Kinematic variability in repetitive occupational tasks as an individual trait from different motor control perspectives

by

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Author’s Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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

Statement of Contributions

Nathalie Oomen was the sole author for Chapters 1, 2, 5 and 8 which were written under the supervision of Drs. Steven Fischer and Ryan Graham and were not written for publication.

This dissertation contains four manuscripts (Chapters 3, 4, 6 and 7) written for publication. The authorship is as following:

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As lead author of these chapters, N. M. C. W. Oomen completed the conceptualization and design of the research, acquisition of the data, analysis and interpretation of the data, writing the manuscripts, and critical revision of manuscripts that have been published. The co-authors provided guidance during the research process and provided feedback on draft manuscripts.

Abstract

Recent ergonomic research suggests that individuals with low motor variability (repeaters) are at higher risk of developing work-related musculoskeletal disorders than individuals with high motor variability (replacers) when performing repetitive tasks. Importantly, the repeaters-replacers hypothesis is dependent on the fundamental condition that motor variability is genuinely an individual trait, which is currently unknown. Therefore, this dissertation aimed to examine several measures of whole-body kinematic variability under different task constraints during lifting, during fatigue development in lifting and in different occupational tasks to evaluate kinematic variability as an individual trait.

Healthy females and males were recruited from the student population for two experimental sessions to perform self-paced repetitive lifting, carrying and simulated sawing tasks. The lifting task was performed four times under different task constraints of foot movement (restricted by instruction versus no restriction) and load weight (low versus high). For these six tasks, the total number of repetitions of each task was limited to 105 repetitions to avoid inducing excessive fatigue. The unrestricted high load lifting task was repeated in a prolonged protocol until volitional fatigue or up to a maximum of 1 hour. Whole-body joint angles and crate trajectories were obtained using optoelectronic motion capture. Kinematic variability was quantified using three different measures, a linear measure of joint angle mean point-by-point standard deviation, nonlinear continuous relative phase (CRP) variability of joint angle couplings, and nonlinear task-relevant and task-irrelevant variability derived from joint angles and crate trajectories. In addition, rate of perceived exertion was assessed as an indicator of fatigue.

In repetitive lifting under different constraints, individual variability demonstrated strong consistency independent of variability measures. However, across individuals, variability increased in

response to removing the foot movement restriction when assessed using linear and nonlinear measures while task-relevant and task-irrelevant variability did not show any differences. When individuals were ranked on variability, strong consistency across measures was also demonstrated although CRP measures appeared to capture a slightly different construct than the other measures. In different repetitive tasks of lifting, carrying and simulated sawing, only moderate consistency was found in linear individual variability. Across individuals, linear variability was affected by task type where the order from highest to lowest variability was carrying, lifting and sawing, respectively. When unrestricted high load lifting was compared to three phases during prolonged unrestricted high load lifting, individual variability demonstrated strong consistency independent of (non)linear measures. In addition, across individuals no changes in variability were observed with different fatigue states. Variability during unrestricted high load lifting was associated with some indicators of fatigue.

This work reveals strong evidence for kinematic variability as an individual trait across investigated task constraints, variability measures, and fatigue development in lifting; however, variability could be task specific. Based on the effects of foot movement and task type on kinematic variability, variability increased when more degrees of freedom were allowed. Also, during lifting kinematic variability showed different responses to task constraint depending on variability measure. However, kinematic variability was related to some fatigue measures. The findings of this dissertation provide insight into kinematic variability as an individual trait in repetitive occupational tasks and therefore contribute to an essential aspect of the repeaters-replacers hypothesis. If kinematic variability can be related to risk of work-related musculoskeletal disorders, risk of injury could be prevented or lowered by altering individuals' variability through training or workplace interventions assuming it is possible to convert a repeater into a replacer.

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

ANOVA	Analysis of Variance
CI	Confidence Interval
CRP	Continuous Relative Phase
DOF	Degrees of Freedom
DST	Dynamic Systems Theory
ELC	EPIC Lifting Capacity Test
EMG	Electromyography
FR	Free (unrestricted foot instruction)
GAQ	Get Active Questionnaire
GEM	Goal-Equivalent Manifold
ICC	Intraclass Correlation
ISB	International Society of Biomechanics
LB	Low Back
LE	Lower Extremity
MIP	Minimum Intervention Principle
MMH	Manual Material Handling
MV	Motor Variability
OFC	Optimal Feedback Control
ORT	Orthogonal (to UCM)
RPE	Rate of Perceived Exertion
RS	Restricted (restricted foot instruction)
SD	Standard Deviation

UCM	Uncontrolled Manifold
UE	Upper Extremity
WB	Whole-body
WRMSD	Work-related Musculoskeletal Disorder

Chapter 1: General Introduction

Work-related musculoskeletal disorders (WRMSDs), defined as pathological impairment of musculoskeletal tissues, are a significant problem in society at the provincial, national, and global levels in terms of prevalence, incidence, treatment costs, cost associated with loss of productivity, and for the employee's quality of life (Baldwin, 2004; Buckle & Devereux, 2002; Coyte et al., 1998; Feeney et al., 1998; Leijon et al., 1998; OHSCO, 2007; Thiehoff, 2002). In Canada, the total cost of WRMSDs was described as the highest in comparison to any other disease-related costs by the Public Health Agency of Canada (Canadian Institute for Health Information, 2013). In 2014, the total cost of WRMSDs was predicted at $CAD 22 billion each year between 2014 and 2018 (Institute of Musculoskeletal Health, 2014). Thus, WRMSDs remain as a significant problem in Canadian society.

A proposed injury mechanism underlying WRMSDs is fatigue failure or cumulative tissue damage which is determined by the interaction of force and repetition (Gallagher & Heberger, 2013; Gallagher & Schall, 2017). Although current work demands have reduced in magnitude of force, moderate to high repetition remains common (e.g. assembly line manufacturing, order picking at distribution centers) (Kermavnar et al., 2021; Marras et al., 2009). Cumulative loading associated with repetitive work could be reduced by an inherent feature of repetitive human movement; the emergence of repetition-to-repetition motor variability (MV) (Bernstein, 1967; Latash et al., 2002; Newell & Corcos, 1993). An increase in MV could lead to more repetition-to-repetition distribution of mechanical loading and muscle activation across tissues and thus reduce the risk of cumulative damage (Bartlett et al., 2007; Hamill et al., 1999; Madeleine, 2010; Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006).

Repetition-to-repetition or between-trial MV reflects variability in motor variables (e.g. kinematics, electromyography (EMG), kinetics) from repeated execution of the same task (Bernstein, 1967). In this context, MV arises from the degrees of freedom (DOF) problem or motor abundance. Traditionally, according to the DOF problem the human motor system consists of more DOF than conceptually necessary to complete a motor task and thus this problem needs to be solved by the central nervous system (Cusumano & Cesari, 2006; Latash, 2000; Latash et al., 2002; Newell & Corcos, 1993). More recently, the DOF problem has been revisited as motor abundance which means that the abundance of DOF is viewed as part of the solution to functions of motor performance such as flexibility (Bartlett et al., 2007; Clark, 1995; Diedrichsen et al., 2010; Latash, 2000, 2012; Latash et al., 2002, 2007). Thus, MV could give insight into underlying motor control or regulation (Latash et al., 2002; Newell & Corcos, 1993).

The functional perspective of motor abundance has been adopted in ergonomics through the development of several working hypotheses on the potential for MV to modify the risk of WRMSDs in repetitive tasks. The overarching variability-risk hypothesis suggests that low variability is associated with higher risk of WRMSDs compared to high variability (Bartlett et al., 2007; Côté, 2012; Madeleine, 2010; Mathiassen et al., 2003; Srinivasan & Mathiassen, 2012). The variability-risk hypothesis is based on associations between variability and measures of WRMSD risk consisting of variability-pain (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008), variability-experience (Granata et al., 1999; Madeleine, Voigt, et al., 2008), variability-fatigue (Côté et al., 2002, 2008; Farina et al., 2008; Sedighi & Nussbaum, 2017; van Dieën, Oude Vrielink, & Toussaint, 1993; van Dieën et al., 2009; Yang et al., 2018), and variability-overuse injury hypotheses (Hamill et al., 1999; Heiderscheit et al., 2002; James et al., 2000). More specifically, low between-trial variability of kinematics and EMG has been associated with pain and earlier onset or faster development of fatigue, whereas low between-trial variability of kinematics has been related to overuse injury while high kinematic and kinetic variability has been associated with more task-specific experience (Côté et al., 2002; Farina et al., 2008; Granata et al., 1999; Hamill et al., 1999; Heiderscheit et al., 2002; James et al., 2000; Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993; Yang et al., 2018).

A recent hypothesis that is gaining attention in ergonomics, the repeaters-replacers hypothesis, could change our current view on the variability-risk hypothesis. The repeaters-replacers hypothesis suggests that when ranking individuals from low to high variability, repeaters with low variability and replacers with high variability can be defined (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). Replacers exploit motor abundance by varying movement strategies which is reflected in high MV magnitude (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). However, repeaters repeat the same patterns and thus exploit motor abundance to a lesser extent which is visible from their lower MV magnitude (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). However, the repeaters-replacers hypothesis is only supported on the condition that MV is genuinely an individual trait which would require individual consistency in different scenarios such as different conditions of the same task and across different tasks (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). In addition, there is currently no direct evidence to support the variability-risk hypothesis within the context of the repeaters-replacers hypothesis. The characteristic of MV as an individual trait is the focus of this dissertation.

The growing body of literature on variability-risk and repeaters-replacers hypotheses in ergonomics has revealed a lack of consensus and standardized techniques to assess MV. However, when focussing on kinematics, traditional or linear measurements such as standard deviation have been primarily considered (Granata et al., 1999; Jackson et al., 2020; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sandlund et al., 2017; Sedighi & Nussbaum, 2017), while nonlinear measurements are relatively understudied (Madeleine & Madsen, 2009; Sandlund et al., 2017; Sedighi & Nussbaum, 2017). Despite the frequent use of linear measurements in gathering evidence on variability-risk and repeaters-replacers hypotheses, these measurements are derived from the traditional motor control perspective of the DOF problem. Therefore, the use of linear measurements does not align with the view of motor abundance from the functional motor control perspective even though these measurements have substantially contributed to the development of these hypotheses. The dependency on linear measurements and misalignment of these measurements based on underlying motor control perspective demonstrates the need to use different measurements of MV to further explore the repeaters-replacers hypothesis.

With respect to tasks, ergonomic research on MV has been focussed on fine motor tasks performed with the upper extremity including simulated filleting/cutting (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008), deboning (Madeleine & Madsen, 2009), reaching/pointing (Lomond & Côté, 2010; Yang et al., 2018), sawing (Côté et al., 2002), hammering (Côté et al., 2008), simulated assembly task (Jackson et al., 2020), and pipetting (Sandlund et al., 2017). However, only some work has assessed gross motor tasks performed with the whole-body such as lifting (Granata et al., 1999; Sedighi & Nussbaum, 2017; van Dieën et al., 2001). Gross and fine motor tasks differ in the amount of DOF that are involved in performing the tasks, which represents differences in opportunity to exploit MV in line with the view of motor abundance present in the repeaters-replacers hypothesis. Furthermore, fine motor tasks often require an element of precision, and increasing accuracy demands have been shown to reduce MV indicative of a loss in motor control flexibility (Soechting, 1984; Srinivasan, Mathiassen, et al., 2015; Tseng et al., 2003). The repeaters-replacers hypothesis has only been investigated in fine motor tasks while gross motor tasks may give different insight into MV

(Jackson et al., 2020; Sandlund et al., 2017). Thus, gross motor tasks such as occupational lifting have only received little attention in occupational MV research and have not yet been assessed in context of the repeaters-replacers hypothesis. Furthermore, the strongest evidence for MV as an individual trait would require assessment of individual consistency in MV across fine and gross motor tasks, which has not been performed to date.

When considering task constraints, fine and gross motor tasks have been investigated under relatively constrained task conditions such as external pacing (Jackson et al., 2020; Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Sandlund et al., 2017; Sedighi & Nussbaum, 2017; Yang et al., 2018) and movement restrictions (i.e. only horizontal plane arm movement during reaching/pointing (Lomond & Côté, 2010; Yang et al., 2018), restrained torso during pipetting (Sandlund et al., 2017), and fixed foot positioning during lifting (Granata et al., 1999; Sedighi & Nussbaum, 2017). These task constraints could restrict the amount of available DOF and thus limit the opportunity to exploit MV. When pacing was increased in a fine motor task, MV was reduced and in combination with an accuracy demand some indication of a speed-accuracy trade-off was demonstrated (Srinivasan, Mathiassen, et al., 2015). Additionally, if constraints are not representative of workplace conditions, they could obscure the external validity of MV assessment. When specifically considering the repeaters-replacers hypothesis, individual consistency has only been assessed in fine motor tasks across different days and temporal task constraints (i.e. pacing and production process) (Jackson et al., 2020; Sandlund et al., 2017). Although task constraints could affect MV and individual consistency in MV has only been investigated in fine motor tasks, it indicates an opportunity to assess individual consistency in MV across varying task constraints of a gross motor task.

1.1 Overall thesis objective

The overall objective of this thesis was to assess between-trial kinematic motor variability during repetitive manual work tasks to test the repeaters-replacers and variability-fatigue hypotheses from both traditional and functional motor control perspectives.

1.2 Specific research objectives

1. To explore the role of task constraints on between-trial motor variability and consistency in individual responses in repetitive lifting using traditional and functional motor variability measures (Study 1 & 2; **Figure 1.1**)

2. To compare individual between-trial motor variability on consistency across all variability measures used in purpose 1, to help inform the use of variability measures in other studies of this dissertation (Study 3; **Figure 1.1**).

3. To determine between-trial motor variability and consistency in individual responses in different repetitive manual work tasks (lifting, carrying, simulated sawing) using measure(s) informed by purpose 2 (Study 4; **Figure 1.1**).

4. To determine between-trial motor variability and consistency in individual responses in repetitive lifting under the development of fatigue using measure(s) informed by purpose 2 (Study 5; **Figure 1.1**)

5. To determine relationships between motor variability and indicators of fatigue development in repetitive lifting under the development of fatigue using measure(s) informed by purpose 2 (Study 5; **Figure 1.1**).

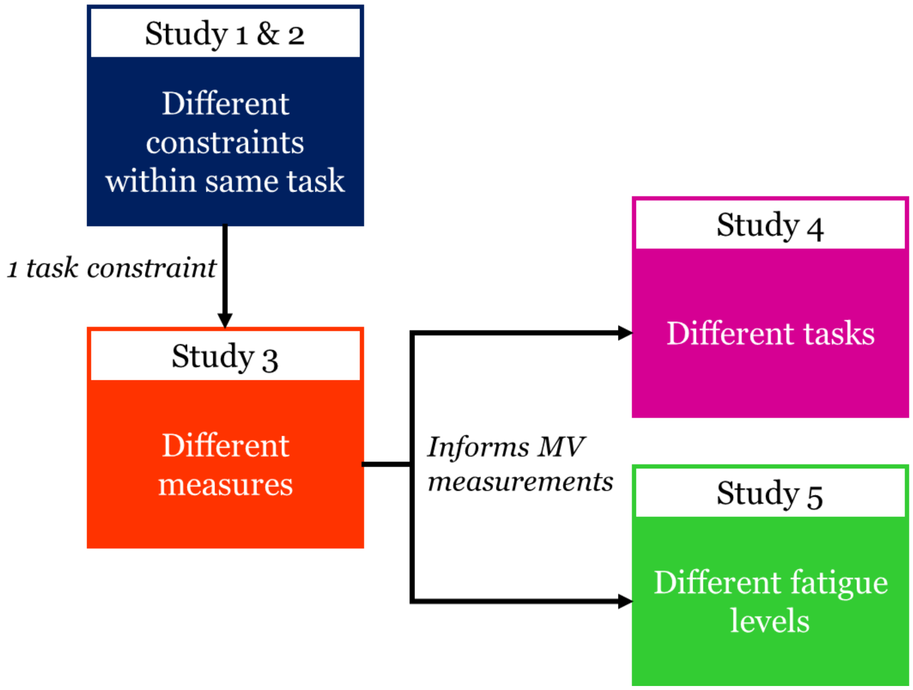

Figure 1.1: Flowchart of the studies for this thesis

Chapter 2: Literature review

2.1 Introduction of literature review

The hypothesized relationship between variability and risk of work-related musculoskeletal disorders (WRMSDs) has been quantified by a range of different motor variables (e.g. kinematics, electromyography (EMG), kinetics) (Madeleine, 2010; Srinivasan & Mathiassen, 2012) and different variability metrics (e.g. standard deviation, entropy, coordination dynamics, uncontrolled manifold (UCM), goal-equivalent manifold (GEM)) (Srinivasan & Mathiassen, 2012). This demonstrates the quantification problem within motor variability (MV), which is a significant issue because the current interpretation of variability with respect to WRMSD risk has been based on the results of these dependent variables. Therefore, the purpose of this literature review is to analyze the different variability-risk hypotheses with respect to the dependent variables specifically used in these studies and to review the chronological development of motor control theoretical frameworks that underlie dependent measures of MV. The lack of consensus and standardized techniques to assess MV limits comparison of results across studies and thus creates a barrier to a comprehensive understanding of the variability-risk hypothesis due to inconsistent results within and between MV metrics. Despite the quantification problem, the historical evolution of MV measures explains why increased MV has recently been considered as functional whereas traditionally it was considered as dysfunctional. This literature review is divided in two sections; the first section will discuss the different variability-risk hypotheses that are relevant for WRMSDs, and the second section will discuss the theoretical frameworks underlying MV metrics in chronological order of their development.

2.2 Variability-risk hypotheses

Four hypotheses have emerged from ergonomics and sport biomechanics that demonstrate that low variability is associated with higher risk of injury and high variability is associated with a lower risk. Collectively, the variability-pain, variability-experience, variability-fatigue and variability-overuse injury hypotheses relate low variability with a higher risk on WRMSDs. In contrast to the variability-risk hypothesis, the repeaters-replacers hypothesis specifically prescribes variability to the individual. However, when combining the variability-risk and repeaters-replacers hypothesis individuals with low variability (repeaters) are expected to be at higher risk on WRMSDs than individuals with high variability (replacers).

2.2.1 Variability-pain hypothesis

Lower MV was found in individuals with pain compared to individuals without pain based on some dependent measures of MV (Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009). However, within these specific studies other dependent variables of MV showed evidence rejecting this statement. In particular, most studies except for the independent variable of experimentally-induced pain (Madeleine, Mathiassen, et al., 2008) showed contrasting findings for different locations and/or measures of kinematic variability.

In simulated cutting chronic neck-shoulder pain among butchers showed a reduction in arm and trunk kinematic variability and shoulder EMG variability, while an increase in cycle time variability was found when compared to healthy controls (Madeleine, Mathiassen, et al., 2008). Newly employed female butchers who developed sub-chronic pain in the upper extremities after six months of employment showed a reduction in arm kinematic variability, but an increase in trunk kinematic variability when performing simulated cutting compared to the same population without pain (Madeleine, Voigt, et al., 2008). Similar contradictions in kinematic MV between different locations were observed in repetitive reaching. Individuals with chronic neck-shoulder pain demonstrated lower relative kinematic variability of the centre of mass and lower shoulder EMG variability compared to healthy controls, whereas the relative shoulder variability was found to be increased in the chronic pain population when compared to healthy controls (Lomond & Côté, 2010). In contrast to investigating individuals that suffer from pain; when pain was experimentally induced in the neck-shoulder region this resulted only in a reduction in shoulder EMG variability, while an increased cycle time variability and kinematic variability of the arm and trunk were found in comparison to no pain during simulated cutting (Madeleine, Mathiassen, et al., 2008). Thus, contrasting findings were reported for the effect of pain on kinematic variability depending on the type of pain (i.e. experimental versus (sub)-chronic), and depending on the body location (i.e. arm versus trunk or center of mass versus shoulder).

The apparent dependency of differences in pain versus no pain on location in kinematic variability was maintained when different variability measures were used to characterize kinematic variability. Butchers with neck-shoulder discomfort in the past year showed lower cycle time variability, linear kinematic variability (coefficient variation of head-shoulder and shoulder-hip displacement) and nonlinear kinematic variability (correlation dimension of head-shoulder displacement), in comparison to butchers without discomfort during a deboning task (Madeleine & Madsen, 2009). However, the same study demonstrated an increase in linear kinematic variability (standard deviation of elbow-hip) and nonlinear kinematic variability (approximate entropy, sample entropy, and correlation dimension of elbow-hip displacement) for neck-shoulder discomfort in comparison to no discomfort (Madeleine & Madsen, 2009). Possibly, these contrasting findings indicate that the loss of variability in the body area of discomfort (i.e. head-shoulder) could be compensated by increasing variability in remote body regions (i.e. elbow-hip) (Madeleine & Madsen, 2009).

Regardless of the controversy in findings within and between different independent variables of pain and different dependent variables of MV, in general the relationship between a reduction in kinematic and EMG variability of the affected area was associated with pain (Madeleine, 2010).

2.2.2 Variability-experience hypothesis

Larger MV was found with short-term experience in female butchers (i.e. 6 months of employment compared to 1 month of employment) during a simulated cutting task for kinematic variability of the arm and trunk, while cycle time variability was reduced and no change in neck-shoulder EMG variability were found (Madeleine, Voigt, et al., 2008). In agreement with short-term experience in simulated cutting, long-term experience (average of 13 years) among male butchers resulted in an increased kinematic variability, while cycle time variability increased and shoulder EMG variability was reduced (Madeleine, Voigt, et al., 2008). Experienced butchers (at least 1 year) performing deboning showed only higher nonlinear kinematic variability of head-shoulder displacement (approximate entropy) in comparison to inexperienced butchers (less than 1 year experience) (Madeleine & Madsen, 2009). On the contrary, linear kinematic variability of head-shoulder displacement (standard deviation) and cycle time variability were reduced among experienced butchers in comparison to inexperienced butchers (Madeleine & Madsen, 2009). Thus, inconsistent results were shown for cycle time variability in simulated cutting and deboning. However, long-term task-specific experience was associated with lower EMG variability. Although the evidence is not completely consistent for different measures of kinematic variability, task-specific experience was associated with higher kinematic variability.

Furthermore, larger MV was found in trunk moments and spinal loads for experienced manual material handlers compared to college students during a lifting task (Granata et al., 1999). However, lower MV was found in trunk velocity and acceleration for experienced compared to inexperienced manual material handlers during lifting (Granata et al., 1999). In addition, experienced workers who regularly performed occupational lifting showed an increase in kinematic task-irrelevant variability during middle and late phases of a fatigue developing protocol compared to university students, while other linear and nonlinear measures did not demonstrate differences for experience (Sedighi & Nussbaum, 2017).

Experience seems to be associated with an increase in kinetic variability and a reduction in EMG variability, and despite inconsistencies some evidence indicates an increase in kinematic variability. The contradictory finding of a decrease in EMG and an increase in kinematic and kinetic variability with experience could be explained by motor abundance as many muscles are involved through muscle synergies that affect the resulting kinematics and kinetics while only a few of those were captured using EMG. Even though both pain and experience resulted in inconsistent findings for different dependent measures of MV, in general pain was associated with low variability while experience was associated with high variability. As a result, it was inferred that for a healthy individual the magnitude of MV determines the risk of developing WRMSDs with a reduction in variability leading to an increase in the risk (Srinivasan & Mathiassen, 2012). This also implies that experience was viewed as a potential protective factor from injury (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008). In general, it was suggested that MV is an important parameter for risk of developing WRMSDs (Côté, 2012; Madeleine, 2010; Mathiassen et al., 2003; Srinivasan & Mathiassen, 2012).

2.2.3 Variability-fatigue hypothesis

MV is possibly related to injury risk by delaying the onset of fatigue (Farina et al., 2008; van Dieën, Oude Vrielink, & Toussaint, 1993) and fatigue can be viewed as a precursor to musculoskeletal disorders (Côté, 2014; Rempel et al., 1992; Sjøgaard & Søgaard, 1998). Furthermore, when tissues have already been subjected to overload, MV could modify the overuse by distributing loads among different tissues (Srinivasan & Mathiassen, 2012). This distribution of the loads applied to the body could possibly reduce the cumulative load on the tissues (Bartlett et al., 2007; Hamill et al., 1999), and therefore decrease injury risk (Kumar, 2001). The distribution of tissue loads (i.e. muscle force development) is regulated by neuromuscular activation and can therefore also be brought into connection with the Cinderella hypothesis. The Cinderella hypothesis can be defined as continuous activation of low-threshold motor units and corresponding type 1 muscle fibers (Visser & van Dieën, 2006). According to the size principle of motor unit recruitment, type 1 muscle fibers are recruited as the first fibers and remain active for the longest time period during prolonged low-effort activity (Henneman, 1957). Therefore, MV could possibly offload these continuously active motor units and fibers and thereby reduce the risk of overuse in these motor units (Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006).

The variability-fatigue hypothesis has previously been demonstrated by changes in muscle activation during fatigue. Individuals who could sustain intermittent isometric contractions of trunk extension for a longer time until fatigue (i.e. average of 12 minutes) showed a larger between-trial variation in corresponding muscle activation, compared to individuals who took a short time (i.e. average of 5 minutes) to fatigue indicating less development of fatigue (van Dieën, Oude Vrielink, & Toussaint, 1993). Also, the high endurance group showed more alternating activity between different parts of the trunk extensor musculature (van Dieën, Oude Vrielink, & Toussaint, 1993). Furthermore, less development of fatigue was observed in the right side of the trunk extensor muscle activity compared to the left side after the left side was targeted in the fatiguing protocol, while the right side showed larger variability in muscle activity compared to the left side (van Dieën et al., 2009). Spatial variability of muscle activity was also positively associated with time to fatigue in a static shoulder abduction task (Farina et al., 2008). Thus, higher variability in both the magnitude and spatial distribution of muscle activation is related to higher endurance during fatigue development, which indicates slower fatigue development.

