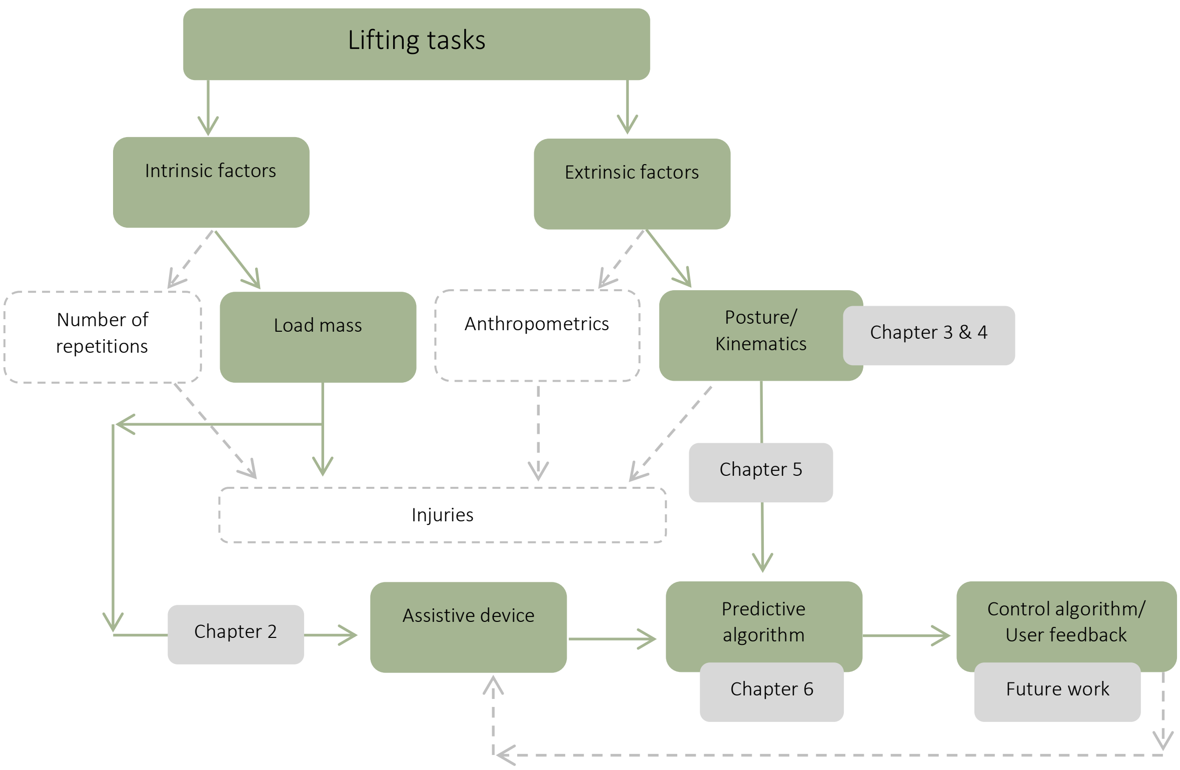

Figure 1 Theoretical Framework for the thesis.

Figure 1 introduces the theoretical framework for the body of work. Use of an exoskeleton may be beneficial to avoid musculoskeletal injuries due to manual handling tasks [Chapter 2: Literature Review]; however, when an exoskeleton should begin to assist depends on multiple factors, such as the person's MAWL (a measure of an individual's physical capacity for continued load carriage). Given that increasing load may influence spine kinematics [Chapter 3: Systematic Review], a system of small sensors along the spine able to detect changes in kinematics due to an increase in loading that approaches MAWL [Chapter 4: Experimental Trials, Chapter 5: Statistical Analysis], could be used to create a predictive algorithm [Chapter 6: Machine Learning Application] and deployed as a control system in MH exoskeletons [Chapter 7: Future Work].

4. Research Aim

The overall aim of this project is the design and development of a predictive model to identify (classify) whether an external load is above a person’s intrinsic ability to lift. This could then go on to be used as part of an assist-as-needed control system for an exoskeleton, to reduce risk injury factors during military manual handling tasks. The research contained within this body of work is based on the assumption that when a lifting load is standardised to a percentage of a person’s maximum lift capacity, the changes in spine kinematics caused by increased external load will be similar between participants and thus, could be used to create a predictive model. Therefore, the overarching research question was asked:

Can spine kinematics be used in a predictive model that

can determine an increased risk of back injury?

The research objectives explored are:

1. Determine the suitability of current exoskeleton technology to support military manual handling tasks (Chapter 2).

2. Determine the effect of increased external load on spine kinematics (Chapter 3 & 4).

3. Determine the kinematic factors that can be used as predictive indicators of a user approaching their maximum acceptable weight of lift (Chapter 5).

4. Develop a predictive model to classify when a lift is above the maximum acceptable weight of lift (Chapter 6).

5. Thesis Structure

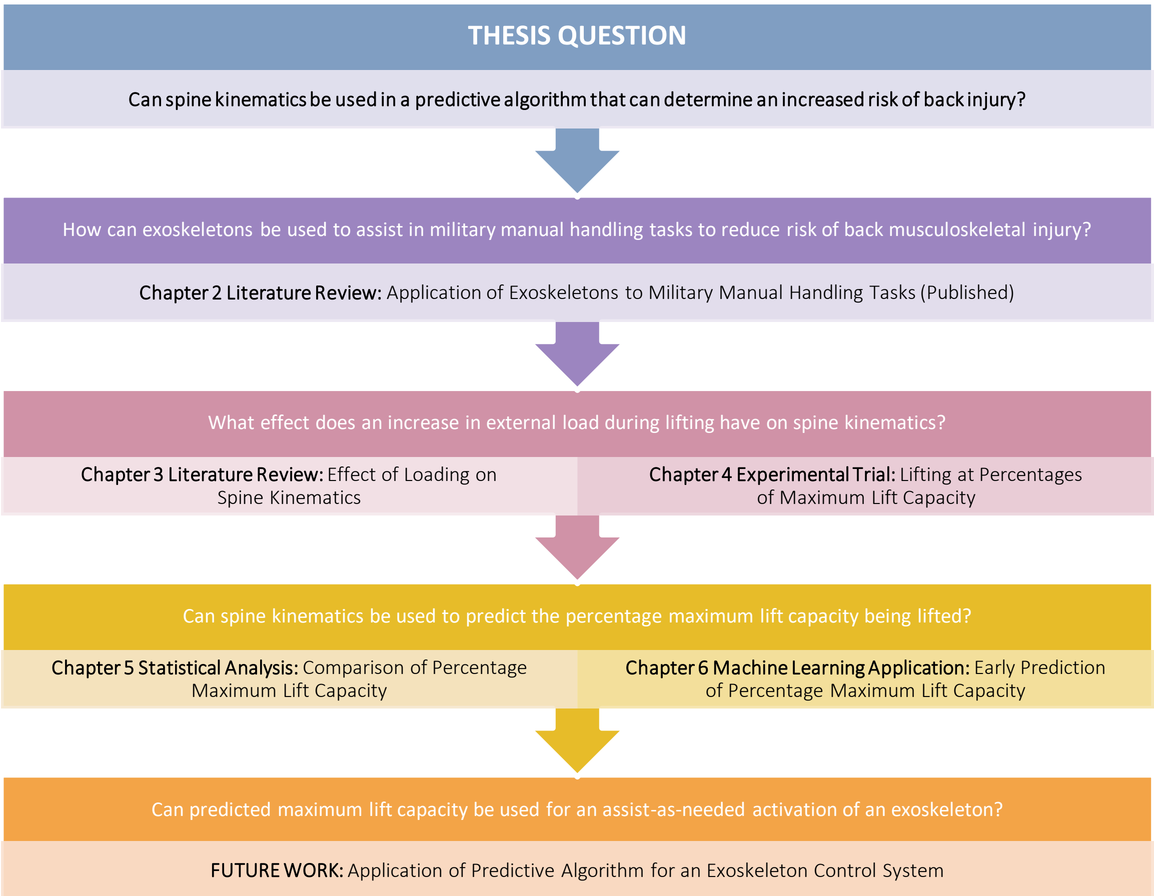

Figure 2 Structure of the thesis.

This body of work followed the structure seen in Figure 2, answering three main questions. The first question asked: 'How can exoskeletons be used to assist in military manual handling tasks to reduce risk of back musculoskeletal injury?', to answer this Chapter 2 evaluated how exoskeletons could be applied to assist personnel in the performance of manual handling tasks by assessing the current state of the systems available in literature and whether they can meet the needs for the predominant

Australian Defence Force tasks. Question two asked: 'What effect does an increase in external load during lifting have on spine kinematics?', Chapter 3 explored the effect that increasing external load had on spine kinematics during lifting tasks via a systematic literature review; followed by Chapter 4 that assessed the relationship between an increase in load and spine kinematics via experimental trial data. The final question assessed in this body of work was: 'Can spine kinematics be used to predict the percentage maximum lift capacity being lifted?', Chapter 5 applied statistical analysis on the experimental trial data to determine if any correlation existed for the effect of increased load on spine kinematics and Chapter 6 applied machine learning techniques to the experimental trial data to predict to which percentage maximum lift capacity class the observation belongs.

6. Contribution to Knowledge & Statement of Significance

The use of spine kinematics to make predictions of when a person is approaching their MAWL could make a significant impact on many industries that require human involvement in manual tasks. Industries that involve manual materials handling (e.g., Defence, logistics, manufacturing) injuries are present [6]. They are painful and costly to both human quality of life and a workplace's profit [6]. While the cause of injuries varies (e.g., hyperflexion, hyperextension, excessive lifting height) [16] a contributing factor is performing tasks above a person's capability [13]. The ability to predict when a person is approaching the limits of their capability and then provide feedback or augmentation, has the ability to reduce the number of injuries seen in industry. The creation of an algorithm that can predict whether a lift is above or below MAWL based on spine kinematic changes has not been previously researched.

This research contributes a novel predictive model that uses spine kinematics to classify IMUs data output into above or below a person's MAWL. The novelty of this research is in the use of IMUs to gather data from six spine segments, using percentages of maximum lift capacity to normalise the effect of loading on spine kinematics across participants and applying multivariate time series classification algorithms to spine kinematic observations for prediction. This research makes a significant contribution to knowledge as it demonstrates, for the first time, an accurate model for early prediction of loads above a person's capability to lift based on spine kinematics is possible.

In future work, when implemented across many manual handling tasks, it has the ability to be employed for the activation of wearable devices that provide augmentation or user feedback immediately as the lift has commenced, this would have the ability of reducing overexertion back injuries. The benefits of this could be applied to any industry setting where manual material handling tasks are performed, including the Defence Force.

Chapter 2. A review of the application of exoskeletons to military manual handling tasks

This chapter is an amended version of the manuscript: Proud, J. K., Lai, D. T. H., Mudie, K. L., Carstairs, G. L., Billing, D. C., Garofolini, A., & Begg, R. K. (2022). Exoskeleton Application to Military Manual Handling Tasks. Human Factors, 64(3), 527–554. Published version in appendix A. This chapter focuses on determining whether current exoskeleton technology is capable of supporting military manual handling tasks to reduce the occurrence of back injuries.

1. Introduction

In Australia 43% of serious injuries in the workplace are due to traumatic joint, ligament, muscle and tendon injuries, at an annual cost of AU$19.5 billion for treatment, over-employment, overtime, retraining and investigation [6]. Forty-five percent of serious workplace injuries were due to manual handling, a term used to describe tasks in which human force is used to manoeuvre an object's position [7]. Manual handling injuries are of particular concern in physically demanding Defence Force occupations. Most manual handling injuries are associated with the upper and lower limbs (37%) and the back/trunk (38%) [6]. This is an internationally recognised problem, as 43% of workers in the European Union experience back, neck or shoulder pain caused by manual handling related workloads and repetitive movements [17].

Musculoskeletal injuries make up 20% of the most common disorders supported for Australian Defence personnel returning from active service. The Australian Government's Department of Veteran Affairs found that 7934 veterans (13%) from the East Timor, Solomon Islands, Afghanistan, Iraq and Vietnam conflicts receive support for lumbar spondylosis [8], a condition causing pain and restricted motion in the lower back attributed to overuse [18]. Also, common in Defence personnel were acute sprain and strain (4%), intervertebral disc prolapse (2%) and thoracic spondylosis (1%) [8]. These musculoskeletal disorders could be caused by manual handling tasks that involve movements that contribute to an increased risk of musculoskeletal injuries. Exploring how exoskeletons can support the body during manual handling tasks may help in reducing the risk of musculoskeletal injuries.

Factors contributing to manual handling injuries include hyperflexion or hyperextension of the lumbar spine caused by external torques, internal torsional forces, fatigue due to increased total work [16] and increased spinal flexion when performing lifting tasks from the floor [11, 12]. Additionally, lifting above an individual's intrinsic capacity can be responsible for injuries [13].

A comprehensive analysis of Australian Army personnel categorised 79% of all physically demanding tasks as manual handling [7] encompassing four movement patterns: vertical lifting (305 tasks), locomotion with load (153 tasks), push/pull (38 tasks) and repetitive striking (30 tasks). These movement patterns were further categorised into ten task-based clusters. While some tasks are unique to Defence personnel the two most common task-based clusters (lift-to-platform and lift-carry-lower) are also prevalent in many manual handling industries. Therefore, this review could be extended to the application of exoskeletons in industries whose workers perform these movement patterns.

Exoskeletons are an externally fitted biomechatronic or mechanical system, designed to assist the human user in order to reduce injury risk, amplify natural ability, rehabilitate movements or assist for physical challenges [9, 19]. Exoskeletons can be categorised by the intended purpose of the system: assistive systems, human amplifiers, rehabilitative systems and haptic interfaces [20]. An assistive system provides additional support to workers through joint bracing and control or transmitting forces away from the musculoskeletal system, a human amplifier increases the strength capabilities of the human body beyond their natural ability and rehabilitative systems assist in recovery of limb movement for people with limited function. A haptic interface exoskeleton provides feedback to the user when using tele-operation devices. This review explores assistive systems and human amplifiers for their use in supporting manual handling personnel.

The aim of this review was to analyse the current literature to identify characteristics of industrial exoskeletons that can be useful to military manual handling tasks. Therefore, the exoskeletons were classified based on: 1. which manual handling task the exoskeleton was developed to perform, and 2. which joint the exoskeleton supports.

2. Methodology

A study of the current exoskeleton literature was performed using Scopus, for articles published between January 1990 and December 2019. The search terms included exoskeleton, wearable robot or robot suit with the additional terms industrial, military, manual handling, material handling, lifting, carrying, pushing, pulling and striking. The included search terms were determined by using the definition of manual handling as set by research into Australian Army tasks [7].

Original studies were considered eligible if they met the following inclusion criteria: 1. the purpose of the exoskeleton was stated using terms such as industrial, military, manual handling, material handling, lifting, carrying, pushing, pulling or striking; 2. the conceptual design of the exoskeleton was progressed to a physical prototype; 3. the manual handling load was supported anterior to the user; 4. the exoskeleton provided actuation on one primary supporting joint (e.g. knee, hip, spine, shoulder) used to execute lift-to-platform and/or lift-carry-lower tasks. We excluded any commercially available exoskeleton (see limitation section) that did not have published scientific evidence.

The initial search resulted in 357 studies. The texts were screened, and 284 studies were excluded. In total, 73 studies were included in the review (Figure 3) that resulted in 67 individual exoskeleton systems. Included studies were categorised based on which movement patterns they permit (e.g., squat/deadlift, shoulder/chest press and isometric arm hold or any combination of these movement patterns) and to which joints they provided actuation.

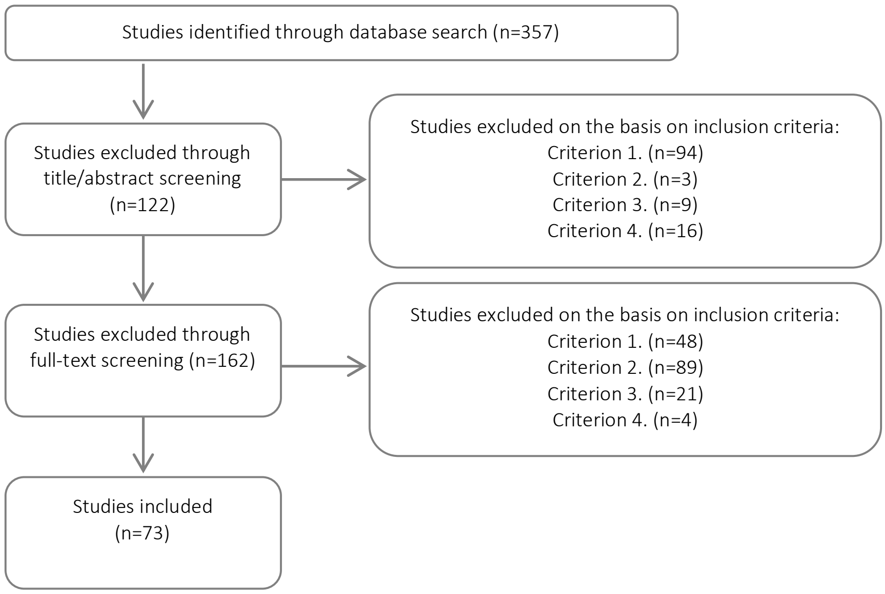

Figure 3 Schematic of the number of studies excluded on the basis on inclusion criteria during the search process. See text for description of criteria.

In order to categorise exoskeletons for their application to military manual handling tasks our focus was on the dominant two task-based clusters, the lift-to-platform cluster (198 tasks) and the lift-carry-lower cluster (100 tasks) which comprised 56% of army manual handling tasks. There was commonality of the major movement patterns (shoulder/chest-press, squat/deadlift and isometric arm hold movements) and the supporting joints used to execute these tasks (Table 1). Exoskeletons were categorised into the key movement patterns they work on, then sub-categorised into the key supported joints (Table 1). We define the supported joint as the joint upon which the exoskeleton provides actuation. Therefore, an exoskeleton can be designed to assist a segment/joint (i.e., the spine) by providing actuation to – supporting – a joint (i.e., the hip).

Table 1 Key movement patterns and supporting joints for task clusters

	Lift-To-Platform		Lift-Carry-Lower
Key Movement Pattern	Squat /Deadlift	Shoulder/ chest-press	Shoulder/ chest-press & Isometric arm hold
Key Supporting Joints	Knee	Shoulder	Shoulder
	Hip	Spine	Spine
	Spine		

Operational details included device name, purpose, targeted assistance, actuation method, actuators, degrees of freedom (DOF), device weight, control method, sensor system and load capability. The purpose of the exoskeleton was classified based on the principal function/s or the motivation for design. These were defined as: 1. “tool holding”, supporting the weight or reducing the transfer of vibrations from a tool to the user, particularly during overhead work; 2. “injury prevention”, reducing the transfer of external loads to the user’s joint and muscle; 3. “amplification”, typically full body suits taking the entire external load through their structure; and 4. “load carrying”, bearing an external load through the exoskeleton’s structure.

Evaluation details included task analysis, testing performed, test details, sample size, participant details and test results. Task analysis outlined any assessments that were performed prior to the design of the exoskeleton to determine its requirements. Testing performed on the exoskeletons were categorised into the following analyses: 1. “exoskeleton structural design”, analysed for how it moves, the workspace it requires and the forces it is able to withstand/exert; 2. “human-exoskeleton analysis” how it interacts with the user to provide assistance, the forces it applies to the user and how the user’s natural motion can be changed by the addition of the device; 3. “accuracy of the sensor system” analysed for its accuracy, resolution, efficiency, speed and output; and 4. “response characteristics of the control system” how the mechatronic system interacts with the user and can be measured by accuracy, speed, sensitivity and complexity.

3. Results

3.1. Operational details

3.1.1. Movement patterns and supported joints

Twenty-four percent of exoskeletons permitted shoulder/chest press and isometric arm hold motions (Table 2), this includes devices that support the elbow and shoulder joints concurrently (n=9) and the shoulder joint only (n=7) (Figure 4). Sixty-four percent of exoskeletons permitted the squat/deadlift movements (Table 3), this includes devices that support the ankle, knee and hip synchronously (n=20), the knee joint only (n=4) and the hip joint only (n=19) (Figure 4), while 12% of exoskeletons permitted major joints for shoulder/chest press, isometric arm hold and squat/deadlift (Figure 4) (e.g. spine (n=5) and full body devices (n=3)) (Table 3).

3.1.2. Purpose

Load carrying was the most common exoskeleton purpose (42%), followed by 22% targeting load carrying and injury prevention (Figure 4). Load carrying included lifting, lowering and/or carrying of external loads. Injury prevention exoskeletons focused on trying to reduce injury risk factors of the lower back while tool holding devices, making up 15% of this review, focused on supporting the shoulder joints through unloading.

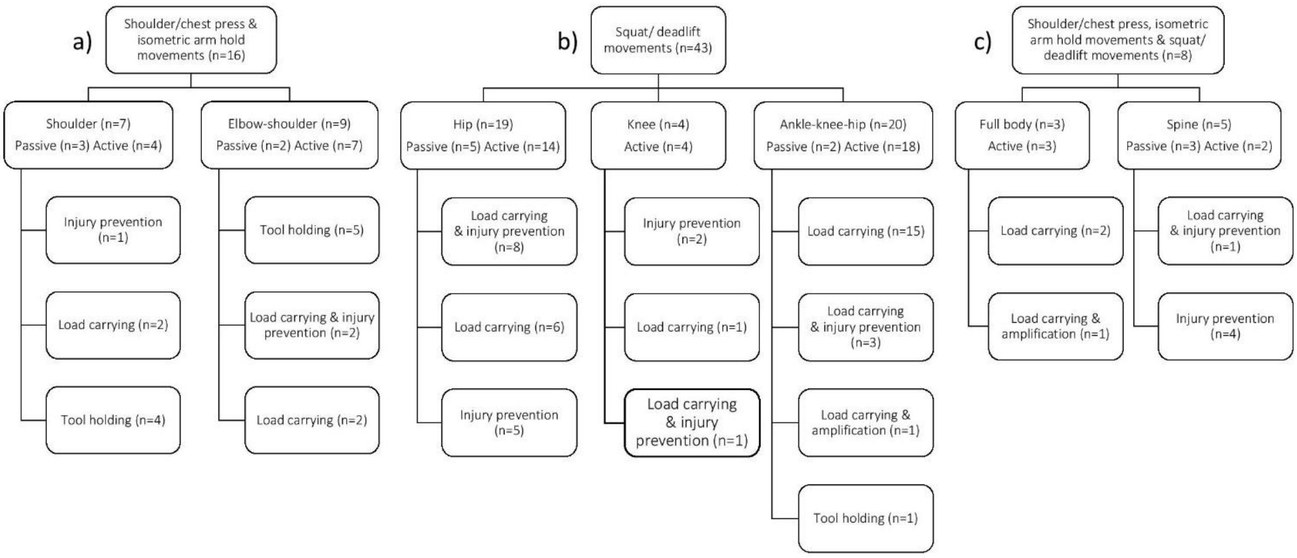

Figure 4 Breakdown of exoskeletons classified into their movement patterns, supporting joints and purpose. a) Shoulder/ chest press & isometric arm hold (Table 2) b) Squat/deadlift (Table 3) c) Shoulder/ chest press, isometric arm hold & squat/deadlift movements.

3.1.3. Actuation system

Ninety percent of the included studies reported the actuation method used (Figure 4); these systems have been classified into four categories: electric (n=38), hydraulic (n=5), pneumatic (n=6) and passive (e.g., springs, pulleys, cables) (n=15). Seventy-eight percent of exoskeletons in this review were active, meaning they provide movement to the user through a mechatronic system and the creation of mechanical power through the use of actuators, while 22% were passive exoskeletons, meaning they used an exclusively mechanical system to provide support.

3.1.4. Task requirement

Task requirements were identified prior to exoskeleton design in 30% of the studies. These studies looked at kinematic modelling (n=10), gait analysis (n=5), or biomechanical analysis (n=5) to optimise their design for specific task requirements by quantifying the range of motion (ROM), DOF, joints supported, and additional torque provided.

3.2. Evaluation details

Human-exoskeleton integration analysis was the most prevalent form of evaluation with 68% of devices included in this review (Figure 5). Evaluations performed included biomechanical, physiological and psychophysical testing. Biomechanical evaluation was the most frequently used measure (n=39), followed by physiological evaluation (n=37) (Figure 5). Many studies used both physiological and biomechanical evaluations to indirectly evaluate device performance. Biomechanical testing captures the kinetics and kinematics of user's joint movement [21], while physiological tests measure the user's energy cost [22], and psychophysiological tests measure user's perception (subjective feedback) whilst using the exoskeleton [23]. Biomechanical evaluations vary and included motion capture (n=9), ground reaction forces (GRF) (n=2) and inertial measurement units (IMUs) (n=6); physiological tests included electromyography (EMG) (n=32), while psychophysical tests included rate of perceived exertion and self-questionnaires (n=5). Only four studies measure performance using a direct method (time to completion).

All studies that tested muscle activation (recorded via EMG) reported reductions in some EMG signals (n=32). Such a reduction in EMG was considered a measure of how the exoskeleton reduced muscle work and thus the risk of injuries. Specific to the back, eight studies reported reductions of muscle activation of the erector spinae muscles between 15% and 54%; one study reported no changes, and one reported increased activation of the antagonist muscles.

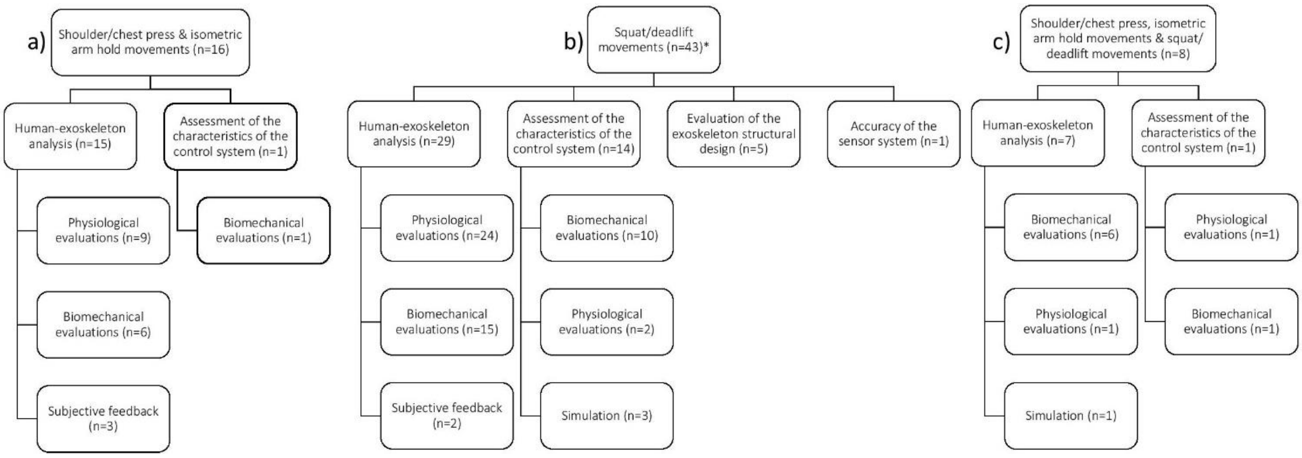

*Figure 5 Breakdown of exoskeletons classified into their movement patterns, testing performed and type of evaluation. a) Shoulder/ chest press & isometric arm hold (Table 2) b) Squat/deadlift (Table 3) c) Shoulder/ chest press, isometric arm hold & squat/deadlift movements (Table 4). * = Some studies have carried out multiple analysis.*

Due to the early stage of development for the majority of devices, participant sample sizes were relatively low (< 13). However, there were two studies [24] and [25] proposing commercially available exoskeletons (the Leavo (Table 3, Row 31) and Airframe (Table 2, Row 15)) that had larger participant cohorts with 18 and 29 participants respectively. The Airframe was also tested with a smaller cohort of 11 participants in a automotive factory environment performing controlled real-work tasks [26], and the Daewoo Shipbuilding & Marine Engineering Hydraulics Wearable Robots (DSME-HWR) (Table 3, Row 20) performance was observed during in-field trials at a shipbuilding yard [27].

Table 2 Exoskeleton classification for shoulder/chest-press and isometric arm hold

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
1	**Elbow – shoulder**	Exhauss Stronger	LC & IP	Arm – Lifting assist	P	Not reported	Not reported	9	Not applicable	Not applicable	Not reported	Not reported	Human-exoskeleton analysis	Lift, carry, place task. With & without exo condition. EMG, IMUs, HR, RPE, CoP, time to complete.	8	4F (31 ± 2 years, 62 ± 10 kg, 166 ± 4 cm) 4M (33 ± 3 years, 78 ± 3 kg, 179 ± 3 cm)	Reduction of anterior deltoid muscle activity (54%) & stacking/unstacking (73%) tasks. No significant difference in back muscle activation. Increased antagonist muscle activity, postural strains, cardiovascular demand & changes in upper limb kinematics	[28]
2		Power assistive exoskeleton robot system for the human upper extremity	LC	Arm – Load assist	A	Not reported	8	Not reported	Human-robot cooperative control	Force sensors	Not reported	Not reported	Human-exoskeleton analysis	Holding a 10kg load. With & without exo conditions. EMG for elbow & shoulder flexion/ extension.	Not reported	Not reported	Reduction in EMG signals of the arms and shoulders while wearing the exoskeleton	[29]
3		Stuttgart Exo-Jacket	TH	Arm - Stabilising	A	Electric (EM & HD)	12	Not reported	PID control	Hall sensors	Not reported	Biomechanical analysis - MoCap & IMUs	Human-exoskeleton analysis	Subjective questionnaire on device comfort while performing flexion & extension.	3	Not reported	Not reported	[30, 31]
4		Iso-elastic upper limb exoskeleton	TH	Arm – Limb support	P	Passive (S)	Not reported	1.9	Not applicable	Not applicable	7.5	Not reported	Human-exoskeleton analysis	Using 4 masses and a spring balance, the effective lifting force at 7 different angles was measured	Not applicable	Not applicable	For higher loads there is a discrepancy between calculated and measured forces. Capable of supporting loads in the range of 40–120 N	[32]
5		Under-actuated upper-body backdrivable	LC	Elbow – Load assist	A	Not reported	1	Not reported	Artificial neural network with a model-based intensity prediction	Myo-Armband	Not reported	Kinematics	Human-exoskeleton analysis	Varying torques in the 2 directions available	7	6 M and 1 F, (20 to 35 years)	RMS Error of 3.8 ± 0.8N at the end effector	[33]
6		4 DOF exoskeleton rehabilitation robot	LC & IP	Arm – Limb support	A	Cable-driven parallel mechanism	4	Not reported	IPC (Industrial Personal Computer)	Cable tension and encoder	Not reported	Kinematics	Characteristics of the control system	The exoskeleton drove robotic arm repetitively track the cubic polynomial trajectory	Not applicable	Not applicable	Trajectories tracking capability was demonstrated	[34]

Table 2 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
7	**Elbow – shoulder**	Upper-limb exoskeleton	TH	Arm – Load assist	A	Electric (EM)	5	9.5	Not reported	Not reported	Not reported	Physiological	Human-exoskeleton analysis	Perform a movement of raising the arm with a drill above the head wearing or not the arm exoskeleton	10	8 M and 2 F, all right-handed, (28.8 ± 3.4 years, 173.3 ± 6.4 cm,72.32 ± 11.97 kg)	Exoskeleton reduces muscle activity	[35]
8		4-DOF upper-body exoskeleton	LC	Arm – Load assist	A	Not reported	4	Not reported	Admittance control & gravity compensation	Force Sensitive Resistor	Not reported	Biomechanics	Human-exoskeleton analysis	With the passive exoskeleton, in which three different payloads in the range of 0 kg to 5 kg were lifted	5	(20-30 years)	the developed method is able to estimate the load carrying status	[36]
9		Wearable upper arm exoskeleton	TH	Arm – Load assist	A	Electric (EM)	1	2	PD adaptive control	Not reported	4.5	Physiological	Human-exoskeleton analysis	Holding position with no mass, repeated with a 1.5, 3, 4.5kg load. With & without exo conditions. EMG for elbow & shoulder flexion/ extension.	5	(23-28 years, 168-183 cm)	The IEMG of every muscle is significantly decreased when the user wears the exoskeleton	[37]
11	**Shoulder**	PAEXO passive exoskeleton	TH	Shoulder – Joint support	P	Passive (S)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Physiological	Human-exoskeleton analysis	T1: Screwing nuts continuously, and T2: Drilling using an electric drill (1.3 kg)	12	6 M and 6 F (24 ± 3 years, 176 ± 15 cm, 73 ± 15 kg)	The mean EMG amplitude of all evaluated muscles was significantly reduced when the exoskeleton was used. This was accompanied by a reduction in both heart rate and oxygen rate. The kinematic analysis revealed small changes in the joint positions during the tasks.	[38]
12		Parallel-structured upper limb exoskeleton	LC	Arm – Load assist	A	Hypoid gear	2	12	Force-position hybrid	Angle sensors	Not reported	Kinematics	Human-exoskeleton analysis	Assisted by the exoskeleton, operator try to lift a 20kg load	1	Not reported	Structure can lift load up to 1.5 times of the exoskeleton's mass	[39]
	(includes wrist)	ABLE exoskeleton	TH	Arm – Load assist	A	Not reported	7	Not reported	Force-position control	Not reported	Not reported	Not reported	Human-exoskeleton analysis	Biomechanical task analysis - tool holding above head with 5 shoulder compensation torques. With & without exo condition.	8	(24 ± 7 years, 63 ± 11 kg, 170 ± 5 cm) right-handed	Setting compensation to 1.935 kg.m led to disturbance of subjects' natural movements. Excluding Trial 5, strongest arm torques reduction occurs for Trial 3 (38.8%)	[40, 41]

Table 2 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
13	**Shoulder**	Shoulder exoskeleton	TH	Shoulder – Joint support	P	Passive (S)	Not reported	2	Not applicable	Not applicable	Not applicable	Physiological	Human-exoskeleton analysis	Repetitive lifting and placement work	5	(20-24 years)	Exoskeleton can reduce the muscle activity of shoulder muscle	[42]
14		Hyundai Vest Exoskeleton (H-VEX)	TH	Arm – Limb support	P	Passive (S)	1	2.5	Not applicable	Not applicable	Not reported	Physiological	Human-exoskeleton analysis	Biomechanical task analysis - tool holding above head. With & without exo conditions. High & low task, with & without load.	10	(34.9 ± 3.96 years, 173.7 ± 6.20 cm, 72.1 ± 12.85 kg)	Assistive torque provided by H-VEX was shown to significantly decrease activation of the shoulder-related muscles during target tasks	[43]
15		Airframe	LC	Arm – Limb support	P	Not reported	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human-exoskeleton analysis	Static task - 3.5 kg on forearm. Repeated manual handling task - pick & place 3.4 kg. Precision task - tracing a continuous wavy line at shoulder height. Cognitive assessment -RPE. Time to complete. With & without exo condition.	29	M (51.5 ± 4.7 years, 81.6 ± 9.1 kg, 174.9 ± 2.3 cm)	Static = 31.1% relative longer time length with exo. Manual handling = Results are comparable. Precision = A significant 33.6% increase of the number of traced arches with exo.	[25, 26]
														Controlled real work tasks: Mounting the clips of brake hoses underbody, sealing underbody using the sealing gun & mounting the seal on the rear door. With & without exo condition.	11	(177.2 ± 5.0 cm, 81.1 ± 7.3 kg, 45.8 ± 6.9 years)	Workers provided positive feedback for the exo as it helped to carry out tasks with less physical & mental effort. There was some potential interference of the exo during the mounting task.	[26]
16	**(includes hip)**	CANE	IP	Back – Joint support	A	Pneumatic (PnC)	Not reported	Not reported	Flow solenoid valve	IMUs	Not reported	Biomechanical task analysis - IMUs	Human-exoskeleton analysis	Lift concrete blocks from the floor to 0.4m platform and return for 3 mins. With & without exo conditions. IMUs.	4	Not reported	A reduction in angle of waist bend by 32 degrees & shoulder twist by 17 degrees was seen while wearing the exo.	[44]

Note: Results interpreted by authors were 'Purpose', 'Task Analysis' and 'Testing Performed'.

Key:

PURPOSE: IP=injury prevention, LC= load carrying, TH= tool holding, Am= amplification.

ACTUATION METHOD: A= active, P= passive.

ACTUATORS: EM= electric motor, BoC= Bowden cable, AM= artificial muscle, PnC= pneumatic cylinder, LA= linear actuator, S= spring, HD= harmonic drive, HyC= hydraulic cylinder.

CONTROL METHOD: PI= proportional-integral, PD= proportional-derivative, PID= proportional-integral-derivative, EMG= electromyography.

SENSORS: FSR= force sensitive resistor, IMUs= inertial measurement unit, EMG= electromyography.

EVALUATION DETAILS: exo= exoskeleton, ROM= range of motion, GRF= ground reaction force, EMG= electromyography, CoP= centre of pressure, CoG= centre of gravity, HR= heart rate, RPE= rate of perceived exertion, IMUs= inertial measurement unit, M= male, F= female

Table 3 Exoskeleton classification for squat/deadlift

Row	**Supported Joint**	**Device Name**	**Purpose**	**Targeted Assistance**	**Actuation Method**	**Actuators**	**DOF**	**Mass (kg)**	**Control**	**Sensors**	**Load Capability (kg)**	**Task Analysis**	**Testing performed**	**Test details**	**Sample size**	**Participant details**	**Results**	**Ref.**
		Operational Details											**Evaluation Details**					
1	**Ankle – knee - hip**	Fortis	TH	Arm – Load transfer	P	Passive (S & counter-weight)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	[45]
2		HEXAR-CR50	LC	Leg – Load assist	A	Electric (EM & HD)	7	Not reported	PID control	Muscle volume sensor	30	Gait analysis for ROM, peak moments & peak power	Human-exoskeleton analysis	Walking at 3 km/h with 10 & 20 kg loads. With & without exo condition. EMG, GRF.	1	(29 years, 75 kg)	Reduction in leg muscle activations & GRF during 30 - 70% walking phases while wearing the exo.	[46]
3		Lower extremity exoskeleton with power-augmenting purposes	LC	Leg – Walking assist	A	Electric (EM & HD)	14	Not reported	Swing control method	Absolute/ incremental encoders, strain-gauge sensor	Not reported	Not reported	Human-exoskeleton analysis	Left leg swings back & forward, EMG measured at the quad.	1	M (34 years)	Reduction in quad muscle activation	[47]
4		Lower extremity exoskeleton	LC & Am	Leg – Walking assist	A	Hydraulic (HyC)	Not reported	30	PID & H∞ control	Encoders, force sensors	60	Kinematic modelling	Characteristics of the control system	Walking carrying 60 kg load. Squat with no load.	Not reported	Not reported	Walking bearing 60 kg load and squat action with no external load are realized effectively by this proposed control method	[48, 49]
5		Servo controlled passive joint exoskeleton	LC	Leg – Load transfer	A	Electric (EM & ratchets)	8	6	Not reported	Force sensor	30	Not reported	Exoskeleton structural design	Finite element analysis for joint reaction forces & moments & resultant deformation of the structure during postural changes.	Not applicable	Not applicable	The ankle joint sees the largest amount of stress and deformation compared to the knee and hip.	[50]
6		Lower-limb anthropo-morphic exoskeleton	LC & IP	Leg – Walking assist	A	Electric (EM)	8	Not reported	Impedance & supervisory control	Torque, position & GRF sensors	Not reported	Gait cycle	Human-exoskeleton analysis	Walking carrying 10 kg load for 10 m. With exo in passive mode, with exo in active mode & without exo conditions. EMG.	4	(25 ± 5 years, 77 ± 7 kg, 169 ± 2 cm)	An average reduction in muscle activity of 43.4% (Right Vastus intermedius) & 60.4% (Right Gastrocnemius) was seen when the exo was worn in active mode compared to no exo.	[51]
7		HIT-LEX	LC	Leg – Load assist	A	Electric (EM & S)	14	Not reported	PID control	In-Sole Sensing Shoe - Film pressure force sensors, strain sensor, angle sensors	Not reported	Gait cycle	Characteristics of the control system	Two experiments of foot lifting & landing & single leg stepping forward.	Not reported	Not reported	Exo could rapidly identify different working conditions & flexibly follow the swing leg movement.	[52, 53]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
8		Hydraulically Powered Exoskeletal Robot (HyPER)	LC	Leg – Load assist	A	Hydraulic (HyC)	10	Not reported	Not reported	Inclinometer, absolute encoders, insole sensor, FSRs	Not reported	Gait cycle for force transmission ratio	Characteristics of the control system	Stand-to-sit movement & walking experiment (0.83 m/s, 0 % grade, 10 min) with no load, 10, & 20 kg. GRF. With & without exo condition.	1	M (35 years, 75.1 kg, 176 cm)	In the standing position the GRF was not affected by a change in the payload & was reduced below wearers body weight in a semi-squat with exo.	[54, 55]
9		Lower Extremity Exoskeleton System	LC	Leg – Load assist	A	Hydraulic (HyC)	10	Not reported	PI control	Force sensors in - shoe, load cells	Not reported	Not reported	Exoskeleton structural design	Mechanical simulation in Matlab.	Not applicable	Not applicable	Not reported	[56, 57]
10		PRMI Exoskeleton	LC & IP	Leg – Walking assist	A	Electric (EM & HD	10	Not reported	Global fast terminal sliding mode & PD control	Encoders, inclinometers, foot pressure sensors	20	Kinematic modelling	Characteristics of the control system	Walking experiment (4.7 km/h) with a 20 kg load.	1	M (25 years, 61 kg, 175 cm)	The joint position tracking errors are maximum of 2° at the hip joint and 4° at the knee joint. These results confirm that the exoskeleton swing leg is able to shadow human motions in time by using the proposed controller.	[58]
11		Under-actuated lower extremity exoskeleton	LC	Leg – Load assist	A	Electric (EM, HD & springs)	6	Not reported	PID control	Muscle volume, insole sensors	Not reported	Not reported	Characteristics of the control system	Measure the effect of the exo on percentage maximum voluntary contraction via EMG. With & without exo condition.	Not reported	Not reported	Average decrease in %maximum voluntary isometric contraction of the leg muscles of 40.5% on level surface and 12.5% climbing stairs when wearing the exo.	[59]
12		Lower extremity exoskeleton (LEE)	LC	Leg – Load assist	A	Electric (EMs & LA)	5	Not reported	Zero moment point control	Force sensors in foot pad	Not reported	Gait cycle for CoP	Characteristics of the control system	Walking test forward & backward.	Not reported	Not reported	The exoskeleton can walk stably with the user.	[60, 61]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
13	**Ankle – knee - hip**	HUALEX	LC	Leg – Load transfer	A	Electric (EM & HD)	10	15	Fuzzy-based variable impedance control	Encoders, IMUs, FSRs in foot pad	40	Kinematic modelling	Characteristics of the control system	Walking test with 30 kg load at speeds of 0.30m/s to 1.20m/s. Comparing the fuzzy-based variable impedance control to normal impedance control.	3	(70.83 kg)	The control fuzzy based impedance control strategy tracked human motion well and decreased interaction forces across all walking speeds compared to normal impedance control.	[62]
14		HUALEX	LC	Back – Load assist	A	Hydraulic (HyC)	7	Not reported	Hybrid Control combining zero-force control and zero-load control	tension and compression pressure sensor	25	Kinematic modelling	Comparison of control systems	Not reported	Not applicable	Not applicable	Hybrid control strategy can reduce interaction force between the pilot and the exoskeleton efficiently	[63]
15		Passive wearable moment restoring device	LC & IP	Back – Load assist	P	Passive (S & cables)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Kinematic modelling	Human-exoskeleton analysis	Lift and lower loads (4.5 & 13.6 kg) twice. With & without exo conditions. Motion capture & EMG.	6	5M & 1F (27.7 ± 6.0 years, 67.7 ± 7.2 kg, 175 ± 0.06 cm)	With the device, back muscles demonstrated a 54% reduction in muscle activity and calculations suggested a reduction in maximum spine compressive forces by approximately 1300 N.	[64]
16		ExoHeaver	LC	Leg – Load assist	A	Electric (EM)	Not reported	26	Servo control	Not reported	15	Kinematic modelling	Exoskeleton structural design	Not reported	Not reported	Not reported	Not reported	[65]
17		Hip,knee, ankle exoskeleton	LC	Leg – Load assist	A	Electric (EM)	Not reported	Not reported	Super twisting sliding mode controller	Not reported	15	Simulation	Characteristics of the control system	Control of the transferring of the force to the hip of a lower extremity exoskeleton while carrying load	Not applicable	Not applicable	It provides better control over PID with uncertainties and disturbances	[66]
18		Biomimetic lower limb exoskeleton (BioComEx)	LC	Leg – Walking assist	A	Variable stiffness actuator & SEA	Not reported	15	Closed-loop impedance control algorithm	Force sensors	Not reported	Biomechanical	Human-exoskeleton analysis	Not reported	1	Not reported	BioComEx is sufficiently satisfactory for walking applications	[67]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										Evaluation Details						
19	Ankle – knee - hip	Wearable lower-body exoskeleton	LC	Leg – Limb support	A	Electric (EM)	6	11	Dual EKF sensor-less (user) joint torque estimation, LQG torque amplification control, and supervisory control	Joint angle potentiometers; and insole GRF sensors on each foot	Not reported	Biomechanical & physiological	Human-exoskeleton analysis	Lift a box weighing 4.3 kg from the floor, hold for a while, and then drop back on the floor, six consecutive times with and without assistance from the prototype exoskeleton suit	5	(28 ± 5 years, 178 ± 2 cm, 76 ± 5 kg)	Average recorded EMG signals taken at the right Vastus Intermedius (Quadriceps) and right Gastrocnemius (calf muscles) of each participant revealed more than 36% reduction in muscle activity from the two-muscle groups	[68]
20		DSME-HWR	LC	Leg – Load assist	A	Electric (LA)	2	4.5	Compliance control algorithm - PD control	Not reported	Not reported	Biomechanical analysis – MoCap & GRF	Human-exoskeleton analysis	Knee joint optimisation. Original knee joint vs. optimised design for user exertion on exo with heavy load (30 kg). Force, joint angle & time to complete.	1	M	Original knee: Force = 392N, Time = 2.3s, Angular velocity = 60.9deg/s. Optimised design 1: Force = 43N, Time = 2.1s Angular velocity = 49.5deg/s. Optimised design 2: Force = 147N, Time = 2.0s, Angular velocity = 60 deg/s.	[27, 69-72]
21	Knee	Knee Assist Robotic Exoskeleton	IP	Leg – Walking assist	A	Electric (EM & S)	Not reported	Not reported	Torque control	Not reported	Not reported	Not reported	Characteristics of the control system	The participant walked & performed a sit-to-stand motion.	1	M (26 years, 85 kg, 171 cm)	The exo performed as expected for its 3 different control phases.	[73]
22		Soft knee exoskeleton	IP	Knee – Joint support	A	Electric (EM)	1	Not reported	Two-level configuration architecture for torque control	IMUs	Not reported	Biomechanics - Physiological	Human-exoskeleton analysis	15 squat cycles in six conditions (without wearing the exoskeleton, power-off exoskeleton, zero torque control, 10%, 30%, and 50% assistance	3	subject1: (25 years, 170 cm, 70 kg) subject 2: (32 years, 178cm) subject 3: (38 years, 175 cm, 85 kg)	The assistive control reduced the muscle effort of knee extensor	[74]
23		Knee exoskeleton	LC & IP	Knee – Load assist	A	Electric (LA)	1	Not reported	Arduino UNO	EMG	Not reported	Biomechanics	Human-exoskeleton analysis	Two cycles of the knee flexion and extension	1	(63 kg, 160 cm)	The experimental and theoretical values of the joint angle and shank's angular velocities are validated for the kinematic design	[75]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										Evaluation Details						
24	Knee	Exoskeleton intelligent portable system	LC	Knee – Load assist	A	Electric & Hydraulic (EM & HyC)	1	Not reported	Hydraulic pressure, PID control	Pressure sensor, encoder	30	Not reported	Characteristics of the control system simulation	Simulation of actual and expected knee angle and actuator location.	Not applicable	Not applicable	Control method can follow the natural motion of the knee.	[76]
25	Hip	Muscle Suit	LC	Leg – Load assist	A	Pneumatic (AM)	Not reported	8.1	Switches	Not reported	Not reported	Not reported	Human-exoskeleton analysis	Hold load (20 kg) for 15 seconds for 3 trials. With & without exoskeleton condition. EMG.	10	Not reported	EMG values averaged across the 3 trials were reduced in the arms while wearing the exo.	[77]
26	Hip	Lower-Back Robotic Exoskeleton	LC & IP	Back – Load assist	A	Electric (SEA & HD)	4	11.2	Admittance control & finite state machine	Encoder, IMUs, torque sensor, strain gauge	Not reported	Not reported	Human-exoskeleton analysis	Symmetrical loading (0, 5, 10, 15 & 25kg) & lift origin asymmetry (45°) (15 & 25kg) lifting & lowering task. With & without exo conditions. EMG.	1	M	The exo significantly reduces muscle activation of the back during symmetrical loading & for the lift origin asymmetry, larger muscle activations occurred with the device assisting the hips for flexion/extension & add/abduction.	[78]
27	Hip	H-WEX	LC & IP	Back – Joint support	A	Electric (EM, HD & Pulley)	8	4.5	Motion & torque control	Hall sensor, IMUs	15	Not reported	Human-exoskeleton analysis	Pick 15kg load from ground to pelvic height. Squat & stoop posture conditions. With & without exo conditions. EMG for hip flexion/ extension.	9	M (33.4 ± 2.4 years, 73.0 ± 9.0 kg, 173.2 ± 4.5 cm)	Decrease in muscle activity of the muscles related to waist motions (back and abdominals) of between 10-30% while wearing the exo.	[79]
28	Hip	APO	LC & IP	Back – Load assist	A	Electric (EM, SEA)	4	Not reported	Lift detection	Encoders, IMUs	Not reported	Not reported	Characteristics of the control system	2 sessions for training lift detection algorithm, using 3 initial positions & 3 lifting techniques for 5 kg box. 1 session for testing algorithm. EMG, IMUs.	7	M (27.9 ± 2.3 years, 70 ± 6.4 kg, 178.1 ± 8.1 cm)	Accuracy of 97.48 ± 1.53% was achieved for lift detection with a time delay of <160ms. EMG showed at least 30% reduction in back muscle activation when the exo provided torque.	[80, 81]
												Not reported	Human-exoskeleton analysis	Walking on treadmill, varied speeds and level of exo assistance. With & without exo conditions. Hip joint angle, torque & motion capture.	5	(29.2 ± 6.3 years, 74.4 ± 6.8 kg, 173 ± 7 cm)	Negligible interference of the exo in human kinematics. Small displacements in the exo-human interaction points.	[82]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
29	Hip	Robo-Mate - Mk2	LC & IP	Back – Load assist	A	Electric (Parallel elastic actuator - EM, HD)	1	Not reported	PD & Torque control	Torque sensor	15	Not reported	Characteristics of the control system simulation	Evaluating the differences in the torque control transparency when used with the parallel elastic actuator and the actuator without parallel elasticity.	Not applicable	Not applicable	Significant improvements in torque-control performance, thus encouraging the use of parallel-spring arrangements	[83]
												Not reported	Human-exoskeleton analysis	Pick & place loads (7.5 kg ,15 kg). With & without exo conditions. EMG, interface pressure, perceived comfort & usability.	12	M (27 ± 2 years, 75.38 ± 10.1 kg, 179.4 ± 0.65 cm)	Reduced muscle activity of the Erector Spinae (12%-15%) & Biceps Femoris (5%).	[84]
												Not reported	Accuracy of the sensor system	Compare 3 strategies for input into controller to follow user intention. IMUs, EMG & finger pressure sensor. Lift & lower load (2 x no load, 5 & 10kg) for each strategy.	13	11M & 2F (28.9 ± 4.3 years, 69.8 ± 10.6 kg, 178 ± 6.6 cm)	The IMUs strategy generated a reference signal that shows little dependence on load, by contrast, the EMG & finger pressure strategies show a stronger relationship.	[85]
								11				Biomechanics - Physiology	Human-exoskeleton analysis	Lifting task with three different techniques; FREE, SQUAT and STOOP, once with NO EXO and three times with the EXO (INCLINATION, EMG &HYBRID)	10	25.0 ± 6.9 years, 70.9 ± 8.8 kg,1.77 ± 0.06 m	Compression forces with the EXO were substantially lower compared to NO EXO. However, no single EXO control mode was superior over the others due to performance limitations of the actuators	[86]
												Kinematic modelling	Characteristics of the control system	Walking, standing and bending	1	Not reported	Study shows that it is possible to perform reliable online classification	[87]
30		Stand-alone powered exoskeleton robot suit	LC	Back – Load assist	A	Electric (EM, HD)	Not reported	8	Not reported	Encoders	Not reported	Biomechanical analysis	Human-exoskeleton analysis	Flexion/extension of trunk with load (33 kg). Torque, time to complete	Not reported	Not reported	The motion was completed in 0.7 seconds with load, where this is 0.49 seconds longer than that of the no-load condition.	[88]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
31		Laevo	IP	Back – Joint support	P	Passive (S)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human-exoskeleton analysis	Objective & subjective measures for 12 functional tasks.	18	M (27.7 ± 5.1 years, 74.7 ± 8.0 kg, 178 ± 6 cm)	Decreased the local discomfort in the back in static holding tasks and at the dorsal side of the upper legs in static forward bending. Showed adverse effects on tasks that require large ROM of trunk or hip flexion including walking.	[24]
												Physiology	Human-exoskeleton analysis	Lift and lower a 10-kg box (0.39 0.37 0.11 m, with 2.5 cm diameter handles) at a rate of 6 lifts per minute (for 5min)	13	28.9 years (4.4), 1.80 m (0.04) m and 76.9 kg (12.0)	Wearing the exoskeleton during lifting, metabolic costs decreased as much as 17%. In conjunction, participants tended to move through a smaller range of motion, reducing mechanical work generation	[89]
32	**Hip**	Laevo V2.4	IP	Back – Joint support	P	Passive (S)	Not reported	Not reported	Not reported	Not reported	Not reported	Biomechanics - Physiology	Human-exoskeleton analysis	Motion and surface EMG were measured during two consecutive periods of at least 30 min, one with and one without the exoskeleton	10	mean age and BMI of the participants was respectively 45.6 (SD 11,64) and 26.9 (SD 2,78)	RMS values were significantly higher for the Trapezius muscle with the exoskeleton (Mdn = 44.02) compared to the measuring period without the device (Mdn = 34.83, T = 0, p < 0.05, r = −.73); No differences were found for Erector Spinae and Biceps Femoris muscle activity. Participants reported significantly higher discomfort scores for the upper back/chest and thigh region with the exoskeleton (both p < 0.05, r = −.68).	[90]
33		Robo-Mate exoskeleton	LC & IP	Back – Load assist	A	Electric (Parallel elastic actuator - EM, HD)	Not reported	Not reported	Not reported	Not reported	15	Biomechanical analysis – MoCap, EMG & GRF	Exoskeleton structural design	Simulation of lifting and lowering tasks with exo to test actuator performance.	Not applicable	Not reported	The results show the improvement in peak torque and peak power by 20%, 50% and 40% respectively as compared with the current prototype	[91]
									Acceleration-based torque control	Trunk angular acceleration	Not reported	Physiology	Human-exoskeleton analysis	Lifting and the lowering of an external load of 5kg and 10kg, repeated at three different speed: fast, normal and slow	7	Not reported	The data on peak muscular activity at the spine show promising trends	[92]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										Evaluation Details						
34	Hip	Hip-type exoskeleton	LC & IP	Back – Load assist	A	Electric (EM)	1	Not reported	Not applicable	Sensor-less force estimator	Not reported	Physiological	Human-exoskeleton analysis	Lift load from 0 to 25 kg (5kg increments) load from the ground. With & without exo condition. EMG.	10	Average age 30 years, height 176 cm & mass 75 kg	EMG value was significantly lower when the exoskeleton on in all loading conditions	[93]
35	Hip	Spine exoskeleton	LC	Back – Joint support	A	Electric (EM)	9	Not reported	Torque control	Torque sensor	Not reported	Biomechanics - Physiology	Human-exoskeleton analysis	Repetitive, stoop-lift of a 10kg box at different speeds	5	(21 – 36 years, 60 – 82.12 kg, 170 – 182 cm)	All cost functions reduced significantly the human torque loads. However, they result in different amounts and distributions of the load reduction as well as different contributions from the passive and active components of the exoskeleton	[94]
36	Hip	VT-Lowe's exoskeleton	LC	Back – Load transfer	P	Passive (Flexible beams)	Not reported	Not reported	Not reported	Not reported	Not reported	Physiology	Human-exoskeleton analysis	Stoop, squat and freestyle lifting trials performed in the sagittal plane, plus lift origin asymmetry (60°) for 0% and 20% of subject bodyweight, both with and without exoskeleton	12	22.75 (4.35) years, 178.92 (6.05) cm, 80.41 (5.59) kg and 25.16 (1.91) kg/m2	Results demonstrated that the exoskeleton could reduce the average peak and mean muscle activation of back and leg muscles regardless of different levels of box mass and lifting types.	[95]
37	Hip	Booster exoskeleton	IP	Back – Joint support	P	Springs	Not reported	Not reported	Not applicable	Not applicable	Not reported	Physiology	Human-exoskeleton analysis	Carry and lift the object weighing 9.5 kg	3	Not reported	With wearing the exoskeleton, the subjects' breathing, and heart rate were significantly reduced	[96]
38	Hip	Back assistance exoskeleton	LC	Back – Joint support	A	Pneumatic artificial muscle	Not reported	7.6	Not reported	Not reported	18	Physiology	Human-exoskeleton analysis	Romanian deadlift motion of lifting 15 kg repeated 10 times at a time, totalling 5 times	1	Not reported	Decreased level of 20% to 30% in muscle activation when lifting the loads with exo	[97]
39	Hip	Wearable waist exoskeleton	IP	Back – Joint support	A	Electric (EM)	1	5	Torque control	Angle, angular velocity and current	Not reported	Physiology	Human-exoskeleton analysis	Symmetrical lifting for six different objects (0, 5, 10, 15, 20, 25 kg) under two conditions of with and without the exoskeleton	10	Average [26 years, 70 kg, 174 cm]	The exoskeleton significantly reduced the back muscular activity during repetitive lifting tasks	[98]

Table 3 continued…

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										Evaluation Details						
40	Hip	HAL	IP	Back – Joint support	A	Not reported	1	Not reported	EMG based control	Triaxial accelerometer and potentiometers	Not reported	Physiology	Human-exoskeleton analysis	2 sessions (one with HAL and one without HAL) of stoop lifting/placing, until they feel they cannot continue. In each session, subjects were asked to lift and place a small box, (for males, 12 kg, for females, 6 kg).	20	13 M, 7 F (31.5 ± 6.6 years)	Muscle coordination changes were dominated by changes in timing coefficients, with minimal change in muscle synergy vectors	[99]
41	Hip	SJTU-EX	LC	Back – Load assist	A	Electric (EM)	8	Not reported	Not reported	Not reported	Not reported	Not reported	Exoskeleton structural design	Walking simulations	Not applicable	Not reported	Not reported	[100]
42	Hip	Wearable Exoskeleton Power Assist System	LC & IP	Back – Load assist	A	Electric (EM)	1	11	User intention via EMG	EMG	Not reported	Kinematic modelling	**Human-exoskeleton analysis**	Lift and lower load 20 kg load from/to ground. With & without exo condition. EMG.	Not reported	Not reported	Muscle activation of the thigh muscles was reduced when wearing the device.	[101]
43	Hip	SPEXOR	LC & IP	Back – Joint support	P	Passive (Flexible beams)	4	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human-exoskeleton analysis	ROM testing, trunk flexion/ extension, lateral bending & rotation. 4 exo configuration conditions. Motion capture.	3	M (30 years, 66 kg, 171.5 cm)	Using flexible beams as a back interface increases the trunk range of motion by more than 25% compared to its rigid counterpart. With the flexible beams, the range of motion is only decreased by 10% compared to not wearing an exo.	[102]

Note: Results interpreted by authors were 'Purpose', 'Task Analysis' and 'Testing Performed'.
Key:
PURPOSE: IP=injury prevention, LC= load carrying, TH= tool holding, Am= amplification.
ACTUATION METHOD: A= active, P= passive.
ACTUATORS: EM= electric motor, BoC= Bowden cable, AM= artificial muscle, PnC= pneumatic cylinder, LA= linear actuator, S= spring, HD= harmonic drive, HyC= hydraulic cylinder.
CONTROL METHOD: PI= proportional-integral, PD= proportional-derivative, PID= proportional-integral-derivative, EMG= electromyography.
SENSORS: FSR= force sensitive resistor, IMUs= inertial measurement unit, EMG= electromyography.
EVALUATION DETAILS: exo= exoskeleton, ROM= range of motion, GRF= ground reaction force, EMG= electromyography, CoP= centre of pressure, CoG= centre of gravity, HR= heart rate, RPE= rate of perceived exertion, IMUs= inertial measurement unit, M= male, F= female

Table 4 Exoskeleton classification for shoulder/chest-press, isometric arm hold and squat/ deadlift

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
1	**Spine**	Passive spine exoskeleton	IP	Back – Joint support	P	Passive (S & pulley)	1	Not reported	Not applicable	Not applicable	Not reported	Kinematic modelling	Human-exoskeleton analysis	Dynamic - flexion/extension for 120 s with a constant speed. Static - hold 3 flexion positions (small, medium, & full-range) for up to 120 s. EMG, IMUs. With & without exo condition.	3	M (26.7 ± 3.3 years, 68.3± 6.7 kg, 172 ± 12 cm)	EMG reduction at lumbar (24%) & thoracic (54%) level with exo & a reduction of intervertebral bending moment (36N.m) & muscle force (479N).	[103]
2		Spine-inspired continuum soft exoskeleton	IP	Back – Joint support	A	BoC	3 for each disc	Not reported	Virtual impedanc e model	Load cell	Not reported	Biomechanics	Human-exoskeleton analysis simulation	Stoop lifting of 15 kg with 10 repetitions	3	Not reported	Able to successfully track the desired force with high accuracy.	[104]
3		FLx	IP	Back – Joint support	P	Passive	Not reported	1.08	Not reported	Not applicable	Not applicable	Biomechanics	Human-exoskeleton analysis simulation	A 3 × 3 x 2 × 2 repeated measures design was employed in this study, in which all combinations of intervention (FLx exo, V22 exo, none), lift origin height (shin, knee, waist), lift origin asymmetry (0° & 45°), & load mass (9.07 kg & 18.14 kg) were evaluated	10	(24.9 ± 5.0 years, 81.1 ± 16.1 kg, 179.4 ± 4.6 cm)	FLx reduced peak torso flexion at the shin lift origin, but differences in moment arms or spinal loads attributable to either of the interventions were not observed. Thus, industrial exoskeletons designed to control posture may not be beneficial in reducing biomechanical loads on the lumbar spine.	[105]
4		V22	IP	Back – Joint support	P	Passive	Not reported	1.29	Effectors worn on the hand	Not applicable	68							
5		Exoskeleton for the back	LC & IP	Back – Joint support	A	Pneumatic (PnC)	Not reported	Not reported	User intention	EMG	25	Biomechanical simulation	Human-exoskeleton analysis simulation	Measure of forces to the back based on a human-machine model.	Not applicable	Not applicable	A decrease of the forces by 35% on the L5-S1 joint & by 43% on the back muscles can be noted at the beginning of the lift.	[106]
6	**Full Body**	Robot Suit HAL	LC	Back – Load assist	A	Electric (EM & HD)	14	Not reported	Torque control based on EMG	EMG, potentiomet ers, IMUs, ground reaction force sensors	50	Kinematic modelling	Characteristics of the control system	Measure joint angles and bio-signals while holding load (50 kg).	1	M (26 years)	The designed locking mechanism included in the power units kept the angles of the upper limbs steady while the user held the load, and the physical burden on the upper limbs of the user was reduced.	[107]

Table 4 continued…

	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Mass (kg)	Control	Sensors	Load Capability (kg)	Task Analysis	Testing performed	Test details	Sample size	Participant details	Results	Ref.
		Operational Details										**Evaluation Details**						
7	**Full Body**	UTRCEXO	LC	Leg – Walking assist	A	Electric (EM & HD)	8	Not reported	Position & torque control. Walking intention	encoders, FSRs, force/torque sensor	Not reported	Gait analysis for GRF & motion capture	Human-exoskeleton analysis	Walking with 10 kg mass.	1	(73 kg, 176 cm)	Detects step initiation using the insole type FSRs prior to movement. Allows the operator to easily walk with a 10 kg load. Does not take the operator's desired step velocity into account.	[108]
8	**Full Body**	Body Extender (BE)	LC & Am	Full body – Load assist	A	Electric (EM)	22	160	User triggered motion	Encoders, accelerometer, force/torque sensors	50	Not reported	Human-exoskeleton analysis	Assess the tracking (with and without load) and the grasping/ lifting/ handling (up to the rated load) capabilities of the device.	Not reported	Not reported	Maximum resistance forces of 30 N are well tolerated by the user, good weight distribution of the device, walking phase somewhat unnatural. At max rated load the system equilibrium becomes unstable	[109]

Note: Results interpreted by authors were 'Purpose', 'Task Analysis' and 'Testing Performed'.
Key:
PURPOSE: IP=injury prevention, LC= load carrying, TH= tool holding, Am= amplification.
ACTUATION METHOD: A= active, P= passive.
ACTUATORS: EM= electric motor, BoC= Bowden cable, AM= artificial muscle, PnC= pneumatic cylinder, LA= linear actuator, S= spring, HD= harmonic drive, HyC= hydraulic cylinder.
CONTROL METHOD: PI= proportional-integral, PD= proportional-derivative, PID= proportional-integral-derivative, EMG= electromyography.
SENSORS: FSR= force sensitive resistor, IMUs= inertial measurement unit, EMG= electromyography.
EVALUATION DETAILS: exo= exoskeleton, ROM= range of motion, GRF= ground reaction force, EMG= electromyography, CoP= centre of pressure, CoG= centre of gravity, HR= heart rate, RPE= rate of perceived exertion, IMUs= inertial measurement unit, M= male, F= female

4. Discussion

The aim of this review was to analyse the current literature to identify characteristics of industrial exoskeletons that can be useful to military manual handling tasks. The high percentage of exoskeletons targeting load carrying reflects the industry need for devices that can support manual handling workers by preventing injuries and improving productivity. Therefore, the application of these exoskeletons to Australian Defence Force personnel performing manual handling could help reduce the substantial personal and financial cost of injuries.

