

Using pattern recognition to detect differences in movement strategy
between high and low relative biomechanical exposure lifters and lifters:
Application to backboard lifting

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.

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Abstract

Introduction:

Backboard lifting is a demanding aspect of paramedic work that results in higher low back moments and sagittal trunk angles compared to other paramedic tasks. Movement strategy in a backboard lift affects resultant biomechanical exposure at the low back so there is a need to identify differences in movement strategies that yield lower relative biomechanical exposure.

Pattern recognition methods can be used to objectively identify features of movement related to biomechanical exposure. In particular, principal component analysis (PCA) is a pattern recognition technique that can identify whole body features of movement that explain variance in a data set. This approach is conceptually compatible with Optimal Feedback Control theory (OFC), which provides a theoretical motor control framework in which to contextualize the pattern recognition analysis.

Research Questions:

- 1) How do features of movement differ between high and low relative biomechanical exposure lifts, and as a function of relative demand in backboard lifting?
- 2) How do features of movement differ between high and low relative biomechanical exposure lifters, and across relative demand in backboard lifting?

Methods:

Twenty-eight participants performed 10 backboard lifting trials within each of a light, medium and heavy relative demand condition. Relative demands were scaled to participants' one-repetition max backboard lift. Full body kinematics and ground reaction forces were collected for backboard lifting trials. A whole-body kinematic model was created in Visual3D to calculate low back moments and sagittal angles for dichotomizing lifts and lifters as low vs. high relative biomechanical exposure, and to provide positional data. PCA was applied on positional data as a pattern recognition technique. For retained principal movements (PM), PM scores were calculated as dependent variables. Six PMs were retained for analysis.

A two-way ANOVA with independent factors of relative biomechanical exposure and relative demand was used to test for differences in PM scores for retained PMs across all lifts for research question 1. A two-way mixed ANOVA with a between factor of relative biomechanical exposure and a within factor of relative demand was used to test for differences in mean of PM scores in lifters to answer research question 2.

Results:

Movement strategies associated with high and low relative biomechanical exposure lifts: Significant main effects of relative biomechanical exposure were detected in 5 of the 6 PMs. PMs were interpreted to deduce that low exposure lifts positioned the body closer to the load, used a distal to proximal strategy and maintained an upright trunk. Significant main effects of relative demand were

seen in 4 of the 6 PMs. Heavy relative demand lifts were interpreted to have the body further from the load, use a distal to proximal strategy, use a more stoop-like strategy and had differences in timing of the lift.

Movement strategies associated with high and low relative biomechanical exposure lifters: High exposure lifters positioned the body further from the load than low exposure lifters. Significant main effects of relative demand were seen in PMs 2 and 5 within lifters, which are interpreted to have a distal to proximal, and more stoop-like strategy in the heavy relative demand lifts.

Discussion:

The application of a pattern recognition technique identified differences in movement strategies between those who experienced relatively less and greater biomechanical exposure. Pattern recognition also revealed how relative demand influenced movement strategies during backboard lifting. Based on effect sizes, the horizontal distance of the body to the load was the most important determinant of relative low back exposure. The influence of relative demand revealed that a distal-to-proximal strategy was more likely when lifting a heavier relative demand, a finding that is consistent with past literature.

The strong relationship of horizontal distance to the load as identified via the pattern recognition approach suggests that some lifters consider biomechanical exposure in their OFC control law by positioning themselves closer to the load. With no significant interaction effects, assessment of backboard lifting can be conducted by evaluating a lifters proximity to the backboard prior to lifting without considering relative demand.

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Table of Contents

List of Figures.....	ix
List of Tables.....	xiii
List of Equations.....	xiv
List of Abbreviations.....	xv
1.0 Introduction.....	1
1.1 The issue.....	1
1.2 Project Rationale.....	4
2.0 Literature Review.....	10
2.1 Determinants of Movement Strategy.....	10
2.1.1 Theoretical Basis.....	10
2.1.2 Implications of Optimal Feedback Control theory in Occupational Lifting.....	14
2.1.3 External Factors influencing the Control Law.....	15
2.1.4 Biomechanical Consequences of Movement Strategy in Lifting.....	16
2.1.5 Modifiers of Movement Strategy in Lifting.....	18
2.2 Pattern Recognition to Quantify Movement Strategy.....	24
2.3 Principal Component Analysis for Pattern Recognition.....	27
3.0 Research Questions and Hypotheses.....	32
4.0 Methods.....	34
4.1 Study Design.....	34
4.2 Participants.....	34
4.3 Instrumentation.....	35
4.3.1 Motion Capture.....	35
4.3.2 Force Plates.....	36
4.4 Protocol.....	36
4.4.1 Session 1 – 1RM testing.....	38
4.4.2 Session 2 – Backboard Lifting.....	39
4.5 Data Processing.....	42
4.5.1 Data Treatment.....	42
4.5.2 Data Analysis.....	43
4.5.3 Dichotomizing into High vs. Low Biomechanical Exposure Lifts and Lifters.....	45
4.6 Statistical Analysis.....	49
4.6.1 Principal Component Analysis for Pattern Recognition.....	49

4.6.2 Statistical tests for hypothesis testing.....	51
4.6.3 Interpreting Differences in Principal Movements	52
4.6.4 Visualizing Principal Movements	54
5.0 Results	56
5.1 Defining High vs. Low Relative Biomechanical Exposure Lifts and Lifters	56
5.2 Retaining and Interpreting PMs for Analysis.....	57
5.3 Comparing Movement Strategy across Lifts	70
5.4 Comparing Movement Strategy across Lifters	75
6.0 Discussion.....	77
6.1 Lift Movement Strategy as a Function of Biomechanical Exposure and Relative Demand	77
6.2 Lifter Movement Strategy as a Function of Biomechanical Exposure and Relative Demand	80
6.3 Implications for Assessing and Teaching Movement Strategy in Backboard Lifting.....	83
6.4 Critiquing the Methodological Framework.....	84
6.5 Limitations.....	86
6.6 Future Directions.....	87
7.0 Conclusion.....	90
References.....	91
Appendix A: Standard Operating Procedure on 1RM Testing.....	107
Appendix B: Tests of Normality for PM scores	109
Appendix C: Changes in subjective fatigue measures over the experimental protocol.....	115

List of Figures

Figure 1 Role of external constraints on the definition of the control law. Adapted from the Grand Unified Theory of Sports Performance (Glazier, 2017) to include OFC closed-loop feedback (Scott, 2004).....	3
Figure 2 Executing a scoop stretcher lift, which poses a similar biomechanical demand to backboard lifting.....	5
Figure 3 Peak L4/L5 angle experienced by paramedics when performing stretcher and scoop stretcher related lifts (Armstrong et al., 2018). Letters indicate significant differences, where ‘A’ is different from ‘B’	6
Figure 4 Peak L4/L5 moment experienced by paramedics when performing stretcher and scoop stretcher related lifts (Armstrong et al., 2018). Letters indicate significant differences, where ‘A’ is different from ‘B’	7
Figure 5 Adapted version of Glazier’s (2017) Grand Unified Theory of Sports Performance where the independent (red) and dependent (blue) measures of this study are identified. Solid green lines represent the relationships tested between independent variables and mean movement strategy, and dashed green lines represent how the relationship is used to infer Optimal Feedback Control Law	9
Figure 6 Closed loop model of optimal feedback control adapted from Scott (2004)	12
Figure 7 Average knee and low back power profiles normalized to percent of lift for participants with the four lowest (P1-P4) and four highest (P5-P8) peak low back flexion angles.....	26
Figure 8 Placement of reflective Vicon markers for motion capture collection.....	36
Figure 9 Protocol overview with estimated associated timing for sessions 1 and 2.....	37

Figure 10 Representation of participant in the motorbike pose from Visual3D from the frontal (left) and sagittal (right) plane..... 40

Figure 11 Sample randomized lifting trial order with rest times..... 41

Figure 12 General flow of data collection, treatment and analysis..... 42

Figure 13 Classifying lifts as high or low relative biomechanical exposure where peak sagittal low back angle, peak low back moment and low back moment at peak sagittal low back angle in a lift were inputs.....46

Figure 14 Classifying lifters as high or low relative biomechanical exposure where peak sagittal low back angle, peak low back moment and low back moment at peak sagittal low back angle in heavy lifts were inputs.....47

Figure 15 Mean aggregate z-scores to calculate biomechanical exposure where mean scores greater than 1 define a high exposure lifter and mean scores less than -1 define a low exposure lifter49

Figure 16 Conceptual examples of single component PC reconstruction of a 95th percentile (blue) and 5th percentile (red-dashed) waveform plotted with the average (black) waveform. These plots demonstrate a magnitude operator (left), difference operator (middle) and phase shift operator (right) for a retained PC. Figure adapted from Brandon et al., 2013..... 53

Figure 17 Single component reconstruction of PM1 from the sagittal (A) and frontal B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....59

Figure 18 Single component reconstruction of PM2 from the sagittal (A) and frontal B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the

95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....61

Figure 19 Single component reconstruction of PM3 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....63

Figure 20 Single component reconstruction of PM4 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....65

Figure 21 Single component reconstruction of PM5 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....67

Figure 22 Single component reconstruction of PM6 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.....69

Figure 23 Mean PM scores for high and low exposure lifts across light, medium and heavy relative demands. Significant main effects of exposure are indicated by a bracket and significant main effects of relative demand are indicated with an asterisk (*) 72

Figure 24 Aggregate reconstruction to illustrate the net differences in movement strategy as a function of relative biomechanical exposure from the sagittal (top) and frontal (bottom) planes. Black tracing represents a low exposure lift and red represents a high exposure lift.....73

Figure 25 Aggregate reconstruction visualizing differences in movement strategy as a function of relative demand from the sagittal (top) and frontal (bottom) planes. Purple represents a light relative demand, green is a medium relative demand and blue is a heavy relative demand.....74

Figure 26 Mean PM scores for high and low exposure lifters across light, medium and heavy relative demands. Significant main effects of exposure are indicated by a bracket and significant main effects of relative demand are indicated with an asterisk (*).....76

List of Tables

Table 1 Participant Demographics.....	33
Table 2 Descriptive statistics of low back biomechanical exposure measures in high vs. low relative biomechanical exposure lifts across relative demand conditions. Independent t-tests were used to determine whether variables significantly differed between lift groups.....	54
Table 3 Demographics of high and low exposure lifters.....	55
Table 4 Descriptive statistics of low back biomechanical exposure measures in high vs. low relative biomechanical exposure lifters in the heavy relative demand condition. Independent t-tests were used to determine whether variables significantly differed between lifter groups.....	55
Table 5 Variance explained compared to variance explained by chance where bolded PMs were retained for analysis. Variance explained by chance was calculated using methods reported by Fischer et al. (2014).....	55
Table 6 Summary of two-way ANOVA results comparing PMS scores between high and low exposure lifts and across light, medium and heavy relative demands. Only significant post hoc results are included....	69
Table 7 Summary of two-way mixed ANOVA results comparing mean PMS scores between high and low exposure lifters and across light, medium and heavy relative demands. Only significant post hoc results are included.....	73

List of Equations

Equation 1 Wathan's (1994) One repetition maximum estimate.....	37
Equation 2 Bell's (1989; 1990) hip joint centre estimation.....	42
Equation 3 5 th percentile single component reconstruction (Brandon et al., 2013).....	50
Equation 4 95 th percentile single component reconstruction (Brandon et al., 2013).....	50
Equation 5 Aggregate single component reconstruction.....	52

List of Abbreviations

1RM	One repetition maximum
CNS	Central nervous system
MSD	Musculoskeletal disorder
PCA	Principal component analysis
PM	Principal movement
OBEL.....	Occupational Biomechanics and Ergonomics Lab
OFC	Optimal Feedback Control theory

1.0 Introduction

1.1 The issue

The movement strategy used in a physical exertion can modulate the biomechanical exposure at the low back (Kingma et al., 2004). Biomechanical exposures that are influenced by movement strategy, including low back angles (Marras et al., 1993), moments (Marras et al., 1993; Norman et al., 1998) and joint reaction forces (Gallagher & Marras, 2012; Waters et al., 1993), have been associated with risk of musculoskeletal disorders (MSD). The movement strategy used can also influence the tissue tolerance, and thus indirectly effect risk of MSD (McGill, 2015; Gunning et al., 2001). Acknowledging that movement strategy influences biomechanical exposure (McGill, 2015; Marras, 2008) it is useful to identify the relationship between movement strategy and biomechanical consequences when attempting to attenuate risks in ergonomics approaches (McGill, 2009). To effectively develop and implement ergonomics approaches based on movement strategy we need to objectively understand how movement strategy relates to biomechanical exposures of interest.

To pursue evaluating and modifying movement strategy as an ergonomic approach a first step is to objectively identify what features of movement strategy are associated with unfavorable biomechanical exposure outcomes. Use of pattern recognition, such as methodology employed to differentiate between elite and novice athletes based on movement strategy (Ross et al., 2018), is a promising framework to identify features of movement associated with biomechanical exposures. In the context of lifting there is evidence that movement strategy influences biomechanical exposures, measured by reaction forces at the low back (Straker, 2003), but this relationship is not well understood. A review by van Dieën et al. (1999) determined that the position of the body relative to the load was the biggest determinant of the resultant biomechanical exposure at the low back opposed to the movement strategy used. However, this review defined movement strategy *a priori* as participants were constrained to either squat or stoop in lifting as defined by discrete measures. This methodology may

not be sensitive enough to capture the subtleties of movement features that could be related to biomechanical exposure when lifters are not constrained to either squat or stoop. Use of pattern recognition method that considers time varying whole body movement patterns would overcome the noted limitation of the van Dieën (1999) review to provide a more robust investigation into how movement strategy influences resultant biomechanical exposures in lifting.

With a goal of objectively assessing movement strategy based on biomechanical exposure it is important to consider underlying theories of motor control which will influence the volitional control of movement. This is argued by Gregor (2008) who states that biomechanics research should consider the underlying neural control in addition to quantifying the consequences of movement (i.e. kinematics and kinetics). We may be able to identify features of movement that are related to biomechanical exposure, but this information cannot be effectively used to inform screening if the control of features of movement on a person level are not understood. To frame this study within a motor control theoretical framework Optimal Feedback Control theory (OFC) can be used to understand the control of movement.

OFC is a prevailing motor control theory that attempts to explain the volitional control of movement strategy to achieve a task goal while considering inherent variability in movement. OFC suggests that our body develops an initial optimal feedback control law to govern our movement strategy as a plan to achieve a task objective (Todorov, 2004). The control law is executed with a closed-loop optimization process where only variability that affects the task objective is controlled (Todorov, 2003). The closed-loop feedback is informed by comparing sensory feedback with the initial motor command to determine if intervention is necessary to maintain task completion. With the abundant degrees of freedom in the body, a motor task objective can be achieved using an infinite number of movement strategy combinations due to the flexibility allowed in movement variability while not compromising the task objective (Scott, 2004). It is possible that some individuals may consider controlling features of movement related to biomechanical exposure in their control law while others do

not. To accurately assess movement strategy, we must understand the underlying control of features of movement related to biomechanical exposure.

OFC outlines how volitional movement is executed via the control law, but the definition of the control law can be influenced by external constraints. The grand unified theory of sport's performance (Glazier, 2017) demonstrates how constraints influence the formation of coordinative structures. This theory is based on Newell's constraints model (Newell, 1986) where task, organism and environment constraints were theorized to influence coordination and control. For this thesis, the grand unified theory of sport's performance has been modified to include OFC (Figure 1). In this amended model, external constraints influence the definition of the control law, which then informs movement strategy consistent with OFC. With a practical goal of assessing movement strategy to infer biomechanical exposures potential confounding effects of constraints on control law formation should be considered.

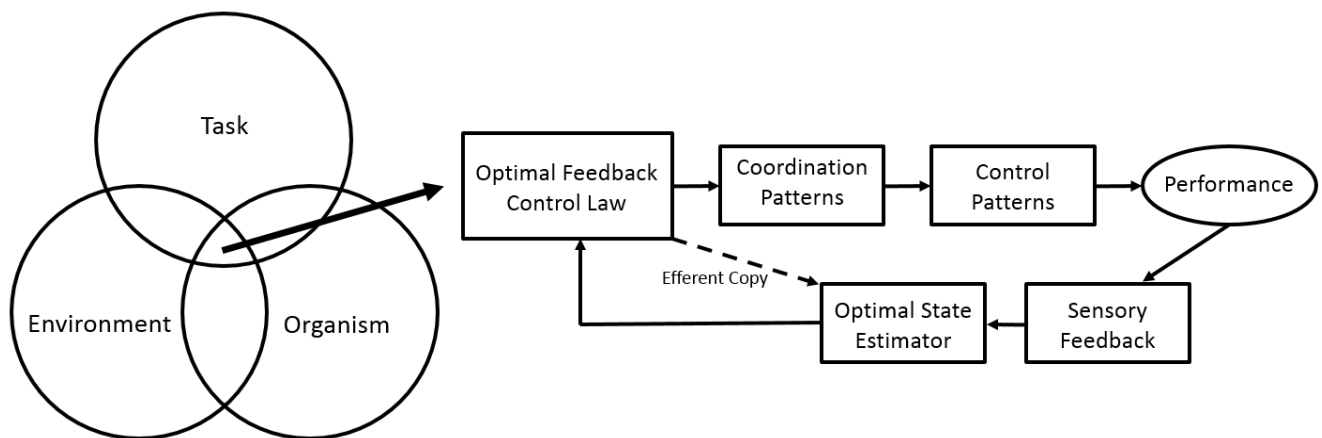


Figure 1: Role of external constraints on the definition of the control law. Adapted from the Grand Unified Theory of Sports Performance (Glazier, 2017) to include OFC closed-loop feedback (Scott, 2004).

1.2 Project Rationale

This thesis explores the utility of pattern recognition to identify movement strategies associated with relatively higher or lower biomechanical exposure during the performance of a backboard lift. Backboard lifting is an essential task of paramedic work (Coffey et al., 2016) which consists of lifting a board with handles in close proximity to the ground to load a patient onto a stretcher (Figure 2). Backboard lifting is similar in nature to scoop stretcher lifting which exposes paramedics to the greatest normalized low back angles (Figure 3) and moments (Figure 4) compared to other paramedic tasks (Armstrong & Fischer, 2018). This supports that backboard lifting is particularly problematic as paramedics experience the highest prevalence of MSDs by sector (Maguire et al., 2005; Maguire et al., 2014) which are in part attributed to high physical demands of the job (Lavender et al., 2000; Cooper & Ghassemieh, 2007). Engineering interventions have already been successful in reducing MSD incidence in this sector, such as redesign of stretchers for example (Armstrong et al., 2017; Fredericks et al., 2009; Studnek et al., 2012), but backboard lifting cannot be replaced by similar engineering interventions. Coaching individuals to improve their self-selected movement strategy is a plausible intervention to reduce MSD risk. Paramedics that do more work with their lower body during lifting exertions, such as the backboard lift, typically experience lower biomechanical exposures, quantified as peak low back moments and trunk flexion angles (Makhoul et al., 2017). As backboard lifting imposes high biomechanical exposures which have the potential to be reduced via movement strategy intervention it is an appropriate medium to be explored in this thesis.

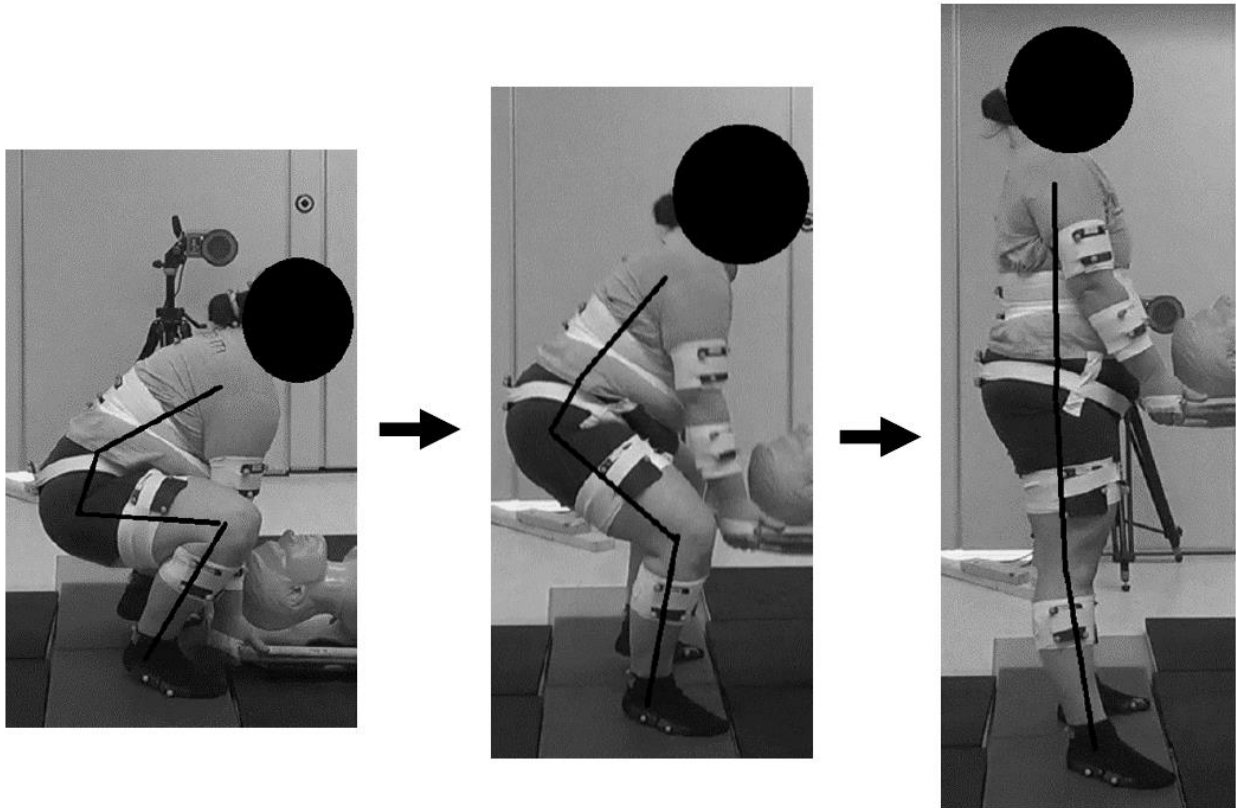


Figure 2: Executing a scoop stretcher lift, which poses a similar biomechanical demand to backboard lifting.

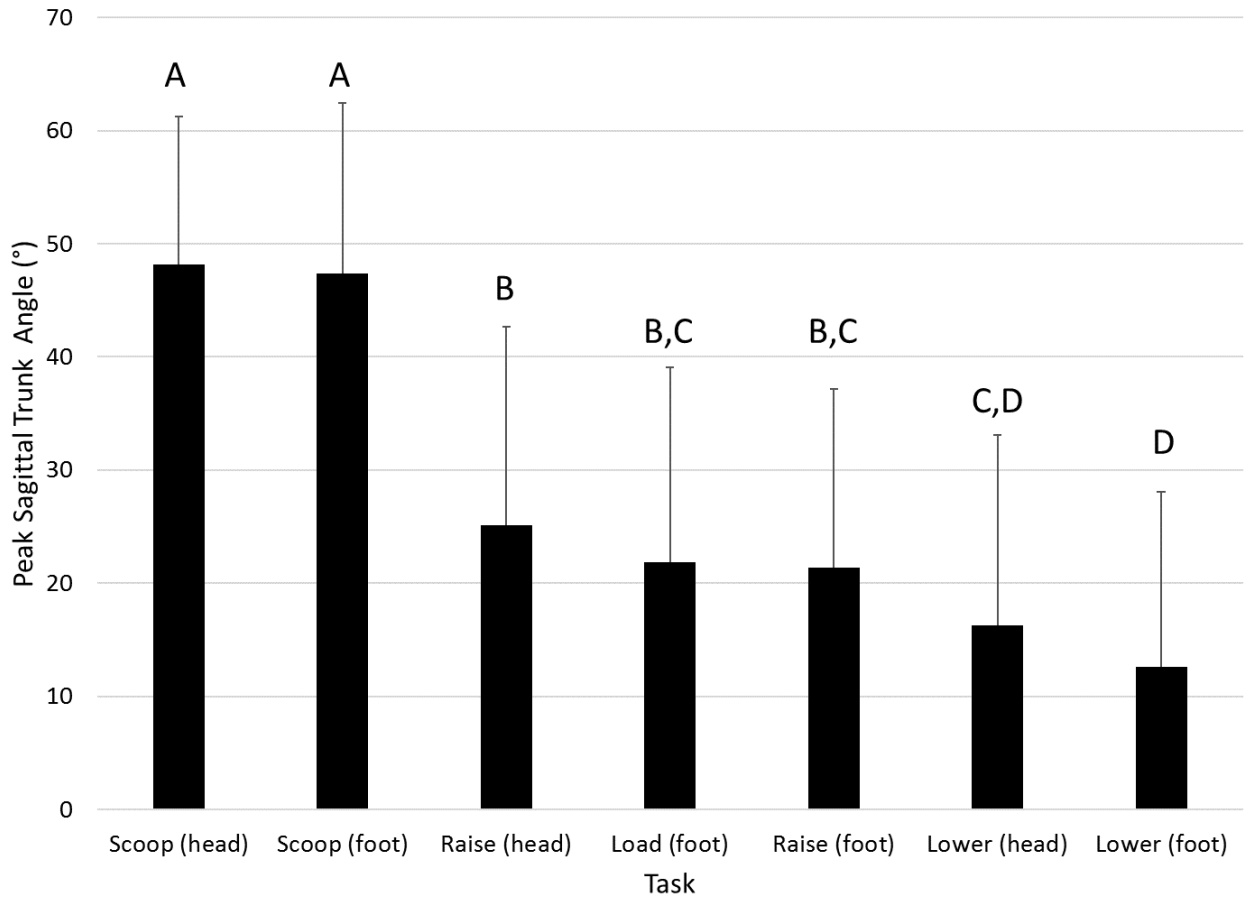


Figure 3: Peak L4/L5 angle experienced by paramedics when performing stretcher and scoop stretcher related lifts (Armstrong et al., 2018). Letters indicate significant differences, where 'A' is different from 'B'.