Although variability in muscle activation could more directly explain the slower development of fatigue with higher variability, the same hypothesis holds for kinematic variability that is not directly reflective of task performance. Neck-shoulder fatigue during a repetitive forward pointing task was associated with increased shoulder-elbow coordination variability, while movement timing errors and spatial variability of the endpoint were predominantly maintained (Yang et al., 2018). When the same task and fatiguing protocol was analyzed with sex as a covariate, an increase in both kinematic task-relevant and task-irrelevant variability was observed for women in contrast to men after fatigue development (Hasanbarani et al., 2021). Task-irrelevant variability was larger than task-relevant variability which was interpreted as control of the task goal (i.e. constant pace) by using flexibility in movement patterns to overcome fatigue (Hasanbarani et al., 2021). Also, task-induced fatigue during repetitive lifting showed an increase in center of mass path variability during late phases of the fatiguing protocol compared to early phases (Sedighi & Nussbaum, 2017). The same study also reported an increase in task-relevant and task-irrelevant variability between late and early fatigue phases, although task-irrelevant variability increased more substantially compared to task-relevant variability with increasing fatigue (Sedighi & Nussbaum, 2017). However, in a repetitive sawing-like task using a handle, task-relevant and task-irrelevant variability of handle kinematics were not affected by fatigue, independent of localized or widespread fatigue development (Cowley et al., 2014; Gates & Dingwell, 2008). In line with previous findings, task-irrelevant variability was larger compared to task-relevant variability for widespread fatigue (Gates & Dingwell, 2008). Linear variability of handle kinematics showed a reduction in timing error and movement speed variability with fatigue, while nonlinear variability (i.e. detrended fluctuation analysis) of handle kinematics showed an increase with local fatigue while widespread fatigue resulted in a reduction (Cowley et al., 2014; Gates & Dingwell, 2008). Despite some inconsistencies, overall changes in movement patterns not related to task performance have been observed with maintenance of task performance variables during fatigue. Specifically for methods that quantify variability in task-relevant and task-irrelevant aspects, an increase in task-irrelevant variability could be a compensation mechanism to control task performance while fatigue develops, where the latter could be reflected by no changes in task-relevant variability (Bartlett et al., 2007; Button et al., 2003).

This observation of compensation has also been indirectly demonstrated. Adaptations of interjoint and intermuscular coordination were shown after fatigue while main movement characteristics remained similar in a repetitive hammering task (Côté et al., 2008). Characteristics relevant to the sawing task (i.e. saw trajectory) were maintained at the cost of changes in movement amplitude during fatigue (Côté et al., 2002). Fatigue resulted in decreased elbow impedance, while the time-on-target was unaffected by fatigue in a target tracking task (Selen et al., 2007). Also, kinematic coordination changes evoked by an increase in work pace could have prevented the observation of fatigue in a repetitive pick and place task (Bosch et al., 2011). Possibly, movement patterns are adapted as a mechanism to ensure task continuation as reflect by no changes in task execution parameters during fatigue.

2.2.4 Variability-overuse hypothesis

The variability-overuse hypothesis is based on associations of overuse injuries with low variability. Individuals with patellofemoral pain showed decreased lower extremity coordination variability (standard deviation of continuous relative phase of knee joint couplings) compared to healthy controls (Hamill et al., 1999). A follow-up study that used a different coordination variability measure (i.e. vector coding) showed similar results that confirmed the initial findings (Heiderscheit et al., 2002). Kinetic variability for injury-prone individuals, based on self-reported history of lower extremity overuse injuries, showed contrasting findings during vertical jump landings when compared to healthy or not injury-prone individuals (James et al., 2000). Injury-prone individuals showed lower variability in time to peak ankle moment, while a larger peak ankle moment variability was demonstrated compared to healthy individuals (James et al., 2000). However, no differences were found between the injury-prone and healthy group with respect to ankle impact impulse, in addition to peak joint moment, time to peak joint moment and impact impulse of the knee and hip joints. Therefore, overuse injury seems to be associated with a reduction in kinematic variability (Hamill et al., 1999; Heiderscheit et al., 2002). In contrast, it seems uncertain whether overuse injury is related to a difference in kinetic variability in comparison to healthy controls (James et al., 2000). In summary, no conclusive support of the variability-overuse hypothesis can be found. In addition, it must be noted that the peak kinetic variables used in James et al. (2000) are not directly related to the underlying cumulative load pathway that would have led to overuse injury.

2.2.5 Repeaters-replacers hypothesis

Recently, variability has been proposed as a consistent individual trait as part of the repeaters-replacers hypothesis where individuals with low MV are described as repeaters while individuals with high MV are described as replacers (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). When the repeaters-replacers hypothesis is contextualized within the variability-risk hypothesis, repeaters are expected to be at higher risk for developing WRMSDs, whereas replacers are hypothesized to be at lower risk to develop WRMSD (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). An experimental study has suggested that kinematic variability in repetitive pipetting differs consistently between individuals over time (i.e. three different days) (Sandlund et al., 2017). Furthermore, individuals showed consistent kinematic and EMG variability across four different temporal task constraints varying in pace (self-paced and imposed) and production process (batch and assembly-line) for a cyclic assembly task (Jackson et al., 2020). Thus, research on the repeaters-replacers hypothesis is still evolving and has only been performed on task performed with the upper extremity with different temporal conditions. More importantly, to date the variability-risk hypothesis has not been explicitly investigated within the context of repeaters-replacers hypothesis, while this connection represents a significant contribution to occupational biomechanics.

2.2.6 Underlying injury pathways related to low variability

The underlying pathway that is suggested to lead to a higher risk on WRMSDs is cumulative loading or fatigue failure, with higher variability leading to more distributed loads (or possibly even muscle activation) across multiple tissues (Bartlett et al., 2007; Hamill et al., 1999; Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006). This injury pathway is considered a different pathway from acute injury where a single load exceeds the failure tolerance of the tissue (McGill, 1997). A lack of variability would imply repetitive loading of tissue in terms of localization, which can result in concentrated stress application on the concerned tissue. If the repetitive loading continues for an extended time, the concentrated stress will accumulate and can lead to micro-damage in the tissue, even when the level of the load is below the acute failure point. Therefore, a lack of variability could lead to fatigue failure of tissue (Hamill et al., 1999). Similarly, for fatigue low variability would be associated with more continuously active motor units in repetitive movement according to the Cinderella hypothesis (Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006). However, the Cinderella hypothesis is limited to only explain continuous activation of type I motor units, whereas it does not provide an explanation of actual muscle fibre damage (Visser & van Dieën, 2006).

2.2.7 Summary of variability hypotheses

The existing research on the variability-pain, variability-experience, and variability-overuse injury hypotheses demonstrates the current speculative state of these hypotheses. There is a quantification problem for MV because MV has been quantified using a range of measures, hence the lack of consensus in MV quantification could explain the inconsistent evidence for the variability-risk hypotheses. Also, research on independent variables of pain, experience and overuse injury is limited due to the cross-sectional design. Even though the MV quantification problem also holds for the variability-fatigue hypothesis, research on this hypothesis provides relatively more convincing support for kinematic variability. Furthermore, the repeaters-replacers hypothesis could strengthen the understanding of the variability-risk hypothesis by connecting individual consistency in MV to variables of risk. However, as part of this investigation the quantification problem must be addressed. Therefore, the quantification problem has to be considered in more detail by putting it in the context of the corresponding underlying theoretical frameworks of motor control.

2.3 Historical overview of motor control perspectives in motor variability

In this section, three different theoretical frameworks important to MV are discussed in chronological order of their development. Firstly, the traditional view is discussed, where MV is considered to be dysfunctional for performance. Secondly, two major functional views are discussed: dynamic systems theory (DST) and optimal feedback control (OFC), which consider MV to have a functional role in performance. Even though the functional view is considered as a replacement of the traditional view, most variability studies have used measures of the traditional view, while inferences have been made based on the functional view.

2.3.1 Traditional perspective

Traditional framework

The traditional perspective represents how MV has been interpreted traditionally and was predominantly used until the end of the 20th century after which the functional perspective gained interest (Robins et al., 2006). This approach is derived from the information theory's concept of variability in motor output signals that is regarded as noise resulting from the transmission process (Slifkin & Newell, 1998). In information processing, movement is controlled by a set of instructions from the motor program (Clark, 1995), and MV is considered dysfunctional because variability is believed to reflect undesirable noise of the neuromuscular system (Newell & Corcos, 1993) or measurement noise (Bartlett et al., 2007). Therefore, MV was viewed as a problem for system control, or even as error that has to be minimized or eliminated (Newell & Corcos, 1993).

The traditional "noise" view of variability was supported by findings of a reduction in task outcome kinematic variability (i.e. end-point variability) with learning or with higher skill level in different sporting tasks (e.g. basketball throwing and dart throwing) among healthy subjects (Button et al., 2003; McDonald et al., 1989). Therefore, sport biomechanists believed that skilled movement patterns were characterized by low between-trial kinematic variability that reflected the invariant movement pattern that should be strived for to obtain skilled performance (Bartlett et al., 2007; Brisson & Alain, 1996). Because of a lack of evidence for the existence of an invariant movement pattern and because training of this pattern did not lead to the hypothesized results, the main implications of the noise view of MV could not be fully supported (Bauer & Schöllhorn, 1997; Brisson & Alain, 1996; S. Miller, 2002; S. Miller & Bartlett, 1993). Interestingly, the initial support for a reduction in kinematic variability with practice and skill can possibly be explained by the location at which variability was considered; in this case the end-effector, which is directly reflective of the task outcome in these accuracy tasks (e.g. basketball throwing and dart throwing). But overall, the invariant movement pattern model was deemed invalid, which suggested a review of the traditional view of variability as noise (Bartlett et al., 2007).

Operationalization of the traditional theory

In the traditional approach variability was considered as the amount of noise from the underlying information processes, and therefore variability was represented by white Gaussian noise superimposed on the deterministic signal (Newell & Corcos, 1993; Slifkin & Newell, 1998). The amount of variability can be quantified by linear metrics such as standard deviation around the mean of a motor variable (e.g. kinematics, kinetics etc.) (Newell & Corcos, 1993; Stergiou & Decker, 2011) and deviation from the mean (i.e. desirable standard movement pattern) is regarded as error that should be minimized (Davids et al., 2003; Stergiou & Decker, 2011).

Because variability is assumed to be modelled as white Gaussian noise, parametric assumptions hold for the corresponding linear metrics (e.g. standard deviation, mean) (Slifkin & Newell, 1998) that consist of the normality assumption and the assumption of independence. The assumption that the distribution of the system parameter (i.e. motor variable) is normal (Newell & Corcos, 1993) generally holds after the sample size has reached N=30 and, therefore, the estimated parameters (i.e. mean and standard deviation) are considered to be an accurate representation if they are derived from a normal distribution. Furthermore, at the observational level, parametric estimates are valid if the observations are unrelated and random (i.e. independent) (Field, 2013).

The use of standard deviation as an operational measure of variability assumes white Gaussian noise as a model of variability, which should be considered with caution. MV is not found to be solely random, but also contains deterministic elements, which implies that deviation from the mean should not always be interpreted as random noise (Dingwell & Cusumano, 2000; Harbourne &

Stergiou, 2003; D. J. Miller et al., 2006; Slifkin & Newell, 1998). Therefore, to characterize both random and deterministic elements, higher order metrics are necessary to capture the predictability of the signal over time (i.e. signal structure or dynamics), which can change independently of the magnitude of variability (Slifkin & Newell, 1998).

Linear measures in variability-risk hypotheses

Most researchers that provided evidence for the variability-risk hypotheses measured variability with linear measures (Granata et al., 1999; Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993). However, an increase in variability by these measures would reflect an increase in noise, which is hypothesized to be undesirable for performance, while these studies have been used to support the functional use of variability as a protective factor against injury risk. Therefore, the traditional approach does not align with the variability hypotheses and therefore variability measures that represent functional variability are recommended to be used when further investigating these hypotheses.

Summary of traditional perspective

Based on the limitations of both the operationalization of the measure of variability and theoretical constructs, the traditional dysfunctional view of variability in motor variables was re-evaluated by also considering potential beneficial effects of variability that are reflected in the functional view of variability. Even though the traditional approach views MV as dysfunctional and more variability is suggested to be undesirable for performance, many researchers have inferred more variability as functional with respect to injury risk in a healthy population. Therefore, it is suggested that traditional quantification methods are not in line with the variability-risk hypotheses because the variability that is quantified is viewed as dysfunctional rather than functional for performance.

2.3.2 Functional perspectives

Two functional approaches will be discussed, the dynamic system theory (DST) and optimal feedback control (OFC). Both functional frameworks have in common that task constraints are most influential for performance out of the three different constraints within the interacting constraints model (Clark, 1995; Newell, 1986).

Dynamic systems theory (DST)

DST framework

The traditional dysfunctional approach to MV is challenged by a functional MV approach that considers variability to be desirable (Robins et al., 2006). One of the computational frameworks that regards MV as functional is DST, also known as nonlinear dynamics or chaos theory, which explains systems that change or evolve over time (Clark, 1995). In contrast to the information processing approach, in DST the control is not based on the motor program but is rather guided by the patterns of a complex dynamic system (Clark, 1995). Patterns emerge through preferred or attractor states of coordinative patterns by a self-organization process based on the inherent connectivity of the anatomical system that narrows down the degree of freedom (DOF) problem to one dynamic pattern that is determined by interacting constraints (Clark, 1995; Davids et al., 2003; Newell, 1986; Turvey, 1990). The task is believed to be the most important constraint since it regulates the possible states and therefore the available patterns (Clark, 1995; Davids et al., 2003).

The variability of the patterns reflects the stability of the system such that stable systems are characterized by low variability, whereas with incremental variability the system becomes more unstable that reflects a system in transition (Clark, 1995). Variability of coordination patterns have been studied as a critical property of the system to ensure flexibility and stability of movement by the process of exploring and abandoning coordinative structures to adapt to the unique constraints (Clark, 1995; Haken et al., 1985; Hamill et al., 1999; Kugler et al., 1980; Turvey, 1990). Since a pattern is the result of emerging constraints, these constraints can be relevant as a control parameter of the system if scaling of the constraints results in changes in the system (Clark, 1995). In the functional view, based on DST, three possible functional roles for variability are mentioned; variability can possibly induce a coordination change, distribute loads, and pose flexibility to facilitate adaptations to changes in the environment (Bartlett et al., 2007).

In DST the previous focus of the dysfunctional approach on common optimal movement patterns is shifted to individual coordination profiling (Schöllhorn & Bauer, 1998), which allows for analysis of specific constraints that shape intrinsic movement system dynamics of the individual (Button & Davids, 1999). Furthermore, in DST group statistics (i.e. parametric estimates of individual data pooled in groups) are suggested to be invalid analyses of motor coordination as averaging across different individuals is undesirable because of different organismic constraints, which is supported by discoveries of refined individual signature movement patterns (Kelso, 1995).

Operationalization of DST

DST operationalization methods address the ignorance of the time domain structure and assumption of complete randomness of the traditional approach by using nonlinear operationalization methods (Davids et al., 2003; Newell & Slifkin, 1998). Even though the task constraints are suggested to play a major role in motor behaviour and MV (Clark, 1995; Davids et al., 2003), task performance is not explicitly included in DST analyses, which could be considered a limitation.

On one side the operationalization has focused on variability of coordination patterns to reflect transitions in coordination that are operationalized by order parameters that can be identified by manipulating control parameters, for example relative phase between body segments or joints (i.e. coupling) (order parameter) in combination with gait speed (control parameter) (Haken et al., 1985;

Hamill et al., 1999; Kelso, 1984). Even though variability and stability are different properties of motor control and increased variability is not necessarily associated with more instability, variability of coordination patterns are used as a measure of stability of the patterns (Stergiou & Decker, 2011). With respect to inclusion of time domain structure, continuous relative phase (CRP) reflects both spatial and temporal information and CRP variability is reflective of transition in phase between coordination patterns (Hamill et al., 1999). Alternatives to CRP analysis to characterize coordination are cross-correlations and vector coding (Glazier et al., 2003).

On the other side, nonlinear times series analysis is used to describe the time evolution of movement patterns with the goal to determine the type of the underlying control process (i.e. random, chaotic) and the time period (i.e. short-term or long-term). Examples of nonlinear time series measures are entropy, correlation dimension, local dynamic stability and fractal dynamics (Cusumano & Dingwell, 2013; Newell & Vaillancourt, 2001; Slifkin & Newell, 1998). Entropy is also described as the complexity of variability (Madeleine, 2010) and reflects the degree of disorder or randomness. A specific measure is approximate entropy, which determines how predictable future values are from previous values in a time series signal (Slifkin & Newell, 1998). Correlation dimension is a measure of dimensionality and reflects the number of degrees of freedom necessary for the movement pattern (Newell & Vaillancourt, 2001). Local dynamic stability determines the temporal stability of a dynamical system upon local perturbations (Cusumano & Dingwell, 2013). Local dynamic stability can be measured by (variations on) Lyapunov exponents, which are also known as local divergence exponents, and Floquet stability multipliers (Cusumano & Dingwell, 2013). Fractal dynamics reflect a fractal process by long-range correlations in time series, which can be assessed by detrended fluctuation analysis (DFA). DFA measures the statistical persistence across multiple time lags

(Cusumano & Dingwell, 2013). All these measures reflect the organization of the temporal structure of a time series.

Nonlinear measures in variability-risk hypotheses

In addition to linear measures, nonlinear measures have also been used to support variability hypotheses (Hamill et al., 1999; Heiderscheit et al., 2002; Madeleine & Madsen, 2009; Yang et al., 2018). Based on the nonlinear DST measures, more variability would lead to less stable movement behaviour, which could either improve or limit task performance depending on the type of task (e.g. accuracy task versus locomotion) and environment (e.g. walking on (un)predictable surfaces). Therefore, in this literature review another functional framework will be explored that directly relates task performance to variability.

Summary of DST

In contrast to the traditional approach, DST assigns functionality to variability, DST addresses the DOF problem as motor abundance, and DST acknowledges the influence of task constraints in movement control. DST operationalization addresses limitations of the traditional approach, such as assumptions of linear measures, and variability is also analyzed in the time domain instead of only in the amplitude domain. The concept of constraints justifies the individual approach, however task performance is ignored in corresponding analysis techniques while task constraints are assumed to primarily determine motor behaviour and MV. The second functional framework is able to address this problem.

Optimal feedback control (OFC)

OFC framework

Optimal feedback control (OFC) is a computational framework that describes movement planning and execution of the motor system as a control process in which the feedback is optimized for successful performance of the task for the individual (Diedrichsen et al., 2010; Scott, 2004). The OFC loop consists of several components as depicted in **Figure 2.1**.

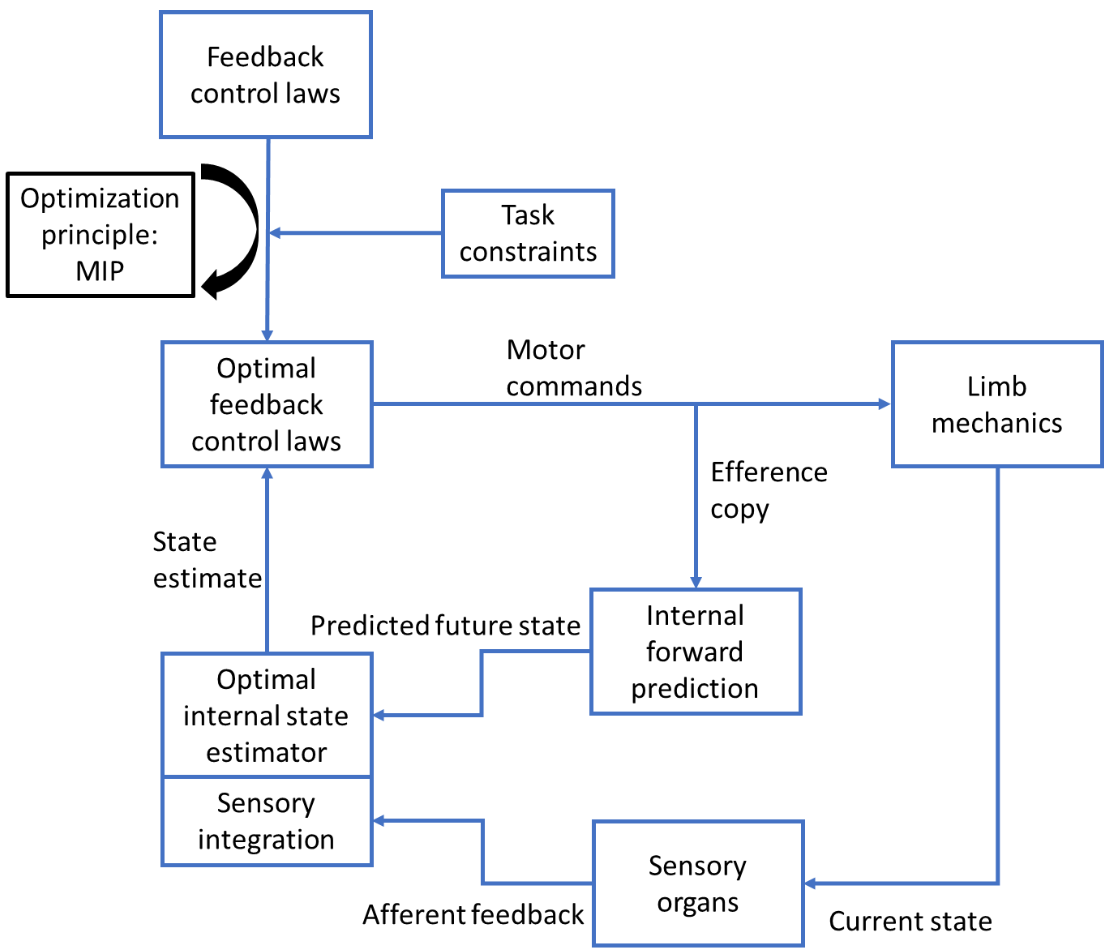

Figure 2.1: Schematic depiction of optimal feedback control theory with respect to movement planning and execution, where MIP stands for Minimum Intervention Principle (modified from Scott, 2002; 2004; Todorov & Jordan, 2002; Todorov, 2004; Diedrichsen et al., 2010).

The current state or performance of the system is estimated by the predicted future state and the afferent feedback, which are both subject to signal-dependent noise in the motor commands and afferent feedback thus OFC is also often defined as stochastic OFC (Harris & Wolpert, 1998; Todorov & Jordan, 2002). The predicted future state is derived by an internal forward prediction based on the efferent copy of motor signals (Diedrichsen et al., 2010; Wolpert et al., 1995). Therefore, the current state estimation is based on properties of both the body and environment (Dingwell et al., 2004). As part of the state estimation the sensory feedback is weighted against the predicted future state to account for sensory time delays and noise, which is also explained as feedback gains (Diedrichsen et al., 2010). The state estimation together with the selected task is used in the OFC laws to determine the motor commands that drive the future limb mechanics (Scott, 2004).

The OFC laws are a central problem in OFC theory and a possible optimization criterion is minimizing the sum of squared motor commands, which has been interpreted to minimize effort and to minimize endpoint variance related to signal-dependent noise (Diedrichsen et al., 2010; Harris & Wolpert, 1998). OFC laws are selected out of feedback control laws based on the constraints of the task that is performed and the optimization principle of OFC (i.e. the minimum intervention principle (MIP)) (Diedrichsen et al., 2010; Scott, 2002; Todorov & Jordan, 2002). In MIP only deviations from the task-relevant goals are corrected, whereas deviations from the task-irrelevant goals are left to accumulate in variability (Diedrichsen et al., 2010; Todorov & Jordan, 2002). This selective correction feature leads to strict control of task-relevant features, whereas task-irrelevant features are allowed to vary (Scholz & Schöner, 1999). Therefore, MV is mostly prevalent in the task-irrelevant dimension because MIP only minimizes variability in the task-relevant dimension to maintain task performance (Franklin & Wolpert, 2011; Todorov & Jordan, 2002).

With respect to the DOF problem, OFC solves motor redundancy at each time step to reach optimal performance (Todorov & Jordan, 2002). In addition to explaining MV and addressing the DOF problem, OFC also provides an explanation of goal-directed corrections and motor synergies, and thus provides a more holistic framework that can explain multiple motor coordination observations compared to the traditional approach and DST (Todorov & Jordan, 2002). For different tasks the underlying optimality principles are the same, however the optimal feedback controller probably has unique characteristics that are only shown in the circumstances of the actual task (Todorov & Jordan, 2002).

Operationalization of OFC

Since the OFC law minimizes deviations from the task-relevant goals and therefore allows task-irrelevant goals to vary, OFC can be operationalized using methods that are able to distinguish task-relevant from task-irrelevant variability (Diedrichsen et al., 2010; Todorov & Jordan, 2002). Uncontrolled manifold (UCM) and goal-equivalent manifold (GEM) analyses separate task-relevant and task-irrelevant variability by decomposing task performance into elemental and performance variables or also described as execution and result variables (Latash, 2012; Latash et al., 2002; Müller & Sternad, 2009). The elemental variables are the execution or action variables, which are the variables used on the axes of the UCM/GEM plots (Latash, 2012; Müller & Sternad, 2009). The performance variable reflects task error and thus the result, where the task goal is depicted on the UCM/GEM plot as a line or curve (Latash, 2012; Müller & Sternad, 2009). Thus, the performance variable determines the task-relevant dimension since deviation away from accurate performance interferes with the task outcome, and the task-irrelevant dimension is defined as the dimension orthogonal to the task-relevant dimension. The actual data points depicted on a UCM/GEM plot are combinations of elemental variables for each repetition, so variability on this plot is reflective of repetition-to-repetition variability. An example during repetitive pointing is shown in **Figure 2.2A**, with shoulder, elbow and wrist angles as elemental variables on the axes and the average joint trajectory as the performance variable represented by the dashed line **Figure 2.2B**. The task-irrelevant dimension is depicted for three time points (t1, t2, T) after the start (S) of the pointing movement, by the black lines orthogonal to the dashed line with two black dots at each time point representing the two illustrated joint configurations from repetitive execution. The black lines represent task-irrelevant variability that led to the same position of the pointer, representing the task-relevant dimension, at each time point.