Most of the exoskeletons included in this review are in early development and are designed to support manual handling via a number of methods, such as providing assistive torque to enhance the ability of joints to carry external loads (e.g., [28, 78, 79, 84], providing loading pathways that bypass the user's joints (e.g., [51] and/or providing support or limiting the joint movement to prevent harmful motions (e.g., [103]).

There were a large number of squat/deadlift (lower limb) exoskeleton devices (56%) with 27% of devices supporting the ankle, knee and hip joint and 26% solely supporting the hip. 95% of the hip supported devices aim to assist the lower back (e.g., [78, 80, 88]). This could be due to the prevalence of lower back injuries and their correlation to lifting from the ground [110] and hyperflexion of the lumbar spine [111], which is controlled by the hip joint (categorised as a part of the squat/deadlift systems). Exoskeletons assisting the back actuate from the hip to minimize the increased torques to the lower back caused by hyper flexion during lifting. However, since spine motion has multiple DOF [112], exoskeletons actuating from the hip on a single plane (1 DOF, i.e. flexion/extension) may result in movement restriction where physiological rotation and lateral bending of the spine are impeded resulting in increased effort [113] or reduced performance [114, 115].

Task analysis prior to the design of an exoskeleton could be beneficial for better support of manual handling tasks. Thirty percent of studies in this review reported performing a priori task analysis. Through this analysis the operational complexity of the exoskeleton (type of actuation, DOF, the control system and the method of power transmission) could be optimised for specific tasks. For instance, with biomechanical analysis of the task, it is possible to identify which joints undergo high moments and which ones are allowed free movement (e.g., [88]); this informs the choice of how many DOF should be allowed at a joint for that task, as well as how much support should be provided. As active actuators can face issues such as big size, heavy mass, bulkiness, inefficient force transmission, low speed and inaccurate control [9, 116], the power-to-weight ratio should be optimized in order to provide the minimum assistance needed to support the specific joint for the requirements of the task (e.g., [91]) and to replace some actively actuated joints with passive actuators where appropriate (e.g., [27, 30]). Optimisation could therefore lead to a reduction in mass, inertia, friction, and complexity of the exoskeleton while increasing its efficiency, thus allowing for lower interaction force between the exoskeleton and the user and better control.

Although the majority of studies indicated that exoskeletons could reduce muscle activation, evidence was not conclusive with studies reporting an increase in muscle activations of the antagonist muscles [28] (Table 2, Row 1). Therefore, EMG signals should be recorded from antagonist muscles, as well as from those muscles acting at joints other than the one supported by the exoskeleton [117]. Although methodologically challenging, the concomitant use of EMG on agonist and antagonist muscles will provide a measure of exoskeleton interference with pattern of muscle activation which are essential for proper movement coordination and low energy cost [99, 118, 119].

Control strategies also play a large part in the optimisation of an exoskeleton system. Exoskeleton designers in this review tested the exoskeleton control strategies for 1. their ability to follow the user's joint motions, 2. exoskeleton stability, and 3. load reduction for the duration of the task. A few exoskeleton systems looked into user intention (e.g., [106]) and task recognition (e.g., [80]) control strategies, as well as impedance control systems, that assist when a movement deviates beyond a threshold of the desired motion [120] (e.g.,[54, 59, 96]). These strategies could provide the information needed to develop smooth motion and predictive human-intention algorithms, creating smarter, more efficient exoskeleton systems. With the development of predictive algorithms there is the ability to provide assist-as-needed control, reducing power consumption and preserving the musculoskeletal capacity of the user.

Findings from this review demonstrated there were no consistent methodologies used to evaluate exoskeletons for manual handling. Further development of current exoskeleton testing and reporting standards (e.g., [23]) to include military manual handling tasks (e.g., ASTM F48 committee on exoskeletons and exosuits) is critical to enable valid and reliable comparisons between future devices. However, it is worth noting that none of the included studies were of a prospective nature and only performed analysis at a single time point. Prospective studies (and the accompaying standards) could be beneficial to validate the use of exoskeletons for injury prevention or augmentation.

4.1. Military manual handling considerations

While the tasks performed by Defence personnel may be similar to those performed in industry, there are additional considerations for the use of exoskeletons in a military workplace. For instance, in-field surfaces can be uneven and loose, requiring exoskeletons to be robust and flexible to compensate for unexpected perturbations. Military manual handling exoskeletons could also face a range of weather conditions, confined spaces where the device's dimensions could be restrictive, limited access to power supply, large amounts of dust and dirt, and rough use, necessitating a durable and efficient exoskeleton design. Additionally, the necessity to integrate the device into Defence personnel's uniform or body armour should be considered.

Devices developed for load carriage, amplification or injury prevention could assist with minimising the risk of injury from carrying large loads and performing repetitive complex movements from the ground, as often performed by Defence personnel [121]. The loading required for military manual handling tasks is heavier than what would be required of personnel in many other industries [122, 123]. For instance, in a military context lift-to-platform tasks (shoulder/chest-press movement) require loads of 25.6 ± 8.5 kg to be lifted while lift-carry-lower tasks (isometric arm hold movement) require loads of 31.1 ± 17.1 kg to be carried distances of 127.8 ± 126.2 m [7]. In comparison, in an industry context, e.g., in large international airports, the mass of baggage handled by security personnel ranges between 10 and 23 kg [124]. This highlights the fact that workplace context can affect the demand of the job, thus the different need for assistance.

Control systems within this review did not provide assist-as-needed control or take into account the wearer's intrinsic abilities. Defence personnel are tested for their ability to perform tasks prior to being matched to work positions [7]. It is important that a person's intrinsic ability matches that of the task that needs to be performed [13] and that the introduction of any intervention does not diminish that capacity. Control systems that recognise and activate an exoskeleton only when required are therefore vitally important.

The findings from this review did not highlight whether current active or passive exoskeleton would be capable of sustaining the loads required by Defence personnel (Table 2-Table 4). It was unclear whether the reported load capability referred to the load limits of the exoskeleton structure and/or actuators, the load limit that the user could support, or the maximum loads required by the task in industry. Additionally, lift-carry-lower tasks are mostly unilateral (load only on one side of the body) (74%) [7] and require asymmetrical muscle activation in the spine to maintain stability due to an increase in internal torsional forces. This review found no studies that tested unilateral loading. However, three exoskeleton devices in this review were tested for lift origin asymmetry (the lift starts at an angle away from the sagittal plane), which could also cause asymmetrical muscle activations, and found that this decreased muscle activation of the ipsilateral muscles while wearing the exoskeleton [78, 95, 105]. It would therefore be beneficial for an exoskeleton to actively compensate for unilateral loads and lift origin asymmetry.

5. Conclusion

The large portion of devices targeting load carrying reflects the industry and military need for devices that can support manual handling workers with the aim of preventing injuries and improving productivity. The joint requirements for the two most common tasks in military manual handling are well represented in the current state of exoskeleton systems. The unique considerations of the military such as heavy external loads, load asymmetry, harsh environments, as-needed assistance and uniform integration mean that an adaption of current technology or a military specific design would be required for introduction into the Australian Defence Force.

6. Key points

- Although this field is fast growing, the majority of the included exoskeletons were in an early stage of development.
- Determining exoskeleton design challenges through task analysis could be useful for understanding how to better support military manual handling tasks.
- Control systems within this review did not anticipate when augmentation/ assistance was needed.
- It would be beneficial for an exoskeleton to actively compensate for unilateral external loads due to their prevalence in military manual handling tasks.
- It was unclear whether current active exoskeleton would be capable of sustaining the loads required by Defence personnel.
- Adaption of current technology would be required for the introduction of exoskeletons into a military setting.

7. Summary

Control systems within this review did not anticipate when augmentation was needed, they were either always providing assistance (e.g., [23,24,29]) or were triggered by the user (e.g., [71,95]). An exoskeleton intervention would need to contain a smart control system that can determine when the wearer is lifting beyond their safe limits and assist accordingly. A large consideration for the adaption of new technologies into the military setting is its effect on the fitness for duty of the personnel [7]. An intervention that would decrease its wearers strength over time due to it replacing the need for the wearer to apply force rather than augmenting the wearers' intrinsic ability would be detrimental [10].

An assist-as-needed control system should be able to recognise when the wearer is entering into movements with increased risk of injury, such as lifting above MAWL [14]. This could be done through the recognition of changes in spine kinematics due to the external load being heavier than the wearer can safely lift (at or above MAWL). However, before being able to develop a predictive model that uses spine kinematics to determine when a person is lifting in a safe range, the effect of increased load on spine kinematics needed to be determined. Specifically, of interest were the features or variables of the lift that were affected by increased load so that they could be implemented within the model. It was also of benefit to understand the method of collection (e.g., equipment used, locations of analysis) to determine the best way to collect a dataset for use in the model.

Chapter 3. Systematic Review: Effect of increased external load on spine kinematics during a manual handling lifting task.

This chapter aimed to determine what effect an increase in external load has on spine kinematics during a lifting task through a systematic review of the available literature. Of interest were what levels of the spine that saw an effect, what kinematics were affected (e.g., acceleration, velocity, angle), what discrete kinematics were affected (e.g., mean, peak, minimum) and how were the kinematics recorded (e.g., motion capture, IMUs). This is of importance because in order to make predictions on when a person is performing a high-risk lift, where and how this is reflected in motion needs to be understood, so those variables are made available to the algorithm. Additionally, to create a database of observations for the predictive algorithm an appropriate method of data collection needed to be performed.

1. Introduction

Lifting is a full body movement; however, it is the back that sustains many of the injuries associated with MH tasks. Biomechanical studies have researched technique, box shape, lifting height and speed of lift for ways to reduce lower back injuries, though for Defence force applications many of these variables cannot be altered.

It has been recognised that matching physical capability to job demands may be a way to reduce musculoskeletal injuries. Analysing changes in spine kinematics, determining the spine segments that are most affected and points of interest in kinematic trace, may be a way to predict when a person is approaching the limits of their physical capability to perform a task.

The aim of this review was to understand the effect that lifting an external load has on spine kinematics. The segments of the spine and the variables that see significant differences due to the increase in load would be used as predictors for classifying kinematic observations into their %MLC. Determining this was done by reviewing previous studies and extracting data to determine how external load alters spine kinematics and if it differs with increasing mass, if any segment is more affected than others and how, and the data collection and analysis techniques.

2. Methodology

2.1. Search strategy

English language journal article searches of Scopus, PubMed and Web of Science were conducted on 16 July 2021 for this review. The following search syntax was included: (lifting OR "manual handling" OR "manual material handling”) AND (spine OR "lower back") AND (biomechanics OR kinematics) AND (load OR weight OR mass).

2.2. Inclusion criteria

All studies included in the review met the following inclusion criteria: 1. evaluated human spine kinematics during experimental trials without the use of an intervention; 2. included healthy adults with no reported pathology; and 3. used two or more load conditions of symmetric external loads held in the hands for a lifting task.

2.3. Data extraction

The following data was extracted from the included studies (Table 5): 1. authors and year of study; 2. participant numbers and demographics; 3. study design; 4. tasks performed; 5. loads lifted; 6. equipment used for recording kinematics; 7. data and statistical analysis; and 8. kinematic results.

Various methods were used to determine the loads lifted such as maximum lift capacity (MLC), maximum isometric back strength (MIBS), percentage of body weight (%BW) or subjective loads. Most studies using participant specific loads, used MIBS and MLC, which were determined using load cell machines, that involved pulling an isometric bar to determine force exerted, while three studies [125-127] defined the loads using task specific methods. Where specific loads (kg) were not given, the mean load (e.g., mean %MLC, mean body weight) was used to interpolate it in Figure 10.

3. Results

3.1. Search results

The flow diagram of the search process is presented in Figure 6. Of the initial 5574 results, 138 full-text articles were read and assessed for eligibility. From the 138 full-text articles, 31 studies were included.

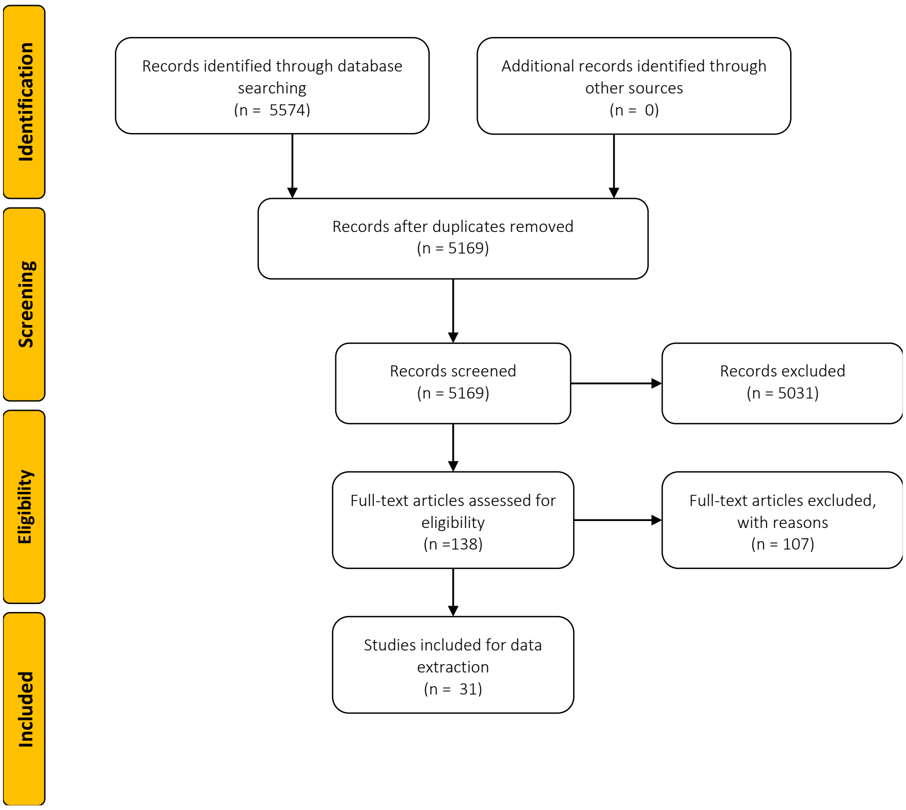

Figure 6 Flow diagram of search process.

Table 5 Extraction of kinematic spine data from reviewed articles

	(Ref) Year	Population Data	Study Design	Tasks	Loads	Equipment	Kinematic Analysis	Kinematic Results
1	[128] 2015	14 (8M, 6F, 19-30y)	Two trials per load (known, progressing low to high) measuring lumbar segmental extension of the L2-S1 vertebrae.	Stoop lifting from height of 30cm (~75° flexion) to standing upright.	4.5, 9.1, 13.6kg	Dynamic Stereo X-ray	Results of 11 participants (7M, 4F). Trials normalised to initial flexed starting position (0%) & static upright position (100%). Effect of load on lumbar spine segment contribution.	L4-L5 was the largest contributor to segmental motion (31.0 ± 3.1%). The increase in external load caused no significant change in the segmental contribution.
2	[129] 2017	14 (8M, 6F, 19-30y)	Two trials per load (known, progressing low to high) measuring lumbar AP & SI instantaneous centres of rotation (ICR) of the L2-S1 vertebrae.	Stoop lifting from height of 30cm (~75° flexion) to standing upright.	4.5, 9.1, 13.6kg	Dynamic Stereo X-ray	Results of 11 participants (7M, 4F). Trials normalised to initial flexed starting position (0%) & static upright position (100%). Effect of load on the ICR of the lumbar spine.	Lifting the heaviest load contributed a larger migration in the SI ICR than the lighter loads in the L2-L3 & L5-S1 segments.
3	[125] 2012	30 (10M, 20F, 18-22y)	Three trials per load (progressing low to high) measuring thoracic & lumbar spine joint angles.	Lifting from a bench to just above head height.	0.85kg (minimal) & safe maximal lift (5-11kg F, 8-19.4kg M)	Video Analysis	Joint angles were extracted from digital video footage. Effect of maximum safe load on spine angles.	During the maximal lift there was a significant increase in thoracic and lumbar extension in the final 3rd of the lift when compared to the minimal lift.
4	[130] 1996	24 (M, 25.1 ± 4.0y, 1.77 ± 0.07m, 73.4 ± 10.2kg)	Three trials per load & start angle for lift & place of a box, measuring lumbar angular position, velocity &	Lift box (three loads) from asymmetrical start placement (three angles) at 0.76m, using one or two	3.4, 6.8, 10.2kg	Lumbar motion monitor	Univariate ANOVA for effect of increased load on kinematics.	A significant increase in peak sagittal flexion & range of motion & lateral average flexion & ROM for the trunk was seen, as well as

			acceleration.	hands, to 1.37m platform.				increased peak lateral & average sagittal velocity.
5	[131] 2018	20 (M)	Repeatedly lift & lower each load (randomly selected) till fatigue, measuring absolute spine angles at T1, T12 & S1.	Repeated lifting (10 per/min) in stoop or squat posture from the ground to bench at waist level, placed & returned.	5, 10 & 15% of MLC	3 x IMUs	Flexion/extension, lateral bending & axial rotation of segments T1-T12 & T12-S1.	There was no significant difference in lumbar or thoracic spine angles when lifting the different loads. However, stoop lifting & increased load did present higher absolute flexion angles.
6	[132] 2018	14 (19-30y)	Two trials per load (known, progressing low to high) measuring facet joint translations of the L2-S1 vertebrae.	Stoop lifting from height of 30cm (~75° flexion) to standing upright.	4.5, 9.1, 13.6kg	Dynamic Stereo X-ray	Results of 10 participants. Trials normalised to initial flexed starting position (0%) & static upright position (100%). Effect of load on lumbar spine.	The increase in external load caused no significant change in the facet translations.
7	[133] 1992	4 (31-34y, 79.4-104.3kg, 1.7-1.8m) Experienced weightlifters	Three trials (known, no load & max load) measuring spine kinematics of the lumbar vertebrae.	First trial was to fully flex & extend the trunk with no load. Second & third trial involved a deadlift style lift with self-selected load on a barbell.	0kg & self-selected (183.7 – 210.9 kg)	Fluoroscopy X-ray	Spine joint angles, distance between ligament attachment points and shear & compressive displacements.	Loaded trials had a reduction in range of motion and less flexion of the lumbar spine when compared to unloaded trials.
8	[134] 2018	14 ([8M, 24 ± 2, 78 ± 9kg, 1.8 ± 0.07m], [6F, 25 ± 2y, 61 ± 8kg, 1.7 ± 0.06m])	Two trials per load (known, progressing low to high) measuring facet joint translation angles of the L2-S1 vertebrae.	Stoop lifting from height of 30cm (~75° flexion) to standing upright.	4.5, 9.1, 13.6kg	Dynamic Stereo X-ray	Results of 11 participants (6M, 5F). Trials normalised to initial flexed starting position (0%) & static upright position (100%). Effect of load on lumbar spine.	An increase in load caused a significant increase in flexion of the L2-L5 facet joints and lateral bending of the L5-S1 during the middle phase of the lift.
9	[135] 2020	26 (26.9 ± 4.7y, 1.7 ± 0.08m, 64.8 ± 11.8kg)	Three trials per load & posture measuring trunk kinematics from sensors placed under the	Lifting load from ground to standing & return in correct (squat) & incorrect (stoop)	1, 2, 5kg	2 x IMUs	ANOVA of kinematic parameters & use of an SVM classifier for posture.	No significant effect on anterior-posterior trunk displacement from differences in load.

			suprasternal notch & the posterior pelvis.	postures.				
10	[136] 2012	10 (F, 30.5 ± 9.2y, 61.6 ± 10.3kg)	Lifting with no trunk, lower trunk or upper trunk support measuring angular displacement of T9 & L3.	Lifting from hip-height standing workstation to hip or shoulder height at an angle of 45° left	0, 5kg	Motion capture	Three-way repeated measures ANOVA of total trunk flexion.	No significant effect on flexion ROM from differences in load.
11	[137] 2000	15 (M, 22.5 ± 2.0y, 1.1 ± 0.05m, 73.4 ± 6.6kg)	Lift, carry and place box (any posture) measuring lumbar angular position, velocity & acceleration.	Lift box from knee height, carry 1.5m & place on self at elbow height at 4.3 lifts/min	9.1, 11.8, 14.5, 17.2, 20.0, 29.9, 32.7, 35.4, 38.1, 41.7kg	Lumbar motion monitor	ANOVA of change in load on kinematic parameters.	No significant effect on peak lumbar positions from differences in load. The lowest two loads resulted in the highest sagittal velocities while the two heaviest loads had the lowest velocities.
12	[138] 2015	18 (4F, 14M, 26.8 ± 4.9y, 1.8 ± 0.1m, 73.3 ± 14.8kg)	Three trials per load (known & unknown, any posture) measuring lumbar angular position, velocity & acceleration.	Lift box from knee height to chest height while the load is known or unknown.	1.1, 5, 15kg	Lumbar motion monitor	Repeated measures ANOVA for effect of load knowledge at each load level.	Load had a significant positive effect on sagittal & lateral angles. Also present was a negative effect for sagittal angular acceleration.
13	[139] 2009	9 (M, 36 ± 14y, 1.8 ± 0.08m, 89 ± 14kg)	Lift, carry & place masonry blocks (any posture) measuring lumbar flexion, lateral flexion & twist angle.	Lift building block from pallet (top & bottom layer), turn, carry & place on wall (floor, iliac crest & shoulder level) using one or two hands.	6, 11, 14, 16kg	Motion capture	Generalised estimate equation regression analysis for effect of lift height, place height, block load & number of hands, on lumber angles.	Lumber angle decreased when lifting and placing at floor level, while there was no difference when placing at hip level and flexion increased when placing at shoulder level due to increased load. Lateral flexion was largest when lifting single handed with lighter loads.
14	[140] 1999	14 (7M, 7F, 31.4 ± 2.7y, 1.7 ± 0.03m, 71.6 ± 4.2kg)	Two trials per condition measuring orientation & position of L1 – S1.	Flexion of the trunk from standing position with no load & 5kg barbell.	0, 5kg	Tethered electromagnetic sensors	Results of 13 participants using linear regression, ANOVA & t-test for range of motion & movement	No significant different in ROM or movement pattern could be attributed to the introduction of load.

							patterns.	
15	[141] 1999	14 (M, 22-34y, 1.79 ± 0.05m, 74.7 ± 7.0kg) 5 experienced handlers	Ten trials per condition (randomised) measuring angular position, velocity & acceleration.	Lift box (two loads) from knee height to standing from 0° & 60° to the right and at preferred & faster-than-preferred velocity.	13.6, 27.3kg	Lumbar motion monitor	Intra-class correlations, Repeated measures ANOVA & post-hoc analysis.	A significant reduction in sagittal velocity & acceleration was seen due to increased box mass. It also reduced the standard deviation associated with sagittal extension velocity & acceleration.
16	[142] 2000	18 (5F, 13M, 23.8 ± 3.1y, 1.71 ± 0.04, 76.8 ± 13.6kg)	Flex & extend trunk with straight legs measuring lumbar spine motion of T10 & S1.	Lift loads (two) from 90° trunk posture to upright at three trunk velocities (15, 30 & 60 °/s).	0.1, 10kg	Tethered electromagnetic sensors	Repeated measures ANOVA. Trials normalised to initial upright posture (0%). Effect of load & speed on lumbar kinematics.	A significant increase in the lumbar to pelvis angle ratio (L/P) was seen due to increased load.
17	[143] 2010	14 (7F, 7M, 23.6 ± 3.7y, 1.7 ± 0.08m, 69.5 ± 9.5kg)	Two trials per condition (randomised) at two lifts/min, measuring angular position, velocity & acceleration.	Lift box (two loads, no handles) in stoop posture from platform (three heights) to elbow height & return using four hand positions.	5, 10kg	Lumbar motion monitor	MANOVA, univariate ANOVA & post-hoc analysis.	A significant decrease in peak sagittal acceleration was seen due to an increase in load. This also increased the probability of high-risk membership, especially when combined with the lowest starting height & asymmetric hand positions.
18	[144] 2007	20 (10F, 35.8 ± 14y, 1.7 ± 0.06m, 70.8 ± 16.8kg; 10M, 30.3 ± 8.1y, 1.8 ± 0.05m, 77.1 ± 10.1kg)	Lift known, unknown & same mass boxes using any posture measuring lumbar angular position, velocity & acceleration at eight lifts/min.	Lift box (three loads, no handles) from shin height in front to conveyor located 90 to the left at waist height, with three box presentations.	4.54, 9.07, 13.61kg	Lumbar motion monitor	MANOVA, repeated measures ANOVA & post-hoc analysis.	A significant effect was seen between load & sagittal flexion.
19	[145] 1998	5 (22.0 ± 1.6y, 1.8 ± 0.07m,	Six trials lifting with load (increasing load, any posture)	Lift box (six loads) from 0.45m to standing knuckle	6 – 66% of body weight	Lumbar motion monitor	Qualitative trend assessment & unpaired t-	There was a significant increase in movement time between the first

		79.6 ± 6.8kg)	measuring lumbar angular position, velocity & acceleration.	height.	(6.32 ± 0.57 – 65.45 ± 1.12kg)		test. Data was normalised to 100% movement time.	four trials (lighter) & last two (heavier), also the start of lumbar extension occurred earlier in the heavier trials. During the extension phase the mean and peak angular velocities decreased & the acceleration curve becomes multi-peaked with heavier loads.
20	[126] 2014	28 (18F, 10M, 20.8 ± 1.02)	Three trials at each load (increasing till max is reached) measuring joint angle of the lumbar spine at L3.	Lift box (two loads) from bench (0.7m) to floor & return, load is increased until maximum safe lift is reached.	Minimum (7kg) & maximum loads (F 12.5-19.0kg, M 15.0-34.8kg)	Video analysis	Intra-class correlations, paired t-test & two-tailed t-test.	A significant increase in lumbar extension was seen when lifting the minimum load than with the maximum load. This trend is seen throughout the lift.
21	[146] 1996	7 (M, 25 ± 2.98y, 1.79 ± 0.08m, 82.9 ± 6.3kg)	Eight trials per condition (hand position randomised, load increasing) measuring lumbar angular position, velocity & acceleration.	Lift box (seven loads, no handles) for the floor to standing & return with different hand positions.	4.5, 9, 13.5, 18, 22.5, 27, 31.5kg	Lumbar motion monitor	Trials normalised to initial upright posture (0%).	When looking at the box with handles, a slight decrease in lumbar angle is seen as the load increases while the velocity becomes incrementally less negative & acceleration decreases.
22	[147] 2019	20 (10F, 10M, 26.0 ± 3.0y, 1.72 ± 0.1m, 70.7 ± 11.5kg)	Ten minutes per condition (load, box start position, randomised) measuring lumbar angular position, velocity & acceleration.	Lift box (two loads, six lifts/minute) from 80% or 120% of knee height in front to conveyor located 90 to the left at standing elbow height.	5 & 10% of body weight	Lumbar motion monitor	Repeated measures ANOVA, post-hoc analysis. Effect of load & starting height on spine kinematics.	No significant effect due to the increased load was seen. However, when the load was increased and starting height decreased a significant increase in peak transverse velocity was noted.
23	[148] 2021	17 (2F, 15M, 36 ± 10y, 1.75 ± 0.08m, 82 ± 15kg)	Four trials per condition (load, start & end height, pace, carry distance) measuring lumbar & trunk angles at T6 -T7 & S1-S2.	Lifting box (two loads, no handles) from pallet, carry & place on pallet.	10, 20kg	Motion capture	Four-way repeated measures ANOVA, post -hoc analysis. Effect of load, height, pace & distance on	Increased load had no significant effect on lumbar or trunk angles.

		experienced handlers					spine kinematics.	
24	[149] 2013	30 (15F, 23.0 ± 2.6y, 1.70 ± 0.06m, 66.3 ± 11.7kg, 15M, 24.2 ± 2.9, 1.85 ± 0.08m, 85.4 ± 10.7kg)	Thirty trials per load (10 lifts/minute, any posture) measuring thoracic & lumbar joint angles at C7, T12 & S1.	Lift box (two loads) from 50% of participants height to floor & return.	0 & 10% of MLC	Motion capture	Principal component analysis, repeated measures ANOVA, post-hoc analysis. Trials normalised to length of lift. Effect of sex & load on spine kinematics.	P-value of <0.001. A significant effect of load on lumbar spine flexion (decrease) was seen.
25	[150] 1995	15 (M, 35.1 ± 7.6y, 1.79 ± 0.06m, 85.83 ± 12.61kg) experienced handlers	Twelve lifts per load (increasing & decreasing, squat posture) measuring lumbar joint angles at C7, T12, L3 & S1	Lift box (five loads) from floor to upright posture & return.	15%, 30%, 45%, 60% & 75% of MLC	Video analysis	Repeated measures ANOVA. Trials normalised to length of lift. Effect of load on spine kinematics.	There was a small but significant decrease in lumbar joint angle at the onset of the lift between the 15% & 75% lifts. As the load increased, lumbar extension started later in the lifting process compared to the knee.
26	[151] 2016	25 (14F, 23.3 ± 1.9y, 1.64 ± 0.07m, 65.2 ± 15.4kg, 11M, 24.1 ± 4.5y, 1.78 ± 0.05m, 80.2 ± 13.1kg)	Five trials per load (10 lifts/minute) measuring thoracic & lumbar joint angles at C7, T12 & S1.	Lift box (three loads) from 50% of participants height.	10, 20 & 30% of MLC	Motion capture	Principal component analysis, repeated measures ANOVA, post-hoc analysis. Trials normalised to length of lift. Effect of sex & load on spine kinematics.	P-value of < 0.005. No significance effect was found of increased load on lumbar & thoracic joint angles.
27	[152] 2014	23 (10F, 13M, 20 - < 55y) 11 younger & 12 older	Three trials per condition (load, lift height, randomised) measuring trunk joint angles from C7/T1 to L5/S1.	Lift box from floor to platform (three heights, wrist, elbow & shoulder).	5%, 15% & 25% of MLC	Motion capture	Repeated measures MANOVA, repeated measures ANOVA & post-hoc analysis. Effect of age, height & load on spine kinematics.	A significant increase was seen in trunk angle due to increase load at the ending position of the lift. Also, peak trunk extension velocity decreased with increased load.
28	[153] 2014	23 (10F, 13M,	Three trials per condition	Lift box from floor to wrist	5%, 15% &	Motion capture	Repeated measures	Significant effects of load were

		20 - < 55y) 11 younger & 12 older	(load, randomised) measuring trunk joint angles from C7/T1 to L5/S1.	height, 60° to the right of the participant.	25% of MLC		MANOVA, repeated measures ANOVA & post-hoc analysis. Effect of age & load on spine kinematics.	seen on peak values of lateral flexion velocity & acceleration & transverse twisting acceleration during the lifting phase. Also, sagittal flexion angle, lateral flexion acceleration & transverse twisting angle during the depositing phase. The depositing phase kinematics increased with increased load; however, the lifting phase saw 15% MLC have the highest peak values.
29	[154] 2000	9 (M, 22.4 ± 1.5y, 1.80 ± 0.07m, 72.7 ± 7.9kg)	Eight trials per condition (load, known/unknown, randomised, any posture) measuring lumbar joint angles at T1 & L5/S1.	Lift box from floor (four loads) to standing as quickly as possible.	1.6, 6.6, 11.6, 16.6kg	Motion capture	Trials normalised to initial upright posture (0%). Repeated measures ANOVA & paired t-test. Effect of load & unknown load on spine kinematics.	A trend of increasing lumbar angle was seen with increased load. Significance was seen in lumbar angles when participants expected to lift 1.6kg and lifted 11.6kg % angles of lifting 11.6kg.
30	[127] 2018	28 (19F, 9M, 18 -22y)	Three lifts per load (any posture) before increase till maximum safe lift was reached measuring thoracic & lumbar joint angles at C7, T7, L3 & S2.	Lift box from bench to shoulder height & return.	Minimum (5.5kg) & maximum loads (F 8.5 – 13kg, M 12 – 23.2kg)	Video analysis	Intra-class correlations & paired t-test. Effect of maximum safe load on spine kinematics.	A significant decrease in mean thoracic joint angles due to maximum load was seen in the ascending part of the lift. No significance was found in the descending part of the lift.
31	[155] 2003	10 (5F, 19-23y, 1.7 ± 0.04m, 59.5 ± 12.6kg, 5M, 19-23y, 1.8 ± 0.06m, 81 ± 7.7kg)	Two lifts per trial (load, lift speed) measuring lumbar range of motion at C7, T7 & L2 to L5.	Lift box (five loads) from the floor to a shelf (chest height) using preferred and faster that preferred velocity.	2.3, 4.5, 6.8, 9.1, 11.3kg	Motion capture	Univariate ANOVA, MANOVA & post-hoc analysis. Effect of load & speed on spine kinematics.	A significant effect of load on time to peak velocity (increase) was seen on the L2 vertebrae & also, on peak gradient (decrease) on the L5 vertebrae.

3.2. Internal factors

The spine can be segmented into four main vertebral sections: cervical (C1 – C7), thoracic (T1 – T12, lumbar (L1 – L5) and sacral (S1 – S5 fixed). The segment of the spine analysed (Figure 7) in the majority of studies was the lumbar spine (90%).

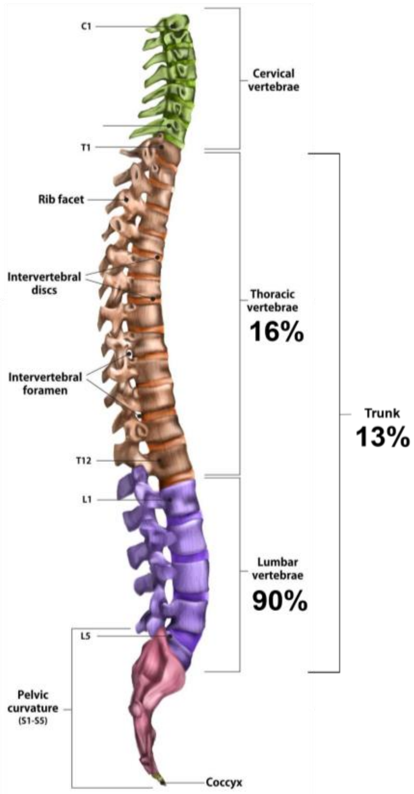

Figure 7 Percentage of studies that investigated each segment of the spine.

Three studies reported a decrease in lumbar angle [133, 146, 150] and two studies a decrease in lumbar acceleration [141, 146] due to increased load, however reported conflicting effects on lumbar velocity [141, 146]. No other studies reported the same kinematic metrics.

Two separate studies looked at the lumbar spine as multiple segments [133, 134] both using X-ray technology, this allowed for exact measurements from the bone landmarks but is invasive, as it applies a small amount of radiation to the participants and can only be measured in a laboratory setting. However, this level of detail did show significant differences in the separate lumbar segments when placed under increased load.

The thoracic vertebrae were measured in 16% (5) of studies. While not all studies found significant changes in thoracic kinematics due to increased load, two studies [125, 127] found there was a significant decrease in the mean thoracic joint angle. Both of these studies compared minimum to maximum safe loads to head and shoulder height, respectively. While the three other studies [131, 149, 151] found no significant difference in thoracic kinematics, all performed lifts to waist height.

The trunk was analysed in 13% of studies, where the thoracic and lumbar spine are a singular segment. Two of the studies [152, 153] found a significant increase in sagittal trunk angle due to increased load during the end phase of the lift (depositing). While two studies [135, 148] found no significance due to increased load, both these studies analysed lifts to standing height, as did [153]. All loads were relatively small (< 25% MLC), apart from in [148], where maximum load was 20kg.

3.3. External factors

The effect of load on lumbar spine kinematics varied and one metric for variation was the end height of the lift (Figure 8). The most studied end height was to standing position/ wrist height (45%) mimicking that of a deadlift movement. Of these, 38% reported no significant effect.

Lifts to the waist/hip height were performed in 14% of studies (Figure 8), of these 80% saw no significant effect on the thoracic or lumbar spine when lifting to waist height [131, 136, 139, 151]. However, a decrease in lumbar spine angle with increased load was present in [149] at waist height and this effect was also present in [139] when lifting to shoulder height.

The method for recording experimental data (Figure 9) shows that motion capture (MoCap) (29%) and the lumbar motion monitor (LMM) (29%) are both most commonly used, while X-ray (16%), inertial measurement units (IMUs) (7%), wired sensors (6%) and video (13%) were less prevalent.

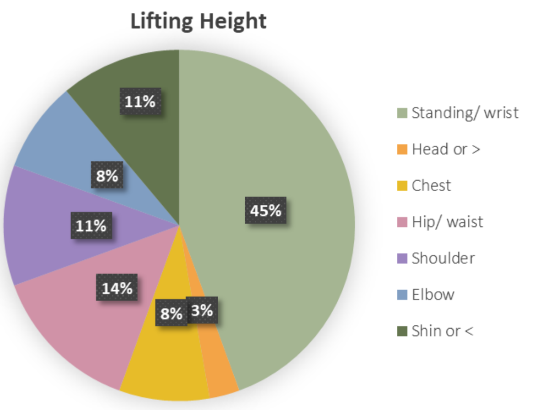

Figure 8 Percentage of studies that performed to the lifting height.

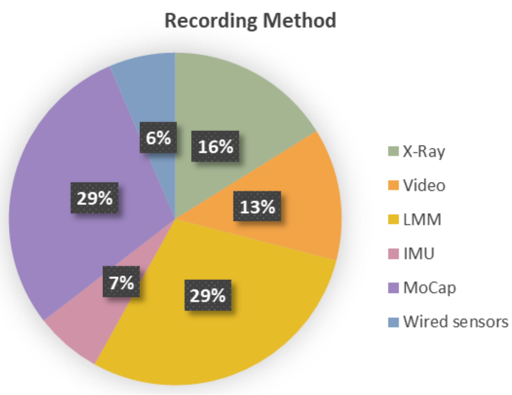

Figure 9 Percentage of studies for each method of recording experimental data.

3.4. Kinematic Results

The spine kinematics studied in this review were varied. The most common being mean angle, velocity, and acceleration, maximum flexion, velocity and acceleration and mean range of motion in the sagittal plane. Many studies also included results from the coronal and transverse planes. To determine if increased external load had an effect on spine kinematics, load was plotted against the results from four kinematic variables that had the most results (Figure 10). Additionally, 11 studies reported no significant changes in kinematics due to increased load.

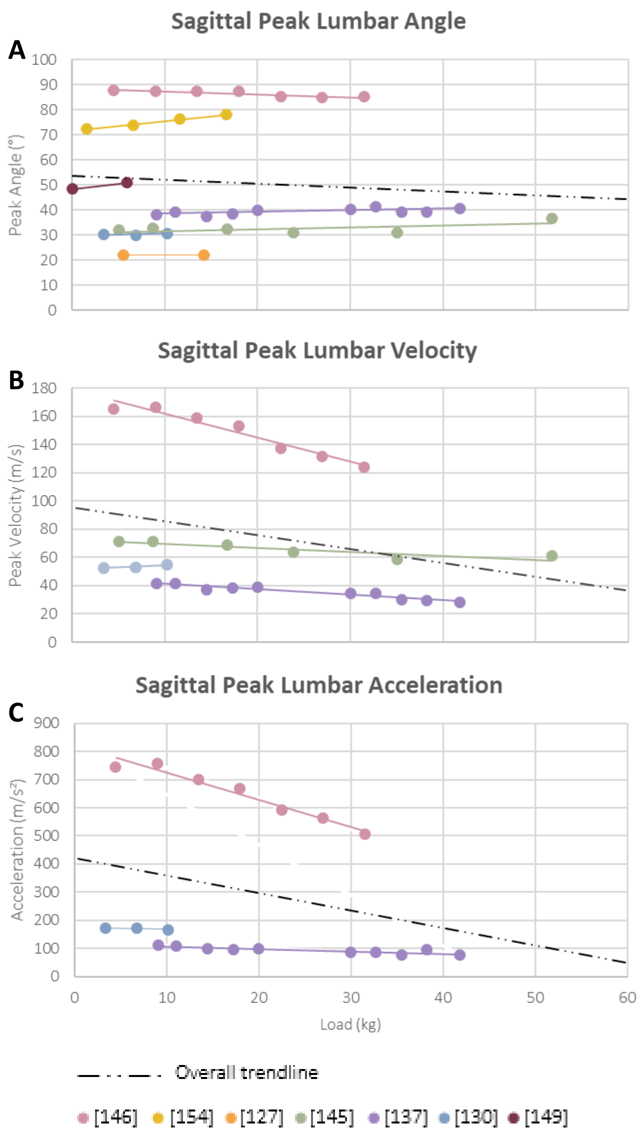

Figure 10 Results of load effects on spine kinematics. Each colour represents a separate study.

As can be seen the results for the three kinematic variables (Figure 10), the effect of load on spine kinematics is not clear. The results between each study are greatly varied, this is especially obvious in Figure 10A, each of the studies appears to have very little change in angle due to load and the results from each study are very spread out. In Figure 10, the pink samples are taken from the study [146]. Particularly in Figure 10B and Figure 10C this study has much larger peak velocities and accelerations. The experimental protocol included using a box with no handles, this protocol was also used in [154] (Figure 10A) the yellow sample, this would place the participant in an extreme flexed starting position, possibly explaining the higher peak velocity and acceleration. The approximate trend in Figure 10A for all except [146] is a positive correlation, with increased load there is an increase in the peak angle. For Figure 10B and Figure 10C the correlation is negative, with increased load the peak velocity and acceleration decreases. These trends help to form an understanding of external loads effect on spine kinematics, however there was not a consensus across studies especially as more than 1/3 reported no significant effect.

4. Discussion

While trends in the data were present; with four studies reporting an increase in sagittal spine angles with an increase in load [138, 152-154], and four studies reporting a decrease in sagittal spine angles with an increase in load [126, 127, 146, 150], the spine segment, mass of loads, method of recording and discrete variable attributed to these studies varied. It is therefore difficult to make assertions of the effect of increased load on spine kinematics.

The lumbar spine was the segment most studied in literature. Although this is the area most studied, research referring to whether injuries are more prevalent in the lumbar spine than the thoracic or sacral spine was not able to be located as injury reporting for Australia and Europe referred to the lumbar and thoracic spine as the back [6, 17]. However, each segment contributes to the transfer of external load forces to the ground and therefore it stands to reason that there would be kinematic variability in all other spine segments as well.

Studies within this review found no effect on the thoracic spine when lifting load to the waist level or below. It could be that changes in thoracic kinematics are only present in lifts that are performed to above the waist level (e.g., [125, 127]). Additionally, for military tasks a large portion are performed to the chest, shoulder, head or above heights [156]. Factors contributing to manual handling injuries include hyperflexion or hyperextension of the lumbar spine [16], these motions could be more prevalent when performing lifts to heights greater than waist level (e.g., [125, 127, 130, 137, 138]).

Of the studies that analysed the trunk (thoracic and lumbar as one section), 50% showed no significant effect of load on kinematics. It could be that analysing the trunk as a single joint does not provide enough detail for the changes in the joint kinematics to be seen (e.g., [135, 136, 148]). No studies analysed the vertebrae higher than C7. The cervical spine has reduced visibility during lifting tasks as it can get covered by the head when the spine is in full flexion. Attaining a more detailed analysis of the spine's kinematics by dividing the spine into multiple segments could help with understanding and predicting when there is a clear effect of load on the spine.

Motion capture is considered the gold standard for motion analysis, however it along with X-ray and video require a direct line of sight, are restricted to a specific area, are not portable and require complex data analysis. Therefore, they have problematic limitations when it comes to in-field testing or use of the data for onboard analysis. The use of portable sensors allows for future development of onboard analysis, monitoring and prediction of kinematics that could lead to injury. IMUs and the LMM are both portable sensor systems that are affixed to the participant. Modern IMUs are small, highly sensitive sensors that contain a tri-axial magnetometer, accelerometer and gyroscope. They can be used to determine absolute position via fusion filters but can suffer from increasing error if not properly compensated for [157, 158]. The LMM is a device that uses an electrical sensor that measures joint angles to determine displacement, velocity and acceleration of the lumbar spine. It is a closed loop system consisting of the device and its own analysis software, making the data easily accessible but difficult for creating an onboard analysis system. Additionally, it only measures the lumbar spine as a single segment and does not include thoracic analysis. A more comprehensive analysis of kinematics for each of the spine segments may provide the detail necessary to make predictions about when injury risk may increase.

Within this review, two studies analysed the spine as more than two segments, [133] using a three-segment model and [134] using four-segment model. However, both analysed the lumbar spine only using X-ray. Significant differences in the motion of the smaller spine segments (e.g., multiple points in the thoracic segment) have been seen when using a multi-segmental (seven segments) spine model compared to one or three segments [2]. The seven-segment kinematic model allowed for differentiation of the complex spine motions that occurred during sitting tasks. The use of a multi-segmental spine model could lead to an understanding of task dependant motions that differ with the introduction of varying loads.

5. Conclusion

Due to the number of different factors being analysed (spine segment, age, sex, hand placement, lift height, pace, posture etc.), the various kinematics that were analysed (displacement, velocity, acceleration, range of motion, angle, peak, mean etc.) and the differences in experimental protocols (loads, starting height, ending height, equipment), a consensus on what effect increased load has on spine kinematics is difficult to make, however many studies reported a significant effect. Overall, there are several reported trends in the data such as, decreased peak angular velocity with increased load and increased peak flexion angle at the beginning of the lift. However, not every study that reported this trend found the results significant.

To determine what the effect is of increased load on spine kinematics, experimentation data needs to be collected that is specific to the task being assessed. In the case of military manual handling, lifting height to the shoulders or above is common and this increased lifting height could present a greater risk of hyperextension. To determine where these risky motions are occurring in the spine, experimental trials should include multiple points of analysis for each segment of the spine.

IMUs present a small, portable, lightweight option for kinematic data collection. While they are not yet considered the gold standard for kinematic data collection many studies have validated their use in comparison to MoCap [157-159]. Using small, portable and readily available sensors, such as IMUs, for the collection of spine kinematics for future use as part of an assistive device with an onboard prediction model is logical. They are portable enough to be used in any location and small enough to be used at multiple points along the spine.

As MAWL has been stated to be 84 ± 8% of MLC for military manual handling tasks [13] across all participants in a study of 70 soldiers, MLC could be used as a method of normalising load between participants. Using task specific methods for determining MLC would give a more accurate load for an individual's intrinsic ability to complete the specific lifting task, than use of a load cell machine.

Performing statistical analysis would aid in the ability to determine which variables are suitable for use in prediction of lifts above MAWL. Studies in this review analysed discrete variables, namely mean and peak values of the spine kinematic. At most three points (start, middle and end) were taken from the duration of the lift for analysis. Therefore, an analysis of the entire lift, using the complete time series of the lift, comparing %MLC at each spine level and defining the points at which there are significant differences in the spine trajectories would be beneficial.

6. Key points

- A significant effect on spine kinematics due to an increase in external loading during manual handling tasks has been reported but there is not agreement across all studies.
- The majority of studies look at the effect of increased external load in the lumbar spine with only two studies including multiple points of analysis for any segment of the spine.
- Many methods of data collection lacked the ability to be used outside the laboratory environment while IMUs showed good consensus to MoCap data, are small, lightweight and portable and have the ability to be used in most environments.
- MLC is a common method used for standardising loads and can be used as an indicator of MAWL loads, thus presenting a cut-off level for increased injury risk (lifting above safe intrinsic capability).

7. Summary

While many studies used %MLC as a metric for standardising the lifting load, no studies used this as a consideration for the participant's ability to perform the task safely. Very few studies using technologies for kinematic data collection would be able to be performed outside the laboratory environment. As this research aimed to show that spine kinematics could be used as a predictor for a lift at an increased risk of injury, it was important that the technology used for the collection of the dataset could be used within an assistive device (e.g., an exoskeleton) and at multiple levels of the spine. IMUs were shown to be a well-researched option that met this criterion for use in experimental trials, they have the benefit of being able to be used outside a laboratory environment and can are small enough to be used at multiple levels of the spine. Only two studies [133, 134] used multiple analysis points for a spine segment and of those none looked at the thoracic spine. When analysing multiple points along the thoracic and lumbar spine, it was expected that there would be inter-segmental variation in the kinematic results [133, 134]. These variations could provide invaluable information for the prediction algorithm as it could offer more unique variables and features for analysis. These limitations were addressed in the development of a dataset through experimental trials using IMUs to measure kinematics at multiple points in the thoracic and lumbar spine and measuring for multiple % MLC, including 100% MLC.

Chapter 4. Biomechanical analysis of military manual handling tasks – Participant laboratory study

This chapter aimed to create a database of spine kinematics, that addresses the research limitations found in Chapter 3, for observationally determining points of interest for each variable. These variables were observed for the changes that an increase in external load has on the spine kinematics during a lifting task while performing a lift-to-platform task for seven %MLC loads. The data from six IMUs placed along the thoracic and lumbar spine was processed using the attitude heading reference system (AHRS) fusion algorithm. Of particular interest was whether a kinematic indicator of MAWL (between 80 – 90% MLC) could be found and any noteworthy differences in the levels of the spine, kinematics variables (e.g., acceleration, velocity, angle) and discrete kinematics (e.g., mean, peak, minimum) due to an increase in %MLC. This is of importance because in order to make predictions on when a person is performing a high-risk lift, where and how this change in motion is reflected needs to be understood, so those variables are made available to the algorithm.

1. Introduction

The prevalence of lower back injuries to manual handling personnel in the Australian Defence Force and industry reflects the need for devices that can support workers with the aim of preventing injuries and improving productivity. This has led to a need for an exoskeleton system that can support, move and adapt to repetitive, fatiguing tasks. The predecessor to this exoskeleton system is the development of a predictive model that can classify when a person is approaching their MAWL and thus be used as an assist-as-needed control system for the exoskeleton once validated.

There are many contributing risk factors associated for musculoskeletal back injuries while performing manual handling tasks. These include hyperflexion or hyperextension of the lumbar spine caused by external torques, internal torsional forces, fatigue due to increased total work [16], increased risk when performing lifting tasks from the floor [11] due to increased spinal flexion [12] and, lifting above an individual's intrinsic capacity can be responsible for injuries [160]. An individual's capacity to lift with minimised risk is known as their maximum acceptable lift. The maximum acceptable weight of a lift is defined as "the maximum amount that could be lifted comfortably and without strain" [160]. This can be equated to to 84 ± 8% of an individual's maximum lifting capacity [13]. Sex does not need to be evaluated as a dependent variable, as it has been found male and female participants have similar lifting techniques when the load is standardised via MLC [149, 151].