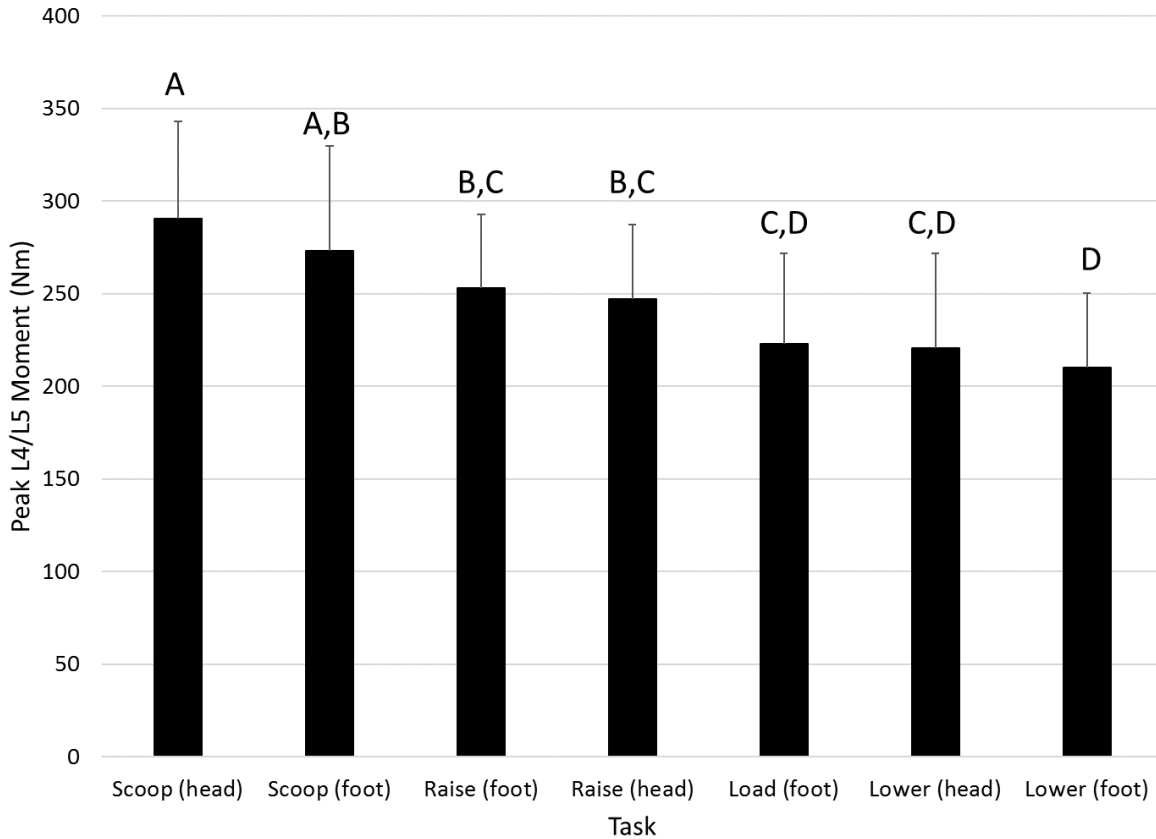


Figure 4: Peak L4/L5 moment experienced by paramedics when performing stretcher and scoop stretcher related lifts (Armstrong et al., 2018). Letters indicate significant differences, where ‘A’ is different from ‘B’.

Principal component analysis (PCA) can be applied as a pattern recognition approach to objectively identify features of movement that explain the most variance in movement strategy during backboard lifting. More specifically, use of a PCA approach with whole body motion as the input allows for the identification of principal movements (PMs) in lifting. This method has been used to describe human gait (Troje, 2002; Maurer et al., 2012), and in sport applications (Federolf et al., 2014; Federolf et al., 2013; Gloersen et al., 2017; Young & Reinkensmeyer, 2014; Ross et al., 2018). The PCA approach is beneficial as it can objectively extract redundant information in large data sets (Daffertshofer et al.,

2004). This PCA approach also considers the variability of movement, which has a deterministic origin in the OFC framework and is not necessarily noise in the system (Stergiou & Decker, 2012).

With a goal of applying findings from this study to assessment, the potential interaction between biomechanical exposure and load on movement strategy should be considered. The load on the board represents a change in task constraint, which can affect the definition of the control law. Past work has demonstrated that the relative demand (load scaled to a person's capacity) is a determinate of lifting behaviour (Albert et al., 2008; Plamondon et al., 2017). The effect of relative demand on movement strategy is included as an independent variable in this thesis as in application of these findings there is a need to know how relative demand could confound movement strategy observed. The consideration of relative demand as a constraint that may influence control law formation within the overarching motor control framework is pictured in Figure 5. This figure demonstrates how the control law will be inferred in this study by assessing a relationship between independent (high vs. low biomechanical exposure lifter and relative demand) and dependent (features of movement) variables.

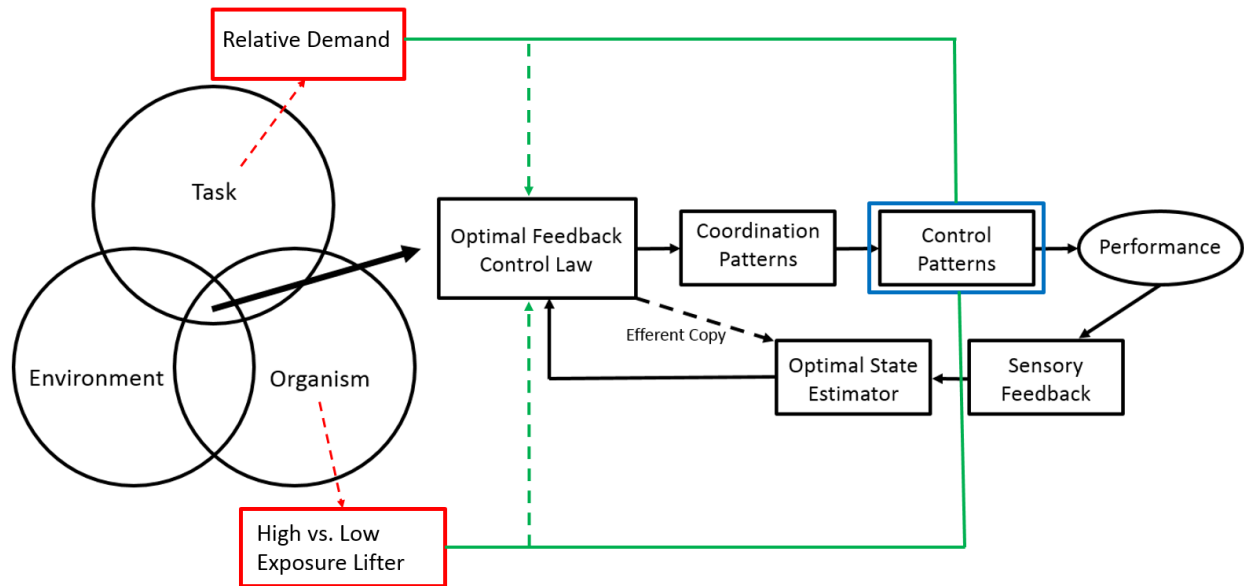


Figure 5: Adapted version of Glazier’s (2017) Grand Unified Theory of Sports Performance where the independent (red) and dependent (blue) measures of this study are identified. Solid green lines represent the relationships tested between independent variables and mean movement strategy, and dashed green lines represent how the relationship is used to infer Optimal Feedback Control Law.

Practically, this thesis aims to identify how features of movement differ as both a function of relative biomechanical exposure and relative demand in backboard lifting. Investigating the relationship between features of movement in a lift and the resultant exposures allows us to identify features that could be trained to reduce exposure. By extending the analysis to explore if differences in mean movement strategy can be identified between high and low exposure lifters in some features of movement, results can inform the assessment of backboard lifting technique. Consideration of mean strategy is important as human movement is inherently variable (Latash, 2012) and so even though some features may be associated with biomechanical exposures in a given lift, these features may not be consistently controlled between high and low exposure lifters to allow for assessment of strategy.

The effect of relative demand is also included in these analyses as it could influence both movement strategy in a given lift, and mean movement strategy.

The primary research question of this study asks; in a healthy population with varied levels of lifting experience how does movement strategy differ between high and low relative biomechanical exposure lifters and across light, medium and heavy relative demand conditions when performing backboard lifting? Second, how does average movement strategy differ between high and low relative biomechanical exposure lifters and across light, medium and heavy relative demand conditions in backboard lifting? By answering research question one we can identify what features of movement are associated with biomechanical exposures in backboard lifting which could inform training approaches. By considering average movement strategy within a motor control framework in research question two, we can understand what features of movement associated with resultant biomechanical exposures at the low back consistently differ between high and low exposure lifters to inform assessment of backboard lifting strategy.

2.0 Literature Review

2.1 Determinants of Movement Strategy

2.1.1 Theoretical Basis

Assessing movement competency presents a promising option to identify those at greater risk of MSDs, but variability in working strategy should be considered in this approach. Human movement is inherently variable because of the motor abundance in our bodies having more degrees of freedom than is needed to achieve task performance (Latash, 2012). With this motor abundance, we see variability in movement from trial to trial in a work context which in bending exertions had small effects on spinal compression variability but large effects on lateral and anteroposterior shear force variability (Mirka & Marras, 1993). Both compression and shear force on the low back have been correlated to risk of MSDs

(Gallagher & Marras, 2012; Waters et al., 1993), therefore the variability in movement influencing these variables has injury risk implications.

Historically, the variability in movement has been attributed to noise in the system (Bernstein et al., 1996) but it was found that even in highly skilled tasks, such as javelin throwing movement strategy in elite athletes, that they were not capable of producing invariant movement across trials (Bauer & Schollhorn, 1997). Findings from this study developed the idea that there is no such thing as a 'representative trial' because of this variability in movement across trials. This was described by Bernstein (1967) as repetition without repetition.

The inherent variability that is present in movement likely exists because the abundance of our joints allows it. Outcome consistency does not require movement consistency because we have multiple options to achieve a given task (Bartlett et al., 2007). The use of movement variability to maintain task performance in experts has been documented but the mechanism of control is not well understood.

OFC is a motor control theory that explains the hierarchical control of movement, including the role of variability to maintain performance (Todorov, 2004). OFC proposes that when completing a motor task only deviations that interfere with the task goal are maintained while variability in task irrelevant aspects of movement are left free (Todorov & Jordan, 2002). This theory argues against the historical notion that we have pre-programmed motor patterns that indicate a specific trajectory of movement. This previously described process of motor control can be described as an open-loop concept whereas OFC control postulates that instead we use a closed-feedback loop where visual and proprioceptive sensory inputs provide afferent information to our motor system, which allow the body to adapt to environmental factors by taking advantage of movement variability to maintain task performance. This feedback loop allows for adaptable control so that as task demands change the motor control system can adapt to maintain task goals.

To illustrate this theory of OFC Figure 6 has been adapted from Scott (2004) to display the closed loop process of controlling volitional movement. For a given task, the central nervous system (CNS) will select an optimal feedback control law, which is a selection of parameters to control to achieve the motor goal in a task (Scott, 2004). In movement execution, noise in the system may influence successful completion of the motor task. This theory suggests that our system allows for online adaptive movement control using information about the initial optimal feedback control law and afferent information on motor performance. This afferent information is continually updated to maintain performance throughout the task. If noise in the system does not compromise the task goal then the CNS will not intervene to correct this task irrelevant variability. However, the CNS will intervene if noise in the system will compromise the completion of the task goal. This control of the task relevant variability but not task irrelevant variability is known as the minimum intervention principle (Todorov & Jordan, 2003).

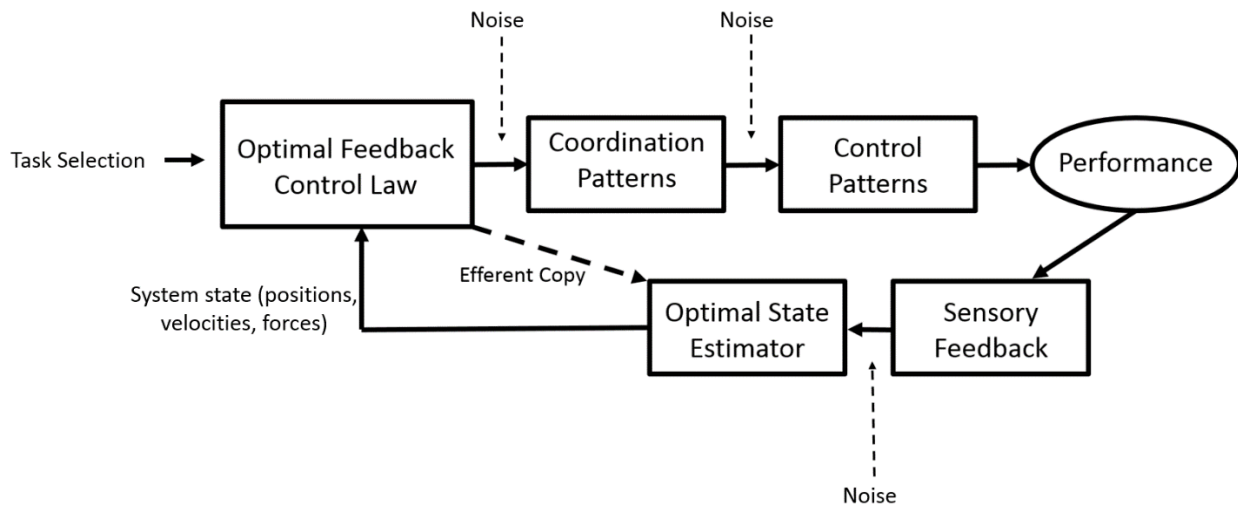


Figure 6: Closed loop model of optimal feedback control adapted from Scott (2004).

To achieve this online adaptive movement control there is a need for an optimal state estimate, which is related to the motor periphery in the task (Scott, 2004). Based on some metric of performance

the neural system synthesizes afferent sensory information and a copy of the efferent signal to provide online feedback to tune movement to achieve the task objective. In the presence of noise, this online feedback comes together at the optimal state estimator to adapt movement strategy to maintain completion of the task goal. To adapt movement behaviour the feedback loop adjusts gains on neural commands to tune movement to achieve task goals (Latash et al., 2005). This results in an updated optimal feedback control law which is geared to better achieve the goals of the task.

To better understand OFC, we can think about it in a contextual example. In a reaching task if there is no perturbation to the arm then the CNS will not intervene as nothing is affecting the ability to achieve the task goal. However, noise that disrupts trajectory of movement largely enough to compromise goal completion will attempt to be corrected within task performance via close loop feedback. This dispels the historical notion that the body does not recall rigid motor commands and instead uses flexible reconfiguration (Diedrichsen et al., 2010). Deviations relevant to the external task goal are corrected but task irrelevant movement (not relating to goal completion) is not compensated and so it can accumulate across repetitions (Diedrichsen et al., 2010). This allows for variance in strategy in the task irrelevant aspects of motion (Bernstein et al., 1996).

There is growing support of the OFC theory has come from experimental studies that have investigated simple motor tasks (Scott et al., 2015; Valero-cuevas et al., 2009) and sport applications (Morrison et al., 2016). However, movement strategy in occupational tasks, such as lifting, have not been investigated within the constructs of these theories. If movement strategy is controlled in lifting as it is in simple motor tasks there may be an allowance of task irrelevant variability if the load being lifted arrives at its desired end point.

2.1.2 Implications of Optimal Feedback Control theory in Occupational Lifting

The existence of OFC has implications when considering movement from a biomechanical standpoint. While biomechanics literature does a good job of describing how parameters such as spine compression are associated with different types of movement, it is often difficult to infer why such movement had occurred in the first place. It has been suggested that biomechanics research shift its focus from descriptive research towards the inclusion of theory-driven research by designing studies that consider both the consequence (biomechanics) and neural control of movement (Gregor, 2008). To better understand the question of 'why' in movement there is a need to consider the function of the neuromuscular system (Davids & Glazier, 2010). This presents an opportunity to consider the objectives of this study within the context of OFC.

In our primary research objective, the aim is to identify differences in movement strategy between high and low relative biomechanical exposure lifts. These differences could be attributed to differences in how some lifters parameterize an optimal feedback control law, within the OFC framework. For example, some lifters may consider "minimizing biomechanical demand on the body" as an aspect of their optimal feedback control law. In this regard, a lifter aiming to minimize biomechanical demand may be more sensitive to sensory feedback about the moment at the low back. While it is extremely difficult to conclusively identify an optimal feedback control law from a given task performance, we use OFC as a framework to infer that some lifters might consider MSD risk (biomechanical demand via sensory information about low back moments as an example) within an optimal performance, where others might not. For example, during a backboard lifting task moving the stretcher from its starting location to the end destination is likely an important outcome. If at any point a lifter's sensory feedback suggests that the load is no longer moving towards its destination, the CNS is likely to intervene and re-optimize the movement to ensure the load continues towards its destination. However, there is a possibility that across individuals there may be other objectives (or constraints) that

contribute to an individual's optimal feedback control law such as lifting 'safely'. A 'safe' lift may be defined as minimizing perceivable biomechanical exposures. Although there is a correlation of low back compression to injury risk it is unlikely that individuals perceive low back compression when lifting (Chaffin & Page, 1994; Thompson & Chaffin, 1993). However, biomechanically relevant exposures such as low back moments could serve as an alternate perceivable variable. Studies challenging participants to choose psychophysically acceptable loads provides evidence suggesting that low back moments were perceived by the lifters (Fischer & Dickerson, 2014; Jorgensen et al., 1999; Kuijer et al., 2012). With this afferent information from low back moments, individuals could have an optimal feedback control law inclusive of sensory feedback related to this biomechanically relevant exposure when controlling movement strategy. It is likely that some lifters will control movement strategy to minimize low back exposures, while others will not consider biomechanics in the approach to maintain the task goal of executing the lift.

2.1.3 External Factors influencing the Control Law

When thinking about lifting within an OFC framework, as noted early, each lifter will select an optimal feedback control law that they believe will be best to control the movement strategy to meet the task goal. As a reminder, we hypothesize that some may choose an optimal feedback control law that considers low back relative biomechanical exposures at heavy relative demand, where others may not. However, it is well established that external constraints can influence movement strategy used in lifting. One example of this is that the relative demand of a lift affects lifting patterns (Albert et al., 2008; Plamondon et al., 2017; Sadler et al., 2011; Sheppard et al., 2016), where lifters change their strategy as the relative demand is decreased. Explained from an OFC perspective, a change in movement at lower relative demands could suggest an accompanying change in the overarching optimal feedback control

law. To visualize how external constraints influence the formation of the control law Figure 1 has been adapted from Glazier (2017) which shows that changes in task, environment and organism constraints (taken from Newell's (1986) constraints model) influence how the control law is defined within the OFC closed feedback loop. Considering relative demand as an external constraint influencing movement strategy in lifting, as the relative demand changes the task constraint is modified. Lifting a lower relative demand would also impose lower biomechanical consequences on the low back (Plamondon et al., 2012), and so it is possible that minimizing biomechanical exposures on the low back may be less important to consider within the optimal feedback control law at this relative demand. Additionally, at lighter loads, lifters may have more movement options available to preserve the task goal. Conversely, during a heavier lift, the inertia of the load is much higher, likely restricting the number of movement options available to a lifter in order to leverage their strength to overcome the inertia of the load (Makhoul et al., 2017). Given the availability of more options, and lower relative biomechanical exposures during lighter lifting task, it is possible that at lower relative demands there is little influence on the development of the control law, whereas at a heavy relative demand the internal definition of the control law is likely influenced. By investigating changes in movement strategy across relative demand conditions it probes the hypothesis that external task constraints influence the internal formation of a control law.

2.1.4 Biomechanical Consequences of Movement Strategy in Lifting

Within the OFC framework task irrelevant variability, by default, does not affect the task outcome, but may affect biomechanical exposures. If the overarching optimal feedback control law does not consider biomechanical consequences when choosing how to control movement strategy to preserve the task goal, it is likely that aspects of task irrelevant variability may inadvertently expose the

mover to higher biomechanical risk. It is documented that across repeated lifting exertions there is trial to trial variability (Granata et al., 1999; Gagnon et al., 2002; van Dieën et al., 2001) but the implication of this variability on biomechanical exposures is not well understood. A potential positive is that trial-to-trial variability can distribute demands across tissues so that the cumulative load on any single tissue is not enough to exceed the tissue tolerance. This form of variability is argued to be beneficial as working with strategy that utilizes more variability has been shown to reduce fatigue in workers (Srinivasan & Mathiassen, 2012). With the intrinsic variability in movement there may be benefits to the worker in avoiding fatigue and injury.

Further evidence of the importance of movement variability is its relation to the development of pain. It is theorized that the loss of variability is believed to increase the probability of developing MSDs in work (Mathiassen, 2006). In the literature, long-term pain conditions have been associated with less motor variability for the knee joint, (Georgoulis et al., 2006; Heiderscheit et al., 2002; Hamill et al., 1999; Sondergaard et al., 2010) low back (van den Hoorn et al., 2012) and shoulder (Falla et al., 2008). Although correlations between pain and low movement variability have been observed, there is no causative link between low movement variability and pain or injury that has been established in the literature. Even without such a link, the association of low movement variability and pain is a concept that should be considered when evaluating factors which could precipitate risk of MSDs.

In the OFC framework, task irrelevant variability is not controlled in the closed feedback loop. From an ergonomics lens, in a repetitive task which allows for variability without compromising task performance having higher task irrelevant variability may be a protective effect (Srinivasan & Mathiassen, 2012). There is a possibility that having variability in redundant degrees of freedom may be considered within the optimal feedback control law to influence workers to exhibit higher variability. To date there is no evidence to suggest that the optimal feedback control law governs movement to maximize variability as suggested. However, exploring whether the optimal feedback control law

considers factors related to injury risk could aid in understanding deterministic origins of movement variability and its relationship to MSD risk.

Although variability offers benefits in reducing injury risk in some regard there may also be a need to control variability in certain scenarios such as when lifting a high external load. Motor abundance allow us many options to move the load but from an injury risk perspective there are some strategies that are more beneficial to use to reduce the loading on any one tissue. Considering backboard lifting, restriction of variability to use a movement strategy which minimizes biomechanical exposure to the body is recommended due to the nature of the task. Over the course of a work shift paramedics only perform 2-3 backboard lifts, albeit with heavy loads. The low number of repetitions does not make using variable strategy a beneficial injury prevention strategy. The high external load gives a greater risk of an acute injury mechanism where a single large force exposure exceeds tissue tolerance (McGill, 2015). For this reason, movement strategy that minimizes biomechanical exposure should be used on every backboard lift repetition.

Considering the demands of the backboard lifting task in a work shift there is a tangible opportunity to recommend ideal strategies to use. By identifying aspects of movement strategy that differ between high and low relative biomechanical exposure lifters we can coach movement strategy to minimize the biomechanical demand in any given repetition without trying to systematically induce variability into strategy which may be more difficult.

2.1.5 Modifiers of Movement Strategy in Lifting

The role of OFC in controlling human movement has been discussed but contextualizing previous experimental findings while considering OFC may explain the basis of movement variability and differences in movement strategy across different lifting conditions. To address our primary objective of

identifying what aspects movement strategy differ between high and low relative biomechanical exposure lifts we must understand how changing task constraints, as conceptualized by Glazier (2017), influences variability and movement strategy in lifting. This will allow us to develop methodology that minimizes confounding factors to best address the research question of interest. For this investigation there is limited research on how variability in lifting changes but there are numerous studies exploring changes in lifting strategy based on altering constraints such as experience, load, sex and relative demand.

Variability has a functional role in motor development (Bartlett et al., 2007). As expertise is built the level and type of variability exhibited in movement changes in task execution. For this reason, it is expected that across different levels of expertise there will be changes in variable movement strategy exhibited in lifting. One may hypothesize that with experience that individuals will take advantage of their bodies abundant degrees of freedom to minimize variables that are associated with risk of MSD development. This hypothesis has support when considering posture, where experts tended to have less low back flexion and more knee flexion in lifting (Plamondon et al., 2014; Plamondon et al., 2012). However, in a study which looked at variability in low back loading evidence does not support the hypothesis where experts exhibited greater mean sagittal and axial low back moments as well as greater mean low back loads (medial-lateral (M-L) shear, anteroposterior (A-P) shear and compression) compared to inexperienced lifters (Granata et al., 1999). Although these measures were significantly greater in the experienced population the variability in these values varied more trial-to-trial compared to the inexperienced group. To explain these findings the authors discussed the relationship between spinal load and tissue tolerance. Although absolute loads were higher in the experienced group the co-activation of flexor and extensors in the trunk was also higher which had been previously suggested to be associated with higher trunk stability (Cholewicki et al., 1999) which is suggested to reduce risk of MSDs (Cholewicki & McGill, 1996). This co-activation as a protective effect may be a result of

experienced lifters updating their optimal feedback control law to better consider trunk stability. With experience, lifters may begin to identify aspects of movement strategy that are related to injury risk and control them via the closed feedback loop. In this study it was also stated that the experienced group likely had higher capacity, which would allow them with more flexibility in their selection of lifting strategy. Similar results were found in a later study looking again at the effect of experience on lifting strategy. Experienced workers had higher peak kinematics and kinetics in lifting but had greater dynamic balance measured by peak horizontal momenta, angular momenta and largest Lyapunov exponent (Lee & Nussbaum, 2014). Findings from these studies demonstrate that expertise does play a role in influencing movement strategy in lifting. These results support the hypothesis that the sensorimotor system in experienced lifters seems to control variables that are related to injury risk, which supports that mitigating MSD injury risk can be considered within the optimal feedback control law.

Although informative, the results of these studies are limited by the low loads used in their lifting trials and the fact that capacity in lifting was not controlled for. In lifting, movement strategy is informed by many environmental factors including expertise and load. In the previous paragraph, which reviews the effect of experience, confounders of load and relative demand are not controlled for in all studies. To understand the role of all factors on lifting strategy the effect of load and relative demand will be discussed in the following paragraphs to better contextualize what factors determine movement strategy in lifting.

Lifting has been investigated under different loads to determine the effect of load on movement strategy. It has been found that as load increase interjoint coordination is more sequential starting with distal movement (Davis & Troup, 1965; Scholz, 1993a, 1993b; Scholz & McMillan, 1995; Burgess-Limerick et al., 1995). To interpret these findings in an OFC framework it is possible that an increase in load resulted in lifters refining their optimal feedback control law dictating movement strategy. The distal to proximal strategy may be adopted as an injury prevention measure to avoid large magnitudes of lumbar

acceleration when the acceleration of the load is greatest (Davis & Troup., 1965). It is likely that low back moments are high at this time point as peak joint moments were reported to occur at 25% of extension duration (De Looze et al., 1993). Delayed extension of the low back will protect the low back from the peak moment demands and instead can shift moment contributions across other joints of the lower extremity. At lower loads, there may be less importance on protecting the low back from peak moments as the absolute moment magnitude is lower which could result in more variable movement strategy. In a heavy load condition, the movement strategy may be controlled to incorporate this temporal delay as a protective effect resulting in less variability in strategy.