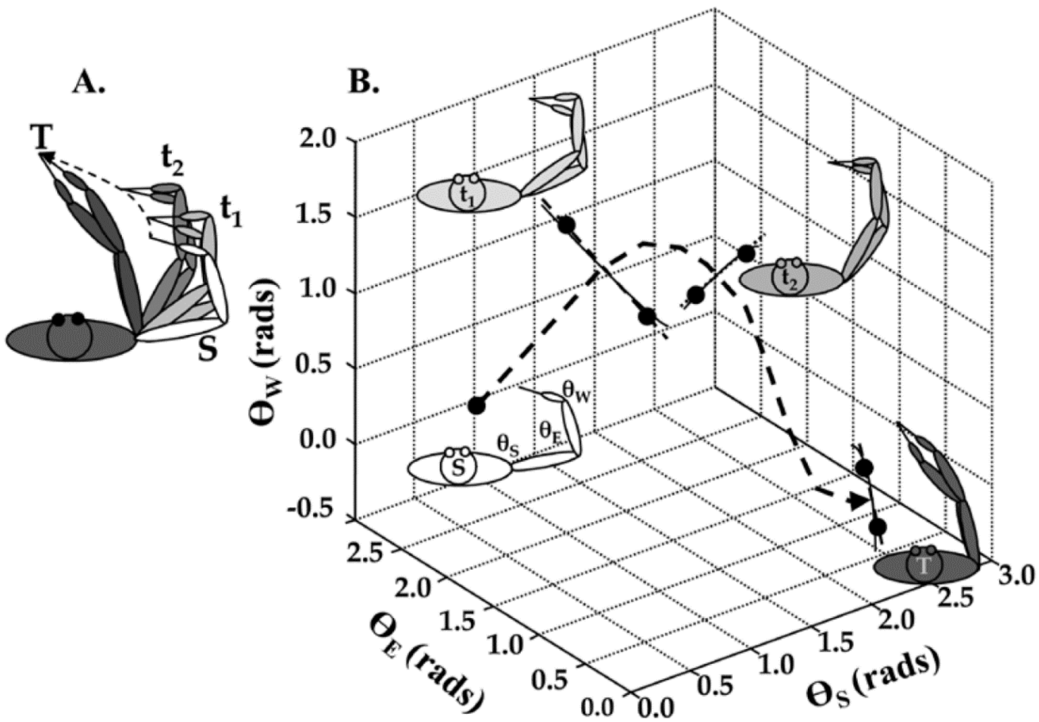

Figure 2.2: (A) Illustrative example of thee-joint planar arm movement using a pointer from starting position (S) to target position (T) with two intermediate time points (t1 and t2), (B) corresponding depiction of UCM plot with the axes representing wrist, elbow and shoulder angles and the dashed line representing average joint trajectory, and for three time points after that start the black lines show the manifold of joint angles that lead to the same end-effector position of the pointer, where the black dots represent the illustrated joint configurations. Figure has been published as Figure 3 in Latash et al. (2007).

Task-relevant variability is operationalized as variability away from the local curvature of the performance variable, and task-irrelevant variability is operationalized as variability along the performance variable. Because of the MIP, task-irrelevant variability is reflective of motor abundance in which the task goal can be met by multiple options of limb mechanics, which is described as the manifold or solution space in UCM or GEM (Müller & Sternad, 2009; Todorov, 2004). Therefore, more variability is manifested within the manifold rather than perpendicular to the manifold of

UCM/GEM. Transformations applied to elemental data points in solution space are suggested to be regulated by the control system (Müller & Sternad, 2009), and when OFC theory is applied the operations would be the result of the OFC laws.

The most notable difference between UCM and GEM is the definition of the manifold. In UCM, the manifold is based on the collected movement patterns (e.g. subject's average patterns) (Scholz & Schöner, 1999). However, in GEM the manifold is also described as the task goal or goal function that is defined by a mathematical relationship between elemental and performance variables, which is equivalent for each subject (Cusumano & Cesari, 2006). Therefore, in GEM the manifold does not necessarily reflect individual performance since it is not directly related to a subject's movement pattern, while this is the case in UCM (Cusumano & Cesari, 2006). To establish the relationship between elemental and performance variables in GEM, common practice is to impose the task goal by using external task constraints such as constant pacing, which has been observed in work on variability and fatigue (Cowley et al., 2014; Gates & Dingwell, 2008; Sedighi & Nussbaum, 2017). However, these constraints are not necessarily reflective of task performance at the workplace and, more relevant for MV, could reduce the use of motor abundance since the task-irrelevant dimension represents motor abundance (Latash et al., 2002; Todorov, 2004). For UCM, there is also the assumption of a mathematical relationship between elemental and performance variables that could be established by estimating the function by regression analysis (de Freitas & Scholz, 2010; Freitas et al., 2010; Greve et al., 2013; Tuitert et al., 2019) or by developing a biomechanical model to define this function (Hasanbarani et al., 2021; Scholz et al., 2000; Scholz & Schöner, 1999). In contrast to GEM, for UCM it is no necessary to explicitly define a task goal.

UCM and GEM measures in variability-risk hypotheses

Only some work has used UCM/GEM methods in the context of the variability-risk hypotheses (Cowley et al., 2014; Gates & Dingwell, 2008; Hasanbarani et al., 2021; Sedighi & Nussbaum, 2017). GEM analysis has been used more often than UCM analysis although for GEM analysis the task was constrained by following a constant pace using a metronome, which could restrict MV. Therefore, UCM analysis could be considered a better alternative when studying MV in occupational tasks, also given that when these constraints are not reflective of the work environment it could improve external validity.

Summary of OFC

In agreement with DST, OFC addresses the DOF problem as motor abundance and OFC also considers the task constraints for motor performance. A shortcoming of DST that is accounted for in OFC is the opportunity to increase variability for a functional role (i.e. increase task-irrelevant variability) without interfering with task performance (i.e. without increasing task-relevant variability). OFC operationalization consists of methods to quantify task-relevant and task-irrelevant variability. UCM, in contrast to GEM, appears to be understudied in the context of variability-risk hypothesis while it allows for minimal constraints applied to the task that could affect MV.

2.3.3 Summary of motor control perspectives in motor variability

Historically, the view on MV has been re-evaluated from the traditional dysfunctional view to the more recent functional view. In the traditional motor control perspective, related to the view of the DOF problem, MV has been quantified using linear measures such as standard deviation. Although linear measurements have significantly contributed to the development of variability-risk hypotheses, the use of these measurements do not align with the view of motor abundance that has been used to explain these hypotheses. Functional motor control perspectives, related to the view of motor abundance, have been discussed using two approaches where MV has been quantified using nonlinear measures. Despite that the underlying functional perspectives align with explanations of variability-risk hypotheses, functional variability measures (i.e. nonlinear and task-irrelevant variability) are relatively underused.

2.4 Conclusion of literature review

This literature review demonstrates the need to further investigate the repeaters-replacers hypothesis because it could change the current view on the speculative variability-risk hypotheses. More specifically, the assumption of MV as an individual trait regardless of task characteristics requires more research. To date, evidence has been established across varying task constraints in fine motor tasks that only require movement of the upper extremity to complete the task. Therefore, in this dissertation, MV across varying task constraints in gross motor tasks that require whole-body movement is assessed. Furthermore, this dissertation also determines MV across both fine and gross motor tasks, which could provide the strongest evidence for MV as an individual trait.

To connect the assumption of MV as an individual trait to variability-risk hypotheses, a risk variable needs to be included. To assess MV as an individual trait, consistency should be determined across the risk variable. In this dissertation, the risk variable is fatigue in context of the variability-fatigue hypothesis, where MV is determined at different fatigue states. To relate risk to individual MV, individual MV should be explicitly related to the individual's risk. In terms of the repeaters-replacers hypothesis, relating risk to individual MV will determine whether repeaters are at higher risk than replacers. Thus, this dissertation relates individual MV to indicators of fatigue development to determine whether repeaters show faster development of fatigue than replacers.

The literature review also shows the diversity in methods to quantify MV. In terms of motor variables, there is more convincing support for the variability-fatigue hypothesis with respect to kinematics. Also, a range of different variability metrics can be applied to kinematics, while this is not applicable to other motor variables of kinetics or EMG. Thus, this justifies the focus of this dissertation on kinematic variability. Traditional and functional variability metrics have different underlying motor control perspectives, where traditional metrics formed the variability-risk hypotheses while functional metrics have aided in interpreting these findings. Therefore, in this dissertation, variability metrics from both traditional and functional motor control perspective are considered. Furthermore, these metrics are compared at the individual level to inform following studies of this dissertation.

Chapter 3: Exploring the role of task constraints on motor variability and assessing consistency in individual responses during repetitive lifting using linear variability of kinematics

This chapter has been published as following:

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3.1 Abstract

To better understand the assessment of motor variability (MV) in an occupational context, this study determined the role of task constraints on MV and consistency in individual MV responses. Twenty participants performed repetitive lifting under four constraints differing in restriction of foot movement and load weight. MV was assessed for three body regions and for the whole-body using linear variability of three-dimensional joint angles. Foot movement caused significant increases of lower body (11-17%), low back (318-439%) and a reduction in upper body variability (4%), whereas no effects of weight nor interaction of foot restriction and weight were found. Good individual consistency (ICC= 0.71 – 0.84) was demonstrated across constraints. Even though MV is affected by constraints, this study supports that MV is largely an individual trait independent of constraints. Future work should evaluate if MV remains an individual trait across different tasks, and if MV is confounded by other task constraints.

3.2 Introduction

The human motor system consists of more degrees of freedom (DOF) than theoretically necessary to complete a given task (i.e. DOF problem) (Cusumano & Cesari, 2006; Latash, 2000; Latash et al., 2002; Newell & Corcos, 1993). Therefore, multiple attempts of the same task can be executed using different movement patterns or by “repetition without repetition” according to Bernstein (1967). Motor variability (MV) that arises from repeated execution of the same task is believed to reflect the inherent motor control strategy (Latash et al., 2002; Newell & Corcos, 1993). Interest in MV is growing within the field of ergonomics because of its potential relevance to work-related musculoskeletal disorder (WRMSD) causation and subsequent prevention (Côté, 2012; Madeleine, 2010; Srinivasan & Mathiassen, 2012).

In general, it is hypothesized that low MV is associated with increased injury risk, while high MV is associated with lower injury risk (Côté, 2012; Madeleine, 2010; Mathiassen et al., 2003; Srinivasan & Mathiassen, 2012). This variability-risk hypothesis is based on findings reporting lower MV in individuals with pain compared to individuals without pain (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008) and findings of high MV in individuals with task specific experience (i.e., healthy workers) compared to individuals without experience (Granata et al., 1999; Madeleine, Voigt, et al., 2008). Also, low MV has been associated with earlier onset of fatigue (Farina et al., 2008; van Dieën et al., 2009; van Dieën, Oude Vrielink, Housheer, et al., 1993) and, from a sports biomechanics perspective, low MV has been associated with overuse injury (Hamill et al., 1999; Heiderscheit et al., 2002; James et al., 2000). An increase in MV could lead to more trial-to-trial distribution of muscle activation and mechanical loading across tissues, which could reduce cumulative loading and the risk of cumulative damage to the tissues (Bartlett et al., 2007; Hamill et al., 1999; Madeleine, 2010; Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006).

Occupationally-relevant MV research has focused on fine motor tasks, and only a few studies have investigated gross motor tasks. Tasks have included simulated filleting/cutting (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008), deboning (Madeleine & Madsen, 2009), and reaching/pointing (Lomond & Côté, 2010; Yang et al., 2018). Few researchers have assessed MV in gross motor tasks such as lifting (Granata et al., 1999; Sedighi & Nussbaum, 2017; van Dieën et al., 2001). Gross motor tasks, in contrast to fine motor tasks, involve whole-body movement and therefore require more DOF, which provides a greater opportunity to exploit MV. Both fine and gross motor tasks have been examined under fairly constrained circumstances that restrict the available DOF and thus lower the opportunity to exploit MV. For example, the simulated filleting/cutting task consisted of five time-paced consecutive hand movements that included pressing a button and applying 20-30 N with a force-sensitive knife to two slots (Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008). In addition, an asymmetric freestyle lifting task was also time-paced and participants were specifically instructed to keep their feet in a fixed position and hold the box continuously (Sedighi & Nussbaum, 2017). In these studies, the task constraints such as pace, spatial requirements and force targets could have been imposed to mimic work conditions such as an assembly line. Foot restriction and pace restriction may have also been required for measurement (e.g. force plate recording) and analysis (e.g. goal equivalent manifold analysis) purposes, respectively. However, it could be argued that the external validity of such experimental task constraints is low, as workplace tasks would likely come with less overall movement constraints. In summary, it is valuable to assess MV in gross motor tasks such as lifting with minimal experimental constraints to enable as many motor solutions (i.e. DOF) as possible and to mimic workplace constraints to enhance external validity of task constraints. In addition, there is also a need to compare MV in unrestricted lifting to lifting under different task constraints that restrict some DOF of the task to assess the effect of task constraints on MV.

Recent research on work-related MV indicated individual consistency in MV responses across days and task constraints; hence MV could be a consistent individual trait (Jackson et al., 2020; Sandlund et al., 2017). Thus, MV could be considered an indicator of individual motor control. Generating evidence on individual consistency in MV is important to explore the repeaters-replacers hypothesis that describes individuals with consistently low MV as repeaters and individuals with consistently high MV as replacers (Jackson et al., 2020; Sandlund et al., 2017). Combining the repeaters-replacers hypothesis with the variability-risk hypothesis leads to the hypothesis that repeaters are at higher risk of developing WRMSDs than replacers (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). Therefore, WRMSD risk may be related to how individuals exploit motor abundance. However, the repeaters-replacers hypothesis is only supported on the condition that MV is genuinely an individual trait. Therefore, an individual's MV should be consistent over time and across different task constraints. In a repetitive pipetting task, repeaters were identified because individuals with low total average MV showed this feature consistently on three different days (Sandlund et al., 2017). In a cyclic assembly task, participants showed consistency of MV under four different temporal task constraints varying in pace (self-paced and imposed) and production process (batch and assembly-line) (Jackson et al., 2020). Although some supporting evidence was found in fine motor tasks across days and task constraints, it is unclear if the repeaters-replacer hypothesis is supported in gross motor tasks such as lifting when repeated under different task constraints.

In summary, the ergonomics literature is lacking studies on MV in gross motor tasks such as lifting and specifically studies assessing MV in minimally constrained lifting while comparing it to different task constraints that restrict some DOF of the task. Furthermore, there is a need to assess the consistency of individual MV responses across different task constraints to investigate if MV is an individual trait, evidence necessary to support the repeaters-replacers hypothesis. Therefore, the objective of this study was to understand the role of task constraints on MV and assess consistency in individual MV responses for a repetitive lifting task. This study has two overarching research questions: 1) What is the effect of DOF constraint and load weight on MV? 2) Do individuals show consistent MV responses across different DOF constraints and load weights? It was hypothesized that when the DOF of the task were more constrained, MV would decrease. When load weight increased, greater mechanical task demands would lead to a reduction in MV (Nordin & Dufek, 2016, 2017) possibly by restricting DOF at low-capacity joints to minimize the development of fatigue or injury. In addition, it was hypothesized that individuals would show consistent MV responses across DOF constraints and load weights.

3.3 Material and Methods

3.3.1 Research design

A cross-sectional experimental study with a two factor repeated measures design was used to answer the research questions. The independent variables consisted of 1) DOF constraint (i.e. restricted versus unrestricted foot movement) and 2) relative load weight (i.e. low versus high). The dependent variables consisted of three-dimensional joint angle variability determined using the traditional linear measure of mean standard deviation (meanSD) (Newell & Corcos, 1993; Stergiou & Decker, 2011).

3.3.2 Participants

Twenty participants (ten females and ten males; 24.3 (± 3.8) years; 169.2 (± 10.2) cm; 67.9 (± 13.0) kg) were recruited from the student population homogeneous on known determinants of MV such as age and acute and chronic pain status as recommended by Sandlund et al. (2017) (Krüger et al., 2013; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009). Participants were excluded if they were not between 18 and 64 years, if they had acute and/or chronic pain that conflicted with performing prolonged lifting within the last seven days prior to testing based on the Nordic MSD questionnaire (Kuorinka et al., 1987) or if they indicated any conditions that would threaten the safety of performing physical activity based on the Get Active Questionnaire (GAQ) (CSEP, 2017). This study was approved by the University of Waterloo's Office of Research Ethics (ORE#40762), and all participants provided informed consent prior to participation.

3.3.3 Instrumentation

A 12-camera (six Vantage v5 and six Vero 2.2) Vicon Nexus 2.6.1 motion capture system (Vicon, Oxford, UK) tracked 58 individual reflective markers placed over anatomical landmarks or tracking locations on the body as well as eight clusters of four markers and two clusters of five markers secured on body segments at 100 Hz (see **Figure 3.1**). After calibration, all calibration-only markers were removed as indicated in **Figure 3.1**. The whole-body marker setup enabled segment-specific anatomical coordinate systems to be defined, consistent with the International Society of Biomechanics (ISB) recommendations (Wu et al., 2002, 2005).

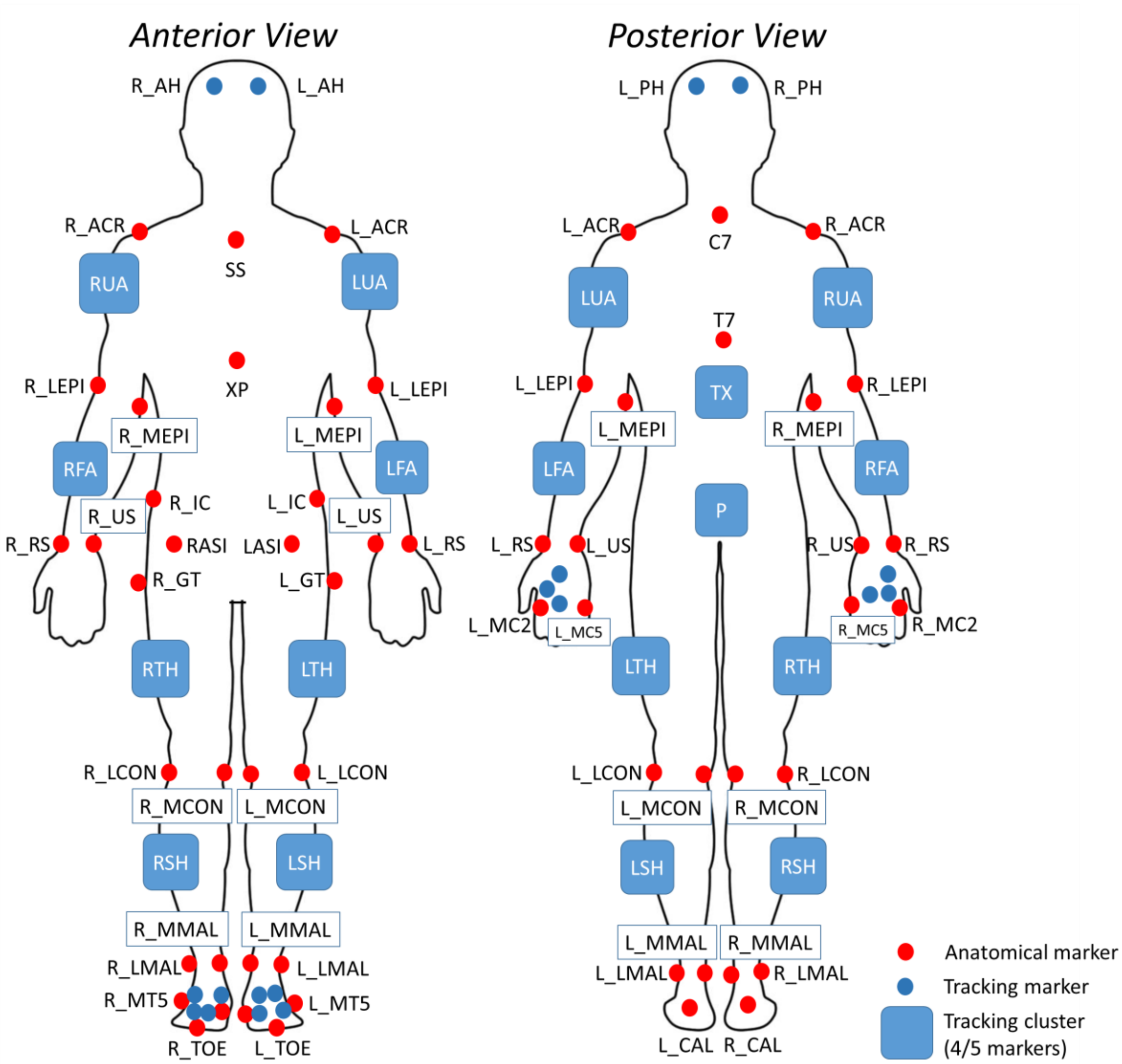

Figure 3.1: Whole-body marker setup consisting of 58 individual markers, eight clusters of four markers, and two clusters of five markers (i.e. thigh clusters).

Three milk crates (1.5 kg and 33.5 × 33.5 × 28 cm) with handles were used as the lifting object. Each crate had an individual reflective marker on each corner (i.e. four markers in total) of the posterior aspect of the crate to limit marker obstruction.

The experimental setup for the lifting tasks consisted of three adjacent shelves with the bottom shelf just above the floor and the top shelf adjusted to the individual's stature-based shoulder height (see **Figure 3.2**).

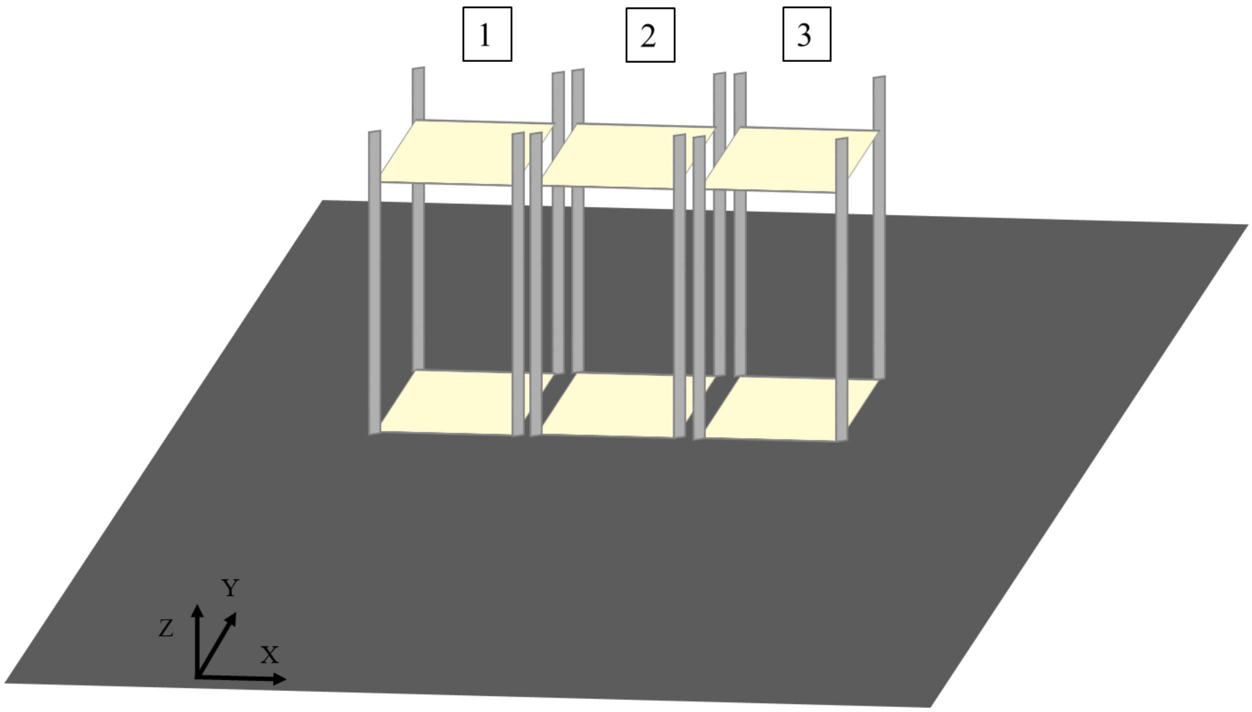

Figure 3.2: Three lifting stations with the bottom shelf just above floor height and top shelf at shoulder height.

3.3.4 Procedures

This study consisted of two data collection sessions for each participant that were 2-7 days apart. This timeframe was deemed appropriate to allow for enough recovery of delayed-onset muscle soreness from the first session and to control for history as an internal bias to the individual's MV.

Session 1

In the first session eligibility was confirmed using demographics, Nordic MSD questionnaire (Kuorinka et al., 1987), and GAQ (CSEP, 2017). Furthermore, the participant's shoulder height was measured to adjust the shelving heights relative to the individual.

To obtain relative weights maximum lifting capacity was assessed using the Matheson's EPIC Lifting Capacity (ELC) test. The ELC test is a psychophysical test to assess functional lifting capacity (Matheson et al., 1995). The original ELC was slightly modified by adjusting the shelf height to individualized height and by only completing subtest 3 (i.e. floor to shoulder height) at 1 cycle per minute (Matheson et al., 1995). The test started with lifting and lowering the crate with a 4.5 kg weight once within a 1 min window, followed by 1 minute of mandatory rest. If certain psychophysical and safety criteria were met the test was repeated with the addition of 4.5 kg. In the ELC, the weight was determined as maximum lifting capacity if, heart rate > 70% of age-predicted maximum, rate of perceived load > 8, they could not perform this 8-12 times per day, unsafe lifting work style was displayed, or if they could not lift heavier (Matheson et al., 1995). The participant was not instructed on how to lift the crate, other than lifting it with both hands.