Modelling of spine biomechanics has been done through both static and dynamic modelling. Static models do not take into account inertia of the external load and the human individual joint segments and therefore tend to underestimate internal joint forces [161]. Dynamic models are more complex and account for external forces, posture, kinetics and kinematics. Parida and Ray [161] suggest that current methods of biomechanical modelling for MH tasks are activity or body segment based and that a task-specific dynamic biomechanical models would allow for better accuracy of joints and/or body segment motions, to tailor more appropriate solutions for particular tasks.

A systematic literature review was performed to determine the effect of increased external load on spine kinematics and due to the number of different kinematics analysed and the differences in experimental protocols (loads, starting height, ending height, equipment) a consensus on the effect of load on spine kinematics is difficult to make (Chapter 3). There were several reported trends in the data such as, decreased peak angular velocity with increased load and increased peak flexion angle at the beginning of the lift. However, not every study who found this trend found the results significant.

From Chapter 3 studies that used MLC to standardise load [125-127, 131, 149, 150, 152, 153], significant results were reported for differences in spine kinematics. It is therefore assumed that a participant's spine kinematics would present with similarities in the shape and features of the trace when the load is standardised to a percentage of a participants MLC, even when the load magnitude is vastly different. Using standardised load (%MLC), a model that uses spine kinematics to predict a Heavy or Light load can be generalised for the population tested in the experimental trials even if the mass of the load at a %MLC is very different.

Laboratory experiments were performed involving a biomechanical task based on common manual handling lifting tasks performed by the Australian Army [160]. Categorisation of physically demanding tasks in the Australian Army found that 56% of manual handling tasks were lift-to-platform with 92% of those tasks starting at ground level and finishing at a height of 141.3 ± 19.2cm [156]. The majority of tasks (74%) involved lifting with two handles [156].

The aim of this study was to create a database of kinematic variables and determine the effect of increased load on spine kinematics within this database. This was achieved through experimental trials of 32 participants performing a lift-to-platform task. This database of spine kinematics was used to perform a validation study of the IMUs output collected during the trials and to determine differences between the %MLC lifts at each spine segment level and between the %MLC for each variable.

2. Methodology

2.1. Participant eligibility

A sample size of 32 participants was recruited from the civilian population for this study: 21 male and 11 females with an age of 29.5 ± 5.6 years, height of 1.77 ± 0.10 metres and mass of 75.2 ± 12.7 kilograms. An age limit of between 18 years (age for adult consent) and 40 years was imposed. Participants were recruited from the student and staff cohort at Victoria University, occupation, prior experience and activity level varied. Prior to participation in the trial, participants were required to provide written confirmation of informed consent (Appendix C) and complete a health survey that gathered demographic information, injury and health history and anthropometric information (Appendix D). Participants were free from musculoskeletal injury and any illness and disease that put them at risk during intensive exercise. Prior to experiments being performed, institutional ethical approval was received from the Victoria University Human Research Ethics Committee (HRE18-231) (Appendix B).

2.2. Data collection

2.2.1. Recording Systems

All experiments were performed in the same testing space at the Victoria University Biomechanics Laboratory. Twelve motion capture cameras (Vicon Motion Systems Ltd., Oxford, UK) recorded the position of 36 9mm and 14mm reflective markers at a sampling frequency of 100 Hz. A force plate (AMTI, Watertown, MA, USA) recorded the ground reaction forces (GRFs) at a sampling rate of 1500 Hz. Six nine-axis inertial measurement units (IMUs) (ImeasureU, Vicon Motion Systems Ltd., Oxford, UK) were used to record acceleration (triaxial accelerometer ±16 g), angular velocity (triaxial gyroscope ±2000 °/s) and magnetic field strength (triaxial magnetometer ±4900 µT) at a sampling frequency of 500 Hz. IMUs trial data was recorded via the IMUs Research app (ImeasureU, Vicon Motion Systems Ltd., Oxford, UK) installed on an iPad (Apple Inc., CA, USA).

2.2.2. Biomechanical Model

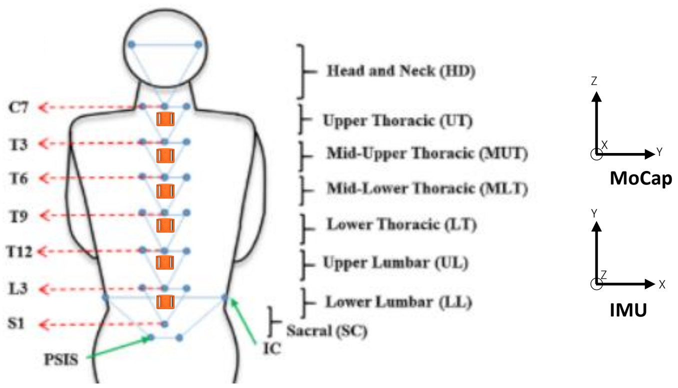

Figure 11 Example of the spine segments, marker placement, sensor placement and orientation used in the experimental trials.
Figure image is adapted from [1, 2].

Many studies have evaluated the head-trunk as a single segment dynamic model. One and two segment models do not exemplify the intricacy of spine motion; therefore, a multi-segment model is required to capture the complexity of the spine kinematics [1]. A seven-segment model (Figure 11) when tested against a two-segment model showed far more complex kinematic patterns are captured, in greater detail [1, 2].

In pilot studies it was found that markers and an IMU placed in the head and neck segment used in [1, 2] (Figure 11) caused discomfort to participants during the lift so the kinematic model was reduced to six segments. Segments were divided into upper thoracic (UT) (C7 - T3), middle upper thoracic (MUT) (T3 - T6), middle lower thoracic (MLT) (T6 - T9), lower thoracic (LT) (T9 - T12), upper lumbar (UL) (T12 - L3) and lower lumbar (LL) (L3 - S1) (Figure 11). The segments were defined using three markers, the superior markers were placed 5cm medial and lateral of the rostral vertebra and the inferior marker was placed on the lower vertebra (18 markers). Additionally, a VICON standard marker placements for the torso, upper limbs and lower limbs [162] was also used . The MoCap orientation (Figure 11) was X-axis in the anterior-posterior (posterior in the positive, anterior in the negative), Y-axis in the medio-lateral (positive to the left, negative to the right) and Z-axis in the vertical (up being positive, down being negative).

The six IMUs were placed mid-way between the C7 -T3 (UT_IMUs), T3-T6 (MUT_IMUs), T6-T9 (MLT_IMUs), T9-T12 (LT_IMUs), T12-L3 (UL_IMUs), L3-S1 (LL_IMUs) spinous process. Three reflective markers (9 mm) were placed on the IMUs sensors to track their trajectories via motion capture (18 markers). The IMUs sensors orientation (Figure 11) was Z-axis in the anterior-posterior (anterior in the positive, posterior in the negative), X-axis in the medio-lateral (positive to the right, negative to the left) and Y-axis in the vertical (up being positive, down being negative).

2.3. Testing procedure

The manual handling task was a 'lift-to-platform', lifting a single crate with side mounted handles (e.g., supply boxes) from the ground to a 1.4m platform. This involved two procedures, the first utilising the MLC procedure and the second a quasi - randomised lift of the %MLC mass that was determined during the MLC procedure. These procedures quantify a participant's physical capacity for load carriage.

On arrival to the lab, participants were verbally informed of the testing procedure and any questions were answered. Participants then had reflective markers and IMUs sensors placed on their body, where possible these were placed directly onto the skin. A 3-minute warm up was performed followed by familiarisation with the task. Prior to each lift, participants were asked to perform a small jump, on the spot, in view of the cameras. The jump acceleration trace was used to help align the MoCap data to the IMUs data. Starting posture for lifting was standardised as per [13]; each lift was performed using a squat posture, with feet positioned parallel at either side of the box, the participants then extended to standing positions, the box was then lifted to the height required to place it on the platform and taking a step forward to a split stance posture, placed the box on the platform.

The MLC procedure was then started with all participants beginning at a box mass of 10kg, this was increased by 5kg after each successful lift (in trials were a participant recorded a rate of perceived exertion (RPE) of three or below the first increase only was upped by 10kg). Three minutes rest was given (or more if requested) between each trial to minimise the effect of fatigue. MoCap, IMUs and RPE data was recorded for each trial. MLC is a one-off test that measures the maximum mass that can be lifted in a single repetition. Participants started with a small mass and completed the lifting task; the mass was then increased by 5kgs after every completion with correct technique (i.e., good posture) until the lift fails or technique deteriorates. Deterioration was characterised based on the lifting technique described in [21] as, a change in posture (stooped position instead of squat position), inability to maintain symmetry in the lift (leaning to one side, twisting), needing to take more than one step in order to reach the platform or excessive hyper-extension of the lumbar spine (where the line of the shoulders is posterior to the pelvis), which was monitored for each lift by two researchers, one being a qualified physiotherapist. The mass was then lowered by 2.5kgs and attempted again. If completed this determined the participants MLC or if failed the previous mass was the recorded MLC.

Once a participants MLC was determined, a quasi-randomised procedure was then performed. Participants first lifted 100% of their MLC three times. Each percentage of MLC (20%, 50%, 60%, 70%, 80% and 90%) was then lifted three consecutive times in a randomised order. Data from 30 participants was included in the analysis. One participant lost their LL sensor during the trial, and it didn’t come back online and another participant’s mocap data was missing a significant number of markers, so the start and end times of the lift could not be confirmed, these participant’s data was therefore excluded. Due to the limitations of the box mass alone (8kgs) some participants were unable to perform the 20% and/or 50% MLC lift, also one participant was unable to complete all three of their 100% MLC lifts. Table 6 lists the number of trials for each %MLC included in the analysis.

Table 6 Number of trials included for each %MLC.

Percentage MLC	Number of trials included
100	88
90	90
80	90
70	90
60	90
50	86
20	48

In order to help with data visualisation, the approximate cycle of the lift (Figure 12) is represented by four phases. These phases were determined a priori and the percentage of the lift that the phases took was based on observation. The lift begins (0%) in the squat postion with hands placed on the box and the entire base of the box in contact with the force platform. Phase 1 (0-10%), the external load is transferred from the ground to being held entirely by the participant. Phase 2 (10-50%), the participant transitions from squat to standing position and the box at waist height. Phase 3 (50-70%), the participant lifts the box from waist height to the height required to clear the platform. Phase 4 (70-100%), the box is placed with its base coming into contact with the platform.

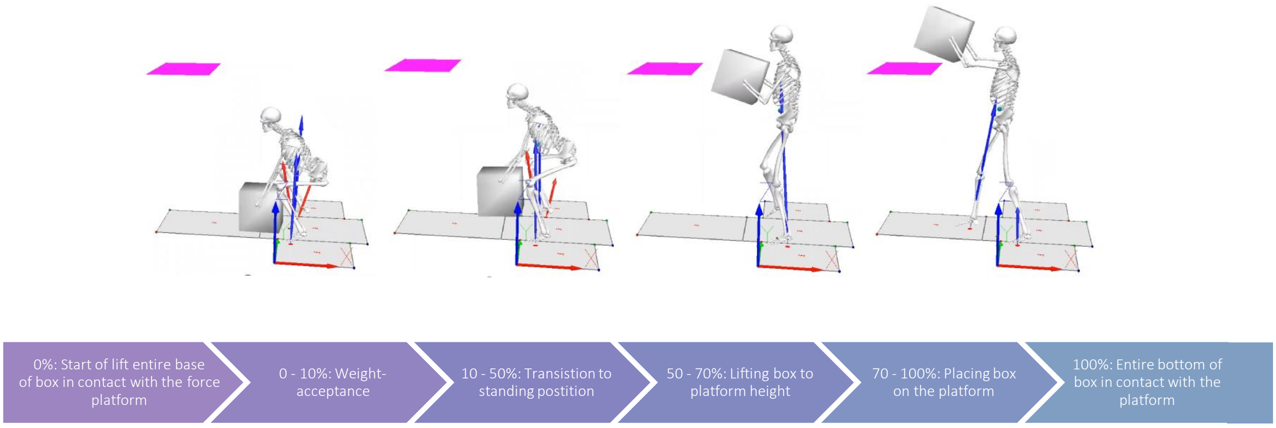

Figure 12 Approximate cycle of the ground to platform lift.

2.4. Data Analysis

2.4.1. Motion capture data analysis

Motion capture data was processed using Vicon Nexus (Vicon Nexus 2, Vicon Motion Systems 2019). A static model was created from a recorded static pose performed by each participant prior to their first lift. A six-segment spine model was created that included the larger marker clusters for each spine segment (UT, MUT, MLT, LT, UL, LL) and the marker clusters placed on the IMUs (UT_IMU, MUT_IMU, MLT_IMU, LT_IMU, UL_IMU, LL_IMU) (Figure 11). Markers were checked for proper labelling and missing markers.

Visual 3D (Visual 3D, C-Motion) was used to crop the trials to only include the lift data frames and export required variables. Marker positions were low pass filtered at 6Hz. Event labels were placed at the jump, start and end of the lift. The jump event was labelled at its peak positive acceleration of the UT segment. The start of the lift was determined to be 40 frames (0.4 seconds) prior to the force platform, on which the box was sitting, having zero ground reaction forces. Including the 40 frames proceeding zero ground reaction force was included so that the weight-acceptance phase of the lift (the period where the load of the box is fully on the ground, to when the load is completely supported by the participant) would be included in the analysis. The end of the lift was determined to be once the entire base of the box came in contact with the platform. The time from Jump-to-Start and Jump-to-End were exported into MATLAB

(The MathWorks Inc., Natick, MA, USA) to determine where the lifts were occurring in the IMUs data. Sagittal absolute angles and angular velocity (normalised to time) for the IMUs marker clusters were exported for trajectory comparison between MoCap and IMUs data.

2.4.2. IMU data analysis

All trial and time synchronisation data for each participant was downloaded off the ImeasureU devices (ImeasueU, Vicon Motion Systems Ltd., Oxford, UK) at the end of each laboratory session using the Lightning desktop application (ImeasueU, Vicon Motion Systems Ltd., Oxford, UK). Raw IMUs data was then imported in MATLAB (The MathWorks Inc., Natick, MA, USA); only trials that were completed were included (no failed lifts).

The IMUs data was down sampled from 500 Hz to 100 Hz (down-sample function, factor of 5). The data was down-sampled so that it would match the frequency of the MoCap data. The data for each spine segment was aligned to the jump acceleration peak of the first lift. It was found that over the approximate hour of recording for each participants %MLC procedure, there was a difference of one to seven seconds of data (100 – 700 frames) between the spine segments. The data was divided into individual trials based on the vertical jump acceleration peak (Y-axis) to the next vertical jump acceleration peak, each individual trial for each spine segment had the vertical acceleration peaks aligned.

The jump-to-start and jump-to-end times from the MoCap trials were imported into MATLAB. The data was cropped to include only the lift data points, based on the timing from the jump acceleration peak to the start of the lift and jump acceleration peak to the end of the lift.

Once the %MLC procedure was divided into its individual lift trials, the orientation of each trial was reordered to align with the north-east-down orientation, X-axis in the anterior-posterior, Y-axis in the medio-lateral and Z-axis in the vertical. The acceleration, angular velocity and magnetometer data was passed through the attitude heading reference system (AHRS) fusion algorithm to estimate orientation

(Sensor fusion & tracking toolbox, The MathWorks Inc., Natick, MA, USA). The AHRS filter uses an indirect Kalman filter, containing an error model to adjust for orientation error, gyroscope offset error and magnetic disturbance error to correct orientation and signal estimates [163]. The AHRS filter then provides corrected Euler angles, quaternions and angular velocities outputs. Based on the quaternions derived from the AHRS filter, rotation matrices were used to align accelerometer data with the world axis.

The mean %MLC was plotted to observe any trends in the data. Only variables in the sagittal plane were analysed as this is where the majority of motion for a two-handed squat lift will occur. The IMUs variables used for comparison were absolute angle and angular velocity around the Y-axis (flexion/extension motion), magnetic field strength in the X and Z-axis (flexion/extension motion), linear acceleration in the X-axis (anterior-posterior motion) and linear acceleration in the Z-axis (superior/inferior motion).

3. Results – IMU Validation Study

While the validity of IMUs for use in recording kinematics is well established [157-159], a small validation study was performed to assure the agreement of the particular IMUs used in these experimental trials (ImeasueU, Vicon Motion Systems Ltd., Oxford, UK) with the gold standard motion capture system (Vicon Motion Systems Ltd., Oxford, UK) for the performed lifting task. Data from 10 participants was used, these participants were selected as they had completed all lifts in the trials including 20% MLC. The LT thoracic segment was analysed as this represented the cleanest motion capture data requiring the least amount of processing due to missing or flipping markers.

Bland-Altman plots, Root-Mean-Square-Error (RMSE) and Percentage-Root-Mean-Square-Error (%RMSE) analysis (Table 7) were performed comparing the LT peak absolute angles and peak angular velocity in the sagittal plane of the MoCap data to the IMUs data of 10 participants that included MLC20% lifts.

Table 7 Formulas for the statistical methods used for MoCap and IMUs agreement

Variable	Formula
Bland Altman Plot	$x\ axis\ values = \frac{x-y}{2}$ $y\ axis\ values = x - y$ $systematic\ bias = \frac{1}{n}\sum_{i=1}^{n} x - y$ $limits\ of\ agreement = \left(\frac{1}{n}\sum_{i=1}^{n} x - y\right) \pm 1.96 \times SD_{x-y}$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x-y)^2}$
Percentage Root Mean Square Error (%RMSE)	$\%RMSE = \frac{RMSE}{Max\ RMSE} \times 100$

The Bland-Altman Plots represents the agreement in the lift data between the MoCap and IMUs by plotting the difference of the MoCap and IMUs signal (y-axis) against the mean of both the signals(x-axis).

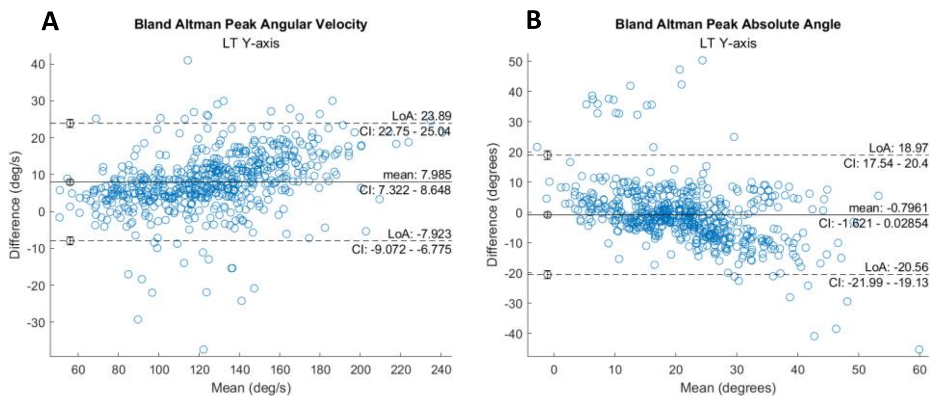

Figure 13 Bland-Altman Plots for IMU & MoCap agreement.
A. Peak Absolute Angle & B. Peak Angular velocity. The dashed lines represent the upper & lower limits of agreement (± 1.96 standard deviations).

The Bland-Altman peak absolute angle plot (Figure 13A) shows the majority of signals falling between ± 1.96 SD, indicating that there is good agreement between the MoCap and IMUs data, however there are a number of outliers. As the signals are distributed above and below the mean, there is no bias towards one method of measurement over the other.

The Bland-Altman peak angular velocity plot (Figure 13B) shows that again majority of signals falling between ± 1.96 SD, indicating that there is good agreement between the MoCap and IMU data, however the outliers have more extreme difference and mean values. As the signals are distributed above and below the mean, there is no bias towards one method of measurement over the other for the peak angular velocity variable.

The RMSE was used to quantify the agreement between MoCap and IMU measurement. The RMSE was calculated using the peak absolute angle and peak angular velocity of each signal. RMSE residuals were calculated as the difference of the MoCap data to the IMU data, of the peak absolute angles. The %RMSE was normalised using the ROM from the MoCap data and is used to give a magnitude to the error .

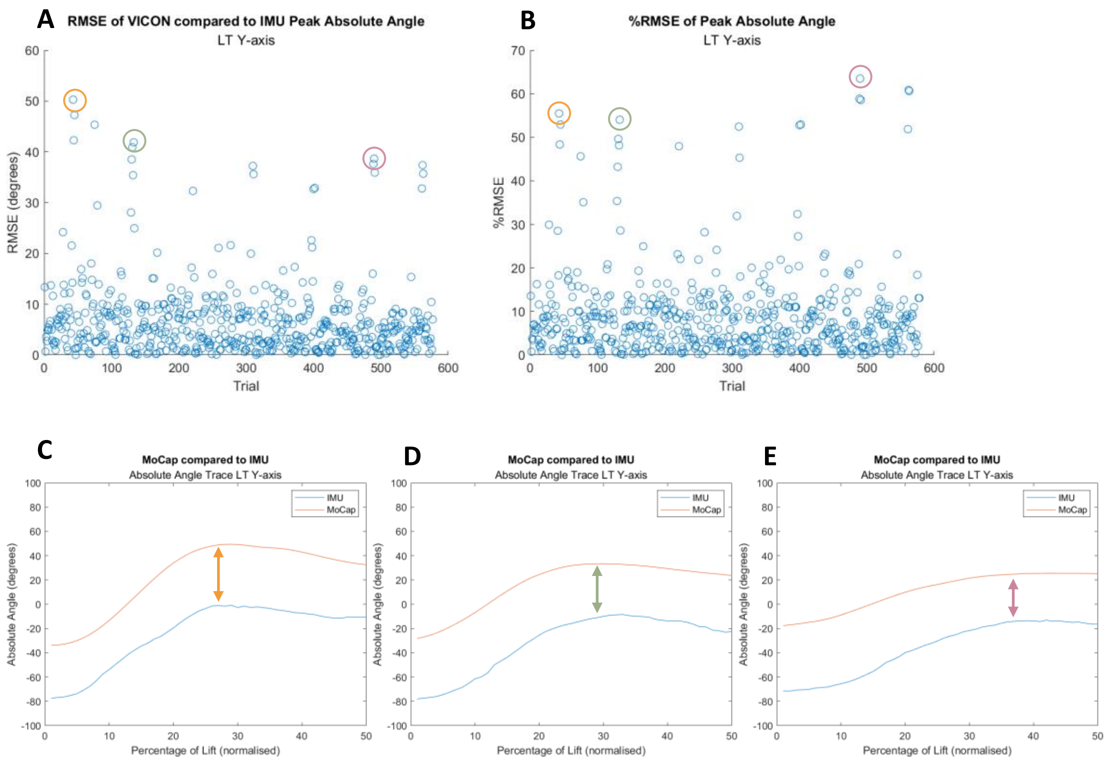

Figure 14 Comparison of the Root-Mean-Square-Error for motion capture and IMUs peak angle for each %MLC of the upper thoracic (UT) segment.

There is good agreement between the MoCap and IMUs peak angles. The majority of RMSE values for peak absolute angle (Figure 14A) sit below 10° (82% of trials), 50% of these trials have an RMSE below 5°. While 70% of trials have a %RMSE below 10 (Figure 14B) and 40% are below 5.

There are outliers present that sit outside the expected RMSE and %RMSE. Figure 14C has an RMSE of 50.3° and %RMSE of 55.5% due to a vertical shift in the peak absolute angle, this is seen all the way through the lift signal. A larger vertical shift is seen in Figure 14D, resulting in a larger RMSE and %RMSE value of 41.9° and 54.0% respectively. A smaller vertical shift can be seen in Figure 14E, resulting in a RMSE of 38.7° and a %RMSE of 63.5%. The horizontal phase shift may be due to the effect of the magnetometer adjustments on the angle calculations in the AHRS filter, as the magnetometer can be sensitive to magnetic fields created by other equipment in the laboratory setting.

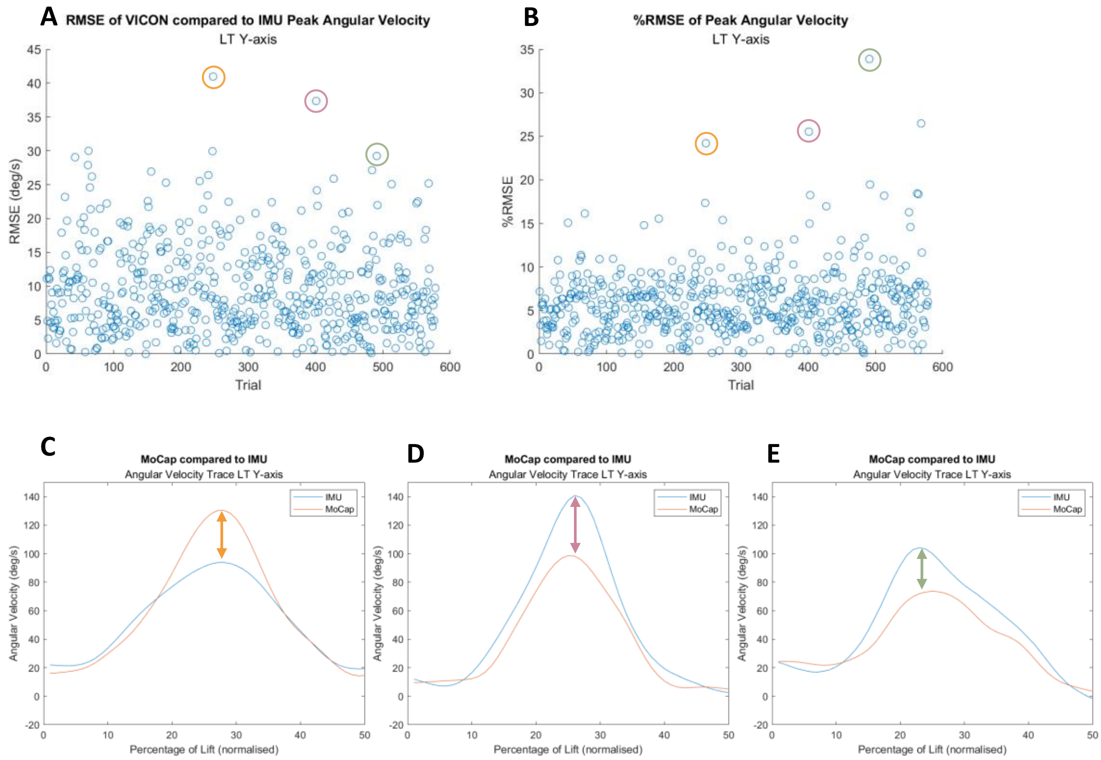

Figure 15 Comparison of the Root-Mean-Square-Error for motion capture and IMUs peak angular velocity for each %MLC of the lower thoracic (LT) segment.

While there is good agreement between MoCap and IMUs peak angular velocity, the RMSE values were expected to be lower, as a %RMSE for peak angular velocity of the trunk compairing MoCap and IMUs was reported to be less than 5% during higher speed activities [157]. The majority of RMSE values for peak angular velocity sit below 10 °/s (60%) (Figure 15A), with 28% of trials sitting below 5 °/s. While 90% of trials have a %RMSE of below 10 (Figure 15B). This is a better result to that of the peak absolute angle %RMSE.

The RMSE and %RMSE outliers still have similar trajectory traces but differ at the peak value. Figure 15C has an RMSE of 41.1 °/s and %RMSE of 24.2% due to a larger peak in the MoCap signal. Figure 15D, resulting in a similar RMSE and %RMSE value of 37.4 °/s and 25.5% respectively. A small spike closely followed by a large spike (160 °/s) in angular velocity can be seen in Figure 15E, resulting in a RMSE of 29.2 °/s and a %RMSE of 19.5%. The differences in peak values could be due to the downsampling (the mean of every five values were taken, reducing the effect on the trace of spikes) or the AHRS filter.

Magnetometer signals are sensitive to electro-magnetic interference and the presented signals were not filtered for noise disturbances. As no magnetic calibration was performed on magnetometer data, this could have an effect on the orientation data and therefore the output from the AHRS sensor (absolute angle). It is possible that agreement between the MoCap and IMUs data would be improved with magnetic calibration. In a study looking at the agreement between MoCap and IMUs during tennis groundstrokes and service for peak AngVel of the trunk in the sagittal plane, results reported an overall RMSE of 10.8 ± 4.1 °/s and a %RMSE of 4.5 ± 2.4 %, concluding good agreement [157]. As the results from this comparison study (Table 8) were similar to that of previous studies [157-159], it was concluded that further calibration (such as magnetic calibration) was not necessary to proceed with use of the IMUs data for analysis of the lifting task.

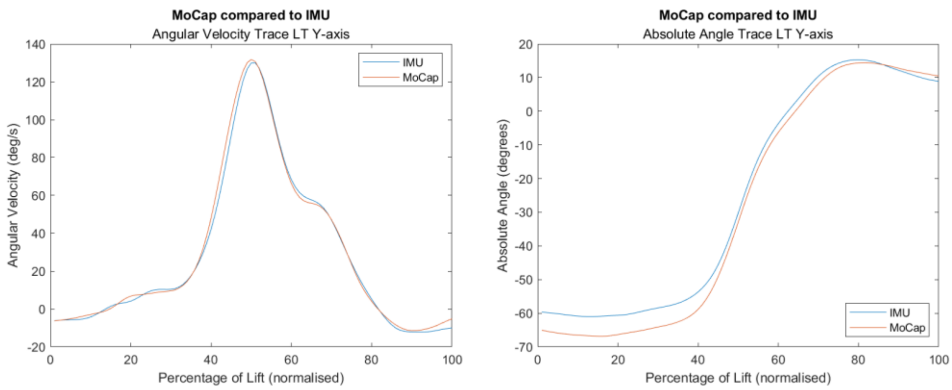

Figure 16 Examples of angular velocity & angle lift trace with low RMSE & %RMSE.
A. Lower thoracic angular velocity trace. B. Lower thoracic absolute angle trace.

As shown in Figure 14A & B and Figure 15A & B, the majority of trial comparisons have low RMSE and %RMSE value and high agreement. Figure 16 are two examples of trials with low RMSE and %RMSE values. Figure 16A has a RMSE value of 1.71 °/s and a %RMSE value of 1.20%, while Figure 16B has a RMSE value of 1.04 ° and a %RMSE value of 1.27%.

Overall, there is good agreement between the MoCap and IMUs peak values (Table 8) with the %RMSE for both peak angle and peak AngVel being below 10%. The mean %RMSE values for all trial comparisons (Table 8) show that peak AngVel has a better agreement than peak angle. This could be due to AngVel coming directly from the IMUs and not being determined via integration of data values (AHRS filter) like the angle.

Table 8 Overall mean RMSE & %RMSE values for peak angle & peak angular velocity IMUs & MoCap comparison.

Variable	Peak Absolute Angle	Peak Angular Velocity
RMSE	6.8 ± 7.5	9.4 ± 6.4
%RMSE	8.9 ± 10.1	5.8 ± 3.8

4. Results - Comparison Graphs for %MLC of IMU data

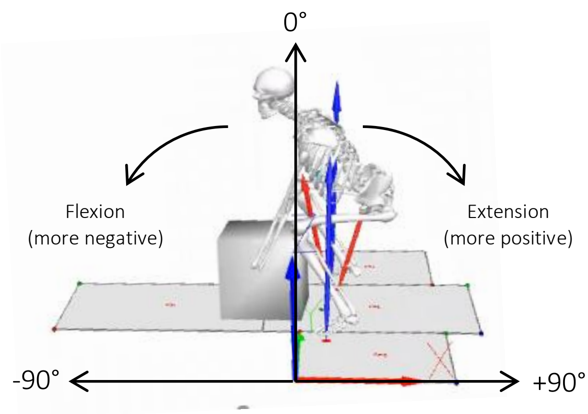

Figure 17 Direction of absolute angle.

The following analysis investigated the effect of increased load on spine kinematics. For comparison of the IMUs variables from the six spine segments, the mean of all the trials for each percentage MLC was plotted.

The absolute angle kinematic results are in the sagittal plane with reference to the global axis (Figure 17). The sagittal plane represents 0°, with flexion creating a more negative signal and extension creating a more positive signal.

4.1. Comparison of mean absolute angle change over the lift for %MLC

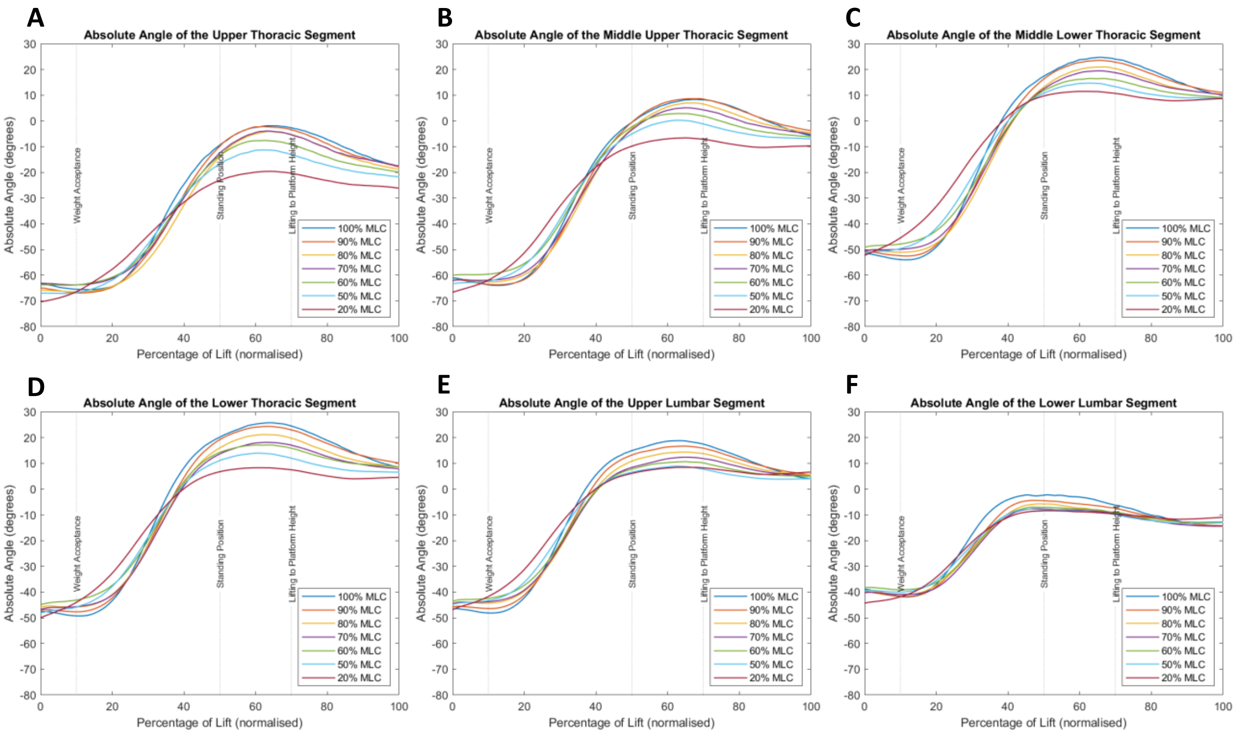

Figure 18 Mean absolute angle for %MLC of all participants for each spine segment.
A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL).

The kinematic trace follows the expected trajectory (Figure 18). The position of highest flexion is in the initial 20% of the lift where the participant is in the squat position, just prior to them extending to standing position. Then during the standing position phase the angle becomes more positive quickly as the participant comes to an upright posture, this is followed by peak extension during the lift-to-platform-height phase as the middle segments of the spine (MLT, LT, UL) (Figure 18C, D & E) go into hyper-extension in order to lift the box to head height or above. All segments, apart from the UT & LL, then return to a neutral posture once the box is placed on the platform. UT (Figure 18A) sits in a slightly flexed position once the box is placed on the platform, this could be reflective of the shoulders being in a forward position. LL (Figure 18F) also is in flexion, as participants use a split stance to place the box on the platform, the lower lumbar segment would remain in a forward tilt.

Peak values for MLT to UL follow a trend of 100% MLC having the highest (positive & negative) peak value, next highest 90% MLC and this continues down to 20% MLC with the lowest peak value. UT (Figure

18A) and LL have the opposite trend at the peak angle, as the load increases the angle value is less negative (smaller), also these segments never enter into extension. The MUT segment (Figure 18B) is of interest as only the heavier lifts (60 – 100% MLC) enter into extension, the 20% MLC remains in flexion and the 50% MLC returns to an vertical orientation at the peak. In the MUT segment 90% MLC has the highest extension peak value, followed by 100% MLC.

Of note, extension occurs sooner during 20% MLC lifts for the upper spine segments (UT, MUT) (Figure 18A & B) and the peak extension angle is lower. These segments also have a more negative 100% MLC trough occuring just after the weight-acceptance lift phase, indicating peak flexion due to the increased load.

4.2. Comparison of mean angular velocity change over the lift for %MLC

The angular velocity is based on the change in absolute angle in the sagittal plane with reference to the global axis.

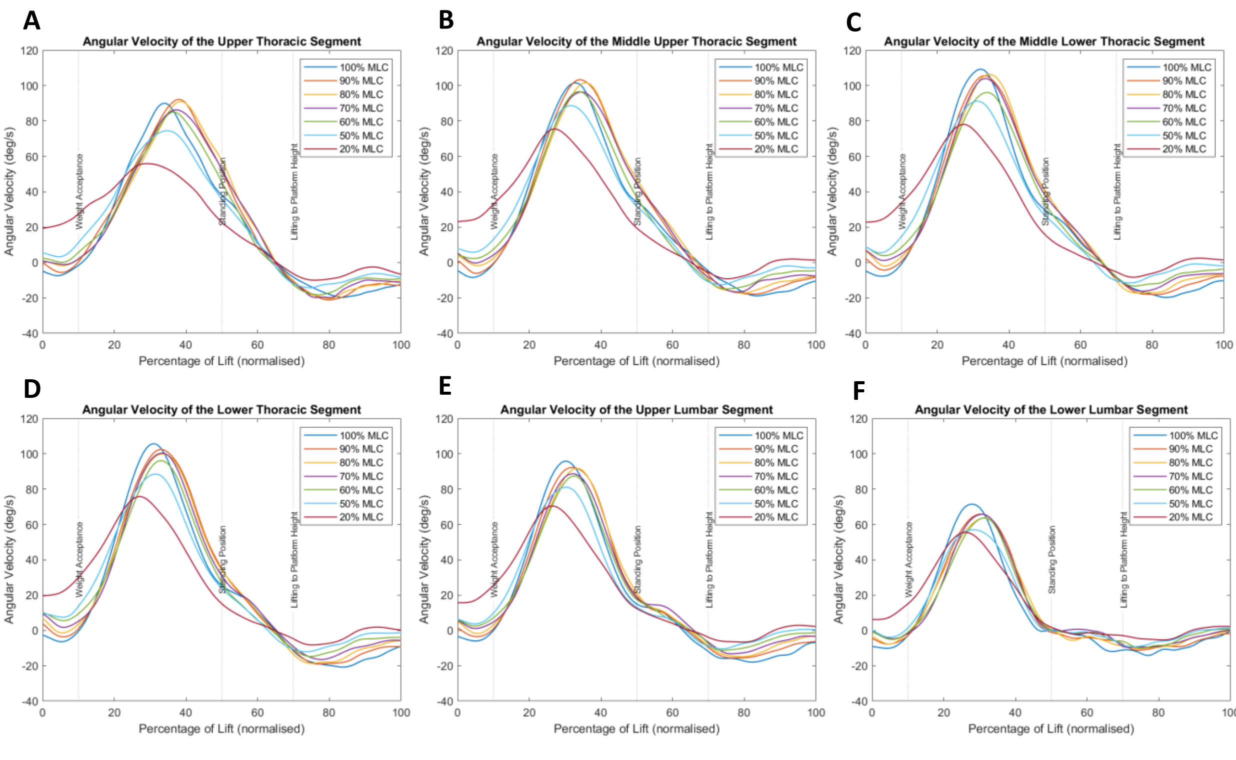

Figure 19 Mean angular velocity for %MLC of all participants for each spine segment.
A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL).

The trough during the weight-acceptance phase is indicative of slight increased flexion speed just prior to to a rapid increase in extension as the participant comes to standing position (Figure 19). Once peak AngVel in extension is reached, a similar gradient downward is present as the AngVel slows before it plateaus during the place-on-platform phase.

The standing position phase saw the fastest change in angle with the UT and MUT segments (Figure 19A & B) having similar peak angular velocity for the 100% MLC, 90% MLC and 80% MLC lifts. The rest of the spine segments have a consistent downward trend of reduced peak angular velocity with reduced %MLC.

The larger the %MLC, the higher the peak AngVel for the lift (Figure 19). During the weight-acceptance phase a trough occurs and 100% MLC has the more negative signal for all spine segments, with the other %MLC, in a downward order, becoming more positive. A second trough occurs in the place-box-on-platform phase which has the same distribution of %MLC variables as the weight-acceptance phase, however the AngVel values are more negative. This, combined with the peak AngVel values in the standing position phase correlating with the higher %MLC, means that the higher the %MLC, the greater the range in AngVel.

Peak AngVel occurs earlier for 20% MLC, followed by 50% MLC and 100% MLC (Figure 19). So at the extremes of the %MLC, peak AngVel is reached sooner. The 20% MLC also has a higher starting AngVel of about 10-20 °/s, this could be due to the participant not needing to set their squat position and not needing to use a transfer of body weight to counteract the external load.

4.3. Comparison of mean vertical magnetic field strength change over the lift for %MLC

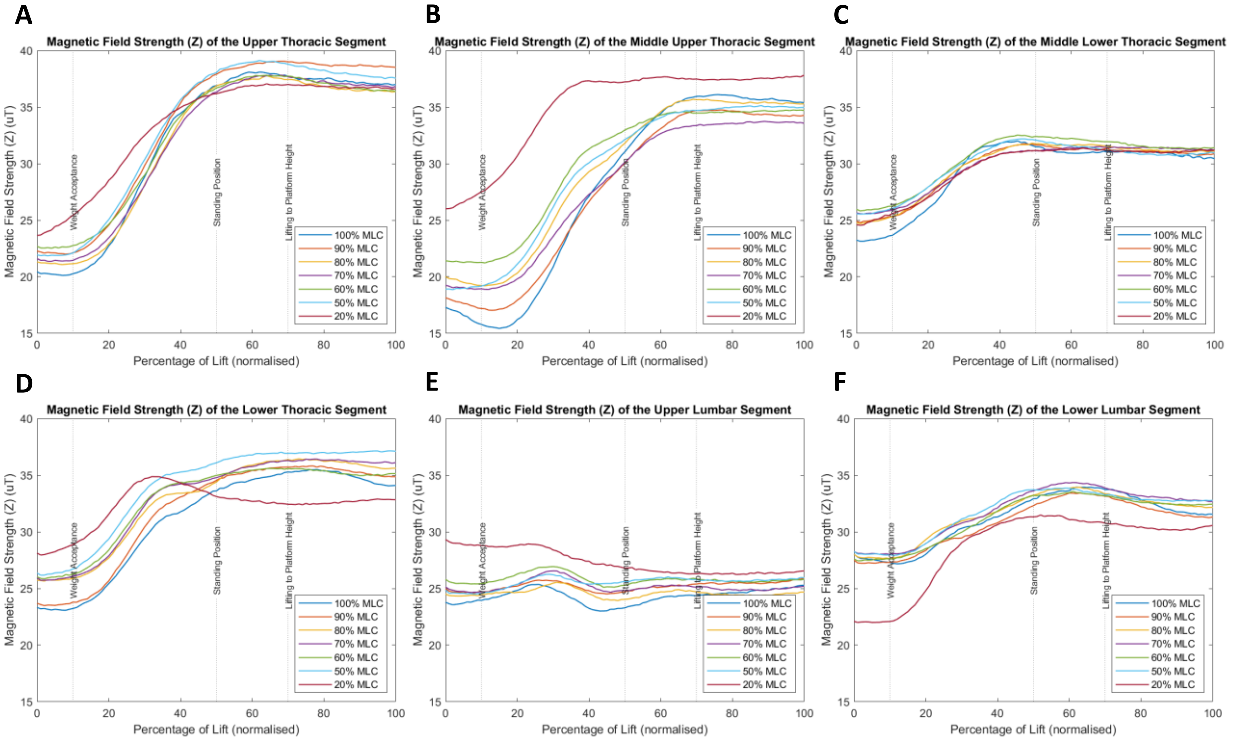

Figure 20 Mean vertical magnetic field strength for %MLC of all participants for each spine segment.
A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL).

The UT and the MLT segments all %MLC follow a very similar kinematic trace (Figure 20A & B). For the MUT, MLT, UL and LL segments the 20% MLC differs in shape and values (Figure 20C-F). The MUT (Figure 20B) and UL (Figure 20E) 20% MLC trace sits above the other %MLC values, meaning that these segments have less movement in the sagittal plane during the lift. The LT (Figure 20D) 20% MLC has less motion than during the lift than the other %MLC, the segment remains more upright during the weight-acceptance phase and during the transition from squat to stand, it then does not go in hyper-extension during the lift-to-platform-height phase. The LL (Figure 20F) 20% MLC trace shows that the segment has more flexion at the beginning of the lift and stays in a more flexed position than the %MLC traces.

4.4. Comparison of mean horizontal magnetic field strength change over the lift for %MLC

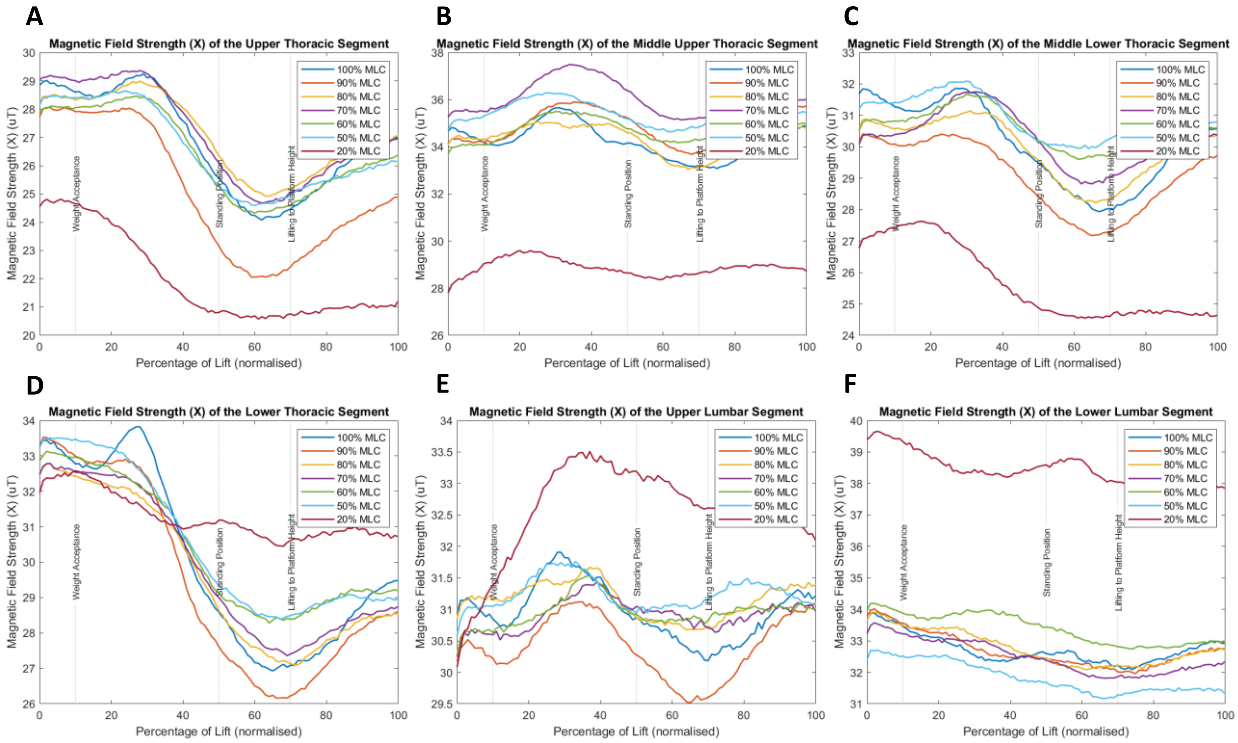

Figure 21 Mean horizontal magnetic field strength for %MLC of all participants for each spine segment. A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL).

For all segments (Figure 21) of the lift there does not seem to be an observational relationship between %MLC and horizontal magnetic field strength. Of note the 20% MLC has a very different values in all spine segments. For the UT – LT (Figure 21A-C) segments it does follow the general shape of the trace but is very different for LT – LL (Figure 21D-F).

4.5. Comparison of mean horizontal linear acceleration over the lift for %MLC

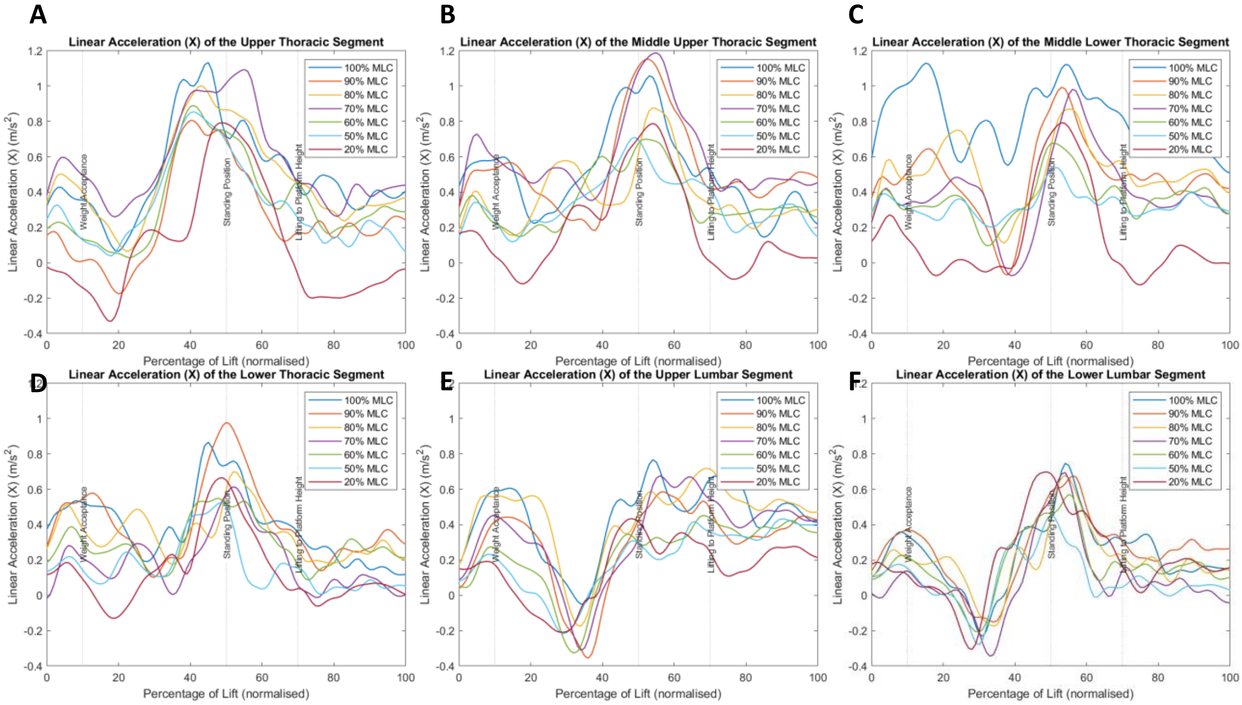

Figure 22 Mean horizontal linear acceleration %MLC of all participants for each spine segment.
A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL).

The peak during the weight-acceptance phase is indicative of an increase in horizontal acceleration while the load is being transferred from the ground to the participant (Figure 22). An acceleration trough transitions to a peak during the standing position phase indicative of a shift of motion from backwards to forwards. This peak carries over into the lift-to-platform-height phase. The peak could also be occuring when the participant steps into the split-stance posture. Once this peak occurs the accelerations plateau to little or no horizontal acceleration.

A trend in the effect of mass on horizontal acceleration is not clear. The weight-acceptance phase peak for the lower spine segments does have trend of the heavier %MLC lifts having higher acceleration. For LT and LL (Figure 22D & F) the 100%, 90% and 80% MLC group together with the highest accelerations and 60% MLC sits slightly lower (for LL the 80% and 60% have similar values), followed by 70%, 50% and 20%. The UL segment (Figure 22DE) has three groups during this initial peak with decending accelarations, 100% and 80% MLC followed by 90% and 70% MLC with 60%, 50% and 20% MLC grouped together.

4.6. Comparison of mean vertical acceleration over the lift for %MLC

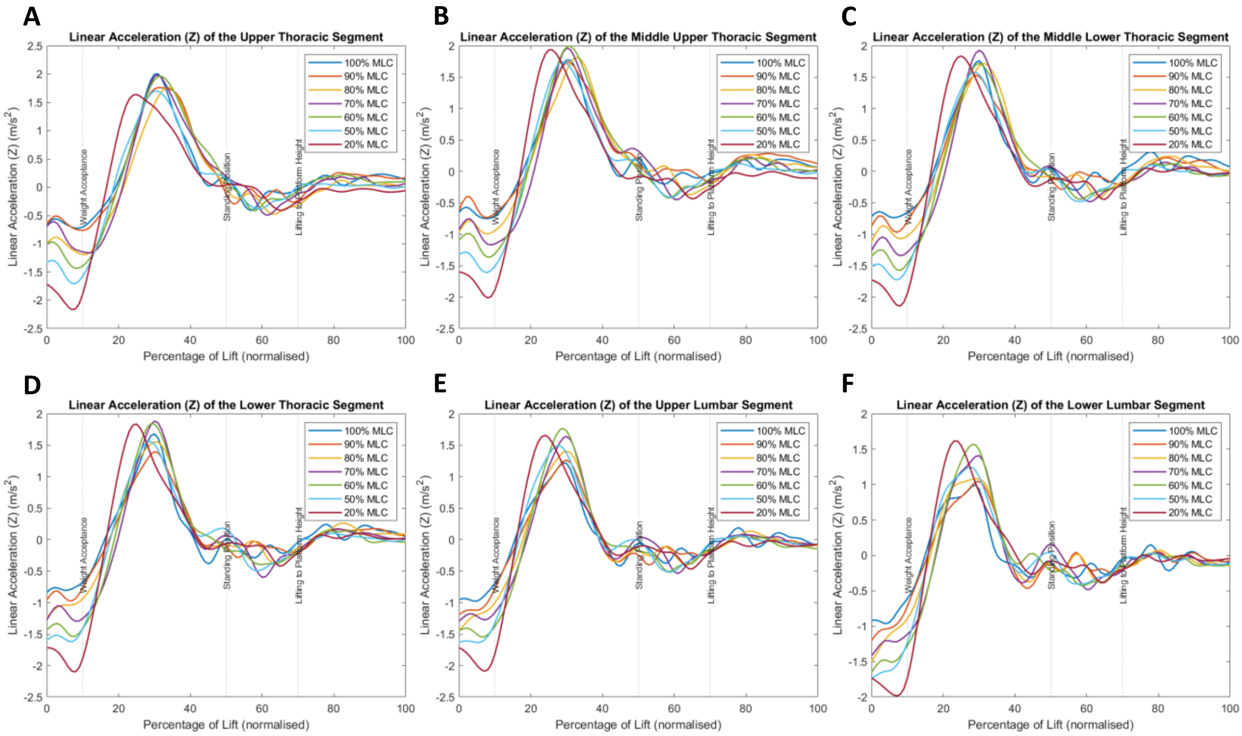

Figure 23 Mean vertical linear acceleration %MLC of all participants for each spine segment.
*A. Upper thoracic (UT) B. Middle upper thoracic (MUT) C. Middle lower thoracic (MLT) D. Lower thoracic (LT) E. Upper lumbar (UL) F. Lower lumbar (LL). * Plots have been reversed (multiplied by -1) so an incline represents upward motion and gravity has been deducted (- 9.81).*

During the weight-acceptance phase there is a clear pattern of 100% MLC having the least negative value and becoming more negative as the %MLC increases (Figure 23), meaning that the higher the load during weight transition the less vertical acceleration and accordingly less vertical motion when under heavier loads. The peak acceleration occurs during the standing position phase (Figure 23), however there is not a consistent pattern for the order in which the %MLC occurs for all segments (e.g., highest to lowest peak). Peak acceleration for 20% MLC does occur first. 20% MLC in all spine segments transfers fastest for weight-acceptance to standing position. There seems to be very little differences in between the %MLC for the lift-to-platform-height and place-on-platform phases, this is expected as there would be little vertical movement in the spine for those phases.

5. Discussion

This chapter addresses the limitations identified in Chapter 3 through the method for data collection, using the combination of three factors: 1. the use of seven %MLC classes determined via a task specific procedure, 2. the use of IMUs, and 3. the inclusion of six spine segments with multiple segments for the thoracic and lumbar spine. The presentation of the data as the mean %MLC (of all participants) for each of the spine segments and for the entirety of the lift (normalised for time) is a novel approach; typically, past studies have made conclusions about the effect of load on spine kinematics based on discrete (peak, mean, minimum) variables (Chapter 3). Additionally, using IMUs over MoCap means that the testing procedure laid out in this chapter is not limited to the laboratory for future data collection.

Looking at only select spine segments and/or discrete variables does not allow the exploration along the entire spine and its trajectory for the duration of the lift. This exploration has revealed multiple points where comparison and analysis may be beneficial for determining the effect of increased load on spine kinematics. For example, many studies reporting significant differences at specific timepoints, such as the end frame of the lift [125, 127, 152, 153]. In this research, for the end frame of the lift the middle segments of the spine (MLT,LT) (Figure 18C, D & E) have a trend of increased flexion with increased load, while the UT, MUT, UL and LL segments have decreased extension with increased load, however the UT, MUT and LL segments do not extend past neutral posture (0°). This means the hyperextension (above 0°) occurs mostly in the thoracic portion of the spine. These finding are in agreement with other studies, with [125, 127] finding a decrease in angle when analysing the thoracic spine at C7 - T7 (UT - MUT) and an increase in angle for the lumbar spine [125]. These studies were a good comparison as they also performed minimum and maximum lifts to shoulder (or above) height, a similar procedure used in the experimental trials.

50 – 100% MLC (apart from LL) follow the trend that the more mass, the larger the initial flexion. The larger flexion angle of 20% MLC at the onset of the lift may be due to less control of lumbar flexion when the mass is unexpectantly light. However, an interesting point along the kinematic trace occurs at approximately 15 – 20% of the lift, where there is a point of peak flexion. At the point of peak flexion, for all lifts except 20% MLC (15-20% of the lift) (Figure 18), the MLT to UL spine segments show a trend of increased flexion with and increase in load. Other studies showed similar results for the hip (10, 20 and

30% MLC) [151] and lumbar spine (3.4, 6.8 & 10.2 kg) [130]. However, [152, 153] found no trend for peak trunk flexion during the lifting phase.