Sex effects have been proposed as a mechanism that influences movement strategy in lifting. Women have been documented adopting a more leg driven strategy whereas men tend to lift more with their back (Li & Zhang, 2009; Marras et al., 2003). In one of these studies, women had significantly lower compressive loading compared to men and these differences between groups became greater as external load increased (Marras et al., 2003). Although differences in sexes were observed in these studies this was attributed to differences in strength between the two groups. In a later study, females were once again shown to have lower low back loading when lifting the same weight as males and a more sequential distal to proximal lifting pattern (Plamondon et al., 2014). Another study which looked at lifting in a paramedic population found that females generated more work with the lower body in lifting and had more neutral low back angles (Makhoul et al., 2017). This was attributed to females adopting a strategy that minimized effort while trying to maintain safety by controlling their low back angle. These studies provide evidence of differences in movement strategy between sexes but in all studies the load lifted was absolute regardless of participant characteristics. If strength was controlled for (i.e., the relative demand of the load) would the same results of been found?

To understand whether participant capacity modulates the effect of absolute load on movement strategy the effect of relative demand on movement strategy should be investigated. By normalizing an

external load to some measure of physical capacity the observed affects represent strategy at a demand which can be compared across participants. This approach is argued to have better external validity compared to lifting an absolute load (Plamondon et al., 2017). When comparing lifting strategy across individuals who were tested for leg and back strength those who had greater back strength adopted a more back like lift and vice versa (Li & Zhang, 2009). This provides an argument that lifting movement strategy is likely influenced by relative demand in some manner.

To further support the importance of relative demand previous work has demonstrated that it is more important than sex when identifying determinants of movement strategy in lifting. A study which investigated lifting strategy while controlling for relative demand found that there were no significant sex effects on postural index, joint range of motion and relative phase angles in lifting (Albert et al., 2008). These findings were echoed in a later study where PCA was used to examine variability in kinematic variables between sexes at a low relative demand normalized to maximum back extensor strength (Sadler et al., 2011). The purpose of these two studies was not to investigate changes in lifting strategy at different relative demands but rather to control for relative demands to assess sex differences in movement. In a separate study, an effect of sex on movement strategy in lifting was found in a repetitive palletizing task where females adopted a more distal to proximal strategy under what was considered the same relative demands (Plamondon et al., 2017). A limitation in this study was that the method to find relative demand was to assume a constant strength capacity within each sex but to assume that females had 2/3 the strength capacity that males did. This would offer a crude estimate of strength capacities of participants, but this approach did not give concrete evidence of what relative demand the participants are working at. Although the selection of 2/3 as a relative demand was supported, (Mital et al., 1997) across a population the strength capacity of people will vary based on a number of factors including anthropometrics, training level, age, etc. (Fuster et al., 1998). Without controlling for any of these factors it is difficult to know how accurate and controlled the representation

of relative demand is. Together these studies highlight the importance of controlling relative demand when assessing movement in strategy.

The previously discussed studies support that relative demand may be an important determinant of changes of movement strategy in lifting but only one relative demand was investigated in all studies reported thus far. The use of one relative demand condition limits the ability to make conclusions about how movement strategy changes as a function of relative demand. A study that investigated differences in lifting movement strategy between sexes at different relative demands found that there was no significant effect of sex on retained principal components (PCs) but there was a significant effect of relative demand on five PCs of the lower extremity (Sheppard et al., 2016). These findings support that movement strategy was different across relative demands conditions in lifting. Although a significant effect of relative demand was found on PCs, a limitation was that the relative demand was normalized to maximum back extensor strength of participants. Although this gives a measure of relative demand, using this methodology capacity of lower extremity is not considered which may compromise the internal validity of the calculation of relative demand. To increase internal validity of the relative demand calculation loads should be normalized to a value that considers total capacity which can contribute to a lift opposed to capacity of a single joint. In the Sheppard et al. (2016) study three relative demand conditions of 10%, 20% and 30% of maximum extensor strength were used. Findings from this study were able to identify differences in strategy between these conditions for some PCs but it is not known how movement strategy will change at higher relative demands. Although this was outside of the scope of the Sheppard et al. (2016) study it can be explored in future directions, which this thesis addresses by considering the effect of greater percentages of relative demand on movement strategy.

From these findings, it seems that a major contributor to movement strategy in a lift is relative demands as relative demand effects washes out the effect of sex on strategy. With the noted

importance of relative demand it is important to control for it to address our research objectives of identifying differences in PMs between high and low relative biomechanical exposure lifts and lifters. With limitations to previous research there is also opportunity to explore how relative demand affects PMs in both high and low relative biomechanical exposure lifters as is proposed in research question 2.

2.2 Pattern Recognition to Quantify Movement Strategy

Whole body movement strategy is a key outcome of interest when considering movement from performance and risk perspectives. Classic approaches to this issue use discrete measures within the lift cycle such as means or peaks that occur at key time points. However, these variables need to be selected *a priori* (Lees, 2002) and there is an aspect of researcher subjectivity in deciding what aspects of the data are important and which are not. With a discrete measures approach there are also limitations associated with only analyzing movement strategy at certain time points, which ignores the time-series of movements over the duration of the action, which could contain important information. Because of these inherent limitations in the use of discrete parameters typically representing individual time points, this approach may not be useful to analyze movement strategy in backboard lifting, particularly within an OFC theoretical orientation.

An example of discrete measures not being the most insightful measure when analyzing similar data was seen in the secondary analysis performed on data published by Makhoul (2017). Work from Makhoul found that doing more work with the lower body lead to lower biomechanical exposures at the low back. With the concept of 'doing work' being an abstract coaching cue we investigated whether there was a relationship between timing of power generation and biomechanical exposures as we believed timing would be more clear to coach. Specifically, we investigated whether timing between peak knee and low back power had any relation to peak low back moment and peak trunk flexion angle.

There were no relationships found between the difference in peak power timing to the measures of low back moments and trunk flexion angles (Armstrong & Fischer, 2017). When considering the power profiles there was rarely a clear peak in power profile magnitude which could be a factor in why no relationship was seen between difference in timing and variables associated with low back MSD risk. Considering sample data of eight participants, four with the lowest and four with highest peak trunk flexion angles in scoop stretcher lifting, there is variability in both knee and low back power profiles (Figure 7). When considering these power profiles by looking at a discrete time point, in this case peak power, most of the waveform is ignored. This highlights the need for a statistical analysis technique that objectively considers the entirety of the lift opposed to using discrete measures at specific joints.

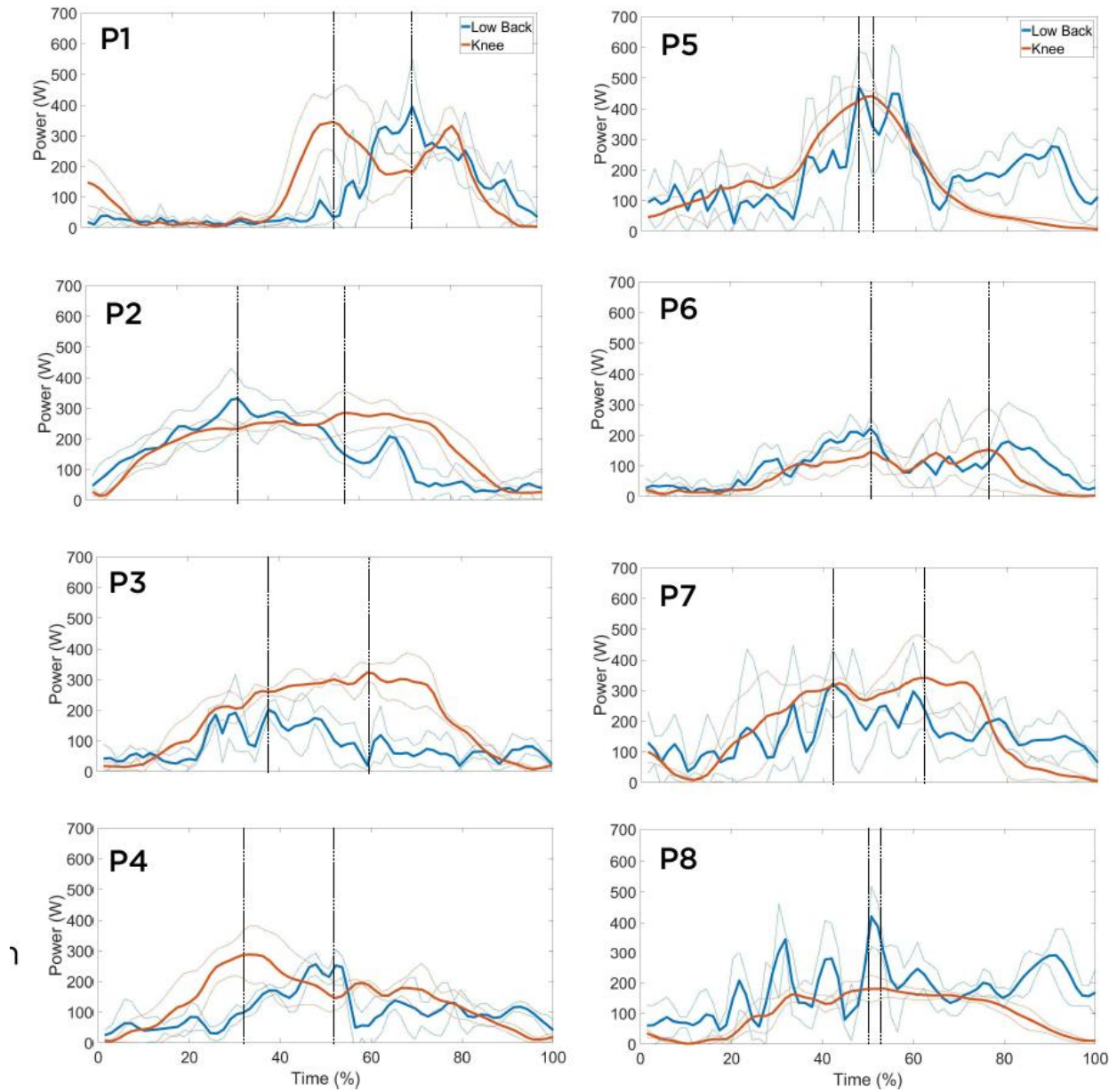


Figure 7: Average knee and low back power profiles normalized to percent of lift for participants with the four lowest (P1-P4) and four highest (P5-P8) peak low back flexion angles.

To quantify movement strategy, it is important to consider whole body motion. Movement strategy in lifting has been quantified in a number of ways including use of a lift index based on body configuration at lift onset (Burgess-Limerick & Abernethy, 1997), analyzing lower body joint angles

(Gagnon & Smyth, 1992; Hwang et al., 2009; Sadler et al., 2011; Zhang et al., 2000), and using relative phase angles to quantify coordination (Albert et al., 2008; Burgess-Limerick et al., 1993; Burgess-Limerick et al., 1995; Lindbeck & Kjellberg, 2001; Plamondon et al., 2017; Scholz, 1993; Seay et al., 2016). While there are pros and cons to using any of these methodological approaches a common drawback to these approaches is that they quantify movement of the lower extremities and trunk while ignoring the upper body. It has been shown that in a repetitive lifting task that participants changed shoulder and elbow posture to bring the load closer to the body (Fischer et al., 2015). This control of the upper extremity supports the need to consider the upper body in this analysis as it can contribute to moving the external load and modulating biomechanical exposures.

Using OFC as a model to explain movement in a lifting task there is flexibility in control of the abundant degrees of freedom to achieve the task objective of moving the backboard to its lifted height. The upper extremity can contribute to the abundant degrees of freedom that can play a role in moving the backboard. Although it is likely that the lift will be driven by movement of the lower body, to quantify lifting movement strategy in its entirety the consideration of the upper body is needed within the OFC framework because of the degrees of freedom it contributes.

For this thesis, a method that objectively quantifies whole body dynamics of movement is needed to analyze movement strategy in lifting within the OFC framework. Pattern recognition techniques present as an option to meet these methodological needs.

2.3 Principal Component Analysis for Pattern Recognition

A pattern recognition method which can consider the entire waveform and is capable of reducing a multidimensional data set to analyze modes of variability in human motion is Principal Component Analysis (PCA) (Lynn & Noffal, 2012; Daffertshofer et al., 2004). PCA considers an entire

waveform and is an unbiased method to extract features of the data set that explain the greatest proportion of variance. In a data set with n dimensions there will be n principal components. However, the first PC will explain the greatest amount of variance in the data set and each subsequent PC will explain a lower proportion of variance, where the first few PCs can often capture much of the variability present in the data. With each PC, there is an associated PC score for each trial that corresponds to how close the trial is to the mean of that PC. A PC score with a larger magnitude represents a greater discrepancy from the mean for that group (Deluzio et al., 2007).

PCA is a pattern recognition technique that is beginning to gain traction in the biomechanics literature. The goal of this analysis is a mode reduction method that can detect variant properties in biomechanical data (Daffertshofer et al., 2004). The technique has upside as it accounts for variability in a data set, which is an asset in biomechanics research because, as noted before, human movement is inherently variable. A second positive aspect of this technique is that it considers the entire waveform of data as opposed to discrete data points. Averages, maximums and minimums of kinematic and kinetic data can be useful in answering some research questions but may miss crucial information by neglecting or reducing aspects of the waveform (Khalaf et al., 1999; Wrigley et al., 2005). In the biomechanics literature PCA has been applied as a waveform analysis technique to examine variability in lifting, (Khalaf et al., 1999; Sadler et al., 2011; Sadler et al., 2013; Wrigley et al., 2005; Wrigley et al., 2006), gait (Deluzio & Astephen, 2014; Donà et al., 2009; Mezghani et al., 2010; Reid et al., 2010; Deluzio et al., 1997), golfing (Lynn & Noffal, 2012) and jump rope (Bruce et al., 2016).

For this thesis the goal was to quantify movement strategy where movement strategy is defined based on whole body motion. Previously mentioned research examines aspects of human motion via analysis of joint specific kinematic and kinetic waveforms, but to best answer the research questions posed in this thesis we need a pattern recognition approach that considers whole body motion. One such technique to consider whole body motion is to quantify principal movements via a PCA modelling

approach where kinematic marker data is used as an input (Federolf, 2016). This approach was originally developed by Troje (2002) where the data reduction technique was used to quantify differences in walking between males and females. This technique has been applied to quantify movement strategy in standing (Federolf et al., 2013), alpine skiing (Federolf et al., 2014), human gait (Maurer et al., 2012), diving (Young & Reinkensmeyer, 2014), a fitness assessment battery (Ross et al., 2018) and cross country skiing (Gloersen et al., 2017).

Using PCA to capture PMs has benefits of capturing whole body motion but is also beneficial as it can be contextualized within the OFC framework. Previously, PCA has been used to quantify variability in joint angles in a reaching task to determine whether variability was task relevant or not (Todorov & Jordan, 2002). PCA was successful in identifying redundancy in the task execution, which supports that PCA is conceptually compatible with the theoretical framework of OFC. By breaking movement strategy down into PMs, we can identify aspects of movement that explain variance in the data set. By testing for differences in PMs between groups, we can begin to understand what components of movement strategy are considered task relevant for low relative biomechanical exposure lifters and controlled in the OFC framework. In this thesis, OFC is used as a theoretical framework to hypothesize why movements might differ between groups and across conditions. This proposed PCA approach allows us to test whether low relative biomechanical exposure lifters control aspects of movement strategy differently than high relative biomechanical exposure lifters by comparing mean PM scores.

With whole body PCA driven pattern recognition approaches a common limitation is that many of the analyses have conducted separate PCA analysis on each participant. This method may result in the principal components explaining different aspects of variance in each participant. Applying this approach with all participants' data in a single PCA model can allow for comparison between participants as with the use of a component reconstruction we can recreate PMs. Gloersen et al., (2017) used this approach to compare differences in alpine skiing movement strategy between athletes with

two levels of proficiency. In their analysis they were able to identify differences in movement strategy between the two levels of proficiency as experts activated hip flexors in phase with release of potential energy from the ski poles and controlled their skis to better align their skis in the forward direction in the gliding phase. The authors recognized that the differences do not imply a causal relationship between PMs and performance but with the visualization of PMs coaches can train skiers to mimic movement strategy of experts to improve performance. Using this approach in an occupational context, we may be able to identify differences in movement strategy between lifts with and without low back sparing strategies. No previous literature has quantified differences in whole body motion during occupational lifting between high and low biomechanical exposure lifters using this PCA approach. This thesis will allow for identification of differences in PMs between the two groups as Gloersen et al. (2017) have done for cross country skiers. With the ability to visualize differences in movement strategy this will provide direction to inform training strategies to improve lifting mechanics in the workplace.

Using this PCA pattern recognition approach, we will be able to identify PMs within a population for a backboard lifting task. An added benefit to this approach is that in addition to identifying differences in movement strategy between high and low relative biomechanical exposure individuals we are able to reconstruct motion using PMs and their respective PM score (Troje, 2002). The outputs of the reconstruction will produce a three-dimensional representation of the body for each group based on differences in PMs that explain most of the variance in the data set. With this visualization, we can display how movement strategy differs as a function of biomechanical consequences to aid in the practical objective of assessing movement strategy.

Considering past use of PCA in biomechanics research, its role has been to identify differences in kinematics between groups. For interpretation of PCA analysis PMs can be classified on the aspect of variability they represent as magnitude, difference or a phase shift operator, which is consistent with descriptions from Wrigley et al. (2005). Magnitude operators look at amplitude of the waveform, phase

shift operator is a temporal shift of the average waveform and a difference operator quantifies where the waveform crosses. Interpretation of PMs as one of the three listed operators will allow us to understand how differences in PMs influence movement strategy.

3.0 Research Questions and Hypotheses

Research Question 1: How does movement strategy differ between high and low relative biomechanical exposure lifts and across light, medium and heavy relative demand conditions when performing backboard lifting?

It is hypothesized that differences in PM scores will be observed in some PMs between high and low relative biomechanical exposure lifts and across relative demand conditions.

This research question aims to objectively identify how features of movement differ between high and low exposure lifts. Relative demand is considered as a second independent variable as it has been noted as a determinant of lifting strategy in past literature (Albert et al., 2008; Plamondon et al., 2017). Results to this research question can be used to develop training interventions that stress features of movement associated with lower biomechanical exposures.

Research Question 2: How does average movement strategy differ between high and low relative biomechanical exposure lifters and across light, medium and heavy relative demand conditions in backboard lifting?

It is hypothesized that there will be significant differences of mean PM scores between high and low relative biomechanical exposure lifters at heavy relative demands in PMs where significant main effects of relative biomechanical exposure were seen in research question 1. Across PMs, it is hypothesized that there will be main effects of relative demand on PM scores consistent with findings from research question 1. In PMs where there are interaction effects between relative biomechanical exposure and relative demand it is hypothesized that there will no differences of PM scores between relative biomechanical exposure groups at the medium and light relative demand conditions as revealed by post hoc testing. No differences are hypothesized between high and low exposure lifters at the light

and medium relative demands is because the greater abundance of available strategies at lower relative demands will allow participants to consider optimizing other factors, such as minimizing energy expenditure, instead of optimizing resultant relative biomechanical exposure.

This research question extends on research question 1 by determining whether features of movement identified to be related to biomechanical exposure are consistently controlled to identify lifters by their resultant exposure within a motor control framework. By comparing the mean movement strategy in the context of Glazier's (2017) motor control model it accounts for the inherent variability in movement because of the motor abundance our bodies have to achieve task performance (Latash, 2012). By considering mean movement strategy, it will inform what features of movement related to relative biomechanical exposure (identified in research question 1) are consistently controlled to inform movement strategy assessment. While many features of movement may be identified as associated with resultant biomechanical exposure in research question 1, only factors which are consistently controlled as probed in research question 2 can be used to inform assessment of strategy. Once again, relative demand is considered as a potential confounding factor where there may be an interaction between relative biomechanical exposure and relative demand on mean movement strategy between high and low exposure lifters. A potential interaction of relative biomechanical exposure and relative demand would have implications for assessing backboard movement strategy in practice.

4.0 Methods

4.1 Study Design

In this cross-sectional within-subjects study design, participants came to the Occupational Biomechanics and Ergonomics lab (OBEL) at the University of Waterloo where kinematic and kinetic data were collected while participants performed backboard lifting actions. Using the kinematic and kinetic data lifts and lifters were stratified into high and low relative biomechanical exposure groups. These data were used to identify PMs. Differences in PM scores were compared between high and low relative biomechanical exposure lifts and lifters to reveal how movement strategies differed between the two groups. Lastly, the research design allowed us to explore if these movement strategy differences were consistent across light, medium and heavy relative demands.

In research question 1, the independent measures included relative biomechanical exposure status and relative demand condition. Relative biomechanical exposure status was determined as high or low for each lift, based on an aggregate measure including peak low back angle, peak low back moment and moment at peak low back angle. PM scores for retained PMs were included as dependent variables. To address the second research the independent variables were once again relative biomechanical exposure status and relative demand condition. However, for the purpose of research question 2, relative biomechanical exposure status was based on a lifter's combined biomechanical exposure across all 10 heavy relative demand lifts. PM scores in retained PMs remained as the dependent variables.

4.2 Participants

Twenty-eight participants were recruited to participate in this research study (Table 1). Lifting experience was considered during enrolment to ensure that the participant pool represented a range of expertise including less experienced lifters and those more proficient in backboard lifting (e.g.,

paramedic’s in training or active duty paramedics). It was important to include a range of expertise in backboard lifting so that the participant pool reflected a range of movement strategies that could be used in backboard lifting. To maintain external validity of findings a portion of the population was recruited from the paramedic sector so that movement strategy used on the job is considered in the analysis. To maximize internal validity all participants were injury free in the previous year to be eligible to participate in the study as injury could affect movement strategy used.

Table 1: Participant Demographics.

Participant Group	Sex	Age (years)	Height (m)	Weight (kg)
Paramedic Experience	7 ♀, 5 ♂	25.1 ± 3.4	1.71 ± 0.10	82.1 ± 15.1
No Experience	7 ♀, 9 ♂	23.2 ± 2.2	1.74 ± 0.12	75.5 ± 17.0
All	14 ♀, 14 ♂	24.0 ± 2.8	1.73 ± 0.11	78.3 ± 16.3

Prior to study commencement, the study protocol was approved by both a University of Waterloo Research Ethics Committee (ORE #22811) and a Conestoga College Research Ethics Board (REB #247). All participants provided informed consent prior to participation in the study.

4.3 Instrumentation

4.3.1 Motion Capture

A 12-camera Vicon system (6 Vero v2.2, 6 Vantage V5, Vicon Motion Capture, CA, USA) was used to capture 3D motion data. Motion data were sampled at 100 Hz using Vicon Nexus (Version 2.0, Vicon, Oxford, UK) software. An illustration of reflective marker placement is seen in Figure 8.

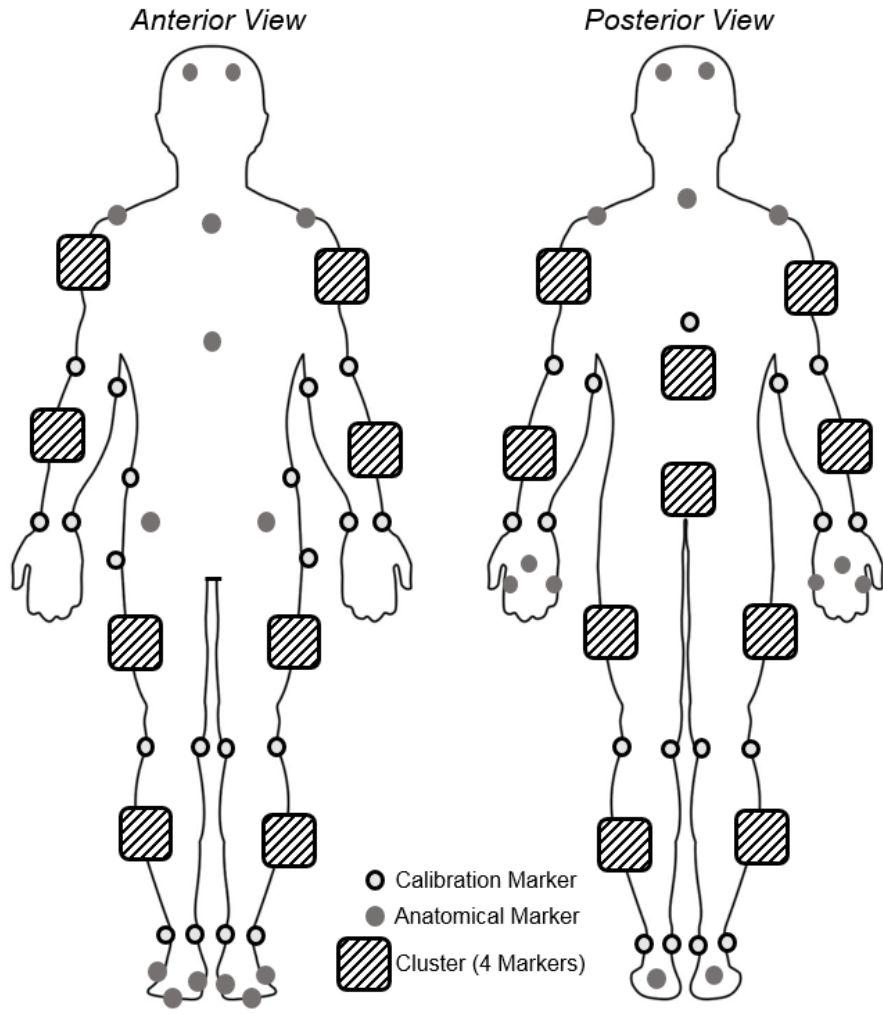


Figure 8: Placement of reflective Vicon markers for motion capture collection.

4.3.2 Force Plates

Ground reaction forces and moments were collected using two force plates (Bertec Corporation, Columbus, OH, USA) synchronized with VICON Nexus 2.0 software at a sample rate of 1000 Hz.

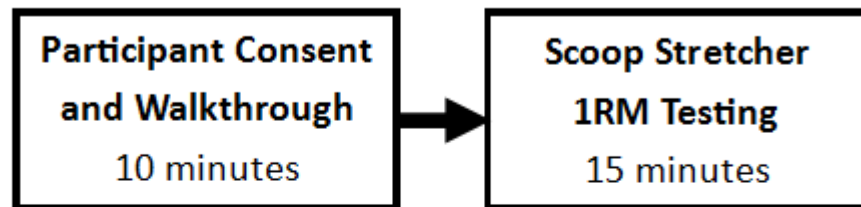
4.4 Protocol

Experimental protocol for the study was broken up into two sessions; a one-repetition maximum (1RM) testing session and a backboard lifting session (Figure 9) which took place on separate

days. In the 1RM session participants began with a walkthrough of the methods and signing consent to participate. After the consent process was completed their 1RM backboard lift was determined through a sub-maximal estimate (LeSuer et al., 1997). Although the sub-maximal estimate equation is validated for use on the squat, deadlift and bench press, the backboard lift was evaluated as if it was a resistance training exercise.

