# Understanding Personal Determinants of Lifting Strategy to Inform Movement-Focused Ergonomic Interventions

by

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## Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

**Abstract**

Introduction:

Lift training interventions are needed to reduce risk in jobs with non-modifiable demands, but to date have been generally ineffective. The lack of lift training effectiveness has been partially attributed to insufficient quality of content in the training programs. One way to improve the effectiveness of future lift training interventions may be to first understand what factors influence how a lifter chooses to move in the workplace (i.e., root causes). Previous research has identified that some lifters seem to consistently minimize resultant biomechanical exposures at the low back, but it is unclear why. If we can understand what personal factors influence how a lifter moves, lift training may be better targeted to address modifiable personal factors to minimize exposures during lifting.

The overarching objective of this thesis was to quantify the variability in low back exposures during lifting and to further determine if variability could be explained by personal factors including ability to perceive proprioceptive information, expertise, and a range of structural (i.e., body mass and stature) and functional (i.e., strength and flexibility) factors. With this understanding, I then aimed to identify which modifiable personal factors have the greatest prospective benefit of biasing a lifter to adopt a movement strategy with lower resultant biomechanical exposures using a computational modelling approach. The impetus for this thesis is to develop critical evidence as needed to inform the development of future, more efficacious lift training interventions.

Methods:

A cross-sectional between-subjects experimental design was used to address the thesis objectives. A sample of 72 participants were recruited to perform a lifting protocol consisting of both job-specific and generic lifting tasks. Purposive sampling was used to recruit participants with a range of experience and demographics. Ability to perceive sensory feedback was assessed using lift force and lift posture matching tests. The average and variability in resultant peak low back compression and A-P shear force, as well as kinematic features of whole-body movement strategy, during lifting were quantified as dependent variables. Consistently lower magnitudes of biomechanical exposures within a personal factor group would support that this group defines a movement objective that aims to minimize resultant exposures on the low back.

Using the experimentally obtained data, a probabilistic model was then developed that predicts the range of movement strategies and corresponding biomechanical exposures that are likely given a combination of underlying personal factors. Simulations were run to determine if improvements in any of ability to perceive sensory feedback, expertise, flexibility and/or strength capacity resulted in predicted reductions of low back exposure magnitude. Simulations were also conducted across a range of non-modifiable structural factors (i.e., sex, stature, and body mass)

to evaluate whether the prospective benefit of improving modifiable factors to reduce low back exposures is generalizable across a working population.

Results:

Ability to perceive proprioceptive information (both force- and posture-sense) was associated with lower average and variability of low back loads. This suggests that individuals with better ability to perceive proprioceptive information may be more likely to define a movement objective to consistently minimize exposures. Albeit small effect sizes were observed with a maximum of 16% of variance in low back loads explained by proprioceptive ability.

Both structural and functional factors were significant predictors of average peak low back loads in lifting. However, except for females having lower variability in exposures than males, no other associations of personal factors to variability in loads was observed. These findings support that the investigated structural and functional factors can bias the range of available movement strategies to lifters, but don’t necessarily influence towards a movement objective aiming to minimize low back loading.

No differences in average or variability in peak low back loads were observed across expertise groups. While this finding highlights that expertise doesn’t seem to influence resultant exposures in lifting, differences in lifting kinematics were observed across groups suggesting other movement objectives may be defined as a function of expertise.

The prospective ability of reducing peak low back loads by improving modifiable personal factors was assessed using the developed probabilistic model. While improving proprioceptive ability, functional knee range of motion and strength were statistically associated with reducing low back loads, only improving functional knee range of motion was interpreted to have clinically significant effects on reducing low back loads during lifting.

Conclusion:

In this thesis the variance in peak low back loads during lifting that could be explained independently and inter-dependently by personal factors was investigated. These findings have implications for the development of future lift training interventions where improvements to functional knee range of motion may lead to retained lifting behaviour changes to reduce resultant peak low back loads during lifting. Secondary benefits may also come from improving proprioceptive ability and strength. Future lift training interventions can be developed to leverage these findings in practice where these results support that improvements to underlying flexibility, strength and proprioceptive ability seem to be important factors allowing individuals to adopt lower exposure lifting strategy.

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## List of Abbreviations

3D – Three-Dimensional

A-P – Antero-posterior

ANOVA – Analysis of Variance

CNS – Central Nervous System

fROM – Functional Range of Motion

MSD – Musculoskeletal Disorder

OFC – Optimal Feedback Control

PCA – Principal Component Analysis

PC – Principal Component

PDF – Probability Distribution Function

SME – Single Muscle Equivalent

VIF – Variance Inflation Factor

# Chapter 1: Introduction

## *1.1 General*

Heavy lifting is a biomechanical risk factor for work-related musculoskeletal disorders (MSDs) (da Costa & Vieira, 2010). Occupational lifting with high load mass or frequency can increase MSD risk where resultant compressive and antero-posterior (A-P) shear loads on the spine can exceed injury risk guidelines (Waters et al., 1993; Gallagher & Marras, 2012). Additionally, lifting can increase exposure to kinematic MSD risk factors including magnitudes of spine flexion (Marras et al., 1993) or trunk extension velocities (Norman et al., 1998).

Ergonomic interventions can be implemented to reduce resultant biomechanical exposures on workers to achieve the goal of reducing injury risk associated with high manual material handling demands. In the hierarchy of ergonomic controls, the elimination of physical demands through engineering solutions for example, is recommended as the most efficacious intervention strategy (Centers for Disease Control and Prevention, 2015). As an example, the success of such interventions has been documented in the paramedic work force where powered stretchers have been shown to reduce peak and cumulative spine and shoulder loads compared to manual stretcher use (Lad et al., 2018), and reduced the incidence of MSDs following implementation to practice (Armstrong et al., 2017; Studnek et al., 2012; Fredericks et al., 2009).

While the implementation of engineering solutions to either reduce or eliminate the physical demands of work is an effective ergonomic strategy, these interventions are not always economically or practically feasible. In such instances ergonomic interventions that aim to intervene on the worker, opposed to the workplace, may help to minimize exposure and therefore injury risk (McGill, 2009). A lab-based study by Kingma et al. (2004) reinforce the potential for movement focused training where they reported differences in net low back moments and compression forces between squat and stoop lifting strategies. While addressing movement strategy in prospective ergonomic interventions is a potentially efficacious approach, there is currently little support for this in the literature where a single best lifting strategy has not been identified (van Dieën et al., 1999; Straker, 2002; Straker, 2003a; Straker, 2003b) and to date lift training interventions have not resulted in reductions of injury incidence (Martimo et al., 2008). This presents as a research gap where there is an understanding that movement strategy influences resultant low back loading in lifting, but no corresponding impactful translation of this understanding into the implementation of successful movement-based ergonomic interventions. Bridging this gap challenges us to better understand personal determinants of lifting strategy during lifting performance as a precursor to developing movement-focused interventions.

Conceptualizing occupational movement within a motor control framework can provide insight to understand personal determinants of lifting. The underlying determinants of movement can be considered by using a theoretical framework, informed by a motor control-based perspective, where interacting constraints influence the definition of a motor control objective, that in turn defines a resultant movement strategy (Armstrong & Fischer, 2020) (Figure 1-1). The resultant movement strategy aims to achieve the motor control objective, but also has consequences in terms of resultant exposure on the body. This proposed theoretical model to understand the determinants of lifting is based on foundational work by Newell (1986), where he hypothesized that an interaction of constraints including personal characteristics, task objectives and environmental factors would influence the resultant coordination and control of movement. More recently, it has been proposed that a model of internal control is also necessary to explain how the interaction of constraints influences resultant coordination and control (Glazier, 2017). I have proposed that Optimal Feedback Control (OFC) theory (Todorov, 2004; Scott, 2004) could be that internal model of control (Armstrong & Fischer, 2020). OFC is compatible with Newell's (1986) hypothesis where based on a given combination of constraints (as suggested by Newell, 1986), an individual will define a unique control law (i.e., movement objective). Based on a defined movement objective, aspects of movement variability related to defined task outcomes will be monitored via relevant sensory feedback and controlled to maintain performance. Meanwhile, aspects of movement variability not relating to performance will be left uncontrolled (Todorov & Jordan, 2002; Todorov & Jordan, 2003). Within this theoretical framework, I postulate that some individuals may define a movement objective that not only operationalizes task performance goals, but also aims to minimize resultant exposure on the body as an injury prevention strategy (Armstrong & Fischer, 2020). Findings from my previous research support the hypothesis that some lifters adopt strategies that minimize biomechanical exposure at the low back, where others do not (Armstrong & Fischer, 2020). However, the reason why some do and do not consider biomechanical exposure remains unknown, in turn limiting the ability to design efficacious interventions. Strengthening our understanding of personal determinants of lifting can provide insight to help us better understand why some lifters do and others do not seem to consider biomechanical exposure when lifting.

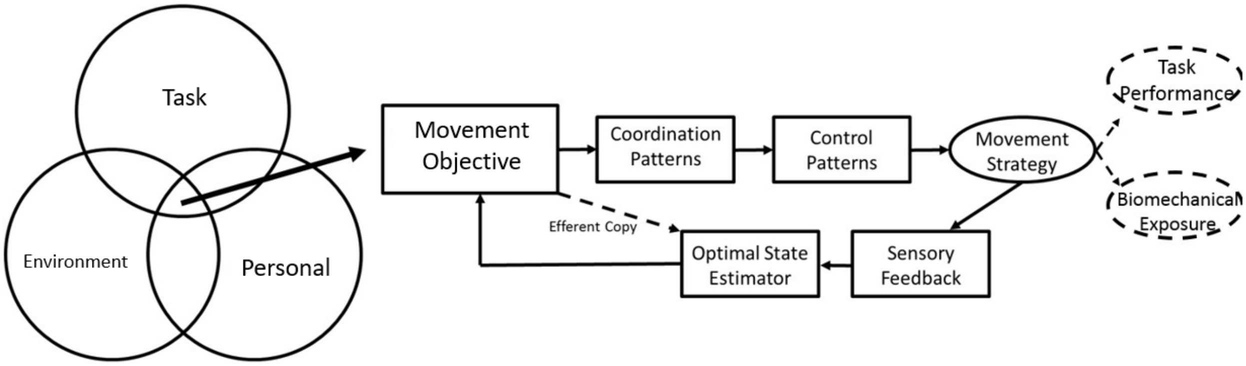


**Figure 1-1:** Theoretical framework of the control of movement strategy where movement objectives are defined in the Optimal Feedback Control Law, as informed by interacting work-demand, environment, and personal constraints.

While the interaction of person, task, and environment constraints on the definition of motor control objectives in lifting are unknown, the most prudent research approach for ergonomics applications is to investigate the influence of personal determinants of lifting strategy. Previous work has demonstrated that changes in task demands, such as lift heights, influences low back and knee flexion angles (Kingma et al., 2004) and resultant low back moments (Hoozemans et al., 2008). Additionally, both physical barriers (Zehr et al., 2018) and lifting on a simulated marine vessel (Holmes et al., 2008; Ning & Mirka, 2010), examples environment constraints, have been shown to influence lifting strategy. However, with a goal of understanding determinants of lifting to inform the development of worker-focused ergonomic interventions personal constraints are likely the most important to consider. If modifiable personal factors influence lifting strategy, then they may be improved as a proactive strategy to reduce the biomechanical demands associated with lifting. Additionally, if movement-based ergonomic interventions are needed to improve lifting strategy, it is likely that the task objectives and work environment are non-modifiable for essential work tasks. However, by identifying modifiable personal factors that are associated with higher exposure lifting strategies, future training interventions can be developed that aim to address these factors and reduce exposure.

Strengthening our understanding of modifiable personal determinants of lifting is broadly important to inform movement-focused interventions. This is particularly important for occupations with non-modifiable heavy lifting demands, such as paramedicine. From a practical perspective, paramedics have the highest incidence of MSDs by work sector (Maguire et al., 2005; Maguire et al., 2014), highlighting the need for ergonomic intervention. Additionally, paramedics perform a high number of essential lifting tasks (Coffey et al., 2016; Fischer et al., 2017), where the resultant exposures on the low back can greatly exceed injury risk thresholds for compressive force on the spine (Armstrong et al., 2020). Also, the physical demand imposed by the need to move patients can not be eliminated by engineering interventions at this time as there is an existing need for paramedics to lift patients from low lying positions onto conveyance devices. To address the heavy demands of paramedic work, lift training that aims to improve a worker's lifting capacity (i.e., underlying strength) and/or competency (i.e., how well a worker moves) can potentially be used to improve movement mechanics. However, the effectiveness of such training interventions could be improved by training to modify personal factors that influence a lifter to consider minimizing resultant biomechanical exposure in their movement objectives.

Acknowledging that non-modifiable differences exist in worker demographics (i.e., sex, body mass, and stature), the prospective benefit of lift training which targets modifiable factors should be evaluated across a diverse sample with varying non-modifiable attributes. This is an important consideration because even though some individuals may attempt to minimize exposures within their movement objectives, their ability to execute this objective may be limited by constraints imposed by non-modifiable features. For example, lifters with greater central adiposity may be unable to minimize the horizontal distance of the load to the body, which is known to influence low back loads (Jorgensen et al., 1999; Kerr et al., 2001). This need motivates investigating the influence of non-modifiable personal factors on lifting strategy to understand whether prospective benefits of improving personal modifiable factors are generalizable across sub-groups of the working population.

*1.2 Personal Determinants of Movement Strategy Worth Investigating*

A first potential determinant of lifting strategy to prioritize investigating is the influence of a lifter's ability to perceive sensory information at the low back. Within the OFC framework, sensory feedback plays a pivotal role in modifying movement strategy online to maintain task-relevant movement (Scott, 2004; Todorov, 2004). It is possible that some individuals may define a movement objective that aims to minimize the resultant biomechanical exposure to their low back when lifting, but due to an inability to perceive relevant sensory information, those lifters are unable to achieve this defined objective. Proprioceptive ability includes both abilities to perceive force and posture in the body (Proske & Gandevia, 2012). With both postural and force-generation demands in lifting, proprioception is a relevant mode of sensory information that is likely relied upon to maintain lifting performance. The potential clinical relevance of ability to perceive proprioceptive information as a determinant of lifting strategy is supported by individuals with low back pain having lower posture-sense proprioceptive ability as measured by a motion perception task (Lee et al., 2010), and active trunk repositioning proprioceptive ability of the trunk being a predictor of knee injuries in female collegiate athletes (Zazulak et al., 2007).

Considering modifiable factors, expertise is a potential personal determinant of lifting strategy to investigate. When manual materials handling experience has been investigated as a personal determinant of lifting strategy experts tend to have less low back flexion and more knee flexion in lifting (Plamondon et al., 2014b; Plamondon et al., 2012). However, in a separate study, experts had greater spine loads compared to novice lifters (Granata et al. 1999), but the higher resultant loads may be to prioritize greater dynamic balance (Lee & Nussbaum, 2014). While some studies have reported on the effect of experience on lifting strategy, the type of experience was limited to a measure of time on the job. Additionally, previous research on the effect of expertise on lifting has not considered theoretical knowledge on lifting mechanics where for example, ergonomists and injury prevention professionals have demonstrated lower low back loading in lifting than untrained individuals (Abdoli-Eramaki et al., 2019). While theoretical understanding of lifting mechanics has been shown to influence self-selected lifting strategy, no previous research has differentiated the effects of contextual and theoretical expertise on lifting strategy. While the differential influence of theoretical and contextual expertise has not been identified, evidence for potential differences is supported by lift training incorporating augmented feedback having greater influence in reducing spine motion in practiced tasks compared to instructional training alone (Chan et al., 2022). Consistent with the overarching theoretical framework, it is possible that contextual expertise may help lifters better perceive sensory information to more likely define a movement objective that aims to minimize biomechanical exposures for example. Conversely, theoretical expertise may not result in a movement objective that aims to minimize exposure, although conceptually they understand how to move to minimize exposure. By identifying the specific influence of either contextual or theoretical expertise on lifting strategy there may be direct implications for the development of lifting training programs.

Structural factors, such as sex, body mass and stature, as well as functional factors such as strength capacity and flexibility, are final examples of personal determinants of lifting strategy worth investigating. Considering previous research, the influence of sex on lifting strategy has been explored where women tend to use a more leg driven strategy compared to men, who tend to lift with their back (Li & Zhang, 2009; Marras et al., 2003). As a result, women tend to exhibit lower absolute compressive spine loads (Marras et al., 2002), lower absolute peak L5/S1 moments (Plamondon et al., 2014a) and more neutral spine angles (Makhoul et al., 2017). However, when the mass of the load is scaled to participants' capacity no differences in lifting strategy between sex groups were observed (Albert et al., 2008; Sadler et al., 2011), suggesting that reported differences in lifting strategy between males and females are attributable to underlying strength differences. With no reported differences in lifting strategy between males and females when the mass of the load is scaled to capacity, it is unclear if sex differences influence the movement strategy used in lifting independent of other factors. However, structural differences in morphology are known to exist between males and females including differences in hip Q angle (Wilson & Davis, 2008), pelvis morphology (Patriquin et al., 2003) and trunk geometry (Marras et al., 2001), which could have unreported effects on resultant lifting strategy.

Further, differences in body mass, stature or flexibility could constrain the range of movement strategies available to a lifter, while not directly influencing the underlying movement objectives. Considering the influence of these structural and functional personal factors, they likely influence the range of movement strategies available to lifters (as quantified by differences in means of movement kinematics), without necessarily influencing their movement objectives (as inferred considering both mean and variability in movement kinematics). By constraining the range of available movement strategies available to a lifter these factors would then in turn influence the resultant biomechanical exposures on their low back. The consideration of these structural and functional constraints on lifting strategy is important to the application goal of this thesis where I aim to evaluate the efficacy of training to improve modifiable personal factors as an approach to proactively reduce low back exposures in lifting.

### *1.3 Informing the Development of Efficacious Ergonomic Interventions*

By understanding determinants of lifting strategy, we can evaluate the prospective benefit of improving modifiable personal factors as an approach to proactively reduce low back exposures in lifting. For example, guided by the OFC theoretical framework (Todorov, 2004; Scott, 2004), I have hypothesized that being better able to perceive sensory feedback at the low back may better allow lifters to move in a manner that considers minimizing biomechanical exposures. Preliminary evidence supports that proprioceptive ability can be improved as shown by improvements in passive joint repositioning ability of the trunk after wearing a lumbosacral orthosis were observed (Cholewicki et al., 2006). Alternatively, experience may mediate a lifters ability to perceive sensory information due to implicit learning gained from time spent on the job.

A goal of this thesis was to determine the influence of modifiable and non-modifiable factors on lifting strategy, but further investigation was needed to evaluate whether improving modifiable personal factors could be an efficacious ergonomics approach at a population level. To facilitate this evaluation a statistical model was needed to predict a range of likely movement strategies and resultant exposures based on a subset of personal factors to simulate the effect of manipulating modifiable personal factors on likely low back exposures. When considering the overarching OFC theoretical framework, modelling the inherent variability in human motion (which is known to exist consistent with the minimum intervention principle (Todorov & Jordan, 2002; Todorov & Jordan, 2003)), suggests that a probabilistic model likely has greater internal validity than a deterministic approach. Given the fact that modelling the range of likely movement strategies is conceptually consistent with the overarching OFC framework, developing a model where a user can specify personal factors as inputs to predict the range of likely movement strategies and corresponding peak low back exposures in a floor-to-waist height lift as model outputs was an appropriate solution (Figure 1-2). With this developed model, simulations could be conducted to evaluate the influence of improving modifiable personal input factors (i.e., ability to perceive sensory feedback, strength capacity or flexibility) on reducing population level predicted low back exposures. Secondly, the prospective benefit of improving modifiable personal factors to reduce low back exposures could be evaluated across a range of non-modifiable factors (i.e., sex, stature, and body mass).

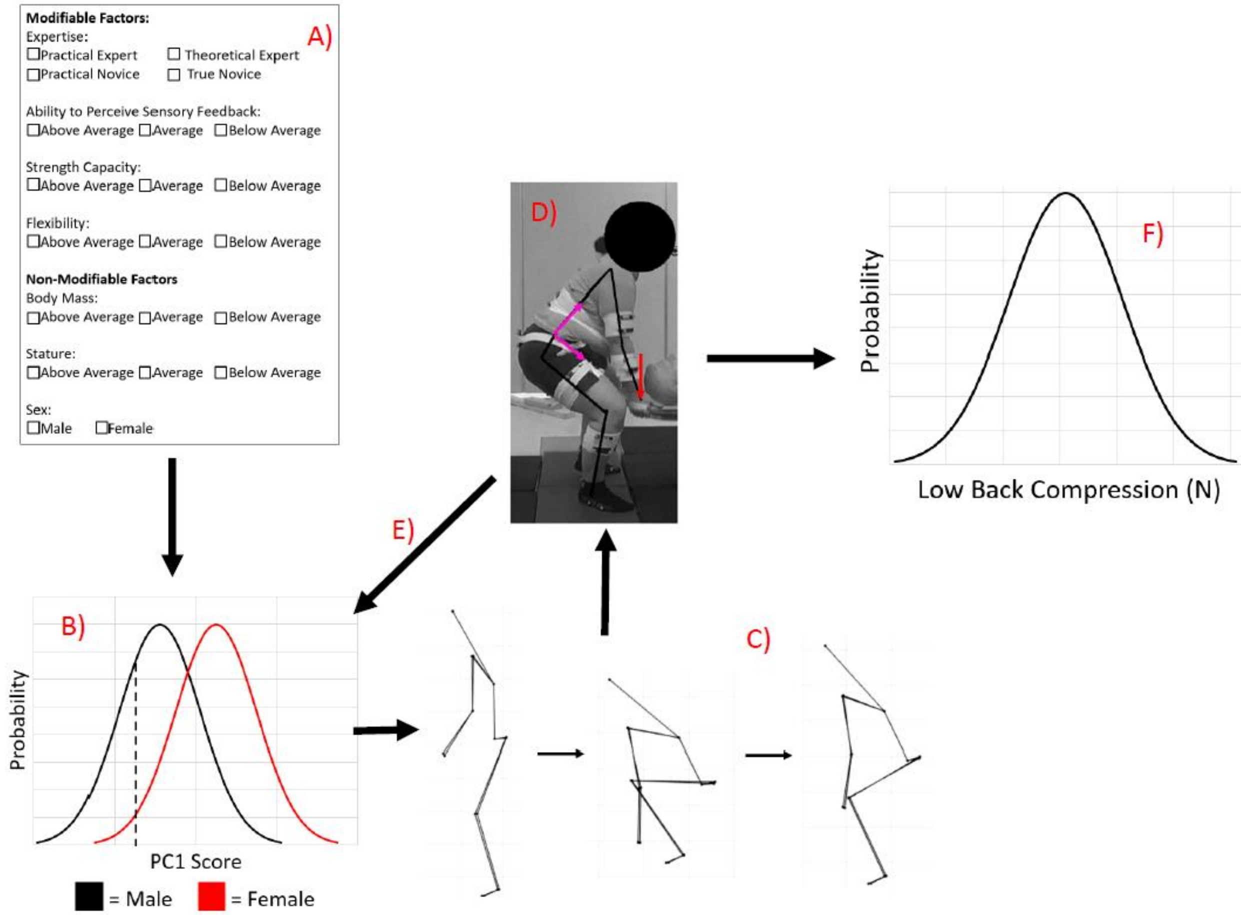


**Figure 1-2:** Overview of probabilistic model processing steps. A) Model input parameters (both modifiable and non-modifiable) are selected. B) For all specified model inputs, kinematic strategies can be generated based on known probability distribution functions of lifting coordination patterns. The dashed line represents an example of a randomly selected principal component score (a measure of kinematic strategy) from the male distribution. C) Based on coordination patterns selected from input factor probability distributions functions, a movement trajectory is generated. D) Known hand loads are applied to the generated movement trajectory to calculate peak low back compression and A-P shear force. E) Processing steps B, C and D are repeated for the specified number of iterations. F) Probability distribution functions of peak low back compression and A-P shear forces are generated as model outcomes.

The model developed in this thesis could provide an *in-silico* approach to test the efficacy of lift training strategies targeted to specific modifiable factors, as well as determine whether these potential benefits are generalizable at a population level across a range of non-modifiable factors. If clinically relevant reductions in predicted low back loads are identified in simulation, then these findings can inform the development of lift training interventions.

### *1.4 Thesis Structure*

This thesis is presented as an initial three background chapters (including an introduction, literature review and overview of thesis objectives), a general methods chapter, a preliminary analysis chapter, four chapters discussing specific studies and a final discussion chapter on the conclusions and impact of this work.

### *1.5 Thesis Objectives and Hypotheses*

The overarching goal of this thesis was to quantify whether variability in low back biomechanical exposures during lifting could be explained independently and/or interdependently by personal factors. Throughout the thesis the term “biomechanical exposures” is used as a reference term for specific measures peak compression force and A-P shear force at the low back. This objective was framed within an OFC theoretical framework to probe whether associations between personal factors and resultant low back loads were attributable to the definition of a motor control objective that aims to consistently minimize exposures when lifting. From these analyses the prospective benefit of improving modifiable personal factors as a proactive ergonomics strategy were investigated.

Since the perception of sensory feedback plays a key role in the OFC closed-loop feedback system the objective of the first study in this thesis was to investigate whether proprioceptive ability (including posture-sense, force-sense, and ability to perceive differences in load mass when lifting) independently and/or interdependently explain variance in peak low back loads and aspects of lifting strategy related to low back loads in generic and paramedic-specific lifting tasks. Second, if significant variance in biomechanical exposures was explained by proprioceptive ability, I aimed to determine whether this was achieved by consistent control of synergistic features of whole-body movement (i.e., kinematic coordination patterns) related to resultant exposures. To address this purpose research questions asked:

1. Does the ability to perceive proprioceptive information explain variance in the average and/or variability of peak low back compression and antero-posterior (A-P) shear forces in both generic (barbell and crate) and occupation-specific (backboard and stretcher) lifting?
2. Does the ability to perceive proprioceptive information explain variance in the average and/or variability of synergistic features of whole-body movement related to biomechanical exposures in both generic (barbell and crate) and occupation-specific (backboard and stretcher) lifting?

   It was hypothesized that lifters who can better perceive sensory information would have lower resultant biomechanical exposures on average, as well as lower variability in both resultant exposures and in features of movement associated with resultant exposures.

To best answer the research questions in study 1 it was important to first determine what measures of proprioceptive ability should be considered as independent variables in study design. This question was answered in a preliminary analysis that is included as Chapter 5.0 in this thesis.

The ability to perceive sensory information at the low back may be influenced by implicit learning gained from experience with manual materials handling tasks. Conversely, explicit learning on lifting mechanics may have a beneficial effect on lifting mechanics without necessarily influencing underlying determinants of movement strategy such as the ability to perceive sensory feedback. Finally, the influence of implicit learning on defining a movement objective may be task dependent where only work specific lifting demands will result in a movement objective that aims to minimize resultant exposures. To address the potential influence of expertise on lifting strategy the purpose of the second study in this thesis was to investigate whether type of expertise influenced biomechanical exposures at the low back or corresponding movement strategy in either occupation-specific or generalized lifting tasks. To address this purpose, I asked the following research questions:

1. Across lifters classified as theoretical experts, contextual experts, and novices, are there differences in either mean or variability in peak low back compression force and anteroposterior (A-P) shear force in lifting?
2. Across lifter expertise groups, are there differences in the mean or variability in synergistic features of whole-body movement (i.e., lifting strategy) that are i) related to low back biomechanical exposures or ii) unrelated to low back biomechanical exposures?
3. Is the effect of expertise on low back biomechanical loading or lifting strategy influenced by the type of load lifted when differentiating between generic and occupation-specific lifts?

   It was hypothesized that both theoretical and contextual experts would demonstrate lower mean biomechanical exposures in both job-specific and generalizable lifting tasks compared to novices. Additionally, it was hypothesized that contextual experts would demonstrate lower variability in biomechanical exposures and features of movement associated with resultant exposures in job-specific lifting tasks compared to theoretical expert and novice groups, suggesting a motor control objective that aims to minimize exposures. Finally, an interaction effect was hypothesized where the benefits of contextual expertise on reducing resultant biomechanical exposures were only anticipated in occupation-specific lifting.

Ability to perceive sensory feedback and expertise were theorized to influence the consideration of biomechanical exposures at the low back within movement objective definition, but this control of movement may be influenced by underlying structural (sex, stature, age, or body mass) or functional (strength capacity or flexibility) personal factors. While perception of sensory feedback and expertise were hypothesized to influence a lifter to minimize resultant exposures, the available lifting strategies allowed by underlying structural and/or functional factors may influence their ability to achieve this goal. The purpose of study 3 in this thesis was to determine how structural and functional personal factors independently and/or interdependently explain variance in peak low back loads and aspects of lifting strategy related to low back loads in generic and occupation-specific lifting tasks. To address this purpose, I asked:

1. Do sex, stature, body mass, age, lower body flexibility, or isometric lift strength explain variance in the mean or variability of peak spine compression and anteroposterior (A-P) shear forces in lifting, and;
2. Do sex, stature, body mass, age, lower body flexibility, or isometric lift strength explain variance in the mean or variability in lifting strategy, as measured by synergistic features of whole-body movement related to biomechanical exposures in lifting?

I hypothesize that differences in mean biomechanical exposures and lifting strategy will be observed as a function of sex, stature, body mass, age, flexibility, and strength capacity because these factors will constrain the available movement strategies to individuals. However, I do not anticipate differences in variability in biomechanical exposures and lifting strategy as a function of any of these independent factors.

Based on the results from these three initial studies, the purpose of the final study in this thesis was to determine which modifiable personal factors have the greatest prospective benefit of reducing exposures at the population level using a simulation approach. To achieve this objective a model was developed that predicts the likely population level range of movement strategies and peak corresponding low back loads given a set of personal factors as model inputs. Using this developed model, I ask:

1. Do modifiable personal factors, including ability to perceive sensory feedback, expertise, strength capacity and flexibility, explain variance in population predicted mean, one standard deviation above the mean, and $95^{th}$ percentile predicted peak compression and A-P shear forces across generic and occupation-specific lifts, and;
2. To what magnitude does improving modifiable personal factors reduce the resultant population predicted peak compression and A-P shear loads?

   I hypothesize that improving all modifiable personal factors will result in reductions in predicted low back loads, with no specific hypotheses on the magnitude of these projected reductions.

*1.6 Relating Thesis Objectives to the Overarching Theoretical Framework*

With a goal of investigating whether combinations of personal factors result in a movement objective that aims to minimize biomechanical exposures in lifting in this thesis, it is important to consider how this would manifest within the context of OFC theory. We have previously demonstrated that some individuals seem to define a movement objective that aims to minimize biomechanical exposures in their control law (Armstrong & Fischer, 2020). For this movement objective it is anticipated that both the mean and variability of biomechanical exposures would be lower. Lower variability of these exposures would be expected because the biomechanical exposure magnitudes would be considered relevant to task performance within the OFC framework, and therefore more tightly controlled (Scott, 2004; Todorov, 2004) consistent with the minimum intervention principle (Todorov & Jordan, 2003). While my previous research highlights that individuals with lower means of biomechanical exposure had corresponding lower variability in exposures (Armstrong & Fischer, 2020), this assumption was investigated within the dataset collected for this thesis to confirm similar trends existed (Appendix A).

If consistently lower biomechanical exposures (i.e., lower means and variability) are observed as a function of personal factors I can further investigate whether kinematic coordination patterns generate these lower resultant magnitudes of exposures as hypothesized in the overarching theoretical OFC model. Principal component analysis (PCA) can be applied as a method to identify kinematic coordination patterns by reducing whole-body kinematic data to independent synergistic features of movement (Federolf, 2016; Armstrong et al., 2021a). Use of this methodology to identify coordination patterns is supported by Todorov (2004) where they suggest that identified principal components (PCs) in underlying muscle electrical activity can be conceptually thought of as 'control knobs' where a subset of these PCs are controlled to maintain task-relevant movement features. If biomechanical exposures are consistently lower within a personal factor group, I can probe whether independent kinematic coordination patterns related to biomechanical exposures, as identified by PCA, are similarly controlled to achieve the resultant lower exposures. With a goal of testing whether personal factors explain consistency and control of low back loads in lifting in this thesis the alignment of independent variables (personal factors) and dependent variables (low back biomechanical exposures and kinematic coordination patterns) within the overarching OFC framework is visualized in Figure 1-3.

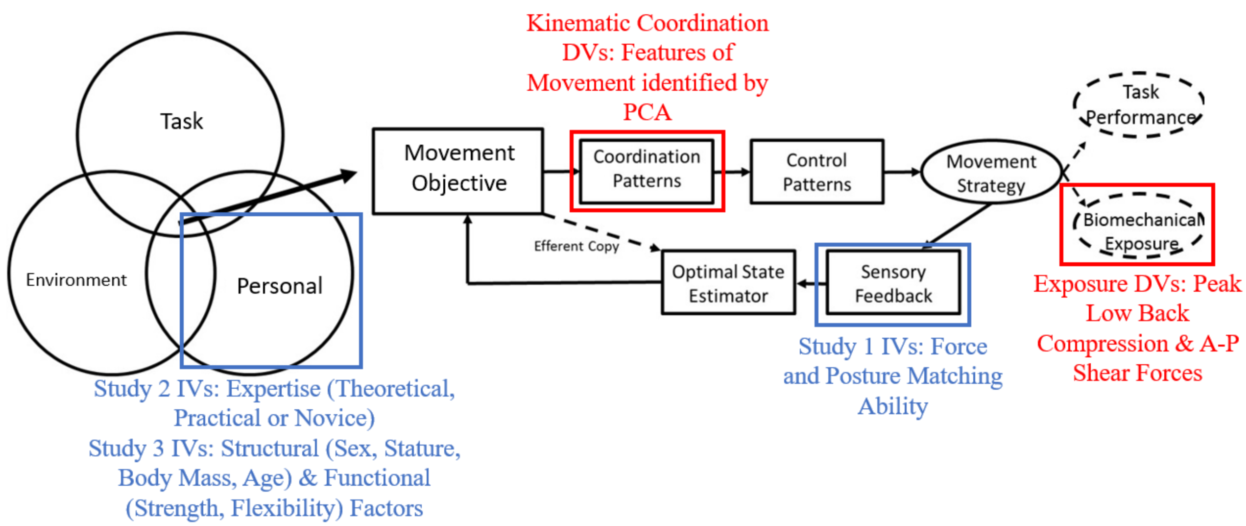


**Figure 1-3:** Visualization of independent and dependent variables for studies 1-3 of this thesis within the overarching OFC model. RQ: Research Question, IV: Independent Variable, DV: Dependent Variable, PCA: Principal Component Analysis.

# Chapter 2: Literature Review

## *2.1 Work-Related Musculoskeletal Disorder Injury Risk*

Heavy physical demands associated with occupational lifting tasks can increase worker's injury risk. This has been documented in a review which identified that both lifting and heavy physical demands were two of the main risk factors associated with likelihood of experiencing an MSD at the low back (da Costa & Vieira, 2010). While a causative relationship between lifting and injury remains debated (Swain et al., 2020), associations have been seen in systematic reviews (i.e., Coenen et al., 2014). The risk of MSDs from lifting can be partially attributed to the resultant loads placed on the low back in lifting. Specifically, magnitude of low back compression (Waters et al., 1993; Wells et al., 2004) and A-P shear (Gallagher & Marras, 2012; Gallagher & Schall, 2017; Wells et al., 2004) forces and well as low back moments (Marras et al., 1993; Norman et al., 1998) have been associated with risk of developing an MSD.

In addition to heavy lifting imposing high magnitudes of low back loading, movement strategy in a lifting task also contributes to MSD risk. The lifting strategy that an individual chooses has been shown to influence low back loads (Kingma et al., 2004; Chaffin & Page, 1994), whereby reducing the horizontal distance of the body to the load reduces resultant reaction forces at the low back (Jorgensen et al., 1999; Kerr et al., 2001). The posture of the low back during lifting exertions is also important where lifting with greater peak low back flexion angles has been identified as a risk factor for MSDs (Marras et al., 1997). Furthermore, within the Wells et al. (2004) model of mechanical exposure, the movement strategy used is highlighted as a modifier of resultant exposure at tissue level, supporting the role of movement strategy as a contributor to MSD risk. The theorized influence of movement on tissue tolerance in the low back, as proposed by Wells et al. (2004), is supported by *in-vitro* research, which has demonstrated that functional spine units have a lower ultimate compressive strength in a flexed posture compared to a neutral posture (Gunning et al., 2001). As both loading and postural outcomes that result from occupational lifting are associated with MSD risk, occupational lifting remains an important essential aspect of work to consider in ergonomic interventions.

The paramedic sector is an example of a working group that may be at risk of sustaining an MSD due to high lifting demands. The high risk of MSDs in paramedic work is demonstrated by paramedics having the highest rate of MSDs by work sector (Maguire et al., 2005; Maguire et al., 2014). These high rates of MSDs have been attributed to high demands of work (Lavender et al., 2000; Cooper & Ghassemieh, 2007), which include essential lifting tasks such as lifting and loading a stretcher, as well as patient and equipment lifts (Coffey et al., 2016). The demands associated with these essential lifting tasks have both been subjectively identified as demanding by front-line paramedics (Fischer et al., 2017) and have been shown to expose paramedics to peak low back compression loads that exceed injury risk thresholds (Armstrong et al., 2020). While ergonomic interventions such as powered stretcher and load systems have been shown to both reduce resultant low back loads (Lad et al., 2018) and MSD incidence following implementation (Armstrong et al., 2017; Fredericks et al., 2009; Studnek et al., 2012), other essential lifting tasks such as lifting a patient on a backboard remain. As such, there is a need for further ergonomic intervention to address the remaining lifting demands in paramedic work as a strategy to reduce MSD risk.

### *2.2 Targeting Worker-Based Ergonomic Interventions*

In the development of ergonomic interventions for the paramedic sector the hierarchy of ergonomic controls should be followed. Following the hierarchy of controls as recommended by the Centers for Disease Control and Prevention (2015), engineering solutions that either eliminate or reduce demands should be the primary course of action. However, in work sectors such as the paramedic field, there are demanding aspects of work that can not readily be modified. Administrative controls that aim to intervene on the worker to reduce injury risk are a secondary option that may be effective in lieu of engineering interventions. Such administrative interventions have been proposed as modifying the way a worker moves could minimize the resultant exposures on their low back and therefore their injury risk (McGill, 2009). Considering the paramedic sector, risk assessment tools have been developed which can classify paramedics as lifting with either a strategy that has higher or lower resultant biomechanical exposures (Armstrong et al., 2019) as an example of an administrative control. However, the development of lift training programs to improve the lifting strategy used by paramedics experiencing higher exposures are needed to mitigate the identified high risk.

The development of lift training programs for paramedics as a proactive ergonomics strategy may be limited in their effectiveness based on past reported successes of lift training interventions. The effectiveness of lift training has been questioned by multiple research groups with a consensus that lift training shows no significant effect on reducing injury risk (Haslam et al., 2007; Martimo et al., 2008; Clemes et al., 2009; Verbeek et al., 2011; Hogan et al., 2014). However, a more recent review (Denis et al., 2020) has concluded that previous reviews only considered the quality of program evaluation, not necessarily the quality of the training program itself. When Denis et al. (2020) considered the quality of training they concluded that prescribing safe lifting techniques was not sufficient to reduce injury risk, but rather the interaction between the worker and the environment should be considered to improve the quality of future training interventions. In moving towards a better consideration of the interaction of the work and the worker, understanding personal factors that contribute to a movement objective that aims to minimize exposure could improve the quality of future training interventions consistent with recommendations made by Denis et al. (2020).

To increase the quality of future training programs, I propose that a greater emphasis of considering underlying determinants of movement strategy in training programs may lead to greater success of programs on reducing MSD risk. By first understanding how external and internal factors influence how a worker moves (referred to as: personal determinants of lifting strategy), motor control-based lift training programs can be developed to target modifiable determinants directly to produce greater positive effects. The efficacy of this approach has support as a motor control-based training paradigm has been shown to have greater improvements in pain reduction, strength and endurance compared to a high-load lift training program (Aasa et al., 2015). Additionally, movement focused strength and conditioning training lead to improvements in spine and knee frontal plane motion in transfer tasks, while no such improvements were seen in a general fitness training group (Frost et al., 2015). Such findings can be paired with other training suggestions that have shown efficacy in reducing spine loads such as incorporating auditory feedback to reduce low back loads based on lifting strategy (Punt et al., 2019; Agruss et al., 2004; Beach et al., 2018) or training to mimic differences in movement strategy between novice and expert lifters (Gagnon, 2003). While a training approach that leverages motor control principles has been shown in the literature to be more effective at inciting changes in behaviour, there is a need to supplement these training approaches with content that will result in changes in movement strategy to reduce injury risk. This thesis aims to quantify the variability in low back exposures during lifting that can be explained by personal factors. These findings could inform the content and personalization of future lift training programs, which can be executed using motor control-based training paradigms that have shown to be effective in past work.

### *2.3 Motor Control Theories*

A motor control framework may give insight as to why different workers adopt different lifting strategies. The consideration of biomechanical analyses in the context of underlying neural control is a recommended direction to understand how outcomes of our motor system (i.e., end effector kinematics and kinetics) are generated (Gregor, 2008; Davids & Glazier, 2010). With a goal of exploring personal determinants of lifting strategy within an overarching motor control framework, a theoretical model of motor control is needed.

To understand the influence of both external and internal factors on movement strategy Newell's model of interacting constraints can be considered. Newell (1986) theorized that an interaction between task, environment and organism constraints influence the resultant coordination and control of movement. Within Newell's model, task constraints are the goals of a task, which for lifting could include specified start and end points for the load. Environment constraints include factors external to the worker that could influence lifting strategy, which in the case of paramedics could be the severity of the call response they are responding to. Finally, the organism constraint refers to factors inherent to the worker which could include expertise on lifting mechanics or demographics for example.

While Newell's model of constraints suggests that interacting task, environment and organism constraints influence the coordination and control of human movement, there is no consideration of an internal model of control. More recently, Glazier (2017) has expanded

Newell's (1986) model and has proposed a grand unified theory of sports performance. Within Glazier's model it is theorized that the interaction of constraints informs the definition of coordinative structures which then in turn directly influence the resultant coordination and control of movement as well as performance outcomes. While Glazier's grand unified theory of sports performance acknowledges that there is likely an internal model of control that is informed by interacting constraints, he is unclear on what this internal model is.

Optimal feedback control (OFC) theory is a prevailing motor control theory that could be considered as an internal model of movement control in a lifting task. OFC proposes a closed-loop feedback model of control where task objectives are defined in a control law (Todorov, 2004; Scott, 2004). Within the OFC model aspects of movement variability relevant to task performance (as defined by a control law) are controlled, whereas task irrelevant aspects of movement variability are left unconstrained consistent with the minimum intervention principle (Todorov & Jordan, 2002; Todorov & Jordan, 2003). The OFC model argues against the historical notion that movement is controlled by pre-planned trajectories and instead allows for flexible reconfiguration of movement to maintain task performance (Diedrichsen et al., 2010). The allowance of task-irrelevant variability to manifest is consistent with how our motor control system operates in practice as human movement is inherently variable (Latash, 2012), which is likely in part because we have multiple motor options to complete a task (Bartlett et al., 2007). Support for OFC as a motor control theory has been demonstrated in simple motor tasks (Scott et al., 2015), postural control (Haid et al., 2018) and sports applications (Morrison et al., 2016).

The OFC closed-loop model of control is an internal control model that can be used to explain the resultant range of movement strategies one may adopt given movement objectives as defined by the control law. However, OFC theory does not consider how movement objectives in the control law are defined. Given that there is no consideration of how interacting constraints influence control law definition, recent work has proposed a modification to Glazier's grand unified theory (2017) to include OFC as a corresponding internal model of control (Armstrong & Fischer, 2020) (Figure 1-1). Within this amended model we have hypothesized that interacting constraints influence the definition of movement objectives within the control law, which then influences resultant coordination and control patterns.

Based on the proposed modification to Glazier's grand unified theory of sports performance, it has been hypothesized that some lifters may define a control law that aims to minimize biomechanical exposures in addition to completing lift demands. This hypothesis was partially informed by research suggesting that more than one movement objective seems to exist in some motor tasks. For example, in gait some individuals aim to both minimize metabolic cost and movement time (Summerside et al., 2018). However, the weighting of minimizing metabolic cost and movement time objectives is not consistent across participants suggesting differing control law definitions that may consider more than one objective. A second study demonstrating a change in task objectives found that as fatigue accumulates joint stability was favoured over energy efficiency (Cashaback & Cluff, 2015), which suggests that as constraints change, movement objectives can change correspondingly. Given this theoretical paradigm we have found preliminary results suggesting that some lifters define a control law to minimize exposure (Armstrong & Fischer, 2020), but a causative link between constraints and attempting to minimize exposure as a movement objective in control law definition has not been identified. With a goal of understanding determinants of lifting strategy in this proposed motor control framework, a pressing research direction is to understand what combination of constraints leads to a control law definition that aims to minimize biomechanical exposure at the low back in lifting.

Consideration of determinants of movement strategy in lifting within an OFC based theoretical framework is conceptually aligned with the practical goal of this thesis of identifying personal factors that explain variance in low back exposures in lifting. It is known that human movement is inherently variable (Latash, 2012), which is likely due to the manifestation of task-irrelevant variability in the OFC theory paradigm. However, to complete a whole-body motor task such as lifting there will be aspects task-relevant variability that will be tightly controlled to maintain task performance. As it has been hypothesized that a defined control law which considers minimizing biomechanical exposures may be a result of interacting task, environment, and organism constraints (Armstrong & Fischer, 2020), there is a possibility to detect differences in task-relevant variability as a function of constraints, which would reflect differences in control law definition. Specifically, lower magnitudes of exposures coupled with lower variability in exposure measures would provide evidence that biomechanical exposures are considered in control law definition. This is in part since less variability in exposure measures would support that these biomechanical exposure outcomes are considered as task-relevant aspects of variability. By quantifying differences in both magnitude and variability in biomechanical exposures across independent factors, there is the opportunity to infer whether any of the personal factors investigated seem to inform a control law definition that aims to minimize biomechanical exposures at the low back in lifting.