The peak flexion point for 20% MLC is at the onset of the lift (Figure 18), these lifts then transition straight to spine extension, this differs from all other %MLC lifts, as these have a higher peak flexion just prior to the onset of spine extension. This could be due to the participant not needing to adjust position once the full amount of the load is taken up by the arms. This position change of increased flexion just prior to transitioning into standing position may be a result of creating inertia in order to lift the box. While the LL segment (Figure 18F) shows a similar trend, the difference is that the lift is clustered into two groups, 20 – 60% MLC and 70-100% MLC. This shows that there may be very similar peak flexion angle in the LL segment when the load is light and when it is heavy.

Peak extension angle occured during the lifting-to-platform-height phase (Figure 18) (except for the LL). This would be due to the spine going into hyperextension in order to get the box into its maximal vertical height. When the loads are lower (sub-maximal) there is less need for the body to be used to counterweight the external load. UT and LL never enter hyper-extension, while MUT only enters hyper-extension with the heavier lifts. This highlights that the middle spine segments are the ones performing the hyper-extension necessary to place the box on the platform when the lifts get heavier.

There was a trend of increased peak angular velocity with increased load in this study (Figure 19). This was not the case in previous studies [137, 141, 145, 146, 152, 153], all reported a trend of decreased peak angular velocity in the lumbar spine with increased load, however all these studies looked at lifting to hip height only (standing position). One study that observed lifting to chest height [130] reported an increasing trend in peak angular velocity with increased load. It may be that the trend in the effect of load on spine kinematics may change with the increase in height of the lift. This could be due to the effect of spine hyperextension when the box needs to be lifted above the hips, whereas hyperextension may not occur at lifts below this height.

6. Conclusion

The effect of an increase in external load on spine kinematics, at all levels of the spine, is evident when comparing variables from the IMUs devices. The correlation is more apparent in Angle, AngVel and Acc Z, with clear positive and/or negative correlations. The use of multiple segments at the thoracic and lumbar spine levels provided detail of opposing trajectories (within that spine level) that would not have been apparent viewing the lumbar or thoracic spine as a whole. For example, the generalised kinematic traces (the mean from all participants) show an increase in the peak values (positive correlation) for Angle for the MLT, LT and UL, while the UT and LL had a negative correlation and the MUT segment had a positive correlation for loads at and above 60% MLC and negative for 50% MLC and below. A threshold representing MAWL (84%) was not observed in the kinematic traces.

7. Summary

A database of spine kinematic variables recorded using IMUs devices was established, and the kinematic traces observed for differences due to increased loading. Observing the kinematic trace of variables recorded for seven %MLC at six spine segments showed correlation between the increase in %MLC and a change in spine kinematics. In order for these variables to contribute to the creation of a predictive model, it was important to know whether these observed changes were significant.

Statistical analysis on the complete kinematic time series (all data points) was performed to determine if the observed changes in the kinematic variables were due to the increase in %MLC. Study of the time series avoided limiting the analysis to discrete data points (peak, minimum, mean) or time frames (start, middle, end). Finding which variables showed significant differences in %MLC ascertained which variables would provide the most value in prediction of lifts above MAWL. In order to see the significance of the correlation, for each of the variables and spine segments, and where the significance lies along the kinematic trace, statistical parametric mapping (SPM) was used as it allowed statistical significance to be determined at each data point in the kinematic trace. Along with this, the shape of the trend and strength of trendline correlation was investigated for the possibility of regression modelling.

Chapter 5. Biomechanical analysis of military manual handling tasks – Statistical analysis

This chapter aimed to determine the statistical significance of changes in spine kinematics due to increased %MLC from a database recorded during experimental trial (Chapter 4). Statistical significance of all sagittal variables (six) from six spine segments were identified through SPM one-way ANOVA and then the significance of the %MLC differences was found via SPM post-hoc ANOVA. Further, the strength of the linear and polynomial correlation of discrete features to an increase in %MLC was explored. The findings are important as statistical significance in the variables would be an indication that the use of spine kinematics for prediction of light and heavy lifts was possible. As, if the kinematic trace has features that are significantly different from another %MLC class, this will be recognised by the predictive model, triggering an exoskeleton/ wearable device to provide feedback only when needed.

1. Introduction

SPM was initially developed for neuroimaging, to map the functional changes in brain activation during a scanning session with greater precision than previous statistical models that compared discrete regions of interest [164]. It was then introduced into human movement and biomechanics to expand kinetic and kinematic statistical analysis from looking just into discrete points in time to make statistical inference on the whole time series [165]. The advantage of using SPM is that no assumptions on the point of interest need to be made as the full time series can be hypothesis tested [166]. The visualisation of the SPM results allows for better interpretation, for example when viewing a time series t-test plot, the point of interest where significance lies can be demonstrated at multiple points on the plot.

A number of biomechanical studies into kinematics have used SPM for statistical inference (e.g., [165-168]). For example, when exploring the variability in lower body joint kinematics, for experienced weightlifters, SPM was used to determine that there was significant intra and inter-participant variability in joint AngVel when performing barbell squat lifts [167]. SPM along with a six-segment spine model was used to analyse the effect of lifting posture on spine loading finding that the recommendations for squat lifting may not be the best approach for every person. These studies showed SPM as a valuable tool, so as not to introduce a bias of what the expected features in the data would be and instead explore the time series trace in full.

Many studies from the literature review into kinematic changes (Chapter 3) used discrete features (e.g., peak, minimum, mean, ROM) (e.g.,[127, 130, 137, 140, 145, 152, 153, 155]) and/or time period (e.g., start, middle, end) (e.g.,[125-127, 131, 150, 152, 153]) to explore the relationship between increased load and spine kinematics. The most commonly used discrete features were peak, mean and ROM and the variables analysed were angles, angular velocity and acceleration. Significant correlations between increased load and these discrete features were found in the literature (e.g., [125-127, 150, 152, 153]), such as a significant increase in trunk extension angle at the end stage of the lift [152, 153], decreased thoracic extension angle (T7) at the end stage of the lift [125, 127] and increase lumbar extension angle (L5) [125]. Observational correlations for an experimental data set were explored in Chapter 4 and it was found that these correlations were also present in the collected data. This chapter aimed to determine whether the observational trends in the experimental dataset were significant and discover any other features that may prove significant in the time series kinematic trace.

The aim of this chapter was to determine which observations (spine segment and/or IMUs variable) and features (e.g., mean, min, max, ROM) show statistically significant differences in their kinematic trace due to an increase in %MLC. Statistical significance means that the changes in the data were due to increased %MLC and that those observations should be of benefit for prediction of light and heavy loads. Additionally, a strong correlation of change in features due to an increase in %MLC to a linear or polynomial trend means that classification may be possible through the use of regression.

2. Methodology

In order to see if the differences between the %MLC traces and if there are any significant differences, SPM technique was used from the open-source spm1d-package (spm1d.org, T. Pataky) in MATLAB (The

MathWorks Inc., Natick, MA, USA). One-way ANOVA (spm1d.anova1) and post-hoc ANOVA (spm1d.anova_posthoc) were used. SPM one-way ANOVA performs a F-test at each point along the time series for each repeated measure, while SPM post-hoc performs two-sample t-tests conducted on all group pairs for each point along the time series. %MLC (20%, 50%, 60%, 70%, 80%, 90%, 100%) was the active independent variable with the dependent variable being the time series observation (spine segment + IMUs variable). The alpha level was set at 0.05, with 7 repeated measures (%MLC) for the one-way ANOVA and Bonferroni corrected for the post-hoc ANOVA tests. For the one-way ANOVA, if significant ($p<0.05$), the p-value for the six sagittal variables of each spine segment was recorded (Table 9). The post-hoc analysis was performed for variables that reported a significant p-value in the one-way ANOVA. For the post-hoc analysis the mean of all participants for Angle, AngVel, Mag X, Mag Z, Acc X and Acc X for each %MLC class was compared to another and the phase (e.g., weight-acceptance or lift-to-platform) in which the significant difference occurred was reported (Table 10). The SPM plots that provided the results for Table 10 can be viewed in Appendix .

Based on the findings from the SPM analysis, linear and 2nd order polynomial trends in the discrete variables for phases of the lift were plotted to determine the strength of their correlation. The peak (max), minimum (min) and range of motion (peak – minimum) of the angle was taken from each lift observation at each level of the spine. The correlation coefficient (R) for the predictability of the %MLC from the angle value were then recorded. This was performed in MATLAB (The MathWorks Inc., Natick, MA, USA) using polynomial fit and evaluation.

3. Results

3.1. Statistical parametric mapping

SPM one-way ANOVA analysis shows that the variables with the largest number of significant differences (significance at all spine levels) between the %MLC variables are Acc Z, Angle Y and AngVel Y (Table 9). Statistical significance for these variables is present for all segments of the spine. Acc X has significance for the MLT and UL segments, while vertical Mag Z show significance only in the MUT segment. Mag X has no significance in this dataset.

Table 9 Results for one-way ANOVA of %MLC for each variable.

	UT	MUT	MLT	LT	UL	LL
ACC X	-	-	0.000	-	0.000	-
ACC Z	0.001	0.000	0.000	0.000	0.000	0.000
MAG X	-	-	-	-	-	-
MAG Z	-	0.029	-	-	-	-
ANGLE Y	0.000	0.001	0.000	0.001	0.000	0.037
ANGVEL Y	0.000	0.000	0.000	0.000	0.000	0.000

SPM post-hoc ANOVA was performed on the variables from showed significant differences due to increase %MLC (Table 10). The majority of SPM significance occurs with values at the extremes of %MLC. So, comparing the lesser loads in the middle sections (50 – 70% MLC) to 100% MLC results in significant differences in the kinematic traces. Additionally, the section with the most significant results is the 20% MLC due to the same reason. Significant results occur up till the 70% MLC section with no results in the 80% - 90% MLC sections. All spine segments, apart from LL, have a similar number of significant results, with LL having less

The UT Acc Z SPM significance mainly occurs during the weight-acceptance phase in the 20 and 50% MLC section showing significance in the weight-acceptance and standing position phase. The Angle significance occurs from the standing position to place-on-platform phases in the 20% MLC section and during the lift-to-platform-height to place-on platform phases in the 50% MLC. The AngVel significance occurs during the weight-acceptance to place-on-platform phases in the 20% MLC section and during the standing position phase in the 50% MLC section.

The MUT segment shows very similar significant differences as the UT segment, however in the 20% MLC section Mag Z has significance occurring during the standing position phase. Acc Z significant differences occur during the weight-acceptance phase of the 20% MLC section and at the extremes of the 50 and 60% MLC section showing results in the weight-acceptance phase. The Angle significant differences occur during the lift-to-platform-height and place-on-platform phases in the 20 and 50% MLC sections.

The AngVel significance occurs across the entire lift in the 20% MLC section and in all phases except lift-to-platform-height in the 50% MLC section.

The MLT segment Acc Z shows significance occurring during the weight-acceptance phase and standing phase for the 20-50% MLC sections and also at the extremes of the 60 and 70% sections. Acc X also shows results at the extremes of the 20% section for the standing position and place-on-platform phases. Angle has significance from the standing position to the place-on-platform phase for the 20 and 50% sections, with the 60% section having results in the lift-to-platform-height and place-on-platform. Results for AngVel are similar to MUT with the addition of the 60 vs. 100% MLC significance occurring in the weight-acceptance and place-on-platform phases.

The LT segment has more significance in the extremes of the 60 and 70% sections. Acc Z shows significance in the weight-acceptance and standing position phases for the 20 to 70% MLC sections. Angle significance occurs in the standing position to place-on-platform phases for the 20 to 70% MLC sections. While AngVel significance occurs throughout the entire lift for the 20 and 50% section and during the weight-acceptance and place-on-platform phases for the 60 and 70% sections.

The UL segment differs, as significant results are present sporadically for the Acc X variable, these are occurring in the weight-acceptance and standing position phases for the comparisons with the 80% lifts. The Acc Z variable shows significance in the weight-acceptance phase for the 20 – 70% sections, and also in the standing position phase in the 60% section. Significance for Angle occurs throughout the entire lift. This is also the case for the AngVel variable but for the comparisons between the heavier lifts (60% section) it is towards to end of the lift.

The LL segment shows results in the Acc Z and AngVel variables. These occur in the weight-acceptance and standing position phase for Acc Z in the 20 – 60% sections. For AngVel significance occurs in the weight-acceptance, standing position and place-on-platform phases for the 20% MLC section and during the place-on-platform phase for the extremes of 50 and 60% MLC sections.

Table 10 Results for post-hoc ANOVA of %MLC for each variable.
Numbers indicate significance (p< 0.05) and the phase of the lift that significance occurred in (1 = Weight Acceptance, 2 = Standing Position, 3 = Lift-to-platform-height, 4 = Place-on-platform).

	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
UT																					
Acc Z	-	-	1 2	1 2	1	1	-	-	1	1	1	-	-	-	-	-	-	-	-	-	-
Angle Y	3 4	2 3 4	2 3 4	2 3 4	2 3 4	2 3 4	-	3 4	3 4	3 4	3 4	-	-	-	-	-	-	-	-	-	-
AngVel Y	1 2	1 2	1 2	1 2 3	1 2 3 4	1 2	-	2 3	2	-	-	-	-	-	-	-	-	-	-	-	-
MUT																					
	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
Acc Z	-	-	1 2	1	1	1	-	-	-	-	1 2	-	-	-	1	-	-	-	-	-	-
Mag Z	-	-	2	-	2	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Angle Y	3 4	3 4	2 3 4	2 3 4	2 3 4	2 3 4	-	-	3 4	3 4	3 4	-	-	-	-	-	-	-	-	-	-
AngVel Y	1 2	1 2	1 2 3 4	1 2 3 4	1 2 3 4	1 2 4	-	-	2 4	1 2 4	1 2 4	-	-	-	-	-	-	-	-	-	-
MLT																					
	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
Acc X	-	-	-	-	-	2 4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Acc Z	-	-	1 2	1	1	1 2	-	-	1	1 2	1 2	-	-	-	1 2	-	-	1	-	-	-
Angle Y	-	-	2 3 4	2 3 4	2 3 4	2 3 4	-	3 4	2 3 4	3 4	3 4	-	-	3 4	3 4	-	-	-	-	-	-
AngVel Y	1 2	1 2	1 2 3 4	1 2 3 4	1 2 3 4	1 2 4	-	1 2 4	1 2 4	1 2 4	1 2 4	-	-	-	1 4	-	-	-	-	-	-
LT																					
	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
Acc Z	-	-	1 2	1 2	1	1	-	-	1	1	1	-	-	1 2	1 2	-	-	1 2	-	-	-
Angle Y	-	2 3 4	2 4	2 3 4	2 3 4	2 3 4	-	-	3 4	2 3 4	2 3 4	-	-	3 4	2 3 4	-	-	2 3 4			
AngVel Y	1 2 3	1 2 3 4	1 2 3 4	1 2 3 4	1 2 3 4	1 2 3 4	-	2 3 4	1 2 4	1 2 4	1 4	-	-	-	1 4	-	-	1 4	-	-	-
UL																					
	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
Acc X	-	-	-	2	-	-	-	-	1 2	-	2	-	-	-	-	-	-	-	-	-	-
Acc Z	-	-	1	1	1	1	-	-	-	-	1	-	-	1 2	1 2	-	-	-	-	-	-
Angle Y	-	-	2	2 3	2 3 4	1 2 3 4	-	-	3 4	2 3 4	2 3 4	-	-	2 3 4	1 2 3 4	-	-	-	-	-	-
AngVel Y	1 2	1 2	1 2 4	1 2 4	1 2 4	1 2 4	-	4	2 4	2 4	1 4	-	-	4	4	-	-	-	-	-	-
LL																					
	20-50	20-60	20-70	20-80	20-90	20-100	50-60	50-70	50-80	50-90	50-100	60-70	60-80	60-90	60-100	70-80	70-90	70-100	80-90	80-100	90-100
Acc Z	-	-	-	1	1 2	1 2	-	-	-	-	1	-	-	1 2	-	-	-	-	-	-	-
Angle Y	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
AngVel Y	-	1 2	1 2	1 2	1 2 4	1 2 4	-	-	-	-	4	-	-	-	4	-	-	-	-	-	-

KEY: ACC = Linear acceleration, MAG = Magnetic field strength, ANGLE = Absolute angle, ANGVEL = angular velocity, X = sagittal Z = vertical, Y = lateral.

To visualise what is occurring for the values at the extremes of %MLC, the generalised mean trace of the %MLC lifts and the resultant SPM hypothesis test were plotted in Figure 24. This plot contains the Angle and AngVel comparisons of the lesser %MLC to the 100% MLC lifts, as these variables had the most results. Performing this analysis provided how and where the kinematic traces were differing in their trajectories when the %MLC was increased.

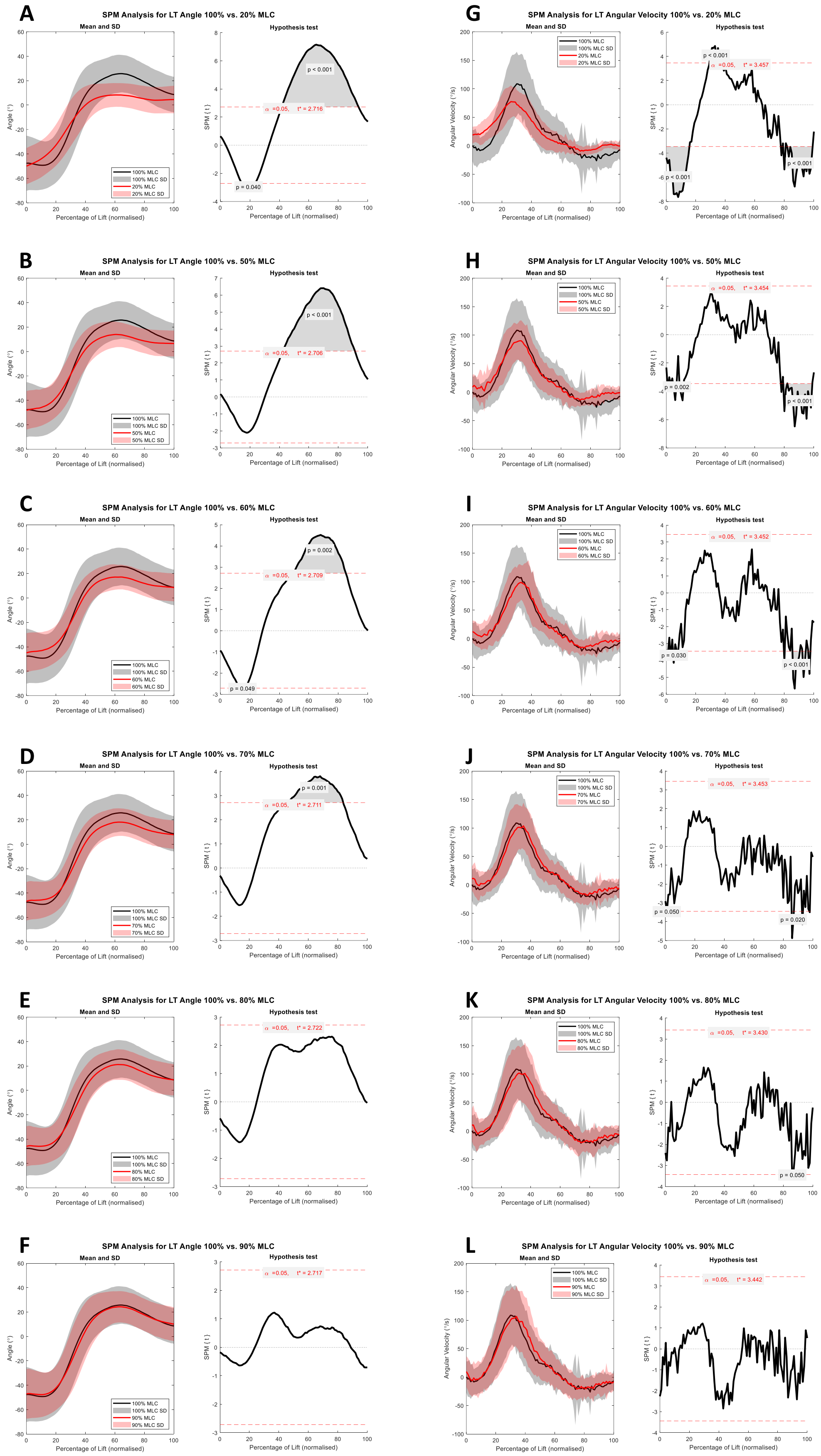

Figure 24 SPM examples of Angle and AngVel in the LT segment.

When looking at the extremes of %MLC for the Angle variable by comparing 100% to 20% MLC (Figure 24A), there are two points at which there are significant differences, the minimum of 100% MLC and the maximum of both 100 and 20% MLC.

The minimum Angle of the 100% MLC occurs at a different point to the 20% MLC (Figure 24A). The 100% minimum occurs at around 15% of the lift, beginning the lift at a less negative (less flexed) position and then dipping down to a more negative value (more flexion). While the 20% MLC minimum occurs at the onset of the lift, this is the posture of most flexion in the 20% MLC. While this difference can be seen when comparing 50 – 80% MLC to 100% MLC, only 60% MLC shows its minimum to be significantly different to the 100% MLC (Figure 24C). As the %MLC load increases more flexion occurs just prior to the transition to extension, more closely matching the 100% MLC trace.

The peak Angle of the 100% MLC lifts is larger than that of the lesser %MLC. So as the load gets larger the peak angle gets larger, however there are only significant differences in the peak values from 20 to 70% MLC (Figure 24A-D). The significant difference in the peak value occurs between 40 – 100% of the lift, starting just prior to the lift-to-platform-height and ending once the box is placed on the platform. As the load gets closer to 70% MLC (Figure 24D), the significance range narrows to approximately 50 – 90% of the lift, encapsulating either side of the peak which is a period of hyper-extension.

The Angle ROM is smaller when the load is smaller (Figure 24A-F). When the %MLC is smaller, it has a less negative minimum and a smaller peak value, this means that the ROM for the angle variable will also differ between the %MLC variables. Although, this would occur between 15 to 60% of the lift and this period is not represented in the area of significance for any of the angle traces.

When comparing the %MLC extremes for AngVel (Figure 24G), there are three points where significance occurs. These are the local minima at the start of the lift, peak AngVel and minimum AngVel.

The local minima at the beginning of the lifts for the 100% MLC represents the fast change in direction occurring during the weight-acceptance phase. This is reflective of the differences in the Angle curve, where the lighter loads do not require extra flexion during the weight-acceptance phase, so there is not velocity in the negative and the heavier loads have a small period of hyper-flexion. The period of significance decreases towards the beginning of the lift as the loads get heavier and is only present in 20 – 70% MLC (Figure 24G-J). After 70% MLC the velocities between the %MLC for this period of the lift becomes similar (Figure 24K-L).

Peak velocity occurs during a phase of rapid extension and then slows as the participant goes into hyper-extension. The significance of this period is only present between 30 – 45% of the lift, when comparing the 20 and 100% MLC (Figure 24G). Due to the large standard deviation of AngVel for the 100% MLC there was no further significance for other %MLC.

The minimum value of AngVel is larger when the %MLC is heavier and occurs at 75 - 85% of the lift. The period of significance occurs between 75 – 100% of the lift, when the participant is placing the box onto the platform. In addition, the lighter the %MLC the earlier the minimum AngVel occurs.

Within the SPM analysis, there were two of the six variables that showed very little to no statistical significance but did present with observational trends in the generalised data (Chapter 4). Those being Acc X and Mag Z. Plotting the mean and standard deviation clarified why there was no significance for these variables (Figure 25).

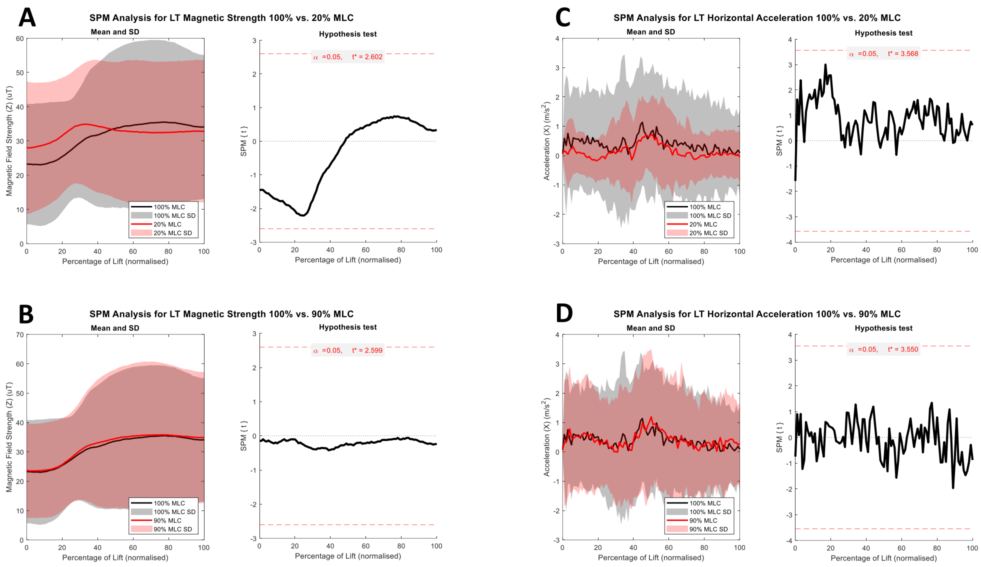

Figure 25 SPM examples of Mag Z & Acc X in the LT segment.

In Figure 25A there are differences in the Mag Z trace between the 100 and 20% MLC, especially compared to that of the 90 – 100% MLC trace (Figure 25B). However, both traces have a very large standard deviation, indicative of a large variation in the Mag Z values for all the participants. This also means that the differences in the generalised trace would need to be quite large for there to be any significance. This is the same for Acc X trace (Figure 25C & D). While the standard deviation of the 20% MLC Acc X is much smaller, it is fully encapsulated by the 100% MLC standard deviation.

The SPM analysis highlighted some key areas of interest for prediction of %MLC based on changes to spine kinematic. The segments of the spine of most interest are UT through to UL, as the LL segment shows less significant results for the IMUs variables. The variables with considerable significant differences are Acc Z, Angles and AngVel, with the discrete features of importance being minimum, peak and ROM. Due to Angle having less noise in the trace (filtered via the AHRS filter) and it having a large number of significant results in SPM, it was used to determine the shape of the relationship between the discrete features (minimum, peak and ROM) and an increase in %MLC at each level of the spine and phase of the lift, to determine which observations would be beneficial to make predictions.

3.2. Generalised correlation of discrete Angle variables with increased %MLC

One method of predicting the light and heavy loads would be through regression. Overall, correlation of the variables to the trendlines was poor to moderate. The peak and ROM discrete features had a higher correlation, but the highest value did not exceed 0.48. The LT segment had the highest correlation for both these discrete features, with the MLT and UL returning slightly lower results. The highest result occurred when the time series included all data up to lift-to-platform-height.

3.3. Linear & Polynomial correlation of peak angle

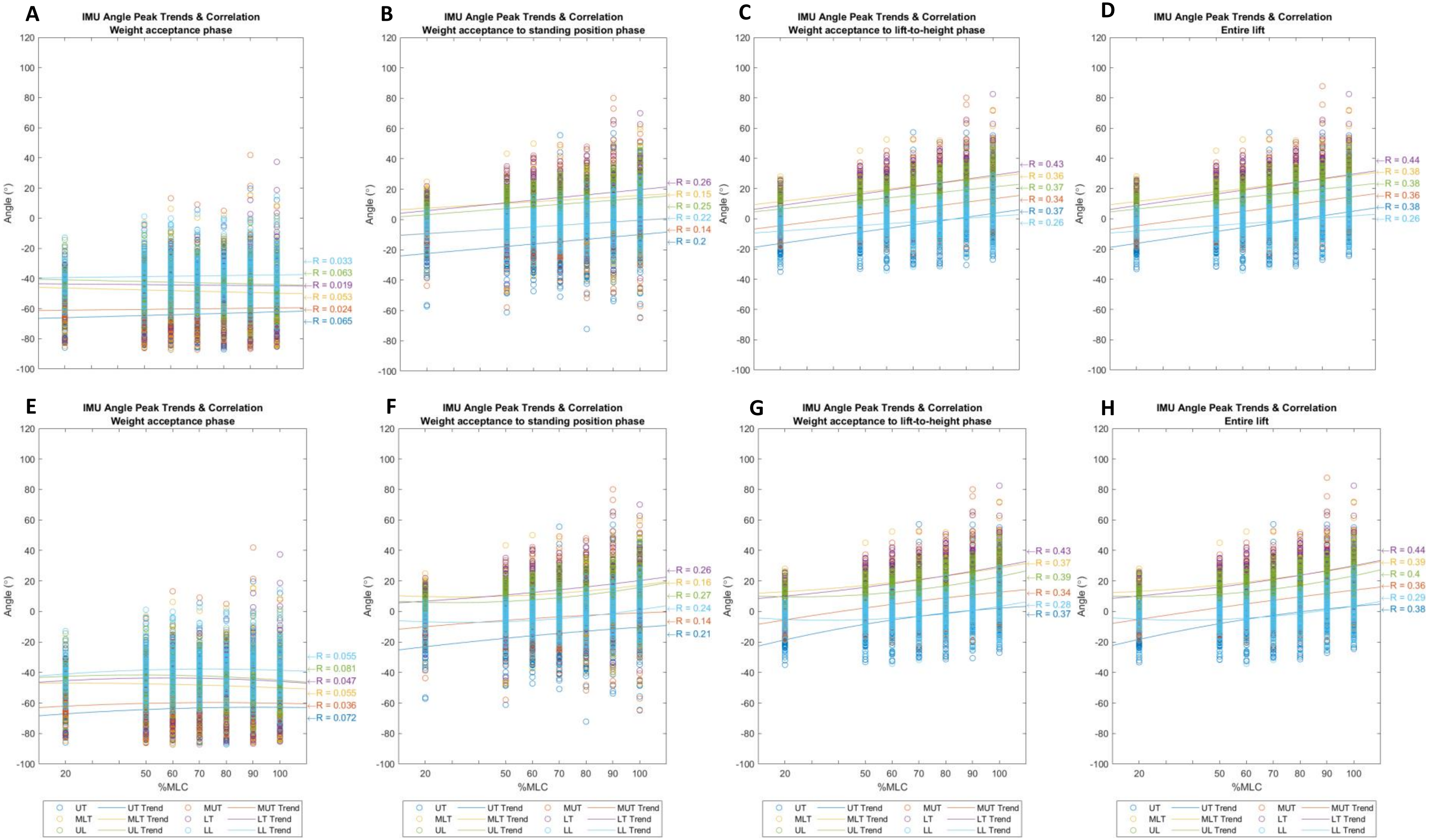

Figure 26 Linear & Polynomial correlation of peak angle during lifting phases.

In Figure 26 peak angle has low to moderate correlation in both linear and 2nd order polynomial trendlines. While some variables had no or only a marginal increase in correlation when looking at the polynomial trend compared to the linear, most variables saw an increased correlation in the polynomial trendlines. The weight-acceptance phase has no correlation (Figure 26A & E); the standing position phase has low correlation at all levels of the spine (Figure 26B & F); the lift-to-height (Figure 26C & G) and entire lift (Figure 26D & H) phases have moderate correlation; this would be due to the peak angle value for the lift occurring during the lift-to-height phase (Figure 18). The lower lumbar segment has a low correlation (<0.3) (Figure 26H), this reflects the results found in the SPM analysis of the lower lumbar segment (Table 10).

For the standing position phase onwards (Figure 26F-H) the top spine segments (UT & MUT) show a logarithmic curve while the lower spine segments (MLT to LL) all show an exponential curve. This means the changes in peak angle, while still positive, slow as there is an incremental increase in MLC% for the UT and MUT spine segments, while the opposite is true for the MLT to LL spine segments, the change in peak angle increases faster with an incremental increase in MLC%.

In all the plots (Figure 26A-H) the upper spine segments (UT & MUT) have a larger spread of the peak angle values than the other segments. It would seem that the peak angle for the UT and MUT segments is more variable. The lower spine segments (UL & LL) have a smaller spread of the data, it seems in the case of peak angle the higher the spine level the more the data spread.

3.4. Linear & Polynomial correlation of minimum angle

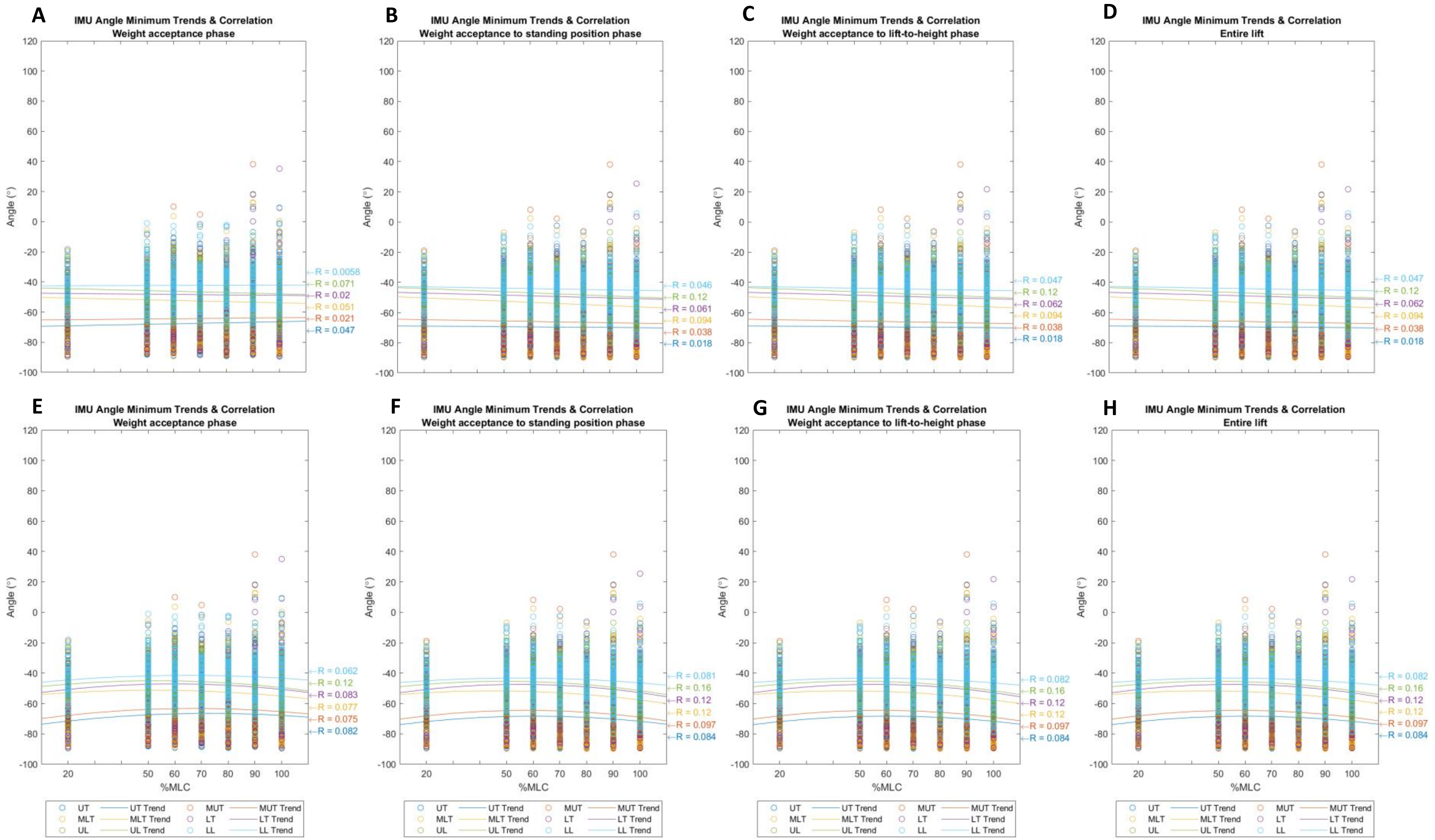

Figure 27 Linear & Polynomial correlation of minimum angle during lifting phases.

In Figure 27 the minimum angle has low to no correlation in both linear and 2nd order polynomial trendlines (<0.16) (Figure 27H). While all variables had very little correlation, there was an increase in correlation in the polynomial trendlines. There was a slight improvement in correlation from weight-acceptance to standing position phases (Figure 27E & F), however, after that the correlations did not improve as the lift progressed (Figure 27G-H). This is in line with the observational results from Figure 18, showing that the minimum angle occurs in the first 15% of the lift.

The extremes of the %MLC had the highest minimum values (most negative) (Figure 27E & H). This was seen in the angle comparison graphs (Figure 18), where 20% MLC had a low starting angle (0% of the lift) while 100% MLC had a similar angle occur just prior to the transition to extension (15% of the lift). Also, the variability in the minimum value of the data increases as the %MLC increases (Figure 27E & H), this is reflected in the large standard deviation for high %MLC values seen in Figure 24, this large distribution of values is also present in the discrete features.

3.5. Linear & Polynomial correlation of angle range of motion

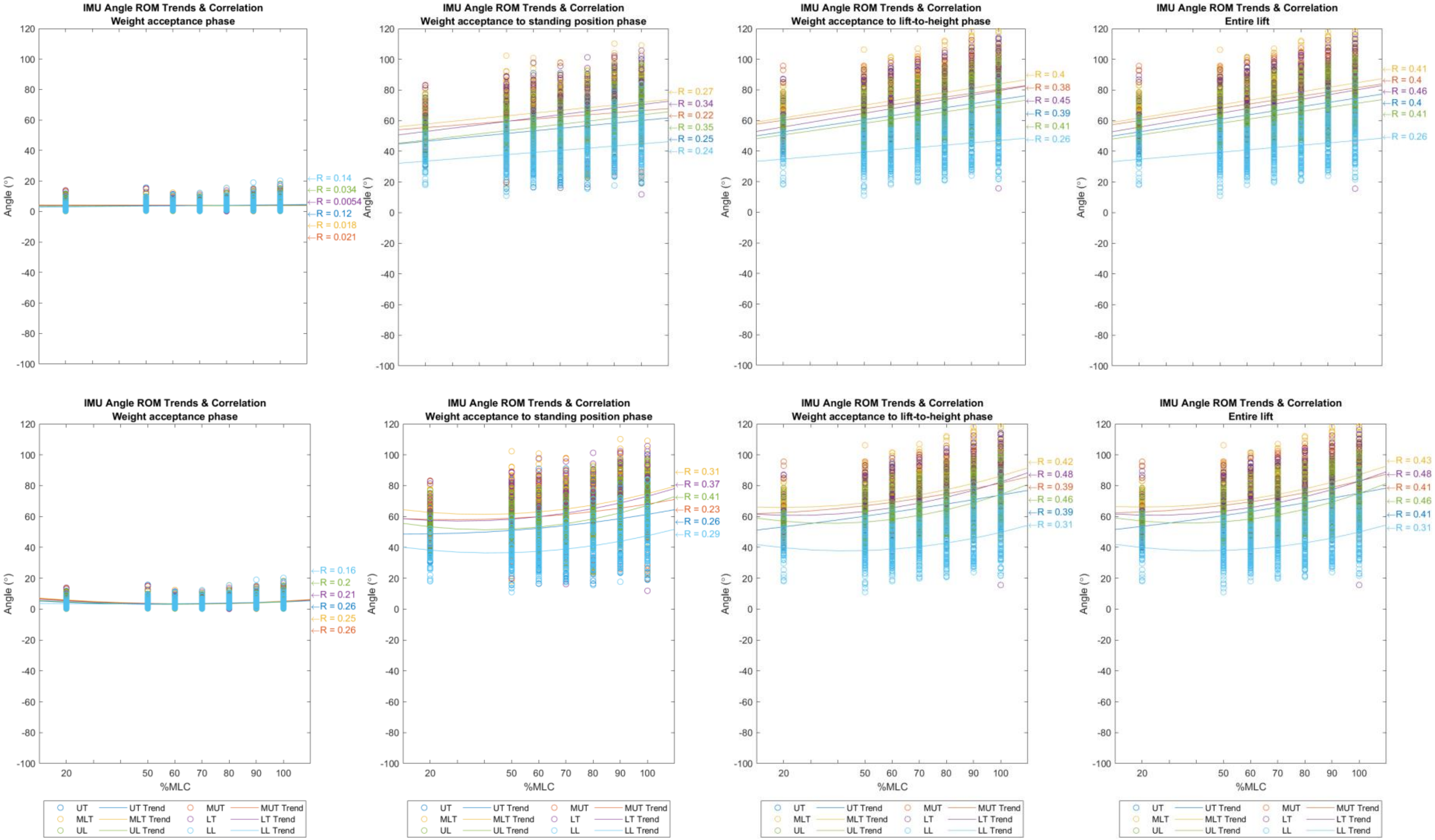

Figure 28 Linear & Polynomial correlation of angle range of motion during lifting phases.

In Figure 28 Angle ROM has low to moderate correlation for both linear and polynomial trendlines, with a small improvement in correlation when viewing the polynomial trendline. The weight-acceptance phase has low correlation (Figure 28A &E), while the standing position phase has low correlation for the upper and lower spine segments (UT, MUT & LL) (Figure 28B & F) and moderate correlation for the middle spine segments (MLT, LT & UL). There is an improvement to correlation for the lift-to-height phase (Figure 28C & G), that is preserved in the entire lift phase with the middle spine segments (MLT, LT & UL) maintaining a higher correlation (Figure 28D & H); this is due to the minimum angle occurring during or just after the weight-acceptance phase and the peak angle occurring during the lift-to-height-phase.

For the standing position phase (Figure 28F-H) onwards all spine segments, apart from UT, have a parabolic curve that has an increase at the higher %MLC values and dips at the 50 -60% MLC values. The UT segment shows an almost positive linear relationship when fitted with a polynomial trendline. Overall, the relationship between increased %MLC and an increase in mean Angle ROM could be described as a positive linear correlation, without much loss in the R-score (Figure 28D).

4. Discussion

The novel contribution this chapter makes to the body of research is that the change in kinematic variables: vertical acceleration, absolute angle and angular velocity, of the UT to UL spine segments show the most statistical significance due to increased external load (Table 10). Significant differences were most likely to occur at the minimum and peak values for Angle (Figure 24) and in the transition to standing for AngVel (Angle ROM). The upper and middle spine segments present more results for changes in spine kinematics than the LL segment. The LL SPM has very few significant results for the Angle variable. This is in agreement with studies reviewed in Chapter 3 who focused on kinematic analysis of the lumbar spine segment and reported no significance for changes to angle [131, 132, 137, 140, 147, 148].

This research found significant changes in angle with an increase in load (Table 10) for spine segments UT to UL, however the correlation for the peak angle and ROM variables were moderate. There are mixed results of the effect of load on the angle variable from reviewed studies (Chapter 3) on the lumbar and thoracic spine; some reporting a significant decrease in the angle with an increase in load [126, 127, 146, 150]; others reporting a significant increase in angle with an increase in load [138, 152-154]. The results from Figure 18 show that this is due to where on the spine the analysis is performed.

The lumbar segment will have different results depending on whether the measurements are taken at the upper lumbar (T12 – L3) or lower lumbar (L3 - S1). When looking at the results in Figure 18F for the LL, at the lift peak, 100% MLC has the lowest angle value. The LL segment has a negative correlation to load, that being there is a decrease in peak angle with an increase in load, this is because this segment never goes into hyper-extension. The UL segment has a positive correlation to load, that being there is an increase in peak angle with an increase in load.

Having many spine segments analysed in this research has allowed to see that each spine segment works in different ways with the introduction of load. Even within larger spine segments (e.g., thoracic & lumbar) there are differences in the way vertebrae react to increased load. This is shown in the shape of the polynomial correlation trend lines in Figure 26. The UT and MUT segment do not enter hyper extension and have a logarithmic shape to the curve. LL however has a more exponential curve even though it has a negative correlation. This could be due to the spread of peak values in the higher lifts.

There are variables that showed a trend in the comparison of mean data (Acc X, Mag X & Mag Z) (Chapter 4) but do not have significance in SPM due to the large standard deviation shown in Figure 25. For these variables to be useful for statistical predictions, a much larger sample of lift observations would be needed. For example, using the sample size calculation for comparing two independent means [169] (Equation 1) for the Mag Z LT data at the minima (at around 10% of the lift) (Figure 25a), where the 100%MLC mean is 29 and standard deviation is 19, the 20%MLC mean is 23 and standard deviation is 18 and the level of significance is set to 5% and power to 90%; due to the large standard deviation in the data, an estimated sample size of 200 would be needed to yield valid results.

$$n = \frac{({\sigma_1}^2 + {\sigma_2}^2)(Z_\alpha + Z_{1-\beta})^2}{|\mu_{1-}\ \mu_2|^2} = \frac{(18+19)^2\ (1.96+1.28)^2}{|29-23|^2} = 199.75$$

Equation 1 Comparing two independent samples to calculate sample size.

The majority of SPM significance occurs with values at the extremes of %MLC, when comparing low %MLC trace to the 100% MLC trace. More significant differences are seen in the 70% MLC sections compared to that of the 80% and above phases. This could be reflective of the point where the increase load has changed the motion of the spine to compensate for the heavy boxes and so 80 vs. 90 vs. 100% MLC may all start to have similar kinematic traces.

5. Conclusion

While certain variables of the time series IMUs data show statistically significant differences in SPM post-hoc ANOVA, there was a low to moderate R-score when looking at linear and polynomial correlation for the predictability of the spine angles from %MLC. The correlation of all discrete values showed poor to moderate correlation to a linear trend and was only slightly improved with a 2nd order polynomial trend. Peak and ROM discrete features showed the highest correlation for the standing position phase onwards; however, it never surpassed an R-score of 0.50. This could be due to the large spread of discrete angle variable values at each level of the spine and for each %MLC. Using linear or polynomial regression for prediction would therefore result in poor accuracy. Further methods of prediction were explored in Chapter 6, this involved prediction of %MLC using machine learning multivariate time series classifiers.

6. Summary

Statistically significant changes in spine kinematics due to an increase in %MLC were present at all levels of the spine for Angle, AngVel and Acc Z variables. However, the predictability of %MLC based on discrete features of the spine Angle showed poor to moderate correlation and the use of polynomial regression would result in poor accuracy. Therefore, supervised machine learning was explored as a method for predicting light and heavy loads.

Experimental trials (Chapter 4) resulted in a database of 30 participants, performing seven %MLC classes, with six IMUs of which six sagittal variables were processed. Chapter 5 showed that increasing the %MLC had a significant effect on many of these variables, specifically Angle, AngVel and Acc Z for all spine segments, however most of the effect is seen when comparing the extremes of %MLC (100% to 20%, 90% to 50%). Chapter 6 used the established database to train and test a machine learning algorithm to predict whether the lifted load was Light (below MAWL) or Heavy (at or above MAWL).

Predicting whether a %MLC observation was in the light or heavy class was a multivariate time series classification problem. This is a branch of supervised machine learning that analyses labelled time series observations and then classifies unseen observations into the class it believes they belong. The benefit of machine learning over statistics is its ability to make predictions on unobserved data without needing to know the best discrete features, variables or spine segments to use [170].

For an exoskeleton to augment lifting early enough to reduce the risk of injury, it needs to assist as early in the lift as possible. This means using variables that show significant difference in the weight-acceptance and standing position phases. The variables that show the most promise for early prediction in are the upper and middle spine segments (UT, MUT, MLT, LT & UL) AngVel and Acc Z. Machine learning additionally allows for analysis of feature importance, it was thought that these variables would most affect the algorithm.

Chapter 6. Machine learning model for classification of lifts above MAWL

This chapter aimed to create a machine learning model capable of accurately predicting the class to which a %MLC observations belonged, using the database of observations recorded in experimental trials (Chapter 4). Statistical inference of the database was established in Chapter 5, with Angle, AngVel and Acc Z showing significance at all studied levels of the spine due to an increase in %MLC. The ML algorithm that showed the highest accuracy (ROCKET) was used in the model for dimensionality reduction (spine segment & number of data frames included in training and testing) based on feature importance. The importance of this chapter is in the model's ability to predict whether a lift exceeds MAWL, if this can be done early and accurately in the lift, the model could be used for exoskeleton activation to supply assist-as-needed augmentation during the lift or in a feedback device that could indicate to personnel not to complete the lift (Future work), thus reducing injury risk.

1. Introduction

Statistics make inferences about the relationship of one variables effect on another through fitting a probability model that can quantify the level of confidence in the effect being true [170], while ML thrives in making predictions without needing to know the relationship between the variables. It is especially useful in data that has more variables than observations.

The problem presented in this research is a multivariate time series classification problem. There are many architectures available for time series classification in the sktime library (https://www.sktime.org) [171]. Using the sktime library provides an array of machine learning architectures for time series problems. It is a scikit-learn (https://scikit-learn.org) compatible interface and an opensource resource using Python, supporting forecasting, classification, regression and clustering. Multivariate refers to multiple variables being observed for a single experimental recording. Time series is the analysis of data points in chronological order for extraction of meaningful statistical information. Classification is a supervised learning task, supervised - meaning the training data has been labelled with its class and the variables separated. Classification models make predictions on what class an observation belongs to, in the case of this research, it provides the ability to classify what %MLC an IMUs observation belongs to, without having to explicitly tell the model which variables and features to use.

An example of human kinematic data being used for multivariate classification was performed by Conforti, et al. [135]. Kinematic data from six IMUs (nine axis), located at six locations along the spine was used to train a machine learning model to classify spine posture. A support vector machine (SVM) was used to classify full body kinematics (data from eight IMUs; Left and right hip, knee & ankle joints plus the sternum & S1 joint) into correct or incorrect lifting posture with an accuracy of 99.4%, while using trunk kinematics only (two IMUs positioned on the sternum & S1 joint) resulted in an accuracy of 76.9% [135]. The SVM classifier used discrete kinematic variables of ROM in the antero-posterior, medio-lateral and vertical planes and the features were normalised ($\frac{feature - mean}{standard\ deviation}$). Stoop lifting was referred to as the incorrect posture, while squat lift was correct posture; participants were asked to put themselves into these postures while lifting the 1, 2 and 5 kg loads. Therefore, the prediction was based on artificial kinematics that were tightly controlled by the researcher. This method may be of value to inexperienced material handlers, who's incorrect lifting posture is due to lack of training but would be less effective with dealing with Defence personnel with training and experience in lifting, where risky changes to posture would more likely be due to loads above their ability.

As multivariate time series classification is a relatively new field, a large review of classification algorithms from the sktime (Python) and tsml (Java) toolkits was performed in Ruiz, et al. [172].

It analysed 30 multivariate time series data sets using multiple machine learning architectures and rated performance via accuracy, seven of these data sets used accelerometer/gyroscope outputs. While the variables used for analysis are similar between the data sets used in Ruiz, et al. [172] and those used in this research, the size of the test/training data, number of dimensions (variables) and number of classes, are different. The top performing classifiers for the seven data sets were Dependent Warping (DTWd), HIVE-COTE (HC), Generalised Random Shapelet Forest (gRSF), Random Convolutional Kernel Transform (ROCKET), Random Interval Spectral Ensemble (RISE), Residual network (ResNet) and Inception Time (IT). The algorithms available with the sktime classifier library were DTWd, HC, gRSF, RISE and ROCKET. ROCKET is the recommended model for multivariate time series classification as an accurate and fast algorithm [172].

The aim of this chapter is to achieve an accurate prediction of lifts above MAWL based on spine kinematic variables collected from IMUs using ML algorithms. Additionally, it is of benefit to reduce the number of IMUs needed for prediction based on which were most valuable to the model. Furthermore, for the exoskeleton to provide most benefit in the reduction of injuries, early activation would be needed, this involved analysing how early the model could accurately predict the class (by limiting the number of data points provided).

2. Methodology

The dataset used for the machine learning model was prepared in MATLAB. Following the preparation of the data collected in Chapter 4, as shown in Table 11, all variables from a single lift (6 x spine segments, 6 x IMUs variables with 101 data points for each, normalised to time) were placed into a single row (3636 columns), with the last column containing the %MLC label for that lift (3637 columns), this is the class that the model classified the observation into. Each row contained a single lift observation (582 rows).

Table 11 Layout of data for Machine Learning models

	Variable 1	**Variable 2**	**Variable 3**	**Variable 4**	**Variable 5**	**Variable 6**	**Variable 7**	**Variable 8**	**Var …** **n = 9: 36**	**Label**
Observation 1	UT Angle n = 1: 101	UT AngVel n = 1: 101	UT Mag X n = 1: 101	UT Mag Z n = 1: 101	UT Acc X n = 1: 101	UT Acc Z n = 1: 101	MUT Angle n = 1: 101	MUT AngVel n = 1: 101	…	**100**
Observation 2: 582 . . .	UT Angle n = 1: 101	UT AngVel n = 1: 101	UT Mag X n = 1: 101	UT Mag Z n = 1: 101	UT Acc X n = 1: 101	UT Acc Z n = 1: 101	MUT Angle n = 1: 101	MUT AngVel n = 1: 101	…	**e.g., 90,80, 70, 60, 50, 20…**

On completion of testing the seven-class classifier for accuracy of classification, the results were poor. As the ability of the model to perform exoskeleton activation is dependent only in recognising a need for assistance, it was thought that binary (two-class) classification may improve results as it increases the number of observations per class. Therefore, an additional label column was added to the dataset that contained Heavy or Light labels. All 80% MLC and above (inclusive) observations were labelled 'Heavy' taking into account, with a safety factor, that MAWL was observed to be 84% of MLC [13] and all 70% MLC and below were labelled 'Light' (inclusive).

The data was divided into training and testing sets using a one two thirds/ one third, test/train split. The training set consisted of 389 (66.6%) observations and the testing set consisted of 193 (33.3%) observations. The Column Concatenator transformer was used to concatenate the 101 time points for each of the 36 variables into a single time series column, so that the classifier can then be applied as to the single column as univariate data. Within the seven-class training dataset there were 29 20%MLC, 52 50%MLC, 54 60-90%MLC and 53 100%MLC class observations and 19 20%MLC, 34 50%MLC, 36 60-90%MLC and 35 100%MLC class observations for the testing data set (Figure 29). For the two-class classifier the training dataset there were 200 Light and 189 Heavy class observations and 114 Light and 79 Heavy for the testing data set (Figure 29).

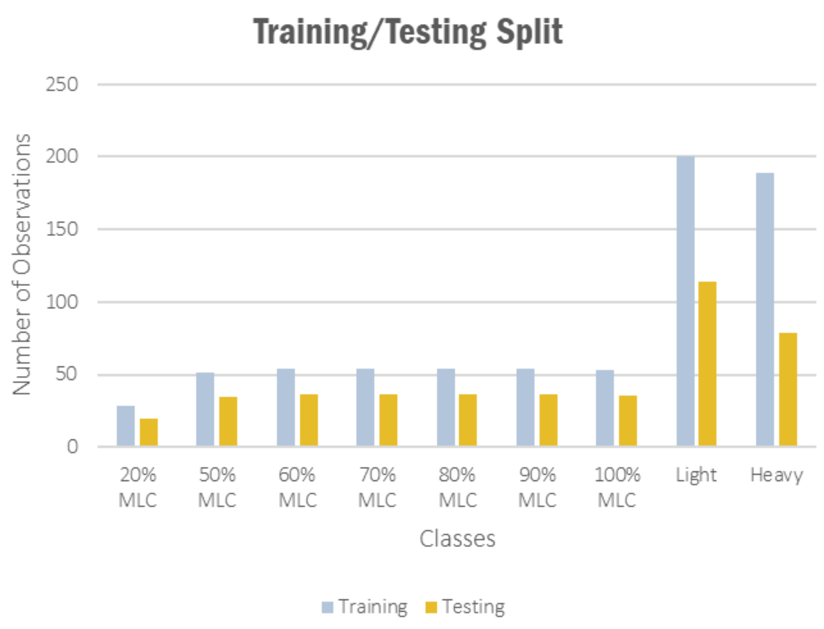

Figure 29 Training & Testing Splits for each class

A number of sktime models were implemented and the results compiled for accuracy. Based on Ruiz, et al. [172] RISE, ROCKET, gRSF, HIVE-COTE and Elastic Ensemble (EE) (contains DTWd) models were implemented as well as some additional interval-based models, originally developed for univariate time series data [171, 173]. In total 17 sktime classifier models were tested: Time Series Forest Classifier, Random Interval Spectral Ensemble, Supervised Time Series Forest (STSF), Column Ensemble Classifier, Individual BOSS, Contractable BOSS, WEASEL, MUSE, Individual TDE, K-Neighbours Time Series Classifier, Proximity Tree, Proximity Stump, Canonical Interval Forest (CIF), Diverse Representation Canonical Interval Forest Classifier (DrCIF), Random Interval Spectral Ensemble, Shapelet Transform Classifier, Arsenal and ROCKET. The parameters changed from default settings for all algorithms are listed in Appendix H.

The parameters changed from default settings for the top four performing algorithms are listed in Table 12. The number of estimators (n_estimators) is essentially the number of trees in the forest, the value of 500 was selected based on [172] who used 500 estimators for CIF and to compare the algorithms like for like, this value was used for all the forest type algorithms (STSF

CIF & DrCIF). The number of jobs for fit and prediction that can be ran in parallel is dictated by n_jobs, with -1 using all available computer processors. All other parameters were left at default for the algorithms.

Table 12 Parameters used for top four performing algorithms for binary classification.

Method	Parameters changed from default
Supervised Time Series Forest	n_estimators = 500, n_jobs = -1
Canonical Interval Forest	n_estimators = 500, n_jobs = -1
DrCIF	n_estimators = 500, n_jobs = -1
Shapelet Transform Classifier	n_jobs = -1
ROCKET Classifier	Default n_jobs = -1

The TSFC, STSF, CIF and DrCIF are time series adaptions of random forest classifiers. A random forest classifier is made of many decision trees working together as an ensemble, each decision tree in the forest makes a class prediction and the class with the most predictions is the result. A decision tree looks for features of an observation that mean that it can be split into groups that are significantly different from each other.

HIVE-COTE, RISE, CEC and EE are ensemble classifiers specific to time series analysis. Ensemble classifiers use a number of models together to improve the overall accuracy. They do this by reducing the variance and bias that each single model may suffer from and then combine the individual model predictions.

ROCKET and Arsenal are time series kernel-based classifiers. Kernel-based classifiers use a linear classifier to solve a non-linear problem by transforming the data. The observations are divided into kernels and the features within each kernel that are associated with different classes are extracted.

Due to computational limitations some models that were also tested failed to complete (not included in results), models were given 12 hours, were then interrupted or failed in this time. The HIVE-COTE model failed to complete after 12 hours of running, the computational cost of this model is noted to be the largest of the sktime models [172]. Additionally, the EE classifier also failed to complete within 12 hours.