In each participant's second session, they arrived at the lab and were prepared with reflective markers for motion capture. When all markers were affixed, static and dynamic calibration trials were collected prior to beginning lifting exertions. They then performed 10 single lifting trials of the backboard in each of three different load conditions corresponding to 25%, 50% and 75% of their 1RM backboard lift. The order of presentation of lifting loads was randomized.

Session 1:



Session 2:

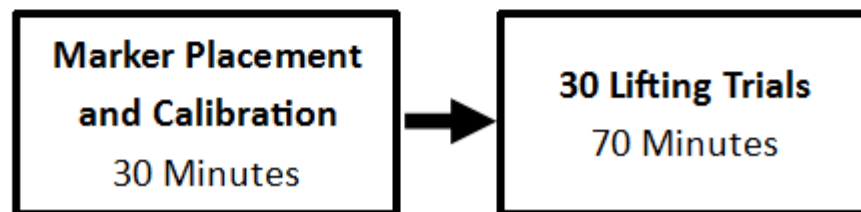


Figure 9: Protocol overview with estimated associated timing for sessions 1 and 2.

4.4.1 Session 1 – 1RM testing

In session one participants tested their backboard lift 1RM. The calculated backboard 1RM was used to scale the loads on the backboard in the second session.

Prior to the sub-maximal testing all participants were lead through a warm up. This warm-up primarily targeted the lower body as the focus of the 1RM testing was a lifting exertion. Warm-up consisted of large steps and twisting to the lead leg, body weight squats, body weight lunges, sagittal plane hip swings and frontal plane hip swings. The 1RM testing protocol was consistent with the Center for Community, Clinical and Applied Research Excellence standard operating procedure on 1RM testing (Appendix A) which refers to Baechle & Earle (2000) and Heyward (2014). In this protocol, participants performed a first set of 10 repetitions with an approximated load ranging between 40-60% of their 1RM. A three minute rest was then taken prior to a second warm-up set of 3-5 repetitions with approximately 60-80% of a participants anticipated 1RM. A five minute rest break was taken prior to the third set in which the number of repetitions performed and mass of the load were used to estimate participants' 1RM. Based on feedback from the participant in set 2 the researcher selected a load corresponding to ~90% of a participants' 1RM for the third testing set. Participants performed the maximum number of repetitions possible in the third set prior to ending the set due to self-reported fatigue. A research assistant could also terminate this testing set if the participant changed their movement strategy mid set. Changing of movement strategy served as a safety criterion where researchers interpreted a change in strategy as an inability to control the load. Participants were encouraged to self-select their movement strategy and were made aware that changes in strategy mid-set would result in termination of the set.

Using the mass of the load and the number of repetitions performed equation 1 was used to estimate a participant's true 1RM (Wathan, 1994). This equation showed the best predictive value when evaluated against other 1RM prediction tools (LeSuer et al., 1997).

$$\text{Equation 1: } 1RM = 100 * \frac{(\text{Repweight (kg)})}{(48.8 + 53.8 * e^{(-0.075 * (\# \text{ of reps}))})}$$

4.4.2 Session 2 – Backboard Lifting

4.4.2.1 Participant preparation and calibration

Session 2 began with participants arriving at the OBEL lab where they were prepped for motion capture collection. Markers were placed on the following landmarks bilaterally for calibration: 1st metatarsal head, 5th metatarsal head, calcaneous tuberosity, 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 head and 5th metacarpal head. Rigid bodies with four reflective markers were attached on each segment of interest (bilateral shanks, thighs, upper arm, forearm, hand, pelvis and thorax). Rigid bodies remained on the participant during active lifting trials and calibration markers were removed. To limit the movement of rigid clusters they were fastened to the participant with Velcro straps.

A static calibration trial was collected with the participant in a 'motorbike' pose which is the recommended posture as written in the Vicon Nexus 2.0 user manual (Figure 10).

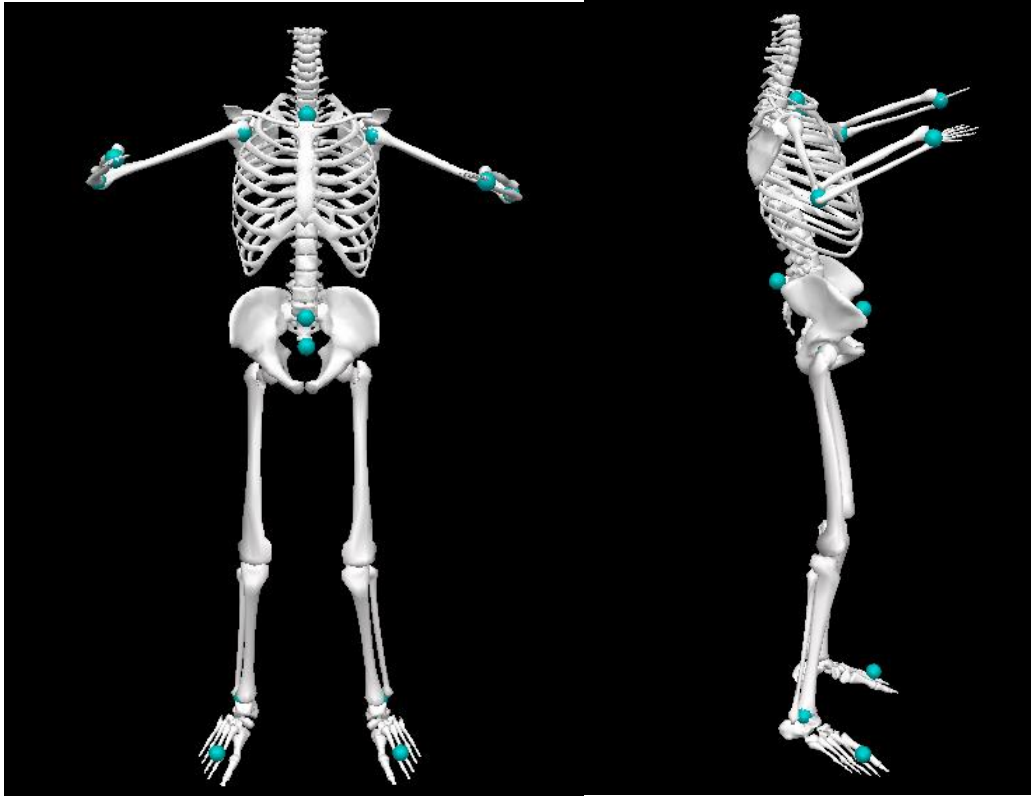


Figure 10: Representation of participant in the motorbike pose from Visual3D from the frontal (left) and sagittal (right) plane.

Dynamic movement calibration trials were also collected where the participant moved all joints through the range of motion that will be used in lifting trials. Vicon recommends using full range of motion calibrations as they result in the best labeling of markers collected in experimental trials. The data points in this dynamic calibration trial were manually labelled and then used to create a model template, which was applied to lifting trials to label markers.

4.4.2.2 Lifting Trials

Participants completed 10 lifting repetitions in each of the three relative demand conditions: low, medium and high. These repetitions were completed with the relative demand on the backboard

being 25%, 50% and 75% of their 1RM backboard lift within ± 2 kg. Barbell plates were used to load the backboard. Because the exertion is a two-person lift, a trained lift partner lifted the opposite side of the board. The participant was responsible for counting and cueing on each lift in an effort to minimize the influence the effect of the lifting partner minimally on a participant's movement strategy. The use of a lifting partner was necessary to increase external validity where a backboard lift is routinely completed as a partnered lift.

The relative demand in the lifting trials was randomized in order to minimize fatigue, learning effects and complacency at a given load. These factors could affect a participant's movement strategy, which would reduce the internal validity of the study design. Randomization also increased external validity, as any given lifting trial will be more representative of the single repetition lifts paramedics perform on the job.

To minimize fatigue in this study mandatory 1-minute breaks were taken after every lifting trial and a 3-minute break was mandated after every 5 repetitions. In a similar repetitive lifting based protocol Sheppard et al. (2016) used these rest times to prevent fatigue. In addition to the mandatory rest periods, participants were allowed to take as much time as they needed to recover between lifting trials so that they were not experiencing subjective fatigue before the next trial. A sample lifting protocol is pictured in Figure 11.

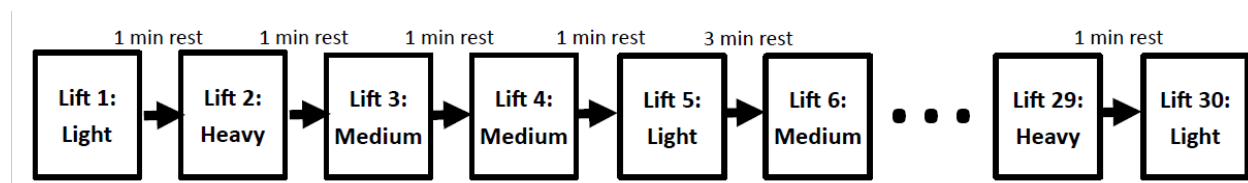


Figure 11: Sample randomized lifting trial order with rest times.

4.5 Data Processing

Figure 12 illustrates the general flow of data treatment and analysis. Methods are described in greater detail in the following sections.

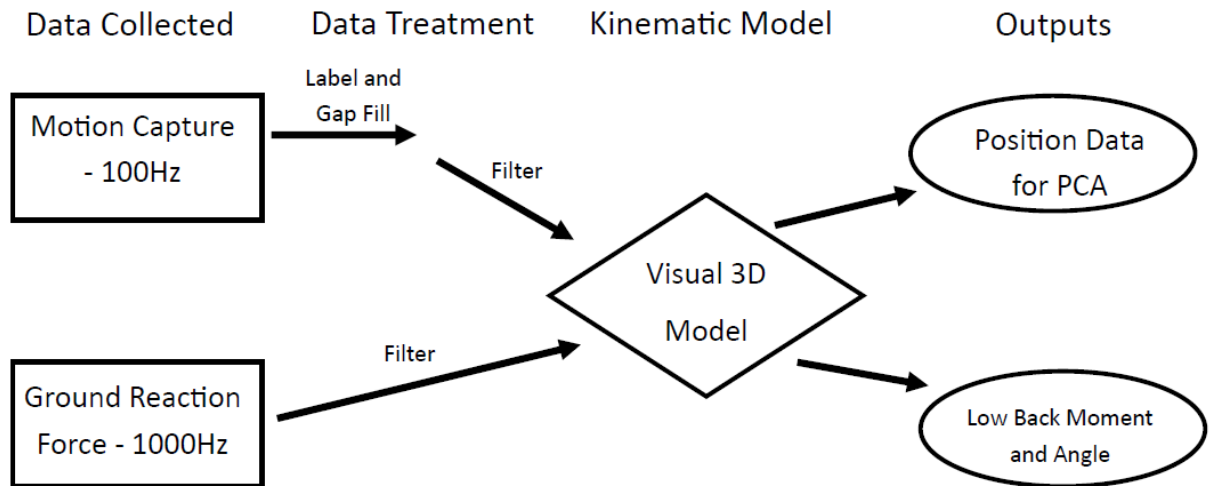


Figure 12: General flow of data collection, treatment and analysis.

4.5.1 Data Treatment

Kinematic data were examined in Nexus 2.0 software for missing or unlabeled data points. Any instances of missing markers were filled using gap filling functions built into Nexus 2.0. For gaps less than 200 ms in duration, a cubic spline was used to fill missing data points. If marker data were missing for more than 200 ms either pattern fill or rigid body fill was used. This is consistent with recommended gap filling techniques outlined by Howarth and Callaghan (2010). The rigid body fill technique was preferred over the pattern fill as it uses the position of three other cluster markers to infer position of the missing data. The pattern fill uses position data of one other marker to interpolate position of the missing marker. Pattern fill was only used when there were not 3 available markers on the rigid body cluster at the time point which the gap needs to be filled.

4.5.2 Data Analysis

Marker trajectories and ground reaction forces were imported into Visual3D (C-Motion Inc., Germantown, USA) software for analysis. Prior to data analysis kinematic and force data were dual pass filtered in Visual3D through a low pass second order Butterworth filter with an effective cut off frequency of 6 Hz (Winter, 2009). To filter at an effective cut off frequency of 6 Hz an initial filter cut off was set at 7.5 Hz for the first pass through the filter as on each pass the effective cut off frequency decreases.

After filtering, a whole body kinematic model was created consisting of pelvis and thorax segments in addition to bilateral foot, shank, thigh, upper arm, forearm, and hand segments. Markers placed medially and laterally on their proximal and distal endpoints defined foot and shank segments. The anatomical markers on the iliac crests, acromia, suprasternal notch, xyphoid process, C7 and T8, defined the thorax segment. The thigh was defined by the medial and lateral markers at the knee joint as well as an estimate of hip joint centre as calculated in equation 2 based on Bell et al., (1989) and (1990). A Coda pelvis was used defined by the right and left ASIS and PSIS as well as the hip joint centres. Markers placed medially and laterally on their proximal and distal endpoints defined the hands 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 60mm from the acromion in the negative direction of the local Y axis of the thorax (Nussbaum & Zhang, 2000).

Equation 2:
$$\text{Hip Joint Centre} = (\pm 0.36 * \text{ASIS_Distance}, -0.19 * \text{ASIS_Distance} + (0.5 \text{RPV_Depth} - \text{Target_Radius_ASIS}), -0.3 * \text{ASIS_Distance})$$

A lifting trial was defined as the initial motion to approach the load through until lift completion. Visual3D was used to create events to detect the lift initiation and completion time points. Only motion and force data within the initiation to completion range were considered in analysis. Time of approaching the load was defined as the local maximum of hand position in the vertical prior to descent. Lift completion was defined as the time point at local maximum of hand position in the vertical axis after the hand segment reached a global minimum in the vertical.

To calculate joint kinematics for the low back ISB recommendations were followed to define segment coordinate systems (Wu et al., 2002; 2005). Joint angles were calculated as the distal segment relative to the proximal segment using an order of Euler rotations of Z-Y-X or flexion/extension, abduction/adduction and axial rotation sequence.

Positional data required for the PCA analysis was calculated based on the Visual3D kinematic model. This included joint centres bilaterally for the wrist, elbow, shoulder, ankle, knee and hip; and centres of gravity for the trunk, head, pelvis and feet, such that each pose is represented by 17 data points.

A bottom-up inverse dynamics approach was used to calculate joint moments about the thorax relative to the pelvis (herein referred to as low back) in Visual3D using kinematic and ground reaction force data. Ground reaction force data from each respective force plate was applied to the centre of pressure for each foot segment, respectively. Visual3D defaults for segment anthropometrics and inertial properties were used for kinetic calculations based on Hanavan's (1964) equations to estimate inertial properties of segments.

Low back moment and sagittal angles for all given lifting trials were exported to Matlab (MathWorks, Boston, MA) where peak values for each variable were identified and extracted. Low back moment was also extracted at peak sagittal low back angle. For both the peak moment and moment at

peak low back angle, values were divided by the sum of the participant's mass and the mass of the load in that trial. This resulted in normalized moments that differed as a function of movement strategy not mass.

4.5.3 Dichotomizing into High vs. Low Biomechanical Exposure Lifts and Lifters

Using low back angles and normalized moments lifts and lifters were identified as high or low relative biomechanical exposure. The flow of data to group lifts and lifters as either high or low relative biomechanical exposure are pictured in Figure 13 and 14 respectively.

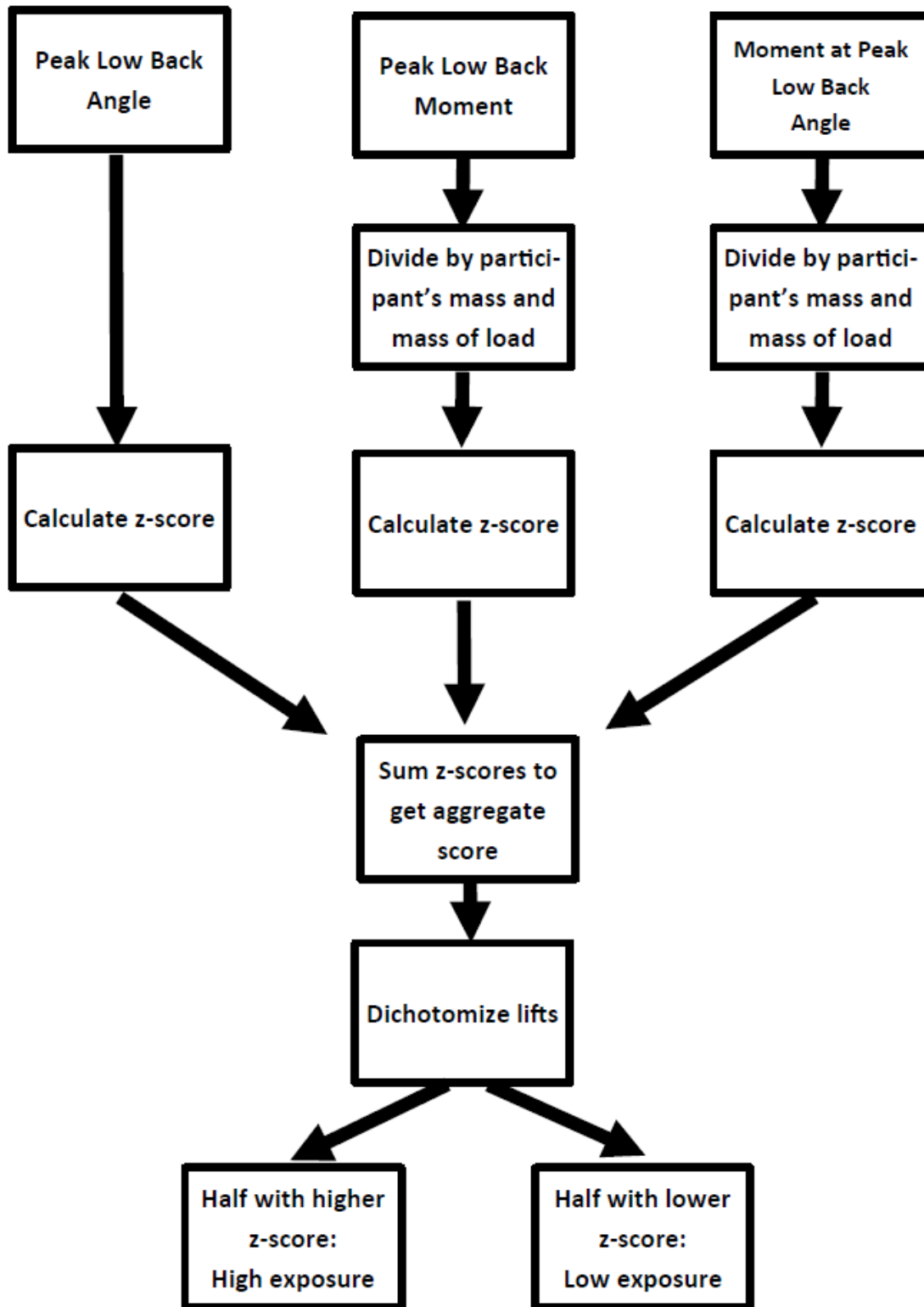


Figure 13: Classifying lifts as high or low relative biomechanical exposure where peak sagittal low back angle, peak low back moment and low back moment at peak sagittal low back angle in a lift were inputs.

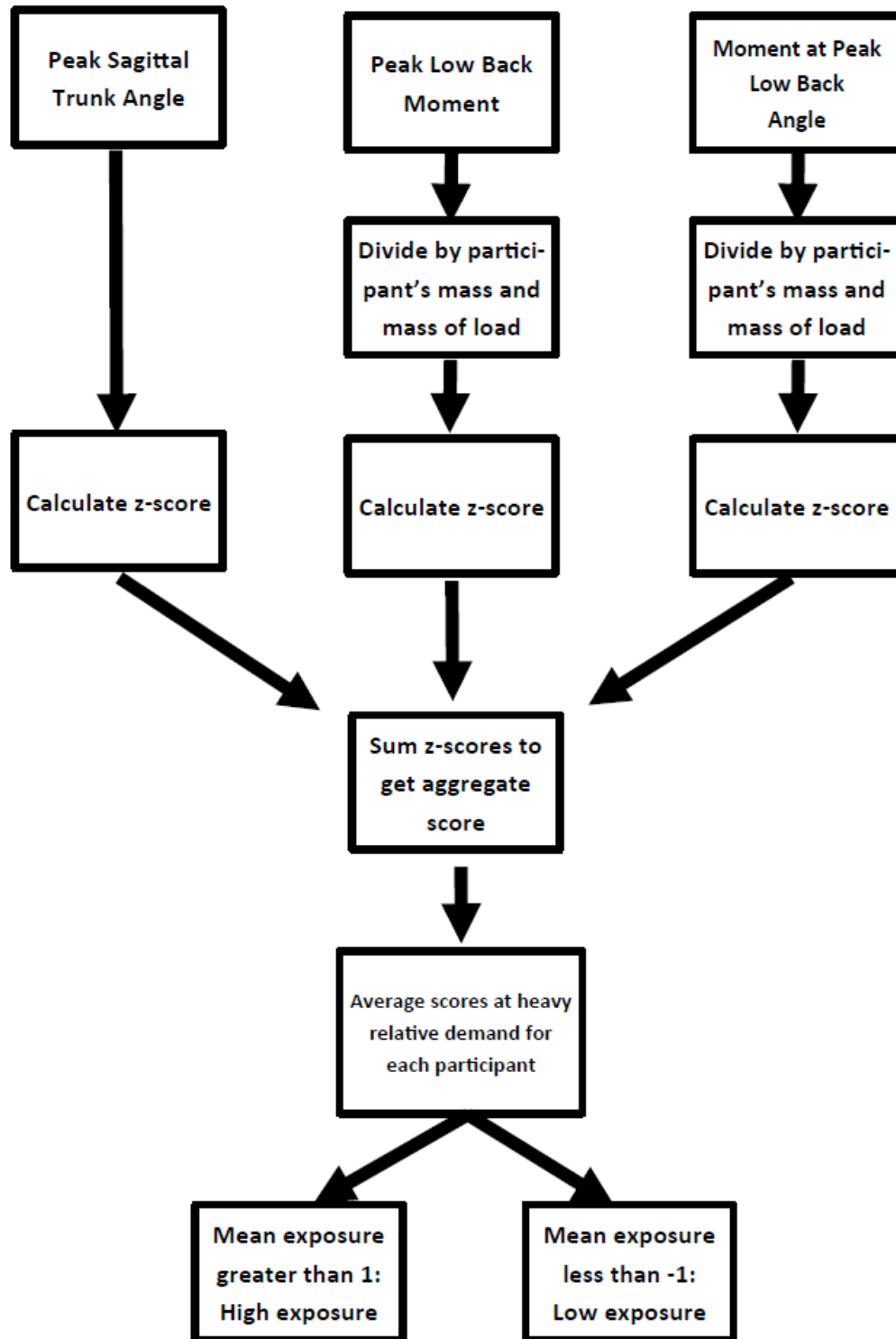


Figure 14: Classifying lifters as high or low relative biomechanical exposure where peak sagittal low back angle, peak low back moment and low back moment at peak sagittal low back angle in heavy lifts were inputs.

To define high and low relative biomechanical exposure lifts peak sagittal low back angle, peak normalized moment and normalized moment at peak sagittal low back angle, were used to calculate an aggregate measure of biomechanical demand where these variables are associated with lowback injury risk (Marras, 1993). There is also evidence that suggests angles and moments can be perceived by participants (Fischer & Dickerson, 2014; Jorgensen et al., 1999; Kuijer et al., 2012), and therefore could provide sensory information within the OFC framework. The z-score was calculated for each variable in each trial relative to data of all lifting trials from all participants. This expressed each value relative to the mean of all data where a positive z-score imposes higher relative biomechanical exposure (higher moment or sagittal angle magnitude) and a negative z-score imposes lower relative biomechanical exposure.

From this analysis, each trial was defined by three corresponding z-scores, one for each variable of interest. To get an aggregate measure of relative biomechanical exposure of a lift the three z-scores were summed for each trial with a lower sum having lower relative biomechanical exposure.

Using the summed z-scores lifts were dichotomized as either high or low relative biomechanical exposures based on the median of summed z-scores. Scores above the median were high relative biomechanical exposure and scores below the median were low relative biomechanical exposure. Grouping ('high' or 'low') based on relative biomechanical exposure was the independent variable.

To define high vs. low relative biomechanical exposure lifters decisions were made based on resultant relative biomechanical exposures in heavy lifting. The normalized biomechanical variables of interest were once again expressed as z-scores only considering heavy lifting trials in the data set. Expressing the biomechanical measures at the heavy relative demand as z-scores without considering measures at the light and medium demands provides a measure of exposure in the relative demand condition that poses the highest MSD risk due to higher associated absolute biomechanical exposures.

Once again, the z-scores were summed for each trial to give an aggregate measure of relative biomechanical exposure, and then these aggregate measures were averaged within each participant. The high exposure lifters were participants with a mean aggregate z-score greater than one and low exposure lifters were those with a mean aggregate z-score less than one (Figure 15). A scalar of one away from the mean was set as a cut off to define lifters as high or low exposure. Since this cut off is based on z-scores, conceptually, the cut offs represent one standard deviation above or below the mean. This resulted in 8 high exposure lifters and 10 low exposure lifters.

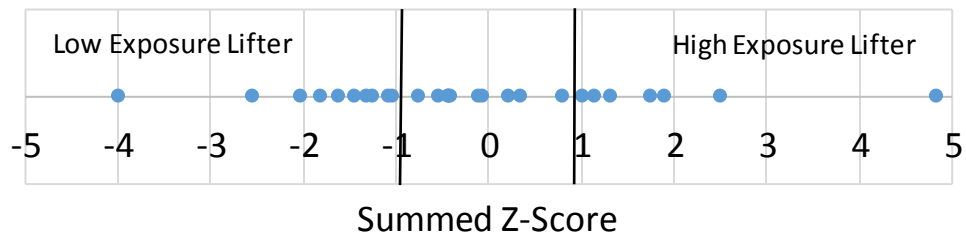


Figure 15: Mean aggregate z-scores to calculate biomechanical exposure where mean scores greater than 1 define a high exposure lifter and mean scores less than -1 define a low exposure lifter.