While aspects of task-relevant variability can be used to infer control law definition, considering task-irrelevant variability is likely an important consideration in the prediction of movement strategies given a set of personal factor inputs. Within the overarching theoretical framework, I expect to see variability in some aspects of movement strategy as we know task-irrelevant variability will exist consistent with the minimum intervention principle (Todorov & Jordan, 2002; Todorov & Jordan, 2003). While these aspects of task-irrelevant variability have been deemed to be of lower importance to the lifter, they may be important to consider in the prediction of lifting strategies. Specifically, some aspects of task-irrelevant variability may influence the resultant biomechanical exposures on the body, while not influencing the task objectives defined in the control law if a lifter does not aim to minimize resultant biomechanical exposures on the body. This is supported by previous research demonstrating differences in low back loading based on the lifting strategy adopted (Kingma et al., 2004; Armstrong et al., 2021a). Since aspects of task-irrelevant variability can influence the range of biomechanical exposures a lifter is likely to experience, it is an important consideration to increase the internal validity of a lifting strategy prediction tool. From a modelling perspective this suggests that the development of a probabilistic model to predict a range of likely lifting strategy and corresponding biomechanical exposures is conceptually consistent with the overarching OFC framework as it can consider variability in predicted outcomes. Conversely, a deterministic modelling approach would ignore the known variability in human movement in model outcome measures, making it an inappropriate modelling solution given the theoretical framework considered in this thesis.

### *2.4 Determinants of Lifting Strategy*

In this thesis I have proposed to investigate whether personal factors can explain variability in observed biomechanical exposures at the low back during lifting. From this understanding I then aim to infer whether personal factors seem to inform a movement objective that aims to minimize biomechanical exposures at the low back. With this overarching thesis objective, it is important to consider factors that influence lifting strategy which have been identified in previous literature. While a bulk of previous research has not explicitly aimed to understand determinants of lifting strategy within Newell's model of interacting constraints, this section will attempt to parse out the relative influence of task, environment, and organism constraints on lifting strategy.

### *2.4.1 Task Constraints as a Determinant of Lifting Strategy*

Perhaps the most intuitive constraint that influences movement strategy are the task demands themselves. For lifting exertions, the task demands are constrained by defined lift start and end points with a goal of moving an external load. Specific to the paramedic sector these defined lifting demands could include lifting a patient from the ground to a stretcher for conveyance purposes. Intuitively, as lift start or end points are changed there are expected differences in resultant movement strategy. This has been demonstrated in the literature where when lifting height was modified there was significant differences in both kinematic variables describing movement strategy and on resultant moments on the low back (Plamondon et al., 2012).

While we can expect changes in lifting strategy as the lifting trajectory changes, more nuanced influences of task demands within the paramedic sector should be considered. One such example is considering the effect of performing a two person lift where a number of essential paramedic lifting tasks require a paramedic on both the head and foot end of equipment (Coffey et al., 2016; Armstrong et al., 2020). When performing team lifts previous work has demonstrated that peak and average low back moments and compression force were approximately 20% lower than loads in an individual lift when the effective mass of the load was controlled (Dennis & Barret, 2002). These differences were attributed to greater pull force on the load, as well as positioning the load closer to the body in the team lifts (Dennis & Barret, 2002).

A final task constraint to consider within the paramedic sector is the difficulty of the lifting task. Work by Sedighi & Nussbaum (2019) showed that as task difficulty increased stability in movement strategy is prioritized over variability. In this study task complexity was compared between symmetrical and asymmetrical lifting, with asymmetrical lifting being considered more challenging. While this experimental design does not necessarily mimic how lifting task difficulty may be influenced in paramedic work, its findings are important to acknowledge. Within paramedic lifting factors such as patient motion may contribute to difficulty of the lift and lead to prioritizing increased stability opposed to variability in strategy.

*2.4.2 Environment Constraints as a Determinant of Lifting Strategy*

Environment constraints represent an additional class of factors to consider as a determinant of lifting strategy. The environment constraint consists of factors extrinsic to the goal of the task and the worker themselves which could influence lifting strategy. One such factor to consider for paramedics is the urgency imposed by the work environment. Emergency call responses that paramedics respond to with higher levels of acuity have been shown to have higher required physical demands as well as higher perception of physical demands (Morales et al., 2016). The increased acuity may have an influence on lifting pace for example, where increased lifting pace has been shown to influence muscle recruitment patterns, but not joint kinematics, in a waist to shoulder height lifting task (Yoon et al., 2012). Physical handling demands following a lift in a paramedic call may also further increase low back loads. This is shown in an experimental study contrasting typical lab-based lifting procedure to a more representative replication of the work by incorporating carrying following lifting, which resulted in greater peak low back moments in the realistic scenario (Faber et al., 2011).

A second example of environment factors that could influence lifting strategy are the shape and mass of the load. Since these factors do not influence task objectives, they can be considered environmental factors where in a paramedic example they may be required to lift a range of load masses over the course of a shift based on variability in patients' body mass. The shape of the load has been shown to influence resultant low back compression force and moments where resultant loads were greater when lifting a crate compared to a barbell of the same mass (Zehr et al., 2018). No corresponding differences in joint kinematics were observed, and differences in loading were attributed to proximity of the load to the body.

The mass of the load has been shown to be an environmental factor that influences lifting strategy. As mass of the load increases the interjoint coordination in the lift tends to use a distal to proximal strategy where extension about joints in the lower extremity precedes extension of the low back (Davis & Troup, 1965; Scholz, 1993a, 1993b; Scholz & McMillan, 1995; Burgess-Limerick et al., 1995). This movement has been hypothesized to be an injury reduction strategy to delay low back extension until after acceleration of the external load is greatest (Davis & Troup, 1965). Similar findings have been found when mass of the load is normalized to participant's capacity where when the relative demand increases a distal to proximal lifting strategy is adopted (Albert et al., 2008; Sadler et al., 2011; Sheppard et al., 2016).

Physical differences in the environment that lifting is being performed is another factor that has been shown to influence lifting strategy. An example highlighting this effect is measured differences in pelvis-thorax coordination between freestyle and a forced spine flexion technique as imposed by physical barriers in the lifting space (Zehr et al., 2018). Further physical environment effects on lifting strategy where observed participants were asked to perform lifting demands in both control and when simulating lifting on a marine vessel (Holmes et al., 2008; Ning & Mirka, 2010).

Finally, the effect of the environment on cognitive factors influences lifting strategy. For example, it has been shown that when cognitive demands are increased there are higher spine loads in lifting, which is attributed to increases in co-contraction and less controlled movement (Davis et al., 2002). Increasing cognitive demands in lifting by enforcing a precision target for load placement has been shown to increase cumulative spine loads as a function of increases in lift time (Beach et al., 2006). A participant's knowledge of the load magnitude can also influence lifting strategy where when lifters are told that loads are greater than their true magnitude higher erector spinae muscle activity was measured prior to lift completion (Courbalay et al., 2017). Finally, the visual perception of object size has been shown to be a determinant of lifting strategy where visual perception of load size has a greater influence on lifting strategy than memory of the load mass (Cole, 2008).

### *2.4.3 Organism (Personal) Constraints as a Determinant of Lifting Strategy*

Organism constraints represent the final class of factors in Newell's model that could influence movement strategy in lifting. Organism constraints are factors inherent to the worker (person) that could influence movement strategy. Considering organism constraints, there are both modifiable and non-modifiable factors which could influence movement strategy. This review will first focus on the influence of non-modifiable factors on movement strategy in lifting, followed by the influence of modifiable factors. With one of the goals of this thesis being to identify what modifiable factors have the greatest influence on lifting strategy to inform the development of future lift training interventions, it is important to differentiate between modifiable and non-modifiable factors.

A first example of non-modifiable personal factors that influence lifting strategy is body morphology including stature, and body mass. Considering stature, individuals of different heights are constrained in the lifting strategy they can use where for example a taller individual may be able to straddle a load to minimize the horizontal distance between the load and the body. Considering body anthropometry related to stature, thigh length, torso length, and thigh-to-shank length ratio were correlated with peak knee angle in squatting (McKean & Burkett, 2012). While stature and corresponding limb length differences are factors that could influence lifting strategy, the influence of stature has not been conclusively determined. It has been shown that in a ground to chest height lift that higher stature individuals have greater peak lumbar extension angles (Kranz et al., 2020), but the influence of stature on floor to waist height lifting is not known.

Body mass is a second morphological factor that could influence lifting strategy. Intuitively, body mass will influence the absolute magnitude of low back reaction forces and moments where individuals with greater mass will have higher resultant exposures (Marras et al., 2003; Pryce & Kriellaars, 2018; Ghezelbash et al., 2020). Higher body mass of lifters is particularly problematic when lifting from the ground, as when the load was on the ground obesity had a greater influence on low back moment magnitude compared to other lifting heights (Corbeil et al., 2019). Higher body mass may also have an influence on lifting kinematics as it has been shown that lifters with higher central adiposity had less hip and low back flexion, but higher trunk to low back flexion angles in lifting (Pryce & Kriellaars, 2018). However, the compensatory kinematic strategy used by higher body mass individuals was not able to offset the increased moment contribution of body mass (Corbeil et al., 2019). The physical constraints of increased body mass may also have further implications for low back loading magnitude in lifting where greater body mass may limit the ability of a lifter to minimize the horizontal distance of the body to the load.

Another non-modifiable factor that has been shown to influence lifting strategy is chronic low back pain. While clinical strategies that aim to either alleviate or eliminate chronic low back pain do exist, given that this thesis does not have a clinical focus the presence of chronic pain will be considered non-modifiable in this literature review. The presence of clinically diagnosed low back pain does have implications on lifting strategy where low back pain patients lift slower, have deeper knee bend, less jerk of the load and more co-contraction (Nolan et al, 2020). There is also corresponding stiffness in lifting where chronic low back pain patients have been reported to have more stable frontal and transverse plane hips in lifting (Asgari et al., 2017). Finally, presence of low back pain has been shown to influence coordination in lifting where chronic low back pain patients had decreased lumbar-hip movement coordination and stiffer knee-hip coordination in lifting (Pranata et al., 2018).

In patients with chronic low back pain there are also corresponding deficiencies in tactile sensitivity at the low back. These tactile deficiencies have been shown to be linked to movement strategies that include encumbered control of the lumbopelvic region in flexion/extension tasks (Luomajoki & Moseley, 2011; Catley et al., 2014; Adamczyk et al., 2018). It is hypothesized that the deficiencies in tactile sensitivity present in individuals with chronic low back pain are from changes in the somatosensory cortex in response to chronic pain perception (Flor et al., 1997; Lloyd et al., 2008). As explored within the OFC theory framework, the perception of sensory feedback plays a key role in maintaining task performance through the comparison of an efferent copy of an initial movement trajectory and afferent sensory information at the optimal state estimator (Scott, 2004; Todorov, 2004). Therefore, these changes in tactile sensitivity brought on by chronic pain may have implications on the control of movement strategy in a lifting task.

The influence of reduced tactile sensitivity at the low back on movement strategy has been explored in flexion/extension testing paradigms. Results have demonstrated that in a repeated flexion/extension task of the trunk that the reduction of cutaneous sensitivity did not influence proprioception or dynamic stability (Beaudette et al., 2016). However, when cutaneous sensitivity was experimentally increased participants reduced the magnitude of end range low back flexion as well as increased thoracic spine flexion variability in a repeated flexion/extension task (Beaudette et al., 2018). While these findings are not specific to a lifting task, it provides initial evidence that the perception of sensory feedback can influence the movement of the low back in a motor task. This allows for the possibility of perception of sensory information to influence lifting strategy where for example lifters more attuned to cutaneous sensory information may limit peak low back flexion angles, consistent with movement strategy observed in repeated flexion/extension of the low back (Beaudette et al., 2018). While evidence supports that chronic pain influences ability to perceive sensory feedback, it is possible that this factor is modifiable in a healthy working population.

The age of lifters can affect lifting strategy where older adults seem to use a slower and more protective kinematic strategy. This is demonstrated by older adults having more neutral spine flexion angles as well as lower low back extension velocities both when compared to young adults (Song & Qu, 2014a) and compared to young adults after prolonged seated work (Gruevski & Callaghan, 2020). While differences in kinematics as a function of age have been reported, no observed differences in low back moments were seen in symmetric lifting (Song & Qu, 2014a). However, older adults exhibited significantly higher absolute moments in asymmetric lifting (Song & Qu, 2014b), which was attributed to age related differences in body mass. No differences in resultant low back loads in symmetric lifting between old and young participants may be in part due to greater muscle activity being observed in the erector spinae muscles in the older lifters (Boocock et al., 2020). The trade off between trunk extension velocity and erector spinae co-contraction likely explains no difference in resultant low back moments between old and young lifters.

The difference in lifting strategy between males and females has been commonly investigated in previous literature. When lifting absolute loads females tend to lift with a strategy that greater leverages their lower body compared to males. This has been shown specific to the paramedic sector where females perform more rotational joint work with joints of the lower extremity compared males in sector specific lifting tasks (Makhoul et al., 2017). Further support for these sex differences when lifting absolute loads are also seen in generic lifting tasks where females tend to use a leg-driven lifting strategy while males rely on extension of the trunk to lift the load (Li & Zhang, 2009; Marras et al., 2003). Additionally, males have been shown to adopt a lifting strategy which involves greater lumbar flexion when an absolute load is lifted (Li & Zhang, 2009; Lindbeck and Kjellberg, 2001). In a separate study, females adopted a distal to proximal coordination strategy in lifting which resulted in reduced low back moments compared to their male counterparts (Plamondon et al., 2014a). These findings would suggest a general trend that when lifting absolute loads females tend leverage greater contributions of their legs, whereas males tend to use a more trunk extension driven lifting strategy.

While differences in lifting strategy with absolute loads have been demonstrated between males and females, these effects may be influenced by perceived demand of the lift. Strength capacity is known to differ between males and females where it is estimated that females have approximately 2/3 the strength capacity of males on average (Mital, 1997). When performing work-related tasks females have been shown to have greater muscle activity and are therefore assumed to be working closer to their physiological limit (Nordander et al., 2008). When lifting absolute loads females have also been shown to have greater muscle activity in the latissimus dorsi and external obliques than male counterparts (Marras et al., 2003). With the differences in load demand relative to capacity between males and females, it is important to understand whether lifting strategy differs between males and females when mass of the load is scaled to capacity.

Comparing lifting strategy between males and females when loads are scaled to capacity results in few reported differences. This has been shown where when mass of the load was normalized to capacity no differences in kinematic dependent measures were observed between male and female groups (Albert et al., 2008; Sadler et al., 2011). This is further supported by sex differences in an upper extremity lifting task being load dependent (Martinez et al., 2019). However, work by Plamondon et al. (2017) maintained that females still leveraged a distal to proximal coordination in strategy compared to more synchronous lifting in males when load magnitude was scaled to capacity. While sex differences were reported, a limitation to the study design was that load mass was scaled based on the assumption that females had 2/3 the strength capacity of males (Plamondon et al., 2017), and no true measures of capacity were collected. Based on the lack of sex differences in lifting strategy when the mass of the load is scaled to capacity it is likely that previously reported sex differences in lifting are in fact a result of load magnitude, not structural differences as a function of sex.

While the review of factors within the organism constraint on lifting strategy have been focused on non-modifiable features thus far, modifiable factors can also have an effect worth exploring. A first example of a modifiable factor on lifting strategy is fatigue. It has been shown that in fatigue there is a decrease in trunk extension velocity and increased phase lag between hip and trunk extension, where these adaptations are hypothesized to be a fatigue minimization strategy (van Dieën et al., 1998). Further studies have identified that greater trunk flexion is observed when lifting in a fatigued state (Bonato et al., 2003; Mehta et al., 2014). Once again, these results would suggest that there is a goal to minimize the physiological effort in lifting where greater trunk flexion corresponds to a more stoop-like lifting strategy, which has lower resultant metabolic demands (Straker, 2003b). While adaptations in lifting strategy when fatigued generally seem to aim to minimize physiological demand of the lift, there are other changes in strategy, such as a reduction in hip stability (Asgari et al., 2017), that should be considered.

Expertise has been proposed as a personal factor that should improve lifting strategy. The hypothesized benefit of expertise on lifting strategy is in part due to higher incidence of MSDs in novice workers (van Nieuwenhuyse et al., 2004). Although expertise has been hypothesized to have a positive influence on lifting strategy, studies investigating lifting mechanics between expert and novice lifters have shown mixed results. For example, some research shows beneficial effects of expertise where experts have lower spine flexion and internal low back moments than novice lifters (Gagnon et al., 2018), or have less lumbar flexion and are closer to the load than novice lifters (Plamondon et al., 2014b). However, negative effects of expertise have also been reported where experts have demonstrated higher mean and variability in sagittal low back moments and loads (Granata et al., 1999), higher peak low back flexion angles and loads (Lee & Nussbaum, 2012), and higher cumulative low back moments in the lateral bend and axial twist axes when fatigued (Lee & Nussbaum, 2014). Additional reported differences in lifting strategy between expert and novice lifters have shown that experts are more variable in their lifting strategy than novice counterparts (Sedighi & Nussbaum, 2017) as well as have differences in knee angles and moments, but not angles and moments at the low back (Ganon et al., 1996).

While inconsistencies in lifting strategy across expertise groups have been seen to date, this may be in part due to laboratory-based studies not replicating the lifting demands of the workplace. Studies tend to recruit expert participants based on time spent performing manual materials work without recent injury (Lee & Nussbaum, 2012; Lee et al., 2014; Marras et al., 2006; Plamondon et al., 2014b; Granata et al., 1999). Lifting protocols then generally consist of generic lifting tasks that do not necessarily represent the workplace that expertise was gained in. This could influence the results comparing expert and novice lifters as expert lifters experienced greater low back loads when lifting at frequencies and load masses they were not accustomed to (Marras et al., 2006). A second reason for the inconsistency in previous results may be due to a lack of formal training on lifting mechanics. When trained lifters, consisting of ergonomists and health and safety professionals, were asked to demonstrate an ideal lift they suggested a squat lift, but had no consensus in squat depth (Abdoli-Eramaki et al., 2019). Further, when lifting strategy was compared between trained and untrained individuals L5/S1 moments were lower in the trained group (Abdoli-Eramaki et al., 2019), suggesting a potential benefit of theoretical knowledge of lifting mechanics on reducing resultant exposures in lifting.

Flexibility is another modifiable personal factor that could influence lifting strategy. Considering the available flexibility to individuals, more flexible lifters may have a greater range of lifting strategies available to use. Conversely, individuals with lower flexibility will be constrained to a limited subset of total strategy possibilities. However, while a greater passive range of joint motion may allow a broader range of movement options to lifters, there are strength demands to use this range of motion in practice. The importance of flexibility on lifting strategy has been demonstrated by Sreenivasa et al., (2018), where when predicting lifting strategy with an optimal control model, model iterations with stiffer imposed constraints had more flexion at the hip and knee opposed to the lumbar spine. Additionally, in a lab-based study lifters with reduced hamstring flexibility were shown to lift with greater trunk flexion angles (Carregaro et al., 2009). This supports that inherent lifter flexibility can influence the lifting strategy they choose to adopt.

A final modifiable personal factor that could influence lifting strategy is strength capacity. Previously in this literature review the importance of capacity on lifting strategy has been noted as when load is scaled to participants one-repetition maximum lift (Albert et al., 2008; Clusiault et al., 2022) or isometric low back extensor strength (Sadler et al., 2011; Sadler et al., 2013; Sheppard et al., 2016) no sex differences in strategy were observed. Extending this understanding, when lifting an absolute load, the relative mass of the load to a lifter's capacity seems to be an important determinant of lifting strategy. Therefore, by increasing capacity the absolute load demands associated with essential work tasks will be perceived as lower and thus will likely result in a lifting strategy that better replicates lifting observed at lighter loads. Further experimental evidence supporting the importance of strength on lifting strategy demonstrates that higher strength individuals tend to self select lifting greater load magnitudes when the option is available (Bartlett et al., 2007). Additionally, strength has been shown to be an important factor in regression models that aim to predict lifting strategy (Kranz et al., 2020). The strength capacity of lifters has also been shown to be correlated to hip-back coordination in lifting, where greater strength resulted in more synchronized hip-back coordination strategy (Yehoyakim et al., 2016).

While total strength capacity has been shown to be an important determinant of lifting strategy, the relative strength capacity of joints in the body could also influence resultant lifting strategy. For example, participants that have greater relative leg to back strength opt to use a leg-driven strategy (Li & Zhang, 2009; Zhang & Buhr, 2002; Puniello et al., 2001). These findings have potential implications as lifters tend to be biased to leverage their strongest joints to perform a lift. Improvements in capacity of specific joints could therefore be a strategy to more greatly utilize a given joint in a lifting task.

*2.4.4 Situational Needs for Differing Movement Objectives*

The influence of task, environment and organism constraints on the movement strategy used in lifting have been discussed, but the potential influence of movement objectives on lifting strategy is a final important consideration. Based on the overarching OFC model it is theorized that aspects of movement variability related to task objectives will be controlled, while task-irrelevant variability will be left unconstrained (Scott, 2004; Todorov, 2004). Specific to lifting we have previously proposed that some lifters may define a movement objective within their control law that aims to minimize resultant biomechanical exposures on the body, in addition to completing task demands (Armstrong & Fischer, 2020). While this is one example of an additional movement goal that lifters may consider, it is not the only possibility.

A second potential movement objective that may be deemed important by lifters is an attempt to minimize metabolic demand. This may be important when workers are exposed to a high level of cardiovascular demand and need to perform a lift. To minimize the metabolic demand associated with lifting, workers may adopt a stoop-like lifting strategy which has been shown to be more metabolically favourable than a squat-like lifting strategy (Straker, 2003b;

Garg & Herrin, 1979). Contrasting the stoop- and squat-like lifting strategies, a stoop-like lift uses greater flexion of the low back to approach the load, whereas a squat-like lift has greater flexion of joints of the lower extremity (Burgess-Limerick & Abernethy, 1997). While the stoop-like strategy is more metabolically favourable, the difference in strategy could affect resultant biomechanical exposures on the body where use of a stoop strategy has greater associated low back moment impulse (van der have et al., 2019).

### *2.5 Identified Research Gaps*

With an overarching thesis objective of quantifying the variability in low back exposures during lifting that can be explained independently and/or interdependently by personal factors, several research gaps have been identified. First, the consideration of one's ability to perceive sensory feedback as a factor influencing the consideration of minimizing biomechanical exposures in their movement objectives is unknown. Within the overarching OFC theoretical framework, the perception of sensory feedback plays a key role in maintaining task-relevant performance (Todorov, 2004; Scott, 2004). With the noted importance of sensory feedback in the OFC theoretical model, a lifter's likelihood of defining a movement objective that aims to minimize exposure may be attributed to their ability to perceive the sensory feedback and modify movement strategy accordingly.

Secondly, contrasting the effect of contextual and theoretical expertise in both job-specific and generic lifting tasks is an existing gap in the literature where to date conflicting effects of expertise on minimizing biomechanical exposures in lifting have been reported (Gagnon et al., 2018; Plamondon et al., 2014b; Granata et al., 1999; Lee & Nussbaum, 2012; Lee & Nussbaum, 2014). The consideration of expertise may also mediate one's ability to perceive sensory feedback, as those who are better able to perceive sensory information at the low back may be able to do so due to implicit learning which has occurred over long periods of time performing job-specific lifting demands.

Finally, when aiming to quantify the variability in low back exposures during lifting that can be explained independently and/or interdependently by personal factors, the consideration of structural (i.e., sex, stature and body mass) and functional (i.e., strength capacity and flexibility) factors should be considered. While it is less likely that these factors may bias a movement objective that aims to minimize resultant biomechanical exposures on the low back, they could constrain the breadth of movement strategies available to a lifter and therefore influence their ability to minimize the magnitude of resultant exposures on the body. Due to the possible effect of structural and functional factors on constraining the movement strategies available to the lifter, they are an important consideration in this thesis.

### *2.6 Overview of Proposed Modelling Approaches*

To achieve the overarching objectives of this thesis both PCA and probabilistic modelling were needed. Specifically, to determine which modifiable personal factors have the greatest influence on reducing biomechanical exposures associated with lifting strategy I developed a probabilistic model which can predict a likely range of movement strategies and corresponding biomechanical exposures on the low back at the population level. This allowed for the comparison of predicted resultant exposures across a range of personal input factors. To facilitate this modelling approach a feature reduction method was also required to reduce the dimensionality of kinematic data. The sections below will discuss principal component analysis as a data reduction method, and then provide an overview of probabilistic modelling approaches in biomechanics.

### *2.6.1 Principal Component Analysis in Biomechanics*

PCA is a data reduction method which can be used to identify synergistic patterns within time-series biomechanical data (Daffertshofer et al., 2004). When applied to waveform/timeseries data PCA is a rudimentary form of functional data analysis that provides consistent outcomes with the application of functional PCA to the same data (Warmenhoven et al., 2021). Specifically, PCA has been applied as a feature reduction method to objectively identify independent modes of variance (referred to as features of movement) from kinematic data of 3D time-series landmark trajectories (Federolf, 2016). These identified features of movement each explain a unique source of variance in whole-body kinematic data, which when aggregated through methods such as aggregate component reconstruction (Armstrong et al., 2021a) can represent an entire movement trajectory (Haid et al., 2018). The use of such PCA methods to identify synergistic features of whole-body movement strategy have been applied in occupational lifting (Armstrong et al., 2019; Armstrong et al., 2021a; Armstrong & Fischer, 2020), balance (Haid et al., 2018; Armstrong et al., 2021b), movement screening (Ross et al., 2018; Remedios et al., 2020), gait (Troje, 2002) and athletic contexts (Federolf et al., 2014; Gløersen et al., 2018).

While previous literature has used PCA to identify features of whole-body movement, for the purpose of this thesis these previously reported methods need to be adopted to allow for PCA outputs to drive a rigid link model. Typically, the reported PCA methods tend to model segments as distal and proximal end points (Armstrong et al., 2019; Armstrong et al., 2021a; Armstrong et al., 2021b; Armstrong & Fischer, 2020; Ross et al., 2018; Remedios et al., 2020; Troje, 2002) which leaves a third axis of motion undefined for the purposes of rigid link modelling. By adapting previously reported PCA methods so that variance in 3D segment trajectory data is identified it will allow for motion trajectories reconstructed from PC scores to be used in rigid link modelling consistent with ISB best practice recommendations (Wu et al., 2002; Wu et al., 2005).

The use of PCA as a feature reduction tool is conceptually compatible with the overarching OFC theoretical framework. Specifically, within the OFC framework it is unlikely that the central nervous system explicitly controls individual joints to maintain task performance. Instead, it is more likely that synergistic features of whole-body movement are controlled to limit task-relevant variability, while aspects of task-irrelevant variability are left unconstrained consistent with the minimum intervention principle (Todorov & Jordan, 2002; Todorov & Jordan, 2003). Conceptually, the features of movement identified by PCA can be considered kinematic coordination patterns, which in the context of the OFC framework are then controlled to generate a final end-effector kinematic strategy (Figure 1-3).

While use of PCA as a feature reduction approach is conceptually consistent with the overarching theoretical framework, it is difficult to interpret modes of variance explained by individual PCs. Typically, methods such as single component reconstruction are used to visually reconstruct the 5$^{th}$ and 95$^{th}$ percentile of a given PC to aid in visual interpretation (Brandon et al., 2013). As the single component reconstructions require subjective interpretation from the researcher, supplementing this interpretation by also considering landmark specific loading vectors can help understand where variance is being explained both on the body and in the time-domain (Armstrong et al., 2021a).

*2.6.2 Probabilistic Modelling Approaches in Biomechanics*

For the final study of this thesis, a model was needed to predict likely low back exposures given a set of personal factors as input parameters. With a goal of predicting a likely range of low back exposures given a set of input parameters, the use of a probabilistic modelling approach is preferred over a deterministic model. A probabilistic model is preferred as based on the overarching OFC theoretical framework used in this thesis capturing variability in motion is an important consideration (Scott, 2004; Todorov, 2004). The consideration of the known variability in movement strategies (Latash, 2012) will therefore increase the internal validity of the movement predictions consistent with the OFC framework. Use of a probabilistic modelling approach has advantages over a deterministic model for this thesis as the variability in input data as well as corresponding uncertainty in output data are considered in this modelling approach (Olofsson, 2005; Laz & Browne, 2010). Conversely, deterministic models would generate a single output solution given a set of input data, which does not reflect the expected variability in human motion I had hoped to consider.

In the development of a probabilistic model, uncertainty in the model inputs is represented as a distribution of values opposed to a single discrete value (Laz & Browne, 2010). To represent the distribution of values a PDF can be used where higher density aspects of the function represent more likely outcomes in continuous data (Haldar & Mahadevan, 2000; Laz & Browne, 2010). In this thesis I aimed to quantify the PDF of anticipated features of movement (as identified using PCA) for the range of personal input factors through studies 1-3. The distribution of input factor PDFs can take different forms (i.e., normally or non-normally distributed), but since PCA is being used a feature reduction approach to treat all input variables, the PDFs will be normally distributed be definition. This is because PC scores are z-scores representing the deviation of a trial from the mean of that PC (Daffertshofer et al., 2004), and therefore should be normally distributed where z-scores by nature are expressed relative to a normal distribution. Therefore, the PDF for each personal input parameter can be calculated based on the corresponding mean and standard deviation of PC scores within each input variable condition.

When using probabilistic models for simulation, Monte Carlo simulation is considered the gold standard approach (Laz & Browne, 2010). Monte Carlo simulation is an iterative approach that given a sufficient number of iterations will elicit a more realistic range of solutions (Laz & Browne, 2010; Haldar & Mahadevan, 2000). While the Monte Carlo simulations are computationally expensive, the greater accuracy in output prediction makes this an appealing simulation tool. More computationally efficient simulation tools such as most probable point methods could have utility as they have demonstrated comparable results to Monte Carlo simulation (Langenderfer et al., 2008; Chopp-Hurley et al., 2016). However, in this thesis rapid model iterations are not needed, where the goal of the proposed probabilistic model is to generate predicted PDFs of peak low back compression and A-P shear forces across combinations of input parameters which can be compared through statistical testing.

The use of probabilistic models has been seen in the biomechanics literature for risk assessment purposes. For example, probabilistic models have been applied to aid in risk assessment for bone fracture of the femoral neck in falls (Bryan et al., 2009) and to calculate a factor of risk for hip fractures at a population level (Martel et al., 2020). Probabilistic simulation has also been applied to assess bone mechanics in loading in conjunction with finite element models to evaluate fracture risk in the femur (Laz et al., 2007) and cervical spine (Thacker et al., 2001). Finally, probabilistic modelling approaches have been applied to evaluate the influence of scapular geometry and kinematics on sub-acromial space at the shoulder (Chopp-Hurley et al., 2016). With previous successes of similar probabilistic modelling approaches to evaluate risk in the biomechanics literature, there is support for the proposed model to predict the likely range of low back exposures in lifting based on personal factors. Perhaps more importantly, the use of a probabilistic to predict a range of lifting strategies has greater internal validity than a deterministic model predicting a single solution within the overarching OFC theoretical framework. Since human movement is inherently variable (Latash, 2012), the variability in movement should be considered in movement prediction whereas single movement trajectory predictions generated with a deterministic model would only give a single estimate.

# Chapter 3: Overview of Thesis Studies

The overarching objective of this thesis was to determine whether the variability in low back exposures during lifting can be explained independently and/or interdependently by personal factors. With this understanding, I then aimed to identify which modifiable factors have the greatest prospective benefit on a lifter adopting a movement strategy with lower resultant biomechanical exposures to inform future lift training interventions.

An initial three experimental studies were conducted that aimed to identify how ability to perceive sensory information, expertise, strength capacity, flexibility, sex, stature, and body mass influenced lifting strategy. Using results from these studies a probabilistic model was developed to predict the likely range of movement strategies and corresponding biomechanical exposures at a population level given a unique set of personal constraints. This model was then be used to evaluate which modifiable personal factors (i.e., ability to perceive sensory feedback or expertise) had the greatest influence on the magnitude of resultant biomechanical exposures at the low back based on predicted lifting strategies across a range of non-modifiable (i.e., sex, body mass and stature) personal factor combinations. From these simulations the modifiable personal factors that have the greatest influence on a lifter using a movement strategy that reduces resultant biomechanical exposures were determined with an application goal of informing the development of future lift training interventions. The interaction of these study objectives is pictured in Figure 3-1.

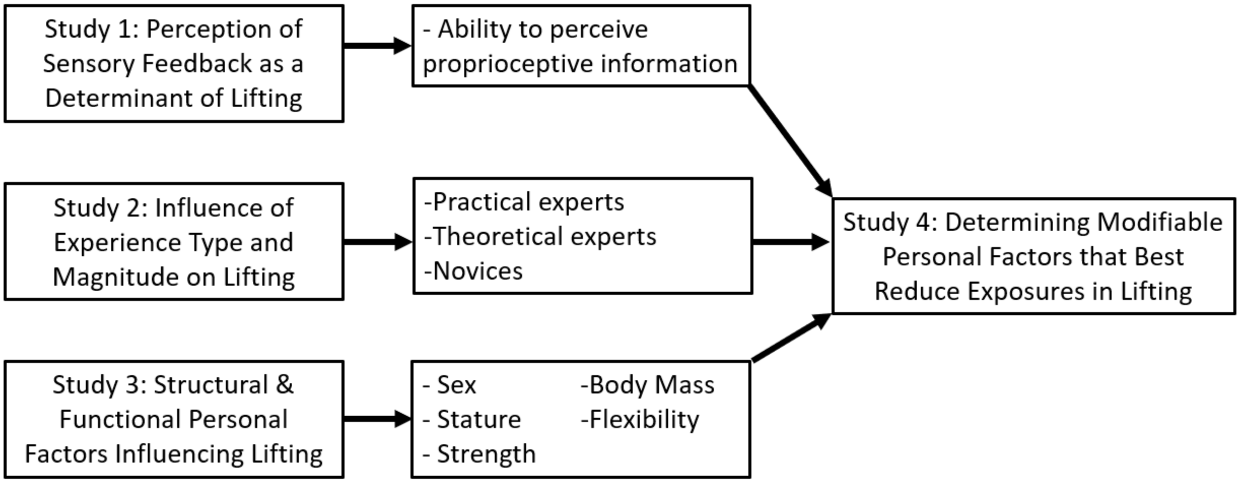


**Figure 3-1:** Overview of proposed thesis studies. Data collected in studies 1, 2 and 3 were used to inform model development in study 4. Specifically, findings from studies 1-3 included mean and standard deviations of kinematic variables which quantify the movement strategy used by each independent factor group (highlighted in the central column). These values were used to generate probability distribution functions for use in the model developed in study 4.

# Chapter 4: Common Experimental Protocol for Studies 1-3

In this thesis, studies 1-3 shared a common experimental protocol which is outlined in this chapter. Study specific chapters will discuss aspects of the overarching protocol related to the specific research questions asked in each study. The use of a common protocol across these three studies is important for this thesis because a large, diverse sample was needed to meet the goal of quantifying both the independent and interdependent influences of personal factors on both lifting strategy and likely biomechanical exposures at the low back. Additionally, using a common protocol across the first three studies allowed for a sufficient sample size to support the modelling approach used in study 4, which was reliant on data from studies 1-3 for model development. To summarize key information, Table 4-1 outlines all independent and dependent variables for studies 1-3 with the corresponding methods section for the collection and processing of each variable for reference.

**Table 4-1:** List of all independent and dependent variables for studies 1-3 with the corresponding relevant methods section where the measure is either collected or processed.

| Measure | Independent or Dependent variable | Relevant Study | Relevant Methods Section |
|---|---|---|---|
| Experience | Independent | 2 | 4.1 |
| Sex | Independent | 3 | 4.1 |
| Stature | Independent | 3 | 4.1 |
| Body Mass | Independent | 3 | 4.1 |
| Functional Lower Body Flexibility | Independent | 3 | 4.7 |
| Isometric Lift Strength | Independent | 3 | 4.4 |
| Ability to Perceive Sensory Feedback | Independent | 1 | 4.5, 4.6, 4.8 |
| Low back compression and A-P shear forces | Dependent | 1,2,3 | 4.11 |
| Features of whole-body movement | Dependent | 1,2,3 | 4.11 |

All data collected for this thesis, including whole-body kinematics and ground reaction forces, were collected in the Occupational Biomechanics and Ergonomics lab at the University of Waterloo.

*4.1 Participants*

Seventy-two participants (Table 4-2) completed the study protocol. A purposive sampling strategy was used to recruit working paramedics and paramedics seeking employment (contextual experts), graduate students with formal training on lifting mechanics (theoretical experts), and novice lifters (no formal experience or education on lifting). This study was approved by the University of Waterloo's Office of Research Ethics, and all participants provided informed consent prior to participation. Exclusion criteria included any musculoskeletal injury preventing the completion of activities of daily living in the previous 12 months and being deemed at risk to complete exercise using the CSEP Get Active! Questionnaire.

**Table 4-2:** Participant demographics reported as frequency counts, group means and (standard deviations) stratified by lifter expertise groups.

| | Contextual Experts (Active duty or in-training Paramedics) (n = 20) | | Theoretical Experts (n = 26) | | Novice Lifters (n = 26) | |
|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female |
| Sex | 11 | 9 | 13 | 13 | 13 | 13 |
| Stature (m) | 1.80 (0.05) | 1.67 (0.07) | 1.77 (0.07) | 1.65 (0.07) | 1.78 (0.10) | 1.64 (0.05) |
| Body Mass (kg) | 100.8 (19.9) | 81.7 (15.7) | 87.5 (11.7) | 70.6 (16.6) | 80.3 (10.4) | 71.2 (15.2) |
| Age (yrs) | 27.8 (5.5) | 25.6 (3.0) | 28.1 (3.8) | 25.6 (3.5) | 23.5 (3.0) | 25.3 (2.8) |

### *4.2 Instrumentation*

Upon arrival to the lab participants were asked to complete a demographic survey and given the opportunity to familiarize themselves with all lift types. Participants were instrumented for motion capture so that whole-body kinematics could be collected during all lifting trials. To track motion, a set of 86 passive reflective markers including 46 calibration markers to define segment endpoints and 40 markers affixed to rigid bodies were attached to participants to track segmental motion (Figure 4-1). Kinematic data were collected at 100 Hz using a 12-camera passive optoelectronic system (Vicon, Oxford, UK).

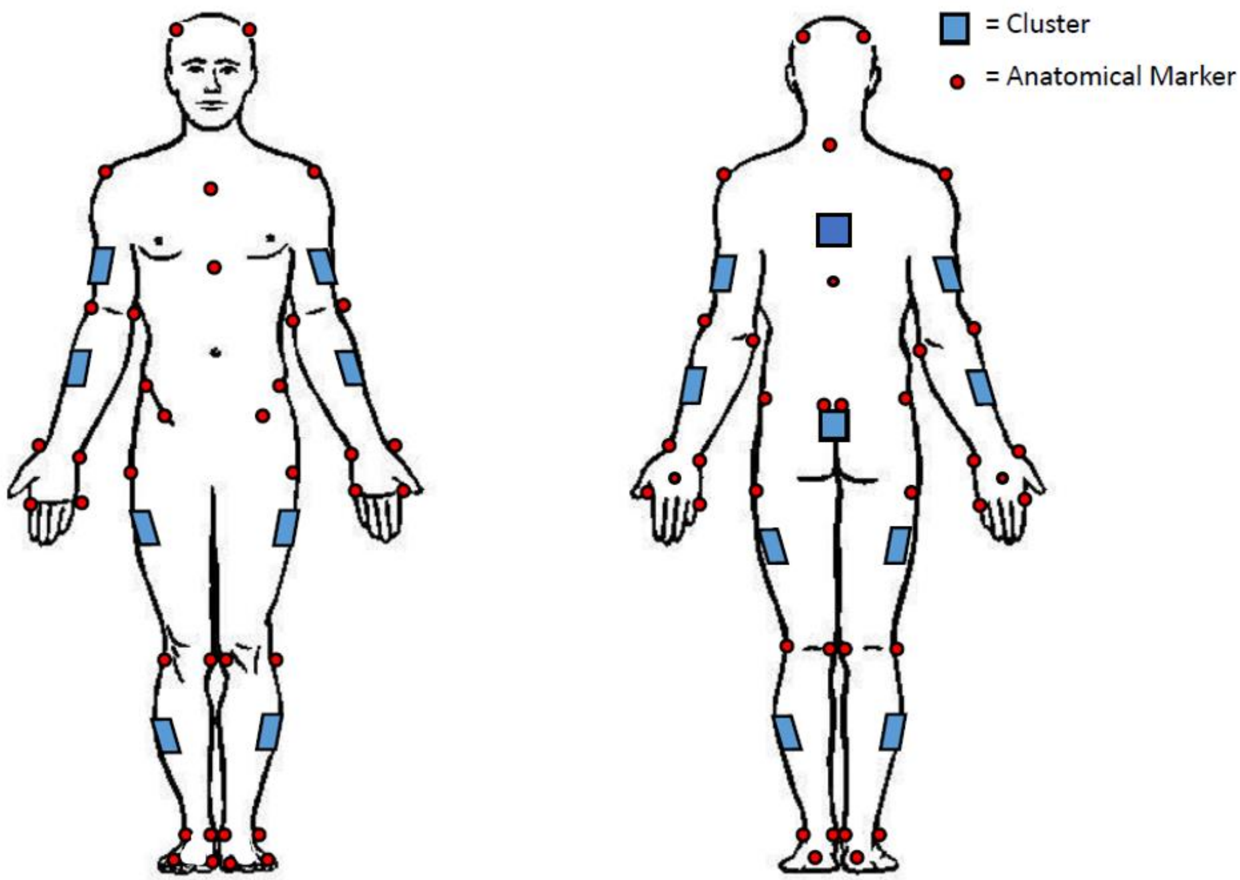


**Figure 4-1:** Placement of anatomical and rigid clusters of reflective markers to track segmental motion.

*4.3 Overview of Experimental Protocol*

The study protocol was conducted over two sessions on separate days that were at least 24 hours apart. In the first session static force and posture matching error protocols were administered as measures of proprioceptive ability, stature and body mass were measured, flexibility and strength testing were completed, and finally participants completed a lifting protocol. In the second session a load discrimination protocol was completed to determine the threshold of load mass difference participants could perceive while lifting as a final proprioceptive ability measure. A block diagram outlining the overarching protocol on day 1 is pictured in Figure 4-2. The remainder of this chapter discusses each aspect of the protocol in greater detail.

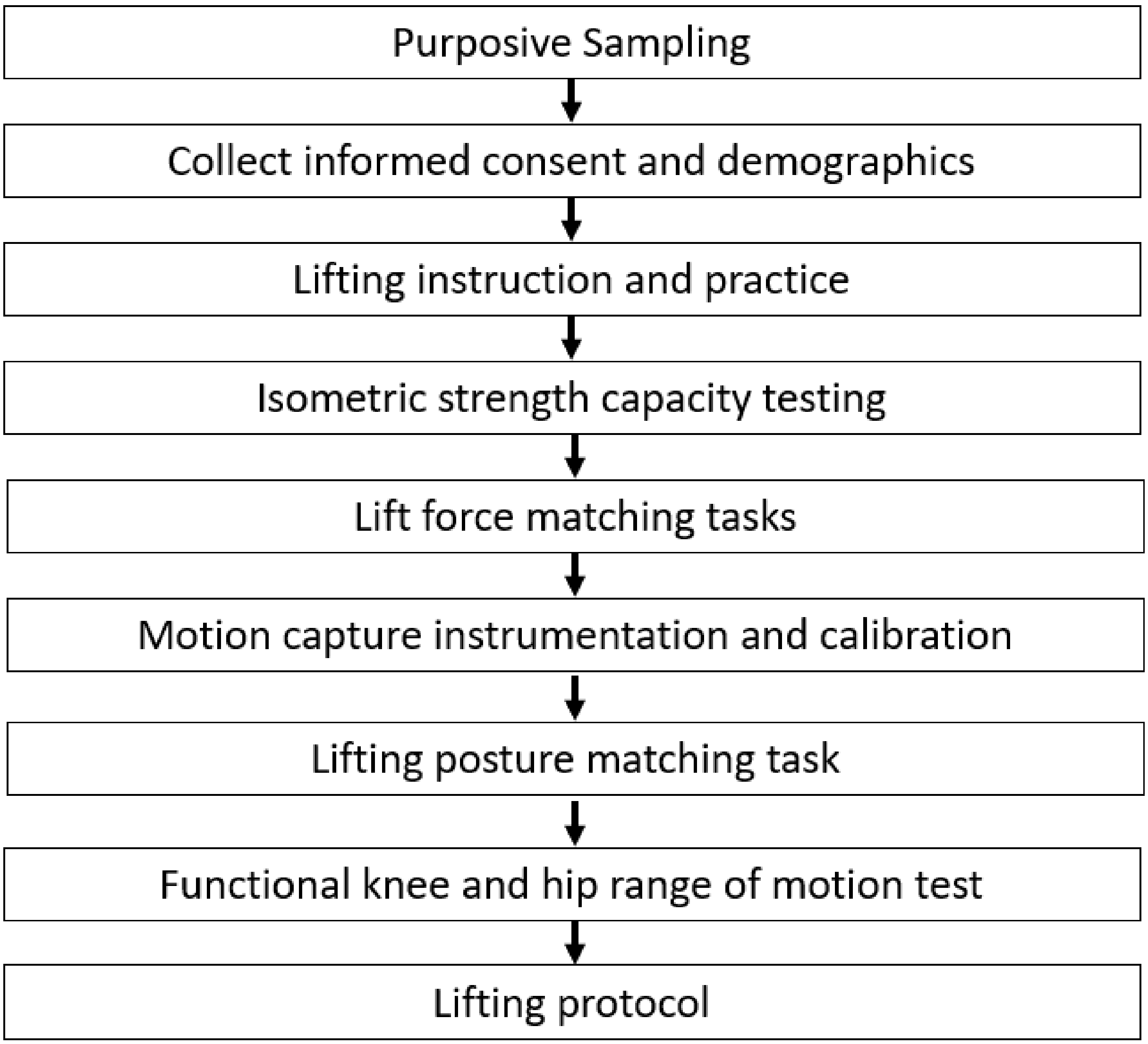


**Figure 4-2:** Common day 1 experimental protocol for studies 1-3.

*4.4 Isometric Lifting Strength Testing*

Following consent and equipment familiarization isometric lift strength testing was completed. In this protocol participants were first asked to perform two maximal static lift trials by pulling on a floor-mounted load cell (Bertec Corporation, Columbus, OH, USA) in the vertical direction using a self-selected lift posture (Figure 4-3) with three minutes of rest between trials. The maximum isometric force generated between the two trials was recorded as an independent variable of lifting strength (adapted from Dolan & Adams, (1998)).

**Figure 4-3:** Maximal isometric lifting force protocol set-up. Participants were asked to maximally pull on the load cell in the vertical direction.

*4.5 Force-Sense Ability Testing*

Force matching was then completed as one of two measures of proprioceptive ability. To complete a force matching trial participants were instructed to generate and hold the target force level in an isometric lift posture as accurately as possible for three seconds. Target force levels were scaled to 25, 50 and 75% of participants peak isometric lift force. Prior to measuring force matching ability, participants practiced the force matching task with visual feedback as a form of calibration (Figure 4-4). Following practice, visual feedback of the force was removed, and participants completed the force matching trials without feedback. Two force matching trials were completed at each force target, where the order of presentation was randomized. Participant's posture was controlled in between practice and holding the force target without visual feedback to control for thixotrophic effects (Gregory et al., 1998).