After the ELC test the participants were equipped with the aforementioned motion capture markers for whole-body kinematic recording. Participants were deceived about the purpose of the study to reduce the effect of demand characteristics on participants' movement variability behaviour (Nichols & Maner, 2008). Participants were informed that the study aimed to estimate the optimal and safe number of lifting repetitions for an 8-h workday and to understand the effect of load and foot movement on the number of lifts. In line with the deception, participants were asked to perform as many repetitions as if they were working an 8-h workday without feeling tired or experiencing strain at the end of the workday. However, participants were also made aware that they were performing each lifting task for 30 minutes maximum. Participants were not explicitly instructed how to move, but the participants had to move the crate using two hands for the possibility of top-down inverse dynamics modelling (not reported in this study). To expose all participants to the same instructions of the study protocol, audio recordings and corresponding written transcripts were used (Beach et al., 2018).

In the first session participants only performed lifting under foot placement and foot movement restrictions. Participants were instructed to keep their feet flat on the floor and place their feet inside rectangles drawn on the floor at each shelf using tape. These rectangles were drawn after they practiced a couple lifts to ensure comfortable foot placement. Participants first completed the restricted task with the low weight (i.e. 10 % of maximum), took a 10-min rest break to limit fatigue development, and then repeated the task with a higher weight (i.e. 30 % of maximum).

Each lifting task was broken down into a maximum of seven sets of five trials, with one trial corresponding to three repetitions of the task (one repetition at each shelf). This resulted in a maximum of 105 total repetitions if the participant completed all trials. Each lifting task had a maximum time limit of 30 minutes to ensure that other tasks that are not included in this study could also be completed within a 3-hr maximum window. In addition to the time limits, the maximum number of 105 repetitions was chosen to obtain a good estimate of variability without inducing excessive fatigue. Participants always lifted the crates in the same order of shelves, and research staff lowered the crates before the next trial was started. As part of the deception, the participants were asked after every set if they were able to complete another set within an 8-h workday without feeling tired or experiencing strain at the end of the workday. This led to some participants to stop the lifting task before the maximum number of 105 repetitions was reached.

Session 2

In the second session eligibility was confirmed by asking the participants to indicate any changes on the Nordic MSD questionnaire and the GAQ that may have occurred in between session 1 and 2. The same general instructions as session 1 including deception were given.

In the second session participants only performed the unrestricted, free lifting task. In contrast to the restricted task, the free lifting task allowed participants to place and move their feet freely. To encourage free foot placement, participants approached the shelves by walking from a 2.5 m distance. Similar to session 1, participants first completed the free lifting task with the low weight (i.e. 10 % of maximum), then took a 10-min rest break to limit fatigue development, and then repeated the task with a higher weight (i.e. 30 % of maximum). Also, the maximum number of repetitions, maximum time per task and order of shelves was identical to session 1.

After the completion of this session the participants were debriefed about the deception and the true purpose of the study was revealed by informing them that their movement variability was studied rather than the number of repetitions. Participants signed another consent form after deception was lifted.

3.3.5 Data processing

Whole-body and crate marker kinematics were labelled by use of a custom-made labelling skeleton in Vicon Nexus and subsequently gap filled using the best practice of applying cubic spline interpolation for gaps ≤ 200 ms and for gaps > 200 ms rigid body fill function of Vicon Nexus was used if three markers on the same segment were visible and otherwise pattern fill function was used (Howarth & Callaghan, 2010). All marker data were imported into Visual3D v6.01.03 (C-motion Inc., Germantown, Maryland, USA) to identify anatomical landmarks in the experimental trials based on the static calibration trials that were subsequently used to define local coordinate systems of the hand, forearm, upper arm, torso, pelvis, thigh, shank, and foot segments according to ISB recommendations (Wu et al., 2002, 2005). Due to frequent marker obstructions of the shank tracking markers the shank segments were tracked using only two visible shank cluster markers, one virtual knee anatomical marker and one virtual ankle anatomical marker for each side. These virtual markers were representative of the lateral condyle at the knee and lateral malleolus at the ankle for each side.

To determine joint angles, the orientation of local coordinate systems of the distal segment relative to proximal segment were decomposed according to the Cardan sequence of flexion-extension, abduction-adduction, and internal-external rotation, except for the shoulder joint that was decomposed using the Euler sequence of plane of elevation, angle of elevation, and axial rotation (i.e. humerus relative to torso) in agreement with ISB recommendations (Wu et al., 2002, 2005). Joint angles together with crate marker trajectories were exported to Python 3.7.

To remove high frequency noise joint angles and crate marker trajectories were filtered with a second order dual-pass low pass Butterworth filter with an effective cut-off frequency of 6 Hz (Winter, 2009). Subsequently, anterior-posterior crate marker velocity was used to segment each trial into three separate lifts while confirming that at least 100 padding points or 1 s before and after each lift were available (Howarth & Callaghan, 2008; Smith, 1989). This led to an overall average of 93 (± 19) lifting cycles. Then, each segmented lift was normalized to 101 data points corresponding to 0 to 100 % of the lift cycle by use of a shape-preserving cubic spline (Graham et al., 2013). The number of cycles was further reduced by excluding outliers in sagittal joint angles that were outside of the ensemble average ± 3.75 standard deviations range. Finally, an overall average of 80 (± 17) cycles were included for further processing.

The resulting time-normalized joint angle cycles were used to determine the point-by-point standard deviation (i.e. standard deviation at each % cycle) which was averaged across the 101 time-normalized data points to obtain joint angle meanSD. An example of time-normalized joint angles is illustrated in **Figure 3.3**. Subsequently, joint angle meanSD of left and right ankle, knee and hip joints were summed for a lower extremity measure and joint angle meanSD of left and right wrist, elbow and shoulder joints were summed for an upper extremity measure. MeanSD of low back joint angle was considered separately. Lastly, meanSD of all joint angles were summed to yield a whole-body variability measure.

3.3.6 Statistical analysis

All statistical analyses were conducted in R 4.0. Lower extremity, low back, upper extremity and whole-body variability were assessed for normality using statistics of skewness, kurtosis and Shapiro-Wilks test and by visual inspection of histograms, Q-Q plots and box plots. The assessment determined that the data violated the assumption of normality, mostly due to positive skew. To confirm the assumption of normality a log transform was applied to all dependent variables for statistical analysis.

To determine the effect of task constraints on MV, lower extremity, low back, and upper extremity variability were used as the dependent variables because preliminary analysis showed that variability at the whole-body level canceled out regional effects. In contrast, to determine the consistency in individual MV responses across different task constraints whole-body variability was used since whole-body consistency would generate the strongest evidence for individual consistency.

The effect of DOF constraint (restricted versus free) and weight (low versus high) on lower extremity, low back and upper extremity variability was examined with a two-way repeated measures ANOVA. If significant main effects were found the direction of the effect was determined by group means. Since this resulted in nine different comparisons (i.e. three body regions in three movement planes) a Bonferroni correction was applied to control familywise error rate and therefore the critical level of significance of .006 was used.

The consistency of whole-body joint variability across all four constraints (i.e. two DOF constraints by two weights) was assessed by intraclass correlation (ICC) using the two-way mixed model for average measures (i.e. ICC(3,k) consistency model). ICC can be used as a measure of dependency between observations that can be attributed to the participants by taking both within-participant and between-participant variability into account (Field et al., 2012). To further investigate the consistency across constraints the correlation between weights for each DOF constraint was determined using Spearman's correlation coefficient. Because a positive relationship between the weights was expected, a one-tailed test was used with a confidence level of 95%.

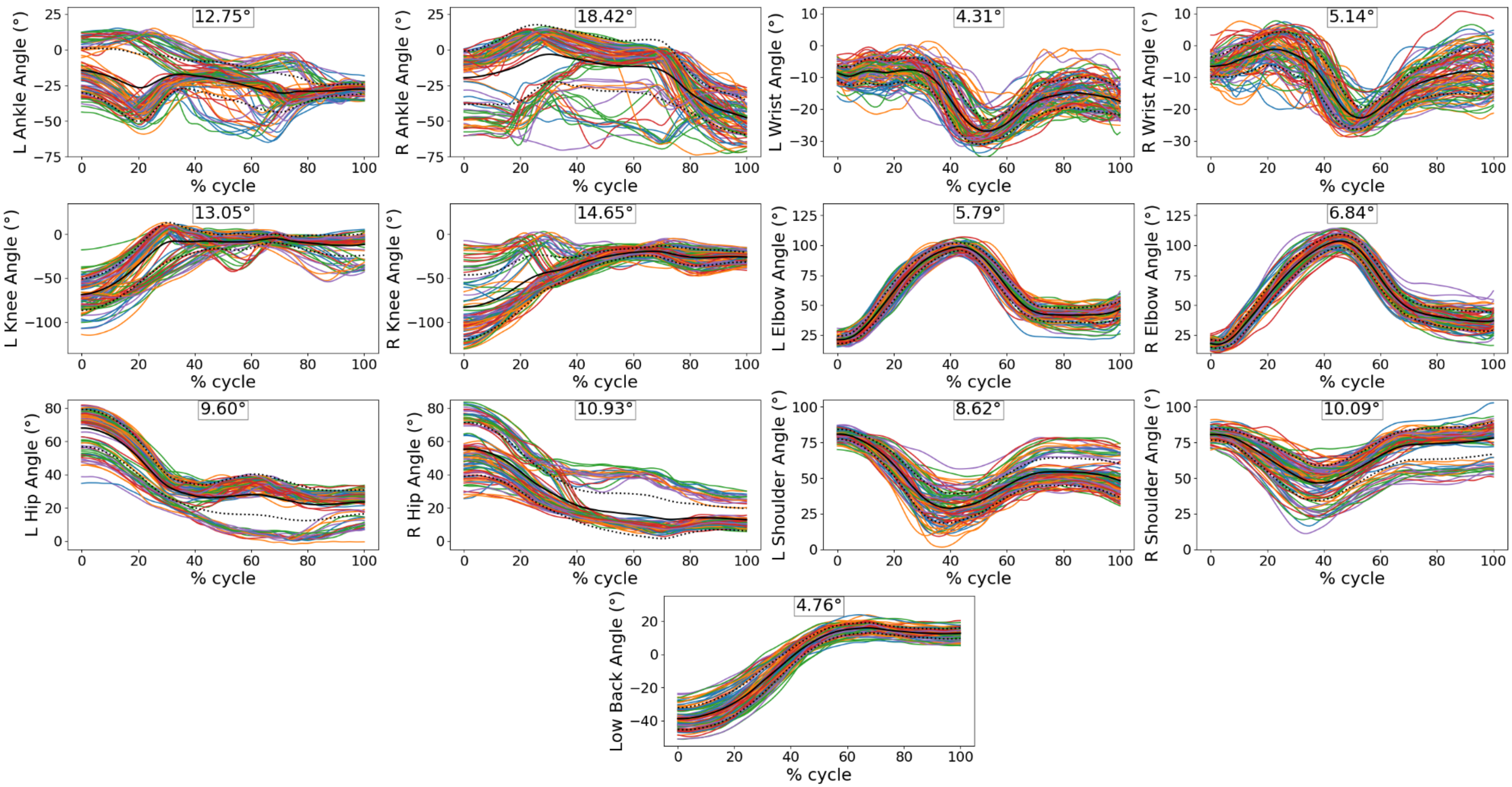

Figure 3.3: Time-normalized sagittal joint angles of a representative participant including the ensemble average (black line), the range of ensemble average ± 1 standard deviation (black dotted lines) and the corresponding meanSD values for the cycles included after removal of outliers of the free DOF constraint by low load weight condition.

3.4 Results

DOF constraint had a significant main effect on lower extremity variability in all movement planes (see **Table 3.1**). The group means revealed that the variability in the free conditions was 15%, 17% and 11% higher in the sagittal, frontal and transverse planes, respectively, compared to the restricted conditions (see **Table 3.1** and **Figure 3.4**). The same main effect of DOF constraint was found on low back variability, but only in the frontal and transverse planes (see **Table 3.1**). Group means revealed that the variability in the free conditions was 318% and 439% higher in the frontal and transverse planes, respectively, in comparison to the restricted conditions (see **Table 3.1** and **Figure 3.4**). DOF constraint also showed a significant main effect on upper extremity variability, but only in the frontal plane (see **Table 3.1**). In contrast to previous main effects of DOF constraint, group means revealed a 4% higher variability in the restricted conditions in comparison to the free conditions for the upper extremity (see **Table 3.1** and **Figure 3.4**). Furthermore, weight did not show any significant main effects (see **Table 3.1**). Lastly, the interaction of DOF constraint and weight did not result in any significant effects (see **Table 3.1**).

Table 3.1: Results of two-way repeated measures ANOVA with DOF constraint and weight as factors for log transformed lower extremity (LE), low back (LB) and upper extremity (UE) variability in sagittal (X), frontal (Y), and transverse (Z) planes. Significant main effects are indicated by p-values and directions in bold, with RS indicating restricted foot movement and FR indicating free or unrestricted foot movement.

	DOF Constraint				Weight				DOF Constraint*Weight			
	F (1,19)	p	η_p^2	Direction	F (1,19)	p	η_p^2	Direction	F (1,19)	p	η_p^2	Direction
LE_X	15.693	**<.001**	0.452	**FR>RS**	4.261	0.053	0.183	n/a	0.190	0.668	0.010	n/a
LE_Y	22.138	**<.001**	0.538	**FR>RS**	0.011	0.917	0.001	n/a	0.267	0.612	0.014	n/a
LE_Z	15.804	**<.001**	0.454	**FR>RS**	0.118	0.735	0.006	n/a	0.591	0.452	0.030	n/a
LB_X	0.189	0.669	0.010	n/a	0.718	0.407	0.036	n/a	0.005	0.942	0.000	n/a
LB_Y	27.075	**<.001**	0.588	**FR>RS**	4.652	0.044	0.197	n/a	0.020	0.889	0.001	n/a
LB_Z	20.422	**<.001**	0.518	**FR>RS**	9.198	0.007	0.326	n/a	0.008	0.928	0.000	n/a
UE_X	0.172	0.683	0.009	n/a	2.188	0.156	0.103	n/a	0.002	0.964	0.000	n/a
UE_Y	12.246	**<.006**	0.392	**RS>FR**	0.355	0.558	0.018	n/a	2.043	0.169	0.097	n/a
UE_Z	9.022	0.007	0.322	n/a	0.005	0.942	0.000	n/a	0.787	0.386	0.040	n/a

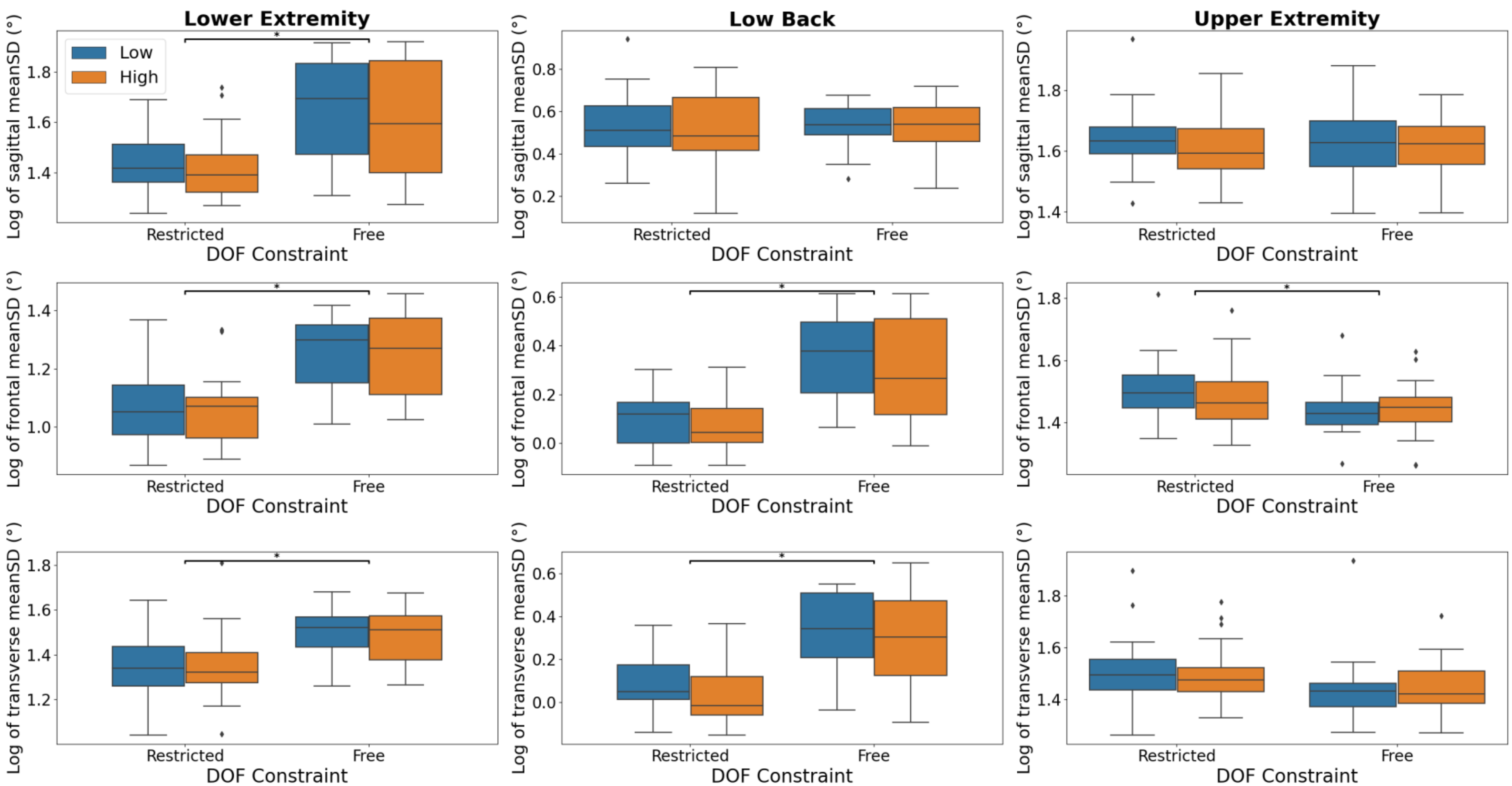

Figure 3.4: Boxplots of each movement axis (row) by body area (column) showing the quartiles (box), 1.5 interquartile range of lower and upper quartile (whiskers) and values outside this range (diamonds). Single plots show one boxplot for each DOF constraint (restricted, free) and weight (low, high). Significant main effects are indicated using brackets with asterisks (*).

Significant ICCs were found for whole-body variability across all movement planes (see **Table 3.2** and **Figure 3.5**). Also, significant correlations between weights for each DOF constraint were found for whole-body variability across all movement planes (see **Table 3.3**).

Table 3.2: Intraclass correlation (ICC) of log transformed whole-body (WB) variability in sagittal (X), frontal (Y), and transverse (Z) planes across all lifting constraints with corresponding p-value and 95% confidence interval (CI). Significant p-values are indicated in bold.

	ICC	p	95% CI
WB_X	0.71	**<.001**	0.49 - 0.86
WB_Y	0.84	**<.001**	0.72 - 0.92
WB_Z	0.84	**<.001**	0.71 - 0.92

Table 3.3: Spearman's correlation coefficient (r_s) of log transformed whole-body (WB) variability in sagittal (X), frontal (Y), and transverse (Z) planes between weights for each DOF constraint with corresponding p-value. Significant p-values are indicated in bold,

	DOF constraint	r_s	p
WB_X	Restricted	0.67	**<.001**
	Free	0.88	**<.001**
WB_Y	Restricted	0.83	**<.001**
	Free	0.82	**<.001**
WB_Z	Restricted	0.85	**<.001**
	Free	0.83	**<.001**

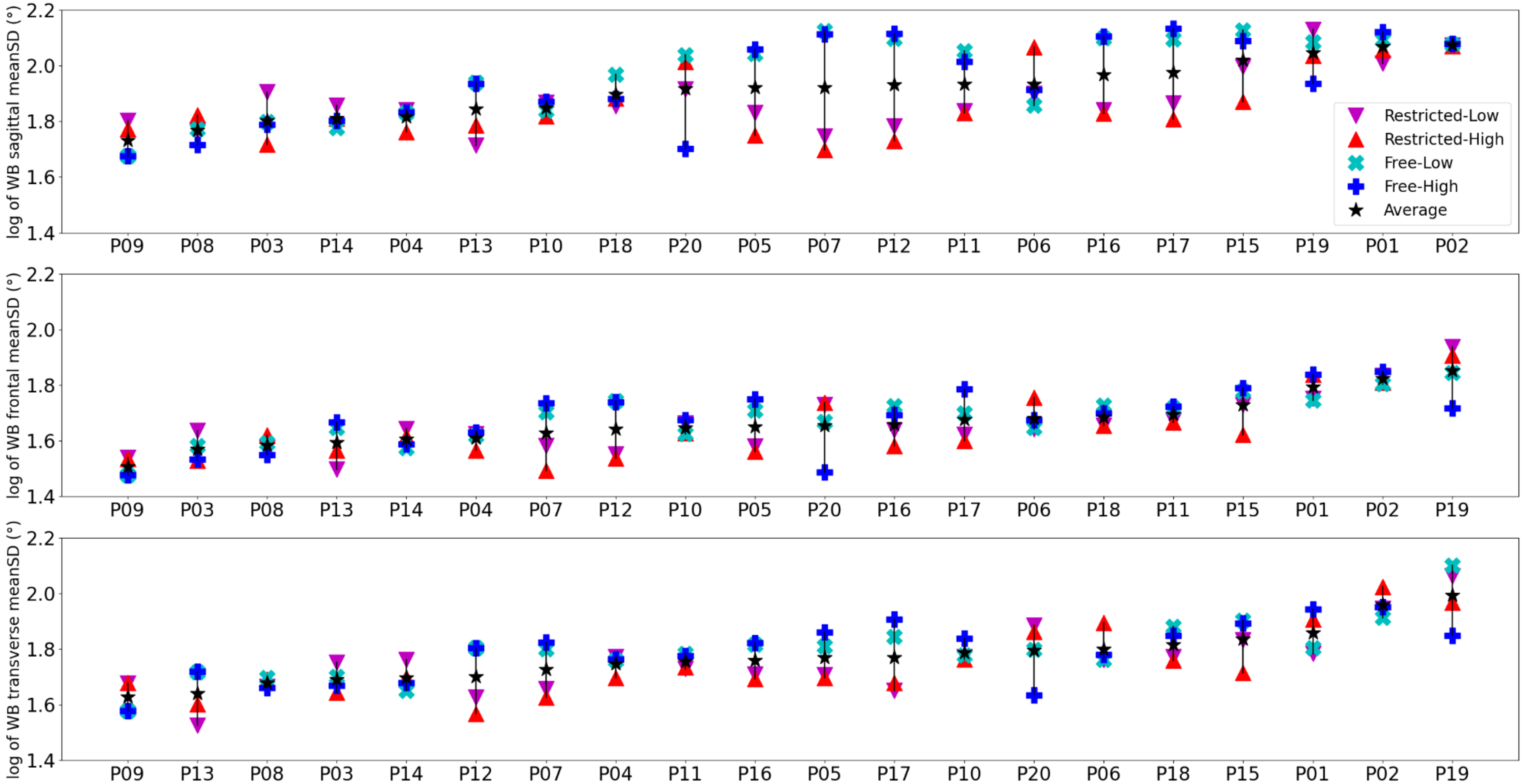

Figure 3.5: Log of whole-body (WB) meanSD for each DOF constraint by weight condition with participants ranked on average meanSD across conditions on the abscissa with each plot showing a different movement axis.

3.5 Discussion

The goal of this study was to assess the impact of task constraints on MV and the consistency in individual MV responses across constraints. Constraining the feet in a repetitive lifting task reduced the amount of lower body variability in all movement planes and low back variability only in the frontal and transverse movement planes. On the contrary, constraining the feet increased the amount of upper body variability only in the frontal movement plane. The other task constraint of load weight did not affect variability in a repetitive lifting task. Therefore, the first hypothesis could only be partially confirmed for DOF constraint but not for load weight. When considering MV as a consistent individual trait, this study showed moderate to good consistency (Koo & Li, 2016) of whole-body variability responses across all task constraints in all movement planes which supports the notion that MV could be an individual trait. Furthermore, when looking at each DOF constraint separately the correlation between weights showed moderate to very strong positive correlation (Chan, 2003) in individual MV responses, which supports consistent individual responses between weights for both DOF constraints. Overall, most participants showed a reduction in whole-body variability (driven by reductions in lower body and low back variability) when the feet were restricted and taken together with the correlation results this supports consistent individual responses across all task constraints. As a result, the second hypothesis was confirmed, where data support that MV may be an individual trait.

In line with previous work, MV can be considered an individual trait based on consistency in individual MV responses across task constraints, providing evidence necessary to support the repeaters-replacers hypothesis. MV appears to be dependent on the individual reflected by moderate to good consistency in individual responses across DOF constraints and weights and reflected by moderate to very strong correlation in individual responses between weights when each DOF constraint was considered separately. In agreement with a previous study, this could reflect that MV responses are consistent within an individual across different task constraints (Jackson et al., 2020). Participants showed consistency of individual MV responses in a cyclic assembly task under different temporal constraints varying in pace and production process (Jackson et al., 2020). Even though the task and MV variables are different from this study, combining these studies supports that MV can be considered an individual trait which is a requirement for the repeaters-replacers hypothesis. Besides consistency across constraints, there should be a continuum of individual MV responses to demonstrate the repeaters-replacers hypothesis. Although some data points are clustered, overall a range of MV responses is demonstrated in **Figure 3.5**. Future work on the repeaters-replacers hypothesis is recommended to include measurements of individual MV responses rather than only considering group-level responses. In addition, now that some evidence exists for the repeater-replacers hypothesis in different task constraints among fine and gross motor tasks future research should determine whether individual MV responses stay consistent across different tasks.