4.6 Statistical Analysis

4.6.1 Principal Component Analysis for Pattern Recognition

All lift cycles were time normalized to 101 points in Matlab. To control for anthropometric differences all raw coordinate data for the 17 anatomical inputs were divided by the participant's height to normalize position data (Ross et al., 2018). At each time point posture was represented by a vector m where the three-dimensional coordinates of the 17 anatomical inputs defined an $m = 51$ dimensional posture vector. For a given trial movement was represented by a vector p which includes the postural vector (m) at each time point resulting in $p = 5151$ for each trial as there are 101 time points. Vector n

represented the number of lifting trials and with 28 participants performing 10 lifting trials in each relative demand condition $n = 840$. Due to two participants dropping out mid-way through the second data collection and a small number of lifting trials being removed due to errors in the data a total of 804 lifting trials were used for analysis ($n = 804$). The data set for the study was then represented as a matrix of $\left(\frac{X}{n \times p}\right)$ where n is the number of row vectors which are all collapsed into one matrix $\left(\frac{X}{804 \times 5151}\right)$. This matrix was then transformed into a covariance matrix $\left(\frac{S}{p \times p}\right)$ which can be used to find PMs (Wrigley et al., 2006). The covariance matrix is used opposed to the correlation matrix as the correlation matrix is better suited for data sets where variables are measured in different units (Jackson, 2001). The covariance matrix was orthonormalized to get the eigenvector matrix $\left(\frac{U}{p \times p}\right)$. The eigenvectors represent the PMs in the data set. These PMs describe the data in a new coordinate space, which are oriented to objectively explain variability in the data set. PMs are all orthogonal to one another and each subsequent PC explains less variability in the data set. With the covariance and eigenvector matrix the eigenvalues, which are a scaling factor to the eigenvectors, were calculated. The eigenvectors for each PM were scaled to the amount of variance explained by a PM to give a loading vector. The loading vector explains where in the time domain variance is explained in a given PM, where a larger magnitude indicates more variance explained at that time point. Using the eigenvectors and eigenvalues a PM score was calculated for each trial in each PM. The PM score is a measure of how far the mode of variability in the trial deviates from the mean of that mode of variability in a PM (Wrigley et al., 2006).

A single PCA model was used which includes all lifting trials. This allowed for comparisons of PMs between high and low relative biomechanical exposure lifts across relative demands (research question 1), and to compare mean PM scores between high and low exposure lifters across relative demands (research question 2).

To determine whether to retain a PM a parallel analysis technique was used. Parallel analysis retains PMs which explain more variability than what would be explained by chance alone (Wrigley et al., 2005). Parallel analysis is reported as the most accurate method of retaining PMs (Hayton et al., 2004) and so was preferred over alternatives such as the trace criterion which retain PMs until a specific amount of variability is captured (Jackson, 1991; Deluzio & Astephen, 2007; Sadler et al., 2011; Reid et al., 2010). Power equations developed by Fischer et al. (2014) were used to provide an estimate of what percentage of variation a random data set will explain for different PMs. If the variance explained in the experimental data set at a given PM was larger than the percentage calculated in the power equation, then that PM was retained.

4.6.2 Statistical tests for hypothesis testing

To test the hypothesis for research question 1 a two-way ANOVA ($\alpha = 0.05$) with factors of relative biomechanical exposure (2 levels: 'high' and 'low') and relative demand (3 levels: 25%, 50%, 75%) was run to test for differences between PM scores. Where significant main effects of relative demand or interaction effects were observed post hoc testing was conducted where p -values were corrected using a Bonferroni adjustment.

For research question 2, a two-way mixed ANOVA ($\alpha = 0.05$) with a between factor of relative biomechanical exposure lifter (high vs. low) and a within factor of relative demand was used to test for differences in mean PM scores for each retained PM. Where significant main effects of relative demand or interaction effects were observed post hoc testing was conducted where p -values were corrected using a Bonferroni adjustment.

Prior to all statistical tests, the normality of the data were assessed using the Shapiro-Wilks test of normality. For two-way mixed ANOVAs Mauchly's test of sphericity was used to assess the

assumption of sphericity of data. SPSS version 22 (SPSS Inc., Chicago, IL, USA) was used for all hypothesis testing.

4.6.3 Interpreting Differences in Principal Movements

Where a significant difference in PM scores emerged in any statistical tests, a follow-up analysis was conducted to identify the operator (magnitude, phase shift or difference) of the PM. To classify the operator of each PM single component reconstruction was used (Brandon et al., 2013). For single component reconstruction the 5th and 95th percentile reconstructed waveforms are calculated using equations 3 and 4 (reproduced from Brandon et al. (2013)) within a PM and then compared to determine operator. The \hat{x}_U and \hat{x}_L represent the reconstructed upper (95th percentile) and lower (5th percentile) waveforms, \bar{x} represents the mean temporal waveform, u_i is the loading vector for the PM of interest and z_{95} and z_5 are the scalar PM scores for the PM of interest. These upper and lower percentile waveforms were plotted for visual examination to determine the operator of the PM of interest. A difference in magnitudes between the two single PM reconstructions represents a magnitude operator, an intersection of the upper and lower reconstructions was a difference operator, and a difference in timing between upper and lower reconstructions was a phase shift operator. Example of magnitude, phase shift and difference operators as defined by Brandon et al., (2013) are illustrated in Figure 16.

$$\textbf{Equation 3: } \hat{x}_L = \bar{x} + U_R * Z_5$$

$$\textbf{Equation 4: } \hat{x}_U = \bar{x} + U_R * Z_{95}$$

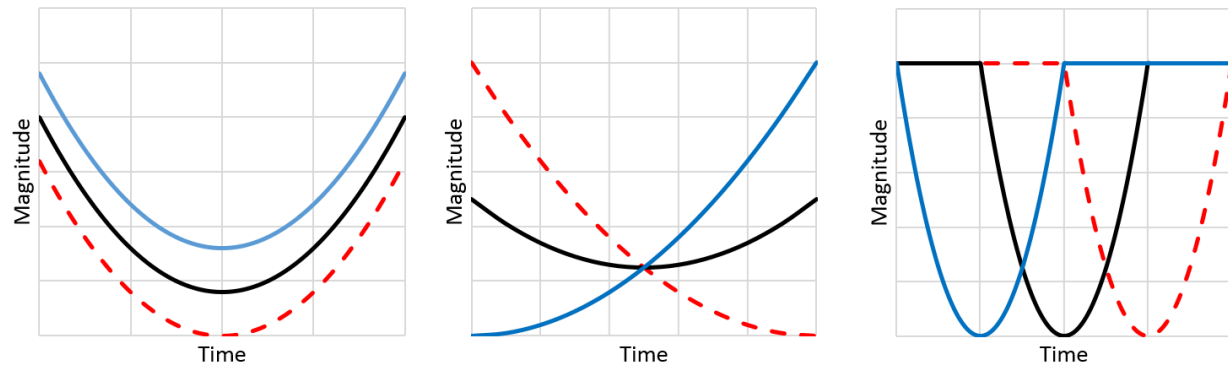


Figure 16: Conceptual examples of single component PC reconstruction of a 95th percentile (blue) and 5th percentile (red-dashed) waveform plotted with the average (black) waveform. These plots demonstrate a magnitude operator (left), difference operator (middle) and phase shift operator (right) for a retained PC. Figure adapted from Brandon et al., 2013.

To aid in the interpretation of each PM the shape of the loading vector was also considered in addition to single component reconstruction. Although single component reconstruction provides a visual reconstruction of the 5th and 95th percentile movement in a particular PM (Brandon et al., 2013) there is still subjectivity in the interpretation in how the movement strategy differs. To add objectivity to this process we can consider the shape of the loading vector, which highlights how much variance is explained by the PM at each point in time along the waveform. As the magnitude of the loading vector moves away from 0 a greater portion of variance is explained. The shape of the loading vector also relates to the mode of variance explained where if the waveform does not cross 0 it suggests a magnitude operator while a waveform that does cross zero is more likely a difference or phase shift operator. For the PCA methodology there is a loading vector magnitude for each anatomical input, in each axis, at each time point. To display the mean loading vector the loading vector magnitude for each

time point is averaged to display a curve with 101 points on the x-axis (time domain) and an averaged magnitude on the y-axis.

Use of the average loading vector provides context on where in the time domain greater variance is explained but does not provide information on which anatomical inputs contribute most to loading vector. To gain insight into which anatomical inputs contribute most to the variance explained the loading vectors for each anatomical input were plotted individually. To do this the loading vector corresponding to the x, y, and z trajectory components of each marker were averaged across all time points and then the resultant averaged anatomical landmark loading vectors are plotted on the same figure. This allows for a comparison of variance explained across the anatomical inputs to guide where to focus interpretation locally. This plotting approach also retains information in the time domain.

4.6.4 Visualizing Principal Movements

To visually display how movement strategy differs between high and low relative biomechanical exposure and as a function of relative single component reconstructions of PMs where significant differences exist were summed to give an aggregate reconstruction (Equation 5).

$$\textbf{Equation 5: } \mathbf{r} = \boldsymbol{\mu} + \sum(\mathbf{LV}_{PMx} * \boldsymbol{\alpha})$$

where r is the reconstructed data, μ is the mean movement across all lifting trials, LV is the loading vector of a retained PM and α is a integer to scale the contribution of the loading vector. Only loading vectors of PMs where significant differences were observed in independent variables were included in the reconstruction. The α was scaled as the mean plus a standard deviation for each condition in each PM where significant differences were observed. In the relative demand reconstruction, the α in the medium condition was scaled to the mean PM score without adding a standard deviation measure.

Separate aggregate reconstructions were done to visualize differences both as a function of relative biomechanical exposure and of relative demand. Aggregate reconstructions were not used for analysis but provide a visual representation of movement to support applications of experimental findings in a practical context.

5.0 Results

5.1 Defining High vs. Low Relative Biomechanical Exposure Lifts and Lifters

High and low exposure lifts were defined based on the aggregate z-score of a lift relative to the median aggregate z-score. A comparison of descriptive statistics between high and low exposure lifts revealed descriptively higher peak low back angle, peak low back moment and low back moment at peak low back angle in high exposure lifts (Table 2).

Table 2: Descriptive statistics of low back biomechanical exposure measures in high vs. low relative biomechanical exposure lifts across relative demand conditions. Independent t-tests were used to determine whether variables significantly differed between lift groups.

Biomechanical Exposure Measure	Low Exposure Lift (Mean \pm Standard Deviation)	High Exposure Lift (Mean \pm Standard Deviation)	t-test results
Peak Low Back Angle ($^{\circ}$)	34.62 \pm 9.30	44.40 \pm 8.52	t(802) = -14.13, $p < 0.001$
Peak Low Back Moment (Nm / body mass kg / load kg)	0.041 \pm 0.013	0.086 \pm 0.050	t(802) = -17.43, $p < 0.001$
Low Back Moment at Peak Low Back Angle (Nm / body mass kg / load kg)	0.020 \pm 0.009	0.053 \pm 0.032	t(802) = -19.29, $p < 0.001$

High and low exposure lifters were defined based on a mean of aggregate z-scores calculated in the heavy lift condition (Table 3). High exposure lifters had descriptively higher peak low back angle, peak low back moment and low back moment at peak low back angle compared to the low exposure lifters (Table 4).

Table 3: Demographics of high and low exposure lifters.

Participant Group	Paramedic Experience	Sex	Age (years)	Height (m)	Weight (kg)
High Exposure (n = 8)	2 yes, 6 no	6 ♀, 2 ♂	24.2 ± 4.4	1.69 ± 0.14	65.4 ± 14.5
Low Exposure (n = 10)	4 yes, 6 no	4 ♀, 6 ♂	24.1 ± 2.5	1.77 ± 0.09	87.2 ± 11.7

Table 4: Descriptive statistics of low back biomechanical exposure measures in high vs. low relative biomechanical exposure lifters in the heavy relative demand condition. Independent t-tests were used to determine whether variables significantly differed between lifter groups.

Biomechanical Exposure Measure	Low Exposure Lifter (Mean ± Standard Deviation)	High Exposure Lifter (Mean ± Standard Deviation)	t-test results
Peak Low Back Angle (°)	32.29 ± 9.69	46.37 ± 11.12	t(594) = -16.52, p < 0.001
Peak Low Back Moment (Nm / body mass kg / load kg)	0.032 ± 0.011	0.059 ± 0.026	t(594) = -12.01, p < 0.001
Low Back Moment at Peak Low Back Angle (Nm / body mass kg / load kg)	0.014 ± 0.005	0.033 ± 0.017	t(594) = -13.14, p < 0.001

5.2 Retaining and Interpreting PMs for Analysis

The parallel analysis retained 6 PMs (Table 5). The retained PMs explained 87.7% of the overall variance in the motion data.

Table 5: Variance explained compared to variance explained by chance where bolded PMs were retained for analysis. Variance explained by chance was calculated using methods reported by Fischer et al. (2014).

Principal Movement	Variance Explained	Variance Explained by Chance
PM1	46.8%	1.5%
PM2	15.8%	1.7%
PM3	9.9%	1.8%
PM4	7.0%	1.9%
PM5	5.8%	1.9%
PM6	2.5%	2.0%
PM7	1.4%	1.9%
PM8	1.0%	1.8%

PM1 was interpreted as a magnitude operator explaining differences in the AP positioning of the body relative to the load. The 5th percentile reconstruction is closer to the load in the AP direction while the 95th percentile reconstruction is further away (Figure 17a). There are no discernable differences in the medio-lateral (ML) direction between reconstructions (Figure 17b). The supplementary loading vector plots (Figure 17c, marker specific; Figure 17d, average) reinforce that this PM is a magnitude operator as the variance explained across both markers is consistent over time and does not cross 0. This PM will herein be referred to as explaining AP body position.

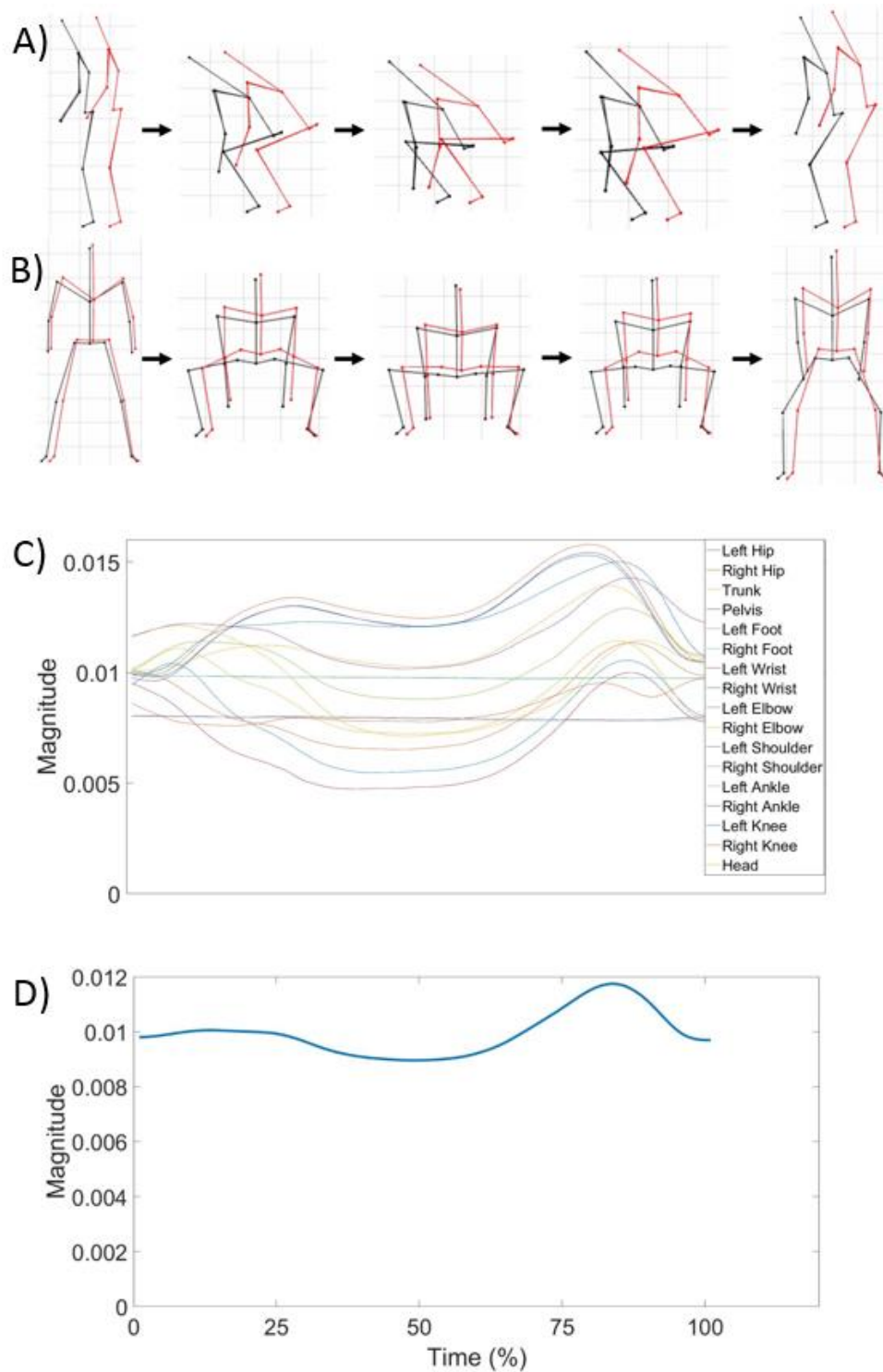


Figure 17: Single component reconstruction of PM1 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

PM2 was interpreted as a magnitude operator explaining differences in lift sequencing. The 5th percentile reconstruction uses a distal to proximal strategy while 95th percentile moves about all joints in phase (Figure 18a,b). Additionally, the 5th percentile reconstruction has more upright trunk and a squat-like movement strategy whereas 95th percentile reconstruction uses more hip and low back driven movement. The average loading vector (Figure 18d) supports that the general mode of variance explained in PM2 is a magnitude operator while in the marker specific loading vector (Figure 18c) the variance explained for the head seems to be a difference operator. This PM will herein be referred to as explaining body sequencing.

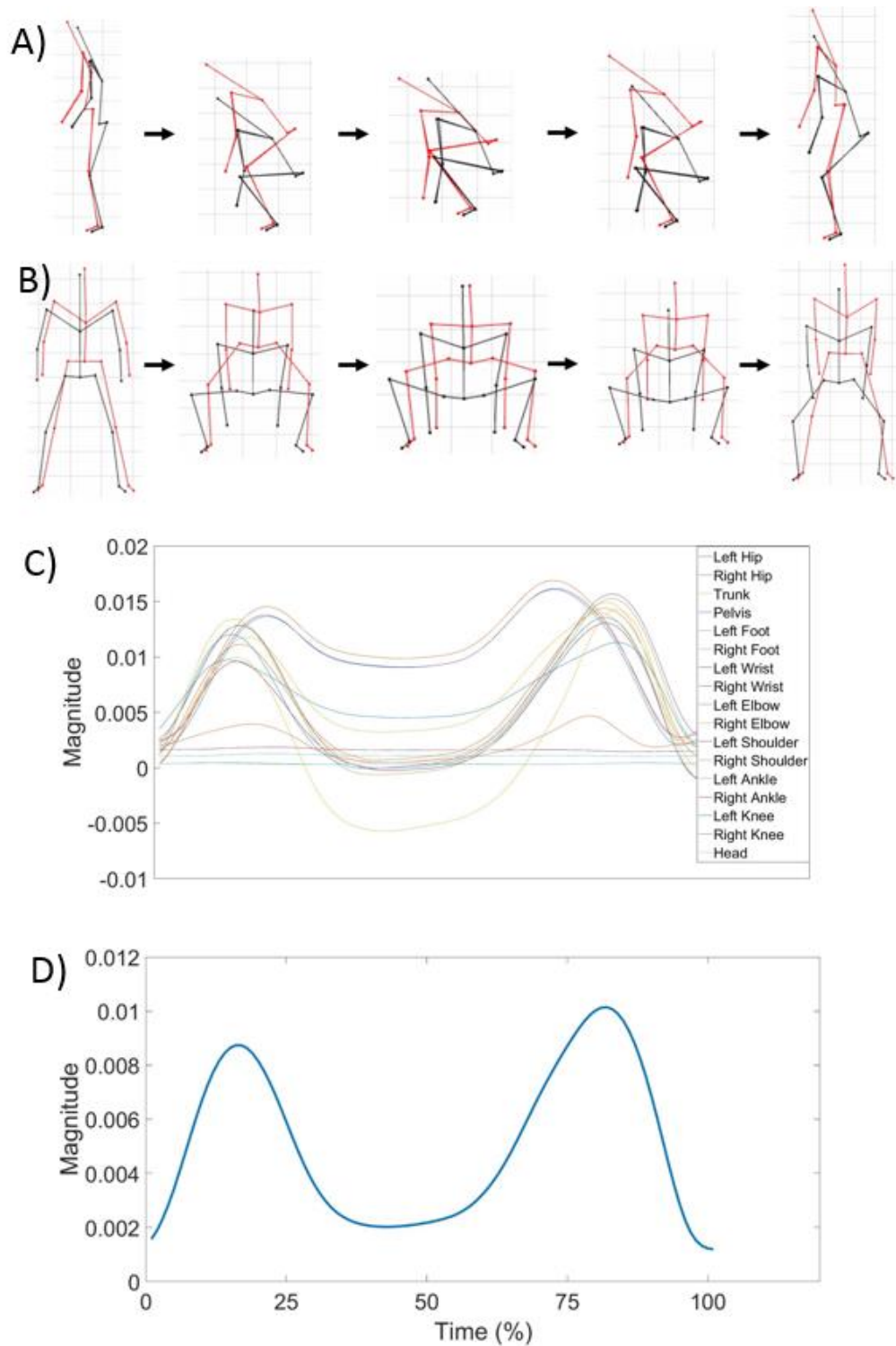


Figure 18: Single component reconstruction of PM2 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

PM3 was interpreted as a magnitude operator explaining differences in ML body position and sagittal trunk angle. The 5th percentile reconstruction has a more flexed trunk while the 95th percentile reconstruction maintains a more upright trunk (Figure 19a). There is an offset in the ML direction between 5th and 95th percentile reconstructions (Figure 19b). The supplementary loading vector plots (Figure 19c, marker specific; Figure 19d, average) reinforce that this PM is a magnitude operator as the variance explained across the average loading vector is consistent over time and does not cross 0. This PM will herein be referred to as explaining ML body position/ trunk angle.

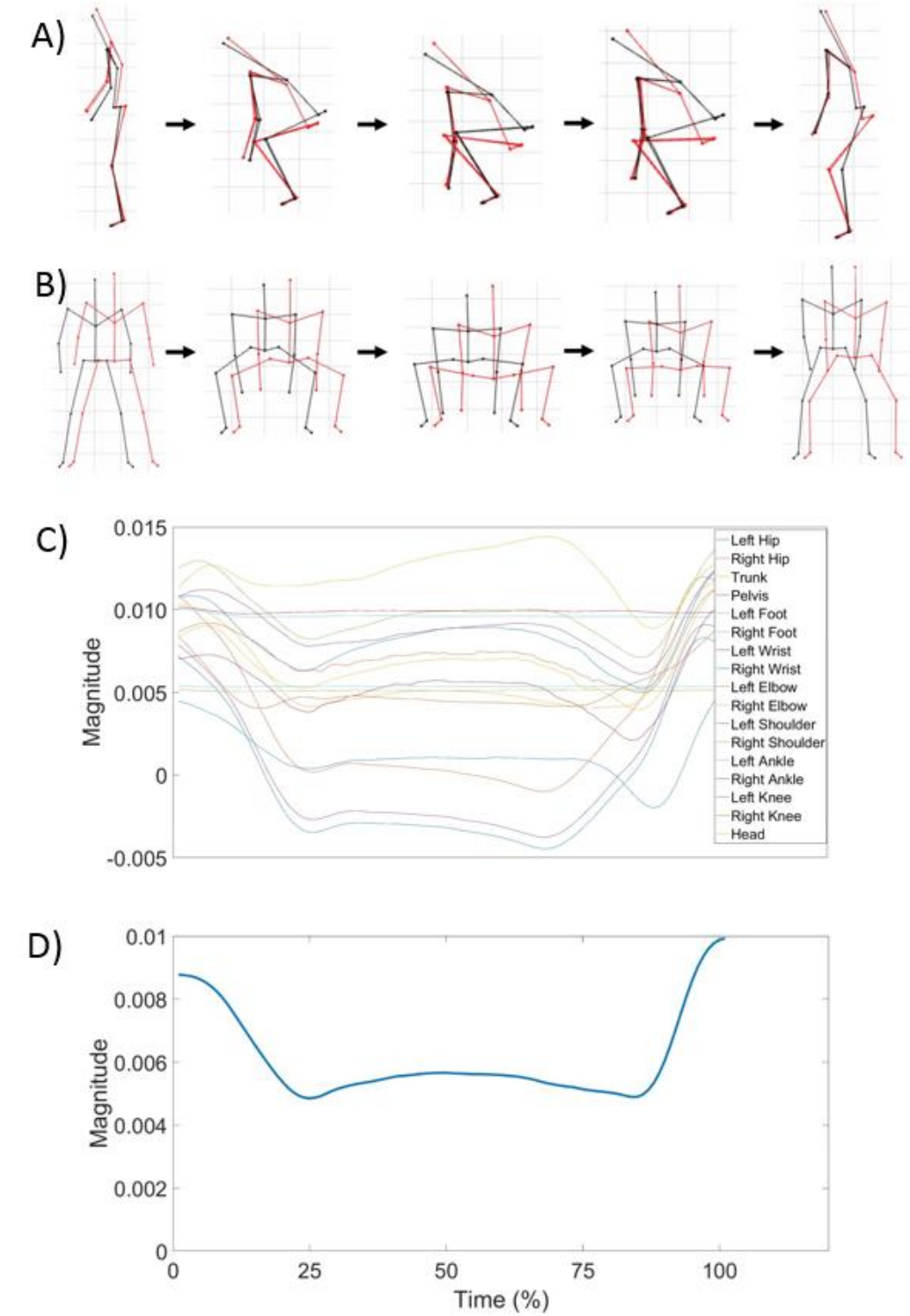


Figure 19: Single component reconstruction of PM3 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PM score and the red tracing is the reconstruction of the 95th percentile PM score. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

PM4 was interpreted as a phase shift operator explaining differences in lift timing. The 5th percentile approaches the load and initiates the lift later than the 95th percentile reconstruction (Figure 20a,b). The supplementary loading vector plots (Figure 20c, marker specific; Figure 20d, average) reinforce that this PM is a phase shift operator as the variance explained across the average loading vector loosely resembles the shape of a sine wave and crosses 0. This PM was described as a phase shift operator opposed to a difference operator as the movement strategy used is consistent across the 5th and 95th percentile reconstructions, which would not hold true for a difference operator. This PM will herein be referred to as explaining lift timing.