Results for comparison of the models were given as Accuracy and Precision for the seven-class classification, with the addition of an f1-score for the two-class classification (Table 13). Accuracy is the percentage of accurately classified observations, while precision is the percentage of positive predictions relative to the total number of positive predictions [174]. The f1-score takes into account the imbalance in the two-class dataset between the Heavy and Light classes, it is the harmonic mean of precision and recall, recall being the percentage of positive predictions relative to the total actual positives [174].

Table 13 Equations for ML accuracy results

Result	Formula
Balanced Accuracy	$= \frac{True\ Positive + True\ Negative}{Total\ Number\ of\ Observations}$
Average Precision	$= \frac{True\ Positive}{True\ Positive + False\ Positive}$
Recall	$= \frac{True\ Positive}{True\ Positive + False\ Negative}$
f1-Score	$= \frac{2 * (Precision * Recall)}{(Precision + Recall)}$

K-fold cross validation was used on the top performing classifier. K-fold cross validation is a method of evaluating machine learning models by dividing the dataset into 'K' number of non-overlapping folds. In this investigation due to computational time, 10 folds were used. Each fold is in turn held back as a testing dataset, while all others are used as a training dataset and the mean result is reported.

Confusion matrices were used to see which classes were performing accurate classifications. A confusion matrix is a visual representation of the number of true positive/negative and false positive/negative results a model predicts. The outputs of the confusion matrices (true label, predicted label & observation number) were aligned with the original seven-class labels to determine which of the seven classes had the most incorrect predictions when using the binary classifier.

Dimensionality reduction was performed via two methods on the top performing model. The first was permutation feature importance, which shows the variables that are most important to the model. Permutation feature importance is performed by altering the arrangement of the values within each of the features and seeing if there is an increase or decrease in the mean squared error between the original arrangement of the values and the altered arrangement. The larger the change in error, the more important the feature. The permutation method for feature importance has the benefit of being able to be used on any ML model. The spine segments that were shown to be less important to the algorithm were then removed from the training/testing dataset.

The second method was reducing the series length (number of data points) for each variable being trained and tested by the model. The series length was determined via the phases of the lift cycle. 10 data points was approximate to the weight-acceptance phase, 50 data points for the standing position phase and 70 data points for the lift-to -platform-height phase.

3. Results

3.1. Model accuracy and performance

Table 14 shows the results for the five models used for the seven-class classifier. When trying to predict %MLC using the seven classes, it resulted in poor accuracy and precision. The STSF resulted in the highest accuracy of classification with 44.8%. The default accuracy (random selection) for seven-classes would be 14.3%, so this does see a three-fold improvement on random selection. However, these results are not sufficiently accurate for use in future work, based on the current size of the dataset.

Table 14 Results of top five performing models for seven class classifiers.

Method	Balanced Accuracy	Average Precision
Time Series Forest Classifier	0.38	0.383
Random Interval Spectral Ensemble	0.370	0.358
Supervised Time Series Forest	0.448	0.420
Column Ensemble Classifier	0.320	0.311
ROCKET	0.311	0.327

The use of a binary classifier, dividing the observations into 'Heavy' or 'Light', showed a large improvement in accuracy (Table 15). In total 17 models were tested for their accuracy (Appendix I), the top four model's results are shown in Table 15. These classifier models used for the two-class classifier all record an accuracy above 90%. The ROCKET classifier showed the highest accuracy with an f1-score of 92.4%. The DrCIF also had good accuracy with an f1-score of 91.2%.

Table 15 Results of top four performing models for binary classifiers.

Method	Balanced Accuracy	Average Precision	f1-score
Supervised Time Series Forest	0.884	0.877	0.903
Canonical Interval Forest	0.890	0.884	0.907
Diverse Representation Canonical Interval Forest	0.895	0.888	0.912
ROCKET	0.912	0.907	0.924

K-fold cross validation of the ROCKET classifier showed that across each fold, a mean accuracy of 91.2% was achieved (Table 16). This means the accuracy achieved in the initial test is consistent across the rest of the dataset and a high accuracy can be achieved when predicting Light/ Heavy loads.

Table 16 K-fold cross validation result for top performing binary classifier.

Method	Number of folds	Mean accuracy
ROCKET	10	91.24 ± 2.72%

The confusion matrices for the top four binary classifiers show which class is more accurately being predicted (Figure 30). When comparing the most accurate model (ROCKET), it is its ability to correctly classify the Heavy class that improves its performance. The reduced accuracy of the STSF and CIF is due to their ability to predict the Heavy class. While the similar accuracy of ROCKET and DrCIF is due to good accuracy across both classes.

From the output of the confusion matrix for the ROCKET classifier, the data was able to be aligned with its original seven-class label to see which class of observations was causing the decrease in accuracy.

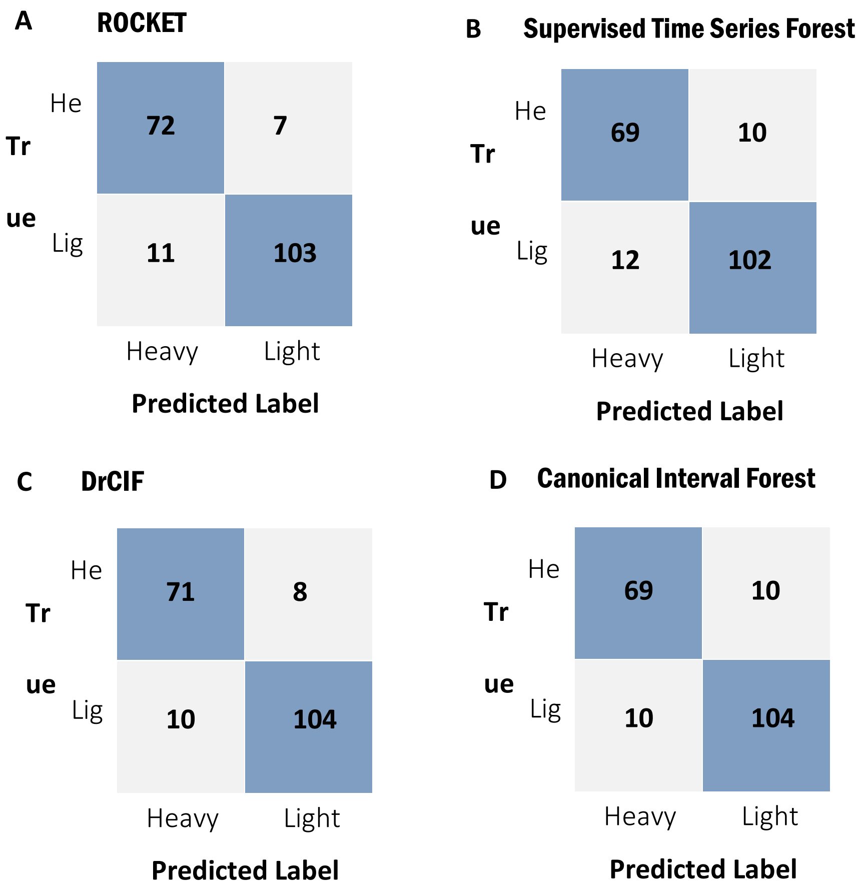

Figure 30 Confusion matrices for binary classifier performance.

Table 17 shows the number of incorrect and correct classifications for each class. It shows that the classes with the highest incorrect classifications are the 70 and 80% MLC with 25.0% and 18.2% of observations incorrectly classified, respectively. Moving away from the Heavy/Light threshold the 60% MLC observations error drops to 5.9%, while the 90% MLC error was 3.2% and the 50% MLC was similar at 3.5%. The observations at the extremes of Heavy and Light (100%, 90%, 50% & 20% MLC) were able to be classified with good accuracy.

Table 17 Binary classifier incorrect & correct predictions according to %MLC.

	Class labels	Incorrect		Correct	
		Number	Percentage	Number	Percentage
LIGHT	R20	0	0.00%	19	100.00%
	R50	1	3.45%	28	96.55%
	R60	2	5.88%	32	94.12%
	R70	8	25.00%	24	75.00%
HEAVY	R80	4	18.18%	18	81.82%
	R90	1	3.23%	30	96.77%
	R100	1	3.85%	25	96.15%
	Total	**17**	**8.81%**	**176**	**91.19%**

3.2. Dimensionality Reduction

Based on the accurate performance of ROCKET in classifying light and heavy observations; this model was used to see if it maintained accuracy with dimensionality reduction. This was done via a reduction in the number of spine segments (IMUs) made available to the model and then by reducing the serial length for each variable (number of data points). Figure 31 shows each of the spine segments and which variables from each were most important to the model's accuracy.

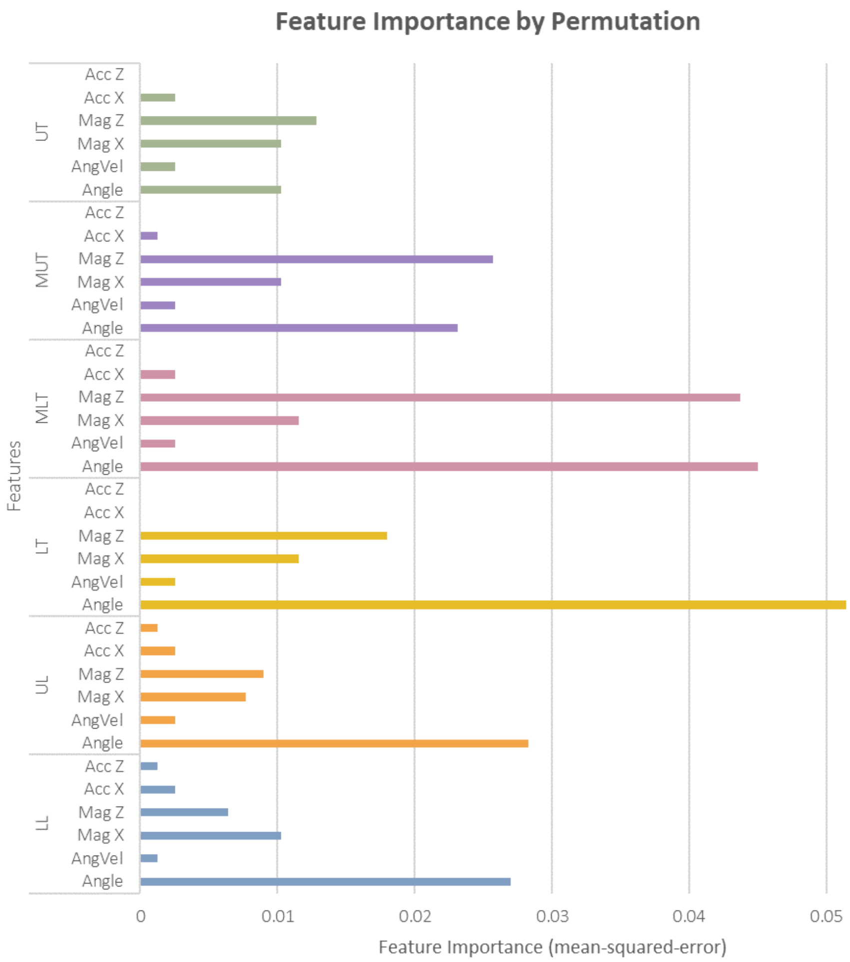

Figure 31 Permutation feature importance.

The most important features according to Permutation Importance method (Figure 31) are LT Angle, MLT Angle, MLT Mag Z, UL Angle, LL Angle, MUT Mag Z, MUT Angle and LT Mag Z. The spine segments of highest importance are the MLT and LT segments. The Angle variable for the LT segment has the most effect on the accuracy of the model. This is followed by the MLT segment, then the MUT, with the Mag Z and Angle variable having a large effect of the model accuracy. The UL and LL segments have as similar contribution, while the UT segment shows the least contribution to model accuracy.

For each spine segment the Angle has importance, and for the lower spine (MLT - LL) this is the variable with the largest contribution. For the upper to middle spine segments (UT – LT) Mag Z is the next most important variable, followed by Mag X, however Acc Z makes no contribution to accuracy for these segments. Based on the most important features according to Permutation Importance method, spine segments were removed from the training and testing of the model, and it was retested to see the effect on the model's performance (Table 18).

Table 18 Spine segment (IMUs) dimension reduction results using ROCKET classifier.

Spine segments included	Balanced Accuracy	Average Precision	f1-score
Six (All Segments)	0.912	0.907	0.924
Five (MUT, MLT, LT, UL, LL)	0.897	0.892	0.911
Four (MUT, MLT, LT, UL)	0.882	0.877	0.897
Three (MUT, MLT, LT)	0.894	0.897	0.898
Two (MLT, LT)	0.871	0.866	0.888
One (MLT)	0.843	0.838	0.866

The ROCKET classifier maintained a moderate f1-score, even when reduced to only one spine segment (MLT). The spine segments were removed from the dataset one-at-a-time and the model retested (Table 18). The order in which the spine segments were removed was based on the importance of it to the accuracy of the model as shown in Figure 31.

There is a drop of 1.3% in the f1-score when the UT segment is removed (91.1%), then a further decline of 0.4% when the LL is also removed (89.7%). The f1-score is maintained with the removal of the UL segment (increase in f1-score by 0.1%) (89.8%), indicating that the UL segment did not contribute to model performance. The f1-score then drops by 1% with the removal of the MUT segment (88.8%) and a further reduction by 2.2% when the model is tested on only one spine segment (86.6%). To further decrease the dimensionality of the dataset, the number of data points per variable for training and testing was reduced to see how early classification can occur with accuracy (Table 19).

Table 19 Spine segment (IMUs) and series length dimension reduction for early classification using ROCKET classifier.

Spine segments included	F1 Score for number of data frames included per feature			
	100	70	50	10
Six (All Segments)	0.924	0.919	0.888	0.767
Five (MUT, MLT, LT, UL, LL)	0.911	0.907	0.872	0.778
Four (MUT, MLT, LT, UL)	0.897	0.892	0.876	0.754
Three (MUT, MLT, LT)	0.898	0.869	0.845	0.740
Two (MLT, LT)	0.888	0.838	0.856	0.766
One (MLT)	0.866	0.842	0.860	0.700

Predicting within the first 10 frames using the ROCKET classifier shows poor accuracy. When comparing the f1-score from all spine segments and 100 data points to that of 10 data points there is a decrease of 15.7%. When classifying using 10 data frames, the highest f1-score is when using data from 5 spine segments (77.8%). With the next highest using all six spine segments (76.7%) and interestingly with a similar f1-score is using only two spine segments (76.6%). There is a drastic drop in the f1-score when using only the MLT spine segment and 10 data frames to 70%. However, at 50 data points the reduction in f1-score from all spine segments and 100 data points is only 3.6%, maintaining much better accuracy.

Removing the UT spine segment from analysis and reducing the data frames to 50 has a small impact on the model accuracy (-5.2%), with the f1-score dropping to 87.2%. There is a slight increase in accuracy with the removal of the LL segment (+0.4%), indicating it may not play a part in the prediction of load within the first 50 frames. There is a drop in accuracy with the removal of the UL segment (-3.1%) but again an increase with the removal of the MUT (+1.1%) and LT segment (1.5%), indicating these segments may be hindering accuracy for the early phases of the lift.

Unlike the 10 and 50 data frame dimensionality reduction, the 70 data frame saw a reduction in accuracy with the removal of each spine segment, except for going from two to one segment.

The largest decrease was when the analysis went from three to two spine segments (-3.1%) with the removal of the MUT segment. There was a slight increase in accuracy (+0.4%) with the removal of the LT segment from the analysis.

A reduction in the number of data points to only include the weight-acceptance to standing position phases (50 data points) with reducing the spine segments to one (MLT) maintains good accuracy of 86%, this is a reduction of 6.4% from the inclusion of all segments and all data points. With the removal of data frames there is a reduction in f1-score, with small reductions from 100 frames to 70 and 70 to 50 frames, then a large reduction from 50 to 10 frames, this is the case in all except the Two and One segment analysis. For these segments there was an increase in accuracy when going from 70 to 50 data frames of 1.8%. This shows that these spine segments may play more of a role in load prediction for the earlier phases of the lift.

4. Discussion

The novel contribution of this chapter is a machine learning model that can accurately predict whether a load is above a person's MAWL, based on spine kinematics. To further broaden the application of the model, dimensionality reduction showed that within the first half of the lift early prediction can be performed using a single spine segment with an accuracy of 86.0%. While there is much room for improvement, this model is a proof-of-concept for predictive, assist-as-needed exoskeleton activation.

The ability to predict the %MLC using a seven-class classifier showed poor accuracy. This could be due to limitations in the size of the data set, as there are only a small number of observations per class. Studies that looked into sample sizes for classification problems found that performance was greatly improved with 100 – 560 observations per class [175, 176]. The ability to classify all classes with accuracy could broaden the application of the model to more fields by allowing for adaption of the Light/Heavy threshold.

The benefit of being able to predict the %MLC that is currently being lifted is that the model could be adapted depending on the situation it is being used. For example, the MAWL threshold determined in Savage, et al. [13] was based on testing Australian Army Infantry, these are highly trained personnel that are required to maintain strength and fitness. This may not be the case for warehousing or manufacturing personnel, so the %MLC threshold, from which augmentation or feedback is given, could be reduced to 70% or 60% MLC, dependent on the requirements of the industry, using the same model.

While a larger dataset could greatly improve accuracy it is possible that a seven-class classifier is not needed for the application explored in this research. The interest of the Australian Defence Force is in the reduction of back injuries, as lifting above MAWL has been reported to increase the risk of back injuries, having the Light/Heavy threshold that reduces this risk addresses the aim.

The classes with the highest incorrect classifications are the 70 and 80% MLC. This was somewhat expected as the cut-off for the Light class was 70% MLC (inclusive). This indicated that at the threshold of Light versus Heavy lifts, the observations have similar features that are harder to distinguish from each other. As seen in Figure 25, the standard deviation of the observations is large and causes the classes to overlap and could be responsible for the errors in the classifier at the 70 and 80% MLC (Table 17). While it is expected that %MLC classes that are close together may have an overlap in their standard deviation, a larger sample of observations should provide the algorithm with more context (i.e., features) for which to make its predictions on. This is especially important as the variables that the classifier was listing as important (i.e., Mag Z) for model accuracy (Figure 31) have no statistical significance due to their large standard deviation (Figure 25). With the inclusion of more data observations per class, this may improve the model's ability to distinguish features that differ between the 70 and 80% MLC classes [175, 176].

Dimensionality reduction reduces the computational time for prediction of an unseen observation. Reducing the number of spine segments included had only a small effect on accuracy, as the largest decrease in accuracy was from two IMUs to one (Table 18), for this task a minimum of two IMUs would be needed to maintain accuracy. A reduction in the number of datapoints to 50, could also be done with a small reduction in accuracy (Table 19), this shows that early prediction within the first half of the lift is possible. Early prediction is vital in reducing injury risk due to lifting above capacity. However, in reducing the spine segments included in the model, it does limit when early prediction can occur. As seen in the comparison traces, different spine segments have greater contribution to the lift at different stages.

5. Conclusion

In this chapter, 17 machine learning algorithms were tested for their ability to predict whether a lift was above or below someone's MAWL (set at 80% MLC). This chapter shows an accurate prediction model (>90%) that can classify whether a load is above a person's intrinsic capability to lift is possible based on spine kinematics alone. In the future, this model can be implemented in a wearable device that provides user feedback when the load is above their capability, the user can then abort the lift and thus reduce their risk of injury. Additionally, the application of this model into an assist-as-needed control system for an exoskeleton means that the exoskeleton can be activated to provide augmentation when it is needed during higher risk lifts.

The ROCKET algorithm proved to be the most accurate with a mean accuracy in k-fold cross validation of 91.2%. Dimensionality reduction showed that light/heavy loads can be predicted with accuracy and efficiency by reducing the number of IMUs and number of data frames per variable included to make accurate predictions. Accurate early prediction was shown to be possible within the standing position phase of the lift using two IMUs (85.6%). Further work needs to be done to improve the accuracy of the model with the reduced dimensions. Reducing the number of spine segments included would improve computation time and prediction of MAWL within the weight-acceptance phase of the lift would further reduce the risk of injury, as it means that augmentation from an exoskeleton or user feedback from a wearable device can occur before the spine begins its extension phase. Chapter 7 provides a general summary of all findings in Chapters 2 – 6, the implications of the research in future work and outlines the limitations of each of the studies.

Chapter 7. Conclusion, Future Work & Limitations

1. Thesis Conclusion

This thesis investigated the ability of spine kinematics to predict when a lifting task is above a person's capability. A novel predictive model was developed using a dataset established via IMUs recording at six points along the spine. The ML model with the highest accuracy was ROCKET for its ability to classify lifts above 80% MLC (MAWL), accurately predicting 91.2% of unseen observations. The aim and contribution of this thesis was presented across four objectives:

1.1. Objective 1. Determine the suitability of current exoskeleton technology to support military manual handling tasks

The problem presented was the human and financial cost of back injuries in the Australian Defence Force due to the physical demands of manual handling tasks [8]. One possible solution was an assistive device, such as an exoskeleton. In reviewing current exoskeleton systems for their application to military manual handling tasks (Chapter 2) a gap was identified; 1. Current exoskeletons do not provide predictive assist-as-needed control. Predictive assist-as-needed activation of an exoskeleton provides personnel with lift augmentation only when it was required, such as when a lift is above a person's capability, so that the strength and stamina of Defence personnel would not be diminished.

1.2. Objective 2. Determine the effect of increased external load on spine kinematics

As back injuries due to loading were the stated problem, the motion of the spine under load could provide a way for the exoskeleton to know when to offer assistance. To find this out, the effect of an increase in external load during lifting has on spine kinematics needed to be studied. A systematic review of the literature (Chapter 3) did not provide a definitive feature in the motion of the spine that could be used as a predictive indicator, but many studies reported that there were significant differences in spine kinematics due to an increased load, meaning that these differences may be able to be predicted with the development of a kinematic dataset. A number of limitations in the in literature were found: 1. Multiple points of analysis for the segments of the spine needed to be included, 2. Use of IMUs for recording kinematic data as they are not limited to a laboratory environment, and 3. %MLC was a way of standardising lifting loads but was not studied as a measure of a person's capability to lift a load. These limitations were addressed in the experimental trials performed in Chapter 4.

Experimental trials on 32 participants were performed, recording IMU data from six positions on the thoracic and lumbar spine, with the load standardised to seven %MLC (Chapter 4). The protocol was based on Savage, et al. [13], who determined that a limit to safe lifting was 84 ± 8% of MLC, this threshold is known as MAWL. The task performed was a common Australian Army manual handling task, lift -to-platform [7, 156]. The mean of six sagittal variables from the IMUs were observationally analysed for trends caused by an increase in the %MLC. There were clear positive and/or negative correlations between a change in kinematics and an increase in %MLC for the Angle, AngVel and Acc Z variables. Additionally, the use of multiple analysis points for the lumbar and thoracic spine segments provided trajectory detail that would not have been available viewing the segments as a whole [1, 2]. However, there was no clear delineation in the data where MAWL occurred. To ascertain which of the differences observed in the data was due to loading effects, statistical inference was performed in Chapter 5.

1.3. Objective 3. Determine the kinematic factors that can be used as predictive indicators of a user approaching their maximum acceptable weight of lift

In Chapter 5, SPM was used for statistical analysis, as no assumptions on the point of interest needed to be made, as the full time series can be hypothesis tested [164, 166]. One-way and post-hoc ANOVA were completed for each of the six variables for the six spine segments. From SPM post-hoc ANOVA the kinematics variables with significant differences were Acc Z, Angles and AngVel at all, with the discrete features of importance being minimum, peak and ROM. Angle discrete features were analysed for their linear and polynomial correlation to %MLC, the predictibility (R-score) never surpassed 0.50, resulting in a poor to moderare correlation and a poor method for predicting %MLC. Therefore, supervised machine learning was explored in Chapter 6 as a method for predicting light and heavy loads.

1.4. Objective 4. Develop a predictive model to classify when a lift is above the maximum acceptable weight of lift

Using the database of observations recorded in experimental trials (Chapter 4) multivariate time series classification algorithms were trained (66.6% of observations) and tested (33.3% of observations) for their ability to accurately predict the %MLC in which a kinematic observation belonged. Trying to classify the observations into seven classes (%MLC) resulted in poor prediction accuracy (42%). As the research was interested in prediction of an increased injury risk, the observations were divided into Light (20 – 70% MLC) and Heavy classes (80 – 100% MLC) with the threshold being just below MAWL at 80% MLC. This was tested on 17 algorithms; ROCKET was the best performer with an accuracy (f1-score) of 92.4%. K-fold cross validation of the model using the ROCKET algorithm resulted in a mean accuracy of 91.2% across 10 folds.

Dimensionality reduction was completed via removal of spine segments and reduction of data frames included in the train/test dataset. Feature importance by permutation provided which of the spine segments could be removed from analysis without affecting the model accuracy, the benefit being less and therefore faster computation required for future predictions and less sensors needed for an assistive device. The benefit of reducing the number of data frames was in the early prediction and therefore early intervention in the lift. Accurate early prediction was shown to be possible within the standing position phase of the lift (50 data frames) using two IMUs (MLT & LT) (85.6%).

2. Limitations

2.1. Chapter 2

Only Scopus was used as the citation database for this review and while it is extensive in the literature it lists, important studies on current exoskeletons may not have been included. We also acknowledge that by searching for research studies, we omit some of the most widely used commercially available exoskeletons for which there are not any published research. Additionally, some of the data included in the tables was interpreted by the authors of this review rather than stated in the reviewed study. The search terms used were based on the definition of manual handling tasks by researchers of Australian Army tasks and may not be inclusive of all manual handling industries. The review applied a broad range of exoskeletons to two specific tasks (lift-to-platform and lift-carry-lower), the exoskeletons in the review were not always intended for these tasks. Furthermore, the review did not include exoskeletons that carried loads posterior to the user, it is possible that these devices could be adapted for these tasks. This review did not explore other systems that could be useful to military manual handling personnel such as smart sensor systems.

2.2. Chapter 3

Only two-handed lifting tasks were reviewed, this is by no means a comprehensive look at the effect of lifting tasks on spine kinematics but a narrow look at the effect of a sagittal lifting task. Additionally, only the sagittal kinematic effects were reported in the results, there will be lateral movement in any task being performed that was not considered. No meta-analysis was performed for the kinematic results reported in this chapter, so statistical inference of the reported results was not able to be made. Furthermore, some of the load masses included in the plots was interpreted by the authors from the mean MLC mass reported in the reviewed studies.

2.3. Chapter 4

The task was based on the most common physically demanding task performed in the Australian Army, however due to access limitations the population included in the study was civilian. Only sagittal variables have been included in this research as the majority of motion for a ground-to-platform lift occurs in the sagittal plane, the inclusion of lateral variables would allow for the addition of asymmetric lifting without the need for extra sensors and were used to process the AHRS filter, so are readily available for analysis. Participants recruited for this study had no existing/recent injuries and aged between 18-40 years. If this research is to be applied to industries outside of Defence the tested population may not be reflective of their workplace.

2.4. Chapter 5

Using SPM for statistical inference means verifying the results against other studies, reviewed in Chapter 3, was not possible. The correlation of the linear and polynomial trends between discrete angle features and %MLC was poor, using light and heavy loads may have improved the correlation.

2.5. Chapter 6

The time series algorithms used on Chapter 6 were limited to the sktime framework, there are many more algorithms available that may outperform the models detailed. Additionally, the parameters for each algorithm could be tuned further to improve accuracy. The number of observations was limited to the amount of data collected in experimental trials, the addition of more observations for training may also be a method to improve accuracy. When performing dimensionality reduction, all the variables associated with a spine segment were removed from the training/testing dataset, further dimensionality reduction could be performed by also removing individual variables (from any spine segment) that the model did not find important, this may improve computational cost.

3. Future work and predictive ML model applications

The data collection and processing outlined in this research, using time series data output from wearable sensors for the application of the machine learning model, could be used to create a large data base of tasks to which MAWL could be predicted. This could be implemented into embedded wearable devices for user feedback or assist-as-needed control algorithms for exoskeleton systems.

In future work, this research may be extended to implement an expanded predictive model (that may include additional recognition for tasks beyond the scope of this research) into an exoskeleton control system, to provide an assist-as-needed trigger for activation. The barrier for implementation of ML models into embedded systems has historically been the limitations of computational processing (speed, performance, size, energy consumption) [177]. With the availability of compact, light and powerful computational processing, the implementation of ML models into a small, portable and wearable assistive device has become a reality [177]. A trained model, created from a large dataset may be implemented in a wearable device to make predictions in real time. A benefit of the ROCKET algorithm is that it is highly efficient when it comes to computational cost [178]. An initial iteration of an assistive device could be developed using embedded machine learning models that provide live feedback, via a basic signaling system, to Defence personnel during manual handling for when they are lifting above their MAWL.

For these assistive devices to become a reality, larger datasets are needed to: 1. Improve the accuracy of predictions and 2. For task recognition and expansion of the prediction model to the main MH tasks performed by ADF. The novel wearable device would then be evaluated through objective and subjective measures during human laboratory trials for its ability to predict MAWL before being expanded into in-field testing.

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Appendix A – Published Paper

Exoskeleton Application to Military Manual Handling Tasks

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Objective: The aim of this review was to determine how exoskeletons could assist Australian Defence Force personnel with manual handling tasks.

Background: Musculoskeletal injuries due to manual handling are physically damaging to personnel and financially costly to the Australian Defence Force. Exoskeletons may minimize injury risk by supporting, augmenting, and/or amplifying the user's physical abilities. Exoskeletons are therefore of interest in determining how they could support the unique needs of military manual handling personnel.

Method: Industrial and military exoskeleton studies from 1990 to 2019 were identified in the literature. This included 67 unique exoskeletons, for which Information about their current state of development was tabulated.

Results: Exoskeleton support of manual handling tasks is largely through squat/deadlift (lower limb) systems (64%), with the proposed use case for these being load carrying (42%) and 78% of exoskeletons being active. Human–exoskeleton analysis was the most prevalent form of evaluation (68%) with reported reductions in back muscle activation of 15%–54%.

Conclusion: The high frequency of citations of exoskeletons targeting load carrying reflects the need for devices that can support manual handling workers. Exoskeleton evaluation procedures varied across studies making comparisons difficult. The unique considerations for military applications, such as heavy external loads and load asymmetry, suggest that a significant adaptation to current technology or customized military-specific devices would be required for the introduction of exoskeletons into a military setting.

Application: Exoskeletons in the literature and their potential to be adapted for application to military manual handling tasks are presented.

Keywords: exosuits, wearable robotics, biomechatronics, biomechanics, assistive technologies, manual materials, industrial

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INTRODUCTION

In Australia, 43% of serious injuries in the workplace are due to traumatic joint, ligament, muscle, and tendon injuries, at an annual cost of AU$19.5 billion for treatment, overemployment, overtime, retraining, and investigation (Safe Work Australia, 2019). Forty-five percent of serious workplace injuries are due to manual handling, a term used to describe tasks in which human force is used to maneuver an object's position (Carstairs et al., 2018). Manual handling injuries are of particular concern in physically demanding Defence Force occupations. Most manual handling injuries are associated with the upper and lower limbs (37%) and the back/trunk (38%; Safe Work Australia, 2019). Internationally, over 40% of workers in the European Union experience lower back, neck, or shoulder pain caused by manual handling-related workloads and repetitive movements (de Looze et al., 2016).

Musculoskeletal injuries make up 20% of the most common disorders supported for Australian military personnel returning from active service. The Australian Government's Department of Veteran Affairs found that 7934 veterans (13%) from East Timor, Solomon Islands, Afghanistan, Iraq, and Vietnam conflicts receive support for lumbar spondylosis (Australian Government, 2017), a condition causing pain and restricted motion in the lower back attributed to overuse (Middleton & Fish, 2009). Also common in military personnel were acute sprain and strain (4%), intervertebral disc prolapse (2%), and thoracic spondylosis (1%; Australian Government, 2017). These musculoskeletal disorders could be caused by manual handling tasks that involve movements that contribute to an increased risk of musculoskeletal injuries. Exploring how exoskeletons can support the body during manual handling tasks may help in reducing the risk of musculoskeletal injuries.

Factors contributing to manual handling injuries include hyperflexion or hyperextension of the lumbar spine caused by external torques, internal torsional forces, fatigue due to increased total work (Neumann, 2009), and increased spinal flexion when performing lifting tasks from the floor (Ferguson et al., 2004; Ngo et al., 2017). Additionally, lifting above an individual's intrinsic capacity can be responsible for injuries (Savage et al., 2012).

A comprehensive analysis of Australian Army personnel categorized 79% of all physically demanding tasks as manual handling (Carstairs et al., 2018) encompassing four movement patterns: vertical lifting (305 tasks), locomotion with load (153 tasks), push/pull (38 tasks), and repetitive striking (30 tasks). These movement patterns were further categorized into 10 task-based clusters. While some tasks are unique to military personnel, the two most common task-based clusters (lift-to-platform and lift-carry-lower) are also prevalent in many manual handling industries. Therefore, this review could be extended to the application of exoskeletons in industries whose workers perform these movement patterns.

Exoskeletons are an externally fitted biomechatronic or mechanical system, designed to assist the human user in order to reduce injury risk, amplify natural ability, rehabilitate movements, or assist in physical challenges (de Looze et al., 2016; Zaroug et al., 2019). Exoskeletons can be categorized by the intended purpose of the system: assistive systems, human amplifiers, rehabilitative systems, and haptic interfaces (Gopura et al., 2016). An assistive system provides additional support to workers through joint bracing and control or transmitting forces away from the musculoskeletal system. A human amplifier increases the strength capabilities of the human body beyond its natural ability, and rehabilitative systems assist in the recovery of limb movement for people with limited function. A haptic interface exoskeleton provides feedback to the user when using tele-operation devices. This review explores assistive systems and human amplifiers with regard to their use in supporting manual handling personnel.

The aim of this review was to analyze the current literature to identify characteristics of industrial exoskeletons that can be useful to military manual handling tasks. We therefore classified the exoskeletons based on (a) which manual handling task does the exoskeleton permit, and (b) what joint does the exoskeleton support.

METHOD

A study of the current exoskeleton literature was performed using Scopus, for articles published between January 1990 and December 2019. The search terms included exoskeleton, wearable robot, or robot suit with the additional terms industrial, military, manual handling, material handling, lifting, carrying, pushing, pulling, and striking. The included search terms were determined by using the definition of manual handling as set by research into Australian Army tasks (Carstairs et al., 2018).

Original studies were considered eligible if they met the following inclusion criteria: (a) the purpose of the exoskeleton was stated using terms such as industrial, military, manual handling, material handling, lifting, carrying, pushing, pulling, or striking; (b) the conceptual design of the exoskeleton was progressed to a physical prototype; (c) the manual handling load was supported anterior to the user; (d) the exoskeleton provided actuation on one primary supporting joint (e.g., knee, hip, spine, shoulder) used to execute lift-to-platform and/or lift-carry-lower tasks. We excluded any commercially available exoskeleton (see "Limitation" section) that did not have published scientific evidence.

The initial search resulted in 357 studies. The texts were screened, and 284 studies were excluded. In total, 73 studies were included in the review (Figure 1), which resulted in 67 individual exoskeleton systems. Included studies were categorized based on which movement patterns they permit (e.g., squat/deadlift, shoulder/chest press, and isometric arm hold, or any combination of these movement patterns) and which joints they provided actuation to.

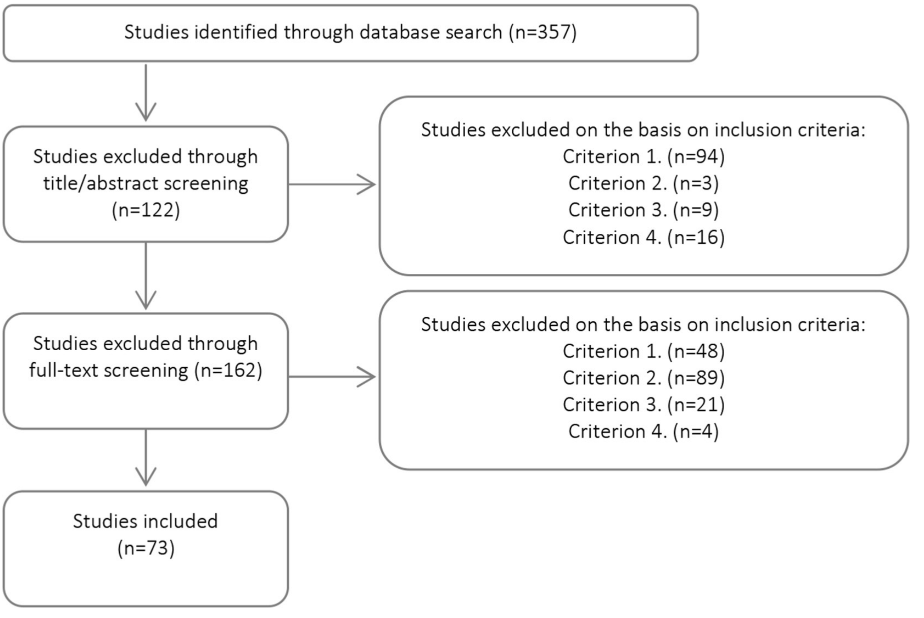

Figure 1. Schematic of the number of studies excluded on the basis on inclusion criteria during the search process. See text for description of criteria.

TABLE 1: Key Movement Patterns and Supporting Joints for Task Clusters

	Lift-to-Platform		Lift-Carry-Lower
Key movement pattern	Squat/deadlift	Shoulder/chest press	Shoulder/chest press and isometric arm hold
Key supporting joints	Knee Hip Spine	Shoulder Spine	Shoulder Spine

In order to categorize exoskeletons for their application in military manual handling tasks, our focus was on the two dominant task-based clusters, the lift-to-platform cluster (198 tasks) and the lift-carry-lower cluster (100 tasks), which comprised 56% of army manual handling tasks. There was a commonality of the major movement patterns (shoulder/chest press, squat/deadlift, and isometric arm hold movements) and the supporting joints used to execute these tasks (Table 1). Exoskeletons were categorized into the key movement patterns they work on, and then subcategorized into the key supported joints (Table 1). We define the supported joint as the joint upon which the exoskeleton provides actuation. Therefore, an exoskeleton can be designed to assist a segment/joint (i.e., the spine) by providing actuation to—supporting—a joint (i.e., the hip).

Operational details included device name, purpose, targeted assistance, actuation method, actuators, degrees of freedom (DOF), device weight, control method, sensor system, and load capability. The purpose of the exoskeleton was classified based on the principle function(s) or the motivation for design. These were defined as: (a) “tool holding”—supporting the weight or reducing the transfer of vibrations from a tool to the user, particularly during overhead work; (b) “injury prevention”—reducing the transfer of external loads to the user’s joint and muscle; (c) “amplification”—typically full body suits taking the entire external load through their structure; and (d) “load carrying”—bearing an external load through the exoskeleton’s structure.

Evaluation details included task analysis, testing performed, test details, sample size, participant details, and test results. The task analysis outlined any assessments that were performed prior to the design of the exoskeleton to determine its requirements. Testing performed on the exoskeletons was categorized into the following analyses: (a) “exoskeleton structural design,” to assess how it moves, the workspace it requires, and the forces it is able to withstand/exert; (b) “human exoskeleton analysis,” to assess how it interacts with the user to provide assistance, the forces it applies to the user, and how the user’s natural motion can be changed by the addition of the device; (c) “accuracy of the sensor system,” to assess its accuracy, resolution, efficiency, speed, and output; and (d) “response characteristics of the control system,” to assess how the mechatronic system interacts with the user and can be measured by accuracy, speed, sensitivity, and complexity.

RESULTS

Movement Patterns and Supported Joints

Twenty-four percent of exoskeletons permitted shoulder/chest press and isometric arm hold motions (Table 2); this includes devices that support the elbow and shoulder joints concurrently (n = 9) and the shoulder joint only (n = 7; Figure 2). Sixty-four percent of exoskeletons permitted the squat/deadlift movements (Table 3); this includes devices that support the ankle, knee, and hip synchronously (n = 20), the knee joint only (n = 4), and the hip joint only (n = 19; Figure 2), while 12% of exoskeletons permitted major joints for shoulder/chest press, isometric arm hold, and squat/deadlift (Figure 2; e.g., spine, n = 5; and full body devices, n = 3; Table 4).

Purpose

Load carrying was the most common exoskeleton purpose (42%), followed by targeting load carrying and injury prevention (22%; Figure 2). Load carrying included lifting, lowering, and/or carrying of external loads. Injury prevention exoskeletons focused on trying to reduce injury risk factors of the lower back, while tool holding devices, making up 15% of this review, focused on supporting the shoulder joints through unloading.

Actuation System

Ninety percent of the included studies reported the actuation method used (Figure 2); these systems have been classified into four categories: electric (n = 38), hydraulic (n = 5), pneumatic (n = 6), and passive (e.g., springs, pulleys, cables; n = 15). Seventy-eight percent of exoskeletons in this review were active, meaning they provide movement to the user through a mechatronic system and the creation of mechanical power through the use of actuators, while 22% were passive exoskeletons, meaning they used an exclusively mechanical system to provide support.

Task Requirement

Task requirements were identified prior to the exoskeleton design in 30% of the studies. These studies looked at kinematic modeling (n = 10), gait analysis (n = 5), or biomechanical analysis (n = 5) to optimize their design for specific task requirements by quantifying the range of motion (ROM), DOF, joints supported, and additional torque provided.

Evaluation Details

Human–exoskeleton integration analysis was the most prevalent form of evaluation with 68% of devices included in this review (Figure 3). Evaluations performed included biomechanical, physiological, and psychophysical testing. Biomechanical evaluation was the most frequently used measure (n = 39), followed by physiological evaluation (n = 37; Figure 3). Many studies used both physiological and biomechanical evaluations to indirectly evaluate device performance. Biomechanical testing captures the kinetics and kinematics of the user’s joint movement (Hamill & Knutzen, 2006), while physiological tests measure the user’s energy cost (Gregorczyk et al., 2010), and psychophysiological tests measure the user’s perception (subjective feedback) whilst

TABLE 2: Exoskeleton Classification for Shoulder/Chest Press and Isometric Arm Hold

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
1	Elbow–shoulder	Exhauss Stronger	LC and IP	Arm–lifting assist	P	Not reported	Not reported	9	Not applicable	Not applicable	Not reported	Not reported	Human–exoskeleton analysis	Lift, carry, place task. With and without exo condition. EMG, IMU, HR, RPE, CoP, time to complete.	8	4F (31 ± 2 years, 62 ± 10 kg, 166 ± 4 cm) 4M (33 ± 3 years, 78 ± 3 kg, 179 ± 3 cm)	Reduction of anterior deltoid muscle activity (54%) and stacking/unstacking (73%) tasks. No significant difference in back muscle activation. Increased antagonist muscle activity, postural strains, cardiovascular demand, and changes in upper limb kinematics	Theurel et al. (2018)
2	Elbow–shoulder	Power assistive exoskeleton robot system for the human upper extremity	LC	Arm–load assist	A	Not reported	8	Not reported	Human–robot cooperative control	Force sensors	Not reported	Not reported	Human–exoskeleton analysis	Holding a 10-kg load. With and without exo conditions. EMG for elbow and shoulder flexion/extension.	Not reported	Not reported	Reduction in EMG signals of the arms and shoulders while wearing the exoskeleton	Lee et al. (2012)
3	Elbow–shoulder	Stuttgart Exo-Jacket	TH	Arm–stabilizing	A	Electric (EM and HD)	12	Not reported	PID control	Hall sensors	Not reported	Biomechanical analysis: MoCap and IMU	Human–exoskeleton analysis	Subjective questionnaire on device comfort while performing flexion and extension.	3	Not reported	Not reported	Ebrahimi, Groninger et al. (2017); Ebrahimi (2017)
4	Elbow–shoulder	Iso-elastic upper limb exoskeleton	TH	Arm–limb support	P	Passive (S)	Not reported	1.9	Not applicable	Not applicable	7.5	Not reported	Human–exoskeleton analysis	Using four weights and a spring balance, the effective lifting force at seven different angles was measured	Not applicable	Not applicable	For higher loads there is a discrepancy between calculated and measured forces. Capable of supporting loads in the range of 40–120 N	Altenburger et al. (2016)
5	Elbow–shoulder	Under-actuated upper-body backdrivable	LC	Elbow–load assist	A	Not reported	1	Not reported	Artificial neural network with a model-based intensity prediction	Myo-Armband	Not reported	Kinematics	Human–exoskeleton analysis	Varying torques in the two directions available	7	6 M and 1 F, (20 to 35 years)	RMS Error of 3.8 ± .8N at the end effector	Treussart et al. (2019)

(*Continued*)

TABLE 2 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
6	Elbow–shoulder	4-DOF exoskeleton rehabilitation robot	LC and IP	Arm–limb support	A	Cable-driven parallel mechanism	4	Not reported	IPC (Industrial Personal Computer)	Cable tension and encoder	Not reported	Kinematics	Characteristics of the control system	The exoskeleton drove robotic arm repetitively track the cubic polynomial trajectory	Not applicable	Not applicable	Trajectories tracking capability was demonstrated	Wang et al. (2019)
7	Elbow–shoulder	Upper-limb exoskeleton	TH	Arm–load assist	A	Electric (EM)	5	9.5	Not reported	Not reported	Not reported	Physiological	Human–exoskeleton analysis	Perform a movement of raising the arm with a drill above the head wearing or not the arm exoskeleton	10	8 M and 2 F, all right-handed, (28.8 ± 3.4 years, 173.3 ± 6.4 cm,72.32 ± 11.97 kg)	Exoskeleton reduces muscle activity	Blanco et al. (2019)
8	Elbow–shoulder	4-DOF upper-body exoskeleton	LC	Arm–load assist	A	Not reported	4	Not reported	Admittance control and gravity compensation	Force Sensitive Resistor	Not reported	Biomechanics	Human–exoskeleton analysis	With the passive exoskeleton, in which three different payloads in the range of 0–5 kg were lifted	5	(20–30 years)	The developed method is able to estimate the load carrying status	Islam and Bai (2019)
9	Elbow–shoulder	Wearable upper arm exoskeleton	TH	Arm–load assist	A	Electric (EM)	1	2	PD adaptive control	Not reported	4.5	Physiological	Human–exoskeleton analysis	Holding position with no weight, repeated with a 1.5, 3, 4.5 kg load. With and without exo conditions. EMG for elbow and shoulder flexion/ extension.	5	(23–28 years, 168–183 cm)	The IEMG of every muscle is significantly decreased when the user wears the exoskeleton	Yan et al. (2019)
10	Shoulder	PAEXO passive exoskeleton	TH	Shoulder–joint support	P	Passive (S)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Physiological	Human–exoskeleton analysis	T1: Screwing nuts continuously, and T2: Drilling using an electric drill (1.3 kg)	12	6 M and 6 F (24 ± 3 years, 176 ± 15 cm, 73 ± 15 kg)	The mean EMG amplitude of all evaluated muscles was significantly reduced when the exoskeleton was used. This was accompanied by a reduction in both heart rate and oxygen rate. The kinematic analysis revealed small changes in the joint positions during the tasks.	Schmalz et al. (2019)

(*Continued*)

TABLE 2 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
11	Shoulder	Parallel-structured upper limb exoskeleton	LC	Arm–load assist	A	Hypoid gear	2	12	Force-position hybrid	Angle sensors	Not reported	Kinematics	Human–exoskeleton analysis	Assisted by the exoskeleton, operator try to lift a 20-kg load	1	Not reported	Structure can lift load up to 1.5 times of the exoskeleton's weight	Zhang et al. (2019)
12	Shoulder (Includes wrist)	ABLE exoskeleton	TH	Arm–load assist	A	Not reported	7	Not reported	Force-position control	Not reported	Not reported	Not reported	Human–exoskeleton analysis	Biomechanical task analysis: tool holding above head with five shoulder compensation torques. With and without exo condition.	8	(24 ± 7 years, 63 ± 11 kg, 170 ± 5 cm) right-handed	Setting compensation to 1.935 kg.m to led to disturbance of subjects' natural movements. Excluding Trial 5, strongest arm torques reduction occurs for Trial 3 (38.8%)	Sylla et al. (2014a, 2014b)
13	Shoulder	Shoulder exoskeleton	TH	Shoulder–joint support	P	Passive (S)	Not reported	2	Not applicable	Not applicable	Not applicable	Physiological	Human–exoskeleton analysis	Repetitive lifting and placement work	5	(20–24 years)	Exoskeleton can reduce the muscle activity of shoulder muscle	Zhu et al. (2019)
14	Shoulder	Hyundai Vest Exoskeleton (H-VEX)	TH	Arm–limb support	P	Passive (S)	1	2.5	Not applicable	Not applicable	Not reported	Physiological	Human–exoskeleton analysis	Biomechanical task analysis: tool holding above head With and without exo conditions. High and low-task, with and without load.	10	(34.9 ± 3.96 years, 173.7 ± 6.20 cm, 72.1 ± 12.85 kg)	Assistive torque provided by H-VEX was shown to significantly decrease activation of the shoulder-related muscles during target tasks	Hyun et al. (2019)
15	Shoulder	Airframe	LC	Arm–limb support	P	Not reported	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human–exoskeleton analysis	Static task: 3.5 kg on forearm. Repeated manual handling task: pick and place 3.4 kg. Precision task: tracing a continuous wavy line at shoulder height. Cognitive assessment: RPE. Time to complete. With and without exo condition.	29	*M* (51.5 ± 4.7 years, 81.6 ± 9.1 kg, 174.9 ± 2.3 cm)	Static = 31.1% relative longer time length with exo. Manual handling = Results are comparable. Precision = A significant 33.6% increase of the number of traced arches with exo.	Spada et al. (2017, 2018)

(*Continued*)

TABLE 2 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
														Controlled real work tasks: mounting the clips of brake hoses underbody, sealing underbody using the sealing gun, and mounting the seal on the rear door. With and without exo condition.	11	(177.2 ± 5.0 cm, 81.1 ± 7.3 kg, 45.8 ± 6.9 years)	Workers provided positive feedback for the exo as it helped to carry out tasks with less physical and mental effort. There was some potential interference of the exo during the mounting task.	Spada et al. (2018)
16	Shoulder (Includes wrist)	CANE	IP	Back–joint support	A	Pneumatic (PnC)	Not reported	Not reported	Flow solenoid valve	IMUs	Not reported	Biomechanical task analysis: IMU	Human–exoskeleton analysis	Lift concrete blocks from the floor to .4m platform and return for 3 mins. With and without exo conditions. IMUs.	4	Not reported	A reduction in angle of waist bend by 32° and shoulder twist by 17° was seen while wearing the exo.	Cho et al. (2018)

Note. Results interpreted by authors were “Purpose,” “Task Analysis,” and “Testing Performed.” A = active; Am = amplification; CoG = center of gravity; CoP = center of pressure; EMG = electromyography; exo = exoskeleton; F = female; FSR = force-sensitive resistor; GRF = ground reaction force; HR = heart rate; IP = injury prevention; IMU = inertial measurement unit; LC = load carrying; M = male; P = passive; PD = proportional-derivative; PI = proportional-integral; PID = proportional-integral-derivative; ROM = range of motion; RPE = rate of perceived exertion; TH = tool holding.

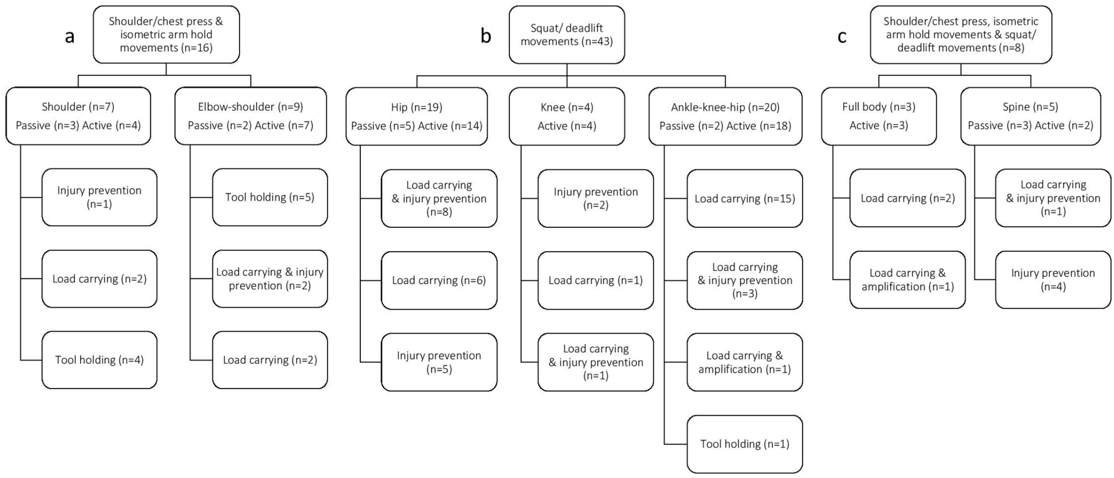

Figure 2. Breakdown of exoskeletons classified into their movement patterns, supporting joints and purpose. (a) Shoulder/chest press and isometric arm hold (Table 2). (b) Squat/deadlift (Table 3). (c) Shoulder/chest press, isometric arm hold, and squat/deadlift movements (Table 4).

using the exoskeleton (Mudie et al., 2018). Biomechanical evaluations vary and included motion capture (n = 9), ground reaction forces (GRF; n = 2), and inertial measurement units (IMU; n = 6); physiological tests included electromyography (EMG; n = 32), while psychophysical tests included rate of perceived exertion and self-questionnaires (n = 5). Only four studies measure performance using a direct method (time to completion).

All studies that tested muscle activation (recorded via EMG) reported reductions in some EMG signals (n = 32). Such a reduction in EMG was considered a measure of how the exoskeleton reduced muscle work and thus the risk of injuries. Specific to the back, eight studies reported reductions of muscle activation of the erector spinae muscles between 15% and 54%; one study reported no change; and one reported increased activation of the antagonist muscles.

Due to the early stage of development for the majority of devices, participant sample sizes were relatively low (<13). However, there were two studies (Baltrusch et al., 2018, and Spada et al., 2017) proposing commercially available exoskeletons (the Leavo [Table 3, Row 31] and Airframe [Table 2, Row 15]) that had larger participant cohorts with 18 and 29 participants, respectively. The Airframe was also tested with a smaller cohort of 11 participants in an automotive factory environment performing controlled real-work tasks (Spada et al., 2018), and the performance of the Daewoo Shipbuilding and Marine Engineering Hydraulics Wearable Robots (DSME-HWR; Table 3, Row 20) was observed during in-field trials at a shipbuilding yard (Chu et al., 2014).

DISCUSSION

The aim of this review was to analyze the current literature to identify characteristics of industrial exoskeletons that can be useful to military manual handling tasks. The high percentage of exoskeletons targeting load carrying reflects the industry need for devices that can support manual handling workers by preventing injuries and improving productivity. Therefore, the application of these exoskeletons to Australian Defence Force personnel performing manual handling could help reduce the substantial personal and financial cost of injuries.