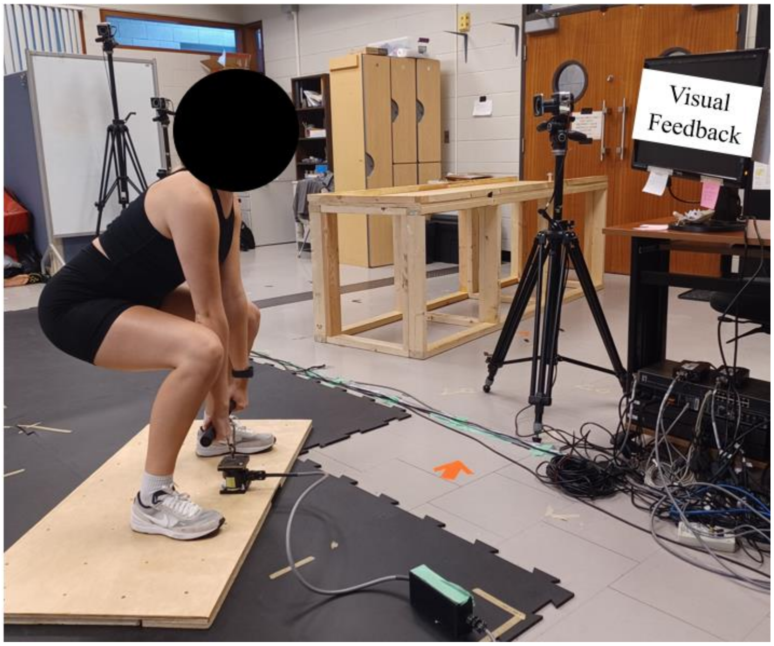


**Figure 4-4:** Static force matching task set-up. Real time visual feedback of force generation was shown on the computer screen during practice exertions.

The time-series forces in the vertical axis of the load cell were used to determine force matching error. In each force matching trial, the absolute error (Brumagne et al., 2000) between the force matching target and true performance was calculated across the trial. The one second window during the trial which had the lowest average absolute error was retained as a measure of force matching performance. The lower average force matching error between the two trials in each condition was retained as an independent variable to represent participants' best demonstrated ability to complete the force matching task. Sample data visualizing force matching performance is provided in Figure 4-5.

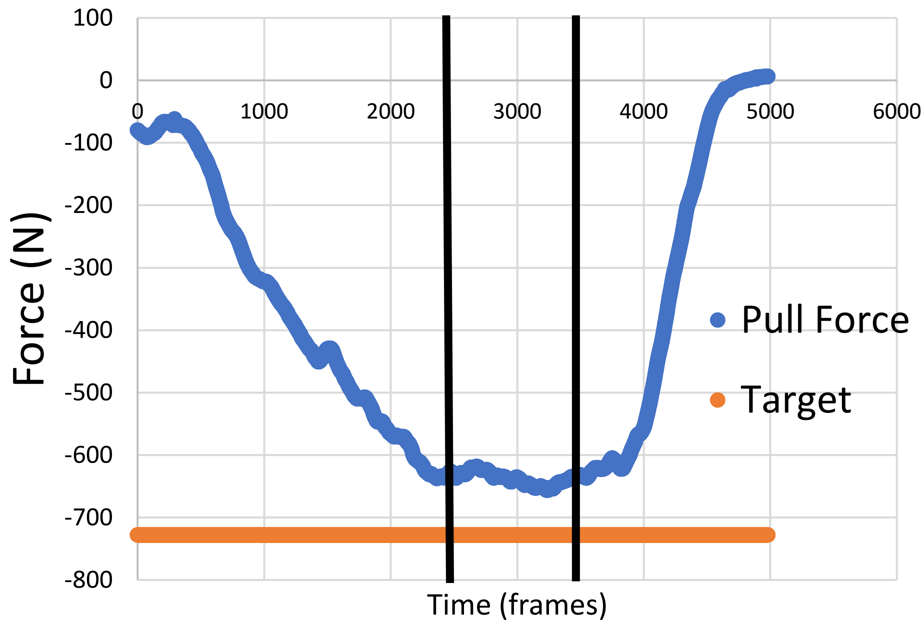


**Figure 4-5:** Exemplar data visualizing force matching performance. The absolute error between pull force and target force within the 1 second window with the lowest average error (start and end point of time window visualized with black vertical lines) was determined as a measure of performance.

*4.6 Posture-sense Ability Testing*

Following the force matching trials participants were instrumented for motion capture so that whole-body kinematics could be collected. Posture matching trials were conducted following instrumentation. Determining both participant's force- and posture-sense of proprioceptive ability was important as movement and force related aspects of proprioception may be processed through differing neural pathways (Han et al., 2016). Evidence supporting this hypothesis is seen in work that has shown that perception of effort in exercise is processed centrally, not peripherally (Smirmaul, 2012). Further, finger pinch movement discrimination accuracy did not differ with and without elastic resistance (Han et al., 2013), which suggest that perception of displacement and force occur through unique processing pathways.

During the posture matching trials participants were asked to start in a standing position, move into a self-selected 'lift posture' to grasp a barbell on the ground, move through a lifting range of motion for five repetitions, and then reassume their initial 'lift posture'. This protocol was completed twice using each of a self-selected, and coached squat- and stoop-like lift postures in a randomized order (Figure 4-6). Use of the coached squat- and stoop-like lift postures were to challenge participants to replicate postures at extremes of lifting strategy options where historically lifting strategy has been defined on a continuum of squat- to stoop-like (Burgess-Limerick & Abernethy, 1997; van Dieën et al., 1999). In the squat-like condition participants were asked to maximally bend their knees while keeping their trunk parallel to the wall in front of them while they put their hands on a barbell in a 'lift posture'. For the stoop-like condition participants were asked to maximally flex through the low back and hips to reach the barbell while attempting to remain fully extended through the knees while assuming their 'lift posture'. Use of the varied lift postures posed different postural challenges to the low back as demonstrated by differences in peak low back flexion angles across lift postures (Table 4-3). Having the participant actively assume lift postures and attempting to best replicate the lifting demands were important considerations when applying this posture matching task as inconsistency in assuming joint position passively vs. actively and limited ecological validity are previous reported limitations in joint position reproduction protocols (Han et al., 2016).

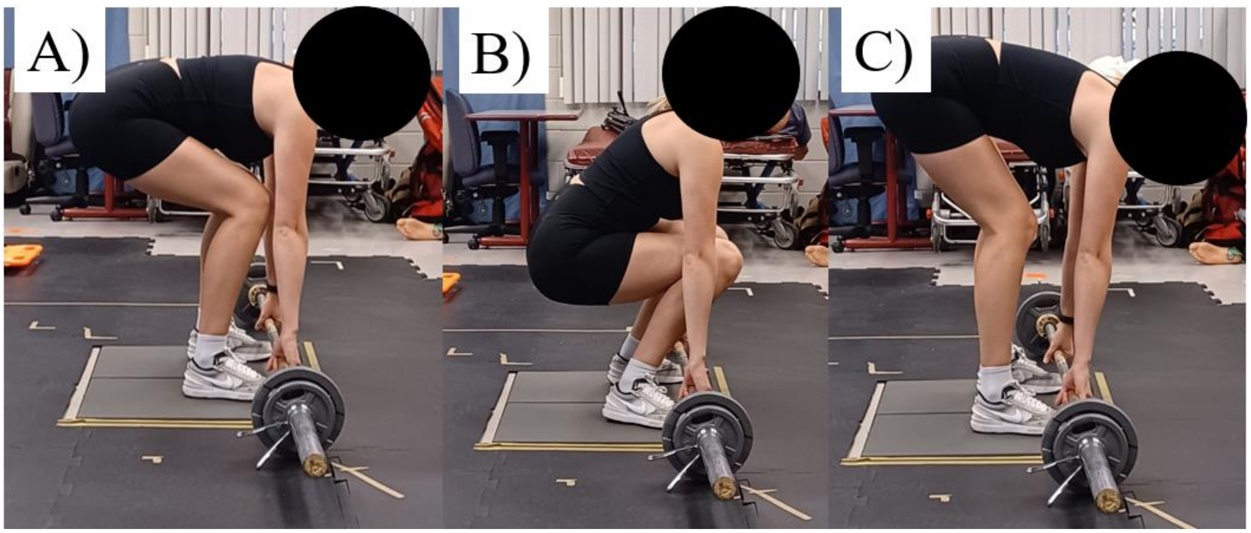


**Figure 4-6:** Visualization of A) self-selected, B) squat-like and C) stoop-like lift postures. Note: the self-selected lift posture varied across participants.

**Table 4-3:** Differences in peak low back flexion angles across self-selected, squat-like and stoop-like lift postures in the posture matching protocol.

| | Self-selected | Squat-like | Stoop-like |
|---|---|---|---|
| Peak Low Back Flexion Angle ($^o$) | 53.4 (20.3) | 50.4 (20.0) | 64.9 (24.7) |

Low back angles (trunk relative to pelvis) about the flexion/extension axis were calculated in the posture matching trials as described in section 4.11. The absolute difference in the low back flexion angles in the initial and final 'lift postures' were calculated for each of the posture matching trials, and the minimum error between the two trials in each condition was retained as an independent variable. Exemplar data visualizing posture matching performance is pictured in Figure 4-7.

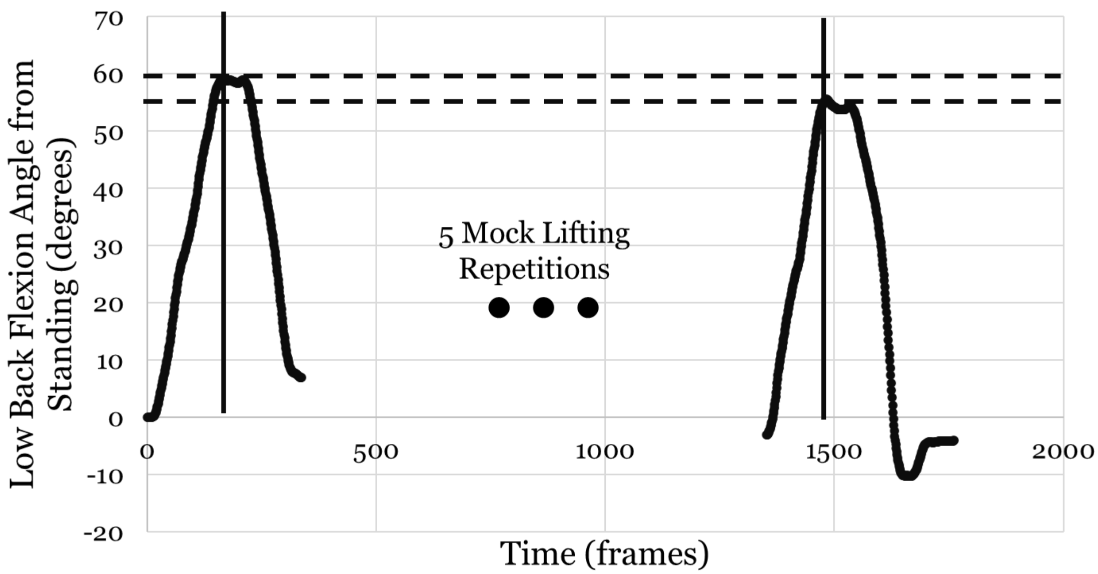


**Figure 4-7:** Exemplar posture matching data. Peak low back flexion angles at the initial and final lift postures (denoted by vertical lines) were compared. Differences in these initial and final angles (denoted by dashed horizontal lines) were taken as a measure of performance.

*4.7 Flexibility Testing*

To determine participants functional flexibility, peak knee and hip angular displacement from standing were determined from the coached squat-like and stoop-like lift postures used in the posture matching tasks, respectively. Use of joint angular displacement of the knee and hip (using joint angles calculated using methods described in section 4.11) within the coached squat and stoop postures provided a measure of available joint functional range of motion (fROM) to participants when performing a lift-like action. To coach the quat-like posture participants were asked to maximally flex through their knees while keeping their trunk parallel to the wall in front of them will placing hands on the barbell. Meanwhile, coaching instructions for the stoop-like posture included asking participants to maximally flex through their hips and low back to place hands on the barbell. No instruction on foot placement was provided for either the squat- or stoop-like postures. This protocol has greater external validity then measuring passive joint range of motion as the full range of passive joint range of motion may not be available to individuals when they need to coordinate their movement to complete a lift.

### *4.8 Dynamic Lifting Proprioceptive Ability Testing*

In the second experimental session a load discrimination protocol was performed. The protocol used an adaptive "running fit" method (Prins & Kingdom, 2018) to determine the threshold of load mass difference that could be detected by participants when lifting from the ground to waist height. Within the protocol participants were asked to subsequently lift two crates from the ground to waist height which differed in mass (while blinded to the contents of the crates) and identify which of the two crates was heavier. An adaptive QUEST algorithm (Watson & Pelli, 1983) within the Palamedes toolbox (Prins & Kingdom, 2018) was used to select the difference in load mass in the subsequent trial. All participants performed 75 trials to determine their load discrimination threshold based on pilot data that showed participants tend to converge on their threshold after approximately 50 trials. To reduce the likelihood of fatigue development, I attempted to minimize the absolute mass of the loads so that all lifts were in a range of 6.8 – 11.3 kg. Further, participants were asked to self-select their pacing throughout the protocol to minimize fatigue accumulation. During the load discrimination protocol, the resolution of load mass differences was 0.11 kg. Load discrimination data were only obtained from 66 participants due to loss to follow-up. Exemplar data visualizing load discrimination performance is shown in Figure 4-8.

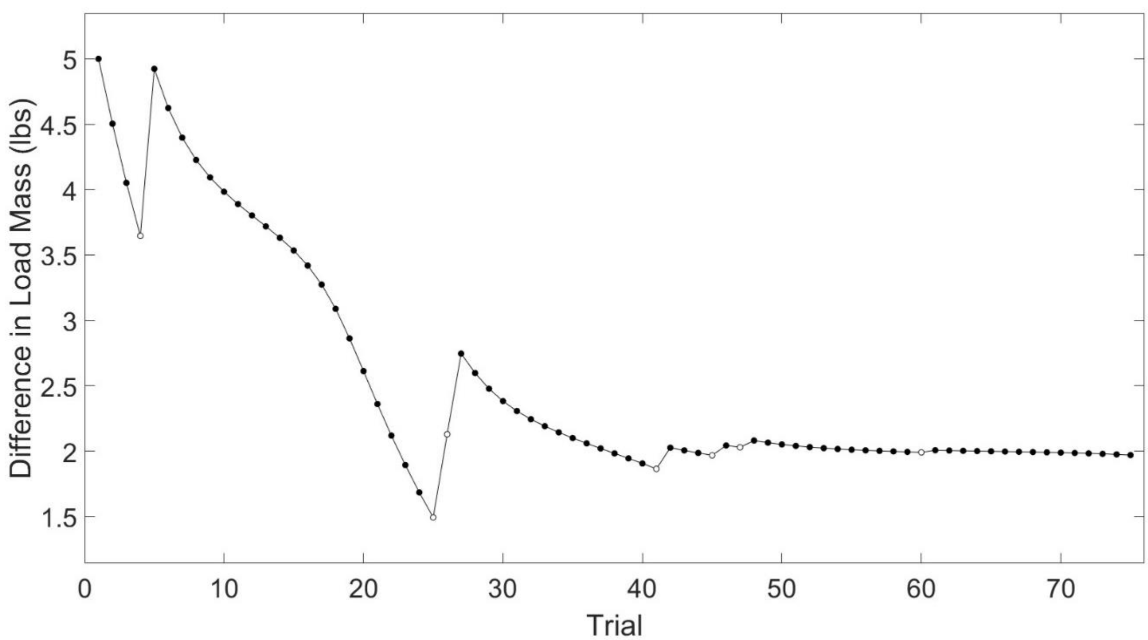


**Figure 4-8:** Exemplar adaptive fit plot from a participant performing the load discrimination protocol. Subsequent correct trials (black circles) result in the difference in load mass progressively decreasing, whereas incorrect trials (white circles) lead to increases in load mass differences. Note: load mass differences reported on the y-axis were reported in imperial units for practical ease in administration of the protocol.

*4.9 Motion Capture Calibration*

Participants were prepared for motion capture collection by affixing passive reflective motion capture markers on anatomical landmarks of the body, as well as the through placement of rigid clusters of passive reflective markers to track segmental motion. Anatomical landmarks to which passive reflective markers were attached included: toe tips, 1st metatarsal heads, 5th metatarsal heads, calcaneous tuberosities, medial and lateral malleoli, medial and lateral femoral condyles, greater trochanters, lateral iliac crests, anterior superior iliac spines, posterior superior iliac spines, acromia, sternum, xyphoid process, C7, T8, medial and lateral epicondyles, ulnar and radial styloid, 2nd metacarpal heads and 5th metacarpal heads. Rigid bodies with four reflective markers were attached on each all segments of interest including the shanks, thighs, pelvis, trunk, upper arm, and forearms, with a redundant marker on the dorsal surface of the hand (Figure 4-1).

Following instrumentation, a static motion calibration trial was performed with participants in a 'motor-bike' pose, which is recommended by the Vicon Nexus 2.0 user manual. Dynamic calibration trials were also collected where participants move all joints through a full range of motion. Both the static and dynamic calibration trials were manually labelled with anatomical landmark and rigid body cluster definitions. The dynamic calibration trial was used to define a model template, which was applied to label markers in experimental trials. Following the motion calibration trials all anatomical markers were removed from the participant so that segmental motion is tracked using rigid marker clusters.

### *4.10 Lifting Protocol*

As a final procedure in the data collection a lifting protocol was completed. During the lifting protocol participants were asked to lift each of a barbell, crate, backboard, and stretcher (Figure 4-9) with an effective mass of 34 kg for 10 repetitions in a block randomized order. To reduce the physical demand on researchers to move loads in and out of the data collection space two subsequent lifts of each lift type were performed by participants with a full randomization of the order of paired lifts. In the barbell, crate and backboard lifting trials participants were asked to lift the load from the ground to waist height, and then return the load to the ground. During the stretcher lifting trials participants were asked to lift and load the stretcher into a mock ambulance. Rest times of 1-2 minutes after every lift, and 3-5 minutes after every 5 lifts were taken to minimize the likelihood of fatigue accumulation. To monitor potential fatigue effects participants were asked to provide their level of perceived exertion after every trial using a Borg scale (Borg, 1998).

Backboard and stretcher lifting were included as occupation-specific lifts as they are an essential task of paramedic work (Coffey et al., 2016) and can expose lifters to low back loads that exceed injury risk guidelines (Armstrong et al., 2020). As lifting a backboard and stretcher are two-person tasks, a trained lifting partner who remained consistent across participants lifted the opposite end of the backboard and stretcher. During all lifting trials participants stood with each foot on individual ground embedded force platforms (Bertec Corporation, Columbus, OH, USA). Ground reaction forces were collected at 1000 Hz. Based on participants' fitness and comfort levels a subset of 63 participants performed the crate lifts, 71 completed the backboard lifts, 70 completed the stretcher lifts, and all 72 participants performed the barbell lifts.

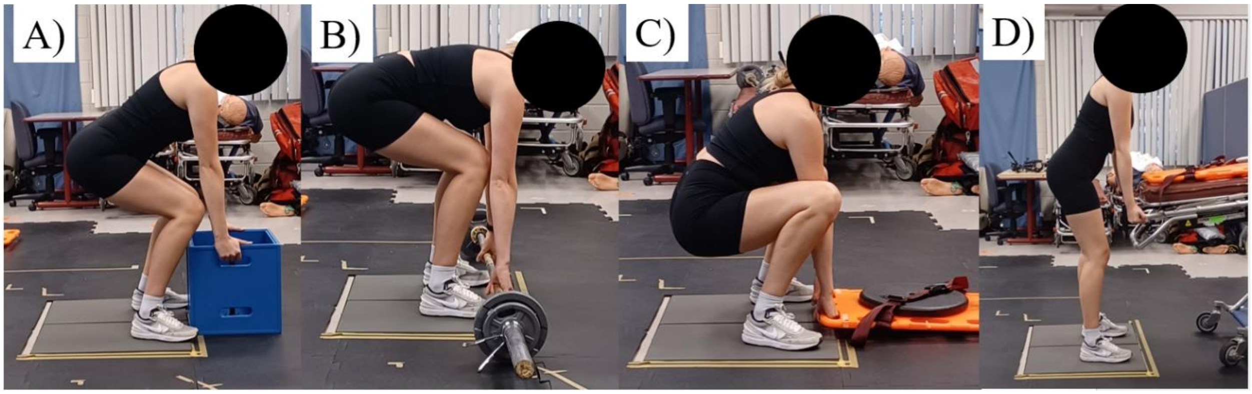


**Figure 4-9:** Visualization of each of the A) crate, B) barbell, C) backboard and D) stretcher lifting conditions.

The mass on the manual stretcher and backboard was 68 kg, which slightly lower than the 75 kg mass of a standard training mannequin. While this mass underestimates average patient mass (Coffey et al., 2016), it is a possible patient mass that may be encountered. Use of a lower mass magnitude than the typical patient response was done to allow for novice lifters to participate safely in the study. The load on the stretcher and backboard consisted of barbell plates to allow for even mass distribution across the equipment which would not be achieved when using a training mannequin. The mass of the barbell and crate lifts were 34 kg so that the even mass distribution on the stretcher and backboard will present the same effective mass to the participants across lift types.

*4.11 Data Processing*

The data processing steps to calculate dependent measures are illustrated in Figure 4-10.

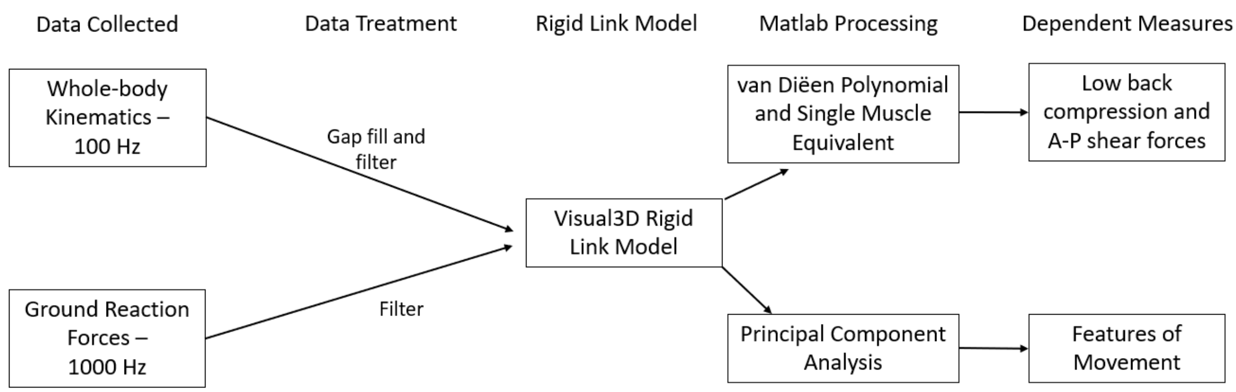


**Figure 4-10:** Block diagram of data processing steps to calculate dependent measures for studies 1-3.

All kinematic data were examined in Nexus 2.6 for missing or unlabeled data points. In the event of missing marker trajectory data, a spline fill function was used for gaps under 200 ms in length, whereas longer gaps were filled with either rigid body or pattern fill functions, consistent with best practice recommendations (Howarth & Callaghan, 2010).

All marker trajectory and ground reaction force data were imported into Visual3D (v6.01.03, C-Motion, Germantown, Maryland) for the purpose of rigid link modelling. All data were dual pass filtered through a low pass second order Butterworth filter with an effective cut off frequency of 6 Hz (Winter, 2009). A whole-body rigid link model was generated using kinematic data consisting of bilateral feet, shank, thigh, upper arm, and forearm segments, as well as pelvis, and trunk segments. The thighs were defined using the medial and lateral markers at the knee joint as well as an estimate of hip joint centre based on Bell et al., (1989) and (1990) recommendations. A Coda pelvis was used defined by the right and left ASIS and PSIS as well as the hip joint centres. The trunk segment was based on the iliac crests proximally and the acromia distally. Markers placed medially and laterally on their proximal and distal endpoints defined the shanks, feet, and forearms. The upper arm was defined distally by markers on the medial and lateral epicondyles and proximally as the glenohumeral joint centre which was approximated at 60 mm from the acromion in the negative direction of the local Y axis of the trunk (Nussbaum & Zhang, 2000).

The aspects of lifting to be considered in analysis included both the approach to the load and lifting the load from the ground to waist height. In Visual3D, lift cycle start and end points were defined as the time point when hand linear velocity in the vertical direction was zero before and after the minimum displacement of the hand in the vertical respectively to consider both the approach to the load and the lift.

Local coordinate systems for all segments were constructed in accordance with ISB guidelines (Wu et al., 2002; Wu et al., 2005). Low back joint angles of the trunk relative to pelvis segment, knee angles and hip angles were calculated using a Z-Y-X (flexion/extension, lateral bend, axial twist) Euler decomposition sequence.

To calculate joint moments a bottom-up inverse dynamics Newton-Euler modelling approached was used. Ground reaction force and moment data from each respective force plate were applied to the centre of pressure of the corresponding foot segment. Body segment parameters including segment mass (Dempster, 1955), moment of inertia (Hanavan, 1964), and COM location (Hanavan, 1964) used Visual3D default settings.

The rigid link model was also used to generate time-series trajectories of anatomical landmarks to represent whole-body motion (Figure 4-11). Specifically, anatomical landmark trajectories included in analysis were toe tips, medial and lateral malleoli, medial and lateral femoral condyles, hip joint centres, glenohumeral joint centres, medial and lateral epicondyles, ulnar and radial styloid, bilateral ASIS, iliac crests and mid-point between the PSIS.

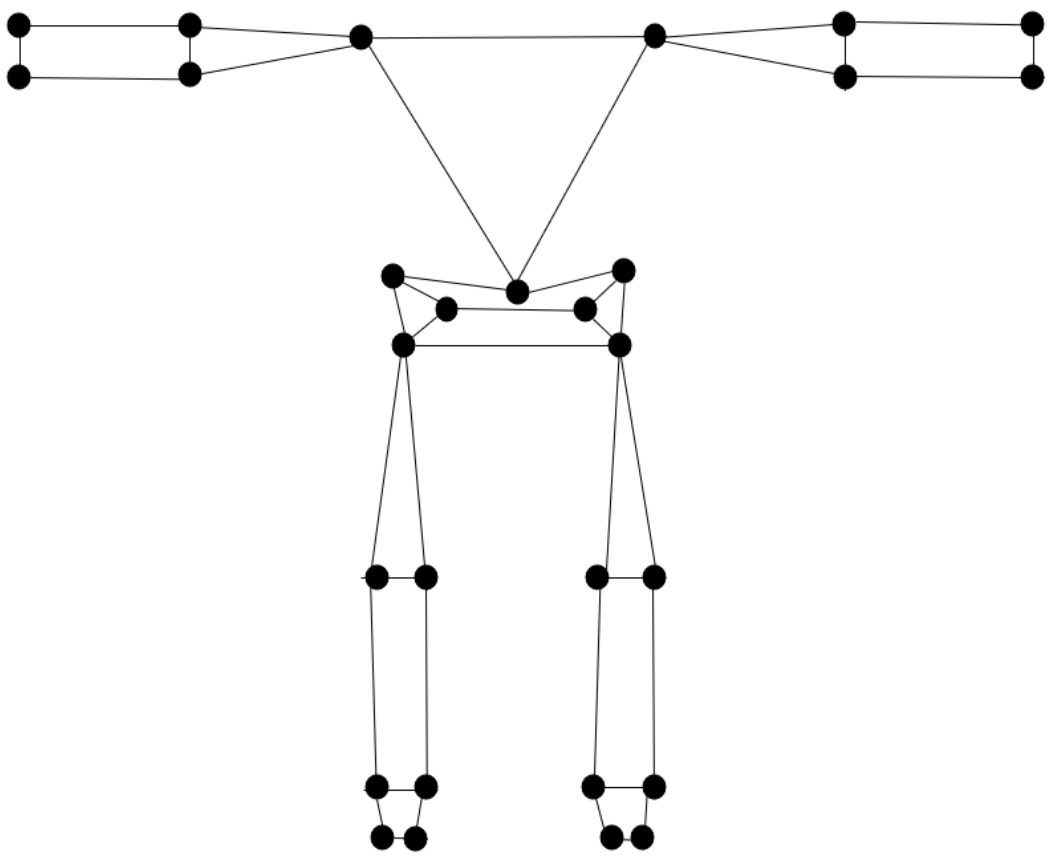

**Figure 4-11:** Visualization of landmarks generated from a rigid-link model to track whole-body motion. These data were used to identify features of whole-body movement strategy using a principal component analysis model.

To calculate low back compression and A-P shear forces at the low back time-series low back flexion/extension angles and moments were exported to Matlab (The Mathworks, Natick, USA). Generated kinetics at the low back were expressed relative to the trunk segment from an internal perspective. Expressing kinetics relative to the trunk was an important consideration as it is noted on the Visual3D wiki that the Coda pelvis tends to be tilted forward approximately 20 degrees. To estimate muscular contributions to resultant low back compression and A-P shear forces a single muscle equivalent model (SME) was used. Changes in low back muscle moment arm and line of action were estimated using a polynomial equation as a function of low back angle (van Dieën & de Looze, 1999). Noting that the orientation of the Coda pelvis does not align with the orientation of the L5/S1 joint in the van Dieën & de Looze polynomial, low back flexion angles input to the polynomial were referenced to standing posture for all participants to account for forward rotation of the Coda pelvis within the global coordinate system as well as inter-individual anatomical differences in pelvis morphology. Peak compression and A-P shear forces within each trial were extracted and then normalized to body mass (normalization assumptions were explored in Appendix B as recommended by Hirsch et al., 2022). The mean and within participant standard deviation of the peak compression and A-P shear loads were calculated for each lift condition to serve as dependent variables.

To identify synergistic features of whole-body movement in lifting PCA was used. This method has utility as it can extract redundant information in large data sets (Daffertshofer et al., 2004). Lift cycles were first normalized in the time domain to 101 points in Matlab to represent 0-100% of a lifting cycle. All landmark trajectory data were expressed in the global reference frame (Armstrong et al., 2021a; Armstrong & Fischer, 2020) and normalized in the amplitude domain to participant stature (Remedios et al., 2020; Ross et al., 2018; Armstrong et al., 2021a). For each time point in a lift cycle, posture was represented by a vector where the normalized three-dimensional coordinates of the 29 anatomical landmarks defined an 87-dimensional posture vector. To represent movement strategy across a trial, posture vectors of each of the 101 timepoints were concatenated to generate a single vector to represent whole-body movement strategy over the time series. With whole-body kinematics of each trial in each lifting condition across all participants expressed as a single vector, a matrix was generated with each trial contributing an independent movement series as a row vector. This generated matrix was input to the PCA function in Matlab which transforms the data into a covariance matrix (Jackson, 1991), which can then be orthonormalized to generate the eigenvector matrix. The calculated eigenvectors represent the PCs in the data set. These PCs explain independent sources of variability in movement trajectory data for the data set. PC scores were calculated for each trial, which measure how far the mode of variability in the trial deviates from the mean of that mode of variability in each PC (Wrigley et al., 2006). Separate PCA models were applied to independently identify features of whole-body movement in each of the four lift types.

To determine the number of PCs to retain for analysis a 90% trace criterion was used (Jackson, 1991; Deluzio & Astephen, 2007; Sadler et al., 2011; Reid et al., 2010). The within participant mean and standard deviation of PC scores were calculated as dependent measures individually for each of the four lift types. Single component reconstruction was used to aid in the interpretation of modes of variance explained by PCs (Brandon et al., 2013). Additionally, the time-series loading vector of each marker trajectory was used to understand which markers explain variance in each PC, and where variance was being explained in the time domain (Armstrong et al., 2021a).

Quantifying differences in the mean and/or variability in features of movement related to resultant biomechanical exposures as a function of independent variables is important to address the thesis objectives. To identify which features of movement were associated with biomechanical exposures regression was used to test whether peak normalized compression or A-P shear forces were associated with PC scores in all retained PCs. If significant associations were observed between low back loads and PC scores, the PC was classified as biomechanically relevant. This classification was used to aid in the interpretation of findings where lower variability in these features of movement with lower corresponding magnitudes of low back exposure magnitudes would suggest a movement objective that aims to minimize resultant exposures.

Within participants, the mean and standard deviation of PC scores for PCs that differ as a function of biomechanical exposure were calculated as dependent measures. The mean of PC scores served as a representative measure of the movement strategy a participant tends to use within each feature of movement. Consideration of the variability in PC scores is an important dependent measure as differential variability in certain features of movement may be used to infer the definition of a movement objective (i.e., control law) according to the overarching OFC theoretical framework.

### *4.12 Statistical Analysis*

Statistical analysis was not consistent across studies 1-3 and is described in study-specific thesis chapters.

# Chapter 5: Association of posture- and force-sense proprioceptive measures

*5.1 Introduction:*

In this thesis I have hypothesized that ability to perceive relevant proprioceptive information at the low back is related to the consistency and control of low back biomechanical exposures in lifting. However, sensory perception is a complex phenomenon, so it is prudent to first consider how to measure relevant proprioceptive ability for research questions posed in the thesis.

It is important to differentiate between force-sense and posture-sense when measuring proprioceptive ability. While proprioception broadly refers to the sensation of both the body in space and resultant forces acting on the body, the afferent sensory systems that perceive these two sources of information differ. Perception of force-sense within the musculoskeletal system has primarily been attributed to golgi tendon organs, and posture-sense has been attributed to muscle spindles (Proske & Gandevia, 2012). With differing afferent receptors attributed to the posture- and force-sense components of proprioceptive ability it is first important to know if the ability to perceive postures and forces respectively are related. This has practical implications for this thesis as lifting an external load has both force and posture demands.

A second important consideration is how proprioceptive ability differs when it is measured statically compared to dynamically. Historically perception of posture and movement were generally considered a single sense referred to as kinesthesis (Bell, 1826), but more recent evidence suggests differences in how they are perceived. Both the perception of posture and movement are attributed to muscle spindles, but experimental findings suggest differences in how they are perceived by the afferent fibres. Primary muscle spindle endings respond to both the length change and rate of length change (Matthews, 1974), but secondary endings seem likely to contribute to position sense (McCloskey, 1973). Thixotrophic effects (reductions in muscle stiffness during and following movement) also support differing perception of posture and movement as following a conditioning contraction there were significant changes in perceived position of the limb without any sensation of movement (Gregory et al., 1988). These experimental findings highlight the need to differentiate between static and dynamic perception of posture/movement when measuring proprioceptive ability.

Considering the differences in proprioceptive perception between static and dynamic contexts experimental methods to measure both phenomena are important to consider. Varying methods have been applied to measure proprioceptive ability including threshold to detection of passive motion, joint position reproduction tasks, and active movement extent discrimination apparatus which have varying ecological, testing and data validity (Han et al., 2016). Considering limitations with commonly applied methods to measure proprioceptive ability, psychophysical methods may be an alternative to measure proprioceptive ability dynamically within an occupational lifting context. A “best Quest” algorithm (Prins & Kingdom, 2018) that employs a running fit method to converge on a psychophysical threshold following application of stimulus intensities dependent on previous trials is an example of such an approach. The “best Quest” algorithm could be applied to identify the threshold at which individuals can perceive a difference in load mass (i.e., load discrimination) when lifting repetitively. A benefit of such an approach would allow individuals to lift through a dynamic range challenging both the posture- and force-sense abilities of the sensory system. However, it is once again important to consider how a psychophysical estimate of proprioceptive ability relates to both force- and posture-sense ability measured in static contexts.

The goal of this preliminary analysis was to determine whether varying lift-specific posture-sense, force-sense and load discrimination measures were associated with one another. It was hypothesized that various posture-sense measures would be associated with one another, while various force-sense measures would be similarly associated with one another because the same afferent systems would be challenged. Since the load discrimination protocol would challenge both posture- and force-sense afferent pathways, significant associations were hypothesized to both static posture- and force-sense measures. However, no significant associations were hypothesized between posture- and force-sense measures.

## *5.2 Methods:*

### *5.2.1 Study Design*

In this study the association between all the proprioceptive measures quantified in this thesis, including posture-sense, force-sense, and load discrimination ability, was examined. Full methodology including participant recruitment, instrumentation, experimental protocol, and data processing methods are presented in the general methodology chapter (Chapter 4.0).

### *5.2.2 Statistical Analysis*

Linear regression was used to quantify the association between all proprioceptive measures with strength of association being measured with $R^2$ values. All statistical analyses were conducted in SPSS (Version 26.0, IBM Corporations, Armonk, NY).

*5.3 Results:*

The mean and standard deviation of all proprioceptive measures are presented in Table 5-1. Based on the regression analyses no significant associations of proprioceptive measures to one another were observed (Table 5-2), where 5% of shared variance (i.e., $R^2 = 0.051$) was the strongest observed correlation between load discrimination and force matching error at the 25% of max target measures.

**Table 5-1:** Descriptive statistics of proprioceptive ability measures reported as group means and (standard deviations) stratified by lifter expertise groups.

| Task | Posture / Force Target | Paramedics / In-training (n = 20) | Trained Lifters (n = 26) | Novice Lifters (n = 26) |
|---|---|---|---|---|
| Posture Matching Error ($^o$) | Self-Selected | 3.4 (1.7) | 3.1 (1.2) | 2.9 (1.6) |
| | Squat | 3.1 (1.9) | 2.9 (1.9) | 3.2 (1.9) |
| | Stoop | 2.4 (1.4) | 2.6 (1.5) | 2.7 (2.9) |
| Force Matching Error (N) | 25% of max | 28.1 (25.0) | 16.7 (12.7) | 14.4 (8.8) |
| | 50% of max | 49.6 (47.4) | 23.5 (11.8) | 30.0 (19.5) |
| | 75% of max | 46.8 (40.6) | 29.3 (22.4) | 27.9 (14.3) |
| Perceivable Load Difference (kg) | | 0.67 (0.25) | 0.76 (0.31) | 0.70 (0.32) |

**Table 5-2:** Strength of association ($R^2$) measures between proprioceptive ability measures.

| $R^2$ Between Measures | Load Discrim. | Force Error – 25% | Force Error – 50% | Force Error – 75% | Posture Error – Self Selected | Posture Error – Squat | Posture Error – Stoop |
|---|---|---|---|---|---|---|---|
| Load Discrim. | 1 | 0.051 | 0.026 | <0.001 | 0.001 | 0.005 | 0.002 |
| Force Error – 25% | | 1 | 0.008 | 0.007 | <0.001 | 0.001 | 0.006 |
| Force Error – 50% | | | 1 | 0.021 | 0.006 | 0.014 | <0.001 |
| Force Error – 75% | | | | 1 | 0.002 | 0.017 | 0.001 |
| Posture Error – Self Selected | | | | | 1 | 0.009 | <0.001 |
| Posture Error – Squat | | | | | | 1 | 0.033 |
| Posture Error – Stoop | | | | | | | 1 |

### *5.4 Discussion:*

The purpose of this preliminary analysis was to investigate whether proprioceptive measures specific to a lifting context covaried. Based on this analysis no significant associations between posture- or force-sense at the low back, or dynamic load discrimination ability were observed. This highlights that the experimental methods to measure proprioceptive ability used in this study all measure unique aspects of sensory perception. As such, when aiming to test the hypothesis that proprioceptive ability is associated with consistently minimizing low back exposures all the proprioceptive measures in this current analysis should be considered as predictor variables.

The lack of shared variance between proprioceptive measures is attributed to different sensory pathways being challenged across tasks. Most notably, lack of association between the force and posture matching tasks are likely attributable to differing proprioceptive sensory pathways being challenged. Muscle spindles were likely primarily involved in the posture matching tasks, while golgi tendon organs would predominantly be involved in the force matching tasks (Proske & Gandevia, 2012). Meanwhile, a combination of both force- and posture-sense proprioceptive pathways would be involved in the load discrimination protocol.

Interestingly, no significant associations were observed when regressing force- or posture-sense measure to differing conditions aiming to challenge the same sensory pathways. The lack of associations even within force- or posture-sense tasks are likely attributable to a reliance on other forms of available sensory information to complete the experimental tasks. Considering other forms of sensory information that could contribute to performance on the force-sense and load discrimination tasks, tactile feedback at the hands is an important consideration. With both tasks participants were asked to hold either a handle or crate in their hands while exerting a lifting force. Anecdotally several participants remarked that they were using tactile perception in their hands to determine force and/or load mass. The strongest measured association of load discrimination ability to force matching error at the lightest target may suggest that tactile perception at the hands was used to a greater extent, whereas force-sense may have been more heavily relied upon as the relative demand of the force matching task increased. This potential for varying the reliance on either tactile and proprioceptive sensory information as force targets changed is supported by experimental findings highlighting that the relative importance of tactile versus proprioceptive information varied as participants were asked to identify the size and compliance of differing foam blocks (Schiefer et al., 2018).

The use of proprioceptive measurement tasks that aimed to replicate lifting demands provided several sensory perception pathways in the body that could have been relied upon to perceive the relevant sensory information. In both the posture- and force-sense tasks nearly the entire body was involved in the task. This availability of various modes of sensory information from differing body regions may have influenced the weak associations of performance measures across participants whereby adopting strategies to perceive sensory information differently across their body may contribute to the lack of association of measures. This possibility is supported by anecdotal evidence where differing strategies to perform all the proprioceptive ability tasks were shared by participants. Examples of differing strategies mentioned by participants included the perception of force in their hamstring muscles compared to a perception of load at the low back specifically.

The reported lack of associations across sensory perception measures has implications for the remainder of this thesis. Since the examined proprioceptive measures were not related to one another it is important to consider them all as independent predictors of low back exposures in lifting. As such, the methodological decision to include all the proprioceptive measures in statistical analyses for study 1 of the thesis was made. Second, the lack of associations between these proprioceptive measures should be considered when interpreting findings to study 1. These observed weak associations likely support that the mode of proprioception measured across task differs and may have differed across participants. This may challenge the ability to conclusively determine whether proprioceptive ability is mechanistically related to consistently minimizing low back exposures when lifting. However, with an end goal of this thesis to inform the development of ergonomic interventions using ‘lift-like’ conditions to measure proprioceptive ability was important to increase the external validity of the study design.

*5.5 Conclusion:*

In this preliminary analysis I show that proprioceptive ability measured across the battery of force-sense, posture-sense, and load discrimination protocols were not associated. This highlights the need to consider all these variables independently as predictor variables when aiming to test the hypothesis that greater proprioceptive ability is associated with consistently minimizing biomechanical exposures at the low back in lifting.

# Chapter 6: Ability to perceive sensory feedback as a determinant of low back loading in lifting

## *6.1 Introduction:*

In the development of ergonomic interventions that aim to fit the worker to the work, it is important to understand what factors influence the way a worker moves. This direction is supported by preliminary work showing that some lifters seem to define a motor control objective that considers both completing lifting task objectives and minimizing resultant biomechanical exposure on the low back (Armstrong & Fischer, 2020). Considering these preliminary findings, it is assumed that within the context of optimal feedback control (OFC) theory (Scott, 2004; Todorov, 2004) that lifters who experience lower biomechanical exposures at the low back when lifting do so because they define a control law considering resultant exposures as relevant to task performance.

Preliminary findings support the hypothesis that some lifters aim to consistently minimizes resultant loads on the body, but factors influencing the closed feedback loop theorized within the OFC framework are not considered. Specifically, OFC theorizes that while movement is being performed sensory feedback is used to determine whether the employed movement strategy is maintaining task performance as defined by the control law (Scott, 2004; Todorov, 2004). If there are discrepancies between the perceived sensory feedback and movement objectives as defined by the control law, then the optimal state estimator intervenes to adapt movement related to task performance online. Meanwhile task-irrelevant movement is left uncontrolled, in accordance with the minimum intervention principle (Todorov & Jordan, 2002; Todorov & Jordan, 2003). In this closed feedback loop the perception of sensory information plays a pivotal role in controlling movement strategy to maintain task performance.

An individual's ability to perceive sensory information may be a determinant of lifting strategy because of its role within the OFC closed feedback loop model. Specifically, those who are better able to perceive feedback associated with resultant biomechanical exposures, such as high magnitudes of joint moments and/or angles, may better move to consistently reduce resultant biomechanical exposures. This hypothesis is supported by evidence that suggests lifters can perceive joint moments, as demonstrated by their ability to choose psychophysically acceptable loads (Fischer & Dickerson, 2014; Jorgensen et al., 1999; Kuijer et al., 2012; Banks & Caldwell, 2019), but can not perceive low back compression force (Thompson & Chaffin, 1993). Clinical evidence reaffirms the potential importance of sensory feedback perception as a determinant of lifting strategy where deficits in tactile acuity were related to guarded lumbopelvic movement observed in chronic low back pain patients (Luomajoki & Moseley, 2011). The previously reported ability to perceive joint moments in lifting suggests the possibility that those better attuned to this sensory information may have the ability to consistently minimize these exposures in practice.

The type of sensory feedback should be considered when testing the hypothesis that ability to perceive sensory information influences biomechanical exposures in lifting. Since low back moments and angles are associated with musculoskeletal disorder risk (Norman et al., 1998; Marras et al., 1993), proprioceptive feedback, which is described as the body's ability to sense the position and force of one's own body (Tuthill & Azim, 2018), is likely an important consideration. Evidence of the importance was demonstrated by Pinardi et al. (2020). When a vibration stimulus was applied to participants to invoke the illusion of faster movement, resultant lifting strategies were executed with lower accelerations (Pinardi et al., 2020). Additionally, when a vibration stimulus was applied to the back to perturb muscle spindle sensory feedback, an aspect of proprioceptive perception, trunk flexion/extension motor task performance decreased (Boucher et al., 2013; Boucher et al., 2015; Kiers et al., 2014; Kiers et al., 2015; Willigenburg et al., 2012; Willigenburg et al., 2013). The influence of vibration on kinematics at the low back supports the hypothesis that inherent ability to perceive proprioceptive feedback could influence lifting strategy and corresponding resultant exposures at the low back. Potential clinical relevance of ability to perceive proprioceptive information as a determinant of lifting strategy is supported by individuals with low back pain having lower posture-sense proprioceptive ability as measured by a motion perception task (Lee et al., 2010). Extending these findings, poor active body repositioning proprioceptive ability of the trunk was shown to predict knee injuries in female collegiate athletes (Zazulak et al., 2007), which highlights a potential relevance of proprioceptive ability to injury risk opposed to just being a product of low back pain.