Since DOF constraints determined the amount of MV, these constraints can confound MV estimates. In research, how well the task in the experiment resembles the available DOF of the task in the workplace could be a key factor to improve external validity in assessing the relation between MV and WRMSD risk. Previous occupational research on MV is based on tasks with limited or restricted DOF and resulted in some supporting evidence for the effect of MV on WRMSD risk (Chehrehrazi et al., 2017; Granata et al., 1999; Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017; van Dieën et al., 2001; van Dieën, Oude Vrielink, Housheer, et al., 1993; Yang et al., 2018). However, this study investigated a gross motor task that offered more DOF to explore MV in contrast to previous research that only included fine motor tasks or restricted gross motor tasks. Across body regions and movement planes, the DOF constraint seemed to reduce MV. Therefore, previous studies with more restricted tasks could have been underestimating the amount of MV that is possible for an individual to demonstrate. Thus, when studying MV it is recommended to design the experiment in such a way that the task would easily be translated to the workplace task in terms of DOF constraints. When experiments are also assessing a measure of WRMSD risk minimizing constraints could provide individuals with the opportunity to explore MV that could possibly be associated to a reduction in risk of WRMSD. Furthermore, future research could explore if other task constraints confound MV estimates.

Restricting movement at one joint did not only lead to a reduction of MV in body parts close to the restriction but also led to a compensatory increase of MV in body parts further away from the restriction. Constraining the feet limited the DOF at the ankle joint which decreased lower body variability through dynamic coupling (Zajac et al., 2002). The reduction in low back frontal and transversal plane variability can also be explained by dynamic coupling (Zajac et al., 2002). In contrast, the increase in upper body frontal plane variability could be explained as a compensation mechanism where the upper body compensated for the restriction in lower body DOF (Bartlett et al., 2007). Most importantly, in whole-body movement the body seemed to explore MV in unrestricted body parts despite reductions in MV in body parts that were close to the restriction. Possibly, at the whole-body level the upper extremities were compensating for the loss of MV in the lower body parts which could in agreement with MV as an individual trait promote individual consistency in MV. Future research could explore whether these findings for a gross motor or whole-body task can also be shown in fine motor tasks that are only performed with certain body parts. An important note to consider when interpreting the grouped variables of joint angle meanSD (i.e. lower extremity, upper extremity and whole-body) used in this study is the difference in range of motion between joints. Therefore, joints with larger range of motion could have disproportionately determined the effect of

DOF constraint. Future research could address this by assessing range of motion and taking this into account when grouping variability across body parts.

The lack of effect of load weight on MV could be explained by small differences between the weights, the related perception of this difference, and that weight in comparison to DOF constraint possibly restricted the DOF of the task more indirectly. Even though the weight constraint was relative to each individual's capacity, the difference between the 10 and 30 % weight could possibly not have been large enough to create considerably different mechanical task demands between the weights to influence MV. To illustrate, in case of the lowest 100 % capacity the difference between 10 and 30 % weight was only 0.7 kg. Besides mechanics, the lack of an effect of load on MV could be explained by negligible differences in perception of these low weights following Stevens' psychophysical power law (Stevens, 1970). According to this power law higher weights could have evoked more distinct perceptions which could have affected MV more than low weights. Therefore, future studies are recommended to use larger differences between load weights or higher relative load weights to further explore how load weight affects MV.

3.5.1 Limitations

The data collection of the tasks presented in this study was part of a larger study including other tasks and EMG measurements of a subset of tasks which were performed in the same session to avoid natural between-day variance in EMG signals and therefore randomization of lifting conditions was prevented. However, the authors have evidence to believe that the effects of lifting conditions on MV can most likely be prescribed to the experimental conditions rather than to presentation order effects. Importantly, explicit effects of presentation order on MV were prevented because participants were not made aware that their MV was studied due to the deception. A 52-57% increase in sagittal ankle joint angle variability when the free condition was compared to the restricted condition makes it most likely that the effect of DOF constraint can be prescribed to the constraint rather than the presentation order (left ankle: $F(1,19) = 29.017$; $p<.001$; $\eta_p^2 = 0.604$; right ankle: $F(1,19) = 21.904$; $p<.001$; $\eta_p^2 = 0.536$). Furthermore, the increase of 318-439% in low back joint angle variability is of comparable magnitude to two previous experiments that resemble the DOF constraint. Specifically, a 261-306% increase in lumbar variability was found when the lifting phase of a palletizing task which allowed considerable foot movement was compared to a lifting task with considerable foot constraint (Granata et al., 1999; Plamondon et al., 2014). In addition, we have evidence that makes it most likely that the absence of load weight effect on MV is due to the constraint rather than presentation order based on similar findings reported on comparable load weights that were randomized. Specifically, no difference in lumbar meanSD between 0 and 10% maximum back strength load weights (Graham et al., 2012) and no difference in sagittal and transverse lumbar variance between 5 and 10% body weight loads (Norasi et al., 2019) were found when lifting with consistent foot placement comparable to our restricted DOF constraint condition. Moreover, the findings of this study are limited by the specific variables and variability measures that were used. In this study only one specific kinematic variable (i.e. joint angle) was used to determine variability using one measure (i.e. meanSD). For example, the use of another kinematic measure such as coordination patterns or the use of other biomechanical measurements such as kinetics or EMG to represent MV offer information on variability in coordination, loading or muscle activation which could provide different results and interpretations compared to joint angle variability. Also, the use of another variability measure for instance a measure of complexity such as entropy or task-(ir)relevant variability provides insight into the time-evolution of variability or how variability changes in task-(ir)relevant components which could provide different results and interpretations compared to meanSD that indicates the average repetition-to-repetition spread. Furthermore, the findings of this study are specific to the task constraints of restricting foot movement and increasing relative load weight. For example, changing the origin and destination of the lifting task impose constraints that could have a different effect on MV. Lastly, the lab-based environment limits the external validity of the lifting task. However, the task constraints are believed to have considerable external validity. Notably, participants only had foot movement restricted in some experimental constraints, choose their own pace, and choose their own movement strategy in contrast to earlier studies on MV in lifting tasks (Granata et al., 1999; Sedighi & Nussbaum, 2017; van Dieën et al., 2001). Similarly, instructing the participants to lift the crate with two hands and the crate having four handles the participants could have elicited less externally valid movement behaviour. However, based on anecdotal evidence the handle design did not lead to the same hand-crate interaction across all participants.

3.6 Conclusion

To conclude, MV can be considered a consistent individual trait across different task constraints in a repetitive lifting task. This study showed consistency in individual MV responses across DOF constraints and weights and correlation for individual MV responses between different weights when separated on DOF constraint. Evidence for MV as a consistent individual trait supports the repeaters-replacers hypothesis which could have important implications when this hypothesis is considered in the context of the variability-risk hypothesis that assigns higher risk to low MV. In addition, MV is also determined by DOF constraint of the lifting task. Thus, MV depends on the DOF available in a task which implies that task constraints should be minimized when feasible both in future research and at the workplace. Overall, this work supports the repeaters-replacers hypothesis and emphasizes the effect of task constraints on MV assessment which are core aspects for future research in the area of variability-risk hypothesis.

Chapter 4: Exploring the role of task constraints on motor variability and assessing consistency in individual responses during repetitive lifting using nonlinear variability of kinematics

4.1 Abstract

Motor variability (MV) can be operationalized by a range of measures derived from different motor control perspectives. In occupational MV research on kinematics, nonlinear measures appear to be understudied. Following our earlier work on linear variability of lifting kinematics under different task constraints, in this study nonlinear measures were explored to assess the effect of constraints on MV and consistency in individual MV responses across different constraints. Twenty participants performed repetitive lifting under four constraints differing in restriction of foot movement and load weight while whole-body and crate kinematics were collected. MV was assessed using sagittal plane continuous relative phase (CRP) variability of joint angle couplings aggregated for the upper body, the lower body, and the whole-body. Also, MV was assessed using uncontrolled manifold analysis based on three-dimensional joint angles and crate trajectories which resulted in task-relevant and task-irrelevant variability. Foot movement significantly increased lower body (55%) and upper body (28%) CRP variability, while task-relevant and task-irrelevant variability remained unchanged. No effects of load weight nor interaction of foot restriction and weight were found. Good individual consistency (ICC = 0.70 – 0.84) was revealed across constraints and measures where CRP variability showed higher consistency than task-relevant and task-irrelevant variability. Despite differences between nonlinear measures in the effect of constraints on absolute variability, both measures support MV as an individual trait independent of constraints based on considerable consistency across constraints for both nonlinear measures. This work demonstrates that MV can respond differently to

constraints based on the variability measure and thus future work should consider the interaction of constraints and variability measure as a determinant when assessing MV.

4.2 Introduction

Motor variability (MV) can be described as repeating the same task without repeating the same movement patterns (Bernstein, 1967). From a motor control perspective, repetition-to-repetition MV arises from an abundant number of degrees of freedom (DOF) available to complete a given motor task and thus MV reflects motor control strategy (Cusumano & Cesari, 2006; Latash, 2000; Latash et al., 2002; Newell & Corcos, 1993). From an ergonomics perspective, MV could have implications for the risk of work-related musculoskeletal disorders (WRMSDs) when performing repetitive work tasks (Côté, 2012; Madeleine, 2010; Srinivasan & Mathiassen, 2012). An increase in MV could reduce cumulative loading by increasing repetition-to-repetition distribution of muscle activation and mechanical loading and thus decrease the risk of WRMSDs, which is also described as the variability-risk hypothesis (Bartlett et al., 2007; Hamill et al., 1999; Madeleine, 2010; Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006). Within ergonomics, MV has been proposed as a consistent individual trait across days and task constraints via the repeaters-replacers hypothesis (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). When connecting the variability-risk hypothesis to the repeaters-replacers hypothesis, individuals with consistently low MV (i.e. repeaters) could be at higher risk of WRMSDs compared to individuals with consistently high MV (i.e. replacers). Thus, from an ergonomics perspective, MV could improve our understanding of WRMSDs. To advance occupational MV research, the connection between the ergonomics and motor control perspectives should be further explored.

MV can be viewed from multiple motor control theories broadly considered from the perspectives of traditional and functional approaches (Bartlett et al., 2007; Hamill et al., 1999).

Traditional approaches to study MV were grounded in information theory, where motor control is regulated by motor programs (Clark, 1995; Slifkin & Newell, 1998). MV is considered dysfunctional because variability is believed to reflect undesirable noise of the neuromuscular system or measurement noise that would impair performance (Bartlett et al., 2007; Newell & Corcos, 1993). Therefore, an increase in MV has been regarded as dysfunctional, in contrast with the variability-risk hypothesis. However, since the end of the 20th century, functional approaches have gained interest for quantifying MV among which dynamic systems theory (DST) and optimal feedback control (OFC) describe two major themes that assign functional characteristics to variability (Bartlett et al., 2007; Hamill et al., 1999; Scholz & Schöner, 1999; Todorov & Jordan, 2002).

Functional motor control approaches regard variability as functional since an increase in variability would not necessarily lead to impaired performance. More specifically, in DST, desirable characteristics such as adaptability and load distribution are assigned to variability (Bartlett et al., 2007) and in OFC, variability which does not interfere with task performance can be defined (Diedrichsen et al., 2010; Scholz & Schöner, 1999; Todorov & Jordan, 2002). In DST, motor control is regulated as a complex dynamic system in which an increase in MV reflects a change in coordination, more flexibility to adapt to changes in the environment, and load distribution (Bartlett et al., 2007; Clark, 1995). With respect to the variability-risk hypothesis, DST could support that variability facilitates load distribution by a change in coordination to lower WRMSD risk. However, it is unclear within DST how variability affects task performance, which could be an important limitation in the context of ergonomics. Another functional approach, OFC, explicitly describes the relationship between task performance and variability (Diedrichsen et al., 2010; Todorov & Jordan, 2002). In OFC, motor control is regulated in a feedback control process and driven by the minimum intervention principle (Diedrichsen et al., 2010; Scott, 2002; Todorov & Jordan, 2002). The minimum intervention principle only corrects variability in task-relevant dimensions while deviations in task-irrelevant dimensions are not controlled and thus free to vary (Diedrichsen et al., 2010; Todorov & Jordan, 2002). Therefore, in OFC, MV is expected to be mostly present in task-irrelevant variability while task-relevant variability is minimized to control task performance (Franklin & Wolpert, 2011; Todorov & Jordan, 2002). When regarding OFC in the context of the variability-risk hypothesis, task-irrelevant variability could take on the functional role of increasing variability to lower WRMSD risk without interfering with task performance. Since the OFC approach supports the pathway to lower WRMSD risk while maintaining task performance when MV is increased, this approach is another interesting candidate to advance occupational MV research.

In ergonomics, MV has been operationalized by a range of measures (Srinivasan & Mathiassen, 2012). The operationalization of MV can be described at two levels, the first level is the biomechanical variable (e.g. kinematics, electromyography (EMG), or kinetics) and the second level is the variability metric which is derived from the underlying motor control approach (Madeleine, 2010; Srinivasan & Mathiassen, 2012). To illustrate, the traditional motor control approach is characterized by use of linear variability measure (e.g. standard deviation), the DST approach is characterized by use of nonlinear measures (e.g. variability of coordination dynamics and entropy), and the OFC approach is characterized by equifinality methods (e.g. uncontrolled or goal-equivalent manifold (UCM or GEM)) (Srinivasan & Mathiassen, 2012). When focussing on kinematics, linear measures have contributed substantially to the development of the variability-risk hypothesis in occupational tasks despite the lack of theorical support for this hypothesis by the underlying traditional motor control approach (Granata et al., 1999; Huysmans et al., 2008; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017). Some studies have explored DST measures of kinematic MV, with the focus on nonlinear time series analysis rather than coordination pattern variability (Cowley et al., 2014; Gates & Dingwell, 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017). Lastly, few studies have performed equifinality analysis and only GEM was used to assess kinematic MV during ergonomic tasks (Cowley et al., 2014; Gates & Dingwell, 2008; Sedighi & Nussbaum, 2017). GEM analysis, in contrast to UCM analysis, requires a task goal such as external pacing, which could reduce the external validity of translating the task to the workplace. In addition, only two previous studies used both DST and equifinality measures to describe kinematic MV in ergonomic tasks; however, these measures consisted of nonlinear time series and GEM analysis which further illustrates that coordination pattern variability and UCM analysis are understudied. In occupational MV research, the use of different measures and motor control perspectives may indicate a lack of consensus. To overcome this problem, there is a need to compare interpretations based on different methods and specifically of understudied nonlinear methods such as coordination pattern variability and UCM analysis.

In an earlier study (Oomen et al., 2022), we explored MV in a lifting task under different task constraints (i.e. (un)restricted foot movement, and different load weights) by operationalizing MV using linear measures thus following a traditional approach. Therefore, the objective of this study was to explore how functional approaches using nonlinear measures of coordination pattern variability and UCM variability affect the results and interpretation of MV under changing DOF constraints and load weight. Specifically, this study has two research questions: 1) What is the effect of DOF constraint and load weight on MV using both DST and OFC measures among healthy adults? and 2) Do healthy adults show consistent MV responses across different DOF constraints and load weights when using DST and OFC measures, in line with the repeaters-replacers hypothesis? It was hypothesized that when the DOF of the tasks were more constrained and when load weight was increased higher mechanical task demands were imposed which resulted in a decrease of DST and task-irrelevant variability (Nordin & Dufek, 2016, 2017). Despite changing the task, task constraints are not expected to affect task-relevant variability since it reflects task performance which is not expected to change considerably across constraints. If the repeaters-replacers hypothesis holds, DST and task-irrelevant variability were hypothesized to show consistent individual MV response across all conditions. Within OFC measures, only task-irrelevant variability would serve a functional role in the repeaters-replacers hypothesis. Furthermore, task-relevant variability is not expected to show consistency because it represents task performance independent of task-irrelevant variability.

4.3 Methods

4.3.1 Research design

The research questions were answered in a cross-sectional experimental study with a two-factor repeated measures design similarly to our companion study that looked at linear measures (Oomen et al., 2022). The independent variables consisted of 1) DOF constraint (i.e. restricted foot movement versus unrestricted foot movement by instruction) and 2) load weight relative to maximum capacity (i.e. low versus high). The dependent variables consisted of two nonlinear variability measures: 1) sagittal plane continuous relative phase (CRP) variability (described in Section 4.3.2) from the DST framework based on sagittal plane whole-body joint angles and 2) task-relevant and task-irrelevant variability expressed in standard deviation from the OFC framework using UCM analysis (described in Section 4.3.2) on three-dimensional whole-body joint angles and crate trajectories.

This study was completed using the same dataset and preprocessing as Oomen et al. (2022). This study was approved by the University of Waterloo's Office of Research Ethics (ORE#40762), and all participants provided informed consent prior to participation. In brief, motion capture data from twenty participants (10 females and 10 males) and three milk crates as lifting objects were recorded while participants performed four different lifting tasks based on the independent variables (i.e. restricted low load, restricted high load, unrestricted low load, and unrestricted high load) for an overall average of 93 (± 19) lifting cycles per task per participant. Whole-body and crate marker kinematics were labelled, gap filled, padded, filtered, and segmented to lifting cycles. Local coordinate systems of the hand, forearm, upper arm, torso, pelvis, thigh and shank and foot segments in agreement with ISB recommendations were derived to determine joint angles of each lifting cycle (Wu et al., 2002, 2005). A local coordinate system was created for each crate of which the origin trajectories were determined of each lifting cycle. Greater detail about the experimental procedure and methodology can be found in Oomen et al. (2022).

4.3.2 Data processing

Removal of outliers

For the DST framework, CRP analysis of only sagittal joint angles was conducted because this represents the primary movement plane of the lifting task. As part of CRP analysis, amplitude centering appeared to be sensitive to some outliers in sagittal joint angles, which led to unrepresentative phase angles. Thus, cycles that were outside of the sagittal joint angle ensemble average ± 3.75 standard deviation range were removed from all analyses performed in this study. As a result, an overall average of 80 (± 17) cycles per participant for each lifting task was retained and further processed.

Continuous relative phase

CRP was determined by use of a Hilbert transformation because it is not sensitive to deviations from sinusoidal signals and avoids magnifying noise related to differentiation (Lamb & Stöckl, 2014; van Emmerik et al., 2014). To minimize data distortion related to the Hilbert transform, each cycle was padded with 100 data points of collected data before and after the nearest lifting cycle (Ippersiel et al., 2019). First, to remove differences in angle amplitude due to the non-sinusoidal nature of kinematics, each joint angle $\mathbf{x}_j(t)$ as a function of time in cycle j was centered such that zero reflected the middle between maximum and minimum displacement in $\mathbf{x}_{\mathrm{cent,j}}(t)$ for each participant and condition (**Equation 1**) (Lamb & Stöckl, 2014).

$$\mathbf{x}_{\mathrm{cent,j}}(t) = \mathbf{x}_{\mathrm{j}}(t) - \frac{\min(\mathbf{x}(t)) + \max(\mathbf{x}(t))}{2} \quad \textbf{Equation 1}$$

Second, the Hilbert transform was determined of the centered angular displacement $\mathbf{y}(t) = \mathrm{H}(\mathbf{x}_{\mathrm{cent,j}}(t))$, where $\mathbf{y}(t)$ is related to $\mathbf{x}_{\mathrm{cent,j}}(t)$ by a 90 degree phase shift. The Hilbert transform results in a complex signal $\boldsymbol{\zeta}(t)$, where $\mathbf{y}(t)$ serves as the imaginary part of the analytic signal (**Equation 2**) (Palut & Zanone, 2005).

$$\boldsymbol{\zeta}(t) = \mathbf{x}_{\mathrm{cent,j}}(t) + \mathrm{i}\mathbf{y}(t) \qquad \textbf{Equation 2}$$

Third, phase angle $\boldsymbol{\theta}(t_i)$ at any time instant i was determined using the four-quadrant arctangent of the transformed signal $\mathbf{y}(t_i)$ divided by the centered angular displacement $\mathbf{x}_{\mathrm{cent,j}}(t_i)$ (**Equation 3**), resulting in a range of [-180, 180] degrees (Hamill et al., 2000; Lamb & Stöckl, 2014).

$$\boldsymbol{\theta}(t_i) = \tan^{-1}\frac{\mathbf{y}(t_i)}{\mathbf{x}_{\mathrm{cent,j}}(t_i)} \qquad \textbf{Equation 3}$$

Fourth, $\mathbf{CRP}(t_i)$ at any time instant i was defined as the absolute relative phase angle of two joints after subtracting the proximal joint from the distal joint (**Equation 4**).

$$\mathbf{CRP}(t_i) = \left|\boldsymbol{\theta}_{\mathrm{dist}}(t_i) - \boldsymbol{\theta}_{\mathrm{prox}}(t_i)\right| \qquad \textbf{Equation 4}$$

After CRP was determined for each cycle, the padding points were removed. To prevent discontinuities from affecting cycle-to-cycle CRP variability, CRP was corrected by subtracting any value greater than 180 degrees from 360 degrees (Seay et al., 2011; van Emmerik et al., 2014). This calculation resulted in a CRP range of [0, 180] degrees (Lamb & Stöckl, 2014). Subsequently, CRP was time normalized to 101 data points (i.e. 0 to 100% lifting cycle). Cycle-to-cycle CRP variability was determined as the point-by-point standard deviation, which was subsequently averaged across all 101 data points to obtain average cycle-to-cycle CRP variability (Hamill et al., 2000). In total, average cycle-to-cycle CRP variability of 12 joint couplings were obtained, and left and right ankle-knee, knee-hip, and hip-low back couplings were summed for a lower extremity measure, and left and right wrist-elbow, elbow-shoulder, and shoulder-low back couplings were summed for an upper extremity measure. Finally, average cycle-to-cycle CRP variability of all joint couplings were summed to obtain a whole-body measure.

Uncontrolled manifold

In the lifting tasks, the elemental variables consisted of whole-body three-dimensional joint angles of 13 joints (i.e. low back and left and right ankle, knee, hip, wrist, elbow, and shoulder joints), that resulted in a total of 39 DOF. The performance variables consisted of three-dimensional position of the origin of the crate local coordination system in global space. For the performance variables, no distinction was made between the three different crates because preliminary analysis showed only small differences between task-relevant and task-irrelevant variability when separating each crate and when not making a distinction between crates. Thus, the performance variable consisted of 3 DOF. Three-dimensional joint angles and crate trajectories were time normalized to each lifting cycle of 101 data points (i.e. 0 to 100% cycle).

In line with previous UCM analyses, a linear approximation of the UCM was obtained at the average elemental and performance variables (Beerse et al., 2020; de Freitas & Scholz, 2010; Freitas et al., 2010; Greve et al., 2013; Scholz & Schöner, 1999). Therefore, at each time interval, the deviation from the mean was determined for elemental and performance variables (respectively $\Delta\mathbf{x}$ and $\Delta\mathbf{r}$) and, also at each time interval, the Jacobian matrix (**J**) relates the two variables (**Equation 5**).

$$\Delta\mathbf{r}_{3\times1} = \mathbf{J}_{3\times39} \cdot \Delta\mathbf{x}_{39\times1} \qquad \textbf{Equation 5}$$

Although typically a forward kinematics geometric model has been used to analytically determine the Jacobian matrix, it is analytically complex to determine this model when the number of DOF is large and when participants are subjected to constraints or interact with objects that limit their range of motion (de Freitas & Scholz, 2010; Freitas et al., 2010). Since this study involved whole-body movement, interaction with the crate and instruction of restricted foot movement, determining a geometric model is complex and thus another approach was used. Hence, the Jacobian matrix was determined by the coefficients of multiple linear regression, which has been presented as an accurate alternative that may even provide a better description of the actual movement data than the geometric model (de Freitas & Scholz, 2010; Freitas et al., 2010; Greve et al., 2013; Tuitert et al., 2019). In this study, three separate multiple linear regressions were performed for each dimension of crate position (i.e. X, Y, Z) and were combined to obtain the Jacobian. The Jacobian consisted of a 3 × 39 matrix for each time interval (i.e. for 101 data points representing 0 to 100% lifting cycle), with each row representing regression coefficients of one performance variable as the dependent variable and each column representing elemental variables as independent variables. Subsequently, the UCM is linearly approximated by the null space of the Jacobian matrix that consisted of the orthonormal basis vectors $\boldsymbol{\varepsilon}$ (**Equation 6**).

$$0 = \mathbf{J} \cdot \boldsymbol{\varepsilon} \qquad \textbf{Equation 6}$$

The null space spanned by basis vectors $\boldsymbol{\varepsilon}$ consisted of a 39 × 36 matrix with each column representing one basis vector, with the total number of basis vectors defined as the elemental DOF minus performance DOF (i.e. 39 – 3 = 36). Then, cycle-to-cycle deviations from the mean were projected into two subspaces, task-irrelevant (i.e. null space or $\mathbf{x}_{\mathrm{UCM}}$) and task-relevant (i.e. orthogonal to the null space or $\mathbf{x}_{\mathrm{ORT}}$) space (**Equations 7 and 8**). With *d* indicating the DOF of the performance variables (*d = 3*) and *n* indicating the DOF of the elemental variables (*n = 39*).

$$\mathbf{x}_{\mathrm{UCM}} = \sum_{i=1}^{n-d} \boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}} \Delta\mathbf{x} \qquad \textbf{Equation 7}$$

$$\mathbf{x}_{\mathrm{ORT}} = \Delta\mathbf{x} - \mathbf{x}_{\mathrm{UCM}} \qquad \textbf{Equation 8}$$

Then, cycle-to-cycle variability was defined as the point-by-point standard deviation per DOF of each subspace (**Equations 9 and 10**). Cycle-to-cycle variability along the UCM subspace $\mathbf{x}_{\mathrm{UCM}}$ and along the orthogonal subspace $\mathbf{x}_{\mathrm{ORT}}$ were defined as task-irrelevant variability $\boldsymbol{\sigma}_{\mathrm{UCM}}$ and task-relevant variability $\boldsymbol{\sigma}_{\mathrm{ORT}}$, respectively.

$$\boldsymbol{\sigma}_{\mathrm{UCM}} = \sqrt{\frac{\sum_{i=1}^{N_{\mathrm{cycles}}} \|\mathbf{x}_{\mathrm{UCM}}\|^2}{(n-d)\cdot N_{\mathrm{cycles}}}} \qquad \textbf{Equation 9}$$

$$\boldsymbol{\sigma}_{\mathrm{ORT}} = \sqrt{\frac{\sum_{i=1}^{N_{\mathrm{cycles}}} \|\mathbf{x}_{\mathrm{ORT}}\|^2}{d\cdot N_{\mathrm{cycles}}}} \qquad \textbf{Equation 10}$$

Finally, task-irrelevant and task-relevant variability were averaged across all 101 data points to obtain average cycle-to-cycle task-irrelevant and task-relevant variability.