Most of the exoskeletons included in this review are in early development and are designed to support manual handling via a number of methods, such as providing assistive torque to enhance the ability of joints to carry

TABLE 3: Exoskeleton Classification for Squat/Deadlift

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
1	Ankle–knee–hip	Fortis	TH	Arm–load transfer	P	Passive (S and counter-weight)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	Sokol (2014)
2	Ankle–knee–hip	HEXAR-CR50	LC	Leg–load assist	A	Electric (EM and HD)	7	Not reported	PID control	Muscle volume sensor	30	Gait analysis for ROM, peak moments, and peak power	Human–exoskeleton analysis	Walking at 3 km/h with 10- and 20-kg loads. With and without exo condition. EMG, GRF.	1	(29 years, 75 kg)	Reduction in leg muscle activations and GRF during 30%–70% walking phases while wearing the exo.	Lim et al. (2015)
3	Ankle–knee–hip	Lower extremity exoskeleton with power-augmenting purposes	LC	Leg–walking assist	A	Electric (EM and HD)	14	Not reported	Swing control method	Absolute/ incremental encoders, strain-gage sensor	Not reported	Not reported	Human–exoskeleton analysis	Left leg swings back and forward, EMG measured at the quad.	1	*M* (34 years)	Reduction in quad muscle activation	Choi et al. (2017)
4	Ankle–knee–hip	Lower extremity exoskeleton	LC and Am	Leg–walking assist	A	Hydraulic (HyC)	Not reported	30	PID and H∞ control	Encoders, force sensors	60	Kinematic modeling	Characteristics of the control system	Walking carrying 60-kg load. Squat with no load.	Not reported	Not reported	Walking bearing 60-kg load and squat action with no external load are realized effectively by this proposed control method	Guo et al. (2015, 2016)
5	Ankle–knee–hip	Servo controlled passive joint exoskeleton	LC	Leg–load transfer	A	Electric (EM and ratchets)	8	6	Not reported	Force sensor	30	Not reported	Exoskeleton structural design	Finite element analysis for joint reaction forces and moments and resultant deformation of the structure during postural changes.	Not applicable	Not applicable	The ankle joint sees the largest amount of stress and deformation compared to the knee and hip.	Naik et al. (2018)
6	Ankle–knee–hip	Lower-limb anthropo-morphic exoskeleton	LC and IP	Leg–walking assist	A	Electric (EM)	8	Not reported	Impedance and supervisory control	Torque, position, and GRF sensors	Not reported	Gait cycle	Human–exoskeleton analysis	Walking carrying 10-kg load for 10 m. With exo in passive mode, with exo in active mode and without exo conditions. EMG.	4	(25 ± 5 years, 77 ± 7 kg, 169 ± 2 cm)	An average reduction in muscle activity of 43.4% (Right Vastus intermedius) and 60.4% (Right Gastrocnemius) was seen when the exo was worn in active mode compared to no exo.	Sado et al. (2018)
7	Ankle–knee–hip	HIT-LEX	LC	Leg–load assist	A	Electric (EM and S)	14	Not reported	PID control	In-Sole Sensing Shoe - Film pressure force sensors, strain sensor, angle sensors	Not reported	Gait cycle	Characteristics of the control system	Two experiments of foot lifting and landing and single leg stepping forward.	Not reported	Not reported	Exo could rapidly identify different working conditions and flexibly follow the swing leg movement.	Zhang et al. (2016); Zhu et al. (2016)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
8	Ankle–knee–hip	Hydraulically Powered Exoskeletal Robot (HyPER)	LC	Leg–load assist	A	Hydraulic (HyC)	10	Not reported	Not reported	Inclinometer, absolute encoders, insole sensor, FSRs	Not reported	Gait cycle for force transmission ratio	Characteristics of the control system	Stand-to-sit movement and walking experiment (.83 m/s, 0% grade, 10 min) with no load, 10, and 20 kg. GRF. With and without exo condition.	1	*M* (35 years, 75.1 kg, 176 cm)	In the standing position the GRF was not affected by a change in the payload and was reduced below wearers body weight in a semi-squat with exo.	Kim et al. (2015); Lee et al. (2015)
9	Ankle–knee–hip	Lower Extremity Exoskeleton System	LC	Leg–load assist	A	Hydraulic (HyC)	10	Not reported	PI control	Force sensors in -shoe, load cells	Not reported	Not reported	Exoskeleton structural design	Mechanical simulation in Matlab.	Not applicable	Not applicable	Not reported	Sahin et al. (2014a, 2014b)
10	Ankle–knee–hip	PRMI Exoskeleton	LC and IP	Leg–walking assist	A	Electric (EM and HD	10	Not reported	Global fast terminal sliding mode and PD control	Encoders, inclinometers, foot pressure sensors	20	Kinematic modeling	Characteristics of the control system	Walking experiment (4.7 km/h) with a 20 kg load.	1	*M* (25 years, 61 kg, 175 cm)	The joint position tracking errors are maximum of 2° at the hip joint and 4° at the knee joint. These results confirm that the exoskeleton swing leg is able to shadow human motions in time by using the proposed controller.	Ka et al. (2016)
11	Ankle–knee–hip	Under-actuated lower extremity exoskeleton	LC	Leg–load assist	A	Electric (EM, HD and springs)	6	Not reported	PID control	Muscle volume, insole sensors	Not reported	Not reported	Characteristics of the control system	Measure the effect of the exo on percentage maximum voluntary contraction via EMG. With and without exo condition.	Not reported	Not reported	Average decrease in %maximum voluntary isometric contraction of the leg muscles of 40.5% on level surface and 12.5% climbing stairs when wearing the exo.	Kim et al. (2013)
12	Ankle–knee–hip	Lower extremity exoskeleton (LEE)	LC	Leg–load assist	A	Electric (EMs and LA)	5	Not reported	Zero moment point control	Force sensors in foot pad	Not reported	Gait cycle for CoP	Characteristics of the control system	Walking test forward and backward.	Not reported	Not reported	The exoskeleton can walk stably with the user.	Low et al. (2005, 2006)
13	Ankle–knee–hip	HUALEX	LC	Leg–load transfer	A	Electric (EM and HD)	10	15	Fuzzy-based variable impedance control	Encoders, IMUs, FSRs in foot pad	40	Kinematic modeling	Characteristics of the control system	Walking test with 30-kg load at speeds of 0.30m/s to 1.20m/s. Comparing the fuzzy-based variable impedance control to normal impedance control.	3	(70.83 kg)	The control fuzzy based impedance control strategy tracked human motion well and decreased interaction forces across all walking speeds compared to normal impedance control.	Tran et al. (2016)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
14	Ankle–knee–hip	HUALEX	LC	Back–load assist	A	Hydraulic (HyC)	7	Not reported	Hybrid Control combining zero-force control and zero load control	Tension and compression pressure sensor	25	Kinematic modeling	Comparison of control systems	Not reported	Not applicable	Not applicable	Hybrid control strategy can reduce interaction force between the pilot and the exoskeleton efficiently	Chen et al. (2019)
15	Ankle–knee–hip	Passive wearable moment restoring device	LC and IP	Back–load assist	P	Passive (S and cables)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Kinematic modeling	Human–exoskeleton analysis	Lift and lower loads (4.5 and 13.6 kg) twice. With and without exo conditions. Motion capture and EMG.	6	5 M and 1 F (27.7 ± 6.0 years, 67.7 ± 7.2 kg, 175 ± .06 cm)	With the device, back muscles demonstrated a 54% reduction in muscle activity and calculations suggested a reduction in maximum spine compressive forces by approximately 1300 N.	Wehner et al. (2010)
16	Ankle–knee–hip	ExoHeaver	LC	Leg–load assist	A	Electric (EM)	Not reported	26	Servo control	Not reported	15	Kinematic modeling	Exoskeleton structural design	Not reported	Not reported	Not reported	Not reported	Yatsun and Jatsun (2018)
17	Ankle–knee–hip	Hip, knee, ankle exoskeleton	LC	Leg–load assist	A	Electric (EM)	Not reported	Not reported	Super twisting sliding mode controller	Not reported	15	Simulation	Characteristics of the control system	Control of the transferring of the force to the hip of a lower extremity exoskeleton while carrying weight	Not applicable	Not applicable	It provides better control over PID with uncertainties and disturbances	Nair and Ezhilarasi (2019)
18	Ankle–knee–hip	Biomimetic lower limb exoskeleton (BioComEx)	LC	Leg–walking assist	A	Variable stiffness actuator and SEA	Not reported	15	Closed-loop impedance control algorithm	Force sensors	Not reported	Biomechanical	Human–exoskeleton analysis	Not reported	1	Not reported	BioComEx is sufficiently satisfactory for walking applications	Baser et al. (2019)
19	Ankle–knee–hip	Wearable lower-body exoskeleton	LC	Leg–limb support	A	Electric (EM)	6	11	Dual EKF sensor-less (user) joint torque estimation, LQG torque amplification control, and supervisory control	Joint angle potentiometers; and insole GRF sensors on each foot	Not reported	Biomechanical and physiological	Human–exoskeleton analysis	Lift a box weighing 4.3-kg from the floor, hold for a while, and then drop back on the floor, six consecutive times with and without assistance from the prototype exoskeleton suit	5	(28 ± 5 years, 178 ± 2 cm, 76 ± 5 kg)	Average recorded EMG signals taken at the right vastus intermedius (quadriceps) and right gastrocnemius (calf muscles) of each participant revealed more than 36% reduction in muscle activity from the two muscle groups	Sado et al. (2019)

(Continued)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
20	Ankle–knee–hip	DSME-HWR	LC	Leg–load assist	A	Electric (LA)	2	4.5	Compliance control algorithm - PD control	Not reported	Not reported	Biomechanical analysis: MoCap and GRF	Human–exoskeleton analysis	Knee joint optimization. Original knee joint versus optimized design for user exertion on exo with heavy load (30 kg). Force, joint angle, and time to complete.	1	M	Original knee: Force = 392 N, Time = 2.3 s, Angular velocity = 60.9 deg/s. Optimized design 1: Force = 43 N, Time vol 2.1 s Angular velocity = 49.5 deg/s. Optimized design 2: Force = 147 N, Time = 2.0 s, Angular velocity = 60 deg/s.	Choo and Park (2017a, 2017b); Chu et al. (2014); Jeong et al. (2014); Kim et al. (2014)
21	Knee	Knee Assist Robotic Exoskeleton	IP	Leg–walking assist	A	Electric (EM and S)	Not reported	Not reported	Torque control	Not reported	Not reported	Not reported	Characteristics of the control system	The participant walked and performed a sit-to-stand motion.	1	*M* (26 years, 85 kg, 171 cm)	The exo performed as expected for its three different control phases.	Noh et al. (2016)
22	Knee	Soft knee exoskeleton	IP	Knee–joint support	A	Electric (EM)	1	Not reported	Two-level configuration architecture for torque control	IMUs	Not reported	Biomechanics: Physiological	Human–exoskeleton analysis	15 squat cycles in six conditions (without wearing the exoskeleton, power-off exoskeleton, zero torque control, 10%, 30%, and 50% assistance	3	subject 1: (25 years, 170 cm, 70 kg) subject 2: (32 years, 178 cm) subject 3: (38 years, 175 cm, 85 kg)	The assistive control reduced the muscle effort of knee extensor	Yu et al. (2019)
23	Knee	Knee exoskeleton	LC and IP	Knee–load assist	A	Electric (LA)	1	Not reported	Arduino UNO	EMG	Not reported	Biomechanics	Human–exoskeleton analysis	Two cycles of the knee flexion and extension	1	(63 kg, 160 cm)	The experimental and theoretical values of the joint angle and shank's angular velocities are validated for the kinematic design	Jain et al. (2019)
24	Knee	Exoskeleton intelligent portable system	LC	Knee–load assist	A	Electric and Hydraulic (EM and HyC)	1	Not reported	Hydraulic pressure, PID control	Pressure sensor, encoder	30	Not reported	Characteristics of the control system simulation	Simulation of actual and expected knee angle and actuator location.	Not applicable	Not applicable	Control method can follow the natural motion of the knee.	Li et al. (2012)
25	Hip	Muscle Suit	LC	Leg–load assist	A	Pneumatic (AM)	Not reported	8.1	Switches	Not reported	Not reported	Not reported	Human–exoskeleton analysis	Hold load (20 kg) for 15 s for three trials. With and without exoskeleton condition. EMG.	10	Not reported	EMG values averaged across the three trials were reduced in the arms while wearing the exo.	Muramatsu et al. (2011)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
26	Hip	Lower-Back Robotic Exoskeleton	LC and IP	Back–load assist	A	Electric (SEA and HD)	4	11.2	Admittance control and finite state machine	Encoder, IMUs, torque sensor, strain gage	Not reported	Not reported	Human–exoskeleton analysis	Symmetrical loading (0, 5, 10, 15, and 25 kg) and lift origin asymmetry (45°; 15 and 25 kg) lifting and lowering task. With and without exo conditions. EMG.	1	M	The exo significantly reduces muscle activation of the back during symmetrical loading and for the lift origin asymmetry, larger muscle activations occurred with the device assisting the hips for flexion/ extension and add/ abduction.	Zhang and Huang (2018)
27	Hip	H-WEX	LC and IP	Back–joint support	A	Electric (EM, HD, and Pulley)	8	4.5	Motion and torque control	Hall sensor, IMU	15	Not reported	Human–exoskeleton analysis	Pick 15-kg load from ground to pelvic height. Squat and stoop posture conditions. With and without exo conditions. EMG for hip flexion/ extension.	9	*M* (33.4 ± 2.4 years, 73.0 ± 9.0 kg, 173.2 ± 4.5 cm)	Decrease in muscle activity of the muscles related to waist motions (back and abdominals) of between 10 and 30% while wearing the exo.	Ko et al. (2018)
28	Hip	APO	LC and IP	Back—load assist	A	Electric (EM, SEA)	4	Not reported	Lift detection	Encoders, IMUs	Not reported	Not reported	Characteristics of the control system	Two sessions for training lift detection algorithm, using three initial positions and three lifting techniques for 5-kg box. One session for testing algorithm. EMG, IMU.	7	*M* (27.9 ± 2.3 years, 70 ± 6.4 kg, 178.1 ± 8.1 cm)	Accuracy of 97.48% ± 1.53% was achieved for lift detection with a time delay of <160 ms. EMG showed at least 30% reduction in back muscle activation when the exo provided torque.	Chen et al. (2018); Lanotte et al. (2018)
												Not reported	Human-exoskeleton analysis	Walking on treadmill, varied speeds and level of exo assistance. With and without exo conditions. Hip joint angle, torque, and motion capture.	5	(29.2 ± 6.3 years, 74.4 ± 6.8 kg, 173 ± 7cm)	Negligible interference of the exo in human kinematics. Small displacements in the exohuman interaction points.	D'Elia et al. (2017)

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TABLE 3 (Continued)

Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
		Operational Details										Evaluation Details						
29	Hip	Robo-Mate -Mk2	LC and IP	Back–load assist	A	Electric (Parallel elastic actuator - EM, HD)	1	Not reported	PD and torque control	Torque sensor	15	Not reported	Characteristics of the control system simulation	Evaluating the differences in the torque control transparency when used with the parallel elastic actuator and the actuator without parallel elasticity.	Not applicable	Not applicable	Significant improvements in torque-control performance, thus encouraging the use of parallel-spring arrangements	Toxiri, Calanca et al. (2018)
												Not reported	Human-exoskeleton analysis	Pick and place loads (7.5 kg, 15 kg). With and without exo conditions. EMG, interface pressure, perceived comfort, and usability.	12	*M* (27 ± 2 years, 75.38 ± 10.1 kg, 179.4 ± 0.65 cm)	Reduced muscle activity of the erector spinae (12%-15%) and biceps femoris (5%).	Huysamen et al. (2018)
												Not reported	Accuracy of the sensor system	Compare three strategies for input into controller to follow user intention. IMU, EMG, and finger pressure sensor. Lift and lower load (2 x no load, 5 and 10kg) for each strategy.	13	11M and 2F (28.9 ± 4.3 years, 69.8 ± 10.6 kg, 178 ± 6.6 cm)	The IMU strategy generated a reference signal that shows little dependence on load; by contrast, the EMG and finger pressure strategies show a stronger relationship.	Toxiri, Koopman, et al. (2018)
												Biomechanics: Physiology	Human-exoskeleton analysis	Lifting task with three different techniques; free, squat, and stoop, once with no exo and three times with the exo (inclination, EMG, and hybrid)	10	25.0 ± 6.9 years, 70.9 ± 8.8 kg, 1.77 ± 0.06 m	Compression forces with the exo were substantially lower compared to no exo. However, no single exo control mode was superior over the others due to performance limitations of the actuators.	Koopman et al. (2019)
												Kinematic modelling	Characteristics of the control system	Walking, standing and bending	1	Not reported	Study shows that it is possible to perform reliable online classification.	Poliero et al. (2019)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
30	Hip	Standalone powered exoskeleton robot suit	LC	Back–load assist	A	Electric (EM, HD)	Not reported	8	Not reported	Encoders	Not reported	Biomechanical analysis	Human–exoskeleton analysis	Flexion/ extension of trunk with load (33 kg). Torque, time to complete	Not reported	Not reported	The motion was completed in .7 s with load, where this is .49 s longer than that of the no-load condition.	Yu et al. (2015)
31	Hip	Laevo	IP	Back–joint support	P	Passive (S)	Not reported	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human–exoskeleton analysis	Objective and subjective measures for 12 functional tasks.	18	*M* (27.7 ± 5.1 years, 74.7 ± 8.0 kg, 178 ± 6 cm)	Decreased the local discomfort in the back in static holding tasks and at the dorsal side of the upper legs in static forward bending. Showed adverse effects on tasks that require large ROM of trunk or hip flexion including walking.	Baltrusch et al. (2018)
												Physiology	Human-exoskeleton analysis	Lift and lower a 10-kg box (0.39, 0.37, 0.11 m, with 2.5 cm diameter handles) at a rate of 6 lifts per min (for 5 min)	13	28.9 years (4.4), 1.80 m (0.04) m and 76.9 kg (12.0)	Wearing the exoskeleton during lifting, metabolic costs decreased as much as 17%. In conjunction, participants tended to move through a smaller range of motion, reducing mechanical work generation.	Baltrusch et al. (2019)
32	Hip	Laevo V2.4	IP	Back–joint support	P	Passive (S)	Not reported	Not reported	Not reported	Not reported	Not reported	Biomechanics: Physiology	Human–exoskeleton analysis	Motion and surface EMG were measured during two consecutive periods of at least 30 min, one with and one without the exoskeleton	10	Mean age and BMI of the participants was, respectively, 45.6 (*SD* 11,64) and 26.9 (*SD* 2,78)	RMS values were significantly higher for the trapezius muscle with the exoskeleton (Mdn = 44.02) compared to the measuring period without the device (Mdn = 34.83, $T = 0$, $p < .05$, r = −.73); no differences were found for erector spinae and biceps femoris muscle activity. Participants reported significantly higher discomfort scores for the upper back/ chest and thigh region with the exoskeleton (both $p < .05$, r = −.68).	Amandels et al. (2019)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
33	Hip	Robo-Mate exoskeleton	LC and IP	Back–load assist	A	Electric (Parallel elastic actuator - EM, HD)	Not reported	Not reported	Not reported	Not reported	15	Biomechanical analysis: MoCap, EMG, and GRF	Exoskeleton structural design	Simulation of lifting and lowering tasks with exo to test actuator performance.	Not applicable	Not reported	The results show the improvement in weight, peak torque, and peak power by 20%, 50%, and 40%, respectively, as compared with the current prototype	Masood et al. (2016)
									Acceleration-based torque control	Trunk angular acceleration	Not reported	Physiology	Human-exoskeleton analysis	Lifting and the lowering of an external weight of 5kg and 10kg, repeated at three different speed: fast, normal, and slow.	7	Not reported	The data on peak muscular activity at the spine show promising trends.	Lazzaroni et al. (2019)
34	Hip	Hip-type exoskeleton	LC and IP	Back–load assist	A	Electric (EM)	1	Not reported	Not applicable	Sensorless force estimator	Not reported	Physiological	Human-exoskeleton analysis	Lift load from 0 to 25 kg (5 kg increments) load from the ground. With and without exo condition. EMG.	10	Average age 30 years, height 176 cm, and weight 75 kg	EMG value was significantly lower when the exoskeleton on in all loading conditions	Xia et al. (2019)
35	Hip	Spine exoskeleton	LC	Back–joint support	A	Electric (EM)	9	Not reported	Torque control	Torque sensor	Not reported	Biomechanics: Physiology	Human–exoskeleton analysis	Repetitive, stoop-lift of a 10-kg box at different speeds	5	(21–36 years, 60–82.12 kg, 170– 82 cm)	All cost functions reduced significantly the human torque loads. However, they result in different amounts and distributions of the load reduction as well as different contributions from the passive and active components of the exoskeleton	Harant et al. (2019)
36	Hip	VT-Lowe's exoskeleton	LC	Back–load transfer	P	Passive (flexible beams)	Not reported	Not reported	Not reported	Not reported	Not reported	Physiology	Human–exoskeleton analysis	Stoop, squat and freestyle lifting trials performed in the sagittal plane, plus lift origin asymmetry (60°) for 0% and 20% of subject bodyweights, both with and without exoskeleton	12	22.75 (4.35) years, 178.92 (6.05) cm, 80.41 (5.59) kg, and 25.16 (1.91) kg/m2	Results demonstrated that the exoskeleton could reduce the average peak and mean muscle activation of back and leg muscles regardless of different levels of box weights and lifting types.	Alemi et al. (2019)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
37	Hip	Booster exoskeleton	IP	Back–joint support	P	Springs	Not reported	Not reported	Not applicable	Not applicable	Not reported	Physiology	Human–exoskeleton analysis	Carry and lift the object weighing 9.5 kg	3	Not reported	With wearing the exoskeleton, the subjects' breathing, and heart rate were significantly reduced	Han et al. (2019)
38	Hip	Back assistance exoskeleton	LC	Back–joint support	A	Pneumatic artificial muscle	Not reported	7.6	Not reported	Not reported	18	Physiology	Human–exoskeleton analysis	Romanian deadlift motion of lifting 15 kg repeated 10 times at a time, totaling five times	1	Not reported	Decreased level of 20% to 30% in muscle activation when lifting the loads with exo	Shin et al. (2019)
39	Hip	Wearable waist exoskeleton	IP	Back–joint support	A	Electric (EM)	1	5	Torque control	Angle, angular velocity, and current	Not reported	Physiology	Human–exoskeleton analysis	Symmetrical lifting for six different objects (0, 5, 10, 15, 20, 25 kg) under two conditions of with and without the exoskeleton	10	Average age 26 years, weight 70 kg, and height 174 cm	The exoskeleton significantly reduced the back muscular activity during repetitive lifting tasks	Yong et al. (2019)
40	Hip	HAL	IP	Back–joint support	A	Not reported	1	Not reported	EMG based control	Triaxial accelerometer and potentiometers	Not reported	Physiology	Human–exoskeleton analysis	Two sessions (one with HAL and one without HAL) of stoop lifting/ placing, until they feel they cannot continue. In each session, subjects were asked to lift and place a small box, (for males, 12 kg, for females, 6 kg).	20	13 M, 7 F (31.5 ± 6.6 years)	Muscle coordination changes were dominated by changes in timing coefficients, with minimal change in muscle synergy vectors	Tan et al. (2019)
41	Hip	SJTU-EX	LC	Back–load assist	A	Electric (EM)	8	Not reported	Not reported	Not reported	Not reported	Not reported	Exoskeleton structural design	Walking simulations	Not applicable	Not reported	Not reported	Miao et al. (2015)
42	Hip	Wearable Exoskeleton Power Assist System	LC and IP	Back–load assist	A	Electric (EM)	1	11	User intention via EMG	EMG	Not reported	Kinematic modeling	Human–exoskeleton analysis	Lift and lower 20-kg load from/to ground. With and without exo condition. EMG.	Not reported	Not reported	Muscle activation of the thigh muscles was reduced when wearing the device.	Naruse et al. (2003)

(*Continued*)

TABLE 3 (Continued)

		Operational Details										Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
43	Hip	SPEXOR	LC and IP	Back–joint support	P	Passive (flexible beams)	4	Not reported	Not applicable	Not applicable	Not reported	Not reported	Human-exoskeleton analysis	ROM testing, trunk flexion/ extension, lateral bending and rotation. Four exo configuration conditions. Motion capture.	3	*M* (30 years, 66 kg, 171.5 cm)	Using flexible beams as a back interface increases the trunk ROM by more than 25% compared to its rigid counterpart. With the flexible beams, the ROM is only decreased by 10% compared to not wearing an exo.	Näf et al. (2018)

Note. Results interpreted by authors were “Purpose,” “Task Analysis,” and “Testing Performed.” A = active; Am = amplification; AM = artificial muscle; BoC = Bowden cable; CoG = center of gravity; CoP = center of pressure; EM = electric motor; EMG = electromyography; exo = exoskeleton; F = female; FSR = force-sensitive resistor; GRF = ground reaction force; HD = harmonic drive; HR = heart rate; HyC = hydraulic cylinder; IMU = inertial measurement unit; IP = injury prevention; LA = linear actuator; LC = load carrying; M = male; P = passive; PD = proportional-derivative; PI = proportional-integral; PID = proportional-integral-derivative; PnC = pneumatic cylinder; ROM = range of motion; RPE = rate of perceived exertion; S = spring; TH = tool holding.

TABLE 4: Exoskeleton Classification for Shoulder/Chest Press, Isometric Arm Hold, and Squat/Deadlift

			Operational Details									Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
1	Spine	Passive spine exoskeleton	IP	Back—joint support	P	Passive (S and pulley)	1	Not reported	Not applicable	Not applicable	Not reported	Kinematic modeling	Human–exoskeleton analysis	Dynamic: flexion/extension for 120 s with a constant speed. Static: hold three flexion positions (small, medium, and full-range) for up to 120 s. EMG, IMU. With and without exo condition.	3	*M* (26.7 ± 3.3 years, 68.3 ± 6.7 kg, 172 ± 12 cm)	EMG reduction at lumbar (24%) and thoracic (54%) level with exo and a reduction of intervertebral bending moment (36 Nm) and muscle force (479 N).	Zhang et al. (2016a)
2	Spine	Spine-inspired continuum soft exoskeleton	IP	Back—joint support	A	BoC	Three for each disc	Not reported	Virtual impedance model	Load cell	Not reported	Biomechanics	Human–exoskeleton analysis simulation	Stoop lifting of 15 kg with 10 repetitions	3	Not reported	Able to successfully track the desired force with high accuracy.	Yang et al. (2019)
3	Spine	FLx	IP	Back—joint support	P	Passive	Not reported	1.08	Not reported	Not applicable	Not applicable	Biomechanics	Human–exoskeleton analysis simulation	A 3 × 3 × 2 × 2 repeated-measures design was employed in this study, in which all combinations of intervention (FLx exo, V22 exo, none), lift origin height (shin, knee, waist), lift origin asymmetry (0° and 45°), and load weight (9.07 kg and 18.14 kg) were evaluated	10	(24.9 ± 5.0 years, 81.1 ± 16.1 kg, 179.4 ± 4.6 cm)	FLx reduced peak torso flexion at the shin lift origin, but differences in moment arms or spinal loads attributable to either of the interventions were not observed. Thus, industrial exoskeletons designed to control posture may not be beneficial in reducing biomechanical loads on the lumbar spine.	Picchiotti et al. (2019)
4	Spine	V22	IP	Back—joint support	P	Passive	Not reported	1.29	Effectors worn on the hand	Not applicable	68							
5	Spine	Exoskeleton for the back	LC and IP	Back—joint support	A	Pneumatic (PnC)	Not reported	Not reported	User intention	EMG	25	Biomechanical simulation	Human–exoskeleton analysis simulation	Measure of forces to the back based on a human–machine model.	Not applicable	Not applicable	A decrease of the forces by 35% on the L5-S1 joint and by 43% on the back muscles can be noted at the beginning of the lift.	Durante et al. (2018)

(*Continued*)

TABLE 4 (Continued)

			Operational Details									Evaluation Details						
Row	Supported Joint	Device Name	Purpose	Targeted Assistance	Actuation Method	Actuators	DOF	Weight (Kg)	Control	Sensors	Load Capability (Kg)	Task Analysis	Testing Performed	Test Details	Sample Size	Participant Details	Results	Ref.
6	Full body	Robot Suit HAL	LC	Back—load assist	A	Electric (EM and HD)	14	Not reported	Torque control based on EMG	EMG, potentiometers, IMUs, GRF sensors	50	Kinematic modeling	Characteristics of the control system	Measure joint angles and bio-signals while holding load (50 kg).	1	*M* (26 years)	The designed locking mechanism included in the power units kept the angles of the upper limbs steady while the user held the load, and the physical burden on the upper limbs of the user was reduced.	Satoh et al. (2009)
7	Full body	UTRCEXO	LC	Leg—walking assist	A	Electric (EM and HD)	8	Not reported	Position and torque control. Walking intention	Encoders, FSRs, force/torque sensor	Not reported	Gait analysis for GRF and motion capture	Human–exoskeleton analysis	Walking with 10-kg weight.	1	(73 kg, 176 cm)	Detects step initiation using the insole type FSRs prior to movement. Allows the operator to easily walk with a 10-kg load. Does not take the operator's desired step velocity into account.	Cha et al. (2015)
8	Full body	Body Extender (BE)	LC and Am	Full body—load assist	A	Electric (EM)	22	160	User-triggered motion	Encoders, accelerometer, force/torque sensors	50	Not reported	Human–exoskeleton analysis	Assess the tracking (with and without load) and the grasping/ lifting/ handling (up to the rated load) capabilities of the device.	Not reported	Not reported	Maximum resistance forces of 30 N are well tolerated by the user, good mass distribution of the device, walking phase somewhat unnatural. At max rated load the system equilibrium becomes unstable	Marcheschi et al. (2011)

Note. Results interpreted by authors were "Purpose," "Task Analysis," and "Testing Performed." A = active; Am = amplification; AM = artificial muscle; BoC = Bowden cable; CoG = center of gravity; CoP = center of pressure; EM = electric motor; EMG = electromyography; exo = exoskeleton; F = female; FSR = force-sensitive resistor; GRF = ground reaction force; HD = harmonic drive; HR = heart rate; HyC = hydraulic cylinder; IMU = inertial measurement unit; IP = injury prevention; LA = linear actuator; LC = load carrying; M = male; P = passive; PI = proportional-integral; PD = proportional-derivative; PID = proportional-integral-derivative; PnC = pneumatic cylinder; ROM = range of motion; RPE = rate of perceived exertion; S = spring; TH = tool holding.

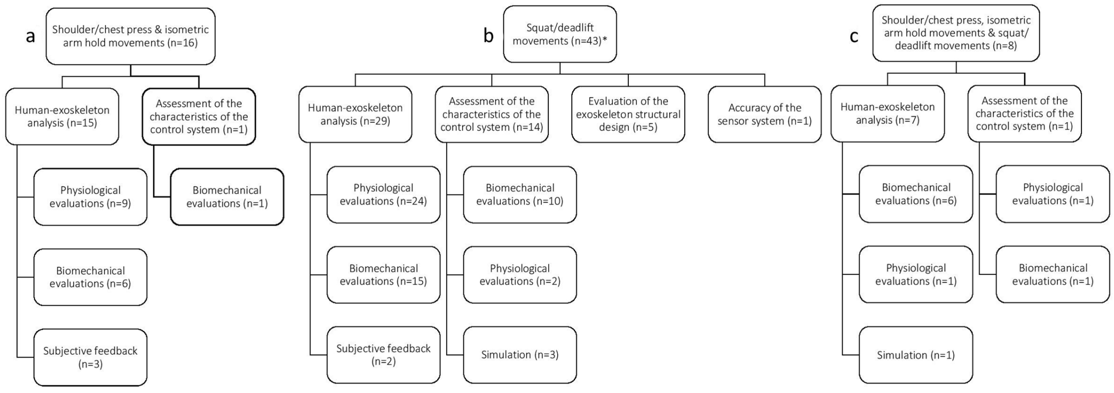

Figure 3. Breakdown of exoskeletons classified into their movement patterns, testing performed, and type of evaluation. (a) Shoulder/chest press and isometric arm hold (Table 2). (b) Squat/deadlift (Table 3). (c) Shoulder/chest press, isometric arm hold, and squat/deadlift movements (Table 4). *Some studies have carried out multiple analysis.

external loads (e.g., Huysamen et al., 2018 [Table 3, Row 29]; Ko et al., 2018 [Table 3, Row 27]; Theurel et al., 2018 [Table 2, Row 1]; Zhang & Huang, 2018 [Table 3, Row 26]), providing loading pathways that bypass the user's joints (e.g., Sado et al., 2018 [Table 3, Row 6]) and/or providing support or limiting the joint movement to prevent harmful motions (e.g., Zhang et al., 2016a [Table 4, Row 1]).

There were a large number of squat/deadlift (lower limb) exoskeleton devices (56%) with 27% of devices supporting the ankle, knee, and hip joint, and 26% solely supporting the hip. Ninety-five percent of the hip-supported devices aim to assist the lower back (e.g., Chen et al., 2018 [Table 3, Row 28]; Yu et al., 2015 [Table 3, Row 30]; Zhang & Huang, 2018 [Table 3, Row 26]). This could be due to the prevalence of lower back injuries and their correlation to lifting from the ground (Karwowski et al., 2005) and hyperflexion of the lumbar spine (Kudo et al., 2019), which is controlled by the hip joint (categorized as a part of the squat/deadlift systems). Exoskeletons assisting the back actuate from the hip to minimize the increased torques to the lower back caused by hyper flexion during lifting. However, since spine motion has multiple DOFs (Wilke et al., 2016), exoskeletons actuating from the hip on a single plane (one DOF, that is, flexion/extension) may result in movement restriction where physiological rotation and lateral bending of the spine are impeded resulting in increased effort (Bellini et al., 2007) or reduced performance (Burgess et al., 2009; Ferguson & Steffen, 2005).

Task analysis prior to the design of an exoskeleton could be beneficial for better support of manual handling tasks. Thirty percent of studies in this review reported performing a priori task analysis. Through this analysis, the operational complexity of the exoskeleton (type of actuation, DOF, the control system, and the method of power transmission) could be optimized for specific tasks. For instance, with a biomechanical analysis of the task, it is possible to identify which joints undergo high moments and which ones are allowed free movement (e.g., Yu et al., 2015 [Table 3, Row 30]); this informs the choice of how many DOFs should be allowed at a joint for that task, as well as how much support should be provided. As active actuators can face issues such as big size, heavy weight, bulkiness, inefficient force transmission, low speed, and inaccurate control (Popov et al., 2017; Zaroug et al., 2019), the power-to-weight ratio should be optimized in order to provide the minimum assistance needed to support the specific joint for the requirements of the task (e.g., Masood et al., 2016 [Table 3, Row 33]) and to replace some actively actuated joints with passive actuators where appropriate (e.g., Chu et al., 2014

[Table 3, Row 20]; Ebrahimi, 2017 [Table 2, Row 3]). Optimization could therefore lead to a reduction in weight, inertia, friction, and complexity of the exoskeleton while increasing its efficiency, thus allowing for lower impedance (interaction force between the exoskeleton and the user) and better control.

Although the majority of studies indicated that exoskeletons could reduce muscle activation, evidence was not conclusive with studies reporting an increase in muscle activations of the antagonist muscles (Theurel et al., 2018 [Table 2, Row 1]). Therefore, EMG signals should be recorded from antagonist muscles as well as from those muscles acting at joints other than the one supported by the exoskeleton (Weston et al., 2018). Although methodologically challenging, the concomitant use of EMG on agonist and antagonist muscles will provide a measure of exoskeleton interference with the pattern of muscle activation that is essential for proper movement coordination and low energy cost (Lay et al., 2002; Tan et al., 2019; Wakeling et al., 2010).

Control strategies also play a large part in the optimization of an exoskeleton system. Exoskeleton designers in this review tested the exoskeleton control strategies for (a) their ability to follow the user's joint motions, (b) exoskeleton stability, and (c) load reduction for the duration of the task. A few exoskeleton systems looked into user intention (e.g., Durante et al., 2018 [Table 4, Row 5]) and task recognition (e.g., Chen et al., 2018 [Table 3, Row 28]) control strategies. These strategies could provide the information needed to develop smooth motion and predictive human-intention algorithms, creating smarter, more efficient exoskeleton systems. With the development of predictive algorithms, there is the ability to provide assist-as-needed control, reducing power consumption and preserving the musculoskeletal capacity of the user.

Findings from this review demonstrated there were no consistent methodologies used to evaluate exoskeletons for manual handling. Further development of current exoskeleton testing and reporting standards (e.g., Mudie et al., 2018) to include military manual handling tasks (e.g., ASTM F48 committee on exoskeletons and exosuits) is critical to enable valid and reliable comparisons between future devices. However, it is worth noting that none of the included studies were of a prospective nature and only performed analysis at a single time point. Prospective studies (and the accompanying standards) could be beneficial to validate the use of exoskeletons for injury prevention or augmentation.

Military Manual Handling Considerations

While the tasks performed by military personnel may be similar to those performed in industries, there are additional considerations for the use of exoskeletons in a military workplace. For instance, in-field surfaces can be uneven and loose, requiring exoskeletons to be robust and flexible to compensate for unexpected perturbations. Military manual handling exoskeletons could also face a range of weather conditions, confined spaces where the device's dimensions could be restrictive, limited access to power supply, large amounts of dust and dirt, and rough use, necessitating a durable and efficient exoskeleton design. Additionally, the necessity to integrate the device into military personnel's uniform or body armor should be considered.

Devices developed for load carriage, amplification, or injury prevention could assist with minimizing the risk of injury from carrying large loads and performing repetitive complex movements from the ground, as often performed by military personnel (Sharp et al., 2006). The loading required for military manual handling tasks is heavier than what would be required of personnel in many other industries (Forde & Buchholz, 2004; Roja et al., 2016). For instance, in a military context, lift-to-platform tasks (shoulder/chest press movement) require loads of 25.6 ± 8.5 kg to be lifted, while lift-carry-lower tasks (isometric arm hold movement) require loads of 31.1 ± 17.1 kg to be carried for distances of 127.8 ± 126.2 m (Carstairs et al., 2018). In comparison, in an industry context, for example, in large international airports, the weight of baggage handled by security personnel ranges between 10 and 23 kg (Gebhardt, 2019). This highlights the fact that workplace context can affect the demand of the job, and thus the different need for assistance.

The findings from this review did not highlight whether current active or passive exoskeletons would be capable of sustaining the loads required by military personnel (Tables 2–4). It was unclear whether the reported load capability referred to the load limits of the exoskeleton structure and/or actuators, the load limit that the user could support, or the maximum loads required by the task in industry. Additionally, lift-carry-lower tasks are mostly unilateral (load only on one side of the body; 74%; Carstairs et al., 2018) and require asymmetrical muscle activation in the spine to maintain stability due to an increase in internal torsional forces. This review found no studies that tested unilateral loading. However, three exoskeleton devices in this review were tested for lift origin asymmetry (the lift starts at an angle away from the sagittal plane), which could also cause asymmetrical muscle activations, and found that this decreased muscle activation of the ipsilateral muscles while wearing the exoskeleton (Alemi et al., 2019 [Table 3, Row 36]; Picchiotti et al., 2019 [Table 4, Row 3]; Zhang & Huang, 2018 [Table 3, Row 26]). It would, therefore, be beneficial for an exoskeleton to actively compensate for unilateral loads and lift origin asymmetry.

CONCLUSION

The large portion of devices targeting load carrying reflects the industry and military need for devices that can support manual handling workers with the aim of preventing injuries and improving productivity. The joint requirements for the two most common tasks in military manual handling are well represented in the current state of exoskeleton systems. The unique considerations of the military such as heavy external loads, load asymmetry, harsh environments, and uniform integration mean that an adaption of current technology or a military-specific design would be required for the introduction of exoskeletons into the Australian Defence Force.

LIMITATIONS

Only Scopus was used as the citation database for this review and while it is extensive in the literature it lists, important studies on current exoskeletons may not have been included. We also acknowledge that by searching for research studies, we omit some of the most widely used commercially available exoskeletons for which there isn't any published research. Additionally, some of the data included in the tables were interpreted by the authors of this review rather than stated in the reviewed study. The search terms used were based on the definition of manual handling tasks by researchers of Australian Army tasks and may not be inclusive of all manual handling industries. The review applied a broad range of exoskeletons to two specific tasks (lift-to-platform and lift-carry-lower); the exoskeletons in the review were not always intended for these tasks. Furthermore, the review did not include exoskeletons that carried loads posterior to the user; it is possible that these devices could be adapted for these tasks. This review did not explore other systems that could be useful to military manual handling personnel, such as smart sensor systems.

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KEY POINTS

- Although this field is fast growing, the majority of the included exoskeletons were in an early stage of development.
- Determining exoskeleton design challenges through a task analysis could be useful in understanding how to better support military manual handling tasks.
- It would be beneficial for an exoskeleton to actively compensate for unilateral external loads due to their prevalence in military manual handling tasks.
- It was unclear whether the current active exoskeleton would be capable of sustaining the loads required by military personnel.

- Adaption of current technology would be required for the introduction of exoskeletons into a military setting.

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Date received: March 31, 2019
Date accepted: August 9, 2020

Appendix B – Ethics Application

Application for Ethical Review of Research Involving Human Participants

Application ID :	0000026012
Application Title :	Development of an exoskeleton to reduce risk factors associated with injury during military manual handling tasks
Date of Submission :	N/A
Primary Investigator :	PROF REZAUL BEGG
Other Investigators :	ASPR TZE HUEI LAI
	DR KURT MUDIE
	MS Jasmine Proud

Introduction

Important Information

Form Version: V.16-02. Last Updated: 6.7.2016.

IMPORTANT INFORMATION FOR ALL APPLICANTS:

- Applicants are advised to follow the guidelines provided on the **Human Research Ethics website** prior to submitting this application.
- Ensure all questions are appropriately answered in plain language with correct spelling and grammar.
- All applications must be sighted and approved by all members of the research team and any relevant parties. Applications will not be reviewed without appropriate authorisation.
- To avoid unnecessary delays, please ensure application is submitted in full by the submission deadline for the relevant HREC.

You are reminded that your project may not commence without formal written approval from the appropriate Human Research Ethics Committee.

Contact:

Ethics Secretary
For help and further information regarding ethical conduct, refer to the Human Research Ethics website:
http://research.vu.edu.au/hrec.php or contact the Secretary for the Human Research Ethics Committee, Office for Research.
Phone: 9919 4781 or 9919 4461
Email: researchethics@vu.edu.au

Quest Service Desk
For technical help, refer to the Quest website: *http://research.vu.edu.au/quest.php* or contact a member of the Quest team.
Phone: 9919 4278
Email: quest.servicedesk@vu.edu.au

External Resources

- NHMRC: National Statement on Ethical Conduct in Human Research
- NHMRC: Human Research Ethics Handbook
- NHMRC: Australian Code for the Responsible Conduct of Research

Quest Guide

Quick Tips for Using Quest

Need Help? For help and instructions, we strongly recommend that you download the full [Quest Online Ethics Guide (.pdf)](). Your questions may also be answered in the [FAQ page on the Quest Website]().

- **Answer All Questions**:

  Most questions are mandatory and must be completed before the application can be submitted. These questions are marked with a red asterisk (*)
- **Access Help and Tips**:

  The help icon, found next to questions and at the top of each page, will provide you with detailed advice on ethical content.
- **Remember to Save**:

  Use the floppy disk icon (and the green tick in some sections) regularly to avoid losing any answers. Each page will save automatically when you click *Next* or *Back*.
- **Print or Save a Copy of Your Application**:

  You can use the report icon at any stage to generate a printer friendly version of the form. Select HTML to print to screen. To save as a .pdf file to your computer select PDF then save a copy from the pop up screen. *(Don't forget to save a copy before you submit!)*
- **Submit Application**:

  When you have completed your application, click on the *Action* tab in the left-hand column and click *Submit Application*. The system will then convert the form to read-only and send it to the Ethics Secretary for review.
  You will receive an email confirmation at submission. Double check that your application has been submitted by viewing the application status in the *My Applications* page.

Responding to comments (if your application is returned)

There may be stages throughout the application process in which the Ethics Secretary will instruct you to amend your application form. These amendments will be communicated to you via 'Comments' within the eForm.

1. **Generate a List of All Comments**:

   Click the report icon, select *Comments Report* from the Document drop-down field and click *OK*. This list will show all comments created in your application and which page they are applicable to. Click *Cancel* to return to the application form.

2. **Revise your Answers**:

   Open the page which shows a red flag; these denote an Action Comment which you are required to respond to. Revise the relevant question(s) in your application form as required. Remember to click save!

3. **Respond to Action Comments**:

   AFTER you have revised your answers, you must provide a response to each Action Comment explaining to the Committee how you have addressed their communication. Open the Page Comments window and click New Comment to enter your response into the textbox. Click the green tick to save your text.

4. **Mark Comments as Responded**:

   Once you have revised your answers AND finished responding to all comments, reopen Page Comments window, use the checkbox to select the *Action Comments* and click *Mark Selected Comments as Responded*. The colour of the flag will change to yellow and the page will become Read Only.

   Important: *DO NOT mark the comments as 'Responded' until you are completely satisfied with your revised answers - you will lose access to edit the page and the comments.*

5. **Submit Revised Application**:

   Once you have addressed all of the Red Flags, open the *Action* tab and click *Submit Revised Application*. The system will then send the form to the Ethics Secretary for review. Remember to save a copy of your application by clicking the Report icon and generating a PDF or printer-friendly version.

SECTION 1 - PROJECT OVERVIEW

General Details

1.1. **Ethics Category***

Human

1.2. **Project Title***

Development of an exoskeleton to reduce risk factors associated with injury during military manual handling tasks

1.3. **Project Summary** (Include brief details of aims, methods and significance of the project in plain language. Maximum of 2000 characters)*

Aim: To determine the human kinetics and kinematics affected by military manual handling tasks (MHT).
Method: Participants (sample size to be determined from a pilot study) aged 18-40 with an equal number of male and females will complete two military MHT (lift to platform and lift-carry-lower). Weights used during these tasks will be determined via two procedures that measure occupational proficiency in the Australian military (maximum lift capacity (MLC) and maximum acceptable weight of lift (MAWL)), thus the tasks are tailored to the individuals ability. Prior to the tasks participants will be fitted with reflective markers to allow precise postural measurement with 3D motion capture, inertial measurement units will be placed along the spine to measure torso accelerations and velocities and electrodes will be placed on the skin above the targeted muscles of the torso and upper legs to measure muscle activations. Subjective ratings of perceived exertion will also be collected. Changes in objective measures will be evaluated with participants performing the three tasks:
1. Lift to platform MLC procedure: Ground to 1.4m platform varying weights
1. Lift to platform MAWL procedure: Ground to 1.4m platform varying weights
2. Lift-carry-lower: Ground to anatomical height to ground carried 128m, weight set as MAWL
Each trial will last no longer than 5 minutes.
Significance: Injury due to manual handling costs government, insurance companies and industry $14.58 billion annually with 20% of all injuries to the back (Safe Work Australia, 2017). With MHT posing significant musculoskeletal injury risk, a comprehensive task analysis within the Australian Army was performed and found that 78% of physical demand tasks are manual handling (Carstairs, 2017). With the large amount of military tasks requiring risky movement patterns, empirical data is needed into the how military MHT affect the body and how soldiers can be physically supported.

1.4. **Primary College or Institute for Application***

COLLEGE OF ENGINEERING AND SCIENCE

Timeline and Funding

1.5. **Period for which ethical approval is sought.** *Note: ethical approval is automatically granted for a period of 2 years from the project commencement date.*

Project commencement date:*

- (●) Immediately upon receiving ethical approval
- ( ) Other date

1.6. **Date the data collection is expected to be completed:***

04/03/2019

1.7. **How will the research be funded?***

- [ ] External grant
- [x] VU grant or funding
- [ ] Sponsor
- [ ] Other
- [ ] Unfunded

VU grant or funding source:*

PhD budget

1.8. **Is the research a collaborative effort with another organisation?***

- (●) Yes
- ( ) No

If YES, does the research need to undergo formal ethical review by the collaborating organisation's HREC?*

- ( ) Yes
- (●) No

SECTION 2 - PROJECT INVESTIGATORS

Investigators

2.1. **Please list all <u>investigators</u> associated with this project.**
The research team is the group of investigators accountable for the conduct of the project. Include details of the Primary Chief Investigator (primary contact for application), as well as all other Chief Investigators and Associate Investigators. *Student details will be requested separately.* Other staff (e.g. technicians) may perform tasks within the project although they are not necessarily investigators. They should be listed as "Other Staff" if appropriate.*

1	*ID Number*	E5024943
	Surname	LAI
	Given Name	TZE HUEI
	Full Name	ASPR TZE HUEI LAI
	College/Institute	O6102
	Email Address	Daniel.Lai@vu.edu.au
	Role in project	Chief Investigator
	Primary contact for application? *Note: Although an application may have multiple Chief Investigators, only one CI may be nominated as the Primary Contact.* *For student projects, the Chief Investigator/Primary Contact <u>must</u> be the supervisor, not the student.*	No
	Direct contact number	0413303554
	Mobile number (for emergency use only)	0413303554
	Qualifications, experience and/or skills relevant to the project.	A/Prof. Lai has over 10years experience in machine learning, signal processing, sensors and wearable electronics for monitoring human movement. He has worked with over 30 industry partners on development products that range from mobile smart classification software to wearable electronics for sports and health. He produced over 110 referred publications focusing on machine learning, wireless communications and nanomaterial sensors. He is currently the Defence Science Institute liasion manager for Victoria University.
2	*ID Number*	E5072330
	Surname	BEGG
	Given Name	REZAUL
	Full Name	PROF REZAUL BEGG
	College/Institute	P9102
	Email Address	rezaul.begg@vu.edu.au
	Role in project	Chief Investigator
	Primary contact for application? *Note: Although an application may have multiple Chief Investigators, only one CI may be nominated as the Primary Contact.* *For student projects, the Chief Investigator/Primary Contact <u>must</u> be the supervisor, not the student.*	Yes
	Direct contact number	99191116
	Mobile number (for emergency use only)	0425796031
		Professor Begg has over 20 years experience in human gait and balance biomechanics and associated experiments, and has made a number of significant scientific contributions in developing new technologies and techniques with

	Qualifications, experience and/or skills relevant to the project.	application to human gait pathologies. These techniques have largely been applied in biomedical diagnostics as well as for the assessment of various interventions aimed at improving gait functions. He has produced 231 refereed publications, mostly focused on gait and balance. His research has been supported by external funding sources including 5 ARC, one NHMRC project and one Defence, Science & Technology (DST) Group grants.
3	*ID Number*	E5108402
	Surname	MUDIE
	Given Name	KURT
	Full Name	DR KURT MUDIE
	College/Institute	VR301
	Email Address	Kurt.Mudie@vu.edu.au
	Role in project	Chief Investigator
	Primary contact for application? *Note: Although an application may have multiple Chief Investigators, only one CI may be nominated as the Primary Contact.* *For student projects, the Chief Investigator/Primary Contact must be the supervisor, not the student.*	No
	Direct contact number	0405259557
	Mobile number (for emergency use only)	0405259557
	Qualifications, experience and/or skills relevant to the project.	Dr Kurt Mudie is employed at the Department of Defence, Science and Technology Group and holds an honorary fellowship position at Victoria University. He completed his PhD (majoring in Biomechanics) in 2017 and completed a 2 year postdoctoral research fellowship between 2016-2018 on assistive technologies at Victoria University. He has lead 15 projects involving human movement, gait, physical assistive technologies biomechanics and neuro-physiological experiments within a laboratory and field setting, and has considerable experience in the experimental setup and analysis of relevant data. Kurt has a special interest in physical assistive technologies and their impact on human performance across a broad range of tasks.

Note: Please click the Question Help icon above for instructions on how to search for personnel and use this table.
Once an Investigator record has been added, click on the name in the table above to open the record and edit the information required.

If you are unable to find a personnel record in this system which must be added to your application, please use the Request to Add Personnel to Research Database form found on the Quest website.

Student Investigators

2.2. **Will any students be involved in the conduct of this project?***

- (•) Yes
- ( ) No

2.2.a. **If YES, is the project:***

- (•) A STUDENT PROJECT for the degree in which the student is enrolled?
- ( ) A STAFF PROJECT that involves a student(s) undertaking some part of the project?
- ( ) Other

2.2.a.i. **If the research is a STUDENT PROJECT, at what level?***

PhD

* Has this project been approved by the Postgraduate Research Committee? (ie. during confirmation of candidature process)*

○ Yes
◉ No

If NO, indicate why ethical approval for the project is being sought prior to gaining approval from the Postgraduate Research Committee.*

Confirmation of candidature took place on October 25th 2018 and was confirmed with minor amendments. The confirmation proposal has been resubmitted and final approval is expected before the ethics committee meets but post application deadline.

2.2.b. **Please list all student investigators involved in this project.**
*Ensure the primary supervisor (not the student), has been marked as the Chief Investigator and primary contact for the application in Q.2.1.**

1	*Student ID*	S4173115
	Surname	Proud
	Given Name	Jasmine
	Full Name	MS Jasmine Proud
	College/Institute	P9102
	Email Address	jasmine.proud@live.vu.edu.au
	Role in project	Student
	Direct contact number	0421878113
	Mobile number (for emergency use only)	0421878113
	Student's experience/qualifications relevant to the procedures and techniques to be used in the research and/or to working with the specific target population.	Jasmine Proud is a PhD candidate at Victoria University working in the development of a postural control wearable robotic device. She has a Bachelor of Engineering Science and experience assisting in experimental setup and analysis of human movement trials when using physical assistive technologies. Jasmine's research is focused in bio-mechatronics, specifically wearable assistive technology.

Note: Please click the Question Help icon above for instructions on how to search for personnel and use this table.
Once a student's record has been added, click on the name in the table above to open the record and edit the information required.

If you are unable to find a personnel record in this system which must be added to your application, please use the [Request to Add Personnel to Research Database form] found on the Quest website.

2.2.c. **What arrangements are in place for the supervision of student(s) when undertaking project activities?***

Regular meetings will occur between all investigators (fortnightly) to discuss project progression and any issues that have arisen during the project.

Involvement of Other Individuals/Organisations

2.3. **Will any individuals who are not members of the research team be involved in the conduct of this project?** (e.g., medical personnel involved in procedures, research contractors, teachers) *

○ Yes
◉ No

SECTION 3 - NATURE OF THE PROJECT

Type of Project

3.1.a. **Is the project a pilot study?***

○ Yes
◉ No

3.1.b. **Is the project a part of a larger study?***

○ Yes
◉ No

3.1.c. **Is the project a quality assurance or evaluation project (e.g., related to teaching, health-care provision)?***

○ Yes
◉ No

3.1.d. **Does the research involve a clinical trial (of a substance, device, psychological or physical intervention)?***

○ Yes
◉ No

3.1.e. **Does the research involve the use of therapeutic/intervention techniques or procedures (non-clinical trial)?***

○ Yes
◉ No

Target Population

3.2.a. **Does the research focus on Australian Indigenous (Aboriginal and/or Torres Strait Islander) populations?***

○ Yes
◉ No

3.2.b. **Does the research involve participants under the age of 18 years?***

○ Yes
◉ No

3.2.c. **Does the research involve participants who are highly dependent on medical care?***

○ Yes
◉ No

3.2.d. **Does the research involve participants who have a cognitive impairment, intellectual disability or mental illness? ***

○ Yes
◉ No

3.2.e. **Does the research involve participants in other countries?***

○ Yes
◉ No

3.2.f. **Does the research involve pregnant women (with a research focus on the pregnancy) and/or the foetus (in utero or ex utero) or foetal tissue?***

○ Yes
◉ No

3.2.g. **Does the research involve participants who are likely to be highly vulnerable due to any other reasons?***

○ Yes
◉ No

Intrusiveness of Project

3.3.a. **Does the research use physically intrusive techniques?***

◉ Yes
○ No

3.3.b. **Does the research cause discomfort in participants beyond normal levels of inconvenience?***

◉ Yes
○ No

3.3.c. **Does the research collect potentially sensitive data? (e.g., related to a sensitive topic or vulnerable group; personal health/medical information; sensitive organisational strategies)***

○ Yes
◉ No

3.3.d. **Does the research involve deception of participants?***

○ Yes
◉ No

3.3.e. **Does the research involve limited disclosure of information to participants?**

○ Yes
◉ No

3.3.f. **Does the research involve covert observation of participants?***

○ Yes
◉ No

3.3.g. **Does the research produce information that, if inadvertently made public, would be harmful to participants?***

○ Yes
◉ No

3.3.h. **Does the research involve accessing student academic records?***

○ Yes
◉ No

3.3.i. **Does the research involve human genetic or stem cell research?**

○ Yes
◉ No

3.3.j. **Does the research involve the use of ionising radiation?***

○ Yes
◉ No

3.3.k. **Does the research involve the collection of human tissue or fluids?***

○ Yes
◉ No

3.3.l. **Does the research involve any uploading, downloading or publishing on the internet?***

○ Yes
◉ No

3.3.m. **Does the research seek disclosure of information relating to illegal activities or is the research likely to lead to disclosure of information relating to illegal activities?***

○ Yes
◉ No

3.3.n. **Does the research involve procedures that may expose participants to civil, criminal or other legal proceedings?***

○ Yes
◉ No

3.3.o. **Does the research involve gaining access to medical/health related personal information from records of a Commonwealth or State department/agency or private health service provider?***

○ Yes
◉ No

3.3.p. **Does the research involve gaining access to personal information (not medical/health) from the records of a Commonwealth or State department/agency or private organisation?***

○ Yes
◉ No

SECTION 4 - PROJECT DESCRIPTION

General Information

Note: All fields have a maximum of 4000 characters (unless otherwise specified) in plain text only.
If supporting documentation needs to be provided for the following questions (images, graphs etc), please upload as referenced appendices in Section 11 - "Required Attachments" below.

4.1. **Aims of the project.** Provide a concise statement of the aims of the project (maximum 2000 characters in plain language).*

The aim of this research is to analyse the biomechanical, physiological and musculoskeletal parameters effected during military manual handling tasks through human laboratory trials and biological computer simulation in order to develop a novel exoskeleton system based on the objective (muscle activations, force loading) and subjective (comfort) human metrics affected. Using established biomechanical apparatus and procedures,this data will be used to perform biomechanical analysis of the baseline parameters of good lifting posture and provide quantitative kinematic and kinetic factors for the development of a prototype intervention.

4.2. **Briefly describe the relevant background and rationale for the project in plain language.***

In Australia 43% of serious claims in the workplace are due to traumatic joint, ligament, muscle and tendon injuries costing $14.58 billion annually as a result of treatment, over-employment, overtime, retraining and investigation (Safe Work Australia, 2017). Additionally, 41% of serious injury claims are due to MH while lifting or carrying objects, with the majority of injuries in the upper and lower limbs (49%) and back (20%) (Safe Work Australia, 2017). With MHT posing significant musculoskeletal injury risk, a comprehensive task analysis within the Australian Army was performed and found that 78% of physical demand tasks are manual handling (Carstairs, 2017).

There are a number of tasks within the deployed and training soldier population that cause lower back pain. Unmounted soldiers carry torso borne loads (e.g. armour, supply packs) for large distances, logistics personnel are required to perform repetitive motions (e.g. manual lifting of supplies) and technical occupations require maintenance and repairs to heavy equipment often involving awkward torso positions for prolonged periods. With the large amount of military tasks requiring risky movement patterns, empirical data is needed into the how military MHT affect the body and how soldiers can be physically supported. Physical assistive technologies, such as exoskeletons, may assist in maintaining a correct (neutral) posture and thus minimise the risk of workplace musculoskeletal injuries.

A number of factors in manual handling contribute to increased risk of back injury, such as external torque of the load, either hyperflexion or hyperextension of the lumbar spine, internal torsional forces and fatigue due to increased total work (Neumann, 2009). Lifting a load away from the body's midline increases the external load torque placing greater force demands on the back muscles. Creating a large and fast contraction of back-extensor muscles during hyperflexion in the lumbar spine can damage the intervertebral discs, which can also be damaged through rotating the torso while lifting due to torsional forces (Neumann, 2009). Hyperextension of the lumbar spine during back-extensor contraction can injure the apophyseal joints. This maximal flexion or extension of the back can also be caused by prolonged lifting or carrying as it increases total work and muscular fatigue. Additionally, the mismatch between personnel capability and job requirement (personnel don’t know what they are able to lift or what is a safe weight lift) is seen as a contributor to injury risk (Savage, 2012).

Testing of all the biomechanical and physiological factors effected is important in order to gain an understanding of how these tasks act upon the body so that they can be supported correctly with as little impact on normal function as possible. The fundamentals of back injury prevention during MH tasks are; i) maintaining the lumbar spine's neutral lordosis and, ii) preventing hyper-flexion and hyper-extension of the torso. Therefore, the principal design features of a novel upper body exoskeleton will be guided by these two factors. This research project will use the data gathered from this testing to design an adaptive postural control spine exoskeleton for back injury prevention during military MH tasks, using an empathic design approach to ensure increased wearability. It will actively support correct lumbar lordosis, provide a secondary loading pathway away from the spine to the hips and prevent spine hyper-flexion/extension.

The benefits of the project are the further development of equipment that will contribute to safer and less physically demanding manual handling in military and other personnel such as logistics, agricultural and emergency service workers, who at present undertake physically stressful load carrying without supporting devices. These devices have the potential to reduce the injury risk factors associated with back injuries caused by manual handling tasks.

4.3. **Methodology and procedures**
Include specific details relating to any measures, interventions, techniques, and/or equipment used in the research.
Provide step-by-step details of the procedures with particular reference to what participants will be asked to do.
Provide details separately for different phases or conditions of the research or, where appropriate, different participant groups.*

Participants will be female and male (50/50) volunteers aged 18 to 40 years who will be individuals recruited from the academic community (staff and students) of Victoria University and neighbouring areas. Prior to testing informed consent will be obtained using procedures approved and mandated by the Victoria University Human Research Ethics Committee. Data collection will be undertaken at the Victoria University (Footscray Park Campus) Biomechanics laboratories (PB301).