Proprioceptive information is linked to control of lifting strategy (and corresponding exposures) but is a composite outcome from several underlying sensations. First, proprioception broadly encompasses both the kinesthetic awareness (i.e., perception of posture and motion) as well as perception of force (Proske & Gandevia, 2012). While the perception of posture, movement and force fall broadly under the proprioception umbrella, they have unique afferent receptors with position sense being primarily attributed to muscle spindles and muscle force sense attributed to golgi tendon organs (Proske & Gandevia, 2012). Considering the ability to perceive posture and muscle force at the low back are important where low back posture (Norman et al., 1998; Marras et al., 1993) and loads (Gallagher & Marras, 2012; Marras et al, 1993; Norman et al., 1998; Waters et al., 1993) are well-established injury risk factors. Additionally, since the perception of muscle force and posture are achieved through differing sensory pathways, the ability to independently perceive posture or force may explain different aspects of variance in lifting performance. Finally, differences in measured proprioceptive ability across static vs. dynamic tasks have been observed and are theorized to be a result of differing contributions of the sensorimotor system in active performance (Elangovan et al., 2014). This is highlighted by primary muscle spindle endings responding to both the length change and rate of length change (Matthews, 1974), while secondary endings seem to contribute to position sense (McCloskey, 1973). As such, considering ability to perceive relevant posture or force information at the low back in a combination of static and dynamic contexts is important when investigating the potential relationship to lifting outcomes.

When investigating whether ability to perceive relevant sensory information results in a control law that aims to minimize biomechanical exposures in lifting it is important to consider how this would manifest within the context of OFC theory. We have previously demonstrated that some individuals seem to define a control law that aims to minimize biomechanical exposures (Armstrong & Fischer, 2020). If a lifter exhibits lower mean and variability in biomechanical exposures, it provides evidence that the lifter is considering biomechanical exposure in their control law. While lower mean exposure is an intuitive outcome that might identify an individual that is considering biomechanical exposure in their control, trial-to-trial variability is a complimentary outcome necessary to support that inference. Lower variability would be expected if the biomechanical exposures were considered relevant to task performance within the OFC framework, or perhaps, more tightly controlled (Scott, 2004; Todorov, 2004). If consistently lower biomechanical exposures (i.e., means and variability) are observed in individuals with greater proprioceptive ability then we can infer that proprioceptive ability may be an important requirement to enable biomechanical exposures to be considered in the control law.  A natural extension of this line of inquiry is then to further probe how coordination patterns generate these lower resultant magnitudes of exposures.

PCA is a methodology that can reduce whole-body kinematic data to independent synergistic features of movement, or kinematic coordination patterns (Federolf, 2016; Armstrong et al., 2021a). Support for PCA to identify coordination patterns is provided by Todorov (2004) where they suggest that identified PCs in underlying muscle electrical activity measured by electromyography can be conceptually thought of as 'control knobs' where a subset of these PCs are controlled to maintain task-relevant movement features. If biomechanical exposures are inversely associated with proprioceptive ability, we can explore PCs as measures of coordination to see which coordinative components (i.e., PCs) are being controlled to cause the lower exposures. With a goal of testing whether proprioceptive ability is related to low back loads in lifting the alignment of independent variables (proprioceptive ability) and dependent variables (low back biomechanical exposures and kinematic coordination patterns) within an overarching OFC framework is visualized in Figure 6-1.

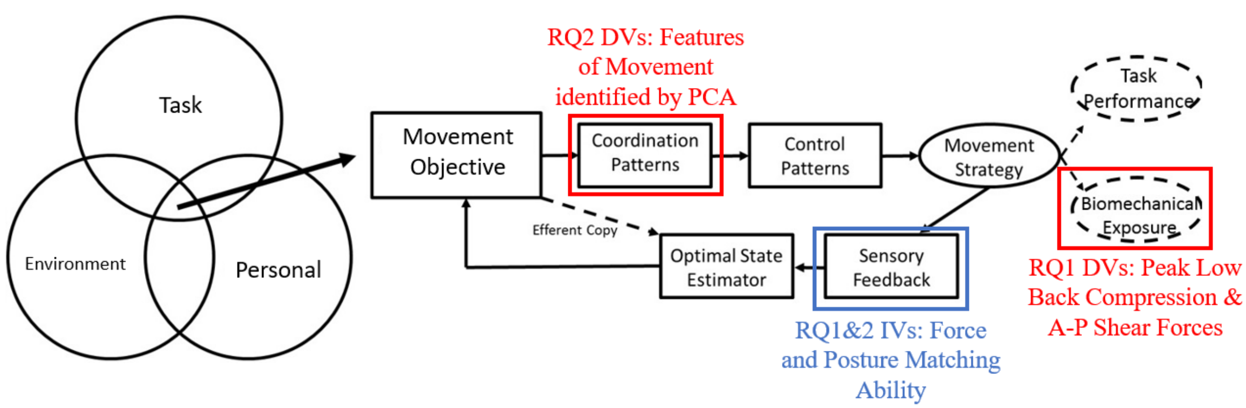


**Figure 6-1:** Visualization of study 1 independent and dependent variables within the overarching OFC model. Figure adapted from Armstrong & Fischer (2020). RQ: Research Question, IV: Independent Variable, DV: Dependent Variable, PCA: Principal Component Analysis.

The purpose of this study was to investigate whether proprioceptive ability (including both posture- and force-sense) independently and/or interdependently explain variance in peak low back loads, and aspects of lifting strategy related to low back loads in generic and paramedic lifting tasks. First, to determine whether proprioceptive ability explained variance in the biomechanical exposures in lifting I asked: Does the ability to perceive proprioceptive information explain variance in the mean and/or variability of peak low back compression and A-P shear forces in both generic (barbell and crate) and occupation-specific (backboard and stretcher) lifting? Second, if significant variance in biomechanical exposures was explained by proprioceptive ability, I aimed to determine whether this was achieved by consistent control of kinematic coordination patterns related to resultant exposures. I asked: Does the ability to perceive proprioceptive information explain variance in the mean and/or variability of synergistic features of whole-body movement related to biomechanical exposures in both generic (barbell and crate) and occupation-specific (backboard and stretcher) lifting?

I hypothesized that increased ability to perceive proprioceptive information (both posture- and force-sense) would have lower resultant mean and variability of peak low back loads, supporting that these exposures are consistently controlled as task-relevant within the defined control law. Second, I hypothesized that significant variance would be explained in the mean and variability of synergistic features of movement (i.e., kinematic coordination patterns) by proprioceptive ability, suggesting that control of these features of movement as task-relevant would explain the control of resultant biomechanical exposures.

*6.2 Methods:*

*6.2.1 Study Design*

In this study posture-sense, force-sense, load discrimination ability, and lift type, were independent variables. The mean and variability of peak low back compression and A-P shear loads normalized to body mass, as well as synergistic features of movement that were related to resultant peak low back loads were dependent variables in the study design. Full methodology including participant recruitment, instrumentation, experimental protocol, and data processing methods are presented in the general methodology chapter (Chapter 4.0).

*6.2.2 Hypothesis Testing*

Since the load discrimination task was completed on day two, loss due to follow-up reduced the number of participants who completed the load discrimination task relative to the other proprioception tests. To maximize the sample available for statistical analysis, a decision tree-based approach (Figure 6-2) was followed. First, linear regression was used to determine whether load discrimination threshold was associated with either the mean or standard deviation of peak low back compression or A-P shear forces. Load discrimination threshold was only significantly associated with a single biomechanical exposure measure (Table 6-1). Since load discrimination thresholds were not consistent predictors of mean or variability in low back loads it was not used as a predictor variable in further analysis so that data from all 72 participants, opposed to the 66 that completed both sessions, could be used.

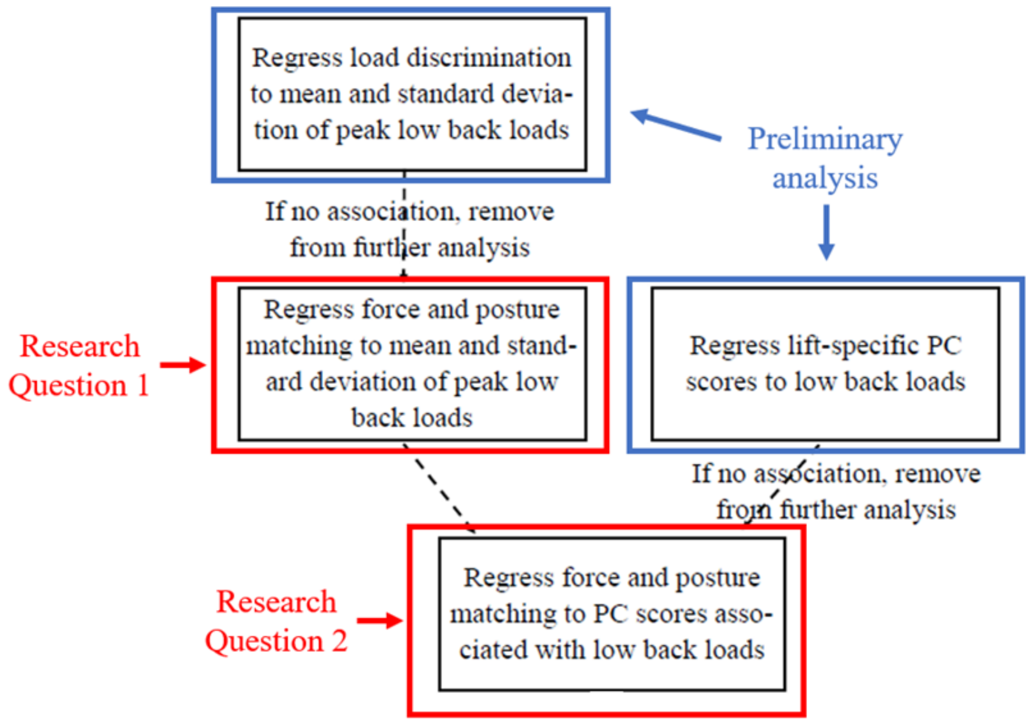


**Figure 6-2:** Visualization of the flow of statistical analysis employed in the study.

**Table 6-1:** Linear regression summary statistics when correlating load discrimination threshold to biomechanical exposure measures across the four lift types.

| | Barbell | Backboard | Crate | Stretcher |
|---|---|---|---|---|
| Mean Comp. | $p = 0.859$<br>$R^2 = 0.001$ | $p = 0.391$<br>$R^2 = 0.012$ | $p = 0.633$<br>$R^2 = 0.004$ | $p = 0.999$<br>$R^2 = 0.001$ |
| Mean Shear | $p = 0.503$<br>$R^2 = 0.007$ | $p = 0.168$<br>$R^2 = 0.030$ | $p = 0.191$<br>$R^2 = 0.030$ | $p = 0.521$<br>$R^2 = 0.007$ |
| Stdev. Comp. | $p = 0.766$<br>$R^2 = 0.001$ | $p = 0.259$<br>$R^2 = 0.021$ | **$p = 0.022$**<br>**$R^2 = 0.092$** | $p = 0.280$<br>$R^2 = 0.020$ |
| Stdev. Shear | $p = 0.143$<br>$R^2 = 0.034$ | $p = 0.273$<br>$R^2 = 0.019$ | $p = 0.978$<br>$R^2 = 0.001$ | $p = 0.101$<br>$R^2 = 0.045$ |

Second, to answer research question 1 backward removal multiple regression models with $\alpha = 0.10$ set as a threshold for predictor removal was used to determine the association between force matching error at the 25, 50 and 75% targets, as well as posture matching error in the self-selected, squat- and stoop-like conditions, to the mean and standard deviation of peak low back loads in the four lift types. Preliminary analysis in the thesis (Chapter 5.0) showed that the various force- and posture-sense measures collected were not associated with one another, and therefore were all included as predictor variables in the multiple regression models.

Third, research question 2 was investigated when significant associations were observed between proprioception ability measures and both the mean and standard deviation of either peak low back compression or A-P shear forces. To answer research question 2 backward removal multiple regression was used to evaluate the association of the significant predictor proprioceptive ability measures found in research question 1 to the mean and standard deviation of PC scores in all features of movement that were related to peak low back loads. The subset of PC scores associated with low back loads were determined by regressing PC scores from all retained PCs to both peak low back compression and A-P shear loads within a given lift type. All regression-based analyses were conducted in SPSS (Version 26.0, IBM Corporations, Armonk, NY). A Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) was applied to control for family-wise error across multiple regression models with a false discovery rate set to 10%. An '*' is used to denote significance in the results accounting for the Benjamini-Hochberg correction.

*6.3 Results:*

Significant associations between proprioceptive ability measures and both the mean and standard deviation of peak low back compression forces were seen across all lift types except to mean compression force during crate lifting (Table 6-2). However, significant associations to the mean and standard deviation of A-P shear loads were only seen in backboard lifting and to the standard deviation of stretcher A-P shear loads (Table 6-3). Descriptive statistics of proprioceptive ability are reported in Chapter 5.3, and descriptive statistics of biomechanical exposure metrics are reported in Chapter 7.3 of this thesis. To contextualize the results of the multiple regression analysis, sample scatter plots visualizing simple regressions between proprioceptive ability measures and the mean and variability of peak low back loads are presented (Figure 6-3).

**Table 6-2:** Backward removal ($p < 0.10$) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of peak low back compression forces normalized to body mass in barbell, backboard, crate, and stretcher lifting. Significant predictors in the final model are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'.

| | Association to 10-trial mean of peak low back compression | | Association to standard deviation of peak low back compression across 10 lifts | |
|---|---|---|---|---|
| | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | Error at 75% Target (β = 0.30), Self-selected Matching Error (β = 0.24) | $p = 0.003$* $R^2 = 0.164$ F = 6.39 | Error at 75% Target (β = 0.29), Self-selected Matching Error (β = 0.22) | $p = 0.006$* $R^2 = 0.147$ F = 5.59 |
| Backboard | Self-selected Matching Error (β = 0.27), Error at 75% Target (β = 0.28) | $p = 0.003$* $R^2 = 0.164$ F = 6.27 | Self-selected Matching Error (β = 0.28) | $p = 0.024$* $R^2 = 0.076$ F = 5.34 |
| Crate | Error at 75% Target (β = 0.24) | $p = 0.064$ $R^2 = 0.057$ F = 3.56 | Squat Matching Error (β = 0.32) | $p = 0.014$* $R^2 = 0.100$ F = 6.46 |
| Stretcher | Squat Matching Error (β = 0.24), Stoop Matching Error (β = -0.22) | $p = 0.049$ $R^2 = 0.057$ F = 3.17 | Squat Matching Error (β = 0.30) | $p = 0.016$* $R^2 = 0.090$ F = 6.15 |

**Table 6-3:** Backward removal ($p < 0.10$) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of peak low back anteroposterior shear forces normalized to body mass in barbell, backboard, crate, and stretcher lifting. Significant predictors in the final model are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. N/A indicates no significant association was found.

| | Association to 10-trial mean of peak low back A-P shear | | Association to standard deviation of peak low back A-P shear across 10 lifts | |
|---|---|---|---|---|
| | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | Error at 50% Target (β = 0.24) | $p = 0.097$<br>$R^2 = 0.041$<br>F = 2.83 | Self-selected Matching Error (β = 0.23) | $p = 0.060$<br>$R^2 = 0.053$<br>F = 3.66 |
| Backboard | Error at 75% Target (β = 0.25), Self-selected Matching Error (β = 0.24) | $p = 0.015$*<br>$R^2 = 0.118$<br>F = 4.47 | Stoop Matching Error (β = 0.25), Error at 75% Target (β = 0.24) | $p = 0.033$<br>$R^2 = 0.101$<br>F = 3.61 |
| Crate | Error at 75% Target (β = 0.22) | $p = 0.090$<br>$R^2 = 0.048$<br>F = 2.97 | N/A | N/A |
| Stretcher | Squat Matching Error (β = 0.24) | $p = 0.061$<br>$R^2 = 0.055$<br>F = 3.63 | Squat Matching Error (β = 0.30), | $p = 0.015$*<br>$R^2 = 0.091$<br>F = 6.21 |

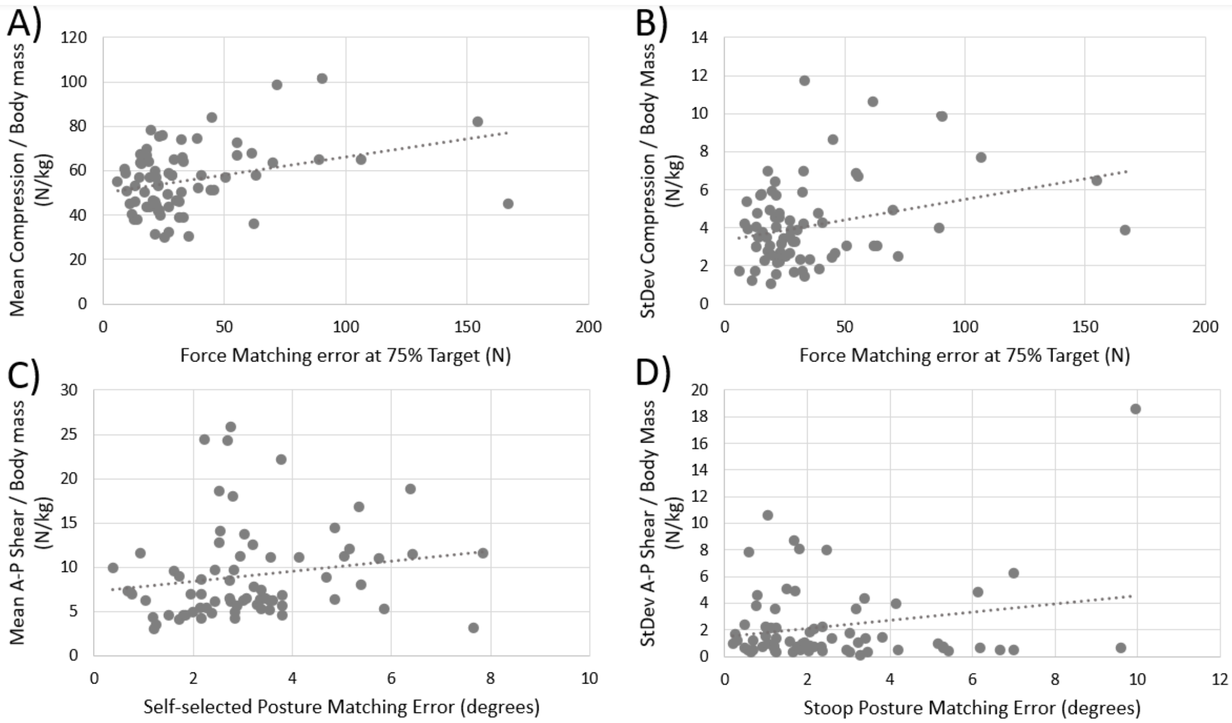


**Figure 6-3:** Scatter plots visualizing the association of proprioceptive ability measures to the mean and standard deviation of peak low back loads normalized to body mass during. Top row: association of force matching ability to the A) mean and B) standard deviation of peak low back compression force during barbell lifting. Bottom row: association of C) self-selected posture matching to mean peak A-P shear loads and D) stoop posture matching to standard deviation of peak A-P shear loads in backboard lifting.

With significant associations of proprioceptive ability measures to a subset of both the mean and standard deviation of low back loads, the association of proprioceptive ability measures to the mean and variability of features of movement related to the low back loads were examined. Across each of the lift conditions a subset of PCs were associated ($p < 0.05$) with either compression or A-P shear loads (Table 6-4) and were considered in this aspect of analysis. Since only force matching error at the 75% target, self-selected and squat-like posture matching error were identified as predictors of both the mean and standard deviation of low back loads, they were the only predictor variables included when regressing to the mean and standard deviation of PC scores.

**Table 6-4:** Variance explained (%) by PCs in each of the barbell, backboard, crate, and stretcher lifting conditions. An '*' indicates that the PC scores within a given PC were associated with either peak low back compression or A-P shear force.

| | Barbell | Backboard | Crate | Stretcher |
|---|---|---|---|---|
| PC1 | 32.25* | 37.04* | 35.01* | 28.79* |
| PC2 | 17.09 | 17.65 | 20.15* | 19.39* |
| PC3 | 10.37* | 7.57* | 9.89 | 11.53 |
| PC4 | 9.44 | 5.77 | 5.12* | 7.14* |
| PC5 | 6.26* | 5.34 | 4.51* | 4.71* |
| PC6 | 5.16 | 4.37 | 3.37* | 3.00 |
| PC7 | 2.38* | 2.32 | 1.74 | 2.84 |
| PC8 | 1.90* | 1.78* | 1.67 | 1.99 |
| PC9 | 1.32 | 1.55* | 1.28* | 1.82 |
| PC10 | 1.17 | 1.10 | 1.25* | 1.46* |
| PC11 | 0.89* | 1.06* | 1.09 | 1.30 |
| PC12 | 0.78* | 1.03* | 0.99 | 0.97 |
| PC13 | 0.74 | 0.91 | 0.88 | 0.88 |
| PC14 | 0.60* | 0.76* | 0.86* | 0.75* |
| PC15 | | 0.72* | 0.77* | 0.73 |
| PC16 | | 0.52 | 0.67 | 0.70 |
| PC17 | | 0.51* | 0.63 | 0.58 |
| PC18 | | | 0.56* | 0.54 |
| PC19 | | | | 0.48* |
| PC20 | | | | 0.46* |
| Sum of variance explained | 90.35 | 90.02 | 90.43 | 90.16 |

Across regressions of proprioceptive ability measures to PC scores related to low back loads, no significant associations to both the mean and standard deviation of PC scores were observed in any given PC. Statistical summaries of regression models correlating proprioceptive ability measures to PC scores are included in Appendix C.

*6.4 Discussion:*

The purpose of this study was to investigate whether the ability to perceive proprioceptive sensory information was related to using a lifting strategy that consistently minimized biomechanical exposure at the low back. I found evidence to support that increased ability to perceive proprioceptive information when both performing a force matching task at a heavy target, and in posture matching tasks, were associated with lower mean and variability in peak low back compression force across barbell and backboard lift types as well as low back A-P shear force in backboard lifting, albeit with small effect sizes. Both associations of proprioceptive ability to the mean and standard deviation of low back loads supports that those better attuned to relevant sensory information were biased to consistently minimize exposures in accordance with the overarching OFC theoretical framework. However, variance in kinematic coordination patterns could not explain how the lower exposures were achieved. This demonstrates that no independent kinematic coordination patterns (as measured in this study) are directly controlled as a function of proprioceptive ability to consistently minimized resultant biomechanical exposures. These findings have practical implications as increasing individuals' ability to perceive proprioceptive information we may be able to induce a small effect of reducing the magnitude of low back loads they experience during work.

The findings from this study have theoretical importance to considering how movement strategy is controlled within the OFC theory model. A key component within OFC theory is the closed-loop feedback system where an efferent copy of the initial movement trajectory is compared to afferent feedback at the optimal state estimator to gain movement strategy online (Scott, 2004; Todorov, 2004). Within this study I provide indirect evidence that afferent information from trunk force and position sense are associated with biomechanical exposures, but the strength of the associations are weak and may indicate that other sources of sensory information may be more important. For example, both somatosensory and visual information seem to work in tandem to point to a target following a visual disruption (Scott et al., 2015), highlighting the potential for contributions from the visual system to lifting performance. Tactile feedback may also be an important mode of sensory information contributing to maintaining task performance as greater tactile stimuli application during low back flexion resulted in reduced range of motion in a repeated flexion/extension task (Beaudette et al., 2018). The noted contributions of visual and tactile feedback in addition to proprioceptive information to completing motor tasks likely suggest that these modes of sensory information also contributed to performance in this lifting paradigm.

The associations to the mean and standard deviation of peak compression forces were stronger than to peak A-P shear forces across lift types. This finding may be due to the compression force being more sensitive to moments while A-P shear forces are more sensitive to posture in the biomechanical modelling approach I used (van Dieën & de Looze, 1999). Within both the force and posture matching tasks perception of force (likely via the golgi tendon organs) would be a relevant mode of afferent information where force perception would directly relate to the force matching task. Additionally, the orientation of the body with respect to gravity in the posture matching tasks would influence the resultant moments on the body (Arjmand et al., 2010) as a second mode of relevant force-sense information. Therefore, both the force and posture matching tasks would challenge the perception of a force-based afferent pathway which is related to the joint moments experienced in lifting. Conversely, the perception of body position via muscle spindles would primarily be challenged in the posture matching, but not force matching, tasks. With only a subset of proprioceptive ability tasks challenging the muscle spindle afferent pathway, the weaker associations (with only posture matching performance being significant predictors) to the posture sensitive A-P shear loads are explained.

Force matching task at the 75% target and self-selected posture matching task being the strongest predictors of low back loads are likely explained by these tasks being most related to lifting demands. To parse out why these two identified proprioceptive ability tasks had the strongest associations to low back loads it is important to consider how other modes of sensory feedback could inform lifting performance. For example, the vestibular system likely provides relevant feedback to balance control (Khan & Chang, 2013) to prevent participants from losing their balance while lifting, visual feedback was relied upon when practicing the force matching task, and tactile feedback could contribute to lifting performances as it has been shown to influence spine neuromuscular control in flexion/extension tasks (Beaudette et al., 2018). Even considering proprioceptive feedback alone, many degrees of freedom were involved in all the experimental tasks (ranging from the distal upper extremity through to the feet). The high number of degrees of freedom available to perceive proprioceptive information could all provide relevant afferent information to aid in task performance. With this richness of sensory information available to participants it is possible that when performing force matching at the lighter targets (25 and 50% of max strength) and when matching prescribed postures (squat- and stoop-like) that sensory pathways other than perception of posture and force at the low back were used to a greater extent. The potential reliance on other types of afferent feedback in the proprioceptive ability tasks less related to lifting could explain why force matching at the heaviest target and posture matching in the self-selected condition had the strongest observed associations to measured low back loads.

This study provides evidence that ability to proprioceptive information is weakly associated with consistently minimizing low back loads, but limited evidence that individual features of whole-body movement (i.e., kinematic coordination patterns) are directly controlled to achieve these resultant loads. Across the four lift types investigated in this study a total of 35 features of whole-body movement identified using PCA were found to be related to either low back compression or A-P shear loads, but ability to perceive proprioceptive information was not associated with the both the average and variability of any PC scores. These findings agree with our previously reported data where we observed stronger effects of lifters with consistently lower biomechanical exposures minimizing variability in exposures directly, opposed to in features of movement related to exposures (Armstrong & Fischer, 2020). The control of low back loads, but not relevant feature of movement variability, aligns with the OFC framework where the performance metric of low back loads is maintained as task-relevant. Conversely, explicit features of movement (i.e., kinematic coordination patterns) are left uncontrolled if their interplay results in the desired biomechanical exposure outcome, thus rendering individual features of movement task-irrelevant.

Stronger associations between proprioceptive ability measures and low back loads in the barbell and backboard tasks may be a result of differing constraints across lift types. As a practical consideration in the crate lifting condition, the crate needed to be in front of the force plates while participants feet remained on the force plates to measure ground reaction forces. Conversely, the barbell and backboard were able to hang over the force plates and give participants more freedom in their posture. Based on Newell's model of constraints (Newell, 1986) the change in task parameters as a function of crate shape likely reduced the range of strategies available to participants to perform the lift. Therefore, a greater proportion of variance in low back loads could be explained by the task constraints when lifting the crate. This finding supports that considering the interacting role of constraints (such as the interaction between proprioceptive ability and load shape) on movement strategy and movement objectives defined within an OFC framework should remain an important consideration in future research (Armstrong & Fischer, 2020).

The experimental design employed in this study was not without limitation. First, across all proprioceptive ability tasks other modes of sensory information could have been used to aid in task performance. For example, tactile perception in the hands during the force matching task or visual information in the posture matching tasks is likely used in-concert with proprioceptive information to aid in task performance. However, while other modes of sensory information were available to lifters, the use of the selected proprioceptive tasks increased the external validity of the study design as they better relate to occupational lifting demands. Second, low back compression and A-P shear forces were used as dependent measures opposed to low back moments and angles which may be more directly correlated with proprioceptive ability in lifting. This decision was made to increase external validity in the study design where risk thresholds of compression and A-P shear forces have been well established in the ergonomics literature (Gallagher & Marras, 2012; Waters et al., 1993). Finally, the experimental design does not allow us to determine whether the relationship between ability to perceive proprioceptive information and low back loads is mechanistic or associative. Future research is suggested to further probe whether reduced mean and variability in low back loads are directly informed by greater proprioceptive ability or whether increased ability to perceive sensory information is a by-product of other factors (i.e., lifting experience or strength) that more directly influence the mean and variability in low back loads while lifting.

The findings from this study have future practical implications for occupational injury risk prevention. Although the way an individual moves when completing physically demanding work tasks (such as lifting) influences biomechanical exposures on the body (Kingma et al., 2004; Armstrong et al., 2021a) there has been no impactful translation of this information into injury prevention interventions (Denis et al., 2020). However, previous interventions have not considered determinants of worker movement strategy within the context of a prevailing motor control theory, such as OFC (i.e., root causes of movement behaviour). Based on the results of this study, increased ability to perceive proprioceptive information seems to bias lifters to minimize low back loads consistently within their movement objective definitions, albeit with weak associated effect sizes. Therefore, training to increase workers' ability to perceive proprioceptive information at the low back may result in consistently minimizing their resultant biomechanical exposures when lifting, and in turn lower injury risk.

### *6.5 Conclusion:*

In this study I demonstrate that increased ability to perceive relevant proprioceptive information at the low back seemed to result in considering minimizing low back loads in movement objectives when lifting. However, there was no strong evidence to suggest that the ability to perceive proprioceptive information was consistently related to the control and consistency of kinematic coordination patterns related to corresponding low back loads. These results support the theoretical importance of how the quality of sensory information can influence an individual's ability to achieve their defined movement objectives within the context of OFC theory. Additionally, findings support the prospect of developing more effective worker-focused injury prevention interventions by increasing workers' ability to perceive relevant sensory information as a proactive strategy to reduce low back loads in lifting, but more research is necessary to inform workplace intervention.

# Chapter 7: Investigating the effect of experience type and magnitude on lifting strategy

## *7.1 Introduction:*

In aiming to develop training interventions for manual materials handling work, it has been proposed to encourage workers to adopt movement patterns consistent with those used by experts. Rationale for such a training approach is supported by novice workers having a higher initial work-related low back disorder onset rate (van Nieuwenhuyse et al., 2004). With initial injury rates being higher in novice employees it is assumed that the movement strategy experts use to complete lifting demands are related to a lower risk of developing a musculoskeletal disorder.

Adopting a movement strategy to mimic how experts move has been recommended, but the current evidence is mixed. For example, Granata et al. (1999) found that experts exhibit higher peak and variability in low back moments and loads about all three axes of motion than novice lifters, whereas Marras et al. (2006) found that experts had significantly lower average low back compression than novices. Further, experts had higher peak low back moments when fatigued in a repetitive lifting/lowering protocol (Lee et al., 2014). Differences in both peak knee angles and moments between experts and novices when lifting have been shown, with no corresponding differences in peak trunk angle or moments (Ganon et al., 1996). Finally, work by Plamondon et al. (2014b) found no differences in peak low back moments between expert and novice lifters but showed that experts had lower peak lumbar flexion angles and positioned themselves closer to the load. It is clear from the literature that both kinetic (i.e., moments and loads) and kinematic (i.e., postures and movement) variables at the low back, which have been associated with risk of developing an MSD (Waters et al., 1993; Gallagher & Marras, 2012; Marras et al., 1993; Norman et al., 1998), do not consistently differ between expert and novice groups. The inconsistency in performance variables related to MSD risk calls the efficacy of emulating expert movement strategy as a proactive ergonomics strategy into question.

The confounding results of expertise on lifting in the literature may be due to how expertise was quantified. In general, most studies investigating the influence of expertise on lifting strategy have used a broad classification of ‘expertise’ that usually consists of spending a minimum amount of time working in the manual materials handling sector without experiencing an injury (Lee & Nussbaum, 2012; Lee et al., 2014; Marras et al., 2006; Plamondon et al., 2014b; Granata et al., 1999). This non-specific criterion ignores several underlying factors that could influence movement strategy, such as theoretical knowledge of lifting mechanics. In addition to time spent completing lifting tasks there may be a need for deliberate practice, which could be informed by theoretical knowledge, to result in consistent improvements in lifting strategy to minimize MSD risk. Without considering other underlying factors that could contribute broadly to ‘expertise’ we can not truly understand the causative relationship between expertise and lifting strategy. To borrow from a common saying: “Practice does not make perfect. Only perfect practice makes perfect.” – Vince Lombardi. This reaffirms that time spent lifting does not necessarily lead to adopting a lifting strategy that aims to consistently minimizing resultant exposures.

To overcome the limitations of previous studies which had broad definitions for expertise classification, it is important to determine how differing types of expertise influence lifting strategy. Specifically, the effect of theoretical expertise on lifting mechanics should be compared to contextual expertise as measured by time on the job. We have previously hypothesized that likelihood of consistently aiming to minimize biomechanical exposures (i.e., lower means and variability in resultant exposures) in lifting may be influenced by contextual experience on the job (Armstrong & Fischer, 2020). Research on lift training supports this possibility where lift training with augmented feedback was more effective at influencing spine motion than didactic training (Chan et al., 2022), and incorporating practical training has been suggested as a solution to improve the content of lift training programs (Denis et al., 2020). Conversely, theoretical experts likely have the knowledge on how to lower mean biomechanical exposures in lifting, but without time spent on the job they may be less likely to lift in a way to consistently minimize these resultant exposures in practice. Finally, novice lifters will likely have higher resultant exposures and corresponding variability as they have neither theoretical knowledge on how to lift in a way to minimize exposure, or time spent lifting to inform definition of a movement objective that aims to minimize exposure.

A second important question relating to the effect of expertise on lifting strategy is whether the influence is specific to the work context in which expertise was developed, or whether it is transferable. When considering the effect of expertise on lifting strategy there may be an interaction between experience and the work sector in which it was gained to influence resultant lifting strategy (consistent with Newell (1986)) opposed to an independent effect of experience. It is therefore important to consider whether the expertise gained in the workplace is transferrable to lifting demands that differ from the specific lifting demands of their work. If for example expertise only influenced lifting mechanics specific to lifting demands present in work, then the use of generalized lifting protocols in previous studies may further contribute to the inconsistency in findings when comparing movements and spine loading variables between expert and novice lifters (Lee & Nussbaum, 2012; Lee et al., 2014; Marras et al., 2006; Plamondon et al., 2014b; Granata et al., 1999). To investigate this potential confounding effect, both demanding sector specific lifts, such as stretcher and backboard lifting for paramedics

(Armstrong et al., 2020), as well as generic lifting tasks should be considered when investigating the role of experience on lifting strategy.

With a goal of investigating how experience influences lifting strategy it is important to consider determinants of lifting strategy within the context of an overarching motor control theoretical framework. We have previously demonstrated that some individuals seem to define a movement that aims to consistently minimize biomechanical exposures (i.e., lower means and variability) in their movement objectives (Armstrong & Fischer, 2020). Expertise may be an explanatory factor that biases a lifter to consistently minimize exposures in lifting by influencing the coordination and control of movement (consistent with Newell's model of constraints (1986)). If consistently lower biomechanical exposures (i.e., lower means and variability) are observed as a function of expertise then I can further probe how movement strategy adopted by experts resulted in the observed exposures. PCA can be applied as a method to quantify coordination patterns in movement strategy by reducing whole-body kinematic data to independent synergistic features of movement (Federolf, 2016; Armstrong et al., 2021a). If biomechanical exposures are consistently lower as a function of expertise, a follow-up question is whether independent kinematic coordination patterns related to biomechanical exposures, as identified by PCA, are similarly controlled to achieve the lower resultant exposures. Alternatively, kinematic coordination patterns not related to resultant biomechanical exposures can be investigated to probe whether other potential movement objectives are adopted by experts in lifting. With a goal of testing whether expertise explain consistency and control of low back loads in lifting, the alignment of independent variables (expertise groups) and dependent variables (low back biomechanical exposures and kinematic coordination patterns) within an overarching theoretical framework is visualized in Figure 7-1.

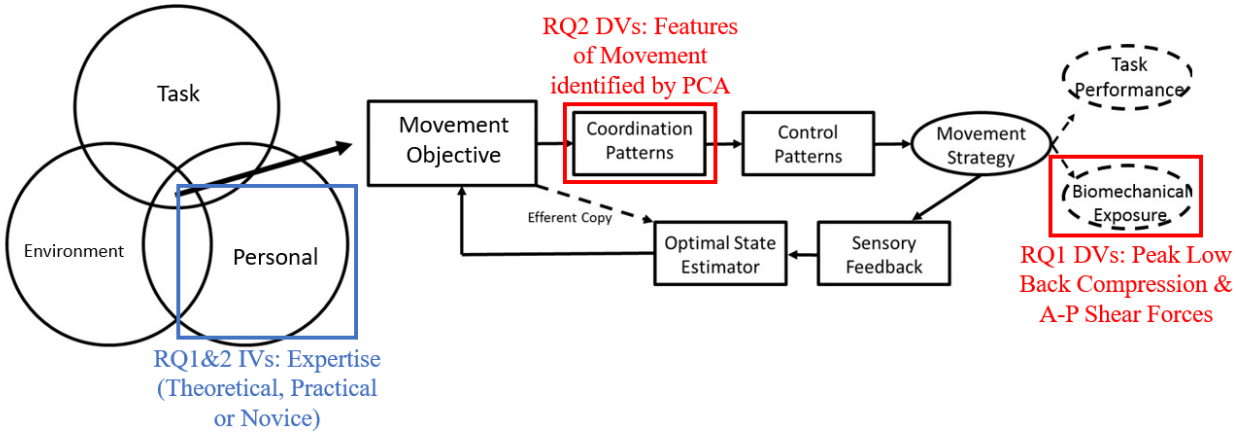


**Figure 7-1:** Visualization of study 2 independent and dependent variables within the study's overarching theoretical framework. Figure adapted from Armstrong & Fischer (2020). RQ: Research Question, IV: Independent Variable, DV: Dependent Variable, PCA: Principal Component Analysis.

The purpose of this study was to investigate whether type of expertise influences biomechanical exposures at the low back or corresponding movement strategy in either paramedic-specific or generalized lifting tasks. To address this overarching purpose, I ask three research questions. First, across lifters classified as theoretical experts, contextual experts, and novices; are there differences in either mean or variability in peak low back compression force and A-P shear force (i.e., low back biomechanical exposures) in lifting. Second, across expertise groups, are there differences in the mean or variability in synergistic features of whole-body movement (i.e., lifting strategy) that are i) related to low back biomechanical exposures or ii) unrelated to low back biomechanical exposures in lifting. Finally, is the effect of expertise on low back biomechanical loading or lifting strategy influenced by the type of load lifted? I hypothesized that contextual experts would have the lowest magnitude and variability in low back biomechanical exposures compared to theoretical expert and novice groups, suggesting they define a movement objective that aims to consistently minimize biomechanical exposures.

Second, I hypothesized that theoretical experts would have comparable low back biomechanical exposure magnitudes to contextual experts but will demonstrate more variability in lifting strategy than contextual experts. Comparatively, I hypothesized that the novice group would have both higher low back biomechanical exposures and would exhibit more variability in lifting strategy than other groups. When considering the final research question, I hypothesized that an interaction effect would emerge between expertise and load type where contextual experts would have lower low back biomechanical exposures that theoretical experts or novices when performing paramedic lifting tasks, but not when performing the generic lifting tasks.

## *7.2 Methods:*

### *7.2.1 Study Design*

In this study both expertise group (contextual expert, theoretical expert, novice) and lift types (barbell, backboard, crate, stretcher) were independent variables. The mean and variability of peak low back compression and A-P shear loads normalized to body mass, as well as both synergistic features of movement that were and were not related to resultant peak low back loads, were dependent variables in the study design. Full methodology including participant recruitment, instrumentation, experimental protocol, and data processing methods are presented in the general methodology chapter (Chapter 4.0).

### *7.2.2 Hypothesis Testing*

To determine the influence of expertise on low back biomechanical exposures across the four lift types, two-way mixed ANOVAs ($\alpha = 0.05$) with a between factor of expertise group, and a within factor of lift type were used. Since PCA was applied separately to kinematic trajectory data for each of the four lift types, one-way ANOVAs ($\alpha = 0.05$) were used to test for differences in biomechanically relevant and irrelevant PC scores in each lift between expertise groups. All statistical analyses were conducted using SPSS v. 25 (IBM SPSS Statistics), using an alpha level set at $p < 0.05$. A Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) was applied to control for family-wise error across multiple ANOVAs with a false discovery rate set to 10%. An '*" is used to denote significance in through the results accounting for the Benjamini-Hochberg correction.

If PC scores were found to differ as a function of expertise than single component reconstruction (Brandon et al., 2013) and consideration of the landmark-specific loading vector (Armstrong et al., 2021a) were used to determine the mode of variance explained by the differing feature of movement. Gross movement differences across expertise groups were also visualized using aggregate component reconstruction using previously reported methods (Armstrong et al., 2021a).

*7.3 Results:*

No significant differences in the mean or variability of peak low back compression or shear loads were observed across expertise groups (Table 7-1). However, the mean peak compression and A-P shear forces, as well as variability in A-P shear force differed as a function of lift type. No significant interaction effects were observed.

**Table 7-1:** Differences in mean and variability of peak low back compression and anteroposterior shear forces normalized to body mass across all lift types and between expertise groups. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. Comp: Compression, Stdev: Standard Deviation, Context: Contextual, Theo: Theoretical, Bar: Barbell, Back: Backboard, Stretch: Stretcher.

| | Expertise | | | Lift types | | | | Statistical Summary | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Novice | Context. | Theo. | Bar. | Back. | Crate | Stretch. | Expertise | Lift | Interact. |
| Mean Comp. (N/kg) | 50.24 (14.14) | 47.21 (16.41) | 48.34 (13.37) | 55.66 (15.52) | 54.11 (15.60) | 55.04 (14.44) | 28.32 (11.56) | $p = 0.669$, $\eta^2 = 0.013$ | $p < 0.001$*, $\eta^2 = 0.775$ | $p = 0.331$, $\eta^2 = 0.037$ |
| Mean Shear (N/kg) | 7.08 (3.54) | 6.76 (3.47) | 6.60 (3.62) | 9.55 (5.40) | 9.19 (5.46) | 6.03 (2.04) | 2.76 (1.18) | $p = 0.933$, $\eta^2 = 0.002$ | $p < 0.001$*, $\eta^2 = 0.538$ | $p = 0.896$, $\eta^2 = 0.012$ |
| Stdev. Comp. (N/kg) | 5.26 (2.38) | 3.89 (2.07) | 4.55 (2.60) | 4.08 (2.26) | 4.69 (2.52) | 4.67 (2.50) | 4.86 (2.34) | $p = 0.019$, $\eta^2 = 0.125$ | $p = 0.200$, $\eta^2 = 0.026$ | $p = 0.117$, $\eta^2 = 0.055$ |
| Stdev. Shear (N/kg) | 1.54 (1.77) | 1.18 (0.96) | 1.42 (1.66) | 1.77 (1.67) | 2.38 (3.15) | 0.85 (0.72) | 0.59 (0.42) | $p = 0.611$, $\eta^2 = 0.017$ | $p < 0.001$*, $\eta^2 = 0.246$ | $p = 0.908$, $\eta^2 = 0.012$ |

Across lift types between 14-20 PCs were retained for analysis, with nearly half of those PCs being related to either peak low back compression and/or A-P shear loads (Table 6-4). PCs associated with resultant peak compression or A-P shear loads are referred to as biomechanically relevant.

While no consistent differences in the means or variability of peak low back loads were seen across expertise groups, there were differences in both backboard and stretcher lifting strategy in both biomechanically relevant (Table 7-2) and biomechanically irrelevant (Table 7-3) PCs.