4.3.3 Statistical analysis

All statistical analyses were conducted in R 4.0. Lower extremity CRP variability, upper extremity CRP variability, whole-body CRP variability, task-relevant, and task-irrelevant variability were assessed for normality using statistics of skewness, kurtosis, and Shapiro-Wilks test and by visual inspection of histograms, Q-Q plots, and box plots. The assessment determined that task-relevant and task-irrelevant variability violated the assumption of normality due to positive skew (i.e. visible from box plots, significant positive skewness ($Skew_{2SE} > 1$ and $p < .05$) and significant

Shapiro-Wilks test ($p < .05$)). To confirm the assumption of normality a log transform was applied to only these variables for statistical analysis.

To determine how DST and OFC variability affected the results and interpretation of MV under changing task constraints, the effect of DOF constraint and load weight on MV and consistency in individual MV responses across task constraints were determined for each measurement approach separately. For the effect of task constraints on MV using the DST approach, regional effects in the lower and upper extremities were studied since the effect of DOF constraint on linear joint angle variability appeared to depend on the body region (Oomen et al., 2022). For the effect of task constraints on MV using the OFC approach, task-relevant and task-irrelevant variability were analyzed in the same comparison. Therefore, both DST and OFC approaches included two measures each, that resulted in two comparisons within each analysis. The effect of DOF constraint (restricted versus free) and weight (low versus high) on variability within each approach was determined with a two-way repeated measures ANOVA. To control familywise error rate related to conducting two comparisons within each approach a Bonferroni correction was applied, which led to the critical level of significance of $\alpha = .025$. For consistency in individual MV responses, the DST approach was represented by whole-body CRP variability since whole-body consistency would generate the strongest evidence for individual consistency. For OFC variability, both task-relevant and task-irrelevant variability reflect whole-body variability relative to different aspects of task performance thus these measures remained the same for consistency analysis. The consistency of each measurement across all four constraints (i.e. 2 DOF constraints by 2 weights) was examined by intraclass correlation (ICC) using the two-way mixed model for average measures (i.e. ICC(3,k) consistency model). To further investigate the consistency across constraints, the correlation between weights for each DOF constraint was determined using Spearman's correlation coefficient. Because a positive relationship between the weights was expected, a one-tailed test was used with a confidence level of 95%.

4.4 Results

For DST coordination variability, both lower and upper extremity sagittal variability showed main effects of DOF constraint (see **Table 4.1** and **Figure 4.1**). When the feet were allowed to move freely lower extremity sagittal CRP variability increased on average by 46.0 degrees, which represents an increase of 55% compared to when the feet were restricted. Similarly, upper extremity sagittal CRP variability increased on average by 35.6 degrees, which represents an increase of 28% when the feet were allowed to move freely in comparison to when the feet were restricted. No main effect of weight or interaction effects were found. Sagittal plane whole-body CRP variability showed significant ICC (see **Table 4.2** and **Figure 4.2**). Moreover, significant correlations between weights for each DOF constraint were found for whole-body CRP variability (see **Table 4.3**).

Table 4.1: Results of two-way repeated measures ANOVA with DOF constraint and load weight as factors for lower extremity (LE) and upper extremity (UE) CRP variability in the sagittal plane. Significant main effects are indicated by p-values and directions in bold, with RS indicating restricted foot movement and FR indicating free or unrestricted foot movement.

	DOF Constraint				**Weight**				**DOF Constraint*Weight**			
	F	p	η_p^2	Direction	F	p	η_p^2	Direction	F	p	η_p^2	Direction
LE	25.800	**<.001**	0.576	**FR>RS**	4.140	0.056	0.179	n/a	1.007	0.328	0.050	n/a
UE	20.484	**<.001**	0.519	**FR>RS**	2.669	0.119	0.123	n/a	0.102	0.753	0.005	n/a

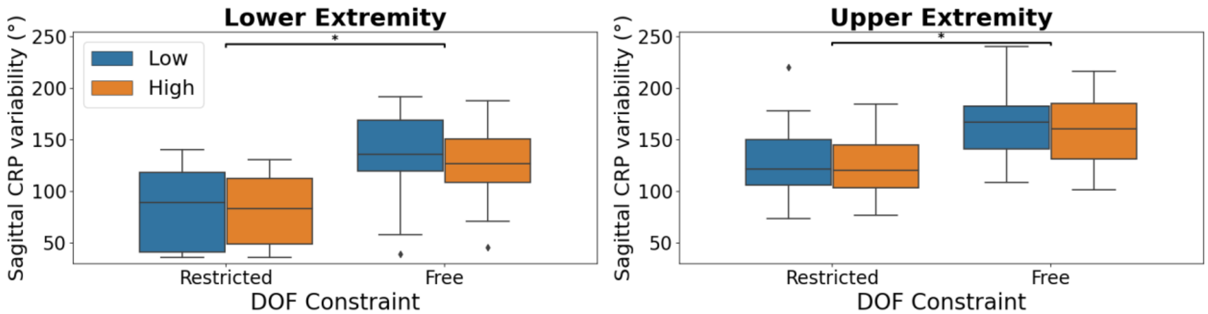

Figure 4.1: Boxplot of lower and upper extremity CRP variability showing the quartiles (box), 1.5 interquartile range of lower and upper quartile (whiskers) and values outside this range (diamonds). Each extremity shows one boxplot for each DOF constraint (restricted, free) and weight (low, high). Significant main effects are indicated using brackets with asterisks (*).

Table 4.2: Intraclass correlation of sagittal whole-body (WB) CRP variability across all lifting constraints with corresponding p-value and 95% confidence interval. Significant p-values are indicated in bold.

	ICC	p	95% CI
WB	0.84	**<.001**	0.71 - 0.92

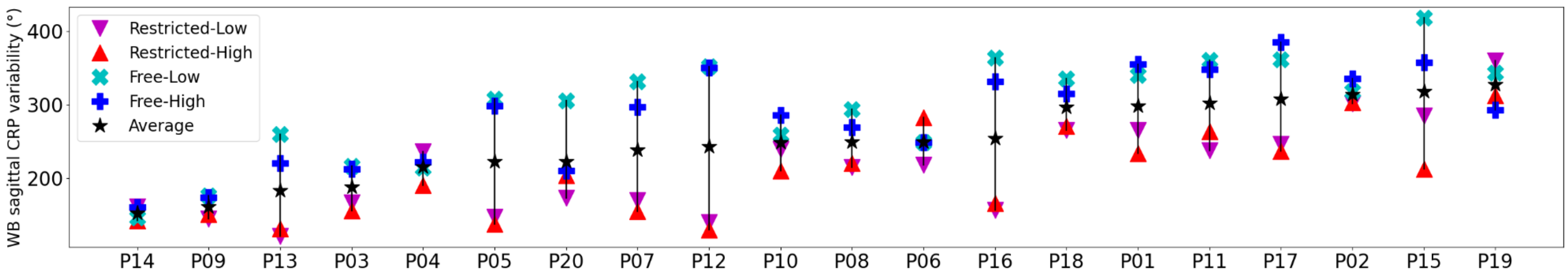

Figure 4.2: Whole-body (WB) sagittal CRP variability for each DOF constraint by weight condition with each participant ranked on average variability across condition on the abscissa.

Table 4.3: Spearman's correlation coefficient (rs) of sagittal whole-body (WB) CRP variability between weights for each DOF constraint with corresponding p-values. Significant p-values are indicated in bold.

	DOF constraint	r_s	p
WB	Restricted	0.88	**<.001**
	Free	0.88	**<.001**

For OFC measures, neither task-irrelevant nor task-relevant variability showed effects of DOF constraints, load weight, or interaction effects (see **Table 4.4** and **Figure 4.3**). However, task-irrelevant variability showed a trend for increased variability when foot movement was allowed (η_p^2 = 0.133) (see **Table 4.4** and **Figure 4.3**). Furthermore, significant ICCs were found for both task-irrelevant and task-relevant variability (see **Table 4.5** and **Figure 4.4**). Moreover, significant correlations between weights for each DOF constraint were found for task-irrelevant variability while only a significant correlation between weights for the restricted feet condition was found for task-relevant variability (see **Table 4.6**). Task-irrelevant variability showed considerably higher correlation coefficients in comparison to task-relevant variability.

Table 4.4: Results of two-way repeated measures ANOVA with DOF constraint and weight as factors for log transformed variability along the UCM (task-irrelevant variability) and orthogonal to the UCM (ORT or task-irrelevant variability).

	DOF Constraint				Weight				DOF Constraint*Weight			
	F	p	η_p^2	Direction	F	p	η_p^2	Direction	F	p	η_p^2	Direction
UCM	2.920	0.104	0.133	n/a	1.505	0.235	0.073	n/a	0.001	0.977	0.000	n/a
ORT	0.395	0.537	0.020	n/a	0.001	0.976	0.000	n/a	0.002	0.969	0.000	n/a

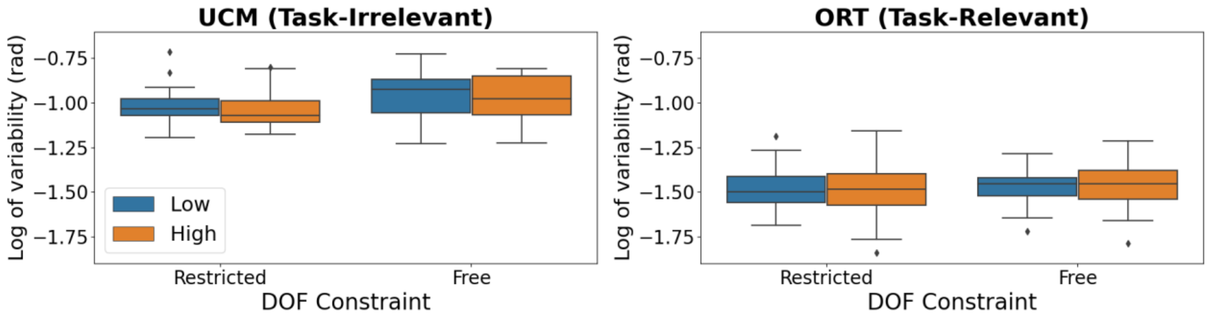

Figure 4.3: Boxplot of log-transformed variability along the UCM and orthogonal to the UCM (ORT) showing the quartiles (box), 1.5 interquartile range of lower and upper quartile (whiskers) and values outside this range (diamonds). Each variability component shows one boxplot for each DOF constraint (restricted, free) and weight (low, high).

Table 4.5: Intraclass correlation (ICC) of log-transformed variability along the UCM (task-irrelevant variability) and orthogonal to the UCM (ORT or task-irrelevant variability) across all lifting constraints with corresponding p-value and 95% confidence interval. Significant p-values are indicated in bold.

	ICC	**p**	**95% CI**
UCM	0.76	**<.001**	0.58 - 0.88
ORT	0.70	**<.001**	0.47 - 0.85

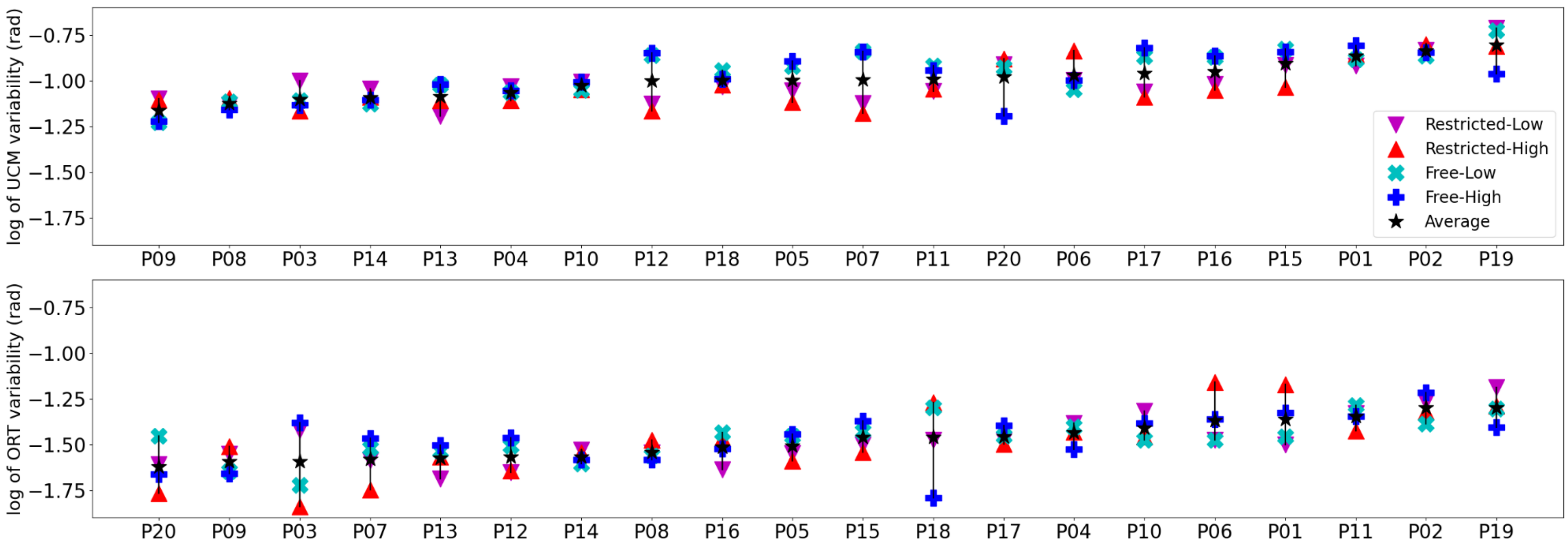

Figure 4.4: Log of variability along the UCM (top) and orthogonal to the UCM (ORT) (bottom) for each DOF constraint by weight condition with each participant ranked on average variability across conditions for each measure on the abscissa.

Table 4.6: Spearman's correlation coefficient (r_s) of log-transformed variability along the UCM (task-irrelevant variability) and orthogonal to the UCM (ORT or task-irrelevant variability) between weights for each DOF constraint with corresponding p-values. Significant p-values are indicated in bold.

	DOF constraint	r_s	p
UCM	Restricted	0.73	**<.001**
	Free	0.82	**<.001**
ORT	Restricted	0.59	**<.01**
	Free	0.20	0.19

4.5 Discussion

The objective of this study was to explore how nonlinear variability measures affect the results and interpretation of constraints on MV and of consistency in individual MV responses. Restricting foot movement only led to changes in coordination variability and not in task-relevant and task-irrelevant variability. More specifically, sagittal lower and upper extremity coordination variability increased when foot movement was allowed. Although no significant difference was found, task-irrelevant variability showed a trend similar to DST variability where foot movement tended to increase task-irrelevant variability. Thus, the first hypothesis can only be confirmed for DST measures and task-relevant variability but not for task-irrelevant variability. With respect to individual consistency, good consistency (Koo & Li, 2016) was found for all nonlinear variability measures, although whole-body coordination variability demonstrated higher consistency than task-relevant and task-irrelevant variability. Furthermore, the correlation between weights of each DOF constraint resulted in a very strong positive correlation for coordination variability and a wide range of poor to very strong positive correlation for task-relevant and task-irrelevant variability, where correlations were interpreted as per definitions provided by Chan (2003). More specifically, task-irrelevant variability showed moderate to very strong correlation while task-relevant variability showed poor to fair correlation (Chan, 2003). Combining outcomes of consistency and correlation, whole-body coordination variability demonstrated a high degree of consistency while task-irrelevant variability also showed consistency but to a lower extent. In addition, task-relevant variability showed the lowest consistency and correlation of which only the correlation between weights within the restricted condition was significant. Therefore, the second hypothesis was confirmed for all measures since a strong indication for consistency was found for DST and task-irrelevant variability while only some indication for consistency was found for task-relevant variability.

With respect to the effect of task constraint on DST variability, DST measures appeared responsive to DOF constraints. The effect of DOF constraints on DST variability reflects an increase in phase transitions between coordination patterns (Hamill et al., 1999). When the feet were not constrained and more DOF were allowed, dynamic coupling could have facilitated more variable phase relationships within lower and upper extremity joint angle couplings (Zajac et al., 2002). Higher coordination variability indicates less stable coordination patterns, which could imply flexibility to adapt to changing environments and to facilitate load distribution (Bartlett et al., 2007; Stergiou & Decker, 2011).

In contrast to DST variability, OFC variability was unaffected by task constraints which can be interpreted in their respective aspects. The absence of an effect of constraints on task-irrelevant variability can be interpreted using the elemental variables of the UCM analysis (i.e. joint angles). In our previous study, linear joint angle variability showed an overall increase with foot movement (Oomen et al., 2022). Therefore, transforming elemental variables into task-irrelevant variability could have considerably lowered the responsiveness to constraints. Possibly, relating joint angle variability to task performance based on crate trajectories and the involved mathematical operations removes responsiveness to constraints present in the original joint angle variability. Since the effect of foot movement on task-irrelevant variability followed a hypothesized trend, it is possible that future work with a larger sample size will be able to find differences due to higher statistical power.

Possibly, the hypothesized trend can be explained by underlying differences in sex, since previous work on repetitive pointing only showed differences in task-irrelevant variability during neck-shoulder fatigue when sex was included as a covariate (Hasanbarani et al., 2021). The absence of an effect of constraints on task-relevant variability could be explained as similar task performance across constraints. Across task constraints, task-relevant variability was lower than task-irrelevant variability which is in agreement with the minimum intervention principle and therefore crate trajectory can be confirmed as a control variable that indicates motor synergy (Scholz & Schöner, 1999). Since task-irrelevant variability was deemed higher than task-relevant variability, task-irrelevant variability could fulfill a functional role.

In line with the repeaters-replacers hypothesis, DST and task-irrelevant variability demonstrated good consistency in individual MV responses. Therefore, this study presents evidence for MV as a consistent individual trait independent of nonlinear MV measures. In the context of other research on the repeaters-replacer hypothesis, MV could not only be an individual trait across days and task constraints (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012) but also across nonlinear MV measures. Good consistency was also found for task-relevant variability which could reflect similar task performance across constraints or even tight control of task-relevant variability based on minimum intervention principle within OFC theory (Diedrichsen et al., 2010; Todorov & Jordan, 2002). Interestingly, while DST measures were affected by task constraints, they showed stronger consistency and correlation than OFC measures. Possibly, the use of a regression model and its related fit for each task constraint within the same individual could have reduced the consistency in its outcome measures of task-relevant and task-irrelevant variability in contrast to coordination variability. Overall, MV appears to be an individual trait independent of nonlinear MV measure and consistent responses in task performance were demonstrated.

Several observations can be made when comparing the results and interpretation of two nonlinear measures to linear measures of our companion study based on the same dataset (Oomen et al., 2022). Although overall an increase in linear variability was observed with more DOF, this was not consistent across planes and body regions as demonstrated in **Table 4.7**. Linear MV showed exactly the same ICC values in the frontal and transverse plane as DST variability (ICC = 0.84), whereas slightly lower ICC values were found in the sagittal plane for linear MV (ICC = 0.71) comparable to the lowest ICC of OFC measures. Linear measures in the frontal and transverse plane showed similar correlation to DST variability ($r_s = 0.82 – 0.85$), while in the sagittal plane a wider range in correlation values was found ($r_s = 0.67 – 0.88$) comparable to task-irrelevant variability. Therefore, DST variability appeared most consistent and responsive to changing task constraints. In addition, linear variability showed slightly lower consistency and less consistent responsiveness while OFC variability showed the lowest consistency and appeared to be unresponsive to changing task constraints. Based on consistency, DST variability provides the strongest support for the repeaters-replacers hypothesis followed by linear variability whereas OFC variability showed considerably lower support. Following motor control theory, increased linear variability would indicate worsening of task performance. Although not grounded in the original theory, linear variability in kinematics could lead to kinetic variability in support of load distribution to lower the risk of cumulative loading. According to DST, increased coordination variability could lead to higher load distribution which could reduce cumulative loading and could help explain the variability-risk hypothesis if a measurement of risk is included. Based on the criteria of constraint effects and consistency, DST variability seems the best candidate to explore variability-risk hypotheses in lifting tasks, although linear measures could also be a good candidate in case less complex analytics are more feasible.

Table 4.7: Summary of main effects of DOF constraint on linear joint variability for lower extremity (LE), low back (LB) and upper extremity (UE) in sagittal (X), frontal (Y) and transverse (Z) movement planes. FR represents the free DOF constraint while RS represents the restricted DOF constraint.

	X	Y	Z
LE	**FR>RS**	**FR>RS**	**FR>RS**
LB	n/a	**FR>RS**	**FR>RS**
UE	n/a	**RS>FR**	n/a

The findings of this study should be interpreted within the context of the following limitations. The tasks presented in this study were part of a larger study in which randomization was prevented due to EMG measurements which were only of interest in a subset of tasks, and to avoid natural between-day variance in these signals relevant tasks were collected in the same session. However, the authors provided evidence which supports that the effects of lifting conditions on MV are most likely because of the experimental conditions rather than presentation order effects due to not randomizing (for details see Oomen et al. (2022)). With respect to the UCM analysis, the use of a multiple linear regression model without validation of a forward kinematics geometric model could be considered a limitation. Research investigating both models revealed no differences and near-perfect agreement (Freitas et al., 2010; Greve et al., 2013) and when discrepancies were found between the methods it was explained by geometric approximations of performance variables rather than by use of a regression model (de Freitas & Scholz, 2010). Most importantly, not the absolute values of task-relevant and task-irrelevant variability but the relative responses of these variables on different constraints were of main interest which reduces the importance of this limitation. In addition, the overall R^2 of the regression models was 0.85, which indicates that 85% of the variance in crate trajectory was shared by the joint angles and thus reflects a good model fit. Therefore, using the geometric approach rather than the regression approach is not believed to affect the results of this study. Lastly, this study was conducted in a lab environment which could limit the external validity of the lifting task. However, the task constraints are believed to have elicited externally valid lifting movement behaviour in the condition where participants were free to move their feet and across all conditions with respect to pace.

4.6 Conclusion

In conclusion, foot movement only affected variability when assessed with DST measures in contrast to OFC measures. Allowing foot movement increased coordination variability while task-irrelevant variability did not show any differences, which implies that task-irrelevant variability considerably reduced existing spatiotemporal variability when expressing variability independent of task performance. Individual consistency in MV appeared independent of measure although stronger consistency was found using the DST measure. Both nonlinear measures support MV as an individual trait which is a crucial condition for the repeaters-replacer hypothesis. Based on the hypothesized responsiveness to constraints and individual consistency, DST variability seems better suited than OFC variability for future work on repeaters-replacers and variability-risk hypothesis when assessing lifting tasks.

Chapter 5: In-depth comparison of different variability measures at the individual level

5.1 Introduction

The goal of this chapter is to more thoroughly examine the different variability measures that were used in Chapters 3 and 4 at the individual level. The previous chapters only assessed individual consistency within each measure. However, a question remains as to what is the degree of individual consistency across different measures? Without answering this question, it is unclear in the context of the repeaters-replacers hypothesis whether individuals have similar ranking across measures and can be considered as repeaters or replacers independent of the chosen measure. If one measure strongly differs from the others it could indicate that an individual assessed as a repeater using one measure could be assessed as a replacer using another measure and thus different measures could be assessing different constructs of individual motor variability (MV) ranking. A secondary goal of this chapter is to justify the choice of measure(s) to assess MV in upcoming studies.

5.2 Data selected for comparison of different measures

The data analysed in this chapter were extracted from the lifting task of Chapters 3 and 4, and the specific lifting task that was selected was performed without restricting foot movement and using a load weight of 30% maximum capacity, where maximum capacity was based on a modified version of the Matheson's EPIC lifting capacity test (Matheson et al., 1995; Oomen et al., 2022). This task was also described as the free DOF constraint and high weight load condition in Chapters 3 and 4. The rationale for selecting this specific lifting task is to further investigate the task that is the most similar to the prolonged repetitive lifting task that is the focus of Chapter 7. MV was characterised at the whole-body level by using the linear and continuous relative phase (CRP) measures and by using the optimal feedback control measures. However, when considering optimal feedback control, only the uncontrolled manifold (UCM) or task-irrelevant measure was extracted for use in this chapter as task-relevant variability does not represent motor variability, but rather task performance. In addition, only the sagittal plane was selected for linear variability since the lifting task requires primary movement in the sagittal plane and selecting one plane for the three-dimensional linear measure further facilitates comparison of different measurements.

5.3 Individual consistency across different measures

A correlation analysis was conducted to analyze individual consistency between different measures. More specifically, non-parametric Spearman's correlation coefficients were calculated since whole-body linear variability and task-irrelevant variability violated assumptions of normality (see Chapter 3 and 4).

To put this into context of the repeaters-replacers hypothesis, the non-parametric correlation allows assessment of the consistency of individuals' MV rank between different measures and thus helps to determine if individuals are consistently repeaters or replacers across measures. Since positive relationships between measures were expected, a one-tailed test was used with a confidence level of 95%.

All combinations of different measures demonstrated very strong positive correlation (all $p < .001$) following interpretation by Chan (2003) (**Table 5.1**). The strongest correlation was found between linear and task-irrelevant variability, followed by the correlation between CRP and task-irrelevant variability and the weakest correlation was found between linear and CRP variability. Noticeably, the correlation between CRP and task-irrelevant variability and the correlation between linear and CRP variability was of comparable magnitude. To support the findings of very strong positive correlation between measures, raw data points and the best line of fit are displayed in **Figure 5.1**. Overall, the results support that task-irrelevant variability measures a similar construct of individual MV as linear measures, whereas CRP variability seems to indicate a slightly different construct of individual MV compared to the two other measures.