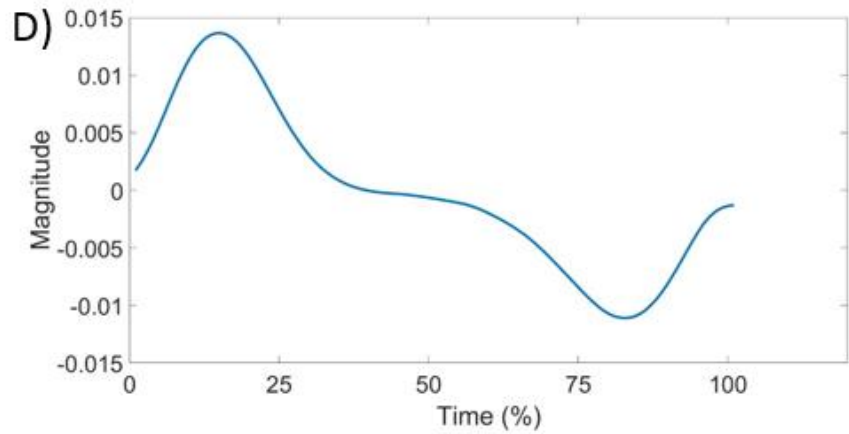
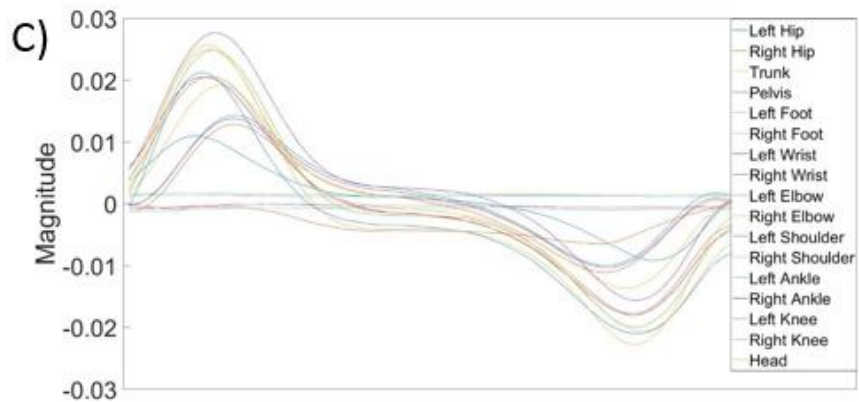
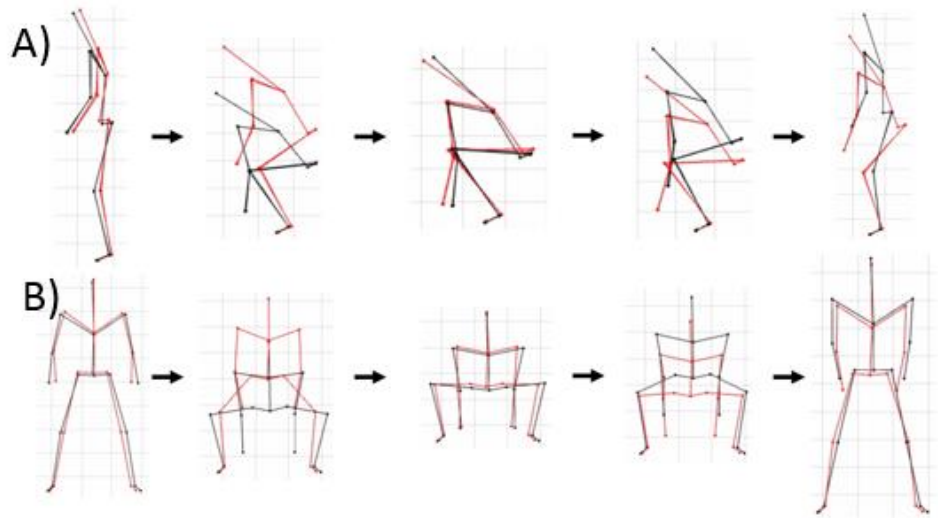


Figure 20: Single component reconstruction of PM4 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

PM5 was interpreted as a magnitude operator explaining differences in how squat or stoop-like a lift was. The 5th percentile reconstruction stoop strategy, characterized by less knee flexion and greater hip and trunk flexion (Figure 21a). Alternatively, the 95th percentile reconstruction uses a squat strategy with greater knee flexion and less hip and trunk flexion. Although the average loading vector suggests a phase shift or difference operator because of the waveform crossing 0 (Figure 21d), the marker specific loading vector demonstrates that variance explained across markers individually is a magnitude operator as 0 is not crossed (Figure 21c). This PM will herein be referred to as explaining squat vs. stoop.

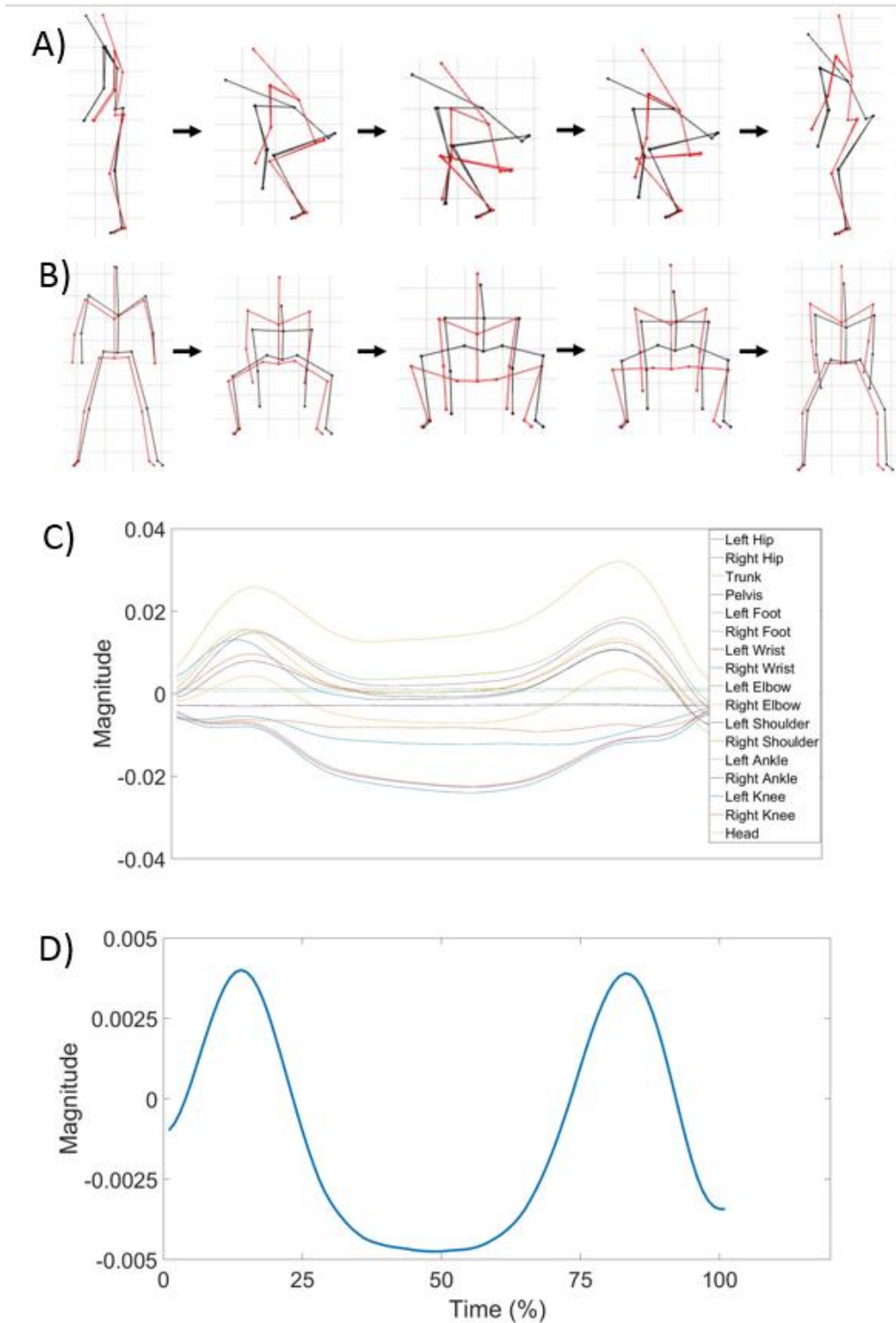


Figure 21: Single component reconstruction of PM5 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PM score and the red tracing is the reconstruction of the 95th percentile PM score. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

PM6 was interpreted as a magnitude operator explaining differences in stance width. The 5th percentile reconstruction had a wider stance width allowing the hands to stay close to the body at lift initiation (Figure 22a,b). As with PM5, the average loading vector suggests a phase shift or difference operator because of the waveform crossing 0 (Figure 22d), but the marker specific loading vector demonstrates that variance explained across markers individually is a magnitude operator as 0 is generally not crossed (Figure 22c). This PM will herein be referred to as explaining stance width.

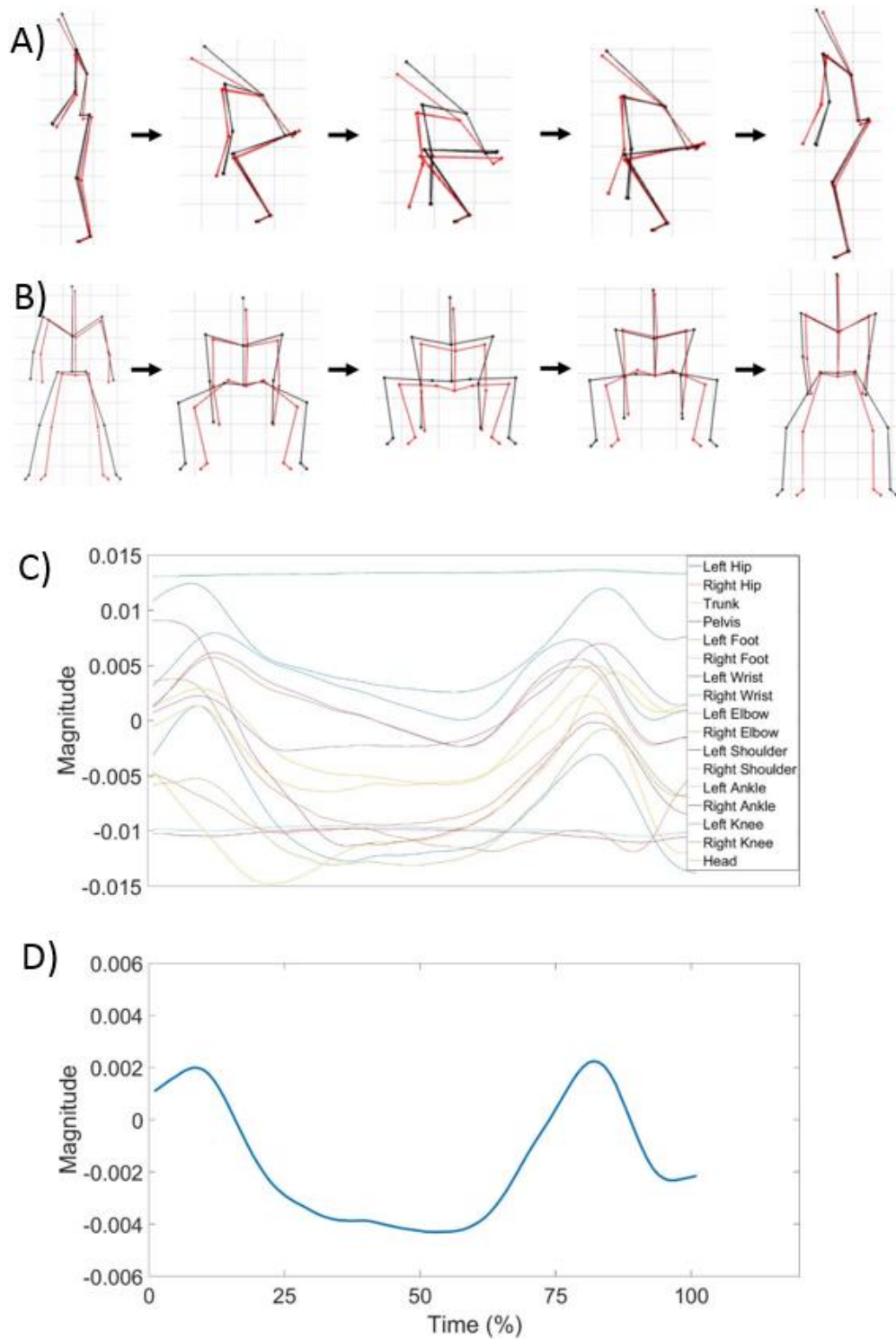


Figure 22: Single component reconstruction of PM6 from the sagittal (A) and frontal (B) views. The black tracing is the reconstruction of the 5th percentile PMscore and the red tracing is the reconstruction of the 95th percentile PMscore. Both anatomical input specific (C) and averaged (D) loading vectors show where variance is explained in the PM.

5.3 Comparing Movement Strategy across Lifts

PM scores for PMs 1-6 violated the assumption of normality ($p < 0.001$ on Shapiro-Wilks test of normality). However, when conducting tests of normality there is a risk of type 1 error when large sample sizes are used (Field, 2013). For this reason, Q-Q plots representing the spread of data relative to the normal distribution were used to confirm findings of the Shapiro-Wilks test. Across all PMs there was a strong visual agreement of PM scores to a normal distribution of equal mean and standard deviation (Appendix B). With the strong visual agreement of experimental data to a normal distribution normality was assumed allowing for the use of parametric statistical tests.

A main effect of relative biomechanical exposure group was detected in five of six retained PMs (1-3, 5, 6) (Table 6). A main effect of relative demand was also detected in four of six retained PMs (1, 2, 4, and 5). No significant interaction effects were observed. Differences in PM scores between relative biomechanical exposure classification and relative demand are pictured in Figure 23.

Table 6: Summary of two-way ANOVA results comparing PM scores between high and low exposure lifts and across light, medium and heavy relative demands. Only significant post hoc results are included.

PM	Biomechanical Exposure			Relative Demand			Interaction			Post Hoc
	F(1,797)	<i>p</i>	η^2	F(2,797)	<i>p</i>	η^2	F(2,797)	<i>p</i>	η^2	
PM1 AP Body Position	89.44	>0.001	0.101	9.28	>0.001	0.023	0.28	0.755	0.001	
PM2 Lift Sequencing	14.80	>0.001	0.018	3.11	0.045	0.008	2.97	0.052	0.007	H < L
PM3 ML Body Position/ Trunk Angle	18.60	>0.001	0.023	1.06	0.347	0.003	1.65	0.191	0.004	
PM4 Lift Timing	0.75	0.384	0.001	3.79	0.023	0.009	0.99	0.370	0.002	H < M
PM5 Squat vs. Stoop	8.13	0.004	0.010	12.33	>0.001	0.030	1.77	0.170	0.004	H, M < L
PM6 Stance Width	39.77	>0.001	0.049	2.94	0.053	0.007	0.10	0.900	0.000	

where significant effects are bolded; L = light, M = medium, and H = Heavy.

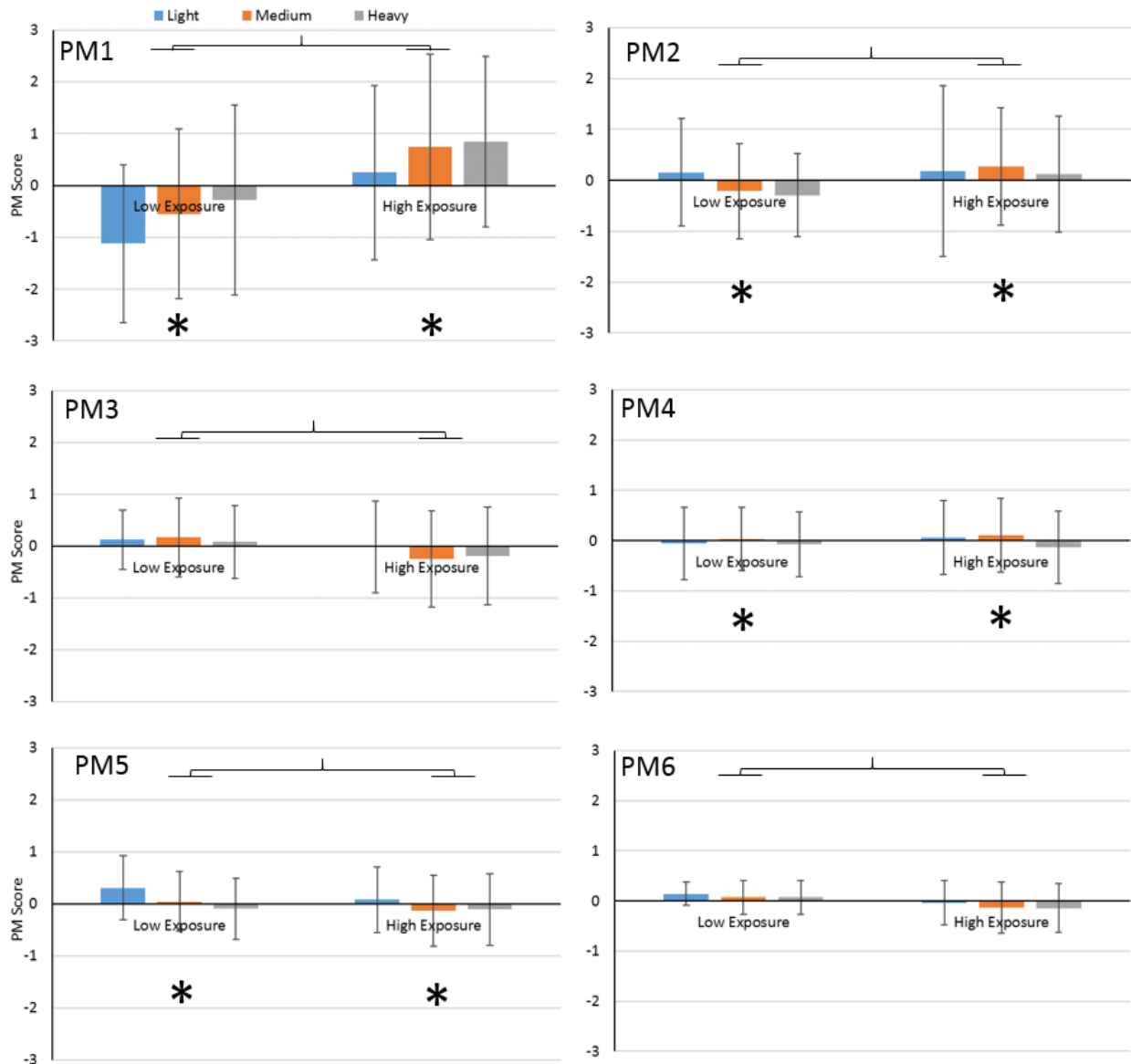


Figure 23: Mean PM scores for high and low exposure lifts across light, medium and heavy relative demands. Significant main effects of exposure are indicated by a bracket and significant main effects of relative demand are indicated with an asterisk (*).

Using results from statistical testing an aggregate reconstruction was used to visualize differences in movement strategy as a function of relative biomechanical exposure (Figure 24). The

scalar used in reconstruction was the mean PM score of a biomechanical exposure condition \pm one standard deviation. Only PMs where significant main effects of relative biomechanical exposure were observed were included in reconstruction. Reconstruction revealed that low exposure lifts minimize the horizontal distance of their body to the load, maintain a more upright trunk and initiated movement with the lower body opposed to using low back extension.

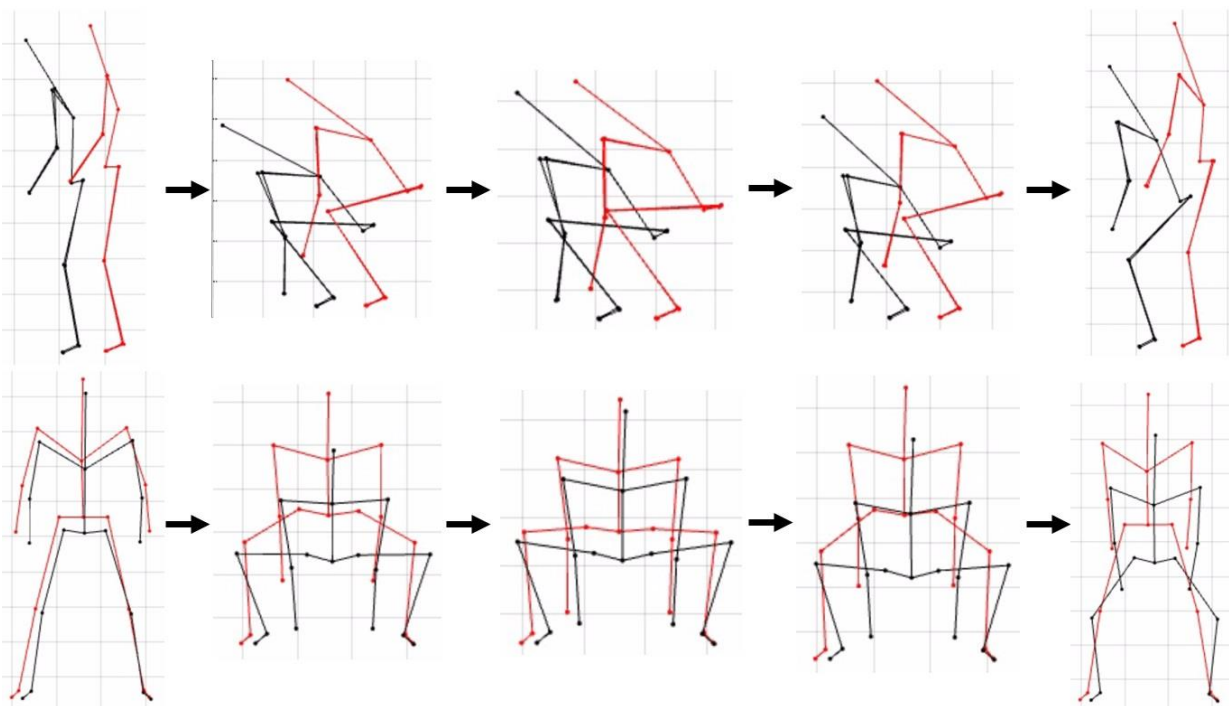


Figure 24: Aggregate reconstruction to illustrate the net differences in movement strategy as a function of relative biomechanical exposure from the sagittal (top) and frontal (bottom) planes. Black tracing represents a low exposure lift and red represents a high exposure lift.

From results of statistical testing an aggregate reconstruction was also completed to reconstruct differences in strategy as a function of relative demand (Figure 25). In this reconstruction, the scalar for

the light and heavy lifts was set to the mean PM score for that condition \pm one standard deviation. The medium condition scalar was set to the mean medium PM score. This reconstruction reveals that in the light condition the horizontal distance to the load is lower, the lift is initiated earlier in the light condition and movement is synchronous across all joints at lift initiation. Conversely, at the heavy relative demand the horizontal distance of the body to the load is greater, lift initiation occurs later temporally and a distal to proximal strategy was used where movement about joints of the lower body preceded extension about the low back.

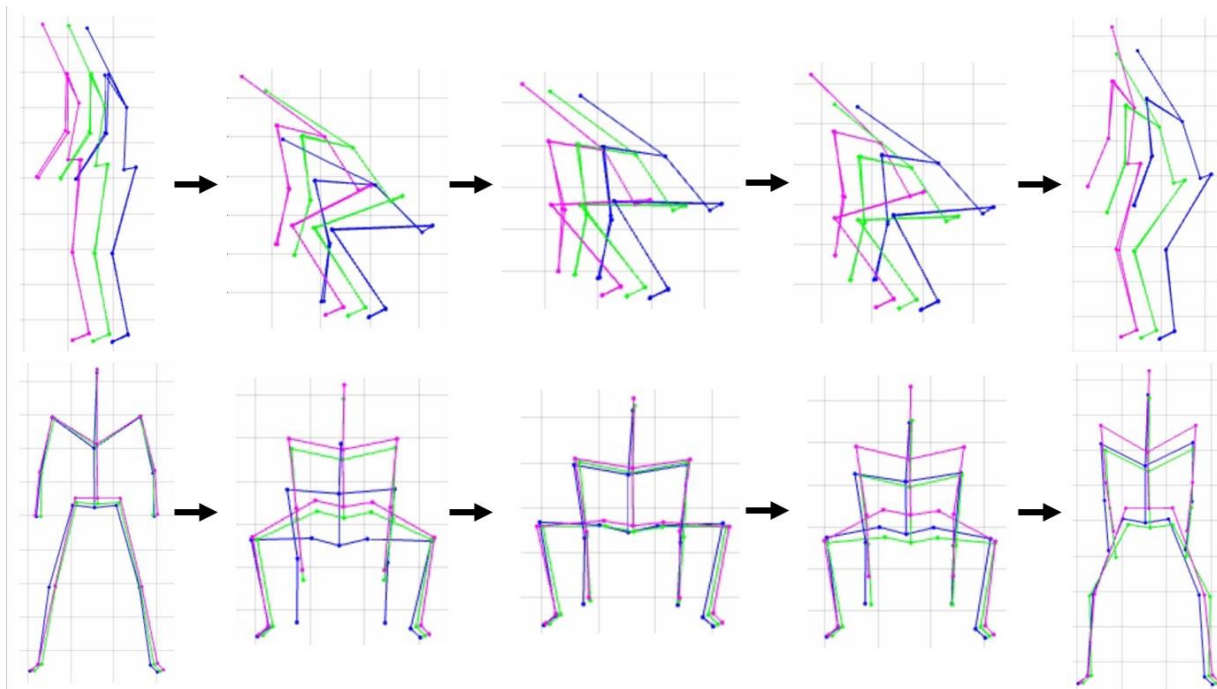


Figure 25: Aggregate reconstruction visualizing differences in movement strategy as a function of relative demand from the sagittal (top) and frontal (bottom) planes. Purple represents a light relative demand, green is a medium relative demand and blue is a heavy relative demand.

5.4 Comparing Movement Strategy across Lifters

Testing for differences in mean PM scores between high and low exposure lifters across relative demands for PMs 1-6 there were no violations of the assumption of normality ($p > 0.05$ in Shapiro-Wilks test of normality). No violations of normality allowed for the use of parametric tests. Across all data, there were also no violations in the assumption of sphericity ($p > 0.05$ in Mauchly's test of sphericity).