**Table 7-2:** Statistical summary (*p*-values and partial $\eta^2$) indicating whether the mean or standard deviation of principal component (PC) scores related to biomechanical exposures differed as a function of expertise group. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'.

| Lift | PC | *p*-values, partial $\eta^2$ | |
|---|---|---|---|
| | | Mean PC scores | Stdev. PC scores |
| Barbell | PC1 | 0.148, 0.054 | 0.056, 0.080 |
| | PC3 | 0.996, 0.000 | 0.267, 0.038 |
| | PC5 | 0.779, 0.007 | 0.632, 0.013 |
| | PC7 | 0.114, 0.061 | 0.953, 0.001 |
| | PC8 | 0.232, 0.042 | 0.461, 0.022 |
| | PC11 | 0.997, 0.000 | 0.399, 0.026 |
| | PC12 | 0.636, 0.013 | 0.398, 0.026 |
| | PC14 | 0.433, 0.024 | 0.010, 0.126 |
| Backboard | PC1 | 0.227, 0.042 | 0.457, 0.023 |
| | PC3 | 0.001*, 0.180 | 0.349, 0.031 |
| | PC8 | 0.068, 0.076 | 0.100, 0.065 |
| | PC9 | 0.129, 0.058 | 0.197, 0.047 |
| | PC11 | 0.085, 0.070 | 0.660, 0.012 |
| | PC12 | 0.027, 0.101 | 0.339, 0.031 |
| | PC14 | 0.344, 0.031 | 0.355, 0.30 |
| | PC15 | 0.342, 0.031 | 0.074, 0.074 |
| | PC17 | 0.023, 0.105 | 0.109, 0.063 |
| Crate | PC1 | 0.910, 0.003 | 0.437, 0.027 |
| | PC2 | 0.573, 0.018 | 0.172, 0.056 |
| | PC4 | 0.066, 0.084 | 0.010, 0.142 |
| | PC5 | 0.055, 0.089 | 0.221, 0.049 |
| | PC6 | 0.419, 0.028 | 0.717, 0.011 |
| | PC9 | 0.683, 0.012 | 0.185, 0.055 |
| | PC10 | 0.133, 0.063 | 0.004*, 0.169 |
| | PC14 | 0.358, 0.033 | 0.425, 0.028 |
| | PC15 | 0.391, 0.030 | 0.340, 0.035 |
| | PC18 | 0.421, 0.028 | 0.878, 0.004 |
| Stretcher | PC1 | <0.001*, 0.299 | 0.023, 0.109 |
| | PC2 | 0.949, 0.002 | 0.963, 0.001 |
| | PC4 | <0.001*, 0.281 | 0.268, 0.040 |
| | PC5 | 0.097, 0.069 | 0.437, 0.025 |
| | PC10 | 0.588, 0.016 | 0.150, 0.057 |
| | PC14 | 0.932, 0.002 | 0.616, 0.015 |
| | PC19 | 0.645, 0.013 | 0.151, 0.056 |
| | PC20 | 0.138, 0.059 | 0.286, 0.038 |

**Table 7-3:** Statistical summary (*p*-values and partial $\eta^2$) indicating whether the mean or standard deviation of principal components (PC) scores not related to biomechanical exposures differed as a function of expertise group. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'.

| Lift | PC | *p*-values, partial $\eta^2$ | |
|---|---|---|---|
| | | Mean PC scores | Stdev. PC scores |
| Barbell | PC2 | 0.084, 0.069 | 0.408, 0.026 |
| | PC4 | 0.932, 0.002 | 0.758, 0.008 |
| | PC6 | 0.011, 0.122 | 0.598, 0.015 |
| | PC9 | 0.109, 0.062 | 0.678, 0.011 |
| | PC10 | 0.080, 0.070 | 0.247, 0.040 |
| | PC13 | 0.625, 0.014 | 0.418, 0.025 |
| Backboard | PC2 | 0.006*, 0.141 | 0.192, 0.047 |
| | PC4 | 0.339, 0.031 | 0.028, 0.100 |
| | PC5 | 0.553, 0.017 | 0.135, 0.057 |
| | PC6 | 0.060, 0.079 | 0.180, 0.049 |
| | PC7 | 0.738, 0.009 | 0.056, 0.081 |
| | PC10 | 0.090, 0.068 | 0.237, 0.041 |
| | PC13 | 0.221, 0.043 | 0.034, 0.094 |
| | PC16 | 0.192, 0.047 | 0.041, 0.090 |
| Crate | PC3 | 0.286, 0.040 | 0.297, 0.040 |
| | PC7 | 0.305, 0.038 | 0.326, 0.037 |
| | PC8 | 0.063, 0.085 | 0.109, 0.071 |
| | PC11 | 0.615, 0.016 | 0.489, 0.024 |
| | PC12 | 0.303, 0.038 | 0.098, 0.075 |
| | PC13 | 0.409, 0.028 | 0.094, 0.076 |
| | PC16 | 0.792, 0.007 | 0.079, 0.081 |
| | PC17 | 0.915, 0.003 | 0.207, 0.051 |
| Stretcher | PC3 | 0.619, 0.015 | 0.759, 0.008 |
| | PC6 | 0.105, 0.067 | 0.845, 0.005 |
| | PC7 | 0.899, 0.003 | 0.082, 0.074 |
| | PC8 | 0.759, 0.008 | 0.206, 0.047 |
| | PC9 | 0.523, 0.020 | 0.500, 0.021 |
| | PC11 | 0.089, 0.072 | 0.085, 0.073 |
| | PC12 | 0.863, 0.005 | 0.095, 0.070 |
| | PC13 | 0.005*, 0.148 | 0.220, 0.046 |
| | PC15 | 0.318, 0.035 | 0.161, 0.055 |
| | PC16 | 0.836, 0.006 | 0.004*, 0.157 |
| | PC17 | 0.766, 0.008 | 0.038, 0.096 |
| | PC18 | 0.520, 0.020 | 0.291, 0.037 |

Based on the statistical differences in PC scores in backboard and stretcher lifting strategy, the gross kinematic strategy adopted by expertise groups is visualized by aggregate component reconstructions (Figure 7-2). Interpreting these differences in backboard lifting the contextual expertise group (paramedics – black line) adopted a deeper squat while maintaining a more upright trunk (Figure 7-2A). In contrast the novices (red line) adopted a more stoop-like lift posture with greater trunk flexion. The theoretical expert reconstruction falls between these two lift postures. In the stretcher lift the paramedics seem to move their body through the greatest range of motion by adopting a deeper squat to initiate the lift, and then lifting the stretcher to higher in the vertical (Figure 7-2B).

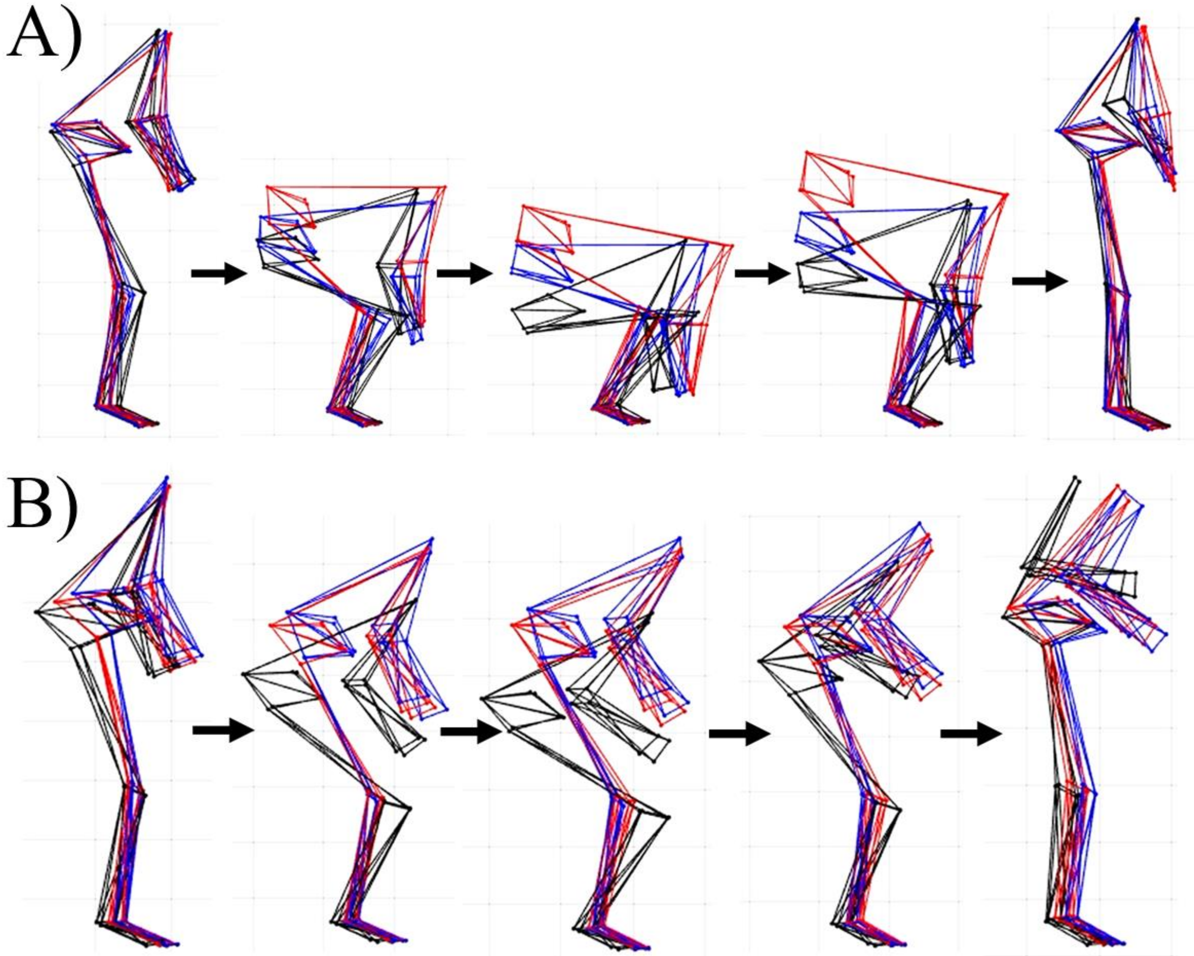


**Figure 7-2:** Aggregate component reconstructions of A) backboard and B) stretcher lifting across contextual experts (black), theoretical experts (blue) and novice (red) lifters.

*7.4 Discussion:*

The purpose of this study was to investigate whether type of expertise was a determinant of lifting strategy in either paramedic-specific or generalized lifting tasks. I found that the means and variability of peak low back compression and A-P shear force generally did not differ across expertise groups, but they did differ as a function of lift type. While no differences in peak low back loads were observed between expertise groups there were differences in both backboard and stretcher lifting strategy (occupationally relevant lifting tasks), with no differences in mean lifting strategy in either barbell or crate (generic) lifting tasks. These findings highlight that experts do not seem to define a movement objective that aims to consistently minimize biomechanical exposures in lifting. Additionally, expertise only seems to influence the lifting strategy used in lifting tasks specific to their occupation while no differences were observed in the generic lifting tasks. Practically, these results suggest that simply emulating expert lifting strategy as a proactive ergonomic intervention to reduce injury risk is not likely to be an effective intervention to reduce occupational injury risk.

Our hypothesis that contextual experts would consistently minimize biomechanical exposures in lifting was not supported. This hypothesis was primarily motivated by epidemiological evidence which demonstrates that injury incidence is greater in inexperienced worker groups (van Nieuwenhuyse et al., 2004), and that augmented feedback while performing lifting tasks more greatly influenced spine motion compared to instructional training alone (Chan et al., 2022). However, the mechanism for this relative difference in injury incidence between novice and experienced workers does not seem attributable to experts consistently moving in a manner that would reduce their corresponding peak biomechanical exposures. Further, theoretical knowledge on lifting mechanics was also not shown to result in consistent reductions low back biomechanical exposures. Previous literature has highlighted that theoretical lifting experts have preferences on lifting technique (Abdoli-Eramaki et al., 2019), but the results of this study demonstrate that these underlying beliefs do not translate into practice contrary to our hypothesis. As such I can conclude that expertise as defined in this study is not a causative factor that biases lifters to consider minimizing biomechanical exposures in their movement objectives as previously speculated (Armstrong & Fischer, 2020).

While no differences in the mean or variability of low back biomechanical exposures were observed as a function of expertise, I did observe differences in backboard and stretcher lifting strategy. Trained paramedics adopted deeper squat postures to initiate both the backboard and stretcher lifting tasks. Correspondingly they also had less trunk flexion at lift initiation compared to the theoretical expert and novice groups. Interestingly, these differences in lift postures did not result in differences in peak low back exposures across groups which is likely due to all groups initiating the lift through leg extension, followed by trunk extension. This lifting strategy is thought to minimize the peak low back extensor moment by delaying back extension until after 25% of the lift cycle where acceleration of the load is greatest (De Looze et al., 1993). The differences in lifting strategy may also be a result of groups aiming to achieve differing movement objectives. For example, by adopting a more upright posture, paramedics were able to better preserve eye contact with their lifting partner. Communication between lifting partners is an important feature of safe lifting for paramedics and many noted (anecdotally) that eye contact was a critical component of lifting. Theoretical or novice lifters may not have understood the importance of eye contact, and thus did not aim to move in a way the preserved line of sight to their lifting partner in the same way. This finding reinforces those contextual factors, like the need to see and communicate with a lifting partner, can play an important role in dictating the corresponding lifting strategy.

Identification of expertise level differences in lifting strategy in job-task specific lifts (i.e., backboard and stretcher lift) but not in generic lifts (i.e., barbell and crate) is novel and important. Based on this finding, it seems that the role of expertise on lifting strategy is relevant to the context in which the expertise was gained, reinforcing the argument related to maintaining line-of-sight earlier. The importance of context in shaping lifting strategy aligns with the conceptual dynamical systems framework on movement (Newell, 1986; Glazier, 2017) where it is hypothesized that the interaction of task (like the implement being lifted in our study), environment and personal constraints (like expertise as considered in our study) influence the control and coordination of movement. Notably, in the dynamic systems framework it is hypothesized that the unique interactions of constraints will influence the resultant control and coordination of movement, where changing a given constraint can result in movement differences in some cases, but not others. Within this study the personal constraint remained consistent across the lifting protocol (i.e., the participants were not changed in anyway), but the task constraint changed (i.e., different lifting requirements). Indeed, as hypothesized, the lift type influenced how participant expertise shaped the resultant control and coordination of lifting strategy. This resulted in experts lifting differently than theoretical experts or novices, but only during occupation-specific lifting tasks.

The findings of this study may explain the previously reported mixed effects of expertise on lifting strategy. Considering previous literature, examples of both positive (i.e., Marras et al., 2006) and negative (i.e., Granata et al., 1999) effects of expertise on resultant biomechanical exposures in lifting have been reported. To clarify these conflicting findings the experimental design of the current study strengthened resolution regarding expertise (i.e., contextual vs. theoretical) and considered both generic and occupation-specific lift types. Considering both findings from this current study and the mixed results reported in previous literature I posit that there is no direct causative link between expertise and minimizing low back exposures in lifting. As such, aiming to emulate lifting strategy adopted by experts is not recommended as a strategy to proactively minimize biomechanical exposures.

Contrasting our results to past work, the type of lifts performed in the experimental protocols may also influence the inconsistency in reported effects of expertise on lifting strategy. Typically, previous studies have used generic lifting protocols that do not necessarily replicate the work environment in which expertise was gained (i.e., Lee & Nussbaum, 2012; Lee et al., 2014; Marras et al., 2006; Plamondon et al., 2014b; Granata et al., 1999). In this study I demonstrate that contextual expertise as a paramedic only resulted in lifting strategy differences in the lifting tasks performed in paramedic work, not the generic barbell and crate lifting tasks. With this noted important interaction between expertise and lift type on resultant lifting strategy it is possible that not directly emulating the work environment that expertise was developed in previous studies could contribute to the mixed reports of expertise on lifting strategy seen in the literature. This may be in part explained by deliberate practice of contextual experts to refine their lifting strategy used in occupational contexts. As such, I believe that when considering how expertise could influence occupational lifting strategy it is important to only consider occupation-specific lifts for which the expertise was gained in.

A secondary finding of this work is the differences in low back loads as a function of lift type. In the experimental protocol care was taken to ensure that the effective mass in all lifts was consistently 34 kg, but differences in peak compression and A-P shear forces were still observed. These resultant differences may be a product of differing load shape influencing lifting strategy independent of lift origin height as a task constraint (Zehr et al., 2018), leading to some lift types having higher resultant low back loads based on the afforded lifting strategy options. For the lift types considered there were noted differences in the start height of the loads which could influence the required postural and kinetic demands at the low back to initiate the lift which could be reflected in the resultant low back loads. Alternatively, the presence of a second lifter in the backboard and stretcher lifting tasks could have influenced resultant low back loads where the pulling force in the two-person lifts has been shown to offset resultant low back loads by up to 20% (Dennis & Barrett, 2002). With these observed differences I highlight the importance of how differing load types can influence lifting strategy and resultant low back loads even when the absolute mass of the item being lifted is unchanged.

This study provides clarity on the effect of expertise on lifting strategy, but it is not without limitation. First, although care was taken to differentiate between novices, contextual experts, and theoretical experts there was still heterogeneity in these sample groups. Of note, individuals across the expertise groups had varying levels strength and conditioning experience. While this strength and conditioning experience was controlled for in the novice group, across the contextual and theoretical expert groups participants there were examples of individuals who frequently participated in lifting within a gym environment which could have influenced their lifting strategy in the barbell and/or crate lifting tasks. Having an extensive strength and conditioning background is likely consistent with deliberate practice to improve lifting strategy, which could have confounded the results of this study. Unfortunately, the varying levels of recreational lifting experience could not be controlled for in the study design and so should be considered in the interpretation of findings. Second, the mass and environment present in the occupation-specific lifting tasks did not directly replicate the paramedic work environment. This is an important consideration as load mass has been shown to influence resultant lifting strategy (Albert et al., 2008; Sadler et al., 2011; Sheppard et al., 2016). However, the load mass used in this study was selected to be within the reported mean patient mass of 65.3-81.9 kg (Coffey et al., 2016), but lower within the range to recruit a diverse sample including novice lifters with potentially lower underlying strength. Finally, the controlled lab environment did not replicate the dynamic and potentially time-sensitive environment that may be present when paramedics are responding to emergency calls. The difference in environment could influence resulting lifting strategy (Newell, 1986) and is therefore an important consideration moving forward when extrapolating these study findings to consider how paramedics lift on the job.

Following this study there are future research opportunities to explore why experts move the way they do when performing occupational lifts. I had initially hypothesized that experts were concerned with minimizing biomechanical exposures in their lifting strategy, but although differences in lifting strategy were observed it did not result in consistent reductions in low back loads among experts. As such, it is possible that experts are considering other objectives in their movement such as maintaining eye contact with a lifting partner in these paramedic-specific lifting examples, or potentially aiming to minimize metabolic demand (Straker, 2003b). Identifying these movement objectives in paramedic work can be explored in future studies. Finally, determining whether paramedics lift consistently between the lab and real-world environments is a recommended future direction because environment differences can influence coordination and control of movement (Newell, 1986). Since the environment at emergency call responses is dynamic and unpredictable, understanding how this environment influences lifting strategy is an important consideration for the paramedic workforce.

### *7.5 Conclusion:*

In this study I investigated whether type of expertise is a determinant of lifting strategy in either occupation-specific or generalized lifting tasks. Expertise did not influence low back biomechanical exposure when lifting, providing evidence that expertise (as described in this study) may not be a causative factor that influences individuals to define a movement objective to minimize peak resultant biomechanical exposures when performing occupational lifts. However, expertise did influence lifting strategy in lifts specific to the occupation that the expertise was gained in. Experts may be choosing lifting strategies specific to the context of those lifting tasks, like preserving line-of-sight for communication with a lifting partner. Future studies can aim to understand why contextual experts move differently in occupation-specific lifts where it is not attributable to minimizing their biomechanical exposures.

# Chapter 8: Influence of structural and functional personal factors on lifting strategy

## *8.1 Introduction:*

Worker-focused ergonomic interventions, such as lift training, are a proactive strategy that aim to minimize injury risk in work sectors with non-modifiable work tasks. However, prevailing evidence suggests that current approaches to lift training are not effective in reducing injury risk (Denis et al., 2020; Haslam et al., 2007; Martimo et al., 2008; Clemes et al., 2009; Verbeek et al., 2011; Hogan et al., 2014). To improve effectiveness, it has been suggested that improving the quality and content of lift training programs could result in retained adaptations in movement strategy to reduce injury risk in practice (Denis et al., 2020). To effectively improve the content of lift training programs it is important to first understand what factors influence individuals' lifting strategy.

When aiming to identify factors that influence lifting strategy in occupations with non-modifiable heavy demands personal factors should be investigated. Personal factors can be further dichotomized into structural and functional factors. Structural factors include constructs that are non-modifiable and intrinsic to the individual, such as stature, body mass, or sex. Conversely, functional factors include constructs like strength capacity and flexibility. Structural and functional factors can constrain the movement strategy options available when lifting, which may have an influence on the resultant biomechanical loads (Kingma et al., 2004; Chaffin & Page, 1994). Conversely, it has been proposed that certain personal factors may bias individuals to define a movement objective that aims to consistently minimize low back exposures (Armstrong & Fischer, 2020). Support for this position is provided by Clusiault et al., (2022), who showed that higher strength individuals had significantly lower resultant normalized peak low back moments. Evaluating how a broader range of structural and functional personal factors influence lifting strategy and resultant low back exposures is important to inform the development of more effective lift training interventions.

Lifter stature and body mass are two structural personal factors that could influence lifting strategy. For example, both stature and body mass have been shown to influence lifting strategy where taller and heavier lifters experience larger peak lumbar extension angles when lifting a load from the ground to a shelf at chest height (Kranz et al., 2020). Additionally, absolute low back loads are related to the body mass of the lifter (Marras et al., 2003; Corbeil et al., 2019), which is likely attributable in part to both having greater mass as well as lifters with high body mass index having greater peak sagittal angular velocity and acceleration of the trunk (Xu et al., 2008). However, no corresponding postural differences were observed during lifting between obese and healthy body mass individuals (Corbeil et al., 2019). While effects of stature and body mass on lifting strategy have been investigated, the interacting role of these factors with other underlying structural and functional factors is not well understood.

Sex is a third structural factor that could influence lifting strategy. Considering past literature comparing lifting strategy of females to males, females tend to use more leg driven (either leveraging the knees or hips) lifting strategies compared to men (Li & Zhang, 2009; Marras et al., 2003), which can result in women having lower compressive spine loads (Marras et al., 2003; Plamondon et al., 2014a), lower peak extensor moments (Makhoul et al., 2017) and less spine flexion (Makhoul et al., 2017). Conversely, men tend to lift with greater lumbar flexion than females when lifting an absolute load (Lindbeck and Kjellberg, 2001). However, when mass of the load is normalized to participant capacity no differences in lifting strategy between males and females were observed (Albert et al., 2008; Sadler et al., 2011) suggesting that supposed sex differences in strategy are attributable to load mass relative to capacity opposed to intrinsic differences in lifting strategy between males and females. While previously reported differences in lifting strategy seem to be driven by load mass, there are known structural differences between males and females, such as hip Q angle (Willson & Davis, 2008) and pelvis morphology (Patriquin et al., 2003) and trunk geometry (Marras et al., 2001). With these underlying structural differences, there are potentially unidentified influences of sex on lifting strategy not previously quantified.

An individual’s strength capacity represents a functional factor that could influence lifting strategy. Previous findings have shown that strength, opposed to sex, influences peak low back extensor moments in lifting (Clusiault et al., 2022). Additionally, no differences in lifting strategy between males and females were observed when the mass of the load was normalized to capacity (Albert et al., 2008; Sadler et al., 2011). However, when the relative load mass increases, independent of sex, evidence demonstrates that lifters transition away from a synchronous strategy towards a lifting strategy with more sequential movement from the distal lower extremity to the low back (Albert et al., 2008; Sadler et al., 2011; Sheppard et al., 2016). Considering both noted effects of strength and load mass on lifting strategy, it is likely that stronger individuals will lift an absolute load mass using a more synchronous lifting strategy typically observed when lifting lighter loads, whereas weaker individuals should exhibit a more sequential strategy. Finally, having greater strength capacity may allow lifters to consistently use a spine-sparing movement technique at the expense of a higher associated metabolic cost. While a squat-based lifting strategy is reported to have higher metabolic demands than a stoop-lifting technique (Straker, 2003b), individuals with higher capacity could perceive the metabolic demands as less when lifting an absolute load. This could result in stronger lifters having a higher likelihood of adopting a spine-sparing lifting strategy compared to low-capacity lifters when lifting an absolute load mass magnitude.

Flexibility, another functional factor, can also influence lifting strategy. More flexible lifters would have a greater range of motion about respective joint, offering a wider array of possible lifting strategies. Conversely, individuals with lower flexibility would have more limited ranges of motion, and thus fewer lifting strategy options available. Preliminary evidence supports the importance of flexibility on lifting strategy has been demonstrated by Sreenivasa et al., (2018). When predicting lifting strategy with an optimal control model, model iterations with stiffer imposed constraints at the low back and hamstring had more flexion at the hip and knee opposed to the lumbar spine (Sreenivasa et al., 2018). Experimental studies also highlight the effects of flexibility on lifting where lifters with lower hamstring flexibility have been shown to lift with higher trunk flexion angles (Carregaro et al., 2009). Unilateral ankle immobilization (i.e., artificially constraining ankle flexibility) also influenced lifting strategy by decreasing knee flexion angles while increasing lumbar spine angles (Beach et al., 2014). With the noted functional limitations low flexibility could impose on lifters, it is important to consider how both flexibility at the knee and hip joints could influence lifting strategy.

While previous literature has investigated how lifting strategy differs as a function of structural and functional factors it is important to investigate the mechanism in which these factors independently and/or interdependently influence lifting strategy. For example, Newell's constraints-based model (1986) suggests that combinations of constraints (such as varying structural and functional factors as an example) can influence the resultant coordination and control of movement. In this example differing combinations of structural and functional factors could influence the range of available lifting options to individuals and therefore result in differing lifting strategies as a function of these factors. Alternatively, combinations of structural and functional factors may influence movement strategy by influencing a lifter's defined movement objectives. We have recently proposed that a lifters likelihood of defining a movement objective that aims to consistently minimize biomechanical exposures in lifting (i.e., lower mean and variability of resultant exposures) can be biased by underlying personal factors (Armstrong & Fischer, 2020). With the goal of leveraging the understanding of how structural and functional personal factors influence lifting strategy to inform the development of ergonomic interventions it is important to probe whether these resultant differences in lifting strategy are a product of influencing the range of available lifting strategies or are attributable to biasing a lifter's defined movement objectives.

When investigating whether structural and or functional factors results in a movement objective that aims to minimize biomechanical exposures in lifting it is important to consider how this would manifest within the context of OFC theory. We have previously demonstrated that some individuals seem to define a movement objective that aims to minimize biomechanical exposures in their movement objective (Armstrong & Fischer, 2020). For this movement objective it is anticipated that both the mean and variability of biomechanical exposures would be lower. Lower variability of these exposures would be expected because the biomechanical exposure magnitudes would be considered relevant to task performance within the OFC framework and therefore more tightly controlled (Scott, 2004; Todorov, 2004), consistent with the minimum intervention principle (Todorov & Jordan, 2003). If consistently lower biomechanical exposures (i.e., lower means and variability) are observed as a function of structural or functional factors then I can further investigate whether coordination patterns are intermediary factors which generate these lower resultant magnitudes of exposures as hypothesized in the overarching theoretical OFC model. PCA can be applied as a method to identify kinematic coordination patterns by reducing whole-body kinematic data to independent synergistic features of movement (Federolf, 2016; Armstrong et al., 2021a). If biomechanical exposures are consistently lower as a function of either structural or functional personal factors, I can probe whether independent kinematic coordination patterns related to biomechanical exposures, as identified by PCA, are similarly controlled to achieve the resultant lower exposures. With a goal of testing whether structural and/or functional factors explain consistency and control of low back loads in lifting, the alignment of independent variables (structural and functional personal factors) and dependent variables (low back biomechanical exposures and kinematic coordination patterns) within the overarching OFC framework is visualized in Figure 8-1.

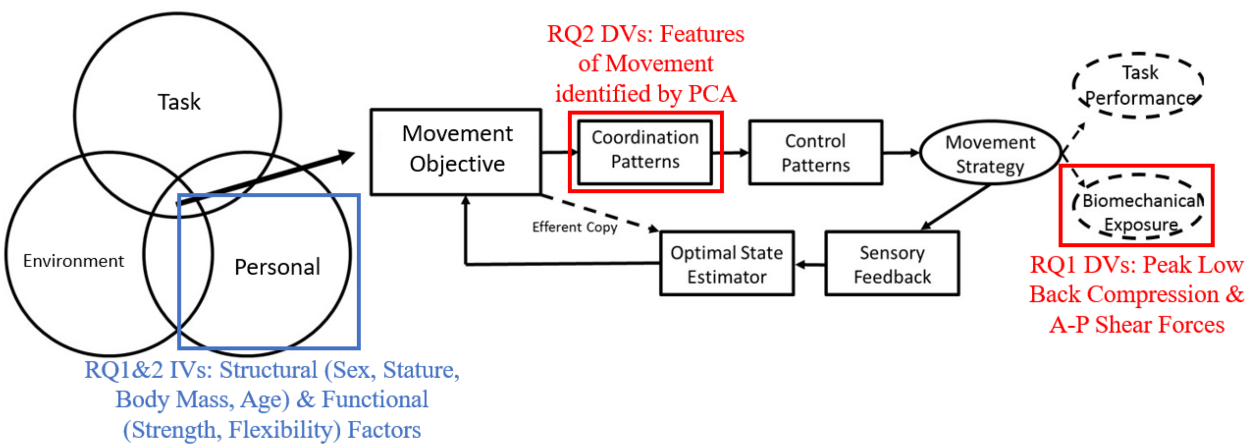


**Figure 8-1:** Visualization of study 3 independent and dependent variables within the overarching OFC model. Figure adapted from Armstrong & Fischer (2020). RQ: Research Question, IV: Independent Variable, DV: Dependent Variable, PCA: Principal Component Analysis.

The purpose of this study was to determine how structural and functional personal factors independently and/or interdependently explain variance in peak low back loads and aspects of lifting strategy related to low back loads in generic and paramedic lifting tasks. Specifically, do sex, stature, body mass, lower body flexibility, or isometric lift strength explain variance in a) mean or variability of peak low back compression and anteroposterior (A-P) shear forces, or; b) mean or variability in lifting strategy, as measured by synergistic features of whole-body movement related to biomechanical exposures.

I hypothesized that all independent variables would explain variance in mean peak low back exposures and corresponding features of lifting strategy. Specifically, I hypothesized that participants of greater stature would lift with the load closer to the body as they could better allow for positioning of paramedic equipment between the feet. Similarly, I hypothesize that more flexible lifters would be able to adopt a movement strategy which minimizes the horizontal distance of their body to the load and their peak low back flexion angle to reduce resultant biomechanical exposures. Conversely, it was hypothesized that higher body mass participants would have the load further from the body resulting in higher exposures. Finally, I hypothesized that both females and stronger individuals would have lower resultant exposures in lifting consistent with previous reported findings (i.e., Makhoul et al., 2017; Clusiault et al., 2022). Across all hypothesized relationships of structural and functional factors to biomechanical exposures I hypothesized corresponding associations would be seen to features of movement to result in the observed exposures. However, I hypothesize that functional or structural factors will not influence movement objective definitions, so no significant associations to dependent variability measures are anticipated.

*8.2 Methods:*

*8.2.1 Study Design*

In this study both structural (sex, stature, body mass) and functional factors (isometric lift strength, knee fROM, hip fROM), as well as lift types, were independent variables. The mean and variability of peak low back compression and A-P shear loads normalized to body mass, as well as synergistic features of movement that were related to resultant peak low back loads were dependent variables in the study design. Full methodology including participant recruitment, instrumentation, experimental protocol, and data processing methods are presented in the general methodology chapter (Chapter 4.0).

*8.2.2 Hypothesis Testing*

Backward removal multiple regression models with $\alpha = 0.10$ set as a threshold for predictor removal was used to determine the association of sex, stature, body mass, strength, knee fROM and/or hip fROM, to the mean and standard deviation of peak low back loads in the four lift types.

If significant associations were observed between structural or functional factors and either the mean and standard deviation of either peak low back compression or A-P shear forces, then backward removal multiple regression was used to evaluate the association of the significant functional and structural measures to the mean and standard deviation of PC scores in all features of movement that are related to peak low back loads. Simple regression was used to quantify whether PCs were associated with either peak low back compression or A-P shear forces in each lift type (Table 6-4). This aspect of the statistical analysis was to investigate whether resultant biomechanical exposures were a product of consistent control of kinematic coordination patterns as hypothesized in the overarching theoretical OFC model. All regression-based analyses were conducted in SPSS (Version 25.0, IBM Corporations, Armonk, NY).

A Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) was applied to control for family-wise error across multiple regression models with a false discovery rate set to 10%. An '*' is used to denote significance in the results accounting for the Benjamini-Hochberg correction.

Since associations are known to exist between predictor variables (i.e., stature is associated with body mass) collinearity was considered in all multiple regression models. Variance inflation factors (VIF) were used to quantify collinearity. Across all regression models it was found that the greatest observed VIF value was 2.55. While there is no consensus on what magnitude of VIF is problematic with recommendations ranging from 2.5-10, the maximum measured VIF value of 2.55 was interpreted to support that significant collinearity was not shared between predictor variables in the final regression models.

Finally, if structural or functional personal factors were significantly associated with biomechanically relevant PC scores than single component reconstruction (Brandon et al., 2013) and consideration of the landmark-specific loading vector (Armstrong et al., 2021a) were used to determine the mode of variance explained by the associated feature of movement.

### *8.3 Results:*

The descriptive statistics of functional personal factors (strength and lower body flexibility) are reported in Table 8-1. Participant demographics including sex, stature and body mass are provided in Chapter 4.1 (Table 4-2). Peak angular displacement of the knee and hip angles from standing in the squat- and stoop-like posture trials were taken as Knee fROM and Hip fROM predictor variables, respectively. Descriptive statistics of mean and standard deviation of peak compression and A-P shear loads are included in Chapter 7.3 (Table 7-1).

**Table 8-1:** Participant functional factor demographics reported as group means and (standard deviations) stratified by lifter expertise groups.

| | Paramedics / In-training (n = 20) | | Trained Lifters (n = 26) | | Novice Lifters (n = 26) | |
|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female |
| Isometric Lift Strength (N) | 1649.4 (315.9) | 950.7 (135.4) | 1515.5 (283.5) | 872.5 (228.7) | 1313.1 (219.8) | 790.4 (191.3) |
| Knee fROM ($^o$) | 111.8 (16.4) | 117.6 (10.4) | 121.3 (19.9) | 115.7 (11.5) | 119.0 (16.9) | 116.7 (12.6) |
| Hip fROM ($^o$) | 58.9 (26.3) | 108.8 (22.2) | 84.0 (29.9) | 104.7 (15.5) | 66.8 (19.1) | 106.7 (23.7) |

Significant associations of structural and functional personal factors were seen to both the mean and standard deviation of peak low back compression (Table 8-2) and A-P shear forces (Table 8-3). Within the statistical summary tables a negative standard beta coefficient indicates that as continuous functional or structural personal factors increase there is lower means and/or variability in normalized low back loads. For the factor of sex, the directionality of associations in all regression models had females having lower means and variability in exposures. To provide context to the multiple regression model results sample simple regressions between independent variables and the mean and standard deviation of peak low back loads are visualized in Figure 8-2.

**Table 8-2:** Backward removal ($p < 0.10$) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of peak low back compression forces normalized to body mass in barbell, backboard, crate, and stretcher lifting. Significant predictors in the final model are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'.

| | Association to mean of peak low back compression | | Association to standard deviation of peak low back compression | |
|---|---|---|---|---|
| | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | Sex (β = -0.74), Strength (β = -0.39) | $p < 0.001$* $R^2 = 0.251$ F = 11.54 | Sex (β = -0.33) | $p = 0.004$* $R^2 = 0.112$ F = 8.86 |
| Backboard | Sex (β = -0.67), Strength (β = -0.44) | $p < 0.001$* $R^2 = 0.194$ F = 8.08 | Sex (β = -0.48), Strength (β = -0.43), Knee fROM (β = 0.20) | $p = 0.004$* $R^2 = 0.149$ F = 3.84 |
| Crate | Sex (β = -0.37), Stature (β = 0.26), Body Mass (β = -0.41) | $p < 0.001$* $R^2 = 0.307$ F = 9.00 | Sex (β = -0.63), Strength (β = -0.35) | $p = 0.001$* $R^2 = 0.194$ F = 7.35 |
| Stretcher | Stature (β = 0.34), Knee fROM (β = 0.19) | $p = 0.006$* $R^2 = 0.146$ F = 5.56 | Sex (β = -0.54), Strength (β = -0.51), Knee fROM (β = 0.23) | $p = 0.003$* $R^2 = 0.184$ F = 4.81 |

**Table 8-3:** Backward removal ($p < 0.10$) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of peak low back anteroposterior (AP) forces normalized to body mass in barbell, backboard, crate, and stretcher lifting. Significant predictors in the final model are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'.

| | Association to mean of peak low back A-P shear force | | Association to standard deviation of peak low back A-P shear force | |
|---|---|---|---|---|
| | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | Sex (β = -0.26), Hip fROM (β = -0.34) | $p < 0.001$*<br>$R^2 = 0.298$<br>F = 14.64 | Sex (β = -0.23), Hip fROM (β = -0.35) | $p < 0.001$*<br>$R^2 = 0.267$<br>F = 13.96 |
| Backboard | Hip fROM (β = -0.43) | $p < 0.001$*<br>$R^2 = 0.187$<br>F = 15.86 | Hip fROM (β = -0.30) | $p = 0.001$*<br>$R^2 = 0.146$<br>F = 11.77 |
| Crate | Stature (β = 0.24), Body Mass (β = -0.36), Strength (β = 0.31), Knee fROM (β = 0.20), Hip fROM (β = -0.21) | $p = 0.001$*<br>$R^2 = 0.306$<br>F = 5.21 | Sex (β = -0.48), Body Mass (β = -0.23) | $p = 0.001$*<br>$R^2 = 0.216$<br>F = 8.41 |
| Stretcher | Stature (β = 0.29) | $p = 0.013$*<br>$R^2 = 0.089$<br>F = 6.47 | Sex (β = -0.39), Body Mass (β = -0.25) | $p = 0.009$*<br>$R^2 = 0.136$<br>F = 5.11 |

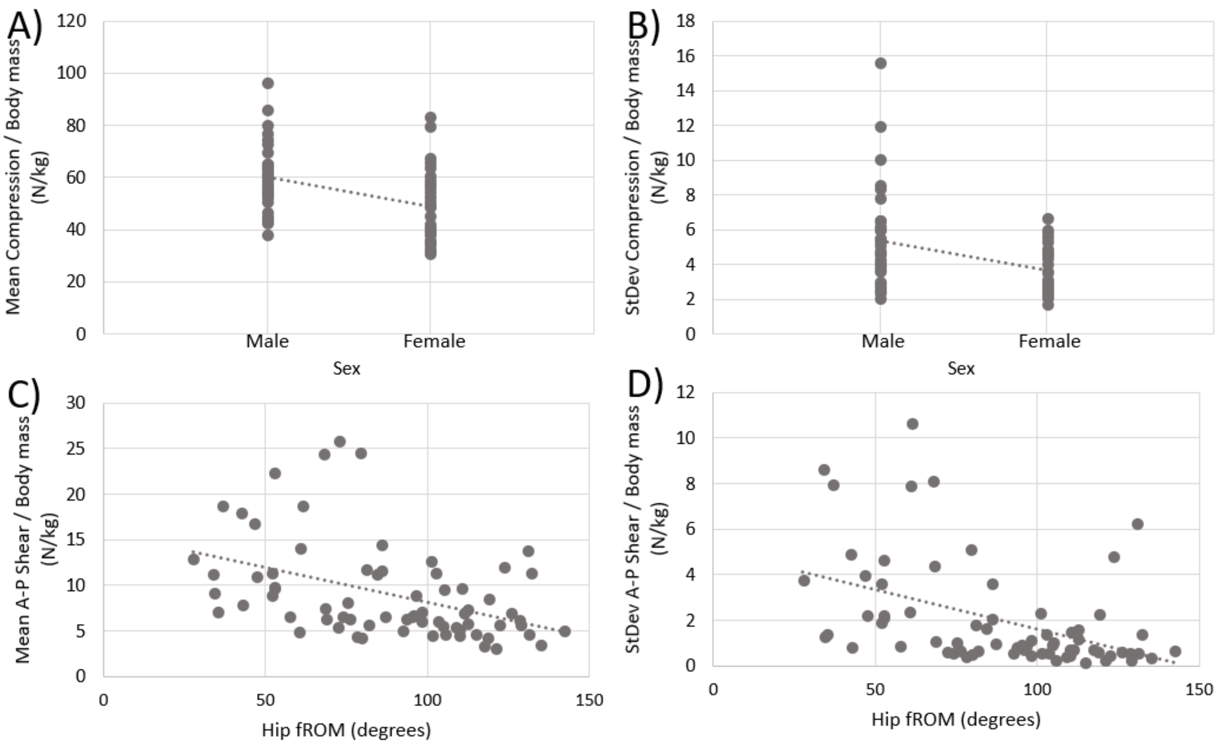


**Figure 8-2:** Scatter plots visualizing the association of select structural and functional personal factors to the mean and standard deviation of peak low back loads normalized to body mass during. Top row: association of sex to the A) mean and B) standard deviation of peak low back compression force during crate lifting. Bottom row: association of hip fROM to the C) mean and D) standard deviation of peak A-P shear loads in backboard lifting.

With significant associations of structural and functional factors to both the mean and standard deviation of low back loads, the association of these measures to the mean and variability of features of movement related to the low back loads were examined. Within each lift type only significant predictors of either the mean or variability in low back loads were input as predictor variables when regressing to biomechanically relevant PCs.

Across backward removal multiple regression models of structural and functional factors to biomechanically relevant PCs, significant variance in mean PC scores were explained for most PCs, while significant variance in the variability of these PC scores was not consistently seen.

An example of these findings is visualized for barbell lifting in Table 8-4. These results are important to consider in relation to the hypotheses that structural or functional factors consistently explain variance in mean, but not variability, of PC scores in most PCs retained for analysis. Additionally, while the PC scores on their own do not provide direct context to how lifting strategy varies as a function of structural and functional factors, the modes of variance in all PCs where significant associations were observed were interpreted and presented in Appendix D. These interpretations in tandem with the regression model results were used to inform the interpretation of lifting strategy of structural and functional factors through the discussion section.

**Table 8-4:** Backward removal ($p$ < 0.10) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of PC scores associated with low back loads in barbell lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | PC1 | Hip fROM (β = 0.34) | $p$ = 0.003*<br>$R^2$ = 0.121<br>F = 9.61 | N/A | N/A |
| | PC3 | Sex (β = 0.47) | $p$ < 0.001*<br>$R^2$ = 0.228<br>F = 20.71 | N/A | N/A |
| | PC5 | N/A | N/A | N/A | N/A |
| | PC7 | Hip fROM (β = -0.31) | $p$ = 0.006*<br>$R^2$ = 0.102<br>F = 7.95 | N/A | N/A |
| | PC8 | Hip fROM (β = -0.33) | $p$ = 0.004*<br>$R^2$ = 0.111<br>F = 8.72 | N/A | N/A |
| | PC11 | N/A | N/A | N/A | N/A |
| | PC12 | Sex (β = 0.35), Strength (β = 0.51), Hip fROM (β = 0.29) | $p$ = 0.002*<br>$R^2$ = 0.190<br>F = 5.33 | N/A | N/A |
| | PC14 | N/A | N/A | N/A | N/A |

Similar to barbell lifting, significant associations of structural and functional factors to mean PC scores were observed in backboard lifting for the majority of biomechanically relevant PCs (Table 8-5). These significant relationships had comparable strengths of association to associations measured in barbell lifting ($R^2$ = 0.079-0.263 in backboard lifting compared to $R^2$ = 0.111-0.228 in barbell lifting). However, unlike barbell lifting significant associations were also seen to variability in PC scores in a subset of PCs. Of note, being female was associated with both the mean and standard deviation of PC scores in PC8.

**Table 8-5:** Backward removal ($p < 0.10$) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of PC scores associated with low back loads in backboard lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Backboard | PC1 | Sex (β = 0.45) | $p < 0.001$* $R^2 = 0.209$ F = 18.20 | Sex (β = 0.30) | $p = 0.009$* $R^2 = 0.095$ F = 7.24 |
| | PC3 | Strength (β = 0.38) | $p = 0.001$* $R^2 = 0.149$ F = 12.12 | Knee fROM (β = -0.19) | $p = 0.099$ $R^2 = 0.039$ F = 2.79 |
| | PC8 | Sex (β = 0.71), Strength (β = 0.44), Knee fROM (β = -0.18) | $p < 0.001$* $R^2 = 0.260$ F = 7.83 | Sex (β = -0.43), Strength (β = -0.51), Knee fROM (β = 0.30) | $p = 0.001$* $R^2 = 0.213$ F = 6.05 |
| | PC9 | Sex (β = -0.37), Hip fROM (β = 0.50) | $p = 0.002$* $R^2 = 0.167$ F = 6.81 | N/A | N/A |
| | PC11 | Hip fROM (β = -0.28) | $p = 0.018$* $R^2 = 0.079$ F = 5.92 | Knee fROM (β = 0.20) | $p = 0.080$ $R^2 = 0.044$ F = 3.16 |
| | PC12 | Strength (β = 0.24), Hip fROM (β = 0.41) | $p = 0.004$* $R^2 = 0.148$ F = 5.90 | N/A | N/A |
| | PC14 | Strength (β = 0.40), Knee fROM (β = 0.41), Hip fROM (β = -0.50) | $p < 0.001$* $R^2 = 0.235$ F = 6.85 | N/A | N/A |
| | PC15 | N/A | N/A | N/A | N/A |
| | PC17 | N/A | N/A | N/A | N/A |

Similar results demonstrating associations of structural and functional factors to the mean and variability of PC scores in crate lifting were observed (Table 8-6). A notable difference in these associations to those measured in barbell and backboard lifting is the strength of association to mean PC scores had instances of being much stronger (i.e., a highest observed $R^2 = 0.746$).

**Table 8-6:** Backward removal ($p$ < 0.10) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of PC scores associated with low back loads in crate lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Crate | PC1 | Stature (β = -0.61), Strength (β = -0.24), Hip fROM (β = 0.18) | $p < 0.001$* $R^2 = 0.746$ F = 59.67 | N/A | N/A |
| | PC2 | Knee fROM (β = -0.27) | $p = 0.029$* $R^2 = 0.074$ F = 5.01 | N/A | N/A |
| | PC4 | Stature (β = -0.66), Sex (β = -0.48), Hip fROM (β = 0.26) | $p < 0.001$* $R^2 = 0.316$ F = 9.41 | Body Mass (β = -0.31), Hip fROM (β = -0.29) | $p = 0.004$* $R^2 = 0.166$ F = 5.95 |
| | PC5 | Stature (β = -0.60), Body Mass (β = -0.64), Strength (β = 0.37), Hip fROM (β = -0.14) | $p < 0.001$* $R^2 = 0.669$ F = 30.36 | Body Mass (β = -0.31) | $p = 0.014$* $R^2 = 0.094$ F = 6.34 |
| | PC6 | N/A | N/A | Stature (β = -0.28), Strength (β = 0.30) | $p = 0.080$ $R^2 = 0.081$ F = 2.63 |
| | PC9 | Stature (β = -0.30), Body Mass (β = -0.55), Strength (β = 0.42), Hip fROM (β = -0.49) | $p < 0.001$* $R^2 = 0.507$ F = 15.42 | N/A | N/A |
| | PC10 | Strength (β = -0.35), Hip fROM (β = -0.27) | $p = 0.014$* $R^2 = 0.128$ F = 4.54 | N/A | N/A |
| | PC14 | N/A | N/A | N/A | N/A |
| | PC15 | N/A | N/A | Stature (β = -0.23), Hip fROM (β = -0.25) | $p = 0.072$ $R^2 = 0.084$ F = 2.74 |
| | PC18 | Stature (β = 0.30), Sex (β = 0.51), Knee fROM (β = -0.20) | $p = 0.002$* $R^2 = 0.221$ F = 5.77 | N/A | N/A |

Finally, associations of structural and functional factors to the mean and variability of PC scores in stretcher lifting once again shared similar significant associations as seen in other lift types (Table 8-7). Notably, the strongest observed association was strength to mean PC2 scores with corresponding associations of stronger individuals having less variability in these scores.