Table 5.1: Correlation matrix of Spearman's correlation coefficients for correlation between sagittal (X) linear whole-body joint angle variability, sagittal (X) continuous relative phase (CRP) whole-body variability and uncontrolled manifold (UCM) or task-irrelevant variability. All coefficients were significant (*p* < .001). All variability measures were extracted from the unrestricted, high load weight, lifting task as presented in Chapters 3 and 4.

	linear X	CRP X	UCM
linear X	1	x	x
CRP X	0.87	1	X
UCM	0.97	0.89	1

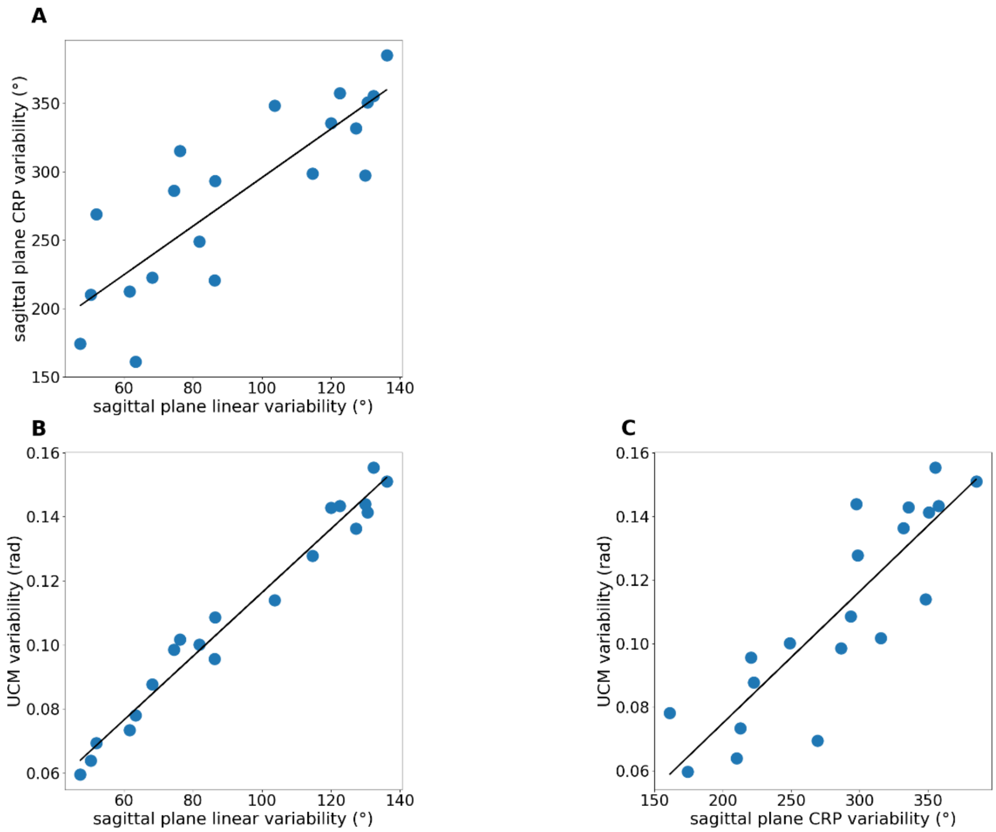

Figure 5.1: Scatterplots of A) whole-body sagittal linear variability and CRP variability, B) whole-body sagittal linear variability and uncontrolled manifold (UCM) or task-irrelevant variability, and C) whole-body sagittal whole-body continuous relative phase (CRP) variability and uncontrolled manifold (UCM) or task-irrelevant variability. One circle represents a single participant, and the line represents the best line of fit.

5.4 Consistency in ranking of individuals across different measures

In this section the ranking of individuals was further explored by converting the values within each variability measure to a ranking (see **Table 5.2** for the ranking results). First, an assessment of overall consistency in individual ranking was conducted. Second, a more pragmatic approach was taken to explore differences in ranking across measures in a pairwise fashion.

Table 5.2: Ranking of participants on sagittal plane (X) linear, sagittal plane (X) continuous relative phase (CRP) and uncontrolled manifold (UCM) or task-irrelevant variability and the change (Δ) in rank between the two measures.

	linear X	CRP X	UCM	range in Δ-rank
P01	19	18	20	2
P02	14	15	16	2
P03	4	4	4	0
P04	6	6	6	0
P05	13	12	13	1
P06	9	7	9	2
P07	17	11	18	7
P08	3	8	3	5
P09	1	2	1	1
P10	7	9	8	2
P11	12	16	12	4
P12	18	17	15	3
P13	10	5	7	5
P14	5	1	5	4
P15	15	19	17	4
P16	16	14	14	2
P17	20	20	19	1
P18	8	13	10	5
P19	11	10	11	1
P20	2	3	2	1

Consistency across individual ranks of different measures was determined by use of intraclass correlation coefficient (ICC). Specifically, a two-way mixed model for average measures (i.e. ICC(3,k) consistency model) was used. This resulted in an ICC of 0.97, 95% CI [0.94 – 0.99], $p <$ .001.

When the ranking of individuals was explored in more detail, very similar ranking on MV was found for linear and UCM measures in agreement with strongest correlation (**Table 5.2**). The change in rank between these two measures showed a range between 0 and 3 ranks. The small range in change of rank further supports that linear and UCM measures assess a similar construct of MV. In contrast, linear and CRP variability showed the weakest relationship based on correlation coefficients. In agreement with the correlation analysis, the individual ranking showed the largest differences between linear and CRP variability (**Table 5.2**). The change in rank between these two measures showed a range between 0 and 6 ranks. Furthermore, CRP and UCM variability showed a comparable weak relationship to linear and CRP variability based on similar correlation coefficients. When considering differences in ranking on individual MV a large range of a change of 0 and 7 ranks was demonstrated (**Table 5.2**). The larger range in change of rank when comparing CRP variability to the other two measures supports that CRP variability may capture a slightly different construct of MV. Across the three different measures, CRP variability seems the most deviating in terms of rank compared to the other two measures.

Across the three measures, the mode of the range in rank change is 2, which indicates that most participants changed 2 ranks across different measures and is in line with the high ICC value across all measures. At the extremes, two participants have consistent ranking across all measures (i.e. no change in rank), while one participant changed 7 ranks followed by three participants changing 5 ranks across measures. Therefore, the consistency in ranking across measures demonstrates diversity for individual participants.

5.5 Consistency in individuals categorized as repeaters and replacers across different measures

To incorporate the repeaters-replacers hypothesis in assessing consistency across measures, individuals could be categorized as repeaters or replacers. Therefore, the entire range of participants was used to determine the terciles that divide the range in MV into three cut offs (i.e. one-third each). This approach was chosen over dichotomization to guarantee enough difference between the two extreme groups that make up the repeaters (first one-third) and replacers (last one-third) which represent low and high MV groups, respectively. In addition, the middle one-third group is considered as the "not-categorized" group, not fitting into the description of either low or high MV. In addition, using terciles two-third of the original sample size is maintained when only considering repeaters and replacers.

When this approach was applied to each measure, this resulted in a group of seven individuals in the repeaters group, seven individuals in the replacers group and six individuals in the not-categorized group for each measurement. Subsequently, a crosstab was used to determine the classification accuracy of each combination of measures. As a result, the accuracy of each group was demonstrated in **Table 5.3, Table 5.4 & Table 5.5**. Across categorizations, replacers showed the highest accuracy of 0.86 – 1, followed by repeaters with an accuracy of 0.71 – 0.86, and the not-categorized group showed the lowest accuracy of 0.50 – 0.83. In line with previous results of correlation coefficients and change in ranks, sagittal linear and UCM variability showed the highest accuracy across groups of 0.83 – 1, followed by sagittal CRP and UCM variability with an accuracy of 0.67 – 0.86, while sagittal linear and CRP variability showed the lowest accuracy of 0.50 – 0.86. Only perfect accuracy was observed using sagittal linear and UCM measures when assessing replacers. Other measurement combinations and groups indicated only few individuals being classified differently when using different measures, which seemed to be the case when comparing linear and CRP variability and when assessing not-categorized individuals. Overall, assessing repeaters and replacers was relatively robust and showed better performance in comparison to the not-categorized group. Therefore, most individuals were mostly consistent deemed repeaters and replacers across measures.

Table 5.3: Accuracy of repeater categorization between different measures of sagittal plane (X) linear, sagittal plane (X) continuous relative phase (CRP) and uncontrolled manifold (UCM) or task-irrelevant variability.

	linear X	CRP X	UCM
linear X	x	x	x
CRP X	0.71	x	x
UCM	0.86	0.86	x

Table 5.4: Accuracy of replacer categorization between different measures sagittal plane (X) linear, sagittal plane (X) continuous relative phase (CRP) and uncontrolled manifold (UCM) or task-irrelevant variability.

	linear X	CRP X	UCM
linear X	x	x	x
CRP X	0.86	x	x
UCM	1	0.86	x

Table 5.5: Accuracy of the not-categorized group between different measures sagittal plane (X) linear, sagittal plane (X) continuous relative phase (CRP) and uncontrolled manifold (UCM) or task-irrelevant variability.

	linear X	CRP X	UCM
linear X	x	x	x
CRP X	0.50	x	x
UCM	0.83	0.67	x

5.6 Discussion of assessment across measures

In general, very strong (as interpreted using Chan (2003)) correlations across measures indicated a high degree of consistency in individual MV, which was also confirmed by excellent consistency (as interpreted using Koo & Li (2016)) across measures when MV was ranked across individuals. Despite diversity in individual MV ranking across measures, most participants changed 2 ranks. In addition, individuals who were deemed repeaters and replacers showed sufficiently accurate classification across different measures. Linear and task-irrelevant variability showed the highest consistency, lowest range in change of rank, and highest accuracy of repeaters-replacers categorization and thus seems to capture very similar construct. In contrast, CRP variability with the two other variability measures showed slightly lower consistency, larger range in change of rank, and lower accuracy of repeaters-replacer categorization. Thus, CRP variability seems to capture a slightly different construct than the other measures. The inconsistency between CRP and the other methods could be explained by the CRP method capturing spatiotemporal or coordination aspects of MV between adjacent unilateral joints (i.e. left-left or right-right), while the linear and UCM method capture spatial MV magnitude which is affected by the range in bilateral movement strategies (i.e. left-right).

To conclude, different variability measures assess overall the same construct of individual MV ranking. Even though DST variability was considered a slightly better candidate than linear variability in Chapter 4, this chapter demonstrates that these measures could rank some individuals differently. Thus, for lifting tasks, it is recommended that future work uses both measures to assess MV. However, it is unknown how this finding applies to tasks other than lifting and for ease of implementation and interpretation linear variability measures could be preferred over DST variability.

Chapter 6: Exploring the role of task on kinematic variability and assessing consistency in individual responses across repetitive manual tasks

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6.1 Abstract

To gain a greater understanding of motor variability (MV) as an individual trait, the effect of task type on MV and individual consistency in MV across three tasks was investigated. Twenty participants performed repetitive carrying, lifting and simulated sawing tasks. MV was assessed using the linear measure of mean point-by-point standard deviation in three-dimensional upper body joint angles. Task type affected MV, where carrying showed higher MV compared to sawing (23-29%) and lifting (12-19%). Furthermore, MV was higher in lifting compared to sawing (12-25%). Poor to moderate individual consistency (ICC=0.42–0.63) was found across tasks. Task type determined MV and only some support for MV as an individual trait across tasks was found. Based on this work, the task influences the amount of MV an individual can exploit, and possibly consistency in MV magnitude is specific to the degrees of freedom afforded by the task.

6.2 Introduction

Motor variability (MV) may influence the risk of work-related musculoskeletal disorders (WRMSDs) in repetitive tasks. The link between MV and WRMSD risk is described by the variability-risk hypothesis. The variability-risk hypothesis assumes a negative relationship between variability and risk (i.e., higher variability comes with lower risk) (Côté, 2012; Madeleine, 2010; Srinivasan & Mathiassen, 2012). MV arises because of the abundance of degrees of freedom (DOF) in the human movement system (Latash, 2000; Latash et al., 2002). Exploiting MV offers an opportunity to repeat the same task without repeating the same movement patterns (Bernstein, 1967; Latash, 2000, 2012). An increase in MV could lead to larger repetition-to-repetition distribution of loads and thus could reduce cumulative loading and the risk of WRMSDs (Bartlett et al., 2007; Hamill et al., 1999; Madeleine, 2010; Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006).

When assessing MV the task could be an important variable to consider since it determines how many body regions and DOF are required to complete the task. Previous work-related MV research has investigated different tasks such as cutting, deboning, reaching/pointing, and lifting (Granata et al., 1999; Lomond & Côté, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017; van Dieën et al., 2001; Yang et al., 2018). Of these tasks, fine motor tasks only require movement of the upper extremity, while gross motor tasks require whole-body movement. Therefore, more DOFs are involved in performing gross motor tasks, which could provide more options to perform the same task with varying movement patterns and thus offer greater opportunity to explore MV. In support of this reasoning, we have demonstrated that task constraints that allow more DOF do indeed evoke higher MV responses (Oomen et al., 2022). However, fine and gross motor tasks have not been compared within the same study population to date, which is required to further test this reasoning.

An additional hypothesis on MV has been proposed that can be connected to the variability-risk hypothesis. The repeaters-replacers hypothesis suggests that MV is an individual trait based on observations of consistent individual MV responses across different days and task constraints of fine motor tasks and across task constraints of a gross motor task (Jackson et al., 2020; Oomen et al., 2022; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). Repeaters represent individuals with low MV and replacers represent individuals with high MV (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012). When the repeater-replacers hypothesis is combined with the variability-risk hypothesis it follows that repeaters are at higher risk of WRMSDs compared to replacers (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012), and that variability-related WRMSD risk could be an individual trait. Therefore, the repeaters-replacers hypothesis has the potential to contribute to our understanding of variability-risk by assigning risk to the individual, in addition to the task. However, individual consistency has only been investigated within fine and gross motor tasks separately, which raises the question if consistency can be generalized to a combination of fine and gross motor tasks within the same study population, as similar questions were raised in previous occupational work (Jackson et al., 2020; Sandlund et al., 2017; Srinivasan & Mathiassen, 2012).

To further advance our understanding of MV and its potential link to WRMSDs the purpose of this study was to identify if the repeater-replacer hypothesis holds across fine and gross motor tasks. Specifically, this work aims to answer the following research questions: 1) what is the effect of tasks with different amounts of DOF on MV among healthy adults? and 2) do healthy adults show consistent MV responses across tasks with different amount of DOFs? It was hypothesized that: 1) tasks with greater DOFs would result in higher MV, where the order from highest to lowest MV would be carrying, lifting and simulated sawing, respectively, 2) despite the expected effect of task, individuals would show consistent MV responses in line with the repeaters-replacers hypothesis.

6.3 Methods

6.3.1 Research design

The research questions were answered using a cross-sectional experimental study with a one factor (task) repeated measures design. The independent variable was task with three levels of carrying, lifting, and simulated sawing. The dependent variable was MV and consisted of three-dimensional joint angle variability determined using the linear measure of mean standard deviation (meanSD) (Newell & Corcos, 1993; Stergiou & Decker, 2011). In the context of lifting, similar results of joint angle meanSD and more analytically complex dynamic systems theory measures of joint coupling continuous relative phase variability were found (Oomen et al., 2022; Chapter 4; Chapter 5). Therefore, in assessing different tasks, joint angle meanSD was selected to facilitate implementation and interpretation of MV.

6.3.2 Participants

This study was part of the same data collection as Oomen et al. (2022). Briefly, twenty healthy participants (ten females and ten males; 24.3 (± 3.8) years; 169.2 (± 10.2) cm; 67.9 (± 13.0) kg) were recruited to volunteer for two data collection sessions 2-7 days apart which was deemed sufficient to recover from any delayed-onset muscle soreness from the first session and to control for history as an internal bias to the individual's MV. This study was approved by the University of Waterloo's Office of Research Ethics (ORE#40762), and all participants provided informed consent prior to participation.

6.3.3 Instrumentation

Briefly, motion capture data of the whole body and of three milk crates, used for carrying and lifting, were recorded. The experimental setup for carrying and lifting consisted of the three-shelf setup with the bottom shelf just above floor height and the top shelf at stature-based shoulder height as previously used in Oomen et al. (2022) (see **Figure 6.1**). The simulated sawing setup consisted of a vertically oriented handle that could slide on a horizontal track, that was mounted on a stationary vertical frame (see **Figure 6.1**). The horizontal track only allowed anterior-posterior push and pull handle movement. The vertical handle was set at a height such that the participant's elbow angle was 90 degrees while grasping the handle in start position (i.e. end of the track away from frame) when standing upright (for start position see **Figure 6.1**). To prevent the handle from hitting the ends of the track two end ranges were visually marked on the track (which marked a horizontal distance of approximately 20 cm). Greater detail about the instrumentation can be found in Oomen et al. (2022).

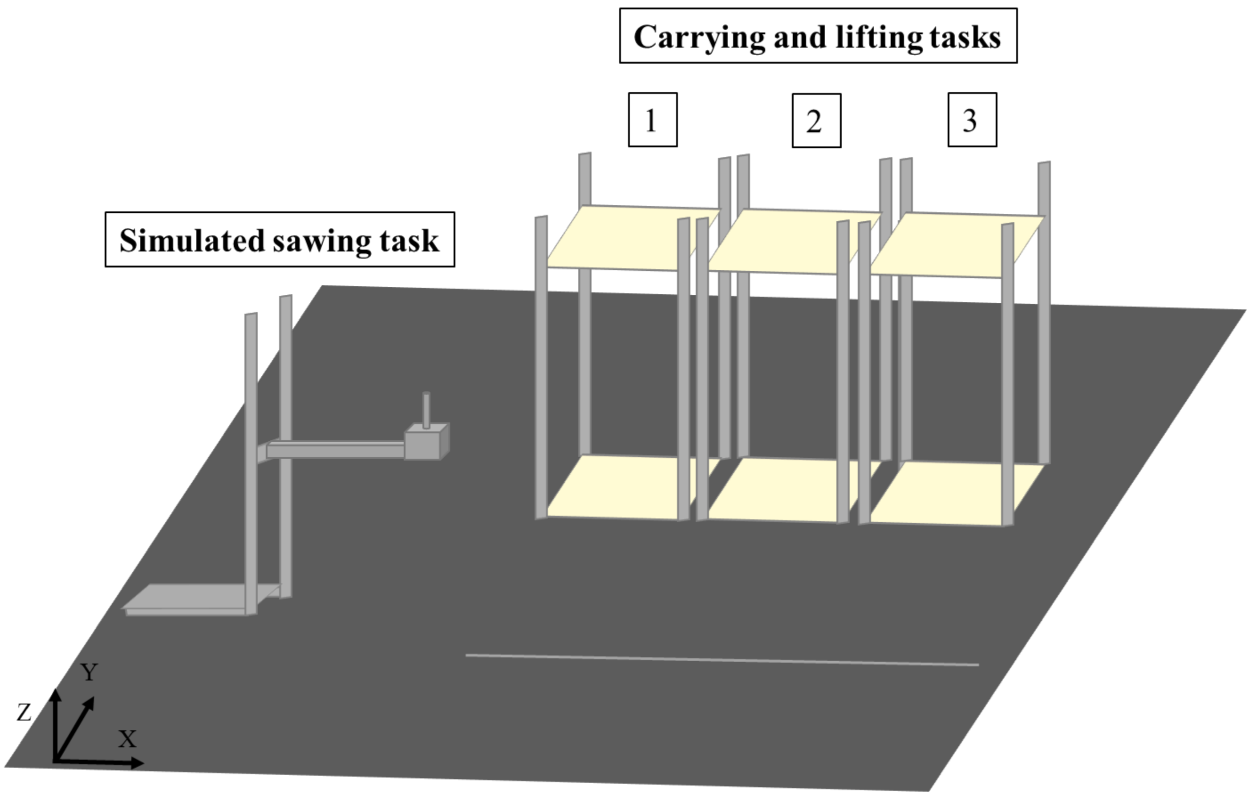

Figure 6.1: Experimental setup consisting of the simulated sawing setup on the left and carrying and lifting tasks setup on the right. The carrying and lifting tasks consisted of the three-shelf setup with the bottom shelf just above floor height and top shelf at shoulder height and a line parallel to the shelves at 2.5 m distance from the shelves.

6.3.4 Procedures

The carrying and simulated sawing tasks were performed in the first session while the lifting task was performed in the second session. The carrying and lifting tasks were performed for 30 minutes each and the sawing task was performed for 8 minutes to obtain approximately 100 cycles to avoid inducing excessive fatigue, and to complete each data collection session including other tasks within a 3-hour maximum window. The lifting task corresponds to one of the four lifting tasks previously presented in Oomen et al. (2022). The lifting task selected for this study was performed without any restrictions to foot placement and movement using the lowest weight and thus corresponds to the free low load lifting task included in previous studies.

To reduce the likelihood of participants displaying movement variability behaviour in a desirable manner based on the study purpose, participants were deceived about the true purpose of the study (Nichols & Maner, 2008). Participants were informed that the study aimed to estimate the optimal and safe number of repetitions for carrying, lifting and sawing for an 8-hour workday, rather than revealing the true purpose which was to study their movement variability. While participants were made aware of the maximum time limits of each task, they were asked to perform as many repetitions as if they were working an 8-hour workday. Participants were instructed to move the crate using two hands for the carrying and lifting tasks, but no other instructions were given. Lastly, audio recordings and corresponding written transcript were provided to ensure that all participants were exposed to the same instructions (Beach et al., 2018).

6.3.5 Carrying task

Participants started 2.5 meters away and parallel to the shelves and walked towards the shelf to carry the crate from the bottom shelf, just above floor height, to the 2.5-meter line from and vice versa to minimize interruptions during the task (see **Figure 6.1**). This resulted in two different sequences (i.e., from shelf to line and from line to shelf). The carrying task was performed with a weight that corresponded with 10% of their maximum lifting capacity based on a modified version of the Matheson's EPIC Lifting Capacity test (Matheson et al., 1995), for more details see Oomen et al. (2022). The carrying task was broken down into a maximum of seven sets of five trials, with one trial corresponding to three repetitions of the task (one repetition at each shelf position). This resulted in a maximum of 105 total repetitions if the participant completed all trials. As part of the deception, after every set participants were asked if they were able to complete another set within an 8-hour workday without feeling tired or experiencing strain at the end of the workday. Therefore, some participants ended the lifting task before the maximum number of 105 repetitions was reached.

6.3.6 Simulated sawing task

After the carrying and before the sawing task a 5-minute rest break was taken to limit fatigue development. Following rest participants performed the simulated sawing task (see **Figure 6.1**). The participants were asked to push and pull the handle at a self-selected pace with their preferred hand while standing. The participants were instructed to only move the handle between the two visually marked targets in one fluid motion as accurately possible (i.e., within the two targets). The sawing task was broken down into a maximum of six trials of 20 repetitions, with one repetition corresponding to one complete cycle of both a push and pull movement. This resulted in a maximum of 120 total repetitions if the participant completed all trials. Similar to the carrying task, participants were asked if they could continue under the given conditions after every set.

6.3.7 Lifting task

The lifting task was performed in the second session in contrast to the carrying and sawing tasks. Participants approached each shelf by walking from the 2.5-meter line to allow voluntary foot placement before lifting the crate from bottom to top shelf (see **Figure 6.1**). The load weight and maximum number of repetitions was identical to the carrying task of session 1. Participants always lifted the crates in the same order of shelves, and research staff lowered the crates before the next trial was started. Similar to the other tasks, participants were asked if they could continue under the given conditions after every set.

After the completion of this session participants were debriefed about the deception and the true purpose of the study was revealed by informing that their movement variability was studied rather than the number of repetitions. Participants signed another consent form after deception was lifted.

6.4 Data processing

Consistent with Oomen et al. (2022), whole-body and crate marker kinematics were processed using best practices for gap filling (Howarth & Callaghan, 2010), padding and filtering (Howarth & Callaghan, 2008; Smith, 1989; Winter, 2009) and ISB recommendations were followed to create local coordinate systems which were used to derive three-dimensional joint angles (Wu et al., 2002, 2005). Subsequently, joint angles were segmented to task cycles based on the anterior-posterior crate marker velocity for lifting. For carrying, task cycles were defined from when the crate was rotated 160 degrees in transverse plane relative to the origin, reflecting when the participant turned around facing the destination after lifting of the crate from the origin, to 90% of maximal cycle vertical crate position, reflecting when the participant started lowering the crate before disposing it at the destination. For simulated sawing, segmentation to task cycles was based on anterior-posterior hand marker velocity, with one cycle consisting of one push and pull motion. This led to an overall average of 92 (± 17) carrying cycles, 104 (± 9) sawing cycles, and 95 (± 18) lifting cycles per participant.

Segmented cycles were time-normalized to 101 data points corresponding to 0 to 100% of the task cycle (Graham et al., 2013). In agreement with Oomen et al. (2022), the number of cycles was further reduced by excluding outliers in sagittal joint angles that were outside of the ensemble average ± 3.75 standard deviations range. This resulted in an overall average of 86 (± 17) carrying cycles, 97 (± 10) sawing cycles, and 83 (± 16) lifting cycles per participant for final inclusion in data analysis. The magnitude of cycle-to-cycle variability was defined as the mean standard deviation (meanSD) by determining the standard deviation between cycles at each normalized time point (i.e. point-by-point standard deviation) and then calculating the mean of the point-by-point standard deviation values. Subsequently, meanSD was summed across left and right wrist, elbow and shoulder joints as a measure of upper extremity variability. Since the lower body was not involved in the sawing task in contrast to the carrying and lifting tasks, upper extremity variability was used to represent MV in the execution of all three tasks.