Participants will wear clothing appropriate to physical activity and appropriate shoes. A typical laboratory session will take approximately 2 - 3 hours per participant, including marker attachment, rest periods and data collection. Rest breaks will be provided as necessary between conditions. Two laboratory staff will be employed for data collection; one will operate the data collection devices and the other will continuously monitor the participant to confirm their comfort and safety. Participants will take part in a repeated measures trial, performing two MH tasks. The first MH task will involve two trials, the first trial utilising a maximum lifting capacity (MLC) procedure and the second trial a maximal acceptable weight of lift (MAWL) procedure.

MLC is a one off test that measures the maximum weight that can be lifted in a single repetition (Savage, 2012). Participants start will a small weight and complete the lifting task, the weight is increased by 5kgs after every completion with correct technique (i.e. good posture) until the lift fails or technique deteriorates. The weight is then lowered by 2.5kgs and attempted again. If completed this determines the participants MLC or if failed the previous weight is the recorded MLC.

MAWL procedure works by lifting light to heavy weight (starting at 33% MLC) and from heavy to light weight (starting 95% MLC) in a random order (Savage, 2012). As the participants are increasing or decreasing their weight, they are asked if they want a small (2.5kg), medium (5kg) or large (10kg) increase/decrease and the participant is blind to the change in mass. The test is complete once they find a point where they feel comfortable to lift without strain or compromised technique. It is expected that the increasing and decreasing weights will match. Lifting weights above MAWL is a large indicator of future injury.

Objective and subjective measures will be taken. Objective measures will include: physiological (sEMG and time to complete), and biomechanical (motion capture, IMU and ground reaction forces (GRF)) factors. Subjective measures will include psycho-psychological (Borg 15-point rating of perceived exertion (RPE) scale on performance) factors.
Measure details:
i. Surface electromyography (sEMG): Electrical signals from muscle activations is measured via electrodes placed on the skin.
ii. Motion capture: Reflective markers are attached to the participant and exoskeleton; movements made during the tasks are then recorded using a motion capture system.
iii. Ground reaction forces (GRF): A force plate embedded in the floor measures the ground reaction forces exerted from the participant in three dimensions (3D).
iv. Inertial measurement units (IMU): Small sensors that can measure acceleration, angular velocity, direction of a magnetic field and ambient temperature of a body on which they are placed.

Use this textbox if additional room is required for Question 4.3.

The two tasks selected for this trial are the most commonly performed military MH movement clusters (Carstairs, 2017). The ‘lift to platform’ will be a single crate with side mounted handles (e.g. supply boxes), while the ‘lift-carry-lower’ task weights will be divided into two boxes with top mounted handles (e.g. jerry cans).

Each participant’s trial will include familiarisation (i.e. procedure, laboratory and testing setup), marker attachment, sensor system attachment, system calibration, movement instruction, recorded trials and rest intervals. Trials will take place on a force plate embedded in the floor of the biomechanics laboratory, in the case of trials that have a carry element, three force plates will be used (initial lift, walk across, final lower). The participants’ movements will be recorded using a 13-camera motion capture system (VICON) that records the position of reflective markers attached to the participant.

The first ‘lift to platform’ trial will be the MLC with the MAWL procedure to follow. The MAWL weight found during the trial will be used for the ‘lift-carry-lower’ task. The ‘lift-carry-lower’ task will then be performed once. The tasks will be self-paced and RPE monitored at set intervals (i.e. start, middle and end of trial) throughout with rest intervals in between tasks to minimise fatigue.

Data Collection

4.4. **Indicate all types of data to be collected.***

- ☑ Questionnaire / survey responses*
- ☐ Individual interview responses*
- ☐ Other data
- ☐ Group interview or focus group responses*
- ☐ Participant observations
- ☐ Blood or tissue samples
- ☑ Physiological measures
- ☑ Biomechanical measures
- ☐ Accessed health / medical records or data
- ☐ Accessed student academic records or data
- ☐ Archival data

* Attach copies of questionnaires to this application in Section 11 - "Required Attachments" below.

4.5. **Does the research only include the collection of anonymous and non-sensitive data (e.g. online survey, observational data) that poses no foreseeable risks or discomfort to participants?** *Any foreseeable risk must be no more than inconvenience.**

○ Yes
◉ No

4.6. **Does the research only include the use of non-identifiable and non-sensitive data from an existing database? (e.g., data mining).**
*Such data should pose no foreseeable risks or discomfort to individuals whose information is contained in the database, or to individuals/organisations responsible for the database.**

○ Yes
◉ No

4.7. **Does the research involve photographing or video recording of participants?***

◉ Yes
○ No

4.7.a. Will the identification of participants, either directly or indirectly, be made available in the public domain at any time during or after the research? e.g. In the reporting of research or in any display/presentation (audio or visual) of the research?*

○ Yes
◉ No

4.7.b. Provide details of both aspects of collecting this data and it being made available.*

Any video recordings of participants will be made available for analysis with the participant's face obscured using a digitally imposed screen.

4.8. **Who will be collecting the data?** (give details for all types of data collected and all persons involved)*

Jasmine Proud
Rezaul Begg
Kurt Mudie

4.9. **Where will the data be collected?** (give details for all types of data collected and all locations)*

Data collection will be undertaken at the Victoria University (Footscray Park Campus) Biomechanics and Exercise Physiology laboratory (PB301).

4.10. **How will the data be analysed?** (give details for all types of data collected)*

Data Processing and Analysis:
i. Motion Analysis: Raw position time data captured by the Vicon system will be transferred to Visual 3D (CMotion,Canada) and conditioned using a 4th order zerolag Butterworth Filter with a cutoff frequency of 6 Hz. From these smoothed data, kinematic characteristics of the tasks will be computed such as position and timing of spine positions and the torso and lower limb joint angles.
ii. Ground Reaction Forces (GRF): 3D forcetime data from the treadmill will be transferred to Visual 3D for processing to determine the effects on ground reaction forces at the lift and lower movements of the experimental conditions.
iii. Electromyography: data will be transferred to Visual 3D for processing. Data will be filtered using a 4th order bidirectional Butterworth bandpass filter with a cutoff frequency of 50 – 500 Hz, full wave rectified and linear envelopes created using a 4th order bidirectional lowpass Butterworth filter with a 6 Hz cutoff frequency.
iv. Rating of perceived exertion will be measured to determine the the perception of effort during the tasks.

Statistical Analysis:
Analysis of variance (ANOVA) will be used to analyse the effect that MH tasks (independent variable) have on the spine position, peak and mean muscle forces of the trunk and upper limbs, and GRFs (dependant variables).

4.11. **Who will have access to the data collected?** (give details of all persons who will have access to the data)*

All investigators will have access to the data.

4.12. **Will individuals or organisations external to the research team have access to any data collected?***

○ Yes
◉ No

SECTION 5 - PARTICIPANTS

Participant Group Details

5.1. **Provide details of all distinct participant groups below.**
Please be as precise as possible, if specific details have not been determined you must indicate that they are approximate.

Group 1
Details of specific participant population:*

Participants will include males and females aged between 18 to 40 years of age.

Number of participants: *

~20

Age range of participants:*

18 - 40

Source of participants:*

Potential participants will be recruited from the Victoria University student and staff population.

*Record details for additional group? (Group 2)**

○ Yes
◉ No

Participant Selection

5.2. **Provide a rationale for the sample size.***

Previous biomechanical analysis of manual handling task studies have used 21 or less healthy participants (O'Sullivan, 2006; Arjmand, 2005; Granata 2001; Hart, 1987), however a pilot study will be performed as apart of this project in order to determine the required number of participants recruited to this study.

5.3. **Does the project include any specific participant selection and/or exclusion criteria beyond those described above in Question 5.1?***

◉ Yes
○ No

If YES, provide details:*

Pre-experimental screening will comprise initial discussions with prospective participants to outline all aspects of the study, including provision of Information to Participants (Attachment) and Informed Consent (Attachment). Prospective participants will also be asked to complete a medical questionnaire (Attachment: Pre-exercise Health Screen) to exclude individuals with any of the following: diabetes (Type 1 or 2), chronic heart disease, severe hypertension (systolic 160-179mmHg systolic, diastolic 100-109mmHg), severely overweight/obese (BMI> 30), if they have had uncontrolled metabolic and/or cardiovascular disease, no significant knee of back injury, any recent significant injury that will impede their ability to perform exercise during the study or any other contraindications that will impede their ability/safety during exercise. Those who circle the "Yes" response on the questionnaire will be further questioned by a Chief Investigator to ascertain the reliability/severity of any possible contraindication. Those judged to be of no additional risk by the Chief Investigator will be allowed to proceed in the study. A common example of this category might include subjects who consider themselves overweight, but who display weight within normal range. Should the Chief Investigator have any uncertainty regarding the reliability/severity of any possible contraindication, the potential subject will not be included.

5.4. **Will there be a formal screening process for participants in the project?** (e.g. medical/mental/health screening)*

◉ Yes
○ No

If YES, provide details. You must provide a clear rationale for inclusion and exclusion in relation to participants.*

As per Item 5.3 (Attachment: ESSA Pre-Exercise Screening tool)

5.5. **Does the research involve participants who have specific cultural needs or sensitivities?** (e.g., in relation to the provision of informed consent, language, procedural details)*

- ○ Yes
- ◉ No

5.6.a. **Does the research involve a participant population whose principal language is not English?***

- ○ Yes
- ◉ No

5.6.b. **Will documentation about the research (e.g., Information to Participants form and Consent form, questionnaires) be translated into a language other than English?***

- ○ Yes
- ◉ No

SECTION 6 - RECRUITMENT OF PARTICIPANTS

Recruitment and Informed Consent

6.1. **Will individuals other than members of the research team be involved in the recruitment of participants?***

- ○ Yes
- ◉ No

6.2. **How will potential participants be approached and informed about the research and how will they notify the investigators of their interest in participating?**
Attach copies of the "Information to Participants Involved in Research" form and any flyers or other advertising material to be used in the research in Section 11 - "Required Attachments" below.

Participants will be recruited via advertisement and VU email alerts and posters on notice boards. Potential participants will be then able to contact the investigators via phone calls or emails.

6.3. **Will potential participants be given time to consider and discuss their involvement in the project with others (e.g. family) before being requested to provide consent?***

- ◉ Yes
- ○ No

6.4. **How will informed consent be obtained from participants?***

- ☑ Participants be required to sign an informed consent form
- ☐ Consent will be implied e.g. by return of completed questionnaire
- ☐ Verbal consent will be obtained and recorded (audio, visual or electronic)
- ☐ Other

Attach copies of Consent Forms to be used in the research in Section 11 - "Required Attachments" below.

6.5. **Provide procedural details for obtaining informed consent:***

Interested parties who have contacted the researchers will be called and, following phone call screening, and having met the inclusion criteria will be asked for contact details so that more detailed information can be sent. Following this, at an agreed time a member of the research team will contact the participant and, should they consent to participate, schedule them for testing at Victoria University. Potential participants who attend the appointment will first be given the Information to Participants Form (Attachment:Information-to-Participants-Involved-in-Research) to read the testing procedures then will have the option to fill and sign the consent form to participate in the testing session or withdraw.

6.6. **Will you be seeking consent in order to contact participants in the future for related research participation and/or use participants' data for related research purposes?***

- ○ Yes
- ◉ No

Competing Interests

6.7. **Will any dual relationship or conflict of interest exist between any researcher and potential or actual participants?** (e.g., a member of the research team is also a colleague or friend of potential participants)*

- ◉ Yes
- ○ No

What is the nature of the dual relationship or conflict of interest?*

It is possible that colleagues or friends of the investigators may be interested in participating in the study.

How will ethical issues arising from the dual relationship or conflict of interest be addressed?*

The investigators will not solicit their friends or colleagues to participate in the study. Colleagues and friends will be treated in the same manner as other participants if they do decide to participate in the study.

6.8. **Does the research involve participants who are in dependent or unequal relationships with any member(s) of the research team or recruiting organisation/agency (e.g. counsellor/client, teacher/student, employer/employee)?***

- ◉ Yes
- ○ No

What is the nature of the dependent or unequal relationship?*

It is possible that some participants may be students of some of the investigators.

What measures will be taken to ensure that participants' voluntary consent is not compromised by the relationship?*

No investigator will be involved in any part of the recruitment process for any of their students.

What procedures are in place to ensure that the dependent or unequal relationship does not disadvantage or prejudice any participants?*

Potential participants will be informed that there is no obligation to participate and that they will not be penalised if they decide not to be involved or to withdraw at any time

6.9. **Will you be offering reimbursement or any form of incentive to participants (e.g., payment, voucher, free treatment) which are not part of the research procedures?***

- ◉ Yes
- ○ No

If YES, provide details:*

Typically reimbursement will be made for food, drink and parking for participants while attending their trial session.

6.10. **Is approval required from an external organisation?** (e.g., for recruitment of participants, data collection, use of premises)*

- ○ Yes
- ◉ No

SECTION 7 - RISKS ASSOCIATED WITH THE RESEARCH

Physical Risks

7.1.a. **Are there any PHYSICAL RISKS beyond the normal experience of everyday life, in either the short or long term, from participation in the research?***

- ◉ Yes
- ○ No

High probability risks:*

None are anticipated.

Low probability risks:*

Exercise involves a risk of sudden death due to myocardial infarct (heart attack) or a vasovagal episode (slow pulse, a fall in blood pressure, and sometimes convulsions). Signs and symptoms may include: sudden drop in heart rate during recovery or exercise; drop in blood pressure; pale complexion; fixed facial expression; pupils constricted; participant becomes uncommunicative or slurs words; restless and irritable; sweating; fatigue (if exercising). While vasovagal episodes are not uncommon, they are reversed quickly when employing a vasovagal management plan, and longterm risks are minimal.

How will the risk(s) be minimised?*

Only those participants deemed acceptably low risk will be accepted into the study. All risks will be minimised by following standard exercise laboratory procedures.
To ensure subject safety during exercise testing the procedures will also be terminated immediately before completion if any of the following criteria are present:
• subject wishes to stop
• subject experiences chest pain, severe shortness of breath or any other pain related to, or caused by exercise.
• subject wishes to continue but there are abnormal signs of metabolic, cardiorespiratory or thermoregulatory distress (e.g. facial pallor, unexpected large increase in HR or RPE).
• subjects sweating responses are inappropriate to the environmental conditions in the laboratory
In addition, subjects will be closely supervised and monitored (HR and RPE) at all times during exercise and testing sessions. All exercise testing procedures will be attended by staff with current CPR and First Aid certification in the unlikely event of an emergency.

How will these risks be managed if an adverse event were to happen?*

Investigators will follow the standard VU Management Plan. This includes the following important procedures: for a vasovagal episode, lay the person down on a soft floor mat as quickly as possible; immediately elevate legs and lay head flat (no pillow); if a medical practitioner is not in attendance, then call a medical practitioner or ambulance if the participant has not begun recovering within 35 minutes of implementing the management plan; attach and monitor ECG for one hour; monitor the participant continuously and frequently give reassurance; during the later stages of recovery, test the person's ability to sit, stand and walk while continuing to monitor ECG; once the participant has recovered sufficiently to leave the laboratory, check signs and symptoms again; accompany the person out of the building; discourage the person driving; encourage the person to go home to rest; follow up the next day with a phone call to check on stability of persons condition. For more serious adverse events during the exercise tests all tests will be supervised by an investigator with current CPR certificate. The investigators will manage any adverse event during the exercise tests. In the case of adverse events requiring any medical consultation, subjects will be given a single (half A4 size) sheet of paper describing their participation in this experiment, and the contact numbers for all investigators. In the event of more serious complications that might arise during any test procedures, an ambulance would be called using the telephone in the laboratory and the Western Hospital is a short distance away. In the event of a soft tissue injury, the recommended first aid treatment of rest, ice, compression, and elevation will be administered. The participant will also be advised to see a medical practitioner for assessment.

Psychological Risks

7.1.b. **Are there any PSYCHOLOGICAL RISKS beyond the normal experience of everyday life, in either the short or long term, from participation in the research?***

○ Yes
◉ No

Social Risks

7.1.c. **Are there any SOCIAL RISKS beyond the normal experience of everyday life, in either the short or long term, from participation in the research.** (e.g., possible inadvertent public disclosure of personal details or sensitive information)*

○ Yes
◉ No

Other Risks

7.2. **Does the research involve any risks to the researchers?***

○ Yes
◉ No

7.3. **Does the research involve any risks to individuals who are not part of the research, such as a participant's family member(s) or social community (e.g., effects of biographical or autobiographical research)?***

○ Yes
◉ No

7.4. **Are there any legal issues or legal risks associated with any aspect of the research that require specific consideration (i.e., are significant or out of the ordinary), including those related to:**

- participation in the research,
- the aims and nature of the research,
- research methodology and procedures, and/or
- the outcomes of the research?

*

○ Yes
◉ No

7.5. **Risk-Benefit Statement:**
Please give your assessment of how the potential benefits to the participants or contributions to the general body of knowledge would outweigh the risks. *Even if the risk is negligible, the research must bring some benefit to be ethical.**

No direct benefits to the participant are expected from participation. However, they may receive an educational benefit from being exposed to the scientific experimental research process

SECTION 8 - DATA PROTECTION AND ACCESS

Data Protection

8.1. **Indicate how the data, materials and records will be kept to protect the confidentiality/privacy of the identities of participants and their data, including all hardcopies, electronic files and forms.** *See help for definitions.**

○ Data and records will be entirely anonymous
◉ Data and records will be coded and non-identifiable
○ Data and records will be coded and re-identifiable
○ Some or all of the retained data and records will include personally identifying information
○ Other

8.2. **Who will be responsible for the security of and access to confidential data and records, including consent forms, collected in the course of the research?***

The Chief investigator Prof Rezaul Begg

8.3. **Where will data, materials and records be stored during and after completion of the project?** Provide full details of the location for all types of data.
Note: The VU Research Storage provides secure digital storage and long term retention for research project data including graduate research projects.

During the project:*

Records will be kept in locked filing cabinets in Prof Rezaul Begg's office, which is also locked. Electronic data will be kept on computers (R: Drive) which are password protected.

Upon completion:*

Upon completion of the project, data will be stored in Prof Rezaul Begg's office for a further five years. The office is locked, as are the cabinets. After five years the electronic files will be deleted from the computers (R: Drive), and all hard copy files will be shredded.

8.4. **Indicate the minimum period for which data will be retained.** See help for definitions.*

○ Indefinitely
◉ 5 years post publication
○ 7 years post publication
○ 15 years post publication
○ 25 years after date of birth of participants
○ Other

8.5. **Who will be responsible for re-evaluating the data/materials after the retention period and considering a further retention period for some or all of the data/materials?***

Prof Rezaul Begg will be responsible for this.

8.6. **Will you transfer your data or materials to a managed archive or repository during the project, after the project, or after the retention period? Which discipline specific or institutional archives will be considered?**
*Note: Some funding agencies and publishers may require lodgement with an archive or repository. Retain a copy at VU where possible.**

No data will be transferred.

8.7. **When further retention of data and materials is no longer required, responsible disposal methods should be adopted. Disposal software should also be adopted if digital software, computer hardware, disks or storage media are reused or retired. What methods of appropriate disposal or destruction will be employed?**
Note: Personal, sensitive or confidential information, both digital and hardcopy, will require secure destruction or disposal. For other materials you may need to refer to the Hazardous Materials Policy, Animal Ethics Standard Operating Procedures, or the Ethics and Biosafety site found on the VU Office for Research website. *

Hard copy files will be shredded and placed in secure destruction bins.

SECTION 9 - DISSEMINATION/PUBLICATION OF RESEARCH RESULTS

Publication Details

9.1. **Indicate how the results of this research will be reported or published.***

- [x] Thesis
- [x] Journal article(s)
- [ ] Book
- [ ] Research report to collaborating organisations
- [x] Conference presentation(s)
- [ ] Recorded performance
- [ ] Other

9.2. **Will any contractual agreement exist between the researchers and a third party that will restrict publication of the research findings?***

○ Yes
◉ No

9.3. **Are there any other restrictions on publications or reports resulting from this project?***

◉ Yes
○ No

Provide details:*

As detailed in the current contract between The Defence Science and Technology Group of the Department of Defence AND Victoria University, all future publications will be initially reviewed by DST group researchers and approval sought to determine the project is of a "nonclassified" nature prior to publication. Overall, DSTG encourage publication of results from this study as a journal article or conference presentation, whether adverse or positive, and it is not anticipated there will be any restrictions on the publication of results.

SECTION 10 - OTHER DETAILS

Comments

10.1. **In your opinion, are there any other ethical issues involved in the research?***

○ Yes
◉ No

10.2. **Additional information and comments to support this application:**

None

SECTION 11 - DOCUMENTS, ATTACHMENTS AND SUPPLEMENTARY FORMS

Required Attachments

The following documentation must be attached to your application:

- Scanned copy of the Declaration Form for External Investigators (if applicable)

- Copy of the '**Information to Participants Involved in Research**' form *(Please use the templates provided on the Human Research Ethics website)*

- Copy of Consent Forms to be used in the research *(Please use the templates provided on the Human Research Ethics website)*

- Any flyers or other advertising material to be used in the research

- Copy of questionnaires

11. **Please attach each of the items specifically listed above as well as any other supporting documentation.**
All documentation must be accurately titled and referenced to within the body of your application where appropriate (i.e. "Appendix A - Declaration Form", "Appendix F - Risk Factor Assessment Questionnaire", etc.). Please limit file types to .doc, .docx, .xls, .xlsx, .pdf, or small-medium images (ie, .gif, .jpg).*

Description	Reference	Soft copy	Hard copy
Consent Form	VU-HRE_Consent Form_JPROUD.doc	✓	
Information to Participants Involved in Research	VU-HREApplication-Information-to-Participants-Involved-in-Research_JPROUD.docx	✓	
Declaration Form for External Investigators	VUHREC-Application-Declaration-Form-External-Investigators_KM Signed.pdf	✓	
Reference List	VU-HRE_References_JPROUD.docx	✓	
Advertising Material (flyers etc.)	VU-HRE_Flyer_JPROUD.pdf	✓	
ESSA Pre-Exercise Screening tool	ESSA Screen tool version_v1.pdf	✓	

Note: Please click the Question Help icon above for instructions on how to upload documents and use this table.

If you are certain that you do not need to supply a Consent Form or Information to Participants Involved in Research (both of which are mandatory), please tick Hard Copy and type 'N/A' in the Reference field.

SECTION 12 - SUBMISSION DETAILS

Declaration

I / we, the undersigned, declare the following:

- I / we accept responsibility for the conduct of the research project detailed above in accordance with:
    a. the principles outlined in the National Statement on Ethical Conduct in Human Research (2007);
    b. the protocols and procedures as approved by the HREC;
    c. relevant legislation and regulations.

- I / we will ensure that HREC approval is sought using the Changes to the Research Project process outlined on the Human Research Ethics website if:
    a. proposing to implement change to the research project;
    b. changes to the research team are required.

- I / we have read the National Statement on Ethical Conduct in Human Research prior to completing this form.

- I / we certify that all members of the research team involved the research project hold the appropriate qualifications, experience, skills and training necessary to undertake their roles.

- I / we will provide Annual / Final reports to the approving HREC within 12 months of approval or upon completion of the project if earlier than 12 months.

- I / we understand and agree that research documents and/or records and data may be subject to inspection by the VUHREC, Ethics Secretary, or an independent body for audit and monitoring purposes.

- I / we understand that information relating to this research, and about the investigators, will be held by the VU Office for Research. This information will be used for reporting purposes only and managed according to the principles established in the Privacy Act 1988 (Cth) and relevant laws in the States and Territories of Australia.

*

1	*Staff/Student ID*	E5024943
	Full Name	ASPR TZE HUEI LAI
	Role in project	Chief Investigator
	Personnel Type	Internal
2	*Staff/Student ID*	E5108402
	Full Name	DR KURT MUDIE
	Role in project	Chief Investigator
	Personnel Type	Internal
3	*Staff/Student ID*	E5072330
	Full Name	PROF REZAUL BEGG
	Role in project	Chief Investigator
	Personnel Type	Internal
4	*Staff/Student ID*	S4173115
	Full Name	MS Jasmine Proud
	Role in project	Student
	Personnel Type	Student
	Sign Declaration? *By clicking the checkbox below, you are agreeing to conduct the research project in accordance with the above declaration.*	Yes
	Date Signed	21/11/2018

Note: Please click on your name in the table above to complete your declaration; or click on the name of an External Investigator to acknowledge that their declaration has been supplied.

Declaration Instructions and Information

- A digital signature must be supplied by each and every member of the research team using the declaration table above.
- The 'Needs Signature' icon shows which records you are responsible for signing.
- Physical signatures are not required for VU staff and students in applications using form version v.13-07.
- External Investigators do not have access to Quest. The Chief Investigator must supply a completed physical declaration on their behalf by following the steps below:
  1. Send the person a copy of the full application form (including any attachments), as well as the **Declaration Form for External Investigators** document.
  2. Once returned, attach the signed *External Investigator Declaration Form* document in 'Section 11 - Required Attachments'.
  3. Enter into the External Investigator's record in the above declaration table and mark the checkbox to indicate these steps have been completed, include the date you have done so.
     The 'sighted by' field will automatically populate with your name. *(Only the Chief Investigator will have permission to complete this step.)*
- The application cannot be submitted until all members of the research team have logged in and completed this declaration.

Finalise Application

Reminders

- All applications must be sighted and approved by all members of the research team and any relevant parties. Please ensure each member of the research team has completed their declaration in *'Section 12 - Declaration'* above, including any declaration forms supplied on behalf of External Investigators. *Applications will not be reviewed without appropriate authorisation.*

- It is strongly recommended that you save a PDF version of your application before submitting as you will lose access to the electronic record while it undergoes formal review.

- **You are reminded that your project may not commence without formal written approval from the appropriate Human Research Ethics Committee.**

Ready to Submit?

* Once the form is complete and all documents are attached, **click on the *'Action'* tab** above the left-hand form navigation, then **click *'Submit Application'*** to forward the application to the Ethics Secretary to be reviewed and assigned to a Committee meeting.

- You will receive an automatic email notification from Quest when your application has been successfully submitted.

- *Note: Only a Chief Investigator is able to submit an application for ethical approval. The Chief Investigator who is marked as the primary contact for this application is:*

PROF REZAUL BEGG

Appendix C – Participant Information & Consent

INFORMATION TO PARTICIPANTS INVOLVED IN RESEARCH

You are invited to participate

You are invited to participate in a research project entitled: *Development of a wearable device to reduce risk factors associated with injury during manual handling tasks.*

Prof Rezaul Begg, A/Prof Daniel Lai, Dr Kurt Mudie, Dr Alessandro Garofolini and Ms. Jasmine Proud from the Institute of Health and Sport (IHES) at Victoria University.

Project explanation

The aim of the project is to determine the human biomechanics affected by manual handling tasks. These results will be used to inform future design and development of a wearable assistive device. The primary research question is to determine the baseline factors for good lifting posture during manual handling tasks. In the experiments described below participants will take part in a repeated measures trial, performing one manual handling tasks involving lifting loads. The project will be administered as part of the Victoria University research and innovation Program in Assistive Technology Innovation (PATI); an association between the Defence Science and Technology Group, Victoria University and The University of Melbourne.

What will I be asked to do?

If you agree to take part in the study, you will be required to visit Victoria University (Footscray Park). Before testing you will be required to sign the Informed Consent Form, after you have read this Participant Information Sheet and had any of your questions answered. A health screening involving questions around general health and injury status will then be performed. The following assessment will be undertaken.

1. Participants' height, body mass and resting heart rate will be measured.

2. A standard three-dimensional (3D) motion capture camera system will be used to record the participants' motion when performing tasks by time-sampling the position of reflective markers attached to the head, neck, abdomen, back, hips, upper arms and legs.

5. Body segment accelerations and velocities will be measured via small sensors (IMUs) attached to the skin of the back along the spine.

6. The manual handling task is 'lift to platform' with a single crate with side mounted handles (e.g. supply boxes). This will involve two trials, the first trial utilising a maximum lifting capacity (MLC) procedure and the second trial a randomised lift of the weights recorded during the MLC procedure. These procedures regulate your physical capacity for load carriage.

All information collected during this study will be kept confidential, coded and secure. Any data published will be non-identifiable. Privacy during marker, electrode and sensor attachment will be provided to ensure your comfort throughout the trial process.

Although this testing session does not require any strenuous activity, you will be able to take as many breaks as you require. You will be able to stop the testing session at any time if you no longer wish to continue.

What will I gain from participating?

The study aims to further biomechanical knowledge of human performance during manual handling tasks, with results used for the future development of a wearable assistive device for reduction of injury risk factors. No direct benefits to you are expected from participation. However, you may receive an educational benefit from being exposed to scientific experimental research process.

How will the information I give be used?

All questions, answers and results of this study will be treated with absolute confidentiality and will be retained in a secure place. This information will be used to develop a research thesis, reports for publication and inform future assistive device design. In any manuscripts, reports or other publications resulting from this study, subject codes rather than names will be used. Therefore, you will not be able to be identified in these publications.

What are the potential risks of participating in this project?

As this study only requires you to perform short periods of physical activity with loads tailored to your physical ability there is a low risk of any problems. However, exercise involves risk of muscle soreness, muscle damage, a low risk of sudden death due to myocardial infarct (heart attack) or a vasovagal episode (slow pulse, a fall in blood pressure, and sometimes convulsions). You will be encouraged to rest between exercises to avoid this and all risks will be minimised by following standard exercise laboratory procedures and providing correct lifting technique training prior to the beginning of the trial. At no time in this study will you be required to perform any strenuous activity; however, you will be able to take as many breaks as you require to ensure you do not become tired. You will not be required to perform any activity that you do not feel completely comfortable doing.

How will this project be conducted?

Prospective participants will complete a questionnaire to confirm that they have no musculoskeletal impairments or other medical conditions that may affect their ability to safely perform the experimental tasks. Prior to testing informed consent will be obtained using procedures approved and mandated by the Victoria University Research Ethics Committee. Data collection will be undertaken at the Victoria University (Footscray Campus) Biomechanics and Exercise Physiology laboratories.

Participants will need to wear minimal clothing in order to ensure attachment of markers to the skin (shorts only for males, shorts and sports bra for females). Appropriate comfortable shoes for exercise must also be worn. A typical laboratory session will take approximately 3 hours per participant, including marker, electrode and sensor attachment, practice trial(s), rest intervals and data collection. Rest breaks will be provided as necessary between conditions. Two laboratory staff will be employed for data collection; one will operate the data collection devices and the other will continuously monitor the participant to confirm their comfort and safety. The second operative will also record heart rate and perceived exertion.

Trials will be performed on a force-plate embedded in the floor. Conditions will include the following: (i) ‘lift to platform’ task with maximum lift capacity (MLC) procedure and (ii) Randomised ‘lift to platform’ task.

MLC is a one off test that measures the maximum weight that can be lifted in a single repetition. Participants start will a small weight and complete the lifting task, the weight is increased by 5kgs after every completion with correct technique (i.e. good posture) until the lift fails or technique deteriorates. The weight is then lowered by 2.5kgs and attempted again. If completed this determines the participants MLC or if failed the previous weight is the recorded MLC.

Who is conducting the study?

Principal Investigator(s)	Prof Rezaul Begg	rezaul.begg@vu.edu.au	Ph. 03 9919 1116
	A/Prof Daniel Lai	daniel.lai@vu.edu.au	Ph. 03 9919 4425
	Dr Kurt Mudie	kurt.mudie@dst.defence.gov.au	Ph. 03 9626 7642
	Dr Alessandro Garofolini	alessandro.garofolini@vu.edu.au	
Student Investigator	Ms Jasmine Proud	jasmine.proud@live.vu.edu.au	Ph. 0421 878 113

Prof Rezaul Begg, Dr Alessandro Garofolini and Ms Jasmine Proud, Institute of Health and Sport, College of Exercise and Sports Science, Victoria University. A/Prof Daniel Lai is with Institute of Health and Sport, College of Engineering and Science, Victoria University. Dr Kurt Mudie, Defence Science and Technology (DST), Melbourne, Victoria.

Any queries about your participation in this project may be directed to the Chief Investigator listed above.
If you have any queries or complaints about the way you have been treated, you may contact the Ethics Secretary, Victoria University Human Research Ethics Committee, Office for Research, Victoria University, PO Box 14428, Melbourne, VIC, 8001, email researchethics@vu.edu.au or phone (03) 9919 4781 or 4461.

VICTORIA UNIVERSITY
MELBOURNE AUSTRALIA

CONSENT FORM FOR PARTICIPANTS

We are pleased to invite you to be a part of a study *Development of an assistive device to reduce risk factors associated with injury during military manual handling tasks.* The aim of the project is to determine the human kinetics and kinematics affected by military manual handling tasks. You are asked to participate in the testing procedures outlined in the attached "Information for participants" documents.

I, ... give my consent to participate in the project mentioned above on the following basis:

I have had explained to me the aims of this research project, how it will be conducted and my role in it.

I understand the risks involved as described in the Participant Information Sheet.

I am cooperating in this project on condition that:

- The information I provide will be kept confidential.
- The information will be used for this project and in future related projects.
- The research results will be made available to me at my request and any published reports of this study will preserve my anonymity.

I understand that:

- There is no obligation to take part in this study.
- I am free to withdraw at any time.

I have been given a copy of the participant information sheet and consent form, signed by me and by one of the principal investigators, as listed on the information sheet, to keep.

Signature of participant ______________________________

Name in full ______________________________

Date ______________________________

Signature of Research Investigator ______________________________

Name in full ______________________________

Date ______________________________

Should you have any complaints or concerns about the manner in which this project is conducted, please do not hesitate to contact the researchers in person, or you may prefer to contact Victoria University Human Research Ethics Committee at the following address:

Ethics Secretary, Victoria University Human Research Ethics Committee,

Office for Research, Victoria University, PO Box 14428, Melbourne, VIC, 8001, email researchethics@vu.edu.au or phone (03) 9919 4781 or 4461.

Appendix D – Health Survey

ADULT PRE-EXERCISE SCREENING TOOL

Name: ______________________________

Date of Birth: ______________ Male ☐ Female ☐ Date: ______________

STAGE 1 (COMPULSORY)

AIM: to identify those individuals with a known disease, or signs or symptoms of disease, who may be at a higher risk of an adverse event during physical activity/exercise. This stage is self administered and self evaluated.

Please circle response

1.	Has your doctor ever told you that you have a heart condition or have you ever suffered a stroke?	Yes	No
2.	Do you ever experience unexplained pains in your chest at rest or during physical activity/exercise?	Yes	No
3.	Do you ever feel faint or have spells of dizziness during physical activity/exercise that causes you to lose balance?	Yes	No
4.	Have you had an asthma attack requiring immediate medical attention at any time over the last 12 months?	Yes	No
5.	If you have diabetes (type I or type II) have you had trouble controlling your blood glucose in the last 3 months?	Yes	No
6.	Do you have any diagnosed muscle, bone or joint problems that you have been told could be made worse by participating in physical activity/exercise?	Yes	No
7.	Do you have any other medical condition(s) that may make it dangerous for you to participate in physical activity/exercise?	Yes	No

IF YOU ANSWERED 'YES' to any of the 7 questions, please seek guidance from your GP or appropriate allied health professional prior to undertaking physical activity/exercise

IF YOU ANSWERED 'NO' to all of the 7 questions, and you have no other concerns about your health, you may proceed to undertake light-moderate intensity physical activity/exercise

I believe that to the best of my knowledge, all of the information I have supplied within this tool is correct.

Signature ______________________________ Date ______________

ESSA EXERCISE & SPORTS SCIENCE AUSTRALIA   Fitness Australia THE HEALTH & FITNESS INDUSTRY ASSOCIATION   SPORTS MEDICINE AUSTRALIA

EXERCISE INTENSITY GUIDELINES

INTENSITY CATEGORY	HEART RATE MEASURES	PERCEIVED EXERTION MEASURES	DESCRIPTIVE MEASURES
SEDENTARY	< 40% HRmax	Very, very light RPE# < 1	• Activities that usually involve sitting or lying and that have little additional movement and a low energy requirement
LIGHT	40 to <55% HRmax	Very light to light RPE# 1-2	• An aerobic activity that does not cause a noticeable change in breathing rate • An intensity that can be sustained for at least 60 minutes
MODERATE	55 to <70% HRmax	Moderate to somewhat hard RPE# 3-4	• An aerobic activity that is able to be conducted whilst maintaining a conversation uninterrupted • An intensity that may last between 30 and 60 minutes
VIGOROUS	70 to <90% HRmax	Hard RPE# 5-6	• An aerobic activity in which a conversation generally cannot be maintained uninterrupted • An intensity that may last up to about 30 minutes
HIGH	≥ 90% HRmax	Very hard RPE# ≥ 7	• An intensity that generally cannot be sustained for longer than about 10 minutes

= Borg's Rating of Perceived Exertion (RPE) scale, category scale 0-10

Appendix E – Participant recruitment flyer

VOLUNTEERS REQUIRED FOR SMART TECHNOLOGY RESEARCH @ VU

Development of a wearable device to reduce risk factors associated with injury during manual handling tasks

WANTED: Healthy participants aged 18-40 for 2 - 3 hours.

AIM: The study aims to further biomechanical knowledge of human performance during manual handling tasks, with results used for the future development of a wearable device.

Participants will perform lifting tasks while being monitored with markers and sensors.

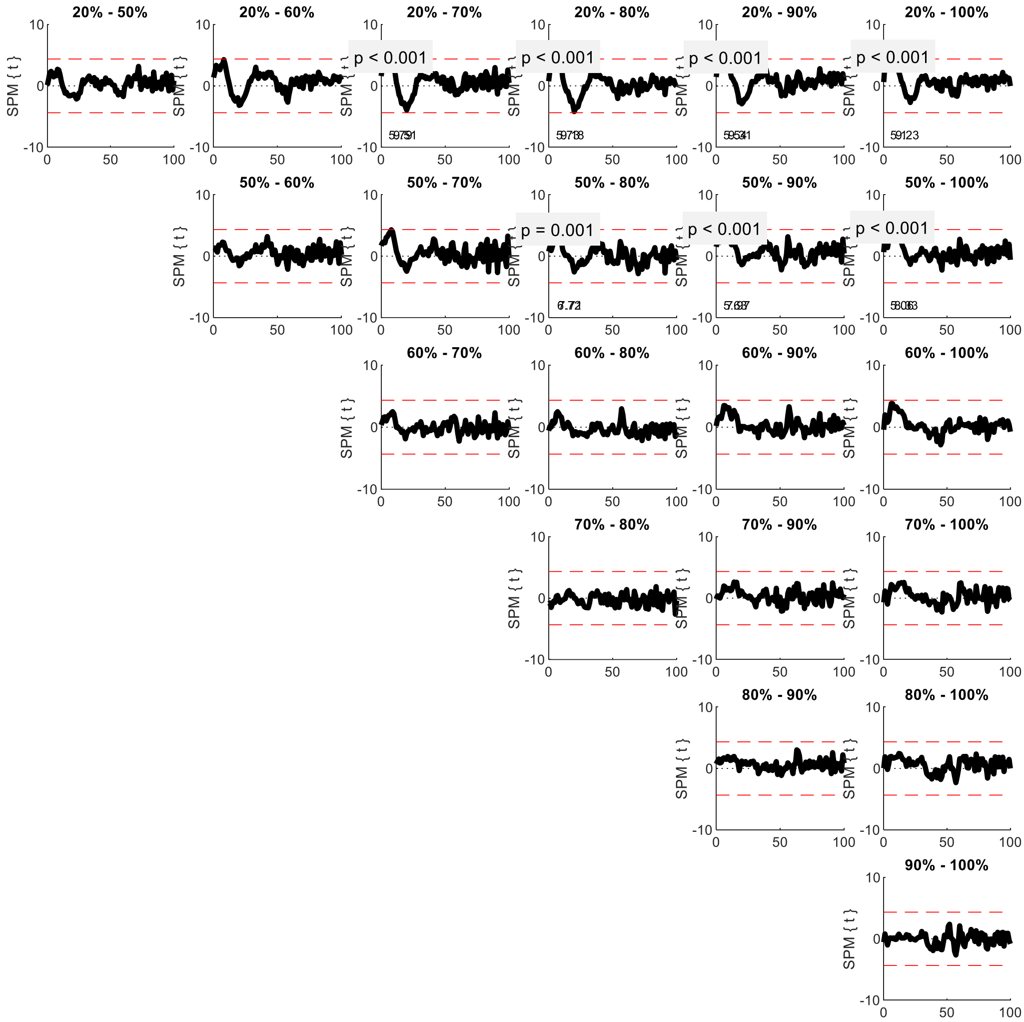
DST GROUP

VICTORIA UNIVERSITY
MELBOURNE AUSTRALIA

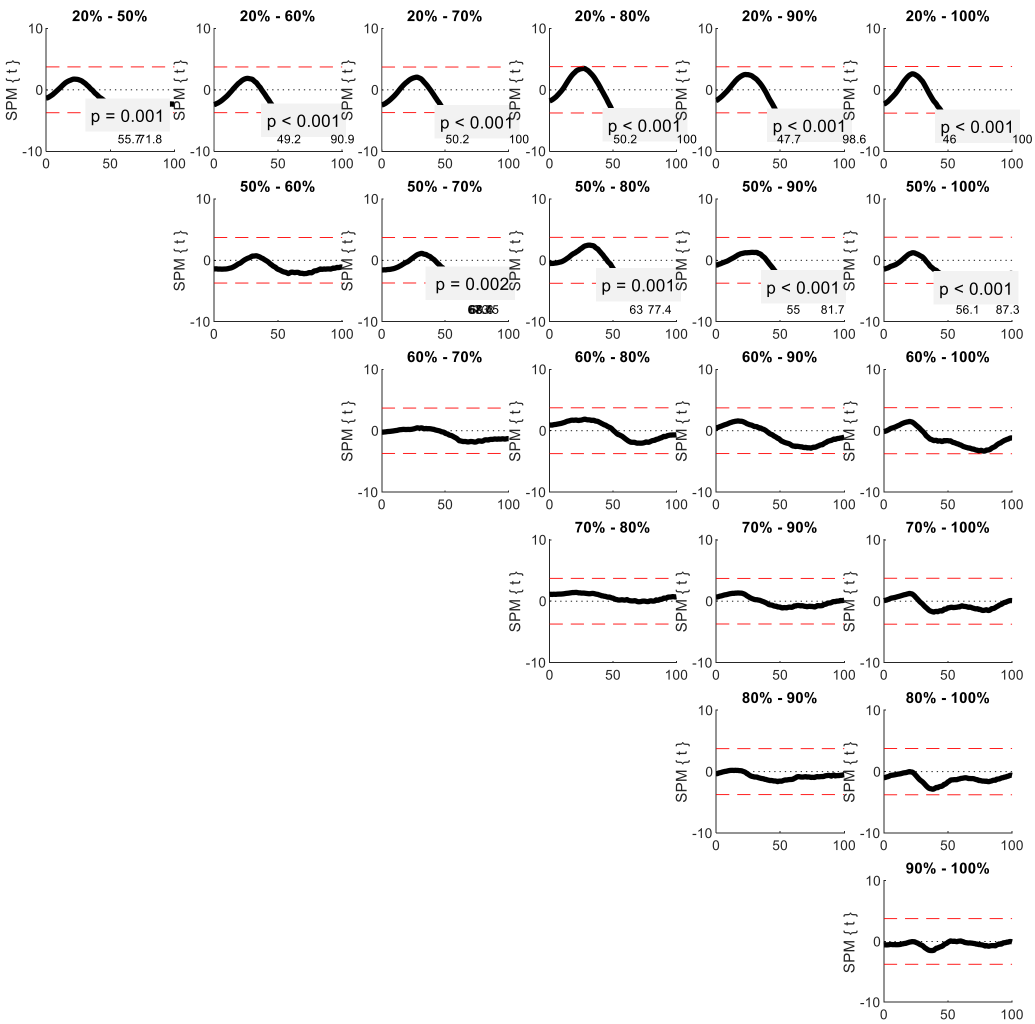
For more information please call/email:
Ms Jasmine Proud | jasmine.proud@live.vu.edu.au | 0421 878 113

Appendix F - SPM Post-Hoc ANOVA Plots

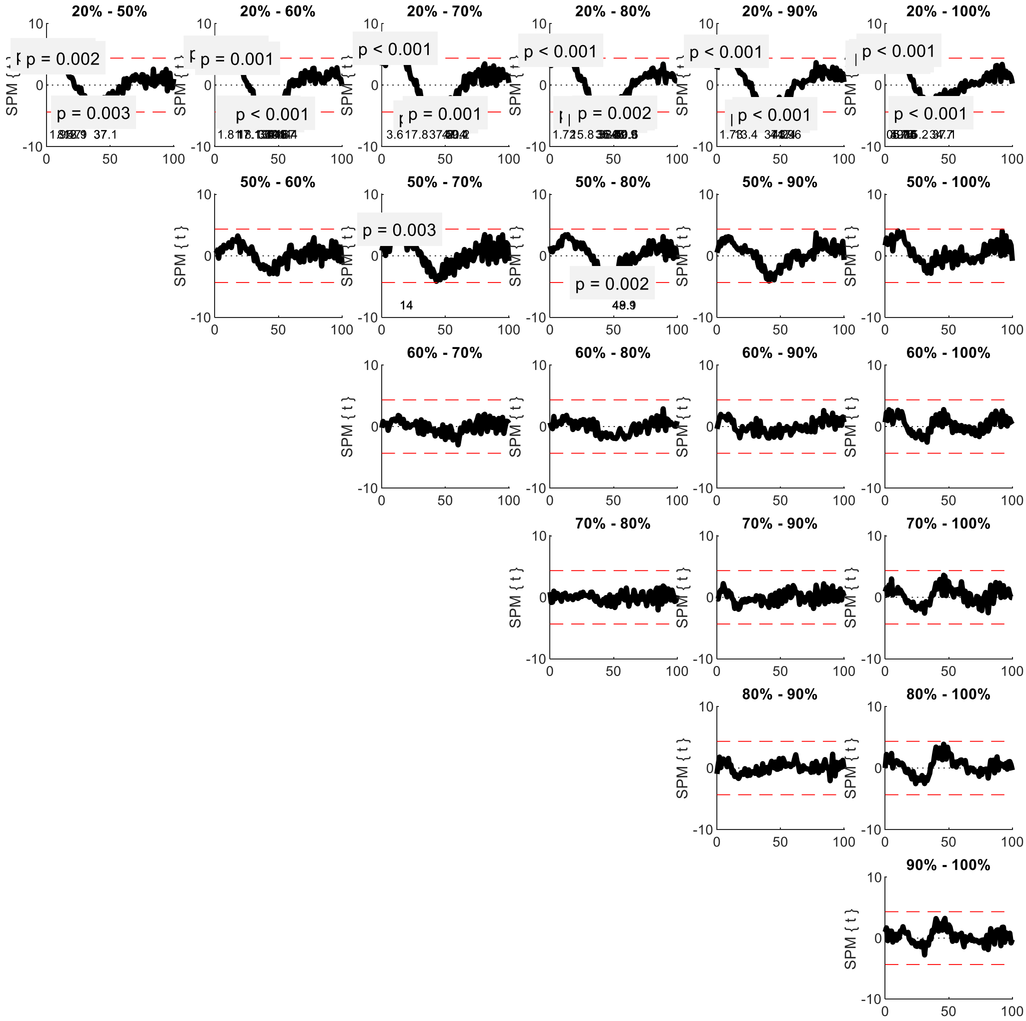
1. UT Acc Z



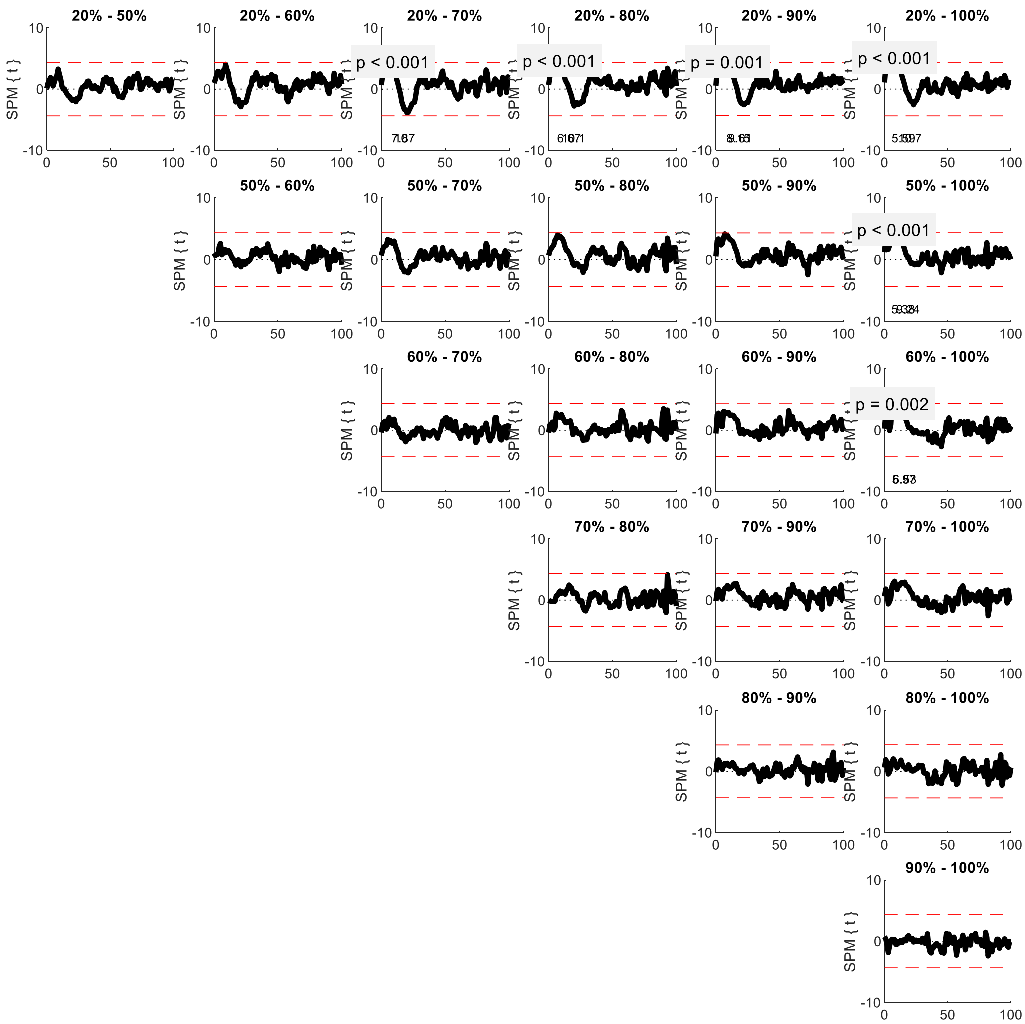
2. UT Angle Y


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
p = 0.001
p < 0.001
p < 0.001
p < 0.001
p < 0.001
p < 0.001
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
p = 0.002
p = 0.001
p < 0.001
p < 0.001
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM { t }

3. UT AngVel Y

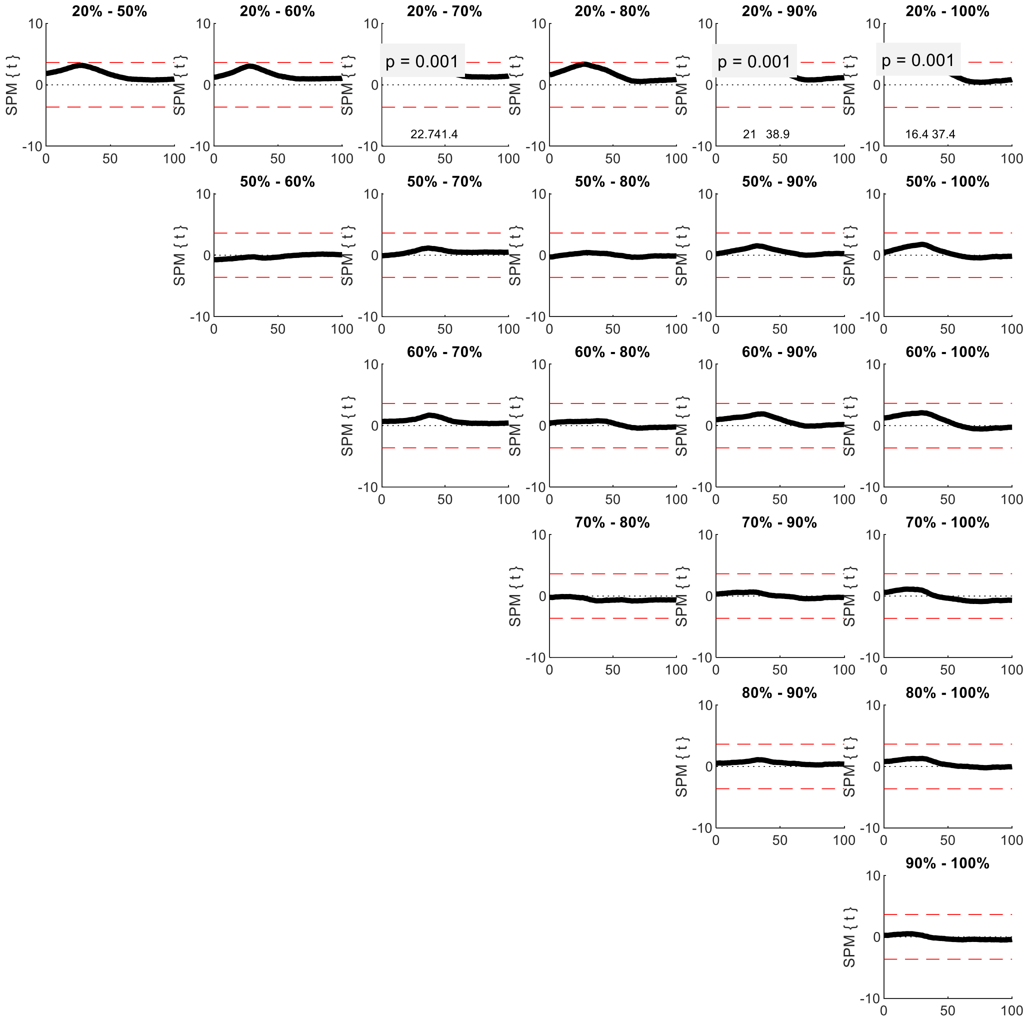

20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}
p = 0.002
p = 0.003
p = 0.001
p < 0.001
p = 0.002
p = 0.003
p = 0.002

4. MUT Acc Z

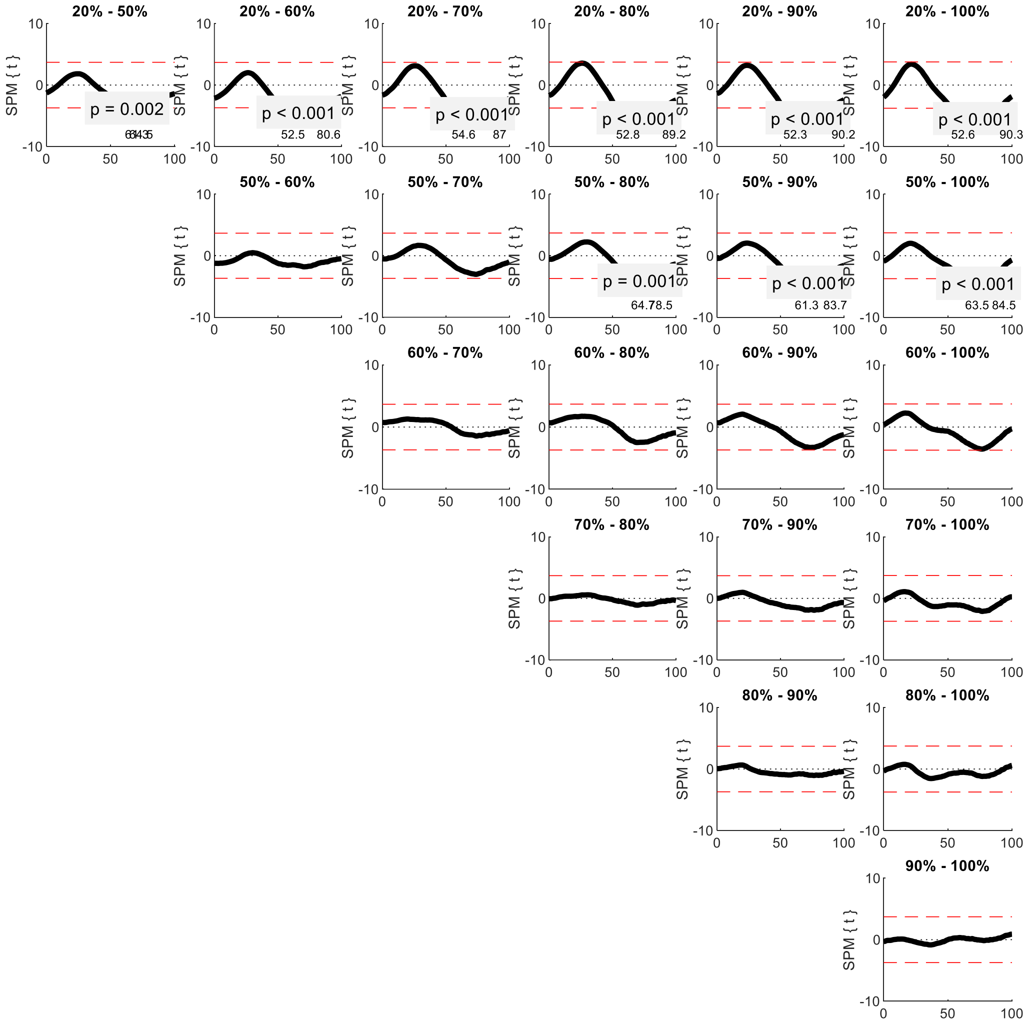


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM { t }
p < 0.001
p < 0.001
p = 0.001
p < 0.001
p < 0.001
p = 0.002