**Table 8-7:** Backward removal ($p < 0.10$) multiple regression model summaries of functional and structural personal factors to the mean and standard deviation of PC scores associated with low back loads in stretcher lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. Significant differences accounting for the Benjamini-Hochberg correction are denoted with '*'. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Stretcher | PC1 | N/A | N/A | N/A | N/A |
| | PC2 | Stature (β = -0.62), Strength (β = -0.25) | $p < 0.001$* $R^2 = 0.627$ F = 54.60 | Strength (β = -0.22) | $p = 0.062$ $R^2 = 0.052$ F = 3.61 |
| | PC4 | N/A | N/A | N/A | N/A |
| | PC5 | N/A | N/A | N/A | N/A |
| | PC10 | Sex (β = 0.70), Stature (β = 0.41) | $p < 0.001$* $R^2 = 0.283$ F = 12.84 | Strength (β = -0.22) | $p = 0.063$ $R^2 = 0.051$ F = 3.57 |
| | PC14 | Sex (β = -0.49), Strength (β = -0.37) | $p = 0.037$ $R^2 = 0.097$ F = 3.47 | N/A | N/A |
| | PC19 | Knee fROM (β = 0.31) | $p = 0.009$* $R^2 = 0.098$ F = 7.18 | Stature (β = -0.23) | $p = 0.051$ $R^2 = 0.057$ F = 3.95 |
| | PC20 | Strength (β = -0.41) | $p < 0.001$* $R^2 = 0.170$ F = 13.50 | Knee fROM (β = 0.31) | $p = 0.081$ $R^2 = 0.045$ F = 3.13 |

*8.4 Discussion:*

The purpose of this study was to determine how structural and functional personal factors independently and/or interdependently explain variance in peak low back loads and aspects of lifting strategy related to low back loads in generic and paramedic lifting tasks. It was found that across lift types being female, stronger, shorter stature, higher body mass, and having greater lower body fROM has associations to lower normalized peak low back compression and/or A-P shear loads (Tables 8-2 & 8-3). Additionally, there were corresponding associations of these independent variables to mean strategy in features of movement related to biomechanical exposures at the low back (Tables 8-4 through 8-7) supporting that their influence on kinematic strategy has resultant implications on low back loads. Across these observed associations females and stronger individuals seem to define a movement objective to consistently minimize peak compression forces. Additionally, females, individuals with greater body mass and greater hip mobility seem to define a movement objective to consistently minimize peak A-P shear forces. Meanwhile, other predictor variables seem to explain variance in mean exposures or movement strategy, but not necessarily variability in these outcomes. This suggests that stature, body mass, and lower body fROM do not necessarily influence the definition of a movement objective, but rather bias the available lifting strategies to participants. Finally, the association of structural and functional personal factors to lifting outcomes differs across lift types, suggesting an interaction between the examined personal factors and specific lift demands on movement strategy. These findings have potential implications in the design of ergonomic interventions that aim to minimize biomechanical exposures during lifting.

I found support for the hypothesis that females would have lower relative biomechanical exposures at the low back. The resultant lower mean peak compression forces in tandem with lower variability in these exposures supports that females seem to adopt a movement objective to consistently minimize biomechanical exposures to achieve this outcome. Previous literature has shown that females had lower normalized low back exposures when performing paramedic lifting tasks compared to males and speculated that this was a product of females prioritizing minimizing these exposures in their movement objectives (Makhoul et al., 2017). While previous studies have highlighted that sex-effects on lifting strategy are not observed when scaling load mass to capacity (Albert et al., 2008; Sadler et al., 2011), both sex and strength independently explaining variance in resultant loads in this study highlight that they are determinants of strategy, opposed to strength alone. The results in this study provide support to this hypothesis where the lower mean and variability in normalized compression forces in females would support that this resultant exposure is considered as relevant to task performance and more tightly controlled within an optimal feedback control (OFC) theory framework (Scott, 2004; Todorov, 2004). With females consistently minimizing exposures it provides preliminary support to the theoretical framework posed by Armstrong & Fischer (2020) where this is an example where a personal constraint seems to inform movement objective definition (within an overarching OFC framework) to minimize exposures. In addition to females seemingly trying to consistently minimize biomechanical exposures as a movement objective in backboard lifting, this seems to also be the case when lifting a barbell and crate.

Greater isometric lift strength was also identified as a functional personal factor associated with consistently minimizing low back loads in backboard lifting. This finding is consistent with work by Clusiault et al. (2022) where it was found that strength, not sex, was the biggest determinant of normalized low back extensor moments when lifting a backboard with a mass scaled to participants strength capacity. However, while Clusiault et al.'s (2022) work highlighted that strength was the primary predictor of exposures, in the current study both sex and strength independently explained variance in mean and variability of peak low back compression forces during backboard lifting. This can potentially be attributed to an absolute, rather than relative, load being lifted in the current study where the effective 34 kg mass could have presented as a greater normalized demand to females further biasing them to consider minimizing their resultant compressive exposure. With both sex and strength explaining variance in resultant exposures in this study when lifting an absolute load, it supports the need to consider how both factors independently influence occupational lifting strategy where the load masses lifted in the workplace will not be scaled to capacity.

Having greater functional hip range of motion was observed to be the strongest predictor of mean and variability of peak A-P shear forces in barbell and backboard lifting. Considering the biomechanical modelling approach, the calculated A-P shear loads are sensitive to low back flexion angles (van Dieën & de Looze, 1999). Greater available hip fROM likely allowed participants to approach the load through greater flexion of the hips, opposed to low back, which would reduce the resultant A-P shear loads when performing the lift. While the greater hip fROM allowed participants to adopt lifting strategy to minimize low back flexion, a novel finding highlights that they choose to use this available range of motion to consistently minimize their low back loads.

Greater body mass was similarly associated with lower means and variability of A-P shear loads in crate lifting. It seems in the crate lifting context that the larger body size associated with greater body mass allowed participants to remain more upright during lifting (as seen in crate PC5 (Appendix D)) which would reduce corresponding low back flexion angle and A-P shear loads. This is potentially a product of the greater body mass serving as a counterweight which allows the body to remain upright without a loss of balance while lifting the crate which had a greater horizontal distance from the body than other lift types.

Significant associations of structural and functional factors to the mean and variability of features of movements explain how the magnitude of low back exposures were consistently controlled in females and stronger individuals. Females and stronger individuals were likely able to achieve consistently lower peak compression forces in backboard lifting as there were corresponding associations to the mean and variability in backboard PC8 scores. In this feature of movement both females and stronger individuals extend their legs to initiate the lift, followed by extending the trunk (Figure 8-3). This is opposite to males and less strong individuals who more synchronously extending the legs and trunk when initiating the lift. By initiating the lift with the legs followed by the trunk it is likely that the peak low back extensor moment was reduced by delaying back extension until after 25% of the lift cycle where acceleration of the load is greatest (De Looze et al., 1993).

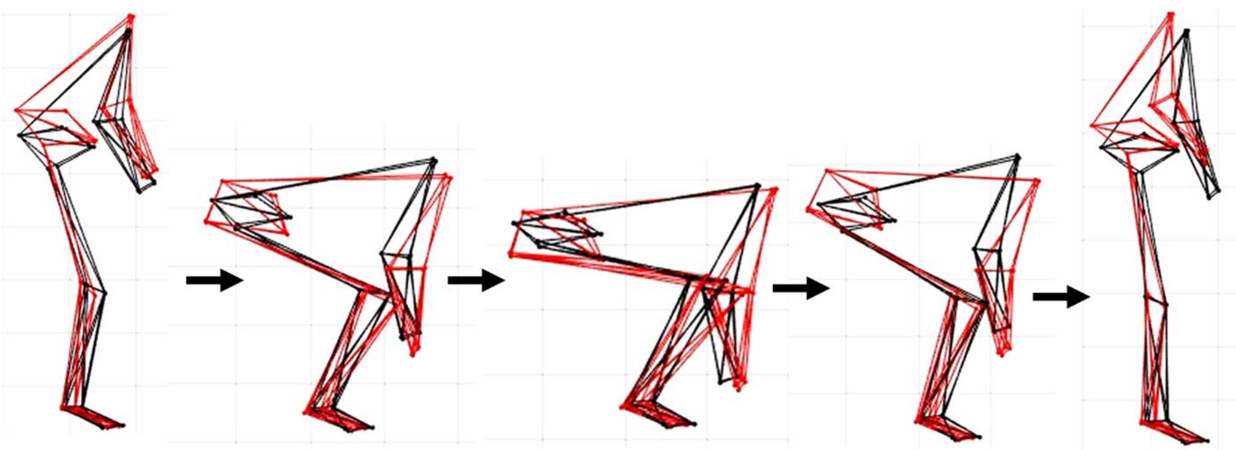

**Figure 8-3:** Single component reconstruction of the 5th (black) and 95th (red) percentile backboard principal component 8. Females and stronger individuals tended to use the 95th percentile reconstruction, while males and less strong individuals used the 5th percentile reconstruction.

Significant associations of structural and functional personal factors to the mean and variability of PC scores were observed without associations of the same personal factors to mean or variability of biomechanical exposures. With this observation it is likely that there are other movement objectives that participants may be considering in addition to minimizing biomechanical exposures when performing these lifting tasks. As an example, a strong association of strength to the mean and variability of stretcher PC2 scores was observed, when strength is not associated to the mean of compression or A-P shear loads in stretcher lifting. Given the stretcher PC2 example, it is likely that stronger individuals are leveraging their strength to perform a more metabolically favourable lift of using their arms and trunk extension (similar to the $5^{th}$ percentile reconstruction), opposed to using both their lower and upper body (similar to the $95^{th}$ percentile reconstruction) that may be required to meet task demands for less strong individuals (Figure 8-4). Given this observation it is prudent to consider how the consistency and control of certain features of movement could be related to achieving other movement objectives in future work.

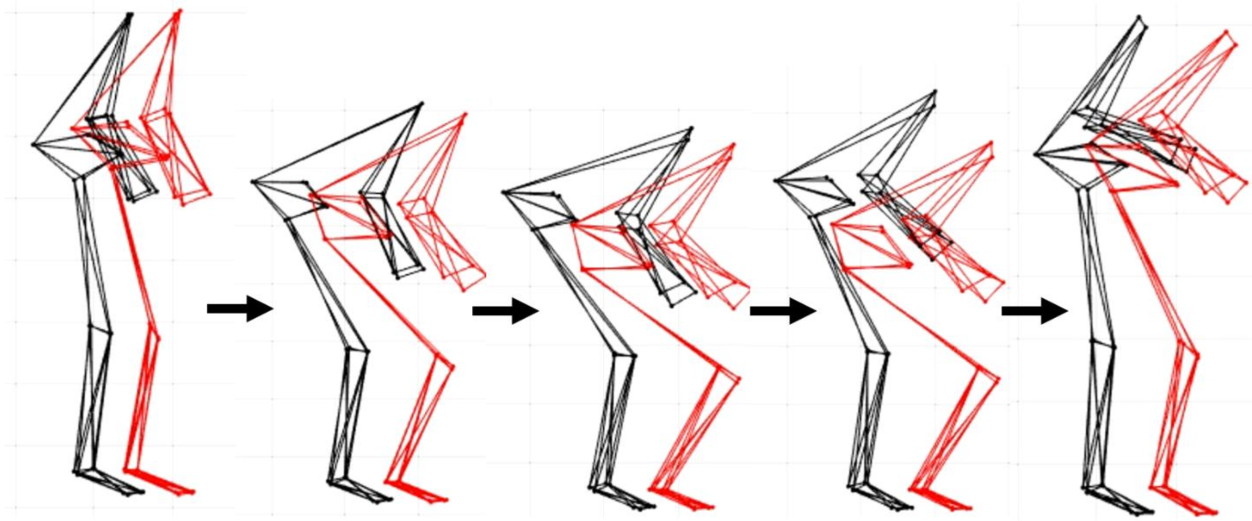

**Figure 8-4:** Single component reconstruction of the 5th (black) and 95th (red) percentile stretcher principal component 2. Females and stronger individuals tended to use the 5th percentile reconstruction, while males and less strong individuals used the 95th percentile reconstruction.

Consistently stronger associations between structural and functional personal factors and the mean, but not variability, of PC scores suggests that these factors are not necessarily influencing movement objectives within an OFC framework. When considering OFC as a theoretical model of motor control, for a movement outcome to be task-relevant it is expected that there will be lower corresponding variability in the outcome as it is controlled by the central nervous system within the defined movement objective (Scott, 2004; Todorov, 2004). Across the regression models associating personal factors to PC scores, it was commonly observed that the strength of the association to the mean of PC scores was greater than the strength of association to the variability in the PC scores. This observation would suggest that the variety of structural and functional personal factors examined in this study seem to influence movement by constraining the movement options available to lifters (reflected in associations to mean PC scores), but do not seem to consistently bias the definition of movement objectives. Influencing movement strategy by constraining available movement options, but not influencing movement objectives, demonstrates a second mechanism by which personal factors influence movement strategy not currently considered in the overarching theoretical framework for this thesis (Figure 1-1). This finding has implications for understanding determinants of movement behaviour where there seems to be two independent mechanisms in which personal factors can influence movement strategy: by influencing movement objective definition or by constraining the availability of movement options.

The observed associations of structural personal factors to biomechanical exposures and features of movement in crate lifting were stronger than the other lift types investigated. Interestingly, the crate lifting task was perceived as the most difficult by participants due to the orientation of the crate relative to the force plates increasing the horizontal distance to the load compared to other lift types. Highlighting this increased difficulty only 63/72 participants could complete this lift in the protocol. This finding highlights that when the range of lifting options is limited by task difficulty greater proportions of variance in lifting kinematics and resultant loads are explained by personal factors.

An interesting finding of this work was that the significant predictors of both low back loads and features of movement were not consistent across the lift types. This finding was unexpected as the experimental protocol was designed to have consistency in the type of lifts performed and ensured that the mass of the load being lifted was consistent across the lift types. The resultant differences in significant predictors of lifting outcomes across lift types may be attributable to dynamic systems theory where it is hypothesized that unique combinations of personal, task and environment factors influence the coordination and control of movement (Newell, 1986; Glazier, 2017). Within this study the differences in load shape could have biased the differences in available movement strategies and subsequent significant predictors where load shape has been shown to influence lifting strategy (Zehr et al., 2018). Additionally, although the absolute load mass remained consistent, differences in moment arms between the body and the load were present between lift types. This would result in a greater perceived demand when lifting an object such as the crate compared to the barbell where the moment arm could be minimized. As load mass has been shown to be a determinant of lifting strategy (Davis & Troup, 1965; Scholz, 1993a, 1993b; Scholz & McMillan, 1995; Burgess-Limerick et al., 1995) the resultant differences in demands as a function of differing moment arms could partially explain the differences in significant predictors across lift types.

This study investigated how structural and functional personal factors influence lifting strategy but is not without limitation. First, only a simplistic measure of isometric lift strength was recorded in the study. The choice of an isometric strength measure may be questioned as it does not necessarily represent dynamic lifting strength (Garg et al., 1980). However, the influence of dynamic lifting strength on lifting strategy has been previously investigated (Clusiault et al., 2022), and isometric lift strength can be more readily measured clinically. Second, the range of motion measures collected were taken while emulating squat- and stoop-like lift strategy. While this does not necessarily measure true range of motion of the knee and hip joints respectively, this decision was made as it quantifies the range of motion about these joints which individuals can functionally achieve in a lift context which has greater external validity. Finally, an absolute load mass was lifted opposed to a relative load mass. Relative mass of the load to strength capacity has been shown to influence lifting strategy (Plamondon et all., 2017), but as occupational lifting demands are not typically scaled to workers' capacity the decision to lift an absolute load mass was made to increase external validity of the study design.

The findings from this study have important implications for the development of ergonomic interventions. First, both increased strength and hip fROM were identified as functional factors that were associated with consistently minimizing peak low back loads across different lift types. Since both strength and hip flexibility can be improved through fitness-based interventions these may be modifiable personal factors one can aim to improve with an end goal of changing occupationally lifting strategy to have lower resultant exposures. Lift training that is inclusive of exercise programing may help yield greater effectiveness relative to current approaches (Denis et al., 2020). However, the exercise as lift training hypothesis should be further tested. Second, the inconsistency in which personal factors explained variance in either low back exposures or features of movement across lift types has implications for movement prediction tools. Based on the findings in this study there is a complex interaction between the investigated personal factors and lift types on resultant lifting strategy. These interactions should be considered when aiming to predict movement or posture in varying types of lift applications opposed to assuming consistent effects of personal factors on lifting strategy regardless of context.

### *8.5 Conclusion:*

The purpose of this study was to determine how structural and functional personal factors independently and/or interdependently explain variance in peak low back loads and aspects of lifting strategy related to low back loads in generic and paramedic lifting tasks. I found that females, stronger individuals, and individuals with greater hip fROM tended to consistently minimize peak low back loads in lifting. Additionally, the battery of structural and functional factors investigated influenced the features of movement in lifts, but interestingly did not do so consistently across a variety of lift types. With the quantified effects of structural and functional factors on lifting strategy it is important to consider these findings both when applying interventions that aim to change worker behaviour to reduce injury risk, as well as predict movement strategy in a lifting context using modelling approaches.

# Chapter 9: Evaluating the prospective benefit of improving modifiable personal factors to reduce low back exposures in lifting

*9.1 Introduction:*

In occupations with non-modifiable demands that predispose workers to injury risk administrative-based ergonomic controls such as lift training are needed. Lift training is particularly relevant when job demands are non-modifiable and less amenable to controls that eliminate or engineer out factors pre-disposing a worker to injury risk. Emergency service work, such as paramedicine, is an exemplar sector that could benefit from administrative controls to reduce injury risk. Paramedics have the highest reported injury incidence by work sector (Maguire et al., 2005; Maguire et al., 2014), partially attributed to high low back exposures when performing essential lifting tasks (Armstrong et al., 2020). While elimination of hazards is preferred, essential lifting tasks, such as lifting a backboard from the ground, can not be easily modified to reduce injury risk. Lift training remains as a viable near-term strategy to reduce injury risk among paramedics.

Though a potentially viable administrative control, lift training is generally ineffective (Haslam et al., 2007; Martimo et al., 2008; Clemes et al., 2009; Verbeek et al., 2011; Hogan et al., 2014). However, we do not know if lift training simply does not work, or if it does not work in the classical way that lift training has been provided (Denis et al., 2020). Within this thesis I have shown that the ability to perceive proprioceptive information (Study 1 - Chapter 6.0), and personal structural (i.e., stature, body mass) and functional (i.e., strength and flexibility) factors (Study 3 - Chapter 8.0) influence resultant biomechanical exposures on the low back in both generic and paramedic-specific lifting tasks. Considering these findings, it is possible that intervening on those factors (where feasible) may provide a more targeted focus for lift training to reduce the magnitude of biomechanical exposures experienced by lifters. Specifically, if modifiable personal factors are intervened upon, and workers are given the opportunity to explore new movements given their improved attributes, then we may expect movement strategies that reduce corresponding biomechanical exposures at the low back. However, with all participants in studies 1-3 of this thesis having a unique set of personal factors it is difficult to interpret whether improving modifiable personal factors deemed to be associated with resultant exposures has efficacy at a population level where any combination of independently measured personal factors may be observed. As such, further investigation is needed to test the prospective benefit of improving modifiable personal factors to reduce low back loads in lifting across the population.

Modelling approaches to predict population level movement strategy and corresponding exposures can be used as a tool to evaluate whether modifying personal factors is a potentially effective intervention to reduce injury risk. Movement prediction is not a new concept, but existing approaches tend to be deterministic in nature predicting a single movement strategy using either regression or optimization (Wolf et al., 2020). As human movement is known to be inherently variable (Latash, 2012), considering the variability in lifting strategy is important when evaluating the prospective benefit of improving modifiable personal factors as a proactive ergonomics strategy. As such, using a deterministic modelling approach to predict lifting strategy would fail to capture variability within all factors influencing the resultant model outcome, which can possibly lead to misleading outcomes (Langenderfer et al., 2006, Laz & Browne, 2010). Given these limitations probabilistic modelling that based on an input can generate a range of likely possible outputs accounting for uncertainty in input parameters (Olofsson, 2005; Laz & Browne, 2010) has utility in this study design. Development of such a model to predict ranges of biomechanical exposures in lifting likely to be experienced at the population level would have similar prospective benefits to other modelling approaches applied for risk assessment such as predicting subacromial space (Chopp-Hurley et al., 2016), as well as evaluating fracture risk in the femur (Bryan et al., 2009; Laz et al., 2007), hip (Martel et al., 2020) and cervical spine (Thacker et al., 2001).

The purpose of this study was to develop a model to predict a range of biomechanical exposures likely to be experienced on a population level as a function of personal factors and use this model to evaluate the prospective benefit of improving modifiable personal factors as an ergonomics solution. To evaluate the prospective benefit of improving modifiable factors to reduce exposures the first objective of this study was to determine which modifiable factors explained variance in population level predicted mean, one standard deviation above the mean and $95^{th}$ percentile low back loads across all simulated possible lifting strategies, given that high magnitudes of these exposures are associated with MSD risk (Waters et al., 1993; Gallagher & Marras, 2012). The secondary objective in this study was then to quantify the magnitude to which modifiable factors independently effect the resultant predicted ranges of peak compression and A-P shear loads. Through this analysis I can determine the prospective benefit of improving modifiable personal factors on reducing likelihood magnitude of resultant biomechanical exposures at the low back in lifting. These results will inform whether modifying personal factors to reduce resultant exposures is likely to be an effective proactive ergonomics intervention.

*9.2 Methods:*

*9.2.1 Study Overview*

To answer the research questions posed in this study a simulation tool to evaluate which modifiable factors most greatly influence minimizing peak low back loads was needed. In the development of this simulation tool a probabilistic model was used to predict a range of movement strategies based on input data, and a deterministic model was used to calculate peak low back compression and A-P shear forces associated with each predicted movement strategy. The inputs and outputs of the developed model are pictured in Figure 9-1. Following model development, simulations could be run across combinations of personal factors to answer the posed research questions.

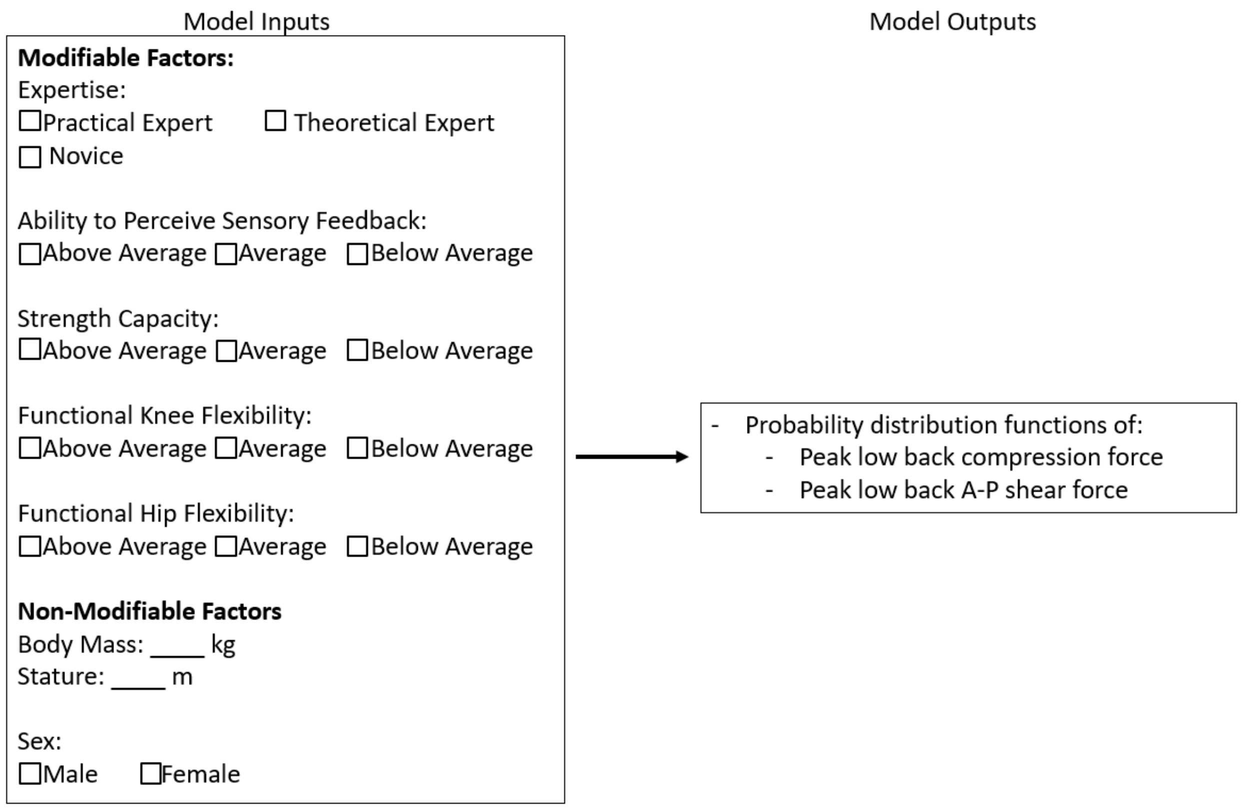


**Figure 9-1:** Visualization of probabilistic model inputs and outputs. For each input parameter option there is an associated probability distribution function of PC scores that is used to generate a predicted range of model outcomes. Body Mass and Stature inputs are categorized as below average, average, or above average based on pre-defined criteria to influence movement strategy, but also directly scale the rigid link model. The model was developed using single load mass (34 kg) and so hand loads for the purpose of rigid link modelling do not need to be specified as inputs.

### *9.2.2 Model Development – Accounting for Movement Variability as a Function of Personal Factors*

Model development was directly informed by findings from studies 1-3 in this thesis where the influence of proprioceptive ability, expertise, structural and functional factors on resultant movement strategy in lifting (as measured by PC scores) were included as model inputs. Separate models were developed for each of the lift types as inconsistencies in personal factors influencing movement strategy across lift types was observed within the preceding thesis studies. Additionally, models were only developed for barbell, crate and backboard lifting since the observed peak normalized low back compression and A-P shear forces in these lifts were approximately double the observed peak loads in stretcher lifting (Study 2 - Chapter 7.0). All model development was completed in Matlab (The Mathworks, Natick, USA).

As a first consideration in model development the variability in lifting strategy as a function of personal factors was quantified. This process is visualized in Figure 9-2. First, PCs identified to quantify kinematic variability in studies 1-3 of this thesis were again used to represent kinematic variability in lifting strategy. To facilitate the modelling approach differences in movement strategy as a function of personal factors needed to be quantified to serve as model inputs. Given that some personal factors were measured with continuous data (i.e., stature or strength), these personal factors were grouped in terciles of 24 participants to each to represent the lowest third, middle third and highest third groups (Table 9-1). The groups are herein referred to below average, near average, and above average, respectively. Using the defined tercile groups, one-way ANOVAs were used to test for differences in PC scores across all retained PCs as a function of personal factor groups. When significant main effects were observed across personal factor groups (e.g., a difference in PC1 scores across the below average, near average, and above average strength capacity groups), group-specific PDFs of PC scores were defined based on the within group mean and standard deviation of PC scores. Since PC scores (the input variable of interest) are conceptually z-scores relative to the mean (Daffertshofer et al., 2004) they are normally distributed by definition, supporting the use of normal distributions to represent personal factor group-specific PDFs of corresponding PC scores. With group-specific PDFs of PC scores defined a methodological decision was made to sample from the 95% confidence interval of all defined PDFs when generating lifting kinematics in model execution. By sampling from the 95% confidence interval within the group-specific PDFs it allowed for a broader range or likely strategies an individual could use to be defined, opposed to limiting the range of these possible movement solutions if a truncated distribution (i.e., less than 95% confidence interval of the PDFs) was used.

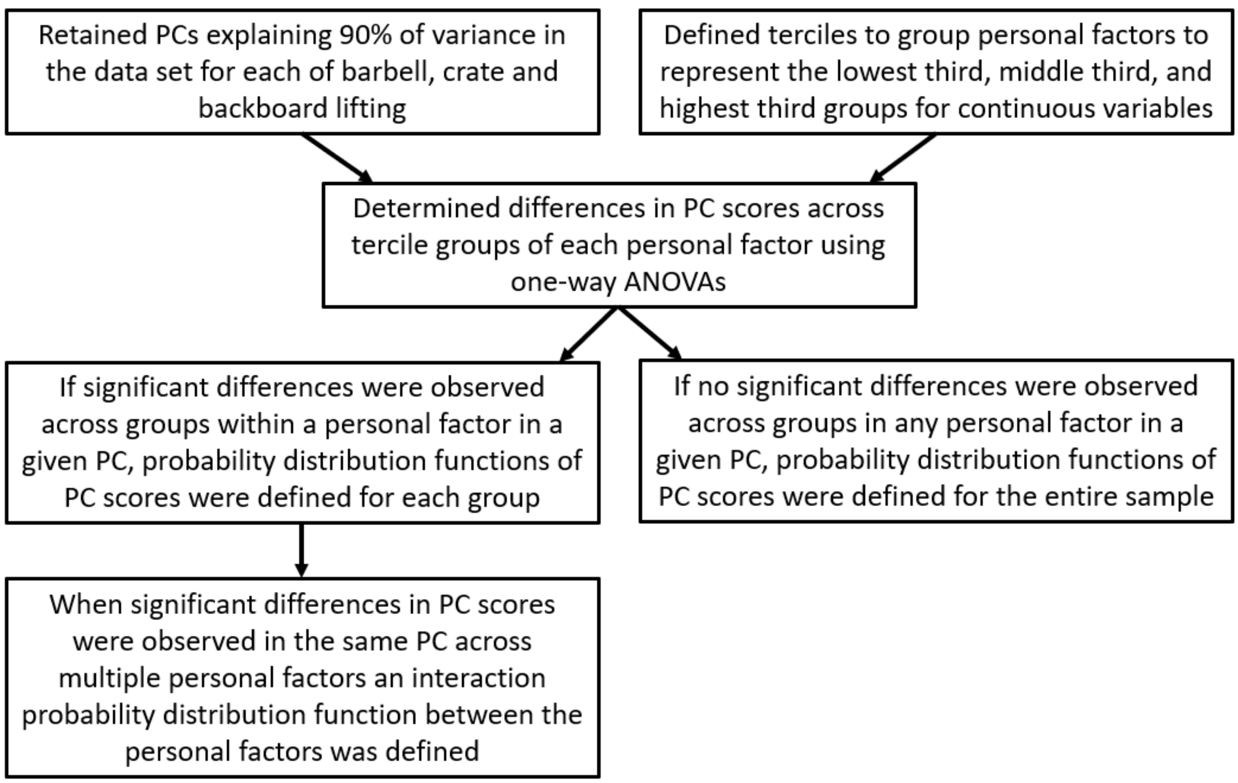


**Figure 9-2:** General methodology to determine the principal component score probability distribution functions for all personal factors serving as model inputs.

**Table 9-1:** Descriptive statistics for personal factors across below average, average and above average tercile groups.

| | Below Average | Average | Above Average |
|---|---|---|---|
| Stature (m) | 1.60 (0.03) | 1.71 (0.03) | 1.83 (0.03) |
| Body Mass (kg) | 63.8 (7.2) | 79.4 (5.3) | 101.5 (12.2) |
| Strength (N) | 756.9 (106.2) | 1136.7 (133.2) | 1651.9 (227.9) |
| Force Matching Error at 75% of max Target (N) | 63.3 (35.9) | 25.7 (3.5) | 15.1 (4.2) |
| Posture Matching Error in Self-selected posture (°) | 4.8 (1.3) | 2.9 (0.3) | 1.6 (0.6) |
| Functional Knee Range of Motion (°) | 100.9 (9.3) | 117.8 (4.0) | 132.7 (8.8) |
| Functional Hip Range of Motion (°) | 53.1 (13.7) | 90.9 (9.9) | 120.1 (9.9) |

During model development it was found that in certain instances multiple personal factors had corresponding differences in PC scores across tercile groups within the same PC (i.e., PC*X* scores differed across both strength and flexibility groups). To account for these interactions between personal factors a PDF was fit to the combination of personal factor group-specific defined PC score PDFs (Figure 9-3).

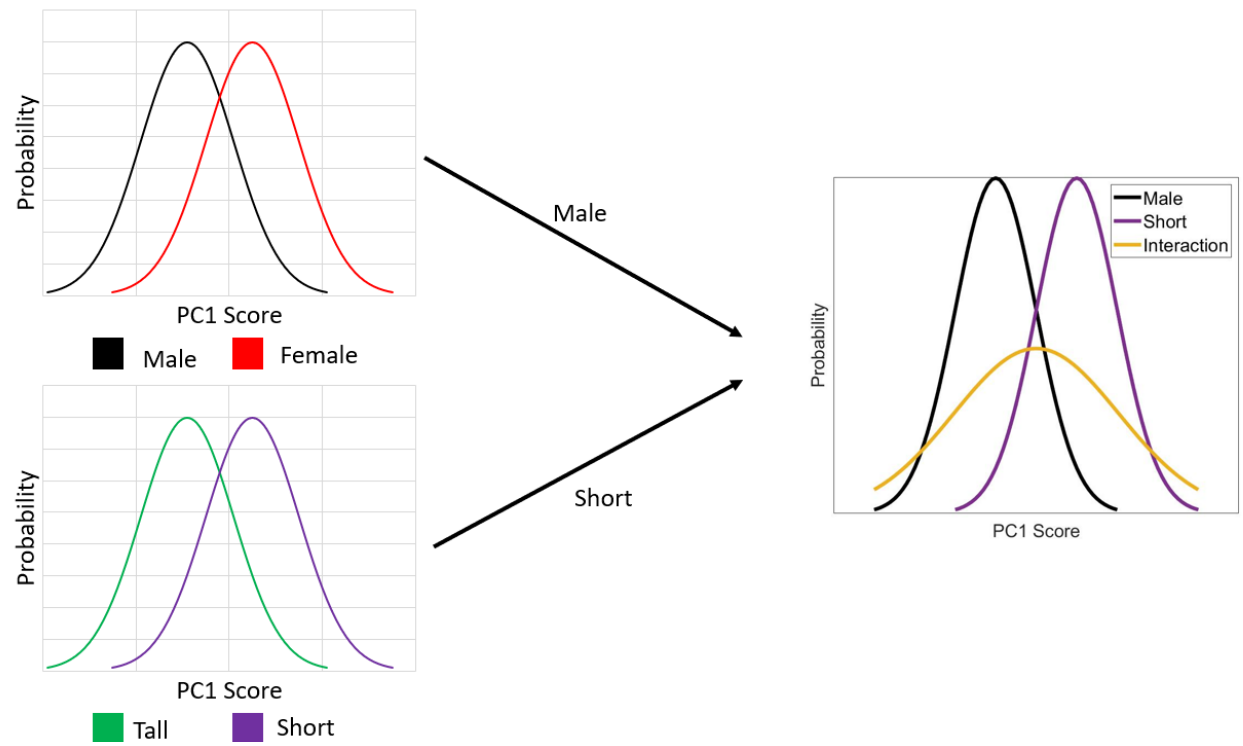


**Figure 9-3:** Theoretical visual representation of the generation of interaction probability distribution function when individual personal factor inputs both have corresponding differences in principal component scores.

As a final consideration to represent movement variability observed across the sample in model design, there were instances when no significant differences in PC scores within a given PC were observed across any personal factor groups. While these PCs, or features of movement, did not differ as a function of any personal factors this mode of variance in movement was identified from the data set and therefore is a true representation of movement variability observed in lifting performance. To account for this, a PDF of PC scores for these PCs was defined using the mean and standard deviation of PC scores across the dataset. In model execution a PC score would be selected from this distribution of PC scores to account for the variability in this feature of movement that is not attributable to any of the examined personal factors.

### *9.2.3 Model Development – Rigid Link Modelling*

The definition of group-specific PC score PDFs was used to account for variability in movement strategy as a function of personal factors. However, for the purpose of this study the influences of these differences in movement variability on resultant low back biomechanical exposures needed to be determined. To achieve this purpose a movement trajectory could be generated with each model iteration and then input into a rigid link model to calculate resultant peak low back loads.

Within model execution Monte Carlo simulation was used to select PC scores from defined group-specific PDFs on each model iteration. The PC scores selected on each model iteration were then used to generate a movement profile using aggregate component reconstruction (Armstrong et al., 2021a). The selected movement profile was then scaled to height by multiplying all *x*, *y*, and *z* values of the height-normalized aggregate component reconstruction by the stature input to the model. The height-scaled movement trajectories were used in a rigid link model to calculate the corresponding peak low back compression and A-P shear loads.

Using the movement trajectory defined on each model iteration the corresponding peak low back compression and A-P shear loads were calculated using a top-down rigid link model. The rigid link model used segment definitions consistent with ISB recommendations (Wu et al., 2002; 2005) and defined sex-specific segment inertial properties based on recommendations from Zatsiorsky & Zaciorskij (2002). Dynamic loads were applied to the model at the distal end point of the forearm based on a known load mass of 34 kg being multiplied by linear accelerations of the distal end point of the forearm. While applying loads to the distal end of the forearm may influence the magnitude of resultant loads on the body, not considering a hand segment relative to the forearm is not anticipated to influence results as there is little wrist motion involved in gross planar motions like lifting (Frievalds et al., 1984). Since the application of PCA distorts the time-domain of kinematic data, an average 3 second lift time (including both approach to the load and lifting the load to waist height) was used in all model iterations. On each model iteration the resultant low back angle and moment (trunk relative to pelvis) was used in a single muscle equivalent model where the muscle moment arm was estimated as a function of posture (van Dieën & de Looze, 1999) to calculate resultant low back compression and A-P shear forces. The peak compression and A-P shear load value was retained on each model iteration, and PDFs of predicted peak low back loads were generated as a model outcome. An overview of the developed model architecture including both the probabilistic and deterministic components is visualized in Figure 1-2.

### *9.2.4 Model Validation*

Prior to applying the developed probabilistic model to answer the proposed research questions, model validity needed to be considered (Lewandowski, 1981). Since the model was developed using data from a large (n = 72), diverse sample that aims to represent the distribution of personal factors observable across the work force it is well suited to predict the range of movement strategies likely to be observed across the population. While the model outputs can not truly be validated against the true range of movement strategies on a population level, given that the model is developed using data from a sufficient sample to approximate the population behaviour it has sufficient content validity for its intended purpose in this study.

Within the model validation process, output sensitivity is a second major consideration. Specifically, the minimum number of Monte Carlo simulations needed to generate consistent model outcomes needed to be considered. Using recommendations provided by Winston (2000) and a measured average standard deviation of predicted peak compression force it was estimated that 935 model iterations would be needed to be 95% confident that the estimate of mean predicted peak low back loads is accurate within ± 50 N. Based on this recommendation 1000 model iterations were used in all simulations to address research questions. It was confirmed that 1000 model iterations provided estimates of mean and $95^{th}$ percentile peak compression and A-P shear loads consistent with 5000 model iterations (Appendix E1).

A final key component in model validation is to ensure comparable magnitudes of predicted biomechanical exposures to the experimental data which the model was built using. When conducting this comparison, it is noted that the top-down rigid link model used in the current study overestimates both peak low back flexion angle and peak low back extensor moment (Table 9-2). However, these differences are primarily attributed to the differences in how the trunk segment was modelled between the approaches. In the top-down model used in this study the trunk segment was defined using the shoulder joint centres as well as a marker on the sacrum as these landmarks were tracked in the PCA analysis. By using the shoulder joint centres to define a trunk local coordinate system internal rotation of the upper arms will increase the measured low back flexion angle compared to if a rigid marker cluster affixed more proximal to the pelvis (as done experimentally) was used. These differences in peak low back flexion angles are seen when comparing experimental to modelling data (Table 9-2). The difference in low back range of motion also has implications on movement dynamics whereby displacing through a greater range of motion within the same time results in greater peak low back extension velocities (Table 9-2), which further contribute to increasing low back extensor moments. Differences in low back flexion angles also contribute in part to the higher peak low back extensor moments by increasing the horizontal distance of the trunk centre of mass from the low back (Table 9-2).

**Table 9-2:** Comparison of peak low back extensor moment, low back flexion angle, low back extension velocity and anteroposterior distance between the trunk and pelvis centre of mass between data collected experimentally in studies 1-3 and calculated from principal component reconstructions in study 4. Comparisons were made using barbell lifting data.

| | Experimental Data (Bottom-up Rigid Link Model) | Study 4 Model (Top-Down Rigid Link Model) |
|---|---|---|
| Peak Low Back Extensor Moment (Nm) | 206.8 (51.1) | 275.2 (50.6) |
| Peak Low Back Flexion Angle (°) | 47.1 (16.5) | 57.5 (10.1) |
| Peak Low Back Extension Velocity (°/sec) | 34.9 (20.9) | 54.9 (8.5) |
| Peak anteroposterior distance between trunk and pelvis centre of mass (m) | 0.166 (0.047) | 0.200 (0.021) |

In addition to differences in trunk segment definition influencing low back loads, use of a top-down rigid link model in the current study compared to a bottom-up rigid link model used with experimental data will further contribute to differences in low back moment magnitudes. It has been shown that a top-down rigid link model overestimates peak low back extensor moments compared to a bottom-up approach by approximately 10% (Kingma et al., 1996). Notably, the differences in low back extensor moment magnitudes were attributed to the top-down approach not adequately accounting for trunk deformation (Kingma et al., 1996), which may be further exacerbated when the trunk segment is modelled using the shoulder joint centres.

Differences in body segment parameter definitions could have added further error to the comparisons between experimental data and the top-down rigid link model used in this study. I opted to use body segment parameter recommendations from Zatsiorsky & Zaciorskij (2002) in this current study while Visual3D defaults were used when modelling experimental data (i.e., Hanavan, 1964; Dempster, 1955). I chose to use body segment parameter scaling from Zatsiorsky & Zaciorskij (2002) in this study as the dataset used to inform these recommendations was more recent and sex differences in body segment parameter scaling are considered. However, use of different body segment parameter scaling could contribute to differences in resultant kinetics.

Finally, an average 3 second lift cycle time was used on all model iterations in this study, where variability in lift times was observed experimentally. Differences in lift times is known to influence resultant kinetics (Lavender et al., 2003), so this may partially contribute to differences in peak low back moments between experimental and top-down model data. While this is a known source of error, it is not anticipated to greatly influence the mean peak extensor moment magnitude as the 3 second lift time was reflective of lift times in the experimental data.

In totality, the discussed differences in trunk segment definition increasing low back angles and moments, top-down vs. bottom-up modelling, body segment parameter definitions and lift times will influence the magnitude of low back loads when using the van Dieën & de Looze (1999) polynomial to scale muscle moment arm and line of action. In particular, the differences in peak low back flexion angles will greatly influence the posture-sensitive A-P shear loads where it was reported by van Dieën & de Looze (1999) that the implications of modelling the muscle moment arm and line of action as a function of trunk posture would have greater than a 300% effect on resultant A-P shear loads.

Within this section a variety methodological decisions explaining why greater low back loads were observed in the study 4 rigid link model compared to experimental data are discussed. In particular, trunk segment definition seems to most greatly contribute to the resultant compression and A-P shear loads being on the high range of what is physiologically reasonable within the study 4 top-down rigid link model. However, while the rigid link modelling approaches employed likely overestimate the absolute low back loads in lifting, this does not compromise the utility of the model to answer the posed research questions. While the rigid-link modelling approach led to overestimations of peak low back loads, these methods were consistent across all model iterations. Therefore, comparisons could still be made between personal factor inputs where the differences in ranges of peak low back loads across model inputs will be reflective of the differing lift kinematics. Since relative differences in predicted low back loads are a product of differing kinematics, the modelling approach is appropriate to determine whether kinematic differences as a function of personal factor groups have implications on predicted ranges of peak low back loads.

### *9.2.5 Analyses to Address Research Questions*

To address the overarching research question in this study the developed models were used to predict the range of peak low back compression and A-P shear loads likely to be observed in the population in all combinations of personal factors for each of the barbell, crate, and backboard lifts. Within each simulation the mean, one standard deviation above the mean, and 95$^{th}$ percentile predicted peak compression and A-P shear forces were retained as dependent variables.

Next, backward removal multiple regression models ($p < 0.10$) were used to determine which categorical personal factors inputs independently explain variance in predicted population level peak mean, one standard deviation above the mean, and 95$^{th}$ percentile peak compression and A-P shear loads. While similar regression-based analysis was used to associate specific personal factors to resultant exposures within participants earlier in the thesis, the use of regression in this study aims to probe whether these associations are similar when all likely lifting strategies that may be observed across a population as predicted using the modelling approach. These regression models were applied as a first pass to identify any modifiable personal factors that explained variance in predicted peak low back loads, as well as calculate the relative impact of modifiable factors on predicted peak low back loads as measured by standardized beta coefficients. Within the statistical summary tables a negative standard beta coefficient indicates that for above average model inputs there is lower means and/or variability in normalized low back loads. For the factor of sex, the directionality of associations in all regression models had females having lower peak low back loads. Regression analyses were conducted in SPSS (Version 26.0, IBM Corporations, Armonk, NY).

When modifiable personal factors (ability to perceive sensory information, strength and/or flexibility) were significant predictors of resultant low back loads, the PDFs of predicted low back loads across different modifiable factor groups were generated. Both the standardized beta coefficients from the regression analyses and generated PDFs of predicted peak low back loads were used to interpret the prospective benefit of improving modifiable personal factors to proactively reduce resultant low back loads in lifting.

*9.3 Results:*
*9.3.1 Barbell Lifting*

Strong associations were seen between categorical variables of personal factors and predicted peak low back compression and A-P shear loads in barbell lifting (Table 9-3). Notably, posture-sense, strength, and functional knee and hip fROM were all modifiable factors identified as significant predictors of resultant peak low back loads. However, while posture-sense, strength and hip fROM were all significantly associated to resultant predicted peak low back loads, they had small relative effects on the magnitude of predicted loads (i.e., Figure 9-4). Conversely, functional knee fROM had stronger associations to predicted peak low back loads with standard β coefficients ranging from -0.138-0.441 and more pronounced differences in predicted PDFs of peak compression (Figure 9-5) and A-P shear (Figure 9-6) loads.