The use of two-way mixed ANOVAs to address research question 2 revealed a significant main effect of relative biomechanical exposure for PM1 and significant main effects of relative demand for PMs 2 and 5 (Table 7). In PM1 low exposure lifters had lower mean PM scores, and for both PMs 2 and 5 heavy conditions had lower mean PM scores (Figure 26).

Table 7: Summary of two-way mixed ANOVA results comparing mean PM scores between high and low exposure lifters and across light, medium and heavy relative demands. Only significant post hoc results are included.

PM	Biomechanical Exposure			Relative Demand			Interaction			Post Hoc
	F(1,16)	<i>p</i>	η^2	F(2,32)	<i>p</i>	η^2	F(2,32)	<i>p</i>	η^2	
PM1 AP Body Position	13.89	0.002	0.465	0.37	0.692	0.023	0.96	0.390	0.057	
PM2 Lift Sequencing	1.56	0.229	0.089	15.27	>0.001	0.488	1.47	0.244	0.084	H, M < L
PM3 ML Body Position/ Trunk Angle	0.96	0.341	0.057	0.30	0.741	0.019	1.52	0.234	0.087	
PM4 Lift Timing	0.597	0.451	0.036	2.92	0.068	0.155	0.09	0.906	0.006	
PM5 Squat vs. Stoop	0.46	0.505	0.028	21.16	>0.001	0.569	0.78	0.463	0.047	H, M < L
PM6 Stance Width	1.70	0.210	0.097	0.46	0.631	0.028	1.22	0.308	0.071	

where significant effects are bolded; L= light, M = medium, and H = Heavy

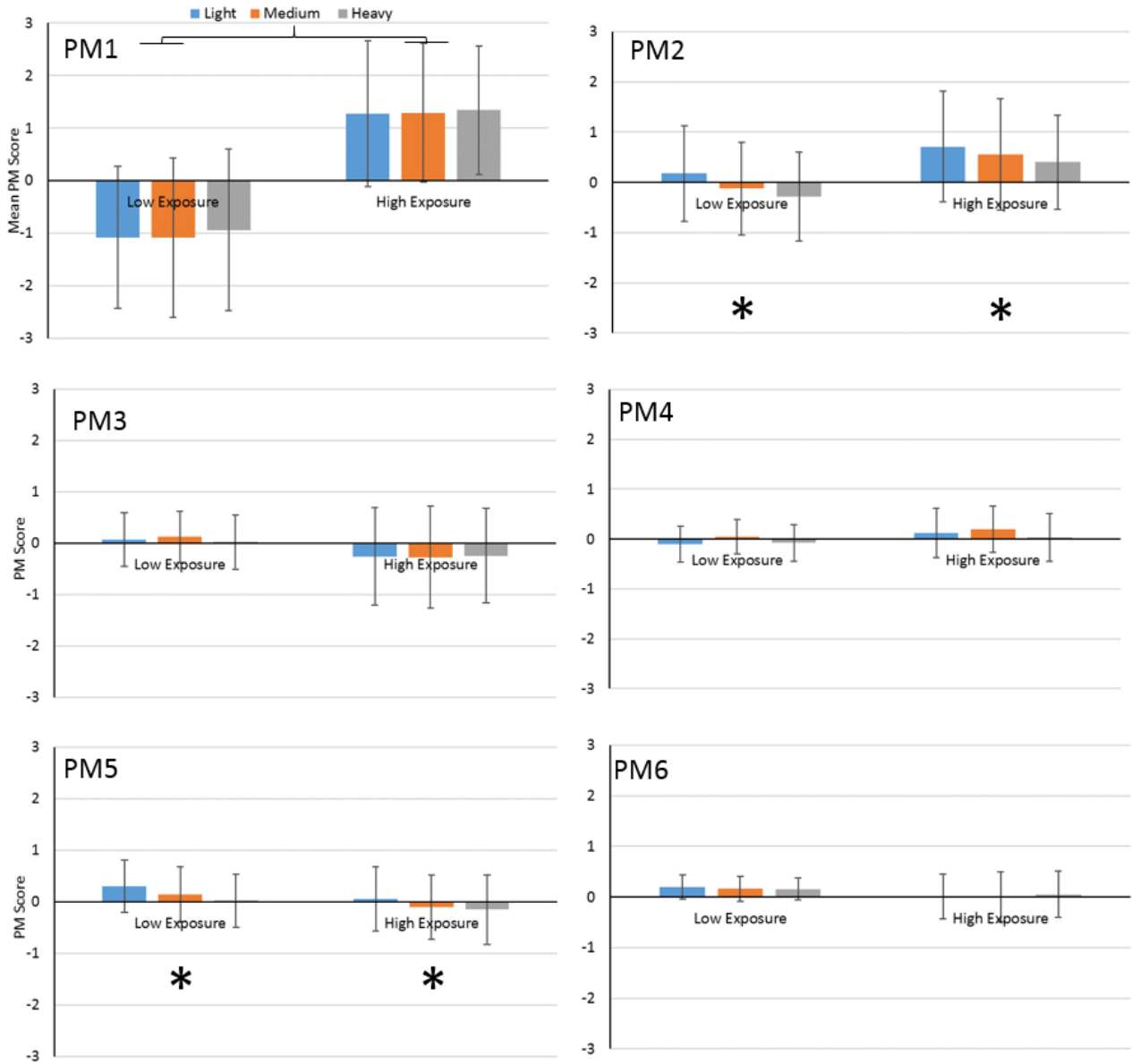


Figure 26: Mean PM scores for high and low exposure lifters across light, medium and heavy relative demands. Significant main effects of exposure are indicated by a bracket and significant main effects of relative demand are indicated with an asterisk (*).

6.0 Discussion

The application of a pattern recognition technique to quantify movement strategy during backboard lifting identified differences in movement strategies between high and low exposure lifts and lifters. The horizontal distance to the load, using a distal to proximal strategy, maintaining an upright trunk, having greater movement about the knees and keeping the hands close to the body were features of movement related to lower relative biomechanical exposure. However, when averaging features of movement within lifters, the only feature that could distinguish between high and low exposure lifters was horizontal distance of the body to the load. In lifts, the relative demand significantly influenced the horizontal distance to the load, sequencing of lift execution, timing of the lift in a trial, and whether a lift was more squat- or stoop-like. After averaging features of movement within lifters, sequencing of the lift and whether a lift was more squat- or stoop-like were the only features that differed as a function of relative demand. Across both lifts and lifters, there were no significant interaction effects between relative biomechanical exposure and relative demand.

6.1 Lift Movement Strategy as a Function of Biomechanical Exposure and Relative Demand

Supporting the first hypothesis, the application of PCA as a pattern recognition technique identified differences in movement strategies between high and low relative biomechanical exposure lifts. Low exposure lifts used a movement strategy that minimized the horizontal distance of the load to the body and initiated the lift with the lower body, compared to greater horizontal distance to the load and low back extension used in high exposure lifts. The horizontal distance of the body to the load was influenced directly by the AP body position and a wider stance width allowing the hands to be closer to the body at lift initiation. A reduction in horizontal distance to the load reduces the moment arm from the load to the low back and therefore lower resultant low back moments (Jorgensen et al., 1999). The

use of a distal to proximal lifting strategy in a low exposure lift is consistent with lower biomechanical exposures experienced when a greater percentage of work is done with the lower body (Makhoul et al., 2017). By initiating the lift with the lower extremities, the lower body would perform a greater portion of the work where extension of the low back would only contribute in the latter portions of the lift. This will avoid the low back performing work at 25% of the extension duration where the acceleration of the external load is greatest (De Looze et al., 1993). The more squat-like strategy in low exposure lifts continues to support the importance of performing more work with the lower body to reduce low back exposure. Although there is no conclusive difference between squat and stoop strategy on low back exposure (van Dieën, 1999; Straker, 2003), the use of a squat strategy with a larger stance width allowing the load to be close to the body reduced biomechanical exposure consistent with findings from the van Dieën (1999) review.

Differences in movement strategy between low and high exposure lifts echoed previous research where relative biomechanical exposure is predominantly determined by horizontal distance of the body to the load. This is highlighted by only AP body position having greater than a medium effect size (where $\eta^2 = 0.06$ is a medium effect and $\eta^2 = 0.14$ is a large effect), while all other significant main effects of relative biomechanical exposure had a small effect (where $\eta^2 = 0.01$ is a small effect). This finding is consistent with a review by van Dieën et al. (1999) which showed that proximity to the load, not movement strategy used in lifting, was the greatest determinant of biomechanical exposure. The agreement of findings from the pattern recognition approach to past literature supports the validity of the employed methodology to identify features of movement related to biomechanical exposure. However, use of the pattern recognition technique was able to discern the same conclusions when considering the entirety of the lift opposed to relying on discrete variables selected *a priori*. The pattern recognition method was also able to reveal the association of movement strategy more efficiently. By considering whole body motion in this study it was able to discern similar results to the van Dieën et al.

(1999) review that relied on a number of studies examining changes in kinematics at specified local areas of interest to glean insight into whole body motion. The approach of considering whole body motion eliminates the need to explore kinematics at individual joints and then inferring how the differences at individual joints contributes to differences in whole body strategy while potentially missing interactions of movements across joints. The accuracy and efficiency of the employed pattern recognition approach support its utility to identify features of movement associated with biomechanical exposures.

The hypothesis that the pattern recognition method would be able to detect differences in movement strategy as a function of relative demand was supported. In AP body position, heavy relative demand lifts had a body position further from the load while light lifts had the lifter closer to the load. For body sequencing, heavy relative demand lifts used a distal to proximal movement strategy compared to a synchronous strategy used in light lifting. This is consistent with past work, which showed as load increases participants tend to lift in a more distal to proximal manner (Davis & Troup, 1965; Scholz, 1993a, 1993b; Scholz & McMillan, 1995; Burgess-Limerick et al., 1995). The use of distal to proximal strategy has been theorized to be a protective measure to avoid low back extension when the acceleration of the load is greatest (Davis & Troup, 1965) which occurs at about 25% of the extension duration (De Looze et al., 1993). Lift timing describes a phase shift where in the medium demand condition the approach to the lift and initiation of the lift was earlier in the time domain than what was observed in light and heavy relative demand lifts. In the squat vs. stoop feature of movement, heavy relative demand lifts used a more stoop-like lifting strategy, while light relative demand lifts used a more squat-like strategy.

Identifying differences in body positioning and timing as a result of the relative demand of the load are novel findings detected by the application of a pattern recognition technique. It was observed that in heavy relative demand lifts there was a greater horizontal distance of the body to the load, which

seems counterintuitive as lifting at the heavy relative demand imposes the highest absolute exposure on the low back. However, because there is no interaction effects between relative demand and biomechanical exposure there is no evidence to support that effect of relative demand on the formation of the control law is related to minimizing biomechanical exposure. Understanding why participants were further from the load in the heavy relative demand condition remains a consideration moving forward. The differences in timing of the lifts as a function of relative demand may be in part due to normalizing lifting trials to percentages distorting the time domain. In general, light relative demand lifting trials were performed in less time than heavy relative demand lifting trials as participants spent more time in the set up at heavy relative demand, and more time under tension lifting the load. By normalizing trial length to a percentage the relative timing in each trial is slightly distorted which could have led to the observed main effect of relative demand in PM4. For all 4 PMs where significant main effects of relative demand were seen, the associated effect sizes were small so even though features of movement differed statistically, these differences may not have clinical implications.

6.2 Lifter Movement Strategy as a Function of Biomechanical Exposure and Relative Demand

The AP body position relative to the load was the only movement feature that was different between low and high relative exposure lifters. This supports the second hypothesis by demonstrating that pattern recognition could detect differences between high and low exposure lifters. However, it is interesting that the results of the lift and lifter analysis are not consistent. With only AP body position differing between high and low exposure lifters it is suggested in the theoretical framework that low exposure lifters minimize exposure by prioritizing close proximity of the body to the load in their control law. Although there were other features of movement related to biomechanical exposure in research question 1, it is not supported that these features of movement are consistently controlled via the

control law in low exposure lifters. The preferential control of AP body position is likely because this feature of movement has the greatest effect on the resultant biomechanical exposure as demonstrated by the greatest effect size in research question 1. Although other features of movement are related to biomechanical exposure their associated effect is likely not substantial enough to warrant consideration in the definition of the control law.

An alternative explanation for the inconsistencies in lift and lifter analysis are a potential interplay between features of movement related to biomechanical exposure. Although body sequencing, ML body position/ trunk angle, squat vs. stoop and stance width are related to biomechanical exposure, these associations are weak as measured by effect sizes in research question 1. It is possible that since these features of movement are not directly considered in the control law that across lifts, a low exposure lifter will have favorable control in some of these features of movement, while having unfavorable control in others. Across multiple repetitions, the PMs controlled favorably can vary, as they are not directly controlled. This resulted in the no statistically significant differences in control of these PMs between high and low exposure lifters contrary to the *a priori* hypotheses.

Pattern recognition identified that some lifters consistently positioned closer to the load where others did not. It is curious that some individuals may position differently than others, but we believe this can be explained by OFC. It is likely that the differences in position to the load between high and low exposure lifters is informed by differences in the control law between groups where in the Glazier model (2017) these control law differences are driven by differences in the organism constraint. Although, it is likely that some internal difference in participants drove the differences in strategy via the organism constraint, this cannot be attributed to paramedic experience as 6 of the 10 low exposure lifters did not have paramedic experience. Therefore, it is likely that there is some other internal difference between lifters that was not quantified in this study that informed the definition of the control law.

In this experiment, the relative demand condition was included as a variation on the constraints of the lifting task. Conceptually, a change in task constraints should elicit a change in movement behavior. Using pattern recognition, we did identify two specific features of movement that had changes in mean movement based on the relative demand; the synchronicity of the lift and use of a squat vs. stoop strategy. With the change in a constraint resulting in a change in observed movement strategy, it can be inferred within the Glazier (2017) framework that the constraint informed the definition of a modified control law (Figure 5). In the case of relative demand, the change in constraint may have resulted in a control law prioritizing energy efficiency in the heavy relative demand condition. When fatigue is induced in repetitive lifting, lifters tend to use a strategy with greater trunk flexion (i.e. more stoop-like) (Bonato et al., 2003; Mehta et al., 2014). This change in strategy is likely an effort to minimize fatigue as stoop strategy has a lower associated metabolic demand compared to a squat strategy (Straker, 2003). In the manipulation of the relative demand as a constraint, it is likely that lifters inform their control law to minimize fatigue under heavier relative demands.

The lack of interaction effects between relative biomechanical exposure and relative demand may be a product of the nature of the backboard lifting task. In practice, paramedics are exposed to backboard lifting with low frequency in a shift (Coffey et al., 2016). To mimic the low frequency of lifting experienced in the work place, each lifting trial was performed independently with rest time provided before the following trial. This allows participants to plan a movement strategy prior to a lift and control aspects of movement that they deem to be important where their internal definition of importance is an example of an organism constraint. Conversely, the hypothesized interaction effects may have been observed in repetitive lifting. When exposed to a greater volume of lifts the lifter may define a control law that aims to balance acute and cumulative biomechanical exposure. In this scenario, low exposure lifters would have a tighter control of features of movement related to biomechanical exposure at the high relative demand where the absolute biomechanical exposures, and risk of MSD through an acute

mechanism, are greater. By tightly controlling the strategy at the heavy relative demand the biomechanical exposure to the body can be reduced to maintain a margin of safety. Conversely, at the light relative demand low exposure lifters may allow for greater variability in repetitive lifting as a protective measure to reduce MSD risk through a cumulative loading mechanism (Srinivasan & Mathiassen, 2012). By maintaining variability at the light relative demand the lifter would differentially load tissues to decrease the likelihood of a single tissue failing. With the non-repetitive nature of backboard lifting low exposure lifters are more inclined to tightly control features of movement in all exertions to reduce the absolute imposed biomechanical exposure. This tight control reduces the risk of MSD from an acute mechanism, which is a more likely injury pathway than a cumulative loading mechanism due to the low frequency and high loads imposed in backboard lifting.

6.3 Implications for Assessing and Teaching Movement Strategy in Backboard Lifting

The use of pattern recognition to detect differences in movement strategy between high and low exposure lifts and across relative demand conditions can inform assessment of backboard lifting. From this study the criteria of interest to determine whether a lift is biomechanically favorable is the proximity of the body to the load. The horizontal distance to the load was the only feature of movement which demonstrated significant differences as a function of relative biomechanical exposure between high and low exposure lifters, and therefore is the only factor that has rationale to assess. Practically, assessment of movement strategy in backboard lifting can be conducted at any relative demand as there was no interaction between relative biomechanical exposure and relative demand on movement strategy.

In addition to informing the assessment of movement strategy, results from this study can influence how to teach backboard lifting to minimize relative biomechanical exposures. In particular, it

seems that to inform training direction that the most important takeaway is that regardless of strategy used lifters should try to minimize the horizontal distance of their body to the load. By focusing on the set up of the body prior to completing the lift to minimize the horizontal distance there may be better efficacy of a training approach opposed to focusing on movement strategy in the lift itself which has been shown to be ineffective (Martimo et al., 2008). As backboard lifting is infrequent, but with high loads, there may be utility in using the results from this study to inform ideal movement strategy in the lift itself even though effect sizes were small and past lift training interventions have been unsuccessful. The high absolute biomechanical exposure in a single backboard lift suggests lifters are likely at a higher risk of injury through an acute mechanism compared to a cumulative mechanism (McGill, 2015). Therefore, to minimize the absolute exposure in any given lift a secondary focus can be placed on using a distal to proximal strategy, maintaining an upright trunk, using a squat-like strategy and using a wide stance to keep hands close to the body. To aid in training these features of movement to further reduce relative biomechanical exposure aggregate reconstruction animations (still frames from these animations were used to create Figures 24 and 25) can be used as a tangible teaching tool.

6.4 Critiquing the Methodological Framework

The pattern recognition methodology used was appropriate for this study as it is conceptually compatible with OFC, it requires no *a priori* hypotheses and whole body motion is considered. The previous use of PCA to quantify aspects of variability support that it is conceptually consistent with the OFC theoretical framework, which defines variability as either task relevant or irrelevant based on the control law (Todorov & Jordan, 2002). Theoretically, a mode of variance explained in a PM is an aspect of variability that can either be task relevant or irrelevant. The identification of PMs as features of movement is done objectively based on variance explained, which eliminates the need for a priori

hypotheses on what aspects of movement to consider, therefore reducing subjectivity in analysis (Lees, 2002). The used pattern recognition methodology has a third noted strength that it considers whole body movement in analysis. Previous application of PCA to analyze movement strategy in lifting has considered joint angle waveforms (Khalaf et al., 1999; Sadler et al., 2011; Sadler et al., 2013; Wrigley et al., 2005; Wrigley et al., 2006) while not considering the entire kinetic chain of movement. Although the body has an abundance of DOF that can form infinite combinations of movement to reach an end trajectory, there is still a relationship between movements of different degrees of freedom as all joints are connected in some way through the kinetic chain. By inputting whole body motion into the PCA analysis, the changes in strategy about the kinetic chain are considered, which is a strength of the approach.

The methodology used was in large part chosen because of the high degree of objectivity, but there is still a reliance on subjectivity for retaining and interpreting PMs. In an effort to be as objective as possible parallel analysis was used to retain PMs that explained more variability than what would be explained by chance (Wrigley et al., 2005), which is reported as the most accurate method of retaining PMs (Hayton et al., 2004). Although this may miss some higher PMs that could identify differences in strategy between high and low exposure lifters across relative demands, the objectivity of the parallel analysis supports this methodological decision. In interpreting PMs, single component reconstruction was used to allow for clear identification of the mode of variability explained by a PM (Brandon et al., 2013). Single component reconstruction was originally developed to be used on waveform data where the operator can be clearly identified by comparing reconstructions of the 5th and 95th percentile PM scores. However, reconstructing whole body movement using this approach still results in a reliance on subjective interpretation of the modes of variance being explained. To aid in the interpretation the loading vector was expressed as an average in the time domain for both the mean movement and individual markers was used to direct interpretation of the single component reconstructions.

In the research design, care was taken to control external constraints that could affect the formation of a participant's control law. Newell's constraints model (1986) identified organism, task and environmental constraints that could affect coordination patterns where Glazier (2017) theorizes this is accomplished by changing a person's control law as a function of the constraints present. It is argued that the experimental protocol was conducted to minimize the effect of constraints acting as confounding variables. The environmental constraint was controlled for strongly as there were no differences in the location of data collection, lab set up or instruction within the protocol across participants. The task constraint was controlled for except for modifying the relative demand of the backboard as this was an independent variable. Most organism constraints were purposefully not controlled in this study to accomplish the research objectives. This research probed the hypothesis that some lifters would consider biomechanical exposure in their control law while others would not, where the choice to consider biomechanical exposure was informed by the organism constraint. Fatigue is an organism constraint that could have influenced movement strategy as localized muscle fatigue has led to changes in lifting technique in cyclic lifting (Bonato et al., 2003). Mandatory rest times were implemented in the study to minimize the effect of fatigue on influencing movement strategy. Changes in subjective measures of fatigue are documented in Appendix C.

6.5 Limitations

The use of pattern recognition yielded objective differences in movement strategy between high and low relative biomechanical exposures and across relative demands, but the approach is not without limitation. The first being that the PCA approach only considers a subset of the data that explains a portion of variance in the overall data set. In this study, parallel analysis was used to only retain PMs that explain more variance than what would be explained by chance resulting in the six PMs explaining

87.7% of variance in the data set. This is less variance explained than other cut offs that have been used in the literature such as a 90% trace criterion (Jackson, 1991; Deluzio & Astephen, 2007; Sadler et al., 2011; Reid et al., 2010) which would retain a higher number of PMs. Although the process to retain PMs was objective, there is a chance that aspects of variability that clearly differentiate lifts by relative biomechanical exposure or relative demand that explain less variance in the data set were overlooked. Secondly, there is difficulty setting criterion for what is high vs. low relative biomechanical exposure. For this analysis, the median value was set as a threshold for this differentiation, but there is no evidence to support that this cut off value is causatively linked to higher incidence of MSD development. However, with a correlation of higher low back angle and moment exposure resulting in higher risks of MSDs (Marras, 1993) this criteria is suitable as a measure of exposure as it differentiates between the higher and lower exposure lifts. Third, use of this PCA approach distorts the time domain as trial time was normalized to a percentage. Therefore, it is difficult for the PCA model to identify differences in timing of lifts between relative biomechanical exposure group and across relative demand. Finally, the high number of lifting trials input into the PCA model increases the likelihood of type I error. To reduce the risk of this error effect sizes in addition to statistical testing results were considered in interpretation.

6.6 Future Directions

Results of this study support the opportunity to apply pattern recognition to identify high and low exposure lifters in practice. Particularly, a similar methodology could be applied to assess movement competency in backboard lifting when administering a physical employment standard for the paramedic sector (Fischer et al., 2017). When assessing movement competency in pre-hire screens there is a current reliance on evaluation through observation (Sinden et al., 2017) leading to a subjective analysis of technique or risk. The reliance on subjective analysis brings the validity and reliability of this mode of

assessment into question (Pransky & Dempsey, 2004). By employing a pattern recognition methodology, the assessment of movement competency can be objective to overcome the limitations associated with evaluation through observation. These proposed methods can be paired with artificial intelligence approaches, such as use of a linear discriminant function (Ross et al., 2018), to classify lifts based on the features of movements identified via pattern recognition. Advances in marker-less motion capture, such as convolutional pose machines (Wei et al., 2016), provide opportunity to capture robust kinematic data outside the lab to make pattern recognition based methodology practical in application.

A second future direction opportunity is to understand mechanisms influencing movement strategy within the Glazier (2017) theoretical framework. The results to this study demonstrate that changes in constraints resulted in differences in control patterns. It was inferred that the changes in control patterns were a product of the constraints informing the definition of the control law as defined in OFC (Scott, 2004). However, in this study none of the control law, coordination patterns or sensory feedback were measured to confirm that differences in control patterns were truly caused by changes in the control law. Future research should be aimed at further probing this theoretical framework to understand the causative mechanisms of how changes in external task constraints influence the formation of a control law and the resultant downstream movement strategy.

As the employed PCA method continues to be developed there is opportunity to develop best practices. In particular, best practices are needed to objectify the interpretation PMs. In this study the average and marker specific loading vectors were used to gain insight into the operator of variance explained as well as where locally and in the normalized time domain variance was being explained. Although the use of loading vectors in conjunction with single component reconstruction provided some supporting information to guide interpretation this process continued to rely on subjectivity. Standardizing of interpretation methods could aid in interpretation of PMs in future work.

A second opportunity to develop the PCA method is to explore best practices for data normalization and expression. For this study, all data were normalized to height so that differences in anthropometrics would not be explained in a PM. However, by normalizing to height the contribution of anthropometrics to variance in the data set is ignored. The position data input in this study was referenced to a global coordinate system opposed to a local system as has been done in previous work (Ross et al., 2018). This decision was made as the position of the origin and the load remained consistent across lifting trials and participants, so capturing the position in the global system (as was done in PM1 – AP body position) was important. However, if similar methods were to be applied to tasks that are more dynamic the position of the body in the global system may be subject to noise and best practice may be to express data in a local coordinate system. A comparison of PCA outputs following different normalization methods and when expressing data in either a global or local coordinate system should be explored to determine best practices.

Finally, the number of anatomical inputs to consider in analysis should be considered moving forward. In this study, each segment of the body contributed an anatomical input except for the feet, which contributed two. This was done by taking the COG of segments in the axial skeleton and the proximal end point of segments in the appendicular skeleton. The COG of the feet were also included to give a representation of the orientation of the foot segments in 3D space. Using this approach, the relative contribution of the segments in the PCA model was nearly equally weighted. Future work should explore whether the addition or subtraction of other anatomical inputs influences the results of the PCA analysis.

7.0 Conclusion

Pattern recognition was applied to successfully identify features of movement in backboard lifting related to the resultant relative biomechanical exposure at the low back and the relative demand of the load. It was found that differences in horizontal position of the body to the load was indicative of whether lifters experienced high or low resultant relative biomechanical exposures. Additionally, this study identified differences in mean movement strategy in features of movement explaining variance in sequencing of lifting and using a squat vs. stoop strategy as a function of relative demand.