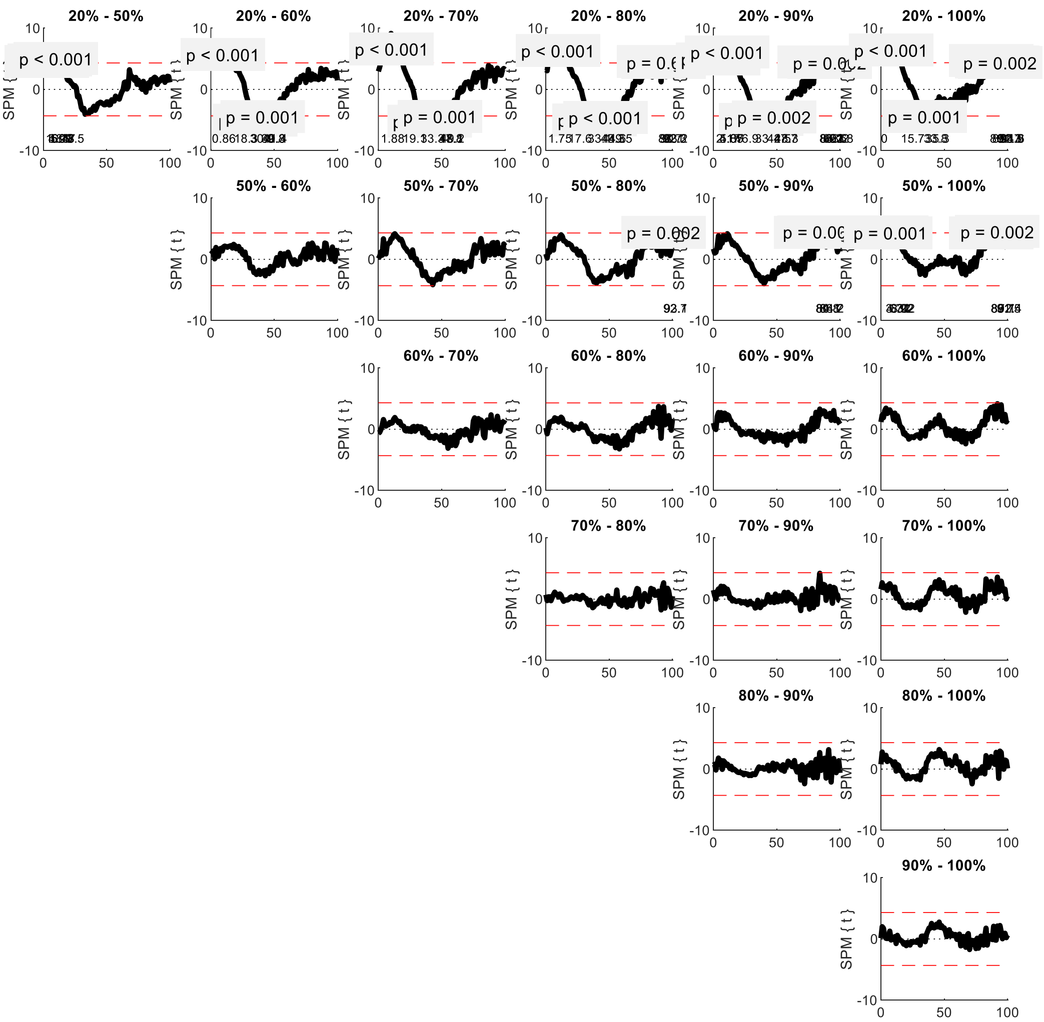
5. MUT Mag Z


20% - 50%
20% - 60%
20% - 70%
p = 0.001
22.741.4
20% - 80%
20% - 90%
p = 0.001
21 38.9
20% - 100%
p = 0.001
16.4 37.4
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM { t }
10
0
-10
0
50
100

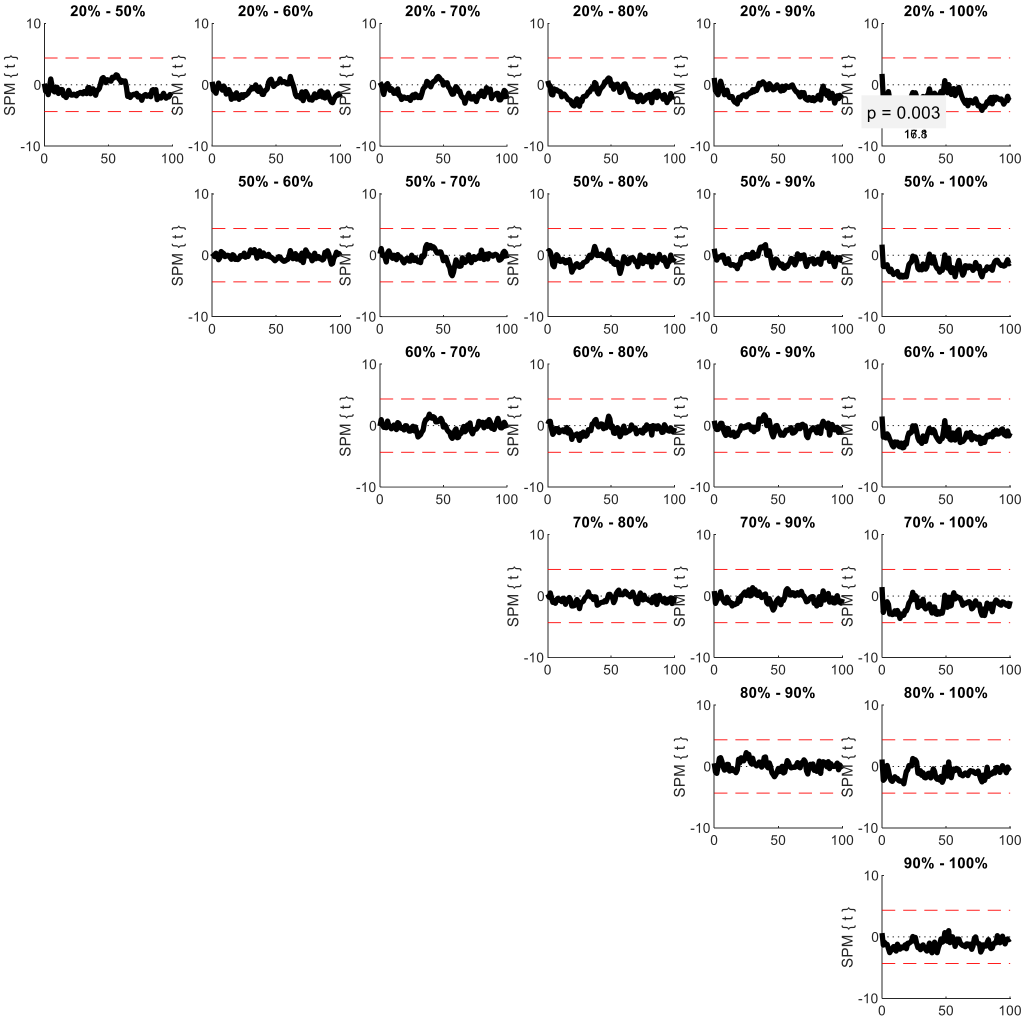
6. MUT Angle Y


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM { t }
p = 0.002
p < 0.001
52.5 80.6
54.6 87
52.8 89.2
52.3 90.2
52.6 90.3
p = 0.001
64.78.5
61.3 83.7
63.5 84.5

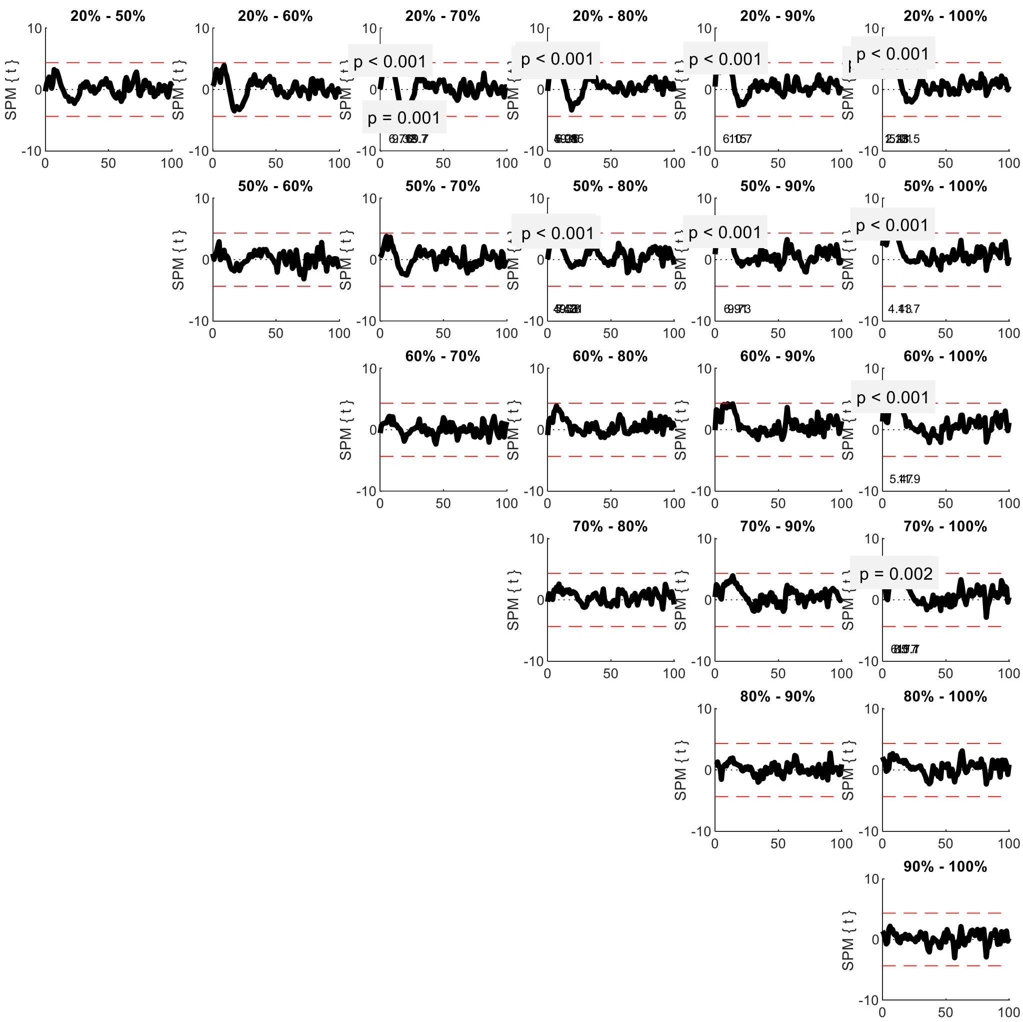
7. MUT AngVel Y



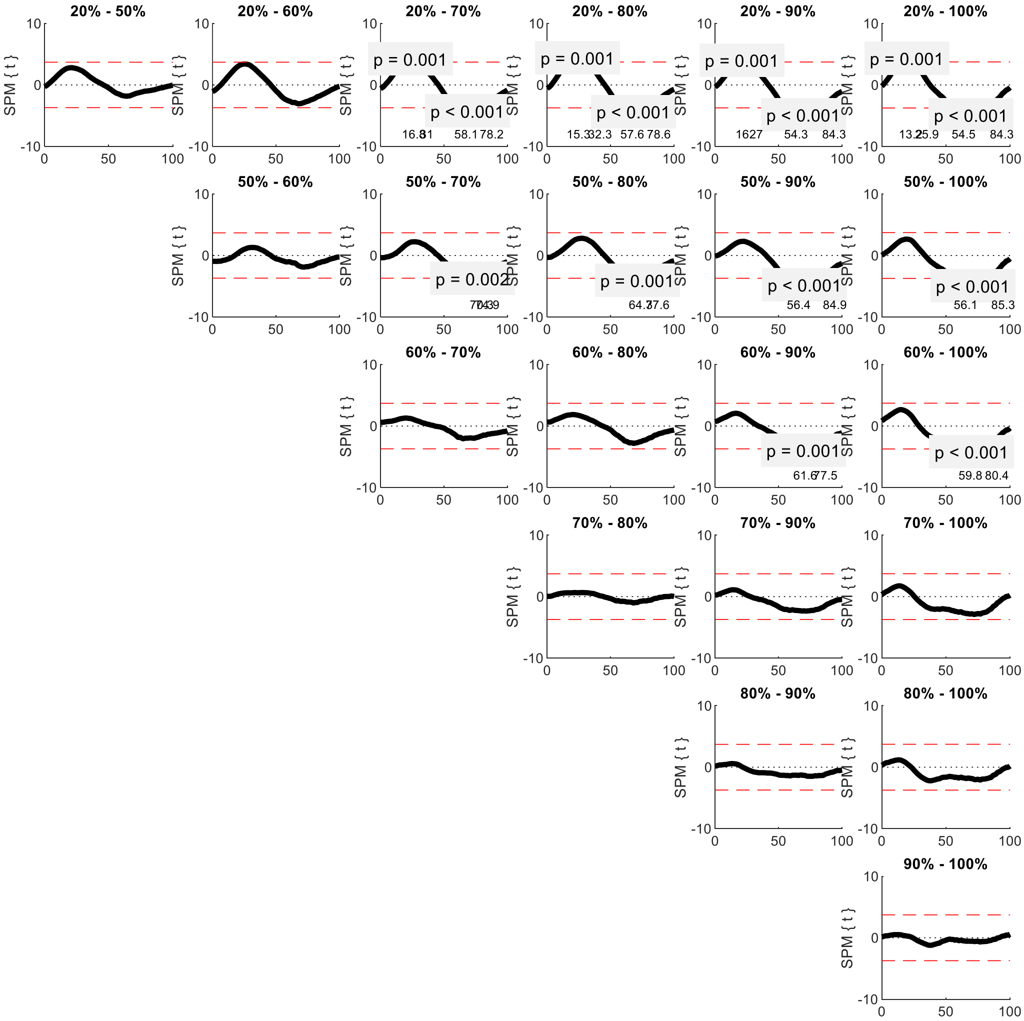
8. MLT Acc X


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
p = 0.003
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}

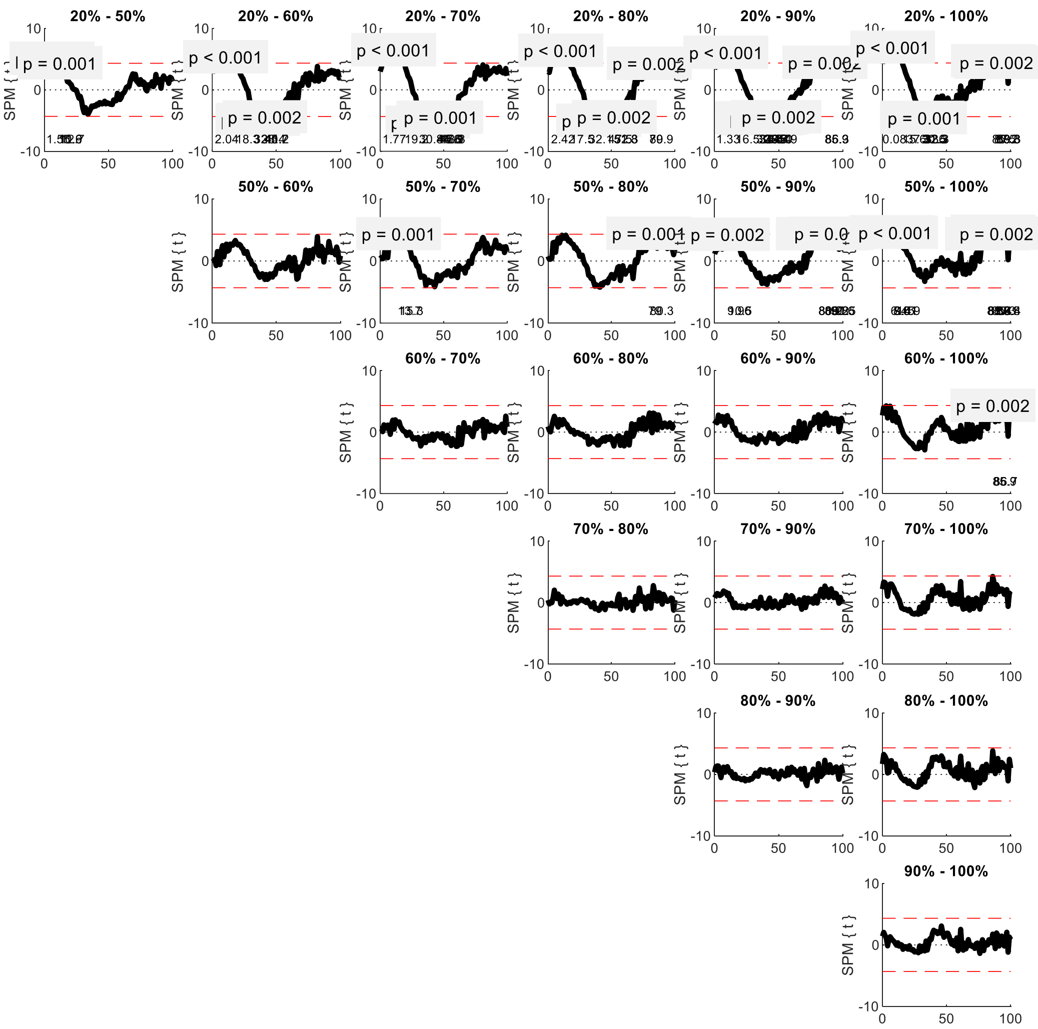
9. MLT Acc Z


20% - 50%
20% - 60%
20% - 70%
p < 0.001
p = 0.001
20% - 80%
p < 0.001
20% - 90%
p < 0.001
20% - 100%
p < 0.001
50% - 60%
50% - 70%
50% - 80%
p < 0.001
50% - 90%
p < 0.001
50% - 100%
p < 0.001
60% - 70%
60% - 80%
60% - 90%
60% - 100%
p < 0.001
70% - 80%
70% - 90%
70% - 100%
p = 0.002
80% - 90%
80% - 100%
90% - 100%
SPM { t }

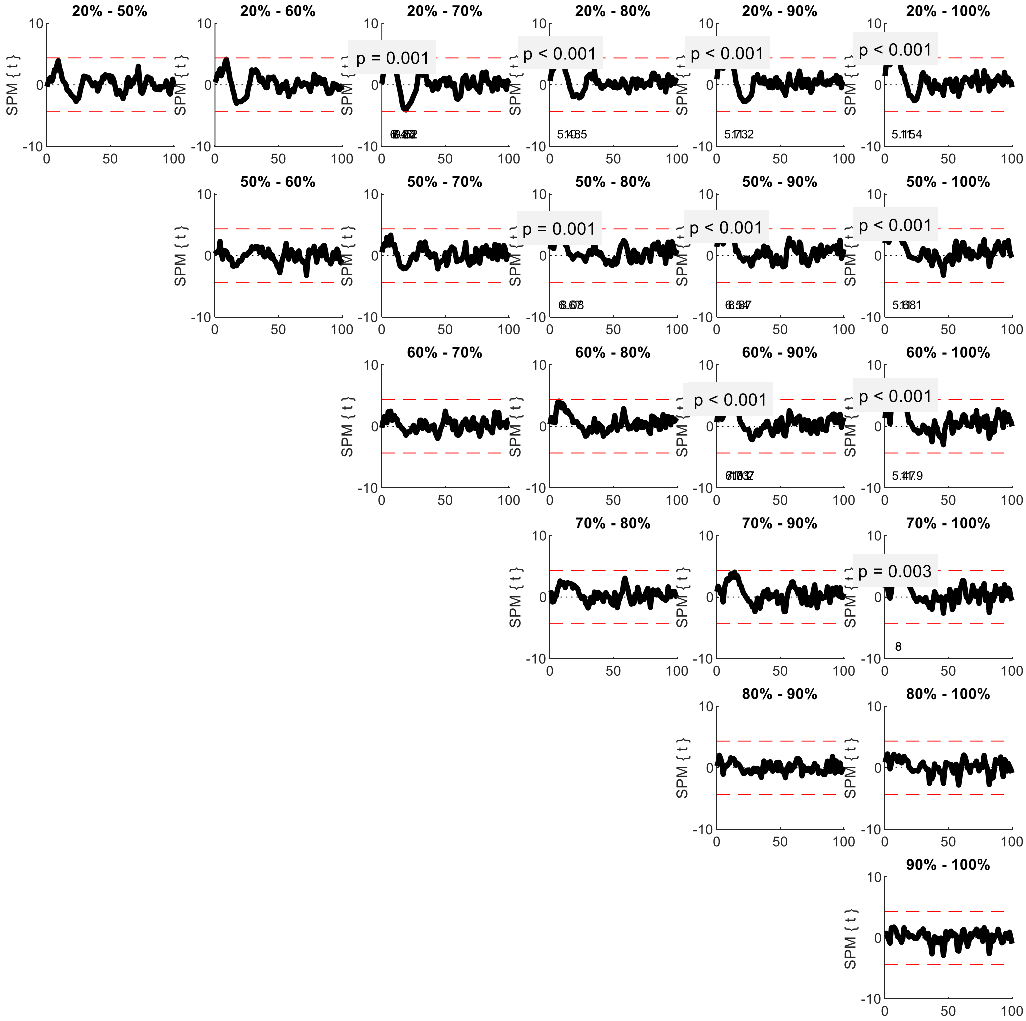
10. MLT Angle Y



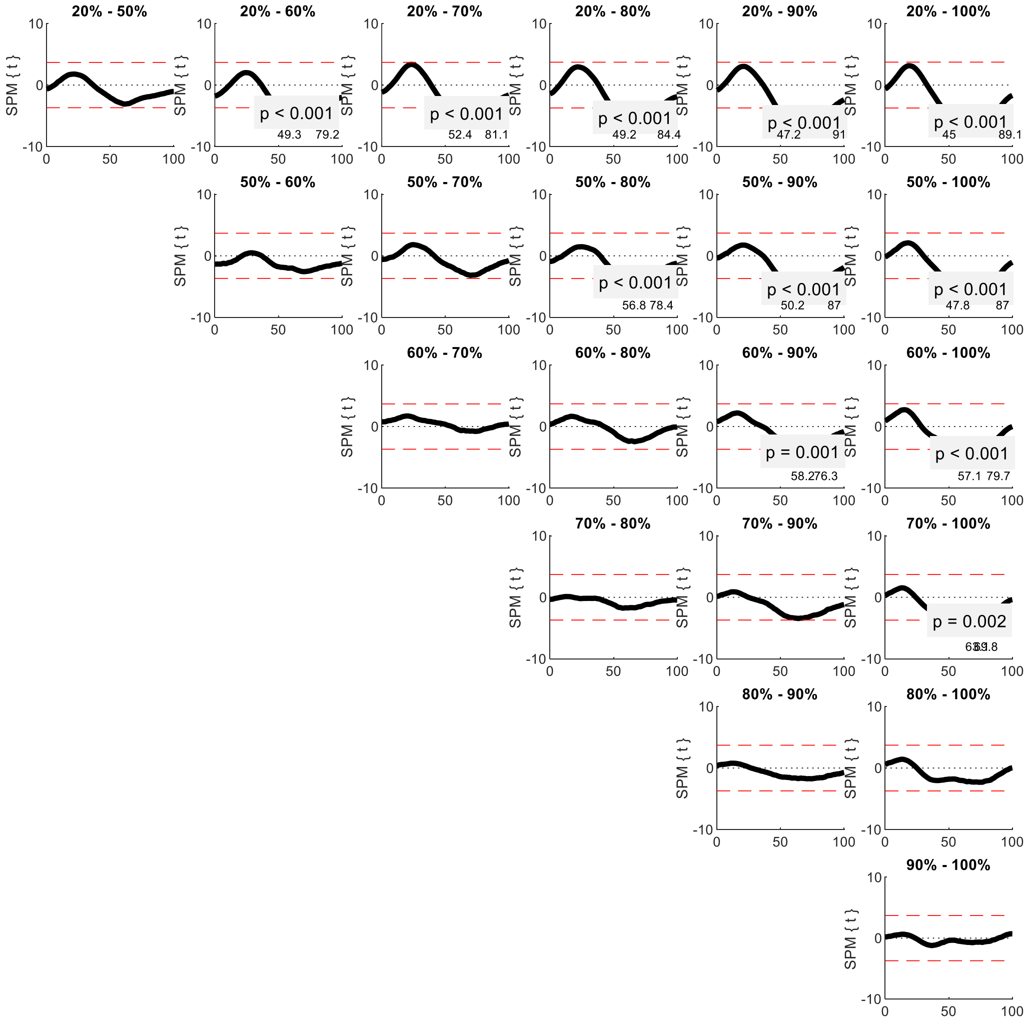
11. MLT AngVel Y



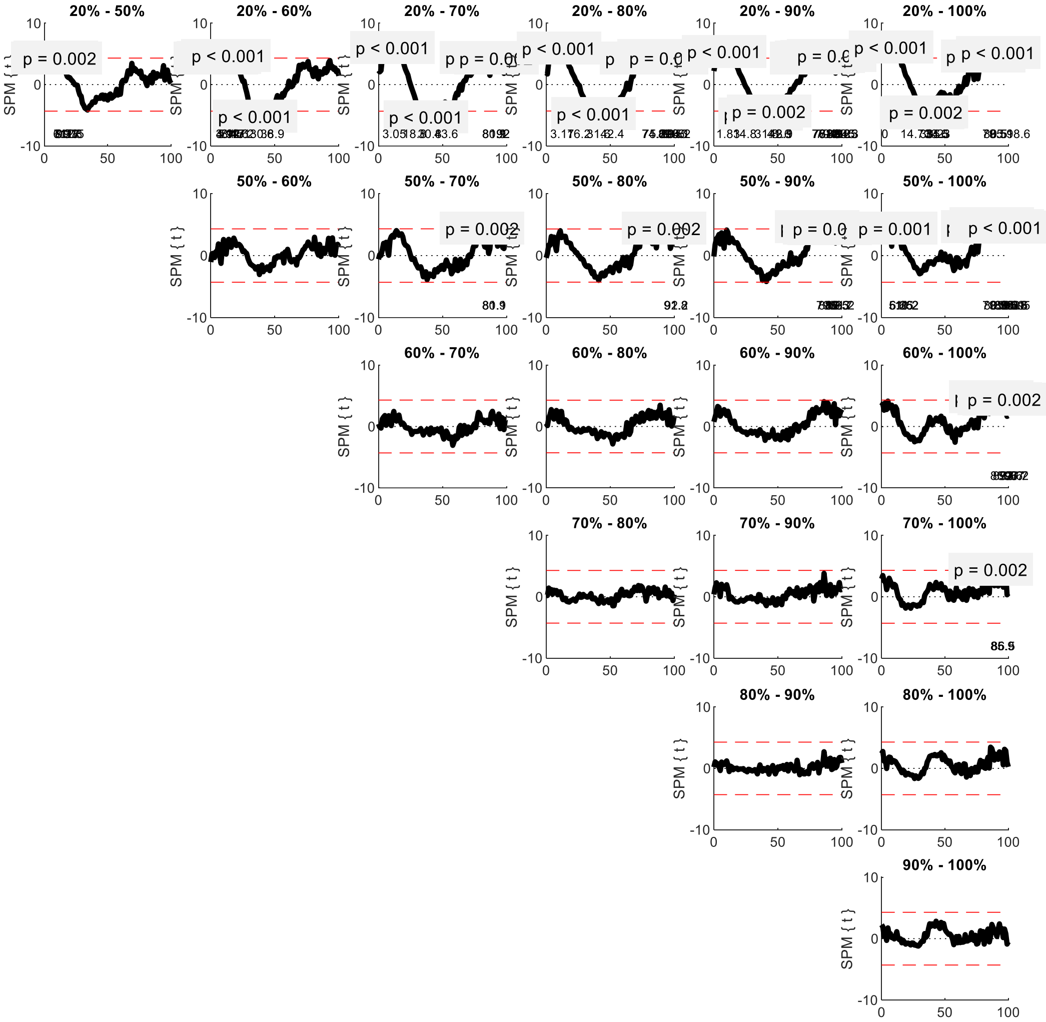
12. LT Acc Z


20% - 50%
20% - 60%
20% - 70%
p = 0.001
20% - 80%
p < 0.001
20% - 90%
p < 0.001
20% - 100%
p < 0.001
50% - 60%
50% - 70%
50% - 80%
p = 0.001
50% - 90%
p < 0.001
50% - 100%
p < 0.001
60% - 70%
60% - 80%
60% - 90%
p < 0.001
60% - 100%
p < 0.001
70% - 80%
70% - 90%
70% - 100%
p = 0.003
80% - 90%
80% - 100%
90% - 100%
SPM {t}
10
0
-10
0
50
100

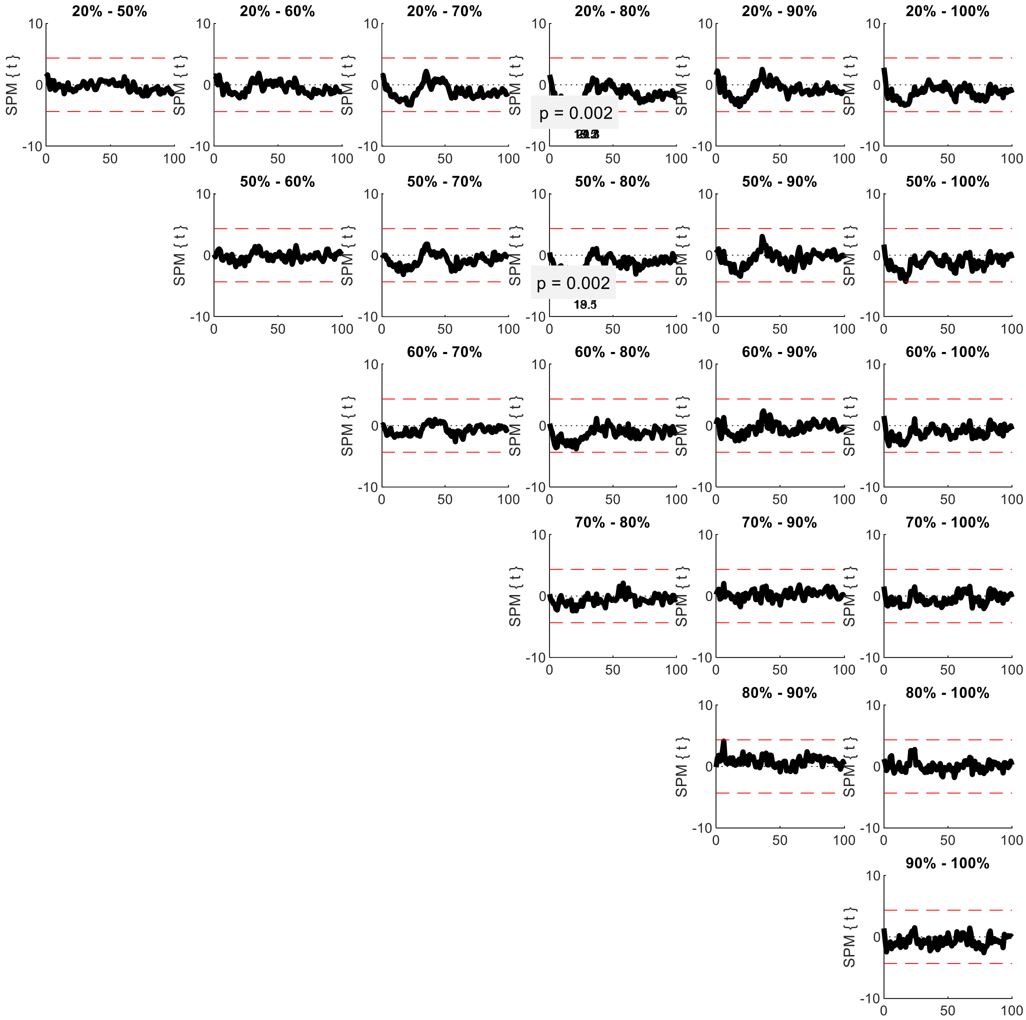
13. LT Angle Y


20% - 50%
20% - 60%
p < 0.001
49.3 79.2
20% - 70%
p < 0.001
52.4 81.1
20% - 80%
p < 0.001
49.2 84.4
20% - 90%
p < 0.001
47.2 91
20% - 100%
p < 0.001
45 89.1
50% - 60%
50% - 70%
50% - 80%
p < 0.001
56.8 78.4
50% - 90%
p < 0.001
50.2 87
50% - 100%
p < 0.001
47.8 87
60% - 70%
60% - 80%
60% - 90%
p = 0.001
58.276.3
60% - 100%
p < 0.001
57.1 79.7
70% - 80%
70% - 90%
70% - 100%
p = 0.002
80% - 90%
80% - 100%
90% - 100%
SPM {t}
10
0
-10
0
50
100

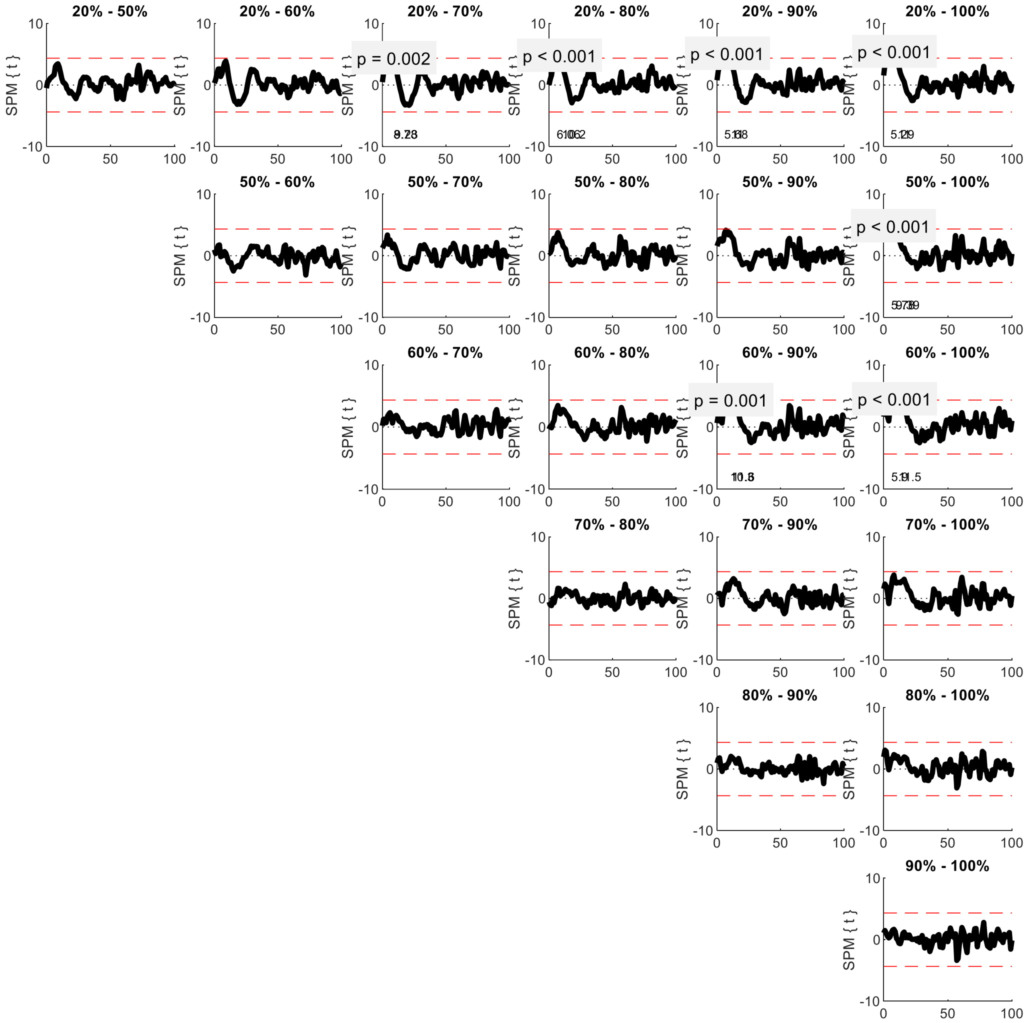
14. LT AngVel Y



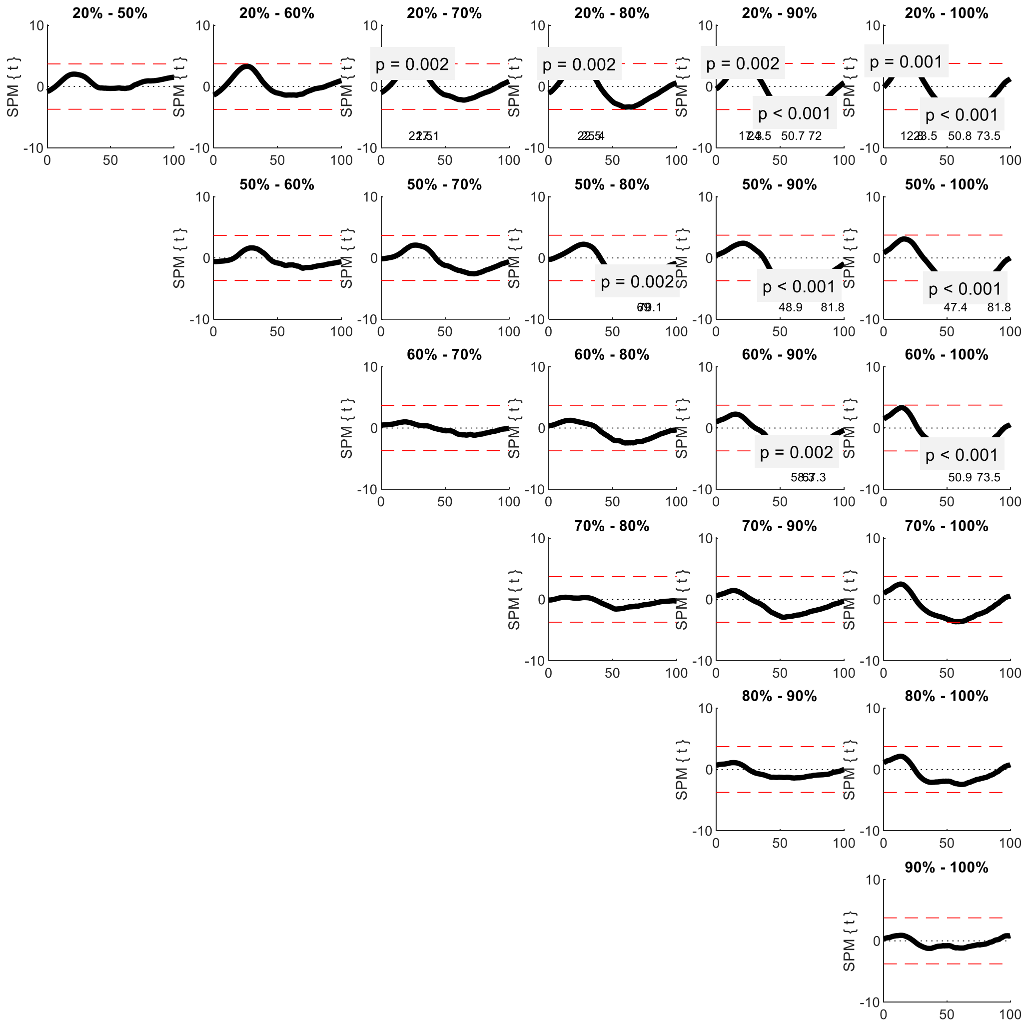
15. UL Acc X


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}
p = 0.002
p = 0.002
19.5

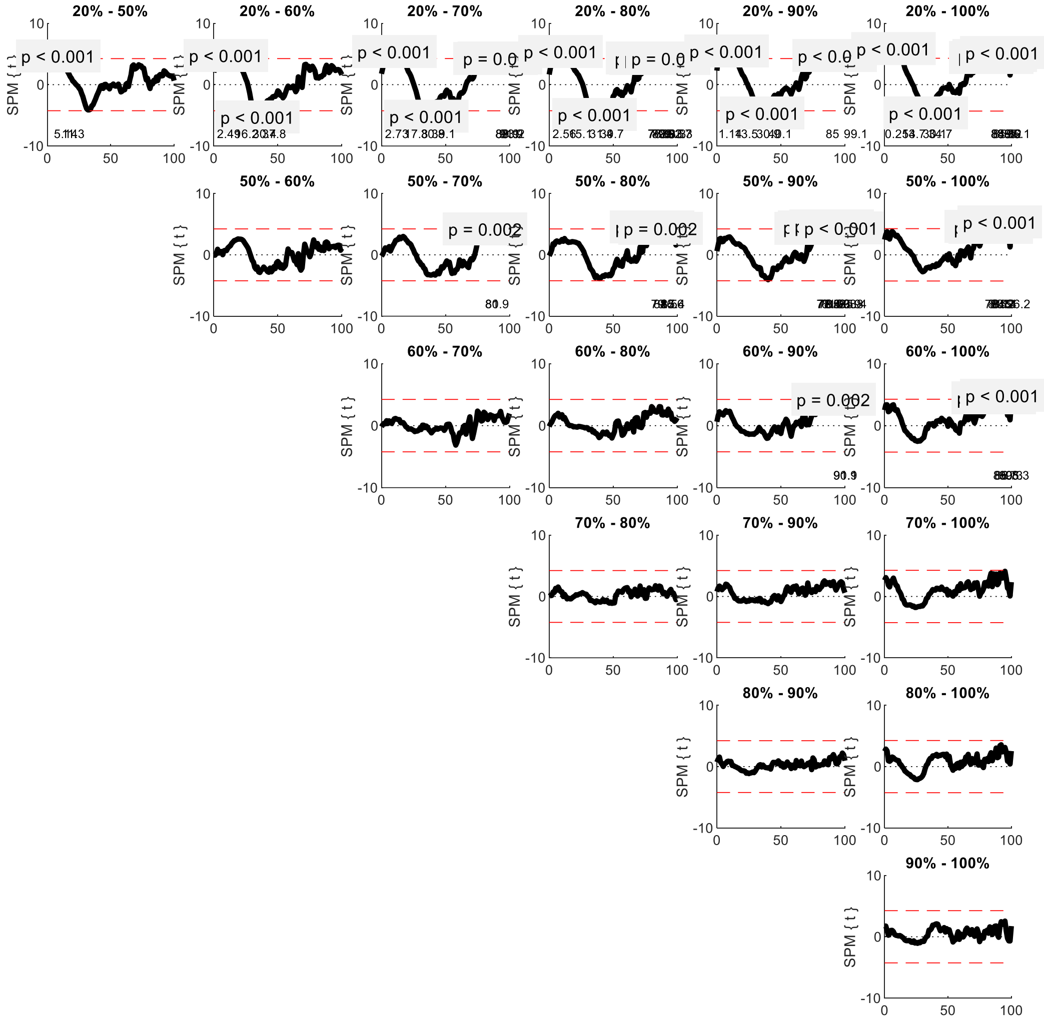
16. UL Acc Z


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}
p = 0.002
p < 0.001
p < 0.001
p < 0.001
p < 0.001
p = 0.001
p < 0.001

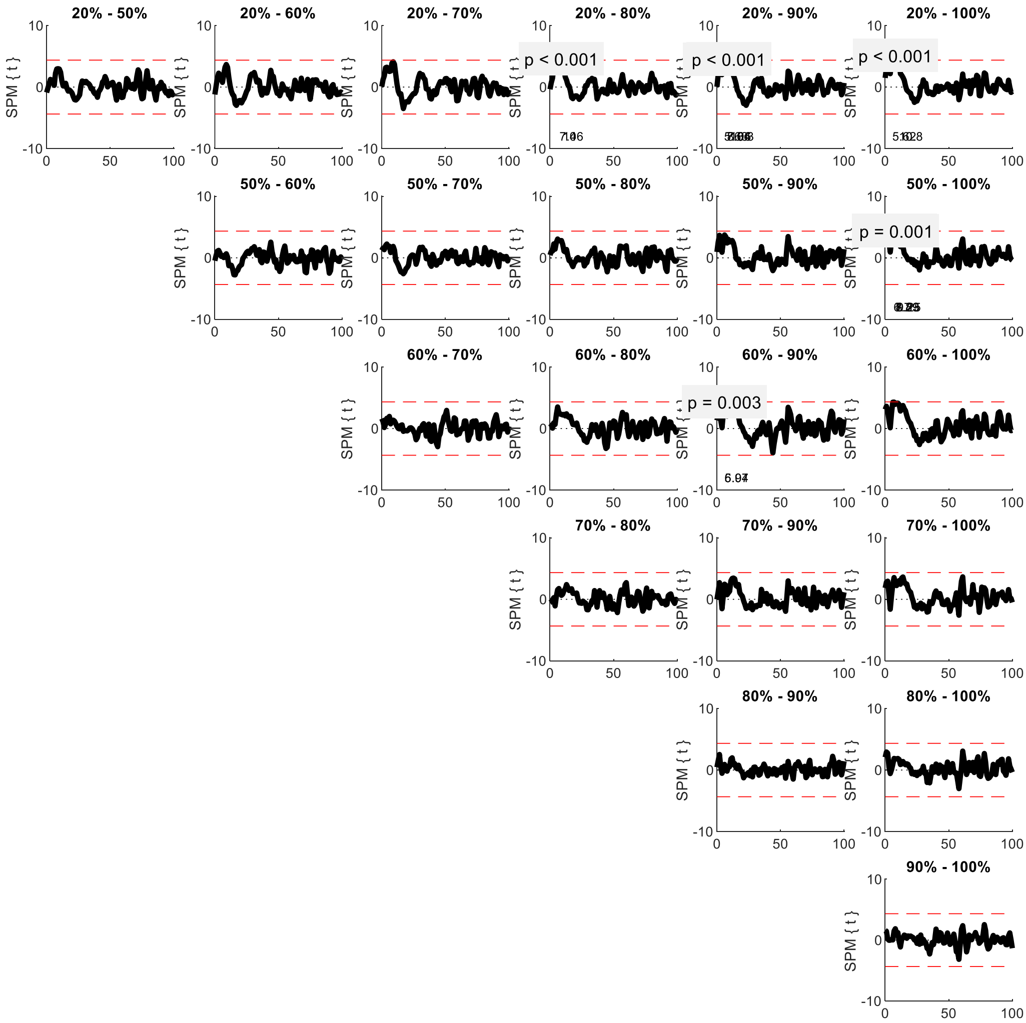
17. UL Angle Y


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM { t }
p = 0.002
p = 0.001
p < 0.001
50.7 72
50.8 73.5
48.9 81.8
47.4 81.8
50.9 73.5

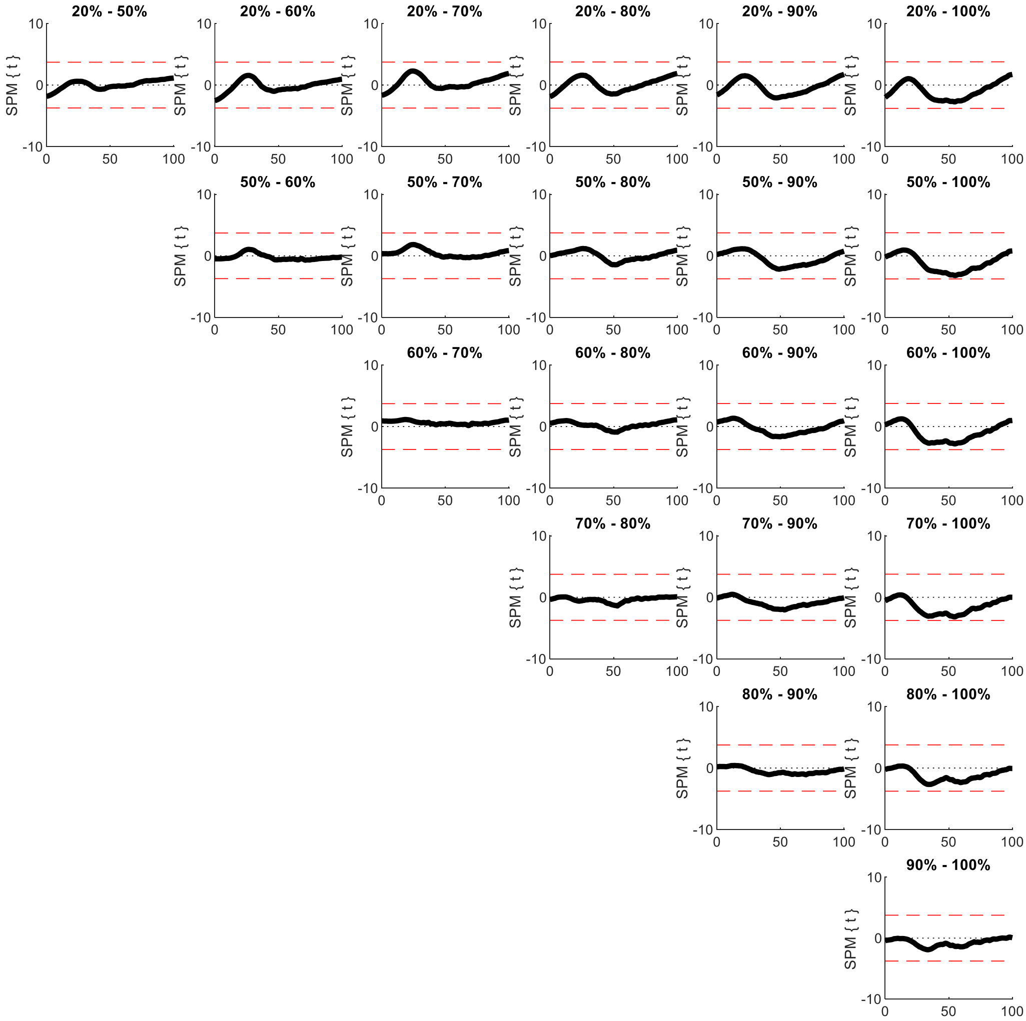
18. UL AngVel Y



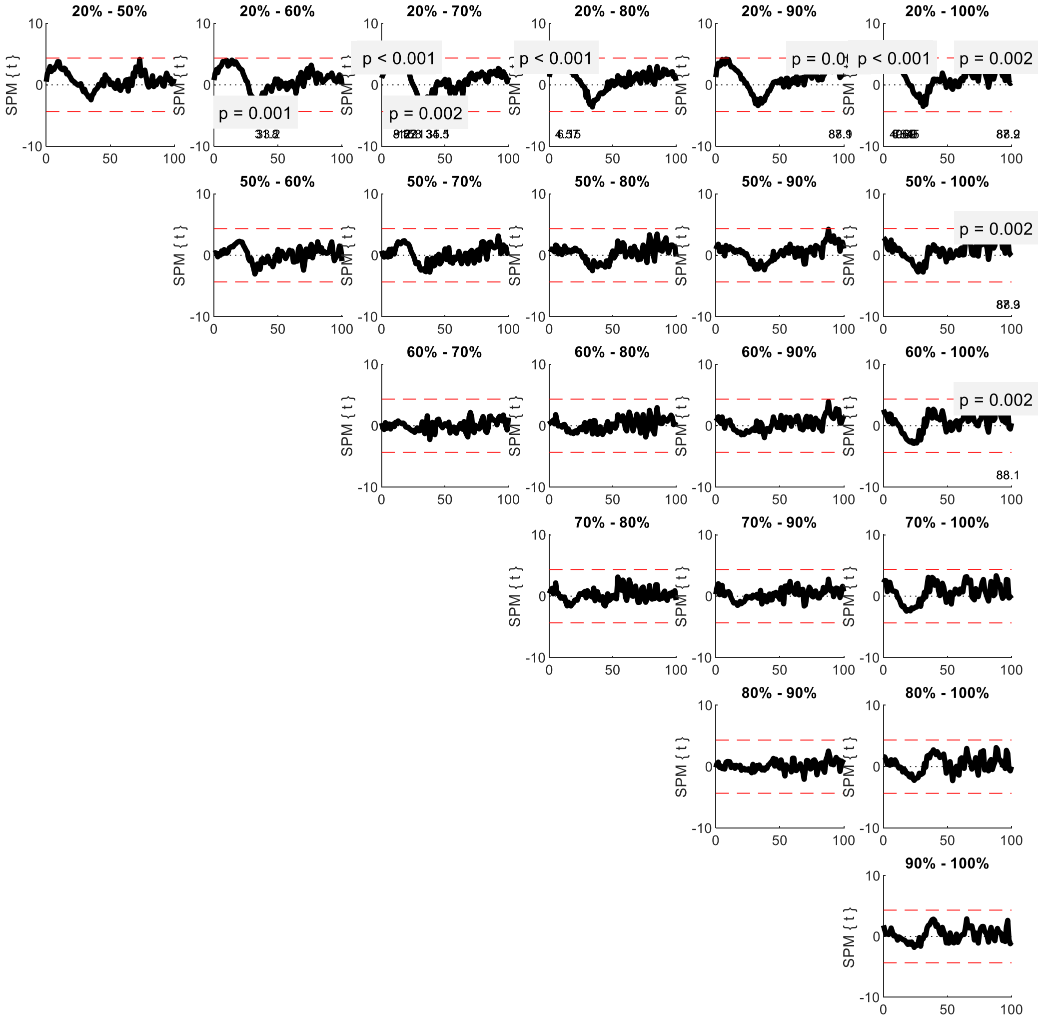
19. LL Acc Z


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}
p < 0.001
p < 0.001
p < 0.001
p = 0.001
p = 0.003

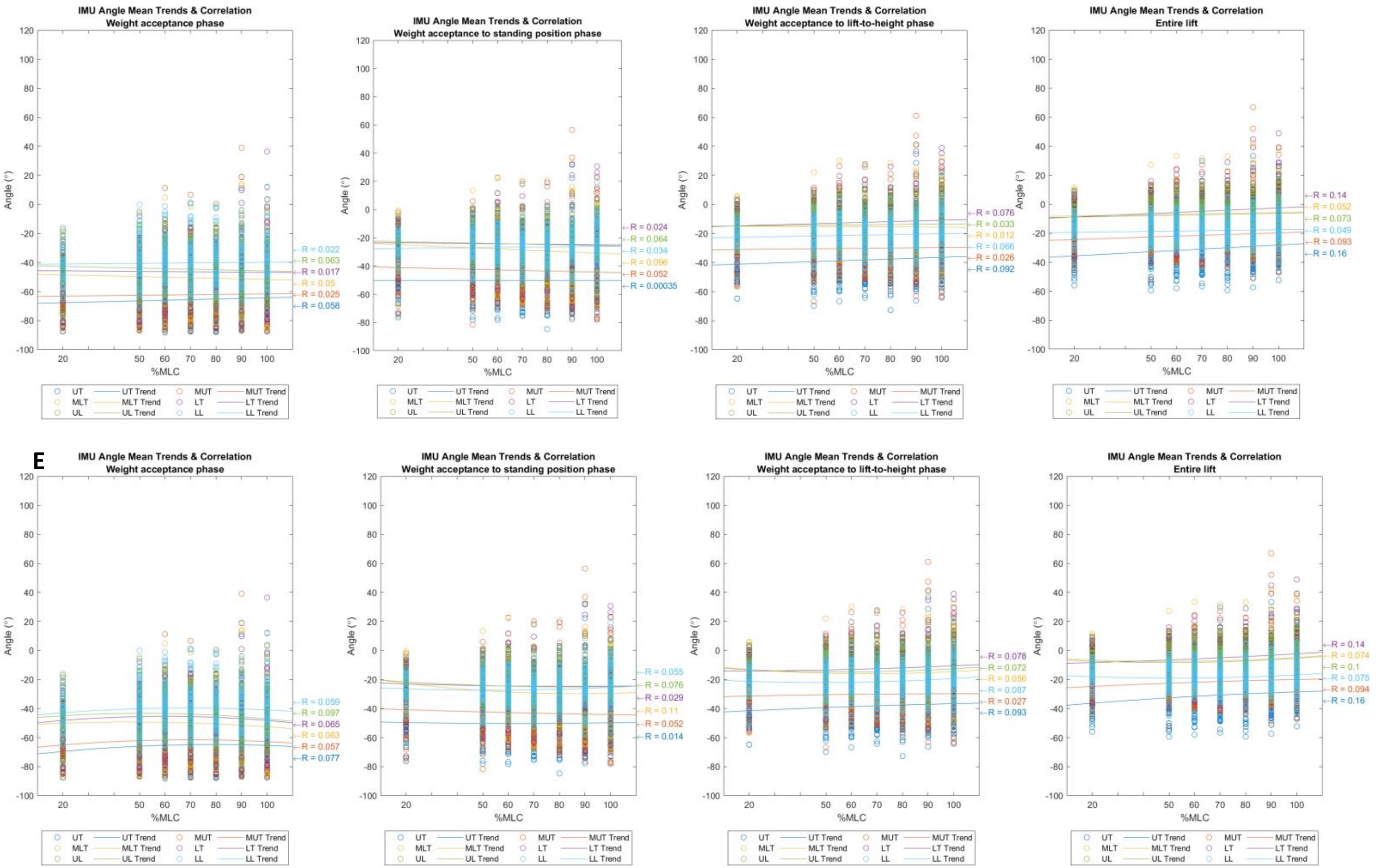
20. LL Angle Y


20% - 50%
20% - 60%
20% - 70%
20% - 80%
20% - 90%
20% - 100%
50% - 60%
50% - 70%
50% - 80%
50% - 90%
50% - 100%
60% - 70%
60% - 80%
60% - 90%
60% - 100%
70% - 80%
70% - 90%
70% - 100%
80% - 90%
80% - 100%
90% - 100%
SPM {t}
10
0
-10
0
50
100

21. LL AngVel Y



Appendix G - Linear & Polynomial correlation of mean angle



Linear & Polynomial correlation of mean angle during lifting phases.

Appendix H - Machine Learning Algorithm Parameters

Method	Parameters
Time Series Forest Classifier	min_interval = 10, n_estimators = 500, n_jobs = -1
Random Interval Spectral Ensemble	n_estimators = 500, n_jobs = -1
Supervised Time Series Forest	n_estimators = 500, n_jobs = -1
Column Ensemble Classifier	TimeSeriesForestClassifier (n_estimators = 500, n_jobs = -1) BOSSEnsemble (max_ensemble_size = 5)
Individual BOSS	n_jobs = -1
Contractable BOSS	n_jobs = -1
WEASEL	window_inc = 4
MUSE	window_inc = 4, n_jobs = -1
Individual TDE	n_jobs = -1
K-Neighbors Time Series Classifier	-
Proximity Tree	n_jobs = -1
Proximity Stump	n_jobs = -1
Canonical Interval Forest	n_estimators = 500, n_jobs = -1
DrCIF	n_estimators = 500, n_jobs = -1
Shapelet Transform Classifier	n_jobs = -1
Arsenal	n_jobs = -1
ROCKET Classifier	n_jobs = -1

Appendix I - Machine Learning Algorithm Results

Method	Balanced Accuracy	Average Precision	f1-score
Time Series Forest Classifier	0.869	0.863	0.889
Random Interval Spectral Ensemble	0.833	0.825	0.865
Supervised Time Series Forest	0.884	0.877	0.903
Column Ensemble Classifier	0.774	0.776	0.807
Individual BOSS	0.627	0.663	0.690
Contractable BOSS	0.773	0.765	0.842
WEASEL	0.802	0.801	0.829
MUSE	0.845	0.842	0.865
Individual TDE	0.722	0.730	0.781
K-Neighbors Time Series Classifier	0.763	0.760	0.825
Proximity Tree	0.612	0.653	0.676
Proximity Stump	0.500	0.591	0.000
Canonical Interval Forest	0.890	0.884	0.907
DrCIF	0.895	0.888	0.912
Shapelet Transform Classifier	0.827	0.819	0.861
Arsenal	0.878	0.870	0.899
ROCKET Classifier	0.912	0.907	0.924