**Table 9-3:** Backward elimination ($p < 0.10$) regression model summaries for barbell lifting with all predictor variables included.

| | Significant predictors | Model Summary |
|---|---|---|
| Mean Compression | Sex (β = 0.014), Stature (β = 0.513), Body Mass (β = 0.634), Strength (β = 0.001), Posture-Sense (β = -0.006), Knee fROM (β = -0.213) | $p < 0.001$<br>$R^2 = 0.994$ |
| Mean A-P Shear | Sex (β = 0.034), Stature (β = 0.478), Body Mass (β = 0.581), Strength (β = -0.008), Posture-Sense (β = -0.006), Knee fROM (β = -0.441) | $p < 0.001$<br>$R^2 = 0.974$ |
| Mean Compression + 1 stdev | Sex (β = 0.014), Stature (β = 0.524), Body Mass (β = 0.634), Strength (β = 0.002), Posture-Sense (β = -0.005), Knee fROM (β = -0.173) | $p < 0.001$<br>$R^2 = 0.995$ |
| Mean A-P Shear + 1 stdev | Sex (β = 0.024), Stature (β = 0.508), Body Mass (β = 0.614), Strength (β = -0.004), Posture-Sense (β = -0.004), Knee fROM (β = -0.307) | $p < 0.001$<br>$R^2 = 0.986$ |
| $95^{th}$ percentile Compression | Sex (β = 0.015), Stature (β = 0.531), Body Mass (β = 0.634), Strength (β = 0.003), Posture-Sense (β = -0.005), Hip fROM (β = -0.003), Knee fROM (β = -0.138) | $p < 0.001$<br>$R^2 = 0.994$ |
| $95^{th}$ percentile A-P Shear | Sex (β = 0.017), Stature (β = 0.532), Body Mass (β = 0.633), Strength (β = 0.002), Posture-Sense (β = -0.005), Hip fROM (β = -0.003), Knee fROM (β = -0.146) | $p < 0.001$<br>$R^2 = 0.994$ |

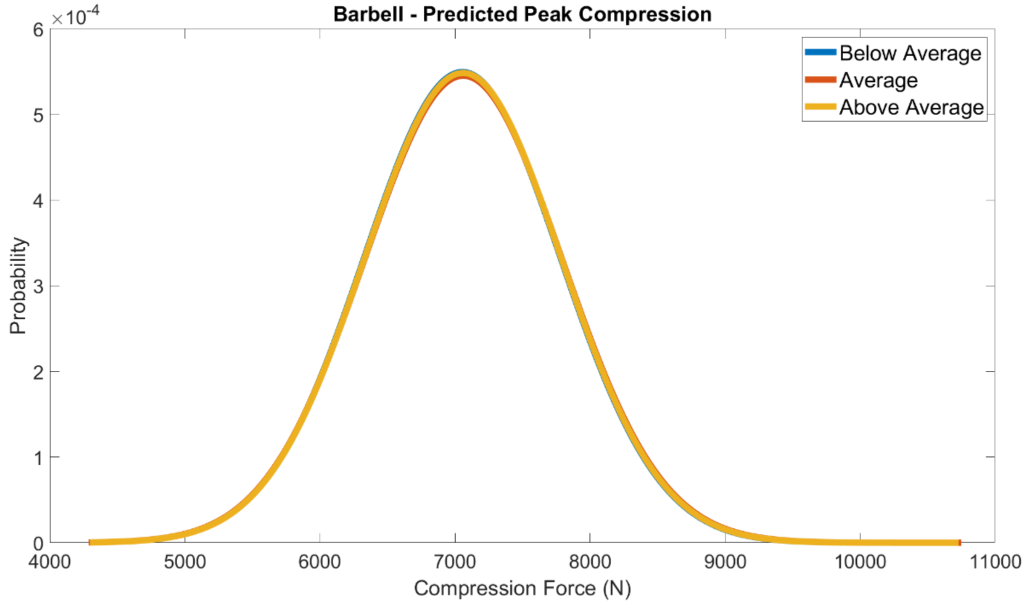


**Figure 9-4:** Predicted range of peak low back compression loads in barbell lifting across individuals with below average, near average, and above average strength.

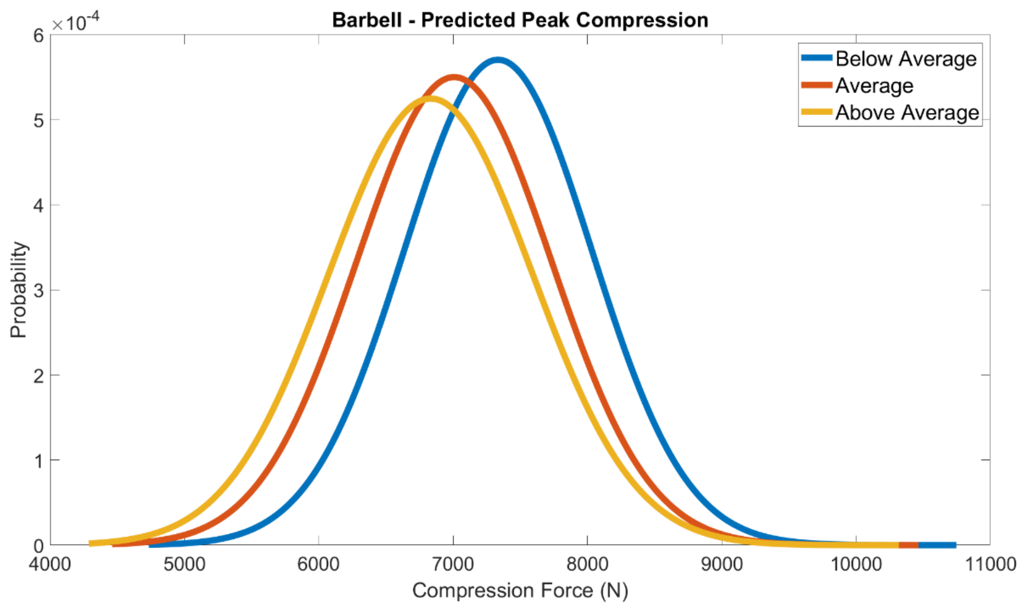


**Figure 9-5:** Predicted range of peak low back compression loads in barbell lifting across individuals with below average, near average, and above average functional knee range of motion.

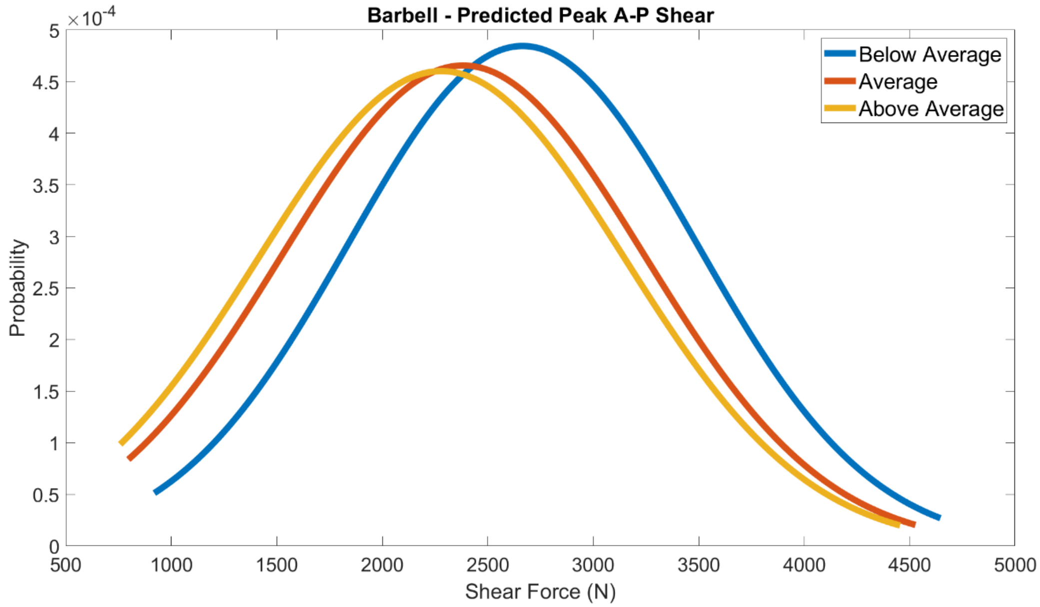


**Figure 9-6:** Predicted range of peak low back A-P shear loads in barbell lifting across individuals with below average, near average, and above average functional knee range of motion.

### *9.3.2 Crate Lifting*

Similarly strong associations were seen between categorical variables of personal factors and predicted peak low back compression and A-P shear loads in crate lifting (Table 9-4). Force-sense, strength and functional knee and hip fROM were all modifiable factors identified as significant predictors of resultant peak low back loads. Once again, knee fROM had the strongest associations to predicted peak low back loads. Knee fROM was more strongly correlated to predicted A-P shear loads (Figure 9-7) with standard β coefficients ranging from -0.189-0.294, while less strongly correlated to peak compression as standard β coefficients ranged from -0.047-0.056.

**Table 9-4:** Backward elimination ($p < 0.10$) regression model summaries for crate lifting with all predictor variables included.

| | Significant predictors | Model Summary |
|---|---|---|
| Mean Compression | Stature (β = 0.453), Body Mass (β = 0.694), Strength (β = -0.030), Force-Sense (β = -0.004), Knee fROM (β = -0.047) | $p < 0.001$ <br> $R^2 = 0.985$ |
| Mean A-P Shear | Sex (β = -0.073), Stature (β = 0.398), Body Mass (β = 0.566), Force-Sense (β = -0.015), Knee fROM (β = -0.189), Hip fROM (β = -0.019) | $p < 0.001$ <br> $R^2 = 0.833$ |
| Mean Compression + 1 stdev | Stature (β = 0.464), Body Mass (β = 0.682), Strength (β = -0.024), Force-Sense (β = -0.004), Knee fROM (β = -0.054), | $p < 0.001$ <br> $R^2 = 0.981$ |
| Mean A-P Shear + 1 stdev | Sex (β = -0.080), Stature (β = 0.396), Body Mass (β = 0.519), Strength (β = 0.012), Force-Sense (β = -0.015), Knee fROM (β = -0.215), Hip fROM (β = -0.022) | $p < 0.001$ <br> $R^2 = 0.777$ |
| 95th percentile Compression | Stature (β = 0.472), Body Mass (β = 0.674), Strength (β = -0.013), Force-Sense (β = -0.004), Knee fROM (β = -0.056) | $p < 0.001$ <br> $R^2 = 0.980$ |
| 95th percentile A-P Shear | Sex (β = -0.113), Stature (β = 0.340), Body Mass (β = 0.391), Strength (β = 0.033), Force-Sense (β = -0.017), Knee fROM (β = -0.294), Hip fROM (β = -0.034) | $p < 0.001$ <br> $R^2 = 0.612$ |

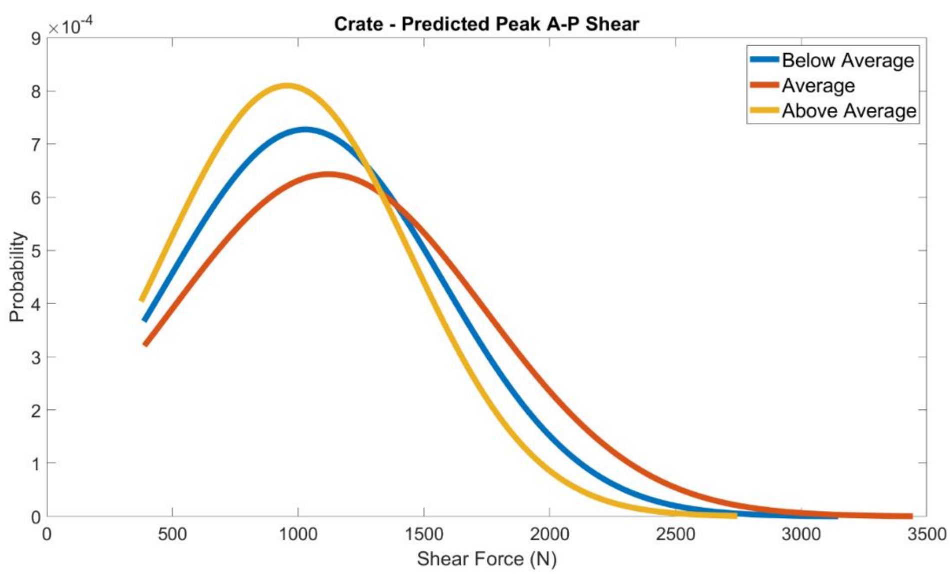


**Figure 9-7:** Predicted range of peak low back A-P shear loads in crate lifting across individuals with below average, near average, and above average functional knee range of motion.

*9.3.3 Backboard Lifting*

Similar to barbell and crate lifting, strong associations were seen between personal factor categories and predicted resultant low back loads (Table 9-5). Expertise, strength, knee fROM and hip fROM were all modifiable factors that explained variance in resultant low back loads. However, the strength of association of these modifiable factors to resultant low back loads was weaker than barbell and crate lifting where the largest observed standardized β coefficient observed for modifiable personal factors was for knee fROM (β = -0.127) when regressing to mean peak A-P shear loads. This results in less pronounced differences in predicted range of A-P shear loads across knee fROM groups (Figure 9-8).

**Table 9-5:** Backward elimination ($p < 0.10$) regression model summaries for backboard lifting with all predictor variables included.

| | Significant predictors | Model Summary |
|---|---|---|
| Mean Compression | Sex (β = 0.021), Expertise (β = 0.010), Stature (β = 0.537), Body Mass (β = 0.645), Strength (β = -0.001), Knee fROM (β = -0.014), Hip fROM (β = 0.005) | $p < 0.001$<br>$R^2 = 0.997$ |
| Mean A-P Shear | Sex (β = 0.065), Expertise (β = 0.017), Stature (β = 0.537), Body Mass (β = 0.664), Strength (β = 0.006), Knee fROM (β = -0.127), Hip fROM (β = -0.005) | $p < 0.001$<br>$R^2 = 0.974$ |
| Mean Compression + 1 stdev | Sex (β = 0.017), Expertise (β = 0.012), Stature (β = 0.539), Body Mass (β = 0.640), Strength (β = -0.001), Knee fROM (β = -0.012), Hip fROM (β = 0.006) | $p < 0.001$<br>$R^2 = 0.996$ |
| Mean A-P Shear + 1 stdev | Sex (β = 0.044), Expertise (β = 0.017), Stature (β = 0.530), Body Mass (β = 0.656), Strength (β = 0.006), Knee fROM (β = -0.099), Hip fROM (β = -0.005) | $p < 0.001$<br>$R^2 = 0.977$ |
| 95$^{th}$ percentile Compression | Sex (β = 0.015), Expertise (β = 0.014), Stature (β = 0.540), Body Mass (β = 0.637), Strength (β = -0.001), Knee fROM (β = -0.011), Hip fROM (β = 0.008) | $p < 0.001$<br>$R^2 = 0.995$ |
| 95$^{th}$ percentile A-P Shear | Sex (β = 0.016), Expertise (β = 0.014), Stature (β = 0.530), Body Mass (β = 0.642), Strength (β = 0.003), Knee fROM (β = -0.034), Hip fROM (β = 0.001) | $p < 0.001$<br>$R^2 = 0.989$ |

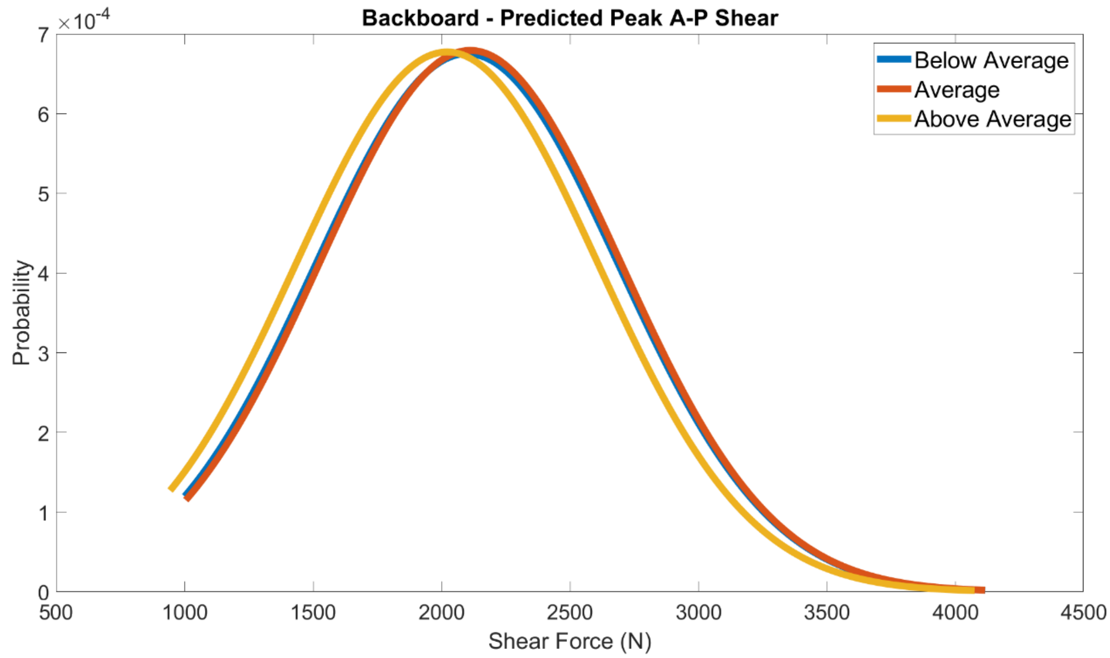


**Figure 9-8:** Predicted range of peak low back A-P shear loads in crate lifting across individuals with below average, near average, and above average functional knee range of motion.

*9.4 Discussion:*

The purpose of this study was to develop a model to predict population level ranges of likely biomechanical exposures as a function of personal factors and use this model to evaluate the prospective benefit of improving modifiable personal factors as an ergonomics solution. It was found that combinations of personal factors explained high percentages of variance in mean, one standard deviation above the mean, and 95$^{th}$ percentile population level predicted peak low back compression ($R^2$ = 0.980 – 0.997) and A-P shear ($R^2$ = 0.612 – 0.994) forces in barbell, backboard, and crate lifting. The strongest predictors of resultant loads were non-modifiable factors including body mass, stature and sex as measured by standardized β coefficients. However, posture-sense, strength, and lower body fROM were identified as modifiable personal factors that significantly predicted peak low back loads across different lift types. While these modifiable predictors were identified as significant predictors of resultant peak low back loads, only improving knee fROM had prospective potential to meaningfully reduce resultant low back loads in practice.

Within this study knee fROM was identified as a modifiable personal factor that has potentially clinically relevant effects on influencing lifting strategy to reduce resultant peak low back loads. This is supported by PDFs of predicted peak low back compression and A-P shear forces across knee fROM groups where there was up to nearly a 1000 N and 500 N difference in predicted peak compression (Figure 9-5) and A-P shear forces (Figure 9-6) between the above and below average knee fROM groups. While the differences in predicted low back loads across knee fROM groups were the greatest compared to other modifiable factors measured in this thesis, relating these predicted differences in peak loading to changes in injury risk is difficult. Comparing these differences in predicted peak low back loads to established injury risk thresholds can help interpret these findings where the differences in predicted means of peak loads are 29-50% of the action limits for compression (Waters et al., 1993) and A-P shear (Gallagher & Marras, 2012) respectively. With improvements in knee fROM influencing resultant peak low back loads during lifting the evidence supports that modifying this personal factor may be a solution to proactively reduce resultant loads experienced by workers when performing occupational lifting demands.

Proprioceptive ability and strength were associated with population level predicted peak low back loads, but do not seem to have clinically relevant impacts on low back loading. The lack of clinical significance of these factors on resultant loads is supported by small standardized $\beta$ coefficients of proprioceptive measures (0.004-0.017) and strength (0.001-0.008) in regression models, and the small differences in generated PDFs of predicted low back loads (i.e., Figure 9-

4). Supporting this interpretation, a case study example in a 50th percentile female demonstrates that the interplay of improving strength and proprioceptive ability in tandem with improving knee fROM led to marginal benefits compared to improving knee fROM in isolation (Figure 9-9). Based on findings within this thesis the lack of clinically relevant effects of proprioceptive ability reducing resultant low back loads is consistent with findings from study 1 (Chapter 6.0) where at best proprioceptive ability only explained 16% of variance in normalized peak low back loads in lifting. Combined, the findings from the current study and study 1 would suggest that improving proprioceptive ability (as measured by lift force and posture matching) in isolation as a proactive ergonomics intervention is not likely to directly result in reductions in peak low back loads during lifting.

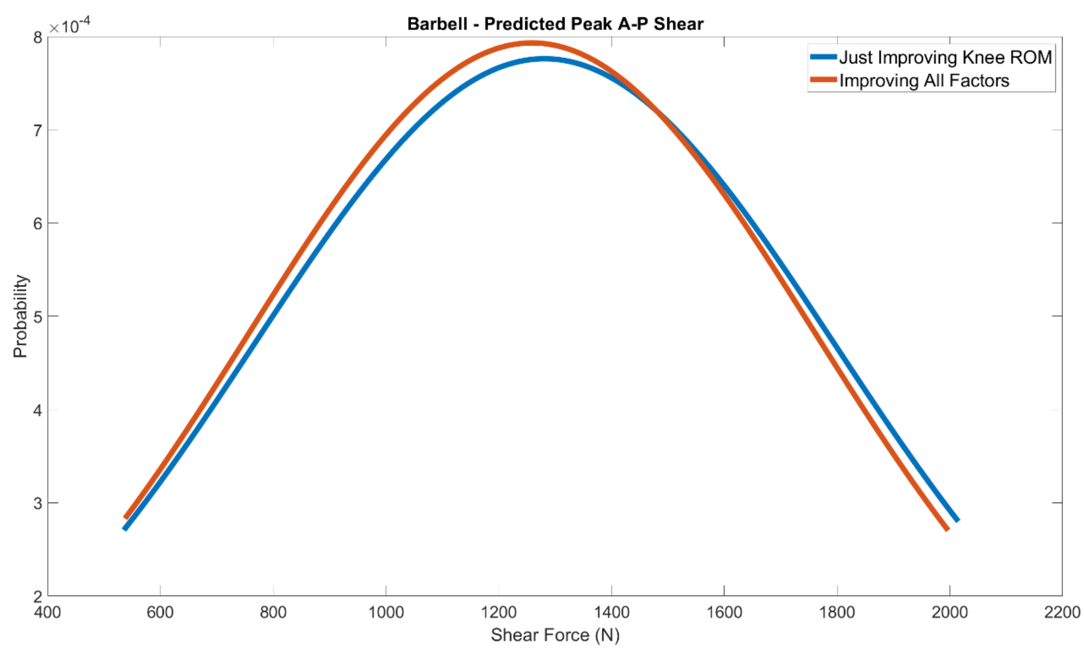


**Figure 9-9:** Case study example of predicted A-P shear forces during crate lifting for a 50th percentile female between a simulation where only knee fROM was improved, compared to improving all knee fROM, strength, and proprioceptive ability in tandem.

The finding that improving strength did not lead to clinically significant reductions in predicted low back loads was unexpected. Based on analysis in study 3 (Chapter 8.0) strength was a predictor of both normalized peak compression forces in barbell and backboard lifting, and peak A-P shear forces in crate lifting with corresponding standardized β coefficients ranging from 0.311-0.397 in magnitude. The discrepancies between findings in study 3 and results in this study may be attributable to normalized loads being the dependent measure in study 3 while absolute loads were predicted in this study. Strength is a personal factor that covaries with body mass (Harbo et al., 2012), and so greater proportions of variance in predicted low back loads in this study may be explained by body mass opposed to strength directly. Alternatively, lower reported effects of strength on predicted low back loads in this study compared to past literature may be due to an absolute rather than relative load mass being lifted. Previous work has highlighted that when load masses are scaled to capacity resultant normalized peak low back moments are significantly lower in higher strength individuals (Clusiault et al., 2022). The previously observed effects of strength on low back loads could be more pronounced when lifting the relative load mass, as relative demand of the load has been shown to influence lifting strategy (Plamondon et al., 2017). As such, it is possible that within the given study design less pronounced effects of strength on population level predicted resultant low back loads are partially attributable to relative load mass more greatly influencing lifting performance than strength.

Body mass, stature and sex were consistently the strongest predictors of peak low back loads across lift types. While these factors explained variance in predicted loads it is important to differentiate whether these findings are a result of influencing lifting strategy, or by influencing rigid link model scaling. Previous literature, in addition to findings within this thesis, have shown that sex (Makhoul et al., 2017; Li & Zhang, 2009; Marras et al., 2003; Lindbeck and Kjellberg, 2001; Plamondon et al., 2014a), stature (Kranz et al., 2020) and body mass (Corbeil et al., 2019; Pryce & Kriellaars, 2018) can influence the movement strategy individuals use during lifting demands. However, these three factors also directly influence the scaling of the rigid link model used to calculate low back loads in this study. To determine how these factors influence resultant low back loads a supplementary analysis was completed which differed movement strategy as a function of body mass and stature, while consistently scaling the rigid link model to a 50$^{th}$ percentile female (Appendix E2). In this analysis it was shown that the impact of differences in movement strategy as a function of body mass and stature had a small effect on predicted peak low back loads, supporting that the observed associations in statistical testing are likely attributable to scaling the rigid link model.

The association of personal factors to predicted peak low back compression and A-P shear loads differed as a function of lift type. These differences in associations are consistent with findings from studies 1-3 in this thesis where the association of personal factors to normalized low back loads differing as a function of lift type and were attributed to the unique interaction of task and personal factor constraints influencing movement strategy (Newell, 1986). The differing associations of personal factors to resultant peak low back loads has practical implications for developing workplace specific ergonomic interventions. For example, the prospective benefit of improving knee fROM has more pronounced effects on reducing peak A-P shear loads in barbell (Figure 9-6) and crate (Figure 9-7) lifting, compared to backboard (Figure 9-8) lifting. This finding does not support a great prospective benefit of reducing exposures in backboard lifting, which is known to be a risky essential paramedic work task (Armstrong et al., 2020). While these findings suggest greater effectiveness for informing the development of interventions to reduce peak low back loads with barbell and crate lifting demands, unfortunately this may not necessarily directly contribute to reducing the high incidence of injuries within the paramedic sector.

The novel modelling approach used in this study has potential future applications as an injury risk assessment tool. Prior to the development of the probabilistic model in this study, risk assessment tools, have tended to be deterministic in nature (Wolf et al., 2020) predicting a single movement strategy and corresponding exposures given a set of model inputs. The use of deterministic modeling approaches to predict movement strategy has been theorized to compromise the prospective ability of these existing models to assess injury risk (Chaffin, 2005). However, the developed model in this study has increased internal validity in its design by considering the likely range of movement strategies and corresponding peak low back loads. This approach of considering the inherent variability in human movement (Latash, 2012) is conceptually consistent with prevailing motor control theories such as optimal feedback control theory which explicitly acknowledge variability in movement when performing motor tasks (Todorov, 2004; Scott, 2004). With the utility of this developed modelling approach to predict the range of likely movement strategies and corresponding exposures at a population in lifting, its predictive ability should be investigated to determine whether it has greater potential to proactively quantify injury risk compared to existing tools.

In this study neither the model development or experimental design were without limitation. First, within the rigid link modelling approach it was assumed that all the lift cycles were 3 seconds in duration. This decision was made as this approximated the average lift cycle time during barbell lifting. However, lift time does vary as a function of personal factor groups

(Appendix E3) and lifting dynamics can influence resultant kinetics calculated by a rigid link model (Marras et al., 2003; Pryce & Kriellaars, 2018; Ghezelbash et al., 2020). Although time differences are not directly considered in current model, the model does provide a method to measure the effect of movement kinematics on resultant peak low back loads as a function of movement/posture. Second, interaction effects were not explicitly considered in defining model input factor PDFs. Instead, one-way ANOVAs were used to test for difference within personal factor groups in isolation opposing to quantifying interaction effects explicitly. This decision was made to ensure sufficient statistical power as using ANOVAs to test for interaction effects across the eight personal factor inputs would not be reasonable with the given sample.

The findings from this study suggest opportunities for the continued development of injury risk assessment models. With the modelling approach there are recommended future steps to improve the model realism. Directly considering differences in movement time as a function of personal factors would be a logical next step to improve the internal validity of the model to better consider the potential role of movement dynamics on lifting strategy opposed to indirectly measuring these effects within the normalized time domain. Second, the model should be expanded to consider other known determinants of lifting strategy to broaden its application. For example, load mass has been shown to influence lifting strategy (Albert et al., 2008; Sadler et al., 2011; Sheppard et al., 2016), and so by incorporating these previous findings into model development there is utility to predict likely peak low back loads in a broader range of lifting applications opposed to just when lifting a 34 kg mass. Finally, the predictive validity of the developed model to estimate likely peak low back loads in lifting should be compared to existing deterministic tools such as digital human models. Conceptually, the model developed in this study has greater internal validity by modelling the range of likely lifting strategies to consider the inherent variability in human movement (Latash, 2012). However, the developed tool should be directly compared to existing tools to determine how the range of predicted peak low back loads compares to the single comparisons made by predictions from a digital human model. Looking toward the future, the broader prospective benefit of the developed model to proactively screen for injury risk can also be explored following the suggested continued model development opportunities.

The results of this study can be leveraged in the development of future lift training programs. Based on the modelling approaches employed improving knee fROM was determined to be a modifiable personal factor that influenced the predicted ranges of peak low back compression and A-P shear loads across the three lift types. This finding can be potentially used in the development of future lift training approaches whereby improving knee fROM there may be corresponding reductions of peak low back loads in lifting, with greater prospective benefits in barbell and crate lift types opposed to backboard lifting. This may be a solution to improve the content of lift training programs to be more effective as suggested as a need by Denis et al. (2020). Therefore, future intervention studies should evaluate the efficacy of improving knee fROM as a proactive ergonomics strategy to reduce peak low back loads in lifting.

*9.5 Conclusion:*

The purpose of this study was to investigate whether variance in population level predicted peak low back loads in lifting could be explained by personal factors and assess whether improvements to modifiable factors results in significant reductions in resultant low back loads. While proprioceptive ability, strength and flexibility were all significantly associated with predicted peak low back loads, only knee fROM was interpreted to influence resultant low back loads to a level of clinical significance. This finding suggests that lift training interventions that aim to improve knee fROM may be an effective way to proactively reduce peak low back loads in lifting as an ergonomic intervention.

# Chapter 10: Global Discussion

*10.1 Overview of Findings:*

The overarching goal of this thesis was to quantify whether variability in biomechanical exposures at the low back during lifting could be explained independently and/or interdependently by personal factors. This objective was framed within an OFC theoretical framework to investigate whether associations between personal factors and resultant low back loads were attributable to the definition of a motor control objective that aims to consistently minimize exposures when lifting. Experimental findings supported the use of this theoretical framework where associations of personal factors to both the mean and variability of exposures was observed. From these analyses the prospective benefit of improving modifiable personal factors as a proactive ergonomics strategy was investigated.

Significant associations between proprioceptive ability and resultant peak low back compression and A-P shear loads were observed in study 1. Additionally proprioceptive ability was also associated with the standard deviation of peak low back loads in lifting. The significant associations of proprioceptive ability to resultant mean and standard deviation of peak low back loads suggests that greater ability to perceive both posture and force during lifting scenarios could bias an individual to define a movement objective that aims to minimize resultant biomechanical exposures in lifting. However, while significant associations were observed between proprioceptive ability and resultant low back loads these findings may not be clinically relevant as proprioceptive ability explained a maximum of 16% of variance in resultant loads.

Similarly, a range of structural (sex, body mass, stature) and functional (strength, flexibility) personal factors explained significant proportions of variance in peak low back loads during lifting. While significant associations were observed with mean exposures, corresponding associations to the variability in these exposures were not seen except for females having both lower means and variability in corresponding peak loads compared to males. While this would suggest females are seemingly more likely to define a movement objective that aims to minimize resultant loads to a greater extent then men, no preferential movement objective definition to minimize exposures was seen in other structural and functional factors groups. Instead, it is likely that the remainder of the structural and functional factors investigated bias the range of available movement strategies to lifters, and in turn influence resultant exposures, as supported by strong associations to features of movement that were correlated with peak low back loads.

While proprioceptive ability, structural factors and functional factors were associated with resultant biomechanical exposures in lifting, expertise was not. There were observed differences in features of movement in occupation-specific lifts across theoretical expert, contextual expert, and novice groups, but these differences in movement did not result in corresponding significant differences in corresponding low back loads. This would suggest that expertise is not a causative factor that biases individuals to minimize resultant biomechanical exposures in lifting.

Based on findings from studies 1-3 the prospective benefit of improving modifiable personal to reduce resultant low back loads in lifting at a population level was examined. While proprioceptive ability, strength, and functional range of motion of the knee and hip were all associated with predicted ranges of peak low back compression and A-P shear loads, only knee fROM was interpreted to have clinically relevant influences on reducing peak low back loads in lifting. This finding can potentially be leveraged in the development of proactive ergonomics interventions such as lift training.

*10.2 Theoretical contributions:*

The findings from this thesis have theoretical contributions to understanding how motor control principles can be applied to understand movement within occupational contexts. This thesis relied on an overarching theoretical framework we previously proposed where we hypothesized that an interaction of personal, environmental and task factors could bias an individual to define a motor control objective that aims to minimize resultant biomechanical exposures (Armstrong & Fischer, 2020). This theoretical framework relied on OFC theory as an internal model of motor control (Scott, 2004; Todorov, 2004), while the influence of external constraints on movement were adopted from Newell's model of constraints (1986) and Glazier's Grand Unified Theory on Sports Performance (2017).

Findings demonstrating the association of proprioceptive ability (as measured by posture and force matching ability) to both the mean and standard deviation of resultant low back loads in lifting support the proposed overarching theoretical model. Based on the theoretical model, if a personal factor were to bias the definition of a movement objective to minimize resultant biomechanical exposures, then it would be expected that there would be lower resultant exposure magnitudes coupled with lower variability in these exposures as they would be considered relevant to task performance consistent with the minimum intervention principle (Todorov & Jordan, 2003). This result was observed with proprioceptive ability being associated with both the mean and standard deviation of peak low back loads (albeit with small effect sizes), supporting that individuals with increased proprioceptive ability consistently minimize resultant biomechanical exposures. This aligns with my hypothesis that increased proprioceptive ability would result in the definition of a movement objective that aims to minimize exposures, and therefore support the proposed theoretical model, as sensory feedback plays a key role in the OFC closed-feedback loop (Scott, 2004; Todorov, 2004).

The investigated structural and functional factors do not seem to bias a movement objective to minimize resultant exposures as postulated within the overarching theoretical framework, but they have clear influences on low back loads. This suggests the need for a revision to the overarching theoretical model as in its current formation it hypothesizes that the only way interacting constraints can influence movement strategy is by influencing the definition of movement objectives, opposed to limiting the available movement strategies to lifters. As such, the theoretical model should be revised to consider how interacting constraints can influence the range of available movement strategies, while not influencing movement objectives. This conceptual relationship of constraints directly influencing the range of available coordination and control of movement could better align with the initial formulation of the constraints-based model proposed by Newel (1986).

The proposed theoretical model amendment is visualized in Figure 10-1 to demonstrate how constraints can directly influence the movement strategy by constraining available movement options, in addition to informing movement objectives. This amended framework accounts for both the observed mechanisms of proprioceptive ability seeming to influence movement objectives, whereas structural and functional factor mechanistically influence movement strategy directly by biasing available movement options.

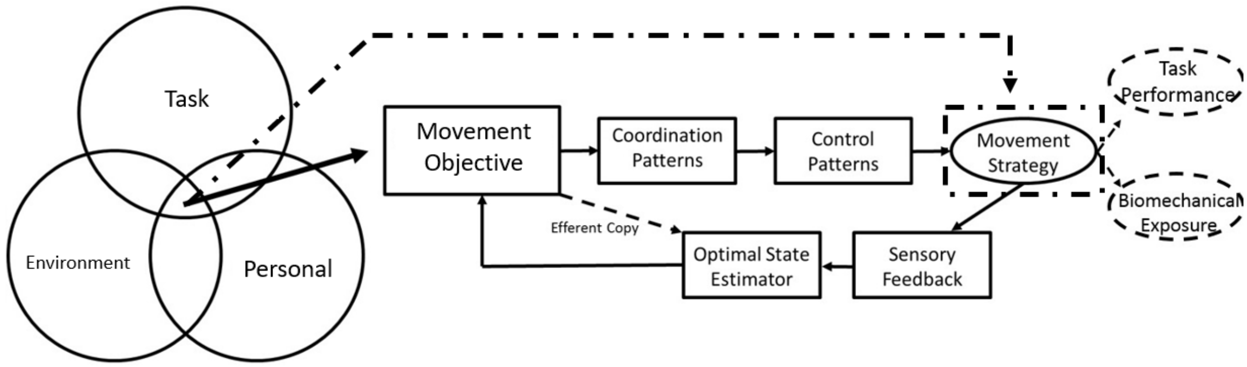


**Figure 10-1:** Revised overarching theoretical framework to conceptualize determinants of movement strategy. The solid arrow highlights that the interaction of personal, environment and task constraints can influence the definition of movement objectives within an optimal feedback control theory paradigm. Alternatively, the dashed line highlights that the interaction of constraints can influence resultant movement strategy by biasing the available movement options to an individual.

A final theoretical contribution of this thesis is that the influence of personal factors on lifting strategy was not generalizable across lift types. While varying personal factors explained variance in both resultant low back loads and features of movement differentially across lift types, the observed influence of expertise on lifting strategy most clearly highlights this finding. Within this thesis movement strategy only differed as a function of expertise groups in occupation-specific lifts, while no corresponding differences in lifting strategy were seen in generic lift types (Chapter 7.0). This finding has theoretical implications as it provides a clear example of how interacting personal and environment constraints interdependently, opposed to independently, influence resultant coordination of movement (as postulated by Newel (1986)). Additionally, these findings have practical importance when interpreting past research on the effect of expertise on lifting strategy where the replicating lifting demands present in the workplace was not rigorously controlled (Lee & Nussbaum, 2012; Lee et al., 2014; Marras et al., 2006; Plamondon et al., 2014b; Granata et al., 1999).

The finding of the interaction of lift type (task constraint) and personal factors (personal constraint) aligns with Newell's model of constraints (Newell, 1986) where the interaction of constraints is hypothesized to result in differences in coordination and control of movement. However, the findings within this thesis demonstrate that even slight variations in the task constraint (i.e., differences in load shape and lift start height while the goals of the lifting to waist height and load mass were controlled) still result in differences in movement strategy. With the noted evidence of the small changes in task constraints in this study on lifting strategy it supports an important need in future research design to closely replicate the demands of work when aiming to investigate how personal factors influence resultant movement strategy and biomechanical exposures in occupational tasks.

Expanding this interpretation, the influence of the environment constraint should also be explicitly considered in both future study design and interpretation. Within this thesis there were systematic changes to the task constraint investigated by using both occupation-specific and generic lift types within the study protocol. However, there are also clear differences in the environment between the lab environment in which the study was conducted and where paramedics work in the real world which were not accounted for. Previous research has demonstrated that greater physical demands are required when paramedics are responding to higher acuity call responses (Morales et al., 2016), supporting the practical need to consider environmental effects in this line of research. As such, findings from this thesis support the need to further investigate the interacting environmental and personal constraint effects on lifting strategy to better understand how the observed lifting strategy translates to practice.

*10.3 Contributions to the Ergonomics Field:*

The findings in this thesis have implications for the development of future lift training programs. Most notably, it was found that simulated improvements in knee fROM resulted in clinically significant reductions in predicted peak low back compression and A-P shear loads. Therefore, there is a possibility that directly intervening to improve knee fROM may be a potential solution to improve the content of lift training programs (Denis et al., 2020) to be more effective.

Since knee fROM encompasses more than just passive joint range of motion it is important to consider how this personal factor could be trained. Within this thesis participants were asked to adopt a squat-like posture to the best of their abilities consistent with the definition of a squat from Burgess & Limerick (1997). By asking participants to adopt their squat posture there are both joint range of motion and balance demands that need to be met to squat to a greater depth. Increasing the available range of motion to complete the squat demands can likely be achieved by relying on established training programs aiming to directly address flexibility (i.e., Hendrick, 2000; Kurz, 1994; Lima et al., 2018). To meet the balance demands of the squat task it is likely that exposure to the movement pattern should be incorporated into any developed training program. To achieve the incorporation of the squat movement into training it is recommended that best practice training approaches be followed such as movement-centric training (Frost et al., 2015) and using augmented feedback to coach movement (Chan et al., 2022).

While improving knee fROM has potential to reduce resultant peak low back loads, considering other identified determinants of lifting strategy in training may be important. For example, in study 1 it was shown that increased proprioceptive ability seemed to result in a movement objective that aimed to minimize resultant low back loads, albeit with small effect sizes (Chapter 6.0). While training proprioceptive ability alone to reduce resultant low back loads will likely not be effective to reduce low back loads in practice, improving proprioceptive ability may be a mechanism to improve the effectiveness of lift training. Since proprioceptive ability encompasses the perception of movement and force within the body (Proske & Gandevia, 2012) providing lifters this relevant sensory information to perceive their movements could help them adopt the prescribed movement sequencing such as achieving greater knee fROM. Additionally, by improving proprioceptive ability it may better allow for lifters to achieve a movement objective of consistently minimizing low back loads due to the significant, but weak, relationship of proprioceptive ability to this outcome quantified in study 1.

Improving strength within lift training interventions should also be considered. While improvements in strength did not influence population level predicted low back loads to clinically significant levels (Chapter 9.0), results from study 3 demonstrated that increased strength resulted in lifters consistently minimizing resultant peak compression forces in backboard lifting (Chapter 8.0). This finding is consistent with work from Clusiault et al. (2022) which highlighted that individuals with greater strength had lower normalized peak low back moments when lifting loads scaled to strength capacity. While strength was not predicted to directly minimize predicted peak low back loads in study 4, it may allow lifters to adopt lifting strategies that better minimized low back loads at the expense of having a higher metabolic cost, such as use of a squat-like strategy (Straker, 2003b). Like increasing proprioceptive ability, increasing strength could potentially better allow lifters to consistently leverage greater knee fROM developed through training to consistently minimize low back loads.

A final practical contribution to the ergonomics field is the development of the movement prediction model used in study 4. Through use of a probabilistic modelling approach to predict a range of likely population level movement strategies and corresponding exposures the inherent variability in human movement is considered (Latash, 2012), where to date this variability has typically been ignored in movement prediction tools such as digital human models (Chaffin, 2005). This modelling approach has improvements in internal validity to be conceptually consistent with established theories on motor control (Scott, 2004; Todorov, 2004). However, it is not broadly applicable in its current formation as it can only reliably predict movement strategies based on the experimental data collected in this thesis (i.e., a subset of three lifts with a 34 kg load). While it is not currently a usable tool for ergonomic practice, this type of modelling approach is a novel contribution to the ergonomics literature which can continue to be refined within an end goal of having sufficient predictive validity to screen for injury risk.

### *10.4 Limitations:*

#### *10.4.1 Experimental Design*

The experimental design in this thesis was not without limitation. As a first consideration the sample size of 72 participants was likely insufficient to statistically power all the analyses conducted across the studies. However, the use of 72 participants in the study was decided upon for practical reasons as the time and financial resources to collect a sample of participants that would allow to consider all the interactions across independent personal factors would not be feasible. The data collections for this thesis were also collected during the Covid-19 pandemic which limited the ability to recruit paramedics. This resulted in the paramedic experience group being only 20 participants compared to 26 participants in each of the novice and theoretical expert groups. Acknowledging the sample size limitation Benjamini-Hochberg corrections (Benjamini & Hochberg, 1995) were applied to control for family-wise error from multiple comparisons across the thesis.

As a second limitation there was heterogeneity in the sample which limited my ability to make conclusions on whether the observed personal factors were mechanistically related to dependent measures. For example, in study 2 I was aiming to differentiate the influence of theoretical and contextual expertise on lifting strategy. However, participants in the paramedic expert group had a range of experience and/or training on lifting mechanics ranging from competitive power lifters to having no stated relevant lifting experience other than paramedic-specific education and time on the job. This underlying heterogeneity in both experience and the remainder of other personal factors which could not be readily controlled or accounted for may explain some variance in the experimental findings.

Considering experimental limitations, the number of trials completed was a limitation in study design. Within this thesis I have used an overarching theoretical paradigm where lower means and standard deviations of low back loads as a function of a personal factor were interpreted to support that the personal factor group defined a movement objective that aims to consistently minimize low back loads. However, while use of ten trials to quantify lifting variability has been reported in previous studies (Granata et al., 1999), greater numbers of trials would likely provide a more reliable variability measure. For example, a recent analysis aiming to quantify variability in lifting used an average of 93 lifting cycles per participant in analysis (Oomen et al., 2022). While this may suggest that ten trials in the protocol is not sufficient, the practical inspiration for this thesis is the high injury risk in paramedic work where workers perform small numbers of lifts with heavy loads over the course of a work shift (Coffey et al., 2016). This motivated the use of a heavier load mass in this experimental protocol, which raises the potential for fatigue accumulation. Fatigue has been demonstrated to influence lifting strategy (van Dieën et al., 1998; Bonato et al., 2003; Mehta et al., 2014) and so only have ten lifting trials in each condition allowed for adequate rest time to prevent fatigue accumulation from confounding results.

Within the thesis only loading at the low back was considered, while investigating biomechanical exposures at other joints of the body (i.e., knees and shoulders) was not. This methodological decision was made due to the back being the most commonly injured body area in paramedic work (Maguire & Smith, 2013), with lab-based evidence supporting that magnitudes of biomechanical exposures at the low back exceed injury risk thresholds (Armstrong et al., 2020). While epidemiological evidence demonstrates that the relative incidence of injury to body areas including the shoulders, knees and ankles in paramedic work exceeds the relative incidence of injury in private industry (Maguire & Smith, 2013), the greatest discrepancy in relative incidence is seen at the low back. These epidemiological findings support the decision to prioritize investigating determinants of low back loading in this thesis, while future work can further explore determinants of loading at other body areas.

Principal component analysis was used as a method to quantify movement strategy in this thesis. The use of PCA was supported by being conceptually compatible with the overarching theoretical framework (Armstrong & Fischer, 2020; Todorov & Jordan, 2002). The identification of independent features of whole-body synergistic movement allows for the consideration of the coordinative structures of whole-body movement (Armstrong et al., 2021a) without the need to rely on the selection of discrete variables *a priori* (Lees, 2002). While use of PCA has noted benefits, it requires a distortion of the time-domain which may cloud the interpretation of velocity and acceleration effects within movement strategy. Second, use of PC scores as dependent variables only allowed me to investigate whether personal factors influenced the consistency in control of individual kinematic coordination patterns, opposed to considering their interaction to meet movement objectives. The methodological decision was made as potential relationships between personal factors and independent kinematic coordination patterns would provide the opportunity for actionable ergonomic interventions. However, future studies could more robustly consider the interacting effects of kinematic coordination patterns on motor control redundancy as it relates to movement objectives using paradigms such as the uncontrolled manifold hypothesis (Latash et al., 2002).

Low back compression and A-P shear forces were selected as dependent measures opposed to low back moments and angles. This methodological decision was made as compression and A-P shear loads are commonly used as injury risk measures in the ergonomics field and have well established injury risk thresholds (Waters et al., 1993; Gallagher & Marras, 2012). However, this decision may compromise the internal validity of the study design as evidence supports that lifters can perceive joint moments, as demonstrated by their ability to choose psychophysically acceptable loads (Fischer & Dickerson, 2014; Jorgensen et al., 1999; Kuijer et al., 2012; Banks & Caldwell, 2019), but can not perceive low back compression force (Thompson & Chaffin, 1993). While evidence has shown that compression forces can not readily be perceived, the SME model used to calculate has been shown to be sensitive to moment magnitude when used to calculate compression force, and sensitive to low back angle when calculating A-P shear force (van Dieën & de Looze, 1999). Given the modelling approaches sensitivity to these directly perceivable biomechanical exposure variables it provides support for the use of compression and A-P shear loads as dependent measures. Finally, the van Dieën & de

Looze (1999) SME modelling approach allows us to consider the interaction between posture and moments on internal loading, which is known to mechanistically be related to injury risk through a fatigue-failure pathway (Gallagher & Schall, 2017).