Practically, the results to this study demonstrate the utility of pattern recognition to assess movement strategy in backboard lifting where to minimize the biomechanical exposures the horizontal distance from the body to the load should be minimized. Assessment of backboard lifting strategy can be conducted at any relative demand, as the effects of biomechanical exposure and relative demand on movement strategy in backboard lifting do not interact. Furthermore, results from this study can be used to develop training approaches to minimize biomechanical exposure by using movement strategy where the body is closer to the load, using a distal to proximal strategy, maintaining an upright trunk and using a squat-like strategy.

The noted success of pattern recognition methods to identify differences in features of movement as both a function of resultant biomechanical exposure and relative demand support the utility of this approach moving forward. By combining pattern recognition with artificial intelligence techniques there is a potential to identify differences in high and low exposure strategy in practice within the paramedic sector, but also in other occupations with where workers are at high risk of MSDs.

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Appendix A: Standard Operating Procedure on 1RM Testing

Department of KINESIOLOGY

STANDARD OPERATING PROCEDURE

A Standard Operating Procedure (SOP) is to be created to direct and guide researchers when performing study protocols, especially those that have the potential to cause harm (or increase risk) to a study participant such as those outlined as a controlled act in the [Regulated Health Professions Act](#) of Ontario (RHPA).

SOPs are to follow the Deming Cycle, a cycle that identifies "Plan-Do-Check-Act." A SOP is created to:

- outline the procedures that must be executed to effectively follow the study protocol and outline the resources/equipment needed (i.e., PLAN),
- provide detailed instructions for research staff of the steps that must be implemented and the training that must be completed (i.e., DO),
- clearly document the study protocol (i.e., CHECK), and
- aid with continuous improvement (i.e., ACT)

All SOPs are to be maintained and controlled by the Principal Investigator/Faculty Supervisor. The Principal Investigator/Faculty Supervisor is responsible for the current and approved versions.

SOPs are reviewed by the Office of Research Ethics reviewers and/or Research Ethics Committee members in conjunction with their review of the procedures section in the Form 101 or Form 104 (modification request).

Submit only new SOP's or those which have not been previously approved in conjunction with a prior application. In the procedures section of the 101 form or 104 form state the SOP name, date, and the previously approved ORE number, if applicable.

Title of SOP: Protocols for Muscular Strength and Endurance Assessment

SOP created on: [October/29/2015] and **Ethics Clearance Received on:**

Revised on: [February/13/2018] and **Ethics Clearance Received on:**

SOP created by: [Caryl Russell, Director of Programs, Madeleine Noble, Senior Lab Demonstrator, Dept. of Kinesiology]

SOP revised by: [Julia Fraser, Research and Operations Manager, Dept. of Kinesiology]

Signature:

Date:

I acknowledge that as the principal investigator/faculty supervisor I am responsible for updating this SOP and notifying the ORE through a modification form (Form 104) if any of the procedures as outlined above change or require revision.

A. PURPOSE AND BACKGROUND

This SOP describes the protocols and safety for muscular strength and endurance assessments including 1 repetition max (1RM), predicted 1RM and stand load testing.

B. PROCEDURES

Are there any controlled act(s) to be performed: Yes X No
If you checked yes, list the controlled act(s) below:

Appendix B: Tests of Normality for PM scores

Normal Q-Q Plots are pictured for PMs 1-6 (Figures 1-6 respectively) to give a visual representation of the spread of data in a PM relative to a normal distribution with the same mean and standard deviation. The visual agreement of PM scores to the Q-Q plot support that the data is normally distributed even though significant effects were seen in the Shapiro-Wilks test of normality for all PMs. Additionally, PM scores are z-scores of the deviation of a trial from the mean PM and therefore are normally distributed by definition.

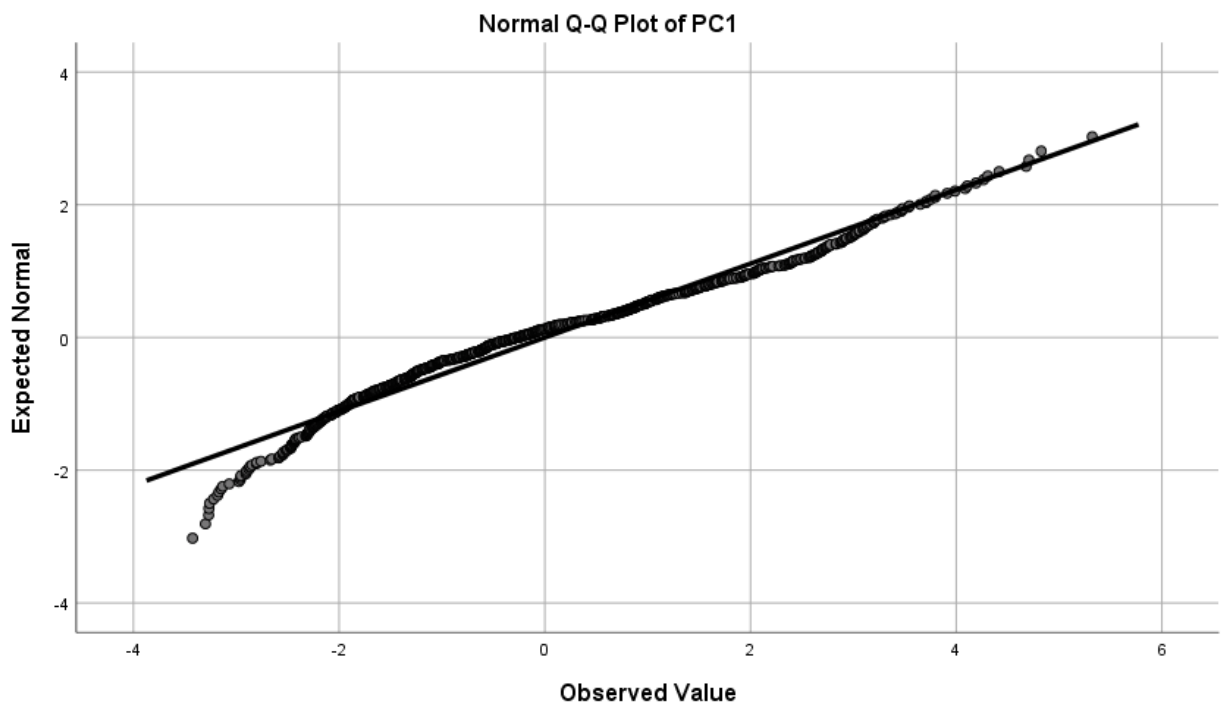


Figure 1: PM scores in PM1 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

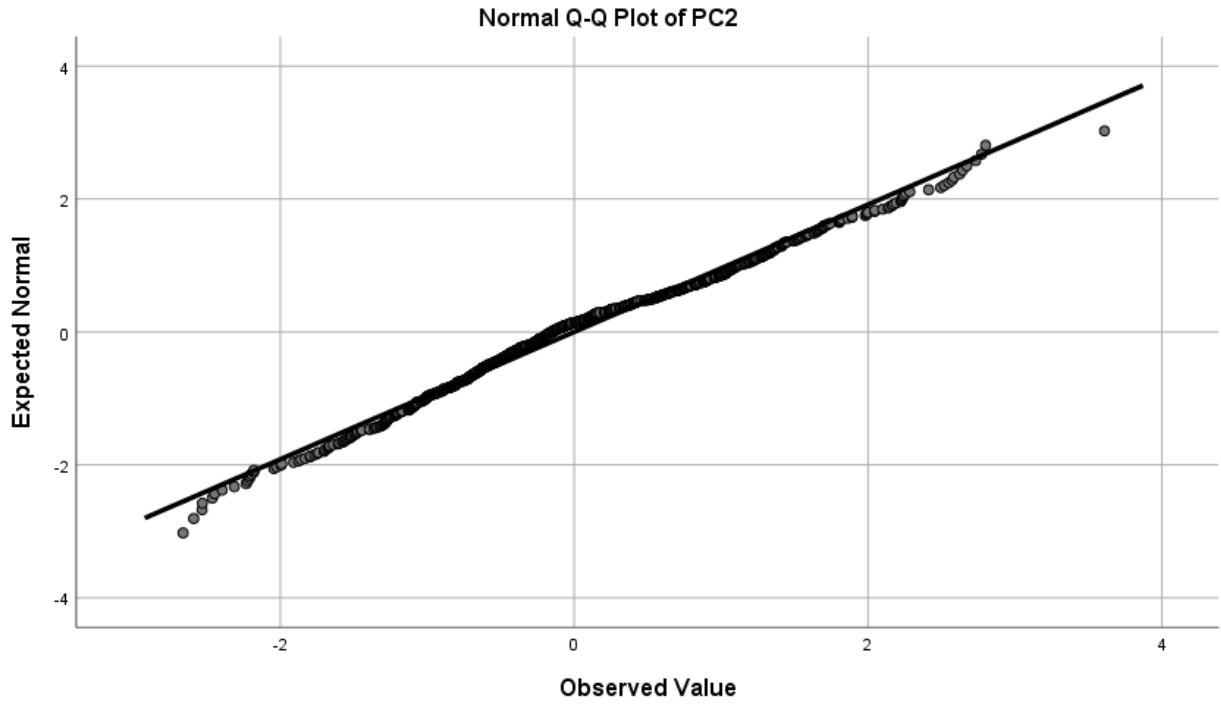


Figure 2: PM scores in PM2 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

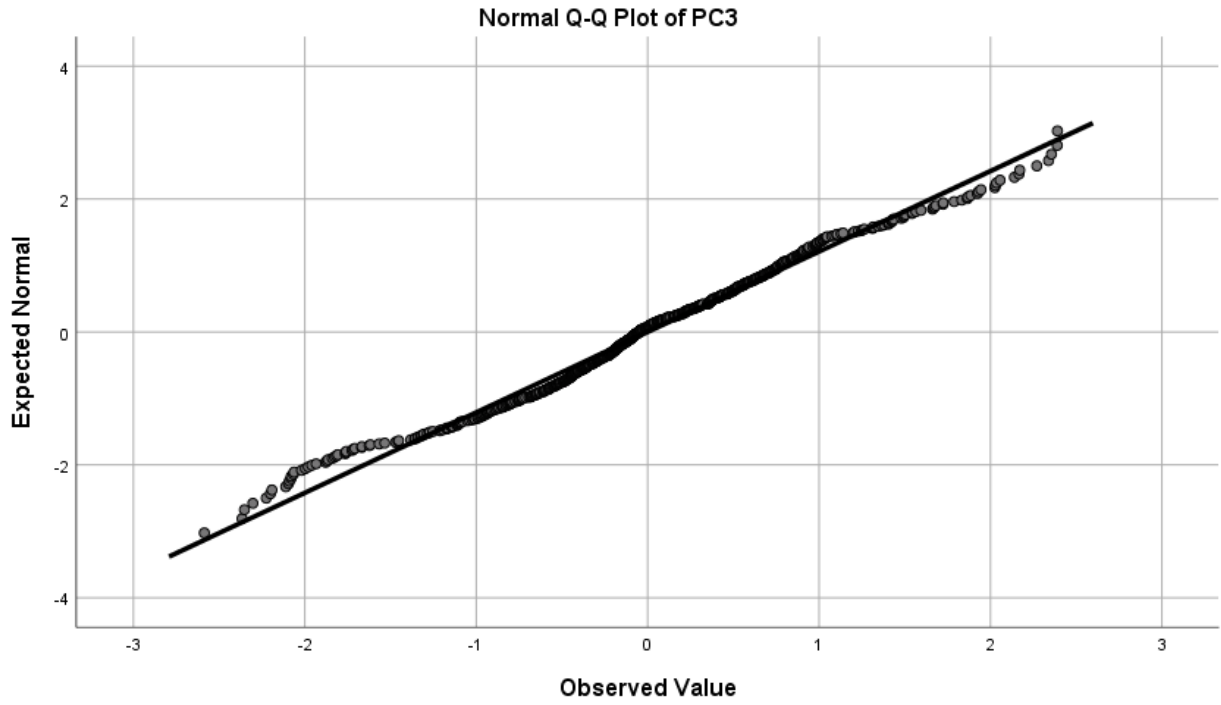


Figure 3: PM scores in PM3 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

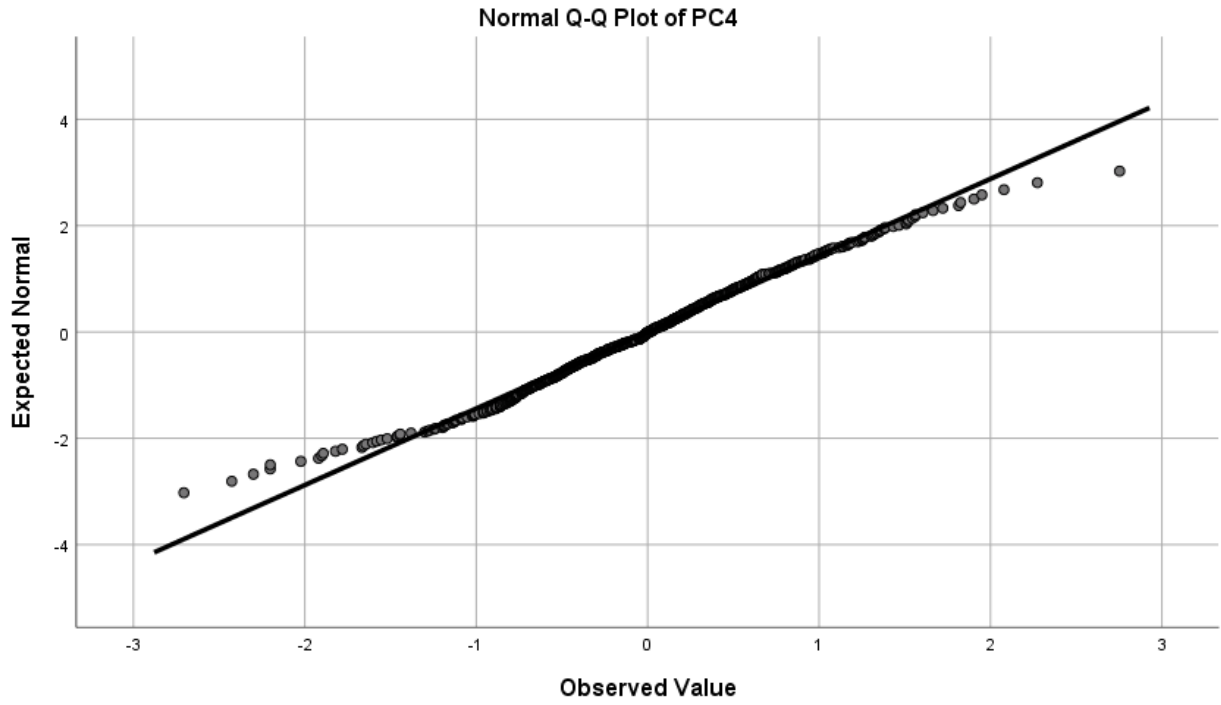


Figure 4: PM scores in PM4 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

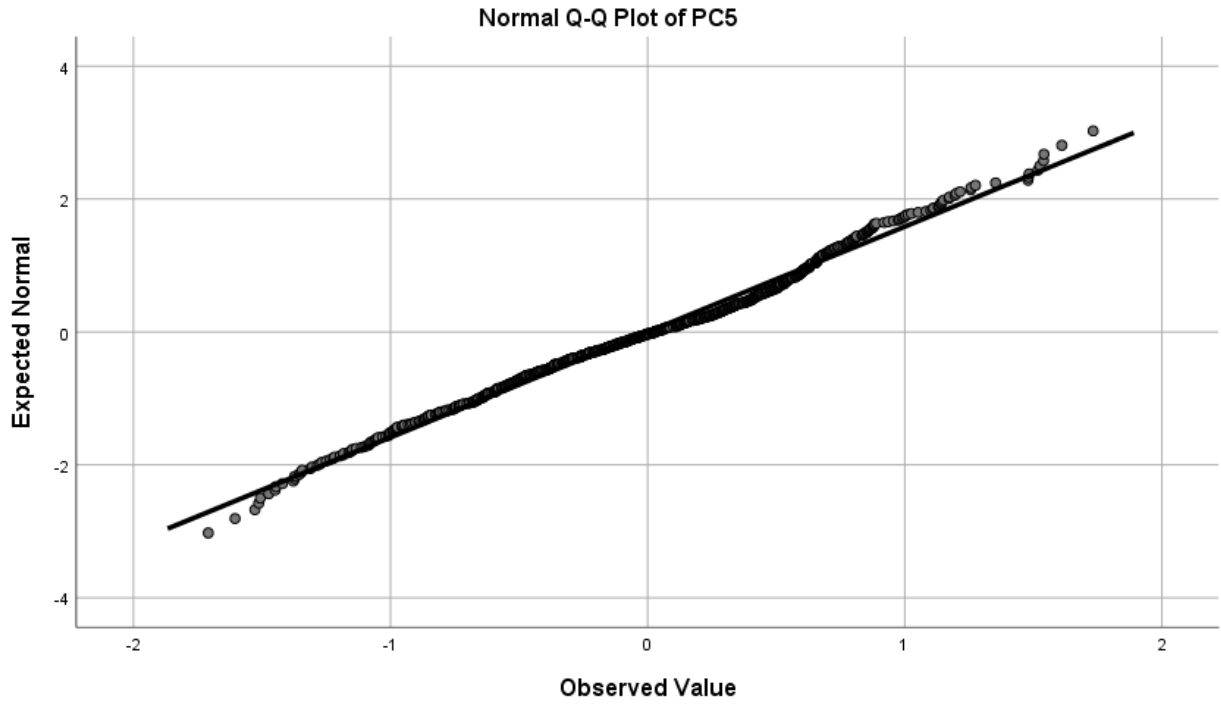


Figure 5: PM scores in PM5 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

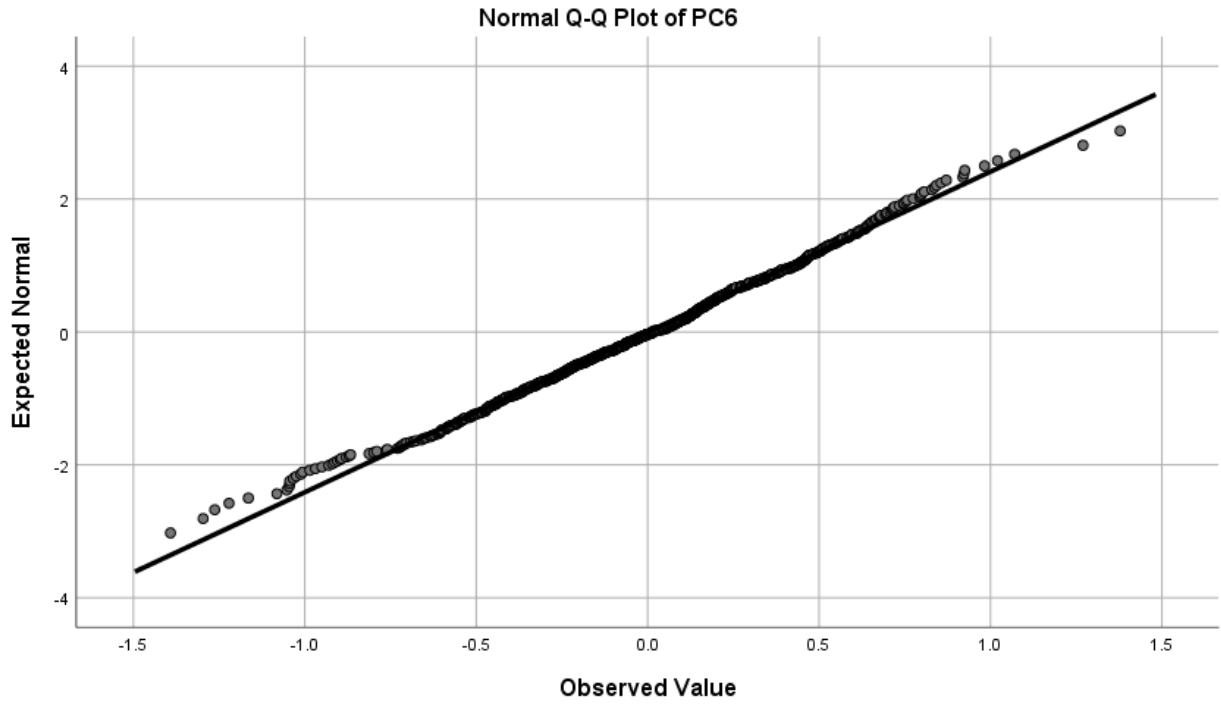


Figure 6: PM scores in PM6 (grey circles) plotted against a normal distribution with the same mean and standard deviation (solid black line).

Appendix C: Changes in subjective fatigue measures over the experimental protocol

To measure fatigue across the study protocol participants rating of perceived exertion (RPE) was collected using a Borg rating of perceived exertion scale (Borg, 1998). As the load did not change in relative demand conditions no changes in RPE would be expected if fatigue was not occurring. To track the changes in fatigue three repeated measures ANOVAs were run (one for each relative demand condition) to assess the change of perceived exertion over the lifting protocol (Figures 1-3). There was no significant change in RPE for light trials ($F(1,25) = 1.14, p = 0.295$), but there were significant increases in RPE in the medium ($F(1,25) = 12.54, p = 0.002$) and heavy ($F(1,25) = 23.73, p < 0.001$) relative demand conditions.

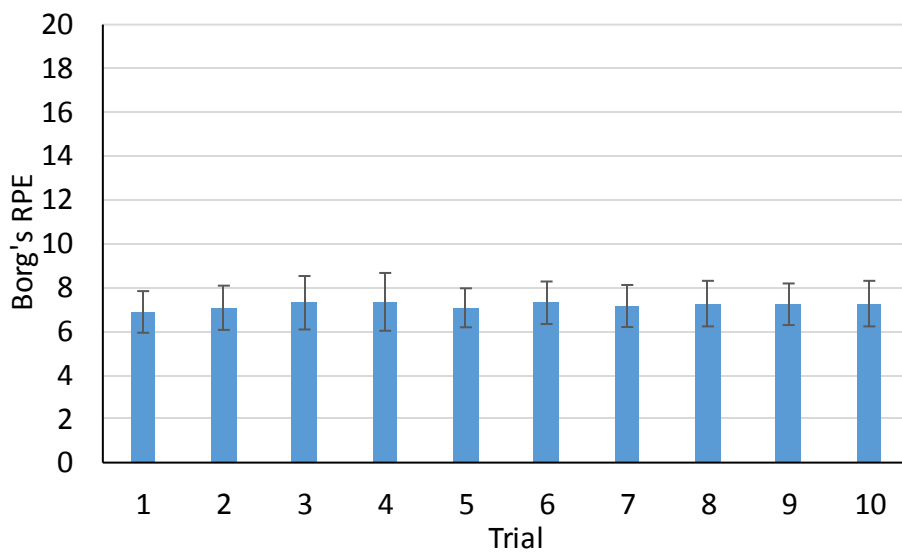


Figure 1: Mean Borg's RPE across light relative demand lifts.

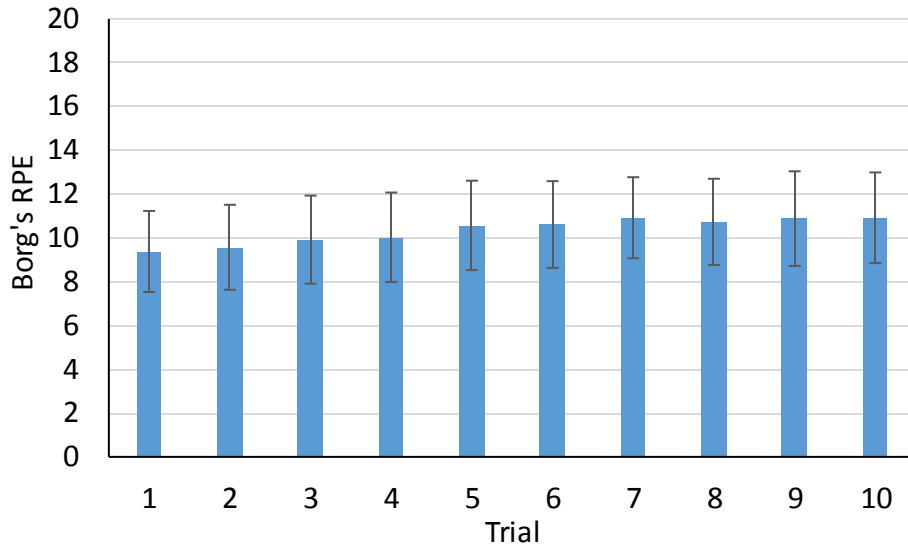


Figure 2: Mean Borg's RPE across medium relative demand lifts.

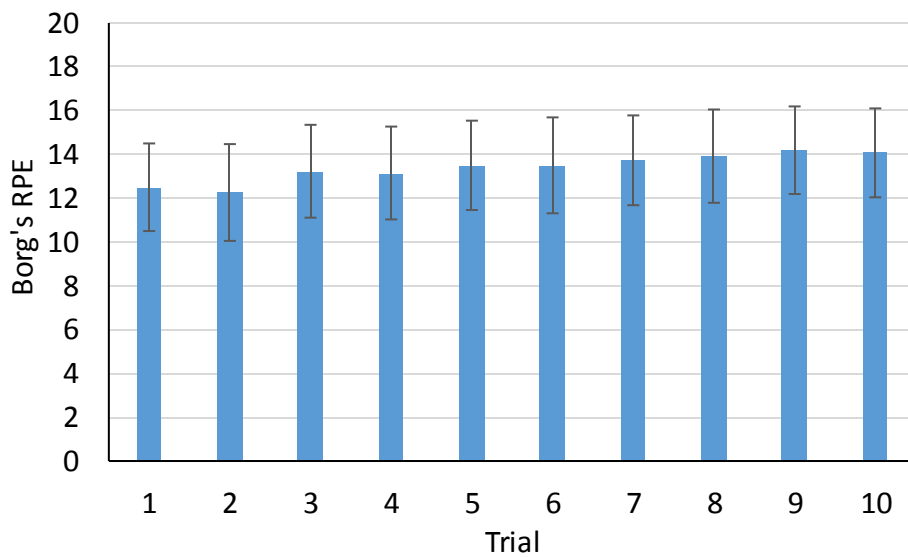


Figure 3: Mean Borg's RPE across heavy relative demand lifts.

Although there were significant main effects of Borg's RPE in both the medium and heavy conditions the absolute mean increase in RPE from trial 1 to 10 was only 1.54 and 1.57 in the medium and heavy relative demand conditions respectively. Even though the increase in RPE was statistically significant it is not believed that this would result in appreciable changes in movement strategy due to fatigue because of the minimal descriptive increases in mean Borg's RPE values.

References:

Borg, G. (1998). *Borg's perceived exertion and pain scales*. Human kinetics.