#### *10.4.2 Relating Thesis Findings to Injury Risk*

A final limitation of this thesis is that it is difficult to relate the predicted peak low back compression and A-P shear loads to person-specific injury risk without considering the effect of personal factors on underlying tissue tolerance. When considering the development of musculoskeletal disorders from a theoretical perspective, an injury occurs when an applied load exceeds a tissue tolerance, which can result through a variety of mechanistic pathways (McGill, 1997). With the established need to consider tissue tolerance when aiming to infer injury risk it is therefore difficult to relate applied loads (as measured in this thesis) to actual risk of sustaining an MSD.

While this thesis only considered applied loads as dependent measures, support for their inclusion is seen in the ergonomics literature. Notably, established risk guidelines for both compression (Waters et al., 1993) and A-P shear (Gallagher & Marras, 2012) magnitudes were used to justify that greater magnitudes of predicted peak low back loads are likely to contribute to injury risk within this thesis. While there are limitations in directly applying findings *in vivo* from the underlying *in vitro* research that was used to determine these guidelines, the well-established nature of these guidelines support the use of these dependent measures to quantify applied loads in this thesis. Finally, the use of compression and A-P shear loads as dependent measures were appropriate in this thesis due to their relevance in the ergonomics practice. For example, the NIOSH lifting equation (which relies on compressive load guidelines to determine risk) is the most used tool by ergonomists and health & safety professionals in Canada (Beliveau et al., 2022).

While use of compressive and A-P shear loads to quantify applied loads in this thesis is supported, not considering tissue tolerance remains an important gap. As a first consideration, tissue tolerance can change within a person as a function of posture where it has been shown that during compressive *in vitro* testing that functional spinal unit specimens have a lower yield point and compressive strength when in a flexed compared to neutral posture (Gunning et al., 2001). Further supporting the importance of posture as it relates to tissue tolerance, work by Wells et al. (2004) highlight the theoretical importance of posture modulating the internal exposures experienced by tissues in response to a given external exposure as a second mechanism in which tissue tolerance can acutely vary within a person. Finally, the battery of personal factors investigated within this thesis may be related to underlying tissue tolerance, which was unaccounted for in study design. For example, greater exposure to load over time (which may have contributed to greater strength in some participants) likely has corresponding higher tissue tolerance of bony structures within the low back due to remodelling of bone as a function of mechanical exposure as described by Wolff's Law (Chen et al., 2010). While this is a subset of examples, the importance of considering tissue tolerance has clear implications when interpreting injury risk from applied loads that was not considered in this thesis but can be investigated in the future.

As a final consideration when relating findings within this thesis to injury risk it is important to acknowledge that there are a variety of mechanisms that can modulate the relationship between applied loads and tissue tolerances as they relate to injury risk. For example, several mechanisms relating applied loads to tissue failure are complex, relying on an interaction between load magnitude and repetition/duration of exposure (i.e., Gallagher & Schall, 2017; Kumar, 2001). The interactions of applied loads to this battery of factors that contribute to MSD risk were not considered in this thesis but could be explored in future work to better relate the predicted likely ranges of low back loads in study 4 to person-specific injury risk.

*10.5 Future Directions:*

The findings in this thesis suggests future research opportunities to both continue to understand determinants of occupational movement strategy and inform the development of ergonomic interventions. From a theoretical perspective it is important to understand whether movement objectives other than minimizing biomechanical exposure are defined in occupational tasks. It has been commonly observed in the literature that minimizing metabolic demand is prioritized in locomotion (Summerside et al., 2018; Cavanagh and Williams, 1982; Williams and Cavanagh, 1987; Moore et al., 2012; Moore et al., 2016) as well as in lifting demands where adoption of a stoop-like lifting strategy is more metabolically favourable (Straker, 2003b). Additionally, there may be occupation-specific job demands where for example lifting smoothly (i.e., minimizing jerk) could be a movement objective defined by paramedics who are lifting human patients. It is recommended that future research both explore what other movement objectives are adopted within occupational contexts, as well as investigate determinants that bias workers to adopt differential movement strategies. Such investigation would provide a more robust understanding of why individuals move the way they do within the overarching theoretical framework (Armstrong & Fischer, 2020), and can potentially further inform the development of more effective ergonomic interventions.

The role of task and environment constraints on occupational movement strategy should be investigated to a greater extent. Within this thesis the primary objective was to determine how personal factors influenced lifting strategy, but secondary findings highlight that even small changes in task constraints (i.e., different lift types) have pronounced differences on which personal factors were associated with resultant movement and exposures. To holistically understand determinants of occupational movement strategy the role of the environment should be considered where in the paramedic example there are clear differences between the lab environment in which this thesis was conducted, and emergency call responses they respond to. Additionally, the influence of personal and environment constraints on movement in a broader range of tasks with high corresponding physical demands (i.e., pushing, pulling and/or carrying) should be explored. This will allow for the consideration of a range of physical demands on MSD risk opposed to just considering lifting.

There are future opportunities to further develop the model used in study 4 to serve as a standalone ergonomic risk assessment tool. To achieve this goal a first step would be to incorporate lift times more directly into the model opposed to assuming a consistent lift time across personal factor inputs. This has practical importance as lifting dynamics are known to influence resultant loading (Marras et al., 2003; Pryce & Kriellaars, 2018; Ghezelbash et al., 2020). Next, the scope of the model should be expanded so it is relevant to a broader range of lifting demands other than just lifting a 34 kg load. With load mass being a noted determinant of lifting strategy (Albert et al., 2008; Sadler et al., 2011; Sheppard et al., 2016) incorporating load mass as a model input to predict range of likely movement strategies and corresponding exposures across a broader range of demands is notably important. Following continued model development, the model predictions should be contrasted to existing tools such as deterministic digital human models or other emerging technologies that aim to predict likely ranges of lifting strategies. Such investigation can be used to understand the prospective ability of the model developed in this thesis to provide novel information on range of likely peak low back loads a lifter would experience. Finally, the utility of the developed model to identify injury risk should be investigated to determine whether prediction of a range of likely exposures has greater predictive validity then existing deterministic solutions. If the probabilistic model does show value, then it can potentially be incorporated into either existing or future digital human models to improve their prospective ability to screen for injury risk (Chaffin, 2005).

A final recommended future direction is to leverage the findings of this thesis in the development of lift training programs. Results from this thesis support that improving knee fROM, proprioceptive ability and strength via lift training programs could reduce biomechanical exposures in practice, but the efficacy of this approach should be investigated. The efficacy of intervening on these factors could be evaluated in lab-based longitudinal training studies to determine whether intervening on these personal factors is effective at reducing peak low back exposures. If these longitudinal studies show positive results, then lift training programs can be applied in practice to evaluate whether they result in reductions in injury incidence over time. If successful, these data could be used to advocate for the implementation of the developed lift training programs more broadly as a proactive ergonomics approach in work sectors within non-modifiable demands.

### *10.6 Conclusion:*

The objective of this thesis was to investigate whether personal factors independently and/or interdependently explained variance in low back during lifting. It was found that increased proprioceptive ability and being female resulted in consistent reductions in low back loads which were attributable to defining movement objectives that aimed to minimize resultant exposures. Stature, body mass, strength and lower body functional range of motion also explained variance in resultant peak low back loads but did not seem to do so by informing a movement objective that aimed to minimize exposures. Meanwhile, expertise did not influence resultant loads in lifting. Improving knee fROM was the only modifiable factor that resulted in clinically relevant reductions in predicted low back loads across lift types. These findings can be leveraged in the development of lift training interventions where directly improving knee fROM may reduce low back exposures in practice, with potential secondary benefits from improving proprioceptive ability and strength. Such lift training interventions may be an effective strategy to reduce injury risk in work sectors with non-modifiable physical demands such as paramedicine.

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## Appendix A: Confirming Association of Mean to Standard Deviation of Peak Low Back Loads

Within this thesis I have contextualized determinants of lifting performance within a motor control framework under the assumption that some individuals define a movement objective that aims to consistently minimize low back loads, while others do not. My previous research supports the definition of this movement objective for some lifters where lifters with lower means in low back biomechanical exposures had lower variability in these exposures (Armstrong & Fischer, 2020). However, given the importance of this assumption to this thesis the purpose of this appendix is to confirm that a similar relationship between mean and variability of peak low back loads existed within the collected data set used to answer the posed research questions. To facilitate this analysis simple regression was used to quantify the association between mean and standard deviation of peak low back loads normalized to body mass (the dependent variables across studies 1-3) within each of the barbell, backboard, crate, and stretcher lift types. Significant positive associations between the mean and standard deviation of peak low back loads would confirm the hypothesis that a movement objective aiming to consistently minimize low back loads was defined.

Significant associations were seen between the mean and standard deviation of peak low back loads in both the compression and A-P shear axes across all lift types, except for between the mean and standard deviation of compressive loads in stretcher lifting (Table A-1). The direction of association within all regression models was positive, indicating that increased means of peak low back loads had higher associated variability.

**Table A-1:** Association of mean to standard deviation of peak low back loads across the barbell, backboard, crate, and stretcher lift types.

| | Compression | A-P Shear |
|---|---|---|
| Barbell | $p < 0.001$<br>$R^2 = 0.216$<br>F = 19.33 | $p < 0.001$<br>$R^2 = 0.673$<br>F = 146.83 |
| Backboard | $p < 0.001$<br>$R^2 = 0.171$<br>F = 14.04 | $p < 0.001$<br>$R^2 = 0.653$<br>F = 128.83 |
| Crate | $p < 0.001$<br>$R^2 = 0.202$<br>F = 15.66 | $p < 0.001$<br>$R^2 = 0.500$<br>F = 62.06 |
| Stretcher | $p = 0.373$<br>$R^2 = 0.012$<br>F = 0.80 | $p = 0.001$<br>$R^2 = 0.164$<br>F = 12.95 |

With the observed significant positive associations between the mean and variability of peak low back loads the hypothesis that individuals previously proposed is supported by the data collected for this thesis.

## Appendix B: Normalization Assumptions for Scaling Low Back Loads to Body Mass

Within this thesis I have made the methodological decision to normalize peak low back compression and A-P shear loads to participant body mass as dependent measures. Conceptually, this decision was made to better understand how the movement strategy in lifting influences the resultant low back loads acknowledging that differences in body mass will directly influence resultant kinetic measures calculated using a rigid link model.

While the use of normalized low back loads as a dependent measure in this thesis is conceptually aligned with the overarching research question, it is important to ensure that three main statistical assumptions are met: the intercept assumption (Hirsch et al., 2022; Allison et al., 1995; Curran-Everett, 2013), the correlation assumption (Hirsch et al., 2022; Allison et al., 1995) and the statistical difference assumption (Hirsch et al., 2022). The purpose of this appendix is to investigate whether normalizing low back loads to body mass meets these stated assumptions.

To determine whether these normalization assumptions are met a supplementary analysis was completed to determine if peak compression forces normalized to body mass measured during barbell lifting met the three stated normalization assumptions.

*Intercept Assumption:*

To investigate the intercept assumption peak compression forces were plotted against body mass (Figure B-1). Based on these data the y-intercept is calculated to be 43.8 N. While a y-intercept of zero is needed to meet this assumption given the fact that within-participant peak compression forces were measured be up to 13000 N, the calculated y-intercept was only 0.33%

of the maximum measured peak compression force. I interpret these results to support that the intercept assumption was met.

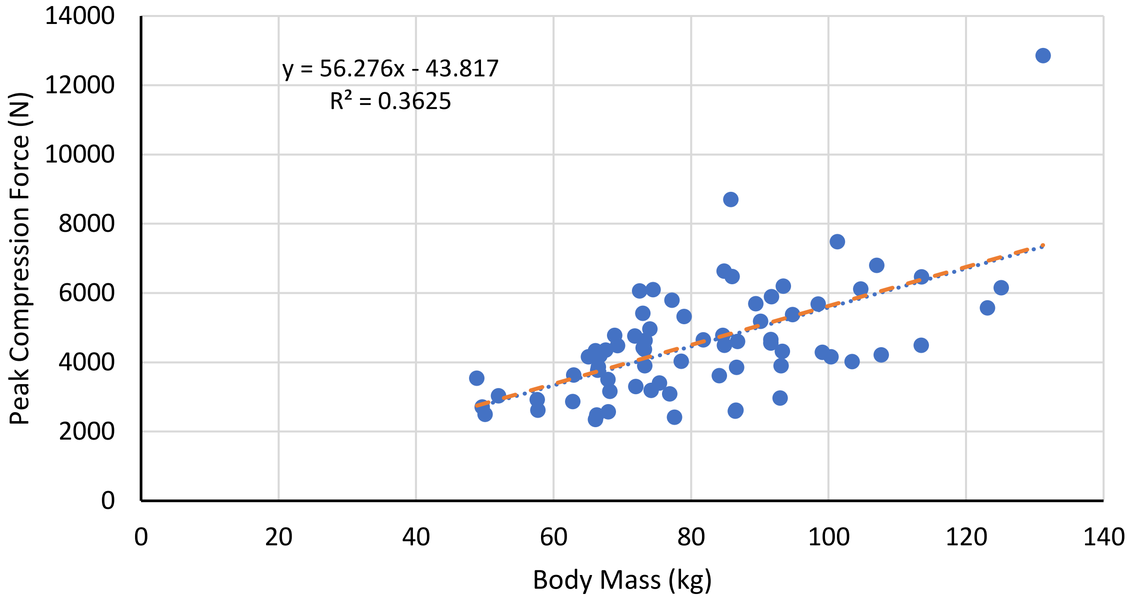


**Figure B-1:** Association of body mass and within-participant averaged peak low back compression forces in barbell lifting. Based on the regression equation fit to the data the y-intercept of the data is at 43.8 N. Participant data and line of best fit are plotted in blue, while the orange trendline is the theoretical line of best fit if the association had the same slope, but a y-intercept of zero.

*Correlation Assumption:*

A second normalization assumption that needs to be met is if when the compression forces are normalized to body mass there should be no association between body mass and the normalized compression forces. This assumption was met as an observed $R^2$ of 0.0005 was measured when correlating the normalized peak compression loads to body mass (Figure B-2).

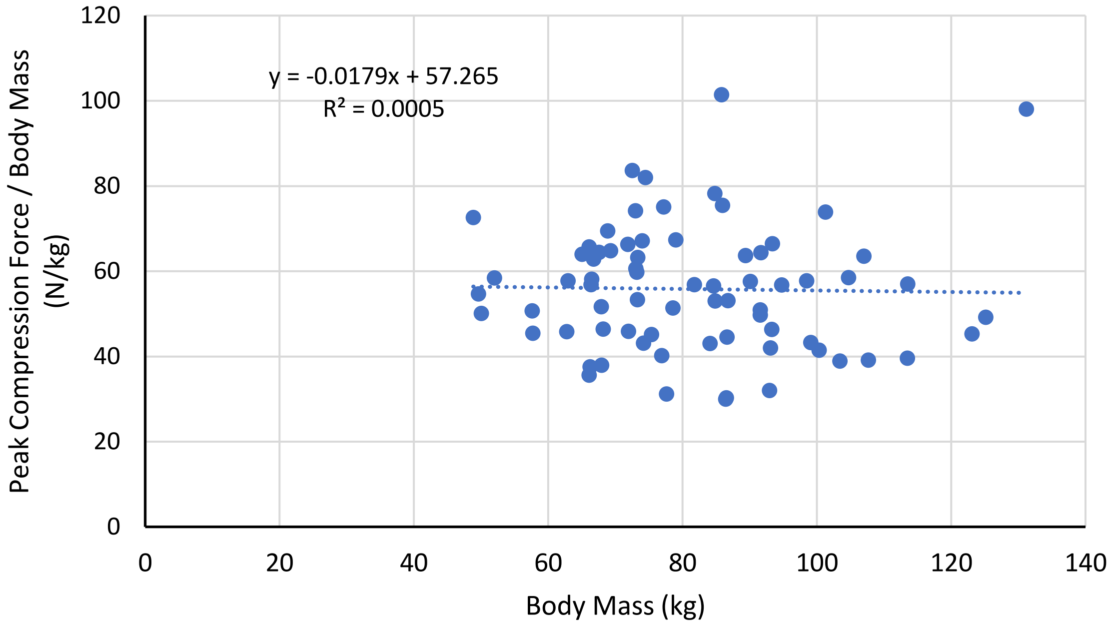


**Figure B-2:** Association of peak compression forces normalized to body mass and body mass.

*Statistical Difference Assumption:*

Finally, the statistical difference assumption was assessed by comparing differences in normalized peak compression forces as a function of sex, as well as comparing differences in peak compression forces as a function of sex with body mass as a covariate in the statistical model. For both comparisons a univariate general linear model was used in SPSS (Version 26.0, IBM Corporations, Armonk, NY). In both statistical analyses significant differences were observed between sex groups with comparable effect sizes (Table B-1).

**Table B-1:** Statistical differences in peak compression forces during barbell lifting with body mass controlled in the linear model, and in peak compression forces normalized to body mass as a function of sex.

| | Male | Female | Statistical Summary |
|---|---|---|---|
| Peak Compression Force (N) | 5501.4 (1713.6) | 3536.6 (800.9) | $p < 0.001$<br>$\eta^2 = 0.215$ |
| Peak Compression / Body Mass (N/kg) | 61.9 (14.5) | 49.2 (12.1) | $p < 0.001$<br>$\eta^2 = 0.188$ |

*Conclusion:*

Based on these supplementary analyses I confirm that the intercept, correlation, and statistical difference assumptions were met when normalizing peak compression loads to body mass as dependent measures. This supports the normalization methodology employed in this thesis.

## Appendix C: Summary of Proprioceptive Ability to PC Score Regression Models

Within this study no significant associations of proprioceptive ability to both the mean and variability of PC scores in features of movement related to biomechanical exposures were observed (after accounting for the Benjamini-Hochberg correction). Regression model summaries are included for barbell (Table C-1), backboard (Table C-2), crate (Table C-3), and stretcher (Table C-4) lifting with all significant regression models accounting for the Benjamini-Hochberg correction noted with '*'.

**Table C-1:** Backward removal ($p$ < 0.10) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of PC scores associated with low back loads in barbell, lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Barbell | PC1 | N/A | N/A | N/A | N/A |
| | PC3 | N/A | N/A | Error at 75% Target (β = -0.34) | $p$ = 0.004*<br>$R^2$ = 0.115<br>F = 9.11 |
| | PC5 | N/A | N/A | N/A | N/A |
| | PC7 | Self-selected Matching Error (β = 0.23), Error at 50% Target (β = 0.27) | $p$ = 0.013*<br>$R^2$ = 0.119<br>F = 4.64 | N/A | N/A |
| | PC8 | Error at 75% Target (β = -0.33) | $p$ = 0.005*<br>$R^2$ = 0.107<br>F = 8.35 | Self-selected Matching Error (β = 0.23) | $p$ = 0.048<br>$R^2$ = 0.054<br>F = 4.03 |
| | PC11 | N/A | N/A | N/A | N/A |
| | PC12 | Self-selected Matching Error (β = -0.28), Error at 75% Target (β = -0.23) | $p$ = 0.007*<br>$R^2$ = 0.133<br>F = 5.31 | N/A | N/A |
| | PC14 | N/A | N/A | Self-selected Matching Error (β = 0.26) | $p$ = 0.026<br>$R^2$ = 0.069<br>F = 5.20 |

**Table C-2:** Backward removal ($p < 0.10$) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of PC scores associated with low back loads in backboard lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Backboard | PC1 | Squat Matching Error (β = -0.23) | $p = 0.054$<br>$R^2 = 0.053$<br>F = 3.84 | Squat Matching Error (β = -0.22) | $p = 0.067$<br>$R^2 = 0.048$<br>F = 3.45 |
| | PC3 | Error at 75% Target (β = 0.22) | $p = 0.066$<br>$R^2 = 0.049$<br>F = 3.50 | N/A | N/A |
| | PC8 | N/A | N/A | Squat Matching Error (β = 0.23) | $p = 0.053$<br>$R^2 = 0.054$<br>F = 3.88 |
| | PC9 | N/A | N/A | N/A | N/A |
| | PC11 | Self-selected Matching Error (β = 0.24) | $p = 0.046$<br>$R^2 = 0.057$<br>F = 4.14 | Squat Matching Error (β = 0.23) | $p = 0.041$<br>$R^2 = 0.060$<br>F = 4.32 |
| | PC12 | N/A | N/A | Squat Matching Error (β = 0.22) | $p = 0.065$<br>$R^2 = 0.049$<br>F = 3.52 |
| | PC14 | Error at 75% Target (β = 0.22) | $p = 0.067$<br>$R^2 = 0.049$<br>F = 3.47 | N/A | N/A |
| | PC15 | Self-selected Matching Error (β = -0.20) | $p = 0.093$<br>$R^2 = 0.041$<br>F = 2.90 | Squat Matching Error (β = 0.23) | $p = 0.003$*<br>$R^2 = 0.121$<br>F = 9.37 |
| | PC17 | N/A | N/A | N/A | N/A |

**Table C-3:** Backward removal ($p$ < 0.10) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of PC scores associated with low back loads in crate lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Crate | PC1 | Error at 75% Target (β = -0.25) | $p$ = 0.040*<br>$R^2$ = 0.066<br>F = 4.38 | N/A | N/A |
| | PC2 | N/A | N/A | Squat Matching Error (β = 0.25) | $p$ = 0.050<br>$R^2$ = 0.061<br>F = 3.98 |
| | PC4 | N/A | N/A | N/A | N/A |
| | PC5 | Error at 75% Target (β = 0.21) | $p$ = 0.096<br>$R^2$ = 0.044<br>F = 2.85 | N/A | N/A |
| | PC6 | Error at 75% Target (β = -0.24) | $p$ = 0.047<br>$R^2$ = 0.062<br>F = 4.09 | N/A | N/A |
| | PC9 | Error at 75% Target (β = 0.22) | $p$ = 0.079<br>$R^2$ = 0.049<br>F = 3.18 | Squat Matching Error (β = 0.24) | $p$ = 0.060<br>$R^2$ = 0.058<br>F = 3.67 |
| | PC10 | N/A | N/A | Squat Matching Error (β = 0.23) | $p$ = 0.071<br>$R^2$ = 0.053<br>F = 3.38 |
| | PC14 | N/A | N/A | N/A | N/A |
| | PC15 | N/A | N/A | Squat Matching Error (β = 0.23) | $p$ = 0.060<br>$R^2$ = 0.058<br>F = 3.68 |
| | PC18 | Squat Matching Error (β = -0.23) | $p$ = 0.030<br>$R^2$ = 0.056<br>F = 3.68 | Squat Matching Error (β = 0.23) | $p$ = 0.007*<br>$R^2$ = 0.116<br>F = 7.85 |

**Table C-4:** Backward removal ($p$ < 0.10) multiple regression model summaries of proprioceptive ability measures to the mean and standard deviation of PC scores associated with low back loads in stretcher lifting. Significant predictors are listed with their standardized β coefficients for the final model including all significant predictor variables. N/A indicates no significant association was found.

| Lift | PC | Association to mean of PC scores | | Association to standard deviation of PC scores | |
|---|---|---|---|---|---|
| | | Significant predictors | Model performance summary | Significant predictors | Model performance summary |
| Stretcher | PC1 | N/A | N/A | Squat Matching Error (β = 0.34) | $p$ = 0.005* $R^2$ = 0.114 F = 8.35 |
| | PC2 | N/A | N/A | N/A | N/A |
| | PC4 | N/A | N/A | N/A | N/A |
| | PC5 | N/A | N/A | N/A | N/A |
| | PC10 | Squat Matching Error (β = 0.23) | $p$ = 0.076 $R^2$ = 0.048 F = 3.25 | N/A | N/A |
| | PC14 | N/A | N/A | Squat Matching Error (β = 0.39) | $p$ = 0.001* $R^2$ = 0.153 F = 11.76 |
| | PC19 | N/A | N/A | N/A | N/A |
| | PC20 | N/A | N/A | Squat Matching Error (β = 0.23) | $p$ = 0.013* $R^2$ = 0.091 F = 6.53 |

## Appendix D: Interpretations of Principal Components Associated with Structural and/or Functional Factors

Interpretations of modes of variance explained by principal components associated with low back loads in barbell (Table D-1), backboard (Table D-2), crate (Table D-3) and stretcher (Table D-4) lifting.

**Table D-1:** Interpretations of all PC that were significantly associated with structural and/or functional personal factors in barbell lifting.

| Lift Type | PC | Interpretation |
|---|---|---|
| Barbell | PC1 | Variance explained is primarily the position of the body in space with the 95$^{th}$ percentile reconstruction being closer to the load, and the 5$^{th}$ percentile reconstruction being further from the load. Additionally, some variance explained includes the pelvis position in the vertical where the pelvis is lower at lift initiation in the 5$^{th}$ percentile reconstruction. |
| | PC3 | Variance explained includes both differences in foot positioning, and differences in lift timing. The 5$^{th}$ percentile reconstruction has a narrower base of support compared to a wider base of support in the 95$^{th}$ percentile reconstruction. Second, there are differences in lift timing where the 95$^{th}$ percentile reconstruction both approaches and lifts the load earlier in time than the 5$^{th}$ percentile reconstruction. |
| | PC7 | The variance explained appears to be a difference operator where the 5$^{th}$ percentile reconstruction lowers their pelvis in the vertical to a greater extent at lift initiation, which is accompanied by greater knee flexion and a slightly more upright trunk compared to the 95$^{th}$ percentile reconstruction. |
| | PC8 | The variance explained seems to be differences in posture at lift initiation. The 5$^{th}$ percentile reconstruction has the pelvis further posterior, and forearms further anterior at lift initiation compared to the 95$^{th}$ percentile reconstruction. |
| | PC12 | Variance explained is a combination of anthropometric differences and movement sequencing when beginning the lift. The pelvis and trunk are higher in the vertical in the 95$^{th}$ percentile reconstruction compared to the 5$^{th}$ percentile reconstruction. The 5$^{th}$ percentile reconstruction initiates the lift by translating the pelvis vertically prior to translating the trunk, compared to the 95$^{th}$ percentile reconstruction that does this synchronously. |

**Table D-2:** Interpretations of all PC that were significantly associated with structural and/or functional personal factors in backboard lifting.

| | | |
|---|---|---|
| Backboard | PC1 | Variance explained is body positioning in the global space. The 95th percentile reconstruction is closer to the load, whereas the 5th percentile reconstruction is further from the load. |
| | PC3 | Variance explained is a combination of lift timing and how squat- or stoop-like the lift is. The 5th percentile reconstruction approaches the load earlier in the time domain, and then completes the lift later in the time domain. The 95th percentile reconstruction adopts a more squat-like lift strategy with greater knee flexion and an upright trunk, compared to a more stoop-like strategy in the 5th percentile reconstruction. |
| | PC8 | The variance explained is a combination of differences in lift sequencing. The 95th percentile reconstruction initiates the lift by extending the legs initially followed by extending the trunk. Conversely, the 5th percentile reconstruction initiates the lift by extending the legs and trunk synchronously. |
| | PC9 | Variance explained is primarily in posture at lift initation. The 5th percentile reconstruction has greater knee flexion and a more upright trunk compared to the 95th percentile reconstruction. Differences are more pronounced in knee posture opposed to trunk posture. |
| | PC11 | The mode of variance explained is predominantly having the pelvis lower in the vertical at lift initiation and the pelvis translating vertically before the wrists after initiating the lift in the 95th percentile reconstruction. |
| | PC12 | The variance explained seems to predominantly be differences in posture at lift initiation. The 5th percentile reconstructions wrists are further from the body at lift initiation than the 95th percentile reconstruction. There are differences in knee angles with the knee flexion angle at lift initiation being greater at lift initiation in the 95th percentile reconstruction, but this is likely attributable to the 95th percentile reconstruction having longer shanks than the 5th percentile reconstruction. |
| | PC14 | The variance explained is a combination of lift posture and timing. The 95th percentile reconstruction has the pelvis lower in the vertical at lift initiation and shoulders and elbows further anterior to the body compared to the 5th percentile reconstruction. Additionally, the 95th percentile reconstruction initiates the lift earlier in the time domain. |
| | PC15 | The variance explained is differences in joint motion sequencing. The 5th percentile reconstruction initiates the lift by translating the trunk in the vertical direction and has delayed full extension of the knees compared to the 95th percentile reconstruction. |

**Table D-3:** Interpretations of all PC that were significantly associated with structural and/or functional personal factors in crate lifting.

| | | |
|---|---|---|
| Crate | PC1 | The variance explained is predominantly body positioning in the global space with the 95$^{th}$ percentile reconstruction being closer to the load. Additionally, there was variance explained in the lift strategy where the 5$^{th}$ percentile reconstruction lowered the pelvis in the vertical to a greater extent and ended the lift with the load closer to the body by flexing the elbows. |
| | PC2 | The variance explained is the range of motion in the lifting movement. The 5$^{th}$ percentile reconstruction adopts a deep squat with flexion of the knees and lowering of the pelvis in the vertical, whereas the 95$^{th}$ percentile reconstruction maintains extended knees and bends through the hips and low back to reach the load. |
| | PC4 | The variance explained differences in base of support and location of the load relative to the body. The 95$^{th}$ percentile reconstruction has a narrower base of support compared to the 5$^{th}$ percentile reconstruction. Additionally, the load is further from the body at lift initiation and is lifted higher in the vertical in the 95$^{th}$ percentile reconstruction compared to the 5$^{th}$ percentile reconstruction. The 95$^{th}$ percentile reconstruction initiates the lift through extension of the legs, while the 5$^{th}$ percentile reconstruction initiates the lift with synchronous leg and trunk extension. |
| | PC5 | The variance explained is a combination of lift sequencing and anthropometric differences. The 5$^{th}$ percentile reconstruction approaches the load earlier in the time domain, but the lift is initiated at the same time between the 5$^{th}$ and 95$^{th}$ percentile reconstruction. The 95$^{th}$ percentile reconstruction seems to have longer thighs as demonstrated by greater knee flexion and the pelvis being further posterior at lift initiation. |
| | PC6 | The variance explained is differences in lift initiation posture, and how high the load is lifted to in the vertical. The 5$^{th}$ percentile reconstruction adopts a slightly deeper squat to initiate the lift, and then raises the load to a greater height in the vertical at the end of the lift. |
| | PC9 | The variance explained seems to be that the 5$^{th}$ percentile reconstruction seems to come to a stop at lift initiation compared to the 95$^{th}$ percentile reconstruction that remains in motion. In particular, the 95$^{th}$ percentile reconstruction has a slight but rapid movement into a deeper squat prior to initiating the lift. |
| | PC10 | The variance explained is a combination of knee movement in the frontal plane, and relative speed of the lift. The 5$^{th}$ percentile reconstruction has the knees translate away from the body in the frontal plane to a greater extent then the 95$^{th}$ percentile reconstruction. Additionally, the 95$^{th}$ percentile reconstruction initially moves faster when initiating the lift, then slows down when coming to standing. This differs from the 5$^{th}$ percentile reconstruction having a consistent lifting pace. |
| | PC15 | The variance explained seems to be body sequencing in the approach to the load. The 5$^{th}$ percentile reconstruction approaches the load by first flexing the trunk followed by lowering the pelvis in the vertical. Both reconstructions come to a similar posture at lift initiation and move consistently while handling the load. |
| | PC18 | The variance explained seems to be that the pelvis and trunk are both lower in the vertical and further anterior at lift initiation in the 5$^{th}$ percentile reconstruction compared to the 95$^{th}$ percentile reconstruction. |

**Table D-4:** Interpretations of all PC that were significantly associated with structural and/or functional personal factors in stretcher lifting.

| | | |
|---|---|---|
| Stretcher | PC2 | The variance explained includes a combination of body range of motion and lift timing. The 5$^{th}$ percentile reconstruction flexes at the trunk in the approach to the load and then smoothly and slowly extends through the trunk to complete the lift. Conversely, the 95$^{th}$ percentile reconstruction squats to a greater extent and more dynamically lifts the load to a higher position in the vertical. The 95$^{th}$ percentile reconstruction is also closer to the load. |
| | PC10 | The variance explained seems to be differences in joint movement sequencing. The 5$^{th}$ percentile reconstruction initiates the lift by pulling the load towards their flexed trunk and then extending through the trunk. Conversely, the 95$^{th}$ percentile reconstruction moves the load by extending the knees prior to flexing the elbows at the end of the lift. |
| | PC14 | The variance explained seems to be body posture when holding the load. The left shoulder (trigger side) is lower in the vertical at the end of the lift in the 5$^{th}$ percentile reconstruction, while there are no differences in right shoulder position between the two reconstructions. The 5$^{th}$ percentile reconstruction also has the load lower in the vertical at the end of the lift. |
| | PC19 | The variance explained is predominantly in trunk posture where the 5$^{th}$ percentile reconstruction is more extended through the trunk across the lift. Additionally, there are differences in lift timing where the 5$^{th}$ percentile reconstruction seems to momentarily pause at approximately the halfway point of the lift. |
| | PC20 | The variance explained is differences in upper body sequencing to initiate the lift. The 95$^{th}$ percentile reconstruction pulls the load towards the body and flexes the elbows to initiate the lift, while upper body posture does not change in the 5$^{th}$ percentile reconstruction. |

# Appendix E: Model Validity Considerations

In the development of a model that could predict the likely range of peak low back compression and A-P shear forces, the underlying validity of the model needs to be considered. In this appendix varying analyses are presented to support methodological decisions in model development.

*1 - Sensitivity of Model Predictions to Number of Model Iterations:*

Within model development, recommendations from Winston (2000) were used to determine the minimum number of model iterations to achieve reliable predictions of mean peak low back loads. However, to confirm this recommendation as appropriate supplementary analysis was completed to confirm that the recommended 1000 model iterations did not lead to significantly different predictions of peak loads than predictions generated from 5000 model iterations.

For this analysis the predicted mean and $95^{th}$ percentile peak low back compression forces were generated for a $50^{th}$ percentile (in body mass and stature) female during barbell lifting. This process was completed 30 times using each of 1000 and 5000 model iterations. Predicted mean and $95^{th}$ percentile peak low back loads were compared with independent samples t-tests.

No significant differences were found between either the mean or $95^{th}$ percentile predicted peak compression or A-P shear loads between 1000 and 5000 model iteration conditions (Table E-1). These findings support that 1000 model iterations were suitable for simulations addressing research questions.

**Table E-1:** Comparison of predicted mean and 95th percentile peak compression and A-P shear forces between 1000 and 5000 model iterations predicting peak loads in barbell lifting for a 50th percentile female.

| | 1000 Iterations | 5000 Iterations | *p* value |
|---|---|---|---|
| Mean Compression (N) | 6123.9 (21.7) | 6131.7 (10.7) | 0.082 |
| Mean A-P Shear (N) | 1754.9 (20.7) | 1760.6 (9.5) | 0.178 |
| 95th Percentile Compression (N) | 7453.8 (48.8) | 7466.5 (21.0) | 0.198 |
| 95th Percentile A-P Shear (N) | 3160.2 (30.0) | 3166.9 (11.1) | 0.253 |

*2 - Influence of Body Mass and Stature on Lifting Strategy:*

In the findings of study 4 in this thesis, it was found that both body mass and stature were consistently associated with population level predicted peak low back compression and A-P shear loads. However, it is important to note that both body mass and stature influenced the predicted movement strategy because PC scores significantly differed across these factors, but also that these factors directly scale the rigid link model used to calculate low back loads. The purpose of this supplementary analysis was to quantify the influence of body mass and stature on predicted loads independently of the effect of these factors on rigid link model scaling.

For this supplementary analysis model simulations were run when both stature and body mass were systematically input as below average, average, and above average as influencers of movement strategy in barbell lifting. Meanwhile, the stature and body mass of the rigid link model used to calculate resultant low back loads was held constant as a 50th percentile (both body mass and stature) female. PDFs of predicted peak compression and A-P shear loads were generated as both a function of stature and body mass to visually appraise the influence of these factors on resultant low back loads independent of scaling the rigid link model.

Across stature conditions the resultant differences in movement strategy had small effects on the population level predicted range of peak compression (Figure E-1) and A-P shear (Figure E-2) loads. Similar results were observed when predicting peak compression (Figure E-3) and A-P shear (Figure E-4) loads as a function of body mass. These findings highlight that the observed correlations between both stature and body mass and predicted peak low back compression and A-P shear loads are primarily attributable to these factors scaling the rigid link model opposed to influencing resultant movement strategy to effect low back loads.

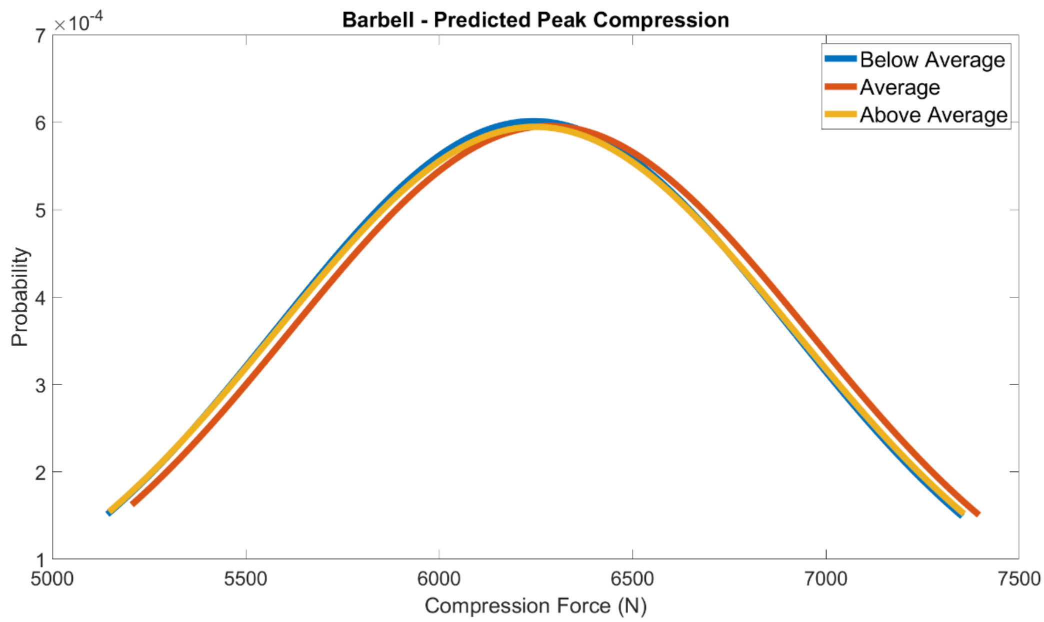


**Figure E-1:** Predicted range of peak low back compression loads in barbell lifting across individuals with below average, near average, and above average stature independent of the influence of body mass and stature on rigid link model scaling.

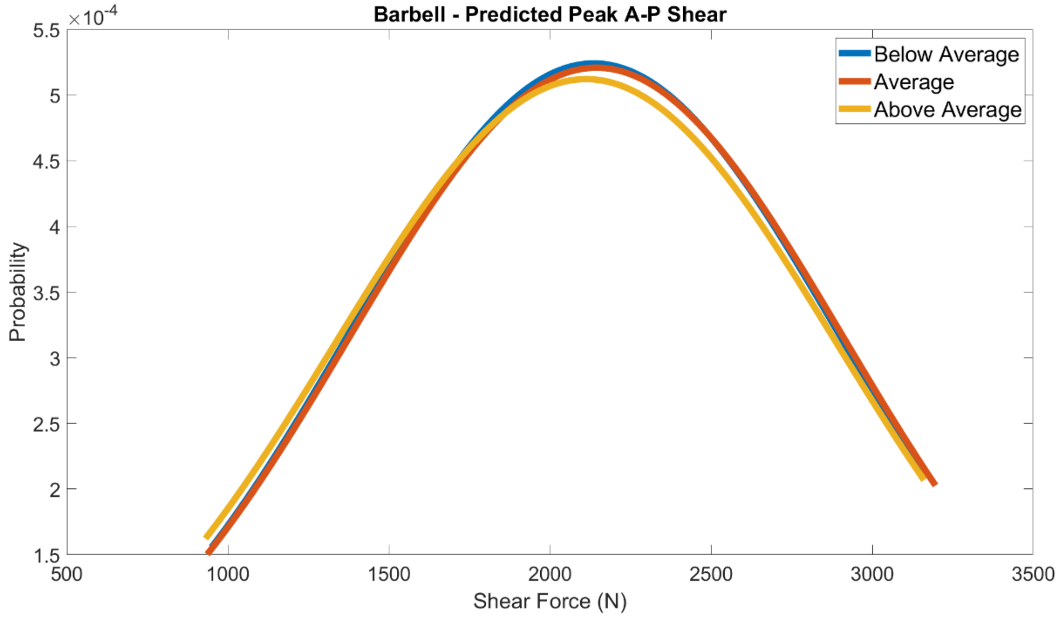


**Figure E-2:** Predicted range of peak low back A-P shear loads in barbell lifting across individuals with below average, near average, and above average stature independent of the influence of body mass and stature on rigid link model scaling.

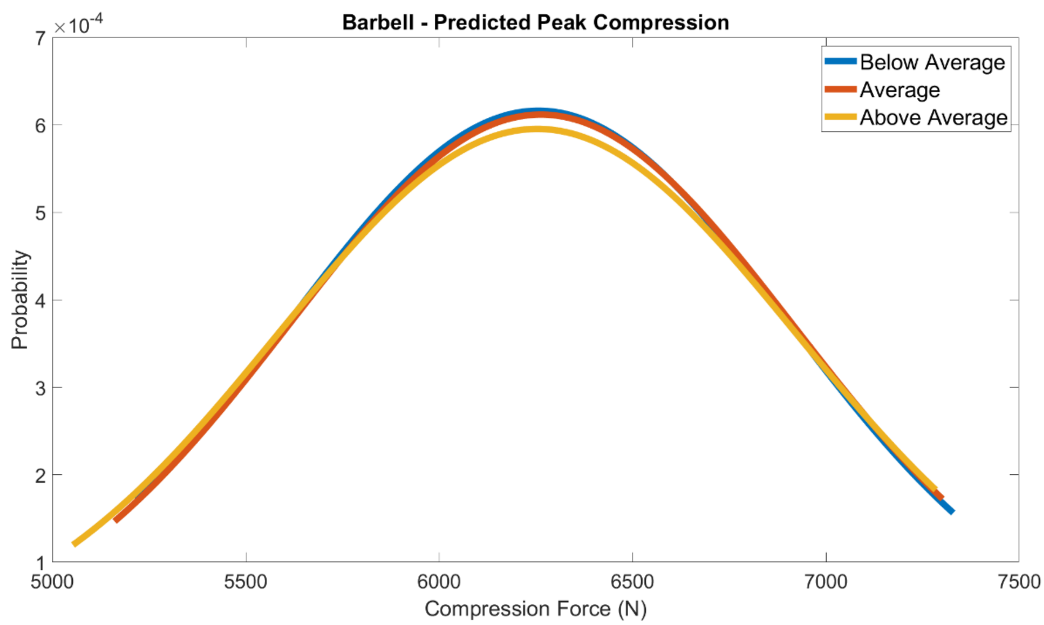


**Figure E-3:** Predicted range of peak low back compression loads in barbell lifting across individuals with below average, near average, and above average body mass independent of the influence of body mass and stature on rigid link model scaling.

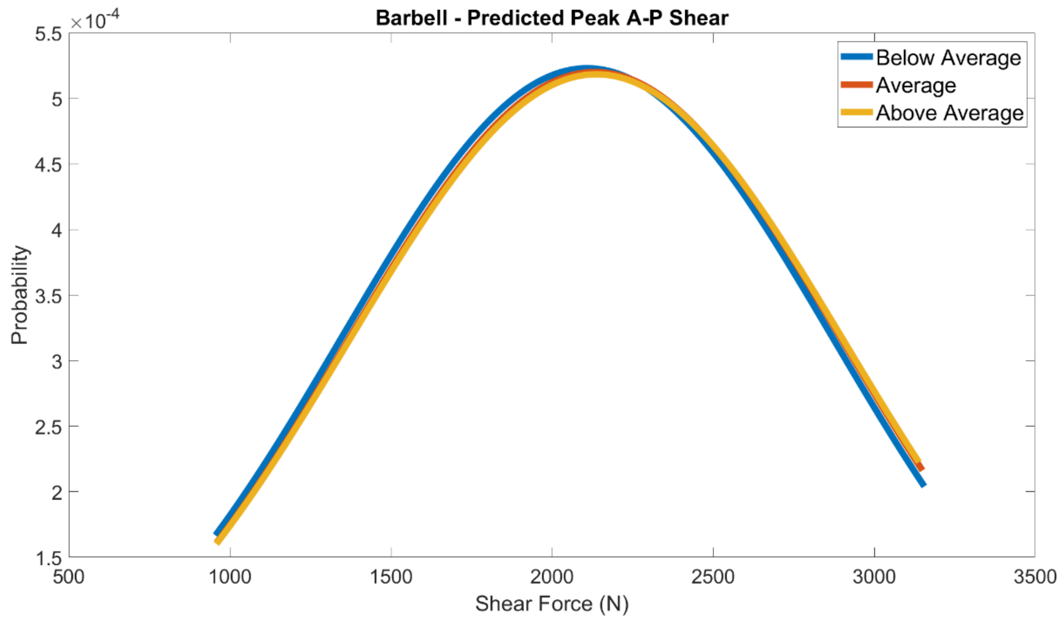


**Figure E-4:** Predicted range of peak low back A-P shear loads in barbell lifting across individuals with below average, near average, and above average body mass independent of the influence of body mass and stature on rigid link model scaling.

*3 - Differences in lift times as a function of personal factors:*

In this study the modelling approach employed does not consider differences in lift time as a function of personal factor inputs. This is a noted limitation as lifting dynamics are known to influence resultant kinetics in lifting exertions (Lavender et al., 2003).

To quantify the relevance of this information to the developed model, this supplementary analysis explored whether any personal factors that served as model inputs were associated with barbell lifting time. Forward addition multiple regression ($p < 0.05$) was used for statistical analysis.

It was found that both strength and posture-sense were significant predictors of barbell lifting time, with a total of 26.3% of variance in lifting time being explained by these variables

(Table E-2). This analysis supports the need for future research that considers differences in lift times within the prediction of lifting strategy and corresponding peak low back loads due to the influence of these personal factors on lift times.

**Table E-2:** Forward addition ($p < 0.05$) regression model summaries for barbell lifting time with all predictor variables included.

| | Significant predictors | Model Summary |
|---|---|---|
| Barbell Lifting Time | Strength (β = -0.49), Posture-Sense (β = 0.22) | $p < 0.001$<br>$R^2 = 0.263$<br>F = 11.43 |

While lift time was found to differ as a function of strength and posture-sense, follow up analysis aimed to quantify whether lift times were normally distributed. Using a Kolmogorov-Smirnov test of normality the distribution of barbell lift times was not found to differ from a normal distribution with the same mean and deviation ($p = 0.200$). Since lift time is normally distributed, the assumption of a consistent 3 second lift time in model development is not anticipated to have unpredictable effects on model outputs.