6.5 Statistical analysis

All statistical analyses were conducted in R 4.0. When the different tasks were assessed for normality, the assumption of normality could not be confirmed visible from histograms, Q-Q plots and box plots, and demonstrated by significant positive skewness and kurtosis ($Skew_{2SE} > 1$, $Kurt_{2SE} > 1$, $p < .05$) and significant Shapiro-Wilks test ($p < .05$)). To confirm the assumption of normality a log transform was applied for all statistical analyses.

The effect of task (carrying, lifting, sawing) on upper extremity variability was examined with a one-way repeated measures ANOVA. Since this resulted in 3 different comparisons (i.e., 3 movement planes) a Bonferroni correction was applied to control for familywise error rate and therefore $\alpha = .016$ was used. The assumption of sphericity was checked according to Girden (1992), if the Greenhouse-Geisser epsilon ≥ 0.75, the Huynh-Feldt correction was used, otherwise the

Greenhouse-Geisser correction was used. If significant main effects occurred, pairwise dependent t-tests with Bonferroni correction were executed to determine where differences occurred between the three tasks. Also, the direction of differences were determined by group means.

The consistency of upper extremity variability across all three tasks (carrying, lifting, and sawing) was assessed by intraclass correlation (ICC) using the two-way mixed model for average measures (i.e. ICC(3,k) consistency model).

6.6 Results

One participant did not have enough visible markers on certain segments during the sawing task and thus not all gaps could be filled. Therefore, only 19 participants were used in the statistical analysis.

Specifically for the carrying task, the data of the two different sequences was collapsed after we established that sequence did not affect upper extremity variability (see **Appendix A**). Task had a significant main effect on upper extremity variability in all movement planes (**Table 6.1**). Pairwise dependent t-tests revealed significant differences between all tasks in each movement plane, except between carrying and lifting in the frontal plane and between lifting and sawing in the transverse plane. Variability in carrying was 23-29% higher than variability in sawing across all movement planes (all comparisons $p<.001$), and 12-19% higher than variability in lifting in only the sagittal and transverse planes ($p<.001$) (**Figure 6.2**). In addition, variability in lifting was 12-25% higher than variability in sawing for only the sagittal and frontal movement planes ($p<.001$) (**Figure 6.2**).

Table 6.1: Result of one-way repeated measures ANOVA with task as factor for log transformed upper extremity (UE) variability in the sagittal (X), frontal (Y), and transverse (Z) movement planes. The first column shows the corrected degrees of freedom (df) due to sphericity corrections. Significant main effects are indicated by p-values in bold.

	df	**F**	**p**	**η_p^2**
UE_X	(1.63,29.41)	60.697	**<.001**	0.77
UE_Y	(1.39,25.06)	66.432	**<.001**	0.79
UE_Z	(2.10,37.75)	41.244	**<.001**	0.70

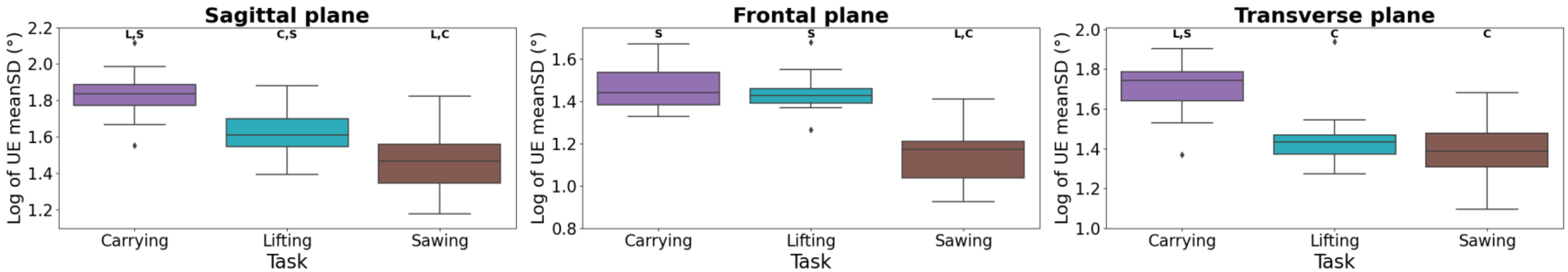

Figure 6.2: Boxplots of log transformed upper extremity (UE) meanSD across tasks for each movement plane. Each individual graph shows the quartiles (box), 1.5 interquartile range of lower and upper quartile (whiskers) and values outside this range (diamonds). Single boxplots show one boxplot for each task. Significant differences between tasks were based on pairwise dependent t-tests and are indicated using the first letter of the task (i.e. L: Lifting; C: Carrying; S: Sawing).

Significant ICCs were only found in sagittal and transverse planes in contrast to the frontal plane (**Table 6.2** and **Figure 6.3**). In addition, similar ICC values and confidence intervals were observed when comparing between sagittal and transverse planes (**Table 6.2**).

Table 6.2: Intraclass correlation (ICC) of log transformed upper extremity (UE) variability in sagittal (X), frontal (Y), and transverse (Z) planes across all tasks with corresponding p-value and 95% confidence interval (CI). Significant p-values are indicated in bold.

	ICC	p	95% CI
UE_X	0.63	**<.01**	0.20 - 0.84
UE_Y	0.42	0.08	-0.25 - 0.76
UE_Z	0.59	**<.05**	0.13 - 0.83

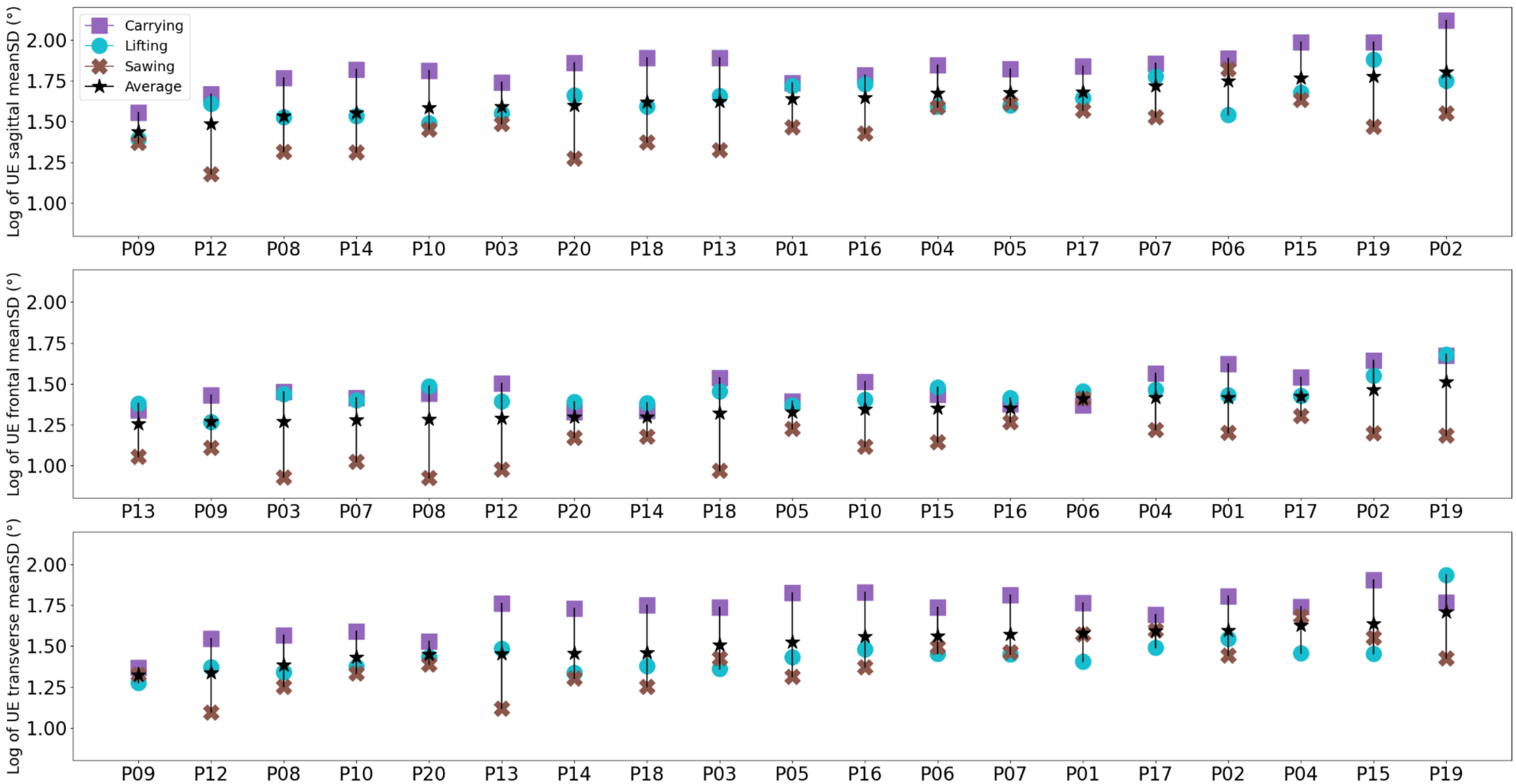

Figure 6.3: Log of upper extremity (UE) variability for each task with each participant ranked on average variability across tasks on the abscissa.

6.7 Discussion

The goal of this study was to assess the influence of task type on MV, and to determine the consistency in individual MV responses across these tasks to test the generalizability of the repeater-replacer hypothesis. Altering task type affected upper extremity kinematic variability in all movement planes, with carrying showing the highest variability compared to simulated sawing across all movement planes. In addition, carrying only showed higher variability compared to lifting in sagittal and transverse plane. Furthermore, differences between lifting and sawing were only detected in the sagittal and frontal movement planes where lifting showed higher variability in comparison to sawing. Overall, the results support the first hypothesis that task, and specifically the DOF afforded by a task, affects MV although not uniformly between pairs of tasks in all planes. Consistency in individual MV responses across tasks showed poor to moderate consistency based on definitions provided by Koo & Li (2016). More specifically, significant moderate consistency was demonstrated in the sagittal and transverse plane, while poor consistency in the frontal plane did not reach significance. Therefore, only moderate support was found for the second hypothesis and for MV as an individual trait independent of task.

Individual consistency across tasks differing in DOF could only be supported to some extent. In comparison to previous work on consistency in MV, our results showed relatively low individual consistency. Despite different MV measures and a different ICC model, ICCs between 0.48 and 0.78 were reported for a repetitive pipetting task performed on three different days (Sandlund et al., 2017). In addition, our earlier work on the same participant sample as present study using comparable MV measures and the same ICC model, reported ICCs between 0.71 and 0.84 for repetitive lifting where the constraints were manipulated (Oomen et al., 2022). Therefore, ICCs across different tasks were noticeably lower by approximately 11-32% compared to ICCs across different days and task constraints. Although sagittal and transverse plane ICCs of this study could be classified as moderate, with values of 0.59-0.63, these values are at the lower end of this definition (Koo & Li, 2016). Thus, this study suggests that the repeaters-replacers hypothesis is task specific rather than generalizable across different tasks. Possibly, an individual deemed a repeater in for example lifting, might not also be a repeater in the sawing task while within different lifting tasks an individual is consistently a repeater. Since investigation of individual consistency in MV has thus far been focused on consistency across days or different task constraints (Jackson et al., 2020; Oomen et al., 2022; Sandlund et al., 2017), future endeavors to assess consistency across different tasks are needed to validate our findings.

The relatively low individual consistency across tasks could have been driven by the large difference in task DOF of sawing compared to lifting and carrying. Simulated sawing only required movement of the upper body to complete the task, while lifting and carrying required whole-body movement. In addition, simulated sawing imposed a constrained movement trajectory for task execution while lifting and carrying allowed considerably larger freedom in movement trajectory for task execution. To test whether MV is specific to the DOF level of the task rather than completely task specific, ICCs were determined of only carrying and lifting which are assumed to have a similar level of DOF for previously mentioned reasons. The results showed significant ICCs classified as moderate to good consistency (**Table 6.3**) (Koo & Li, 2016). Sagittal and frontal plane ICCs increased (21-83%), while the transverse plane ICC was reduced (2%) compared to the consistency across all tasks. Therefore, MV as individual trait could be specific to tasks with comparable levels of DOFs. Thus, it seems more likely that the repeater-replacers hypothesis holds for tasks with similar levels of DOF than for tasks with considerably different levels of DOF. Future work is recommended to determine individual consistency of MV of upper extremity versus whole-body movement tasks with more versus less trajectory restriction to distinguish how these two task characteristics affect possible DOF specificity of repeater-replacers hypothesis.

Table 6.3: Intraclass correlation (ICC) of log transformed upper extremity (UE) variability of only the carrying and lifting tasks in sagittal (X), frontal (Y), and transverse (Z) planes across all tasks with corresponding p-value and 95% confidence interval (CI). Significant p-values are indicated in bold.

	ICC	p	95% CI
UE_X	0.76	**<.01**	0.37 - 0.91
UE_Y	0.76	**<.01**	0.39 - 0.91
UE_Z	0.58	**<.05**	-0.09 - 0.84

Another alternative explanation for task-specificity in consistency of individual MV could lie in differences between individuals in their task-specific experience. Experience has been found to increase kinematic MV (Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017), and could be considered a confounder of individual MV as a trait variable (Sandlund et al., 2017). As part of the experiment, participants were asked to report their work experience. With respect to sawing, all participants lacked experience except one. However, half of the participants reported experience with lifting and just below half of the participants reported experience with carrying. Experience in only lifting or carrying could be viewed as similar experience since these tasks are rarely executed in isolation when performing manual material handling (MMH) of objects in the workplace. Therefore, participants with MMH experience (i.e. either lifting or carrying) but without sawing experience (i.e. all but one participant) could have demonstrated relatively consistent large MV for MMH tasks. However, they could have showed relatively low MV during sawing due to lack of experience, which could have confounded individual MV consistency by experience. This reasoning would be supported by individuals with MMH experience showing relatively large difference in MV between sawing versus MMH tasks. Although most participants show the highest values for carrying, followed by lifting and sawing, the pattern of a lower sawing variability compared to MMH tasks could not be supported (see **Figure 6.3**), for both participants with and without MMH experience. Possibly, since our study population was predominantly made up of students, their MMH experience is likely to be for shorter time periods than of professionals and thus could have prevented the expected patterns. Future research is recommended to address experience when investigating different tasks to establish MV as an individual trait.

In agreement with our earlier work, MV increased with tasks that have more available DOF (Oomen et al., 2022). The carrying and lifting tasks offered the largest amount of DOF because many trajectories were possible to move the crate between the origin and destination. However, carrying was expected to offer a higher amount of DOF since the task allowed participants to select the height at which the crate was carried whereas in lifting less freedom of crate trajectory was anticipated due to closer proximity of origin and destination. In contrast, simulated sawing only allowed one movement trajectory of the handle between the origin and destination and only upper extremity movement rather than whole-body movement was necessary to complete the task. Therefore, tasks with different DOF determined the amount of MV, in addition to task constraints that imposed DOF restrictions as we showed in lifting (Oomen et al., 2022). Since low MV has been associated with a higher risk on WRMSDs in repetitive tasks (Côté, 2012; Madeleine, 2010; Srinivasan & Mathiassen, 2012), in agreement with Oomen et al. (2022) DOFs of the task could be important to consider at the workplace although direct evidence is needed by including a measure of WRMSD risk. For example, rotation schedules may be recommended to consider task DOF to ensure that workers are also executing tasks where they can explore variability.

The findings of this study should be interpreted within the context of the following limitations. The tasks presented in this study were part of a larger study and only a subset of tasks required EMG measurements which prevented randomization of tasks to avoid natural between-day variance in EMG signals. Importantly, explicit effects of presentation order on MV were prevented because participants were not made aware that their MV was studied due to the deception. In addition, carrying and sawing were always the first tasks in the first session just as lifting was always the first task in the second session which minimizes potential effect of fatigue development related to presentation order effects. Thus, the authors believe the effects of task conditions on MV can most likely be prescribed to the experimental conditions rather than to presentation order effects. Operationalizing MV by only upper extremity variability rather than whole-body variability could be interpreted as a limitation. The different tasks in this study imposed the challenge of MV being influenced by the amount of movement in terms of body regions required to complete the task. Although we attempted to normalize the point-by-point standard deviation of each joint to the range of motion, this actually removed differences between point-by-point standard deviation of joints since the standard deviation represents a statistical property (i.e. % of surface area following the normal distribution) of the entire range. Therefore, using upper extremity variability was considered the best solution to remove differences due to different amount of body region movement with these tasks.

6.8 Conclusion

Evidence from this study supports the repeaters-replacers hypothesis, but with the following caveats. Across all tasks only moderate support was found, whereas for only carrying and lifting stronger support was found. Therefore, the repeaters-replacers hypothesis could be specific to gross motor tasks offering similar DOF and less generalizable to simulated sawing as a fine motor task offering less DOF. Furthermore, tasks with more DOF resulted in higher MV. There is an opportunity to further explore how different determinants of task DOF such as gross versus fine motor tasks and restricted versus unrestricted movement trajectory contribute to changes in MV. If the variability-risk hypothesis holds, risk of WRMSDs could be managed by taking an individual approach by limiting tasks in which a worker shows low MV and incorporate tasks that evoke high MV for the worker wherever feasible.

6.9 Appendix A: Comparison of two different sequences of carrying task

The effect of two different sequences (i.e. from shelf to line and from line to shelf) on three-dimensional upper extremity variability was statistically tested. After confirmation of the assumption of normality through statistics of skewness, kurtosis and Shapiro-Wilks test and by visual inspection of histograms, Q-Q plots and box plots a dependent t-test was performed. The two different sequences of the carrying task did not reveal any differences in upper extremity variability across movement planes (sagittal: $t(19)=0.27$, $p=0.79$; frontal: $t(19)=1.10$, $p=0.29$; transverse: $t(19)=0.58$, $p=0.57$). Thus, subsequent analysis on the collapsed data set of the carrying task was justified.

Chapter 7: Exploring the relationship between kinematic variability and fatigue development during repetitive lifting

This chapter has been submitted for publication as following:

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7.1 Abstract

To investigate the variability-fatigue and repeaters-replacers hypotheses, motor variability (MV) and indicators of fatigue were assessed during repetitive lifting. Eighteen participants performed sequential repetitive bouts of lifting divided into a short bout, and three phases of a prolonged bout until volitional fatigue (or until a 1-hour time limit). Whole-body kinematics were collected to calculate variability in three-dimensional joint angles and in continuous relative phase of sagittal joint angle couplings, which were summed for the upper and lower body, and whole-body. Excellent individual consistency (ICC=0.95–0.97) was demonstrated across lifting bouts as fatigue developed. Therefore, strong evidence was obtained for MV as an individual trait in support of the repeaters-replacers hypothesis. Associations were found for endurance and initial fatigue with lower body variability, while no associations were found for rate of fatigue. Thus, some support was found for the variability-fatigue hypothesis which suggests that repeaters are less fatigue-resistant than replacers.

7.2 Introduction

Work-related musculoskeletal disorders (WRMSDs), defined as pathological impairment of musculoskeletal tissues, are a significant worldwide problem in terms of prevalence, incidence, treatment costs, costs associated with loss of productivity, and for the employee's quality of life (Baldwin, 2004; Buckle & Devereux, 2002; Canadian Institute for Health Information, 2013; Coyte et al., 1998; Feeney et al., 1998; Institute of Musculoskeletal Health, 2014; Leijon et al., 1998; OHSCO, 2007; Thiehoff, 2002). Two commonly described aspects of work that contribute to the development of WRMSDs are force and repetition (da Costa & Vieira, 2010). Although traditional work demands in developed countries are characterized by high force and moderate levels of repetition such as assembly line manufacturing, the introduction of assistive devices such as exoskeletons and e-commerce has shifted these demands to low force but possibly higher repetition (e.g. order picking at distribution centres) (Kermavnar et al., 2021; Marras et al., 2009). Combined low force, high repetition loading can lead to cumulative tissue damage through fatigue failure, which is one of the proposed injury mechanisms underlying WRMSDs (Gallagher & Heberger, 2013; Gallagher & Schall, 2017). As a result of this altered work landscape more research is required to understand and mitigate the effects of repetition on WRMSD risk.

Repetitive work as a risk factor for cumulative loading could be modulated by motor variability (MV), defined as repetition-to-repetition variation in human movement when performing the same task (Bernstein, 1967). MV present in execution of repetitive tasks arises from an abundant number of degrees of freedom and thus reflects how an individual exploits MV as part of their motor control strategy (Bernstein, 1967; Latash, 2000; Latash et al., 2002; Newell & Corcos, 1993). In repetitive tasks, occupational health researchers have associated elevated WRMSD risk with low MV and reduced WRMSD risk with high MV by measures of WRMSD risk such as fatigue, pain and injury in the variability-risk hypothesis (Côté, 2012; Granata et al., 1999; Madeleine, 2010; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Mathiassen et al., 2003; Sedighi & Nussbaum, 2017; Srinivasan & Mathiassen, 2012; Yang et al., 2018). This hypothesis implies that repetition-to-repetition distribution of muscle activation and mechanical loading could be increased with higher MV; while concurrently reducing cumulative loading and related risk of cumulative damage (Bartlett et al., 2007; Hamill et al., 1999; Madeleine, 2010; Srinivasan & Mathiassen, 2012). Furthermore, WRMSD risk could be of concern for individuals consistently showing low MV independent of contextual factors such as task constraints and days (Jackson et al., 2020; Oomen et al., 2022; Sandlund et al., 2017). These individuals would be classified as repeaters in the repeaters-replacers hypothesis, while replacers would show consistently high MV. However, the repeaters-replacers hypothesis can only be supported under the condition of consistency in individual MV and it is unknown whether consistency remains present among variables of WRMSD risk such as fatigue.

In a healthy population, the variability-risk hypothesis can be investigated by using fatigue as a surrogate measure for risk of WRMSD. Fatigue, defined as an activity-related reduction in muscle force generating capacity (Bigland-Ritchie & Woods, 1984), can be viewed as a precursor to WRMSD (Rempel et al., 1992; Sjøgaard & Søgaard, 1998). Fatigue development revealed an increase in both the magnitude and spatial distribution of variability in muscle activation (Farina et al., 2008; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993). Also, higher variability was associated with longer endurance and less development of fatigue (Farina et al., 2008; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993). Therefore, the variability-fatigue hypothesis indicates a negative relationship between variability and fatigue development which implies that individuals with low MV ('repeaters') should fatigue quicker compared to individuals with high MV ('replacers').

Contemporary research on the relationship between variability and fatigue has focused on comparing kinematic MV between different stages of fatigue development. In line with previous work on variability in muscle activation, an increase in kinematic MV with fatigue development has been reported (Sedighi & Nussbaum, 2017; Yang et al., 2018). More specifically, joint angle variability and continuous relative phase variability of joint couplings increased after a fatiguing repetitive pointing task (Yang et al., 2018). Also, center of mass path length variability and goal-irrelevant variability of center of mass path and velocity increased with fatigue development during a repetitive lifting and lowering task (Sedighi & Nussbaum, 2017). In the context of variability-fatigue hypothesis, an increase in MV with fatigue development could indicate a response to impede further fatigue development (Farina et al., 2008; van Dieën, Oude Vrielink, & Toussaint, 1993). Although some research has been carried out on kinematic variability and fatigue, it remains unclear how variability affects indicators of fatigue which would provide more direct evidence for the variability-fatigue hypothesis. In addition, the repeaters-replacers hypothesis has not yet been explored in the context of variability-fatigue and thus presents an opportunity to investigate individual variability during the development of fatigue.

To advance the variability-fatigue and repeaters-replacers hypotheses, the purpose of this study was to assess MV and individual consistency of MV across repetitive lifting bouts during development of fatigue, and to explore relationships between MV and indicators of fatigue during prolonged lifting. Specifically, this work aimed to answer the following research questions: 1) Do lifting bouts with different levels of fatigue development affect MV?, 2) Do individuals show consistent MV across lifting bouts with different levels of fatigue development?, and 3) Do relationships exists between MV at baseline and indicators of fatigue development? It was hypothesized that 1) lifting bouts with greater development of fatigue resulted in higher MV (i.e., lifters exploit MV to continue task execution as fatigue develops), 2) in line with the repeaters-replacers hypothesis individuals will show consistent MV across bouts of different levels of fatigue development, and 3) negative relationships exists between baseline MV and indicators of fatigue response, such that higher MV demonstrated slower development of fatigue (i.e., repeaters will demonstrate an earlier increase in fatigue responses than replacers).

7.3 Material and Methods

7.3.1 Research design

This cross-sectional experimental study used a one-factor within-subject design and a correlational analysis to answer the research questions. The independent variable consisted of lifting bout with four levels (one short bout and a prolonged lifting protocol that was split into an early, middle and late phase). This independent variable was assessed on two kinematic MV measures, 1) three-dimensional joint angle variability determined using the linear measure of mean standard deviation (meanSD), and 2) nonlinear sagittal plane continuous relative phase (CRP) variability based on joint angle couplings. These two MV measures were selected based on demonstrating slightly different construct when assessed on MV ranking within the specific lifting task in Chapter 5. Lastly, for correlational analysis both MV measures of only the short bout were selected as the independent variables and RPE as the dependent variables serving as an indicator of fatigue.

7.3.2 Participants

In brief, twenty healthy participants (ten females and ten males; 24.3 (± 3.8) years; 169.2 (± 10.2) cm; 67.9 (± 13.0) kg) were recruited from the student population, representing the same study population as in Oomen et al. (2022). This study was approved by the University of Waterloo's Office of Research Ethics (ORE#40762), and all participants provided informed consent prior to participation. However, one participant did not perform the prolonged task thus only nineteen participants (ten females and nine males) were included in the analyses.

7.3.3 Instrumentation

Briefly, motion capture data of the whole body and of three milk crates used as lifting objects were recorded. Also, rate of perceived exertion (RPE) was assessed using Borg's 6-20 scale (Borg, 1982). In agreement with our previous work, participants lifted crates using the three-shelf setup from the bottom shelf just above floor height to the top shelf at stature-based shoulder height (Oomen et al., 2022) (see **Figure 7.1**). More detail about the instrumentation can be found in Oomen et al. (2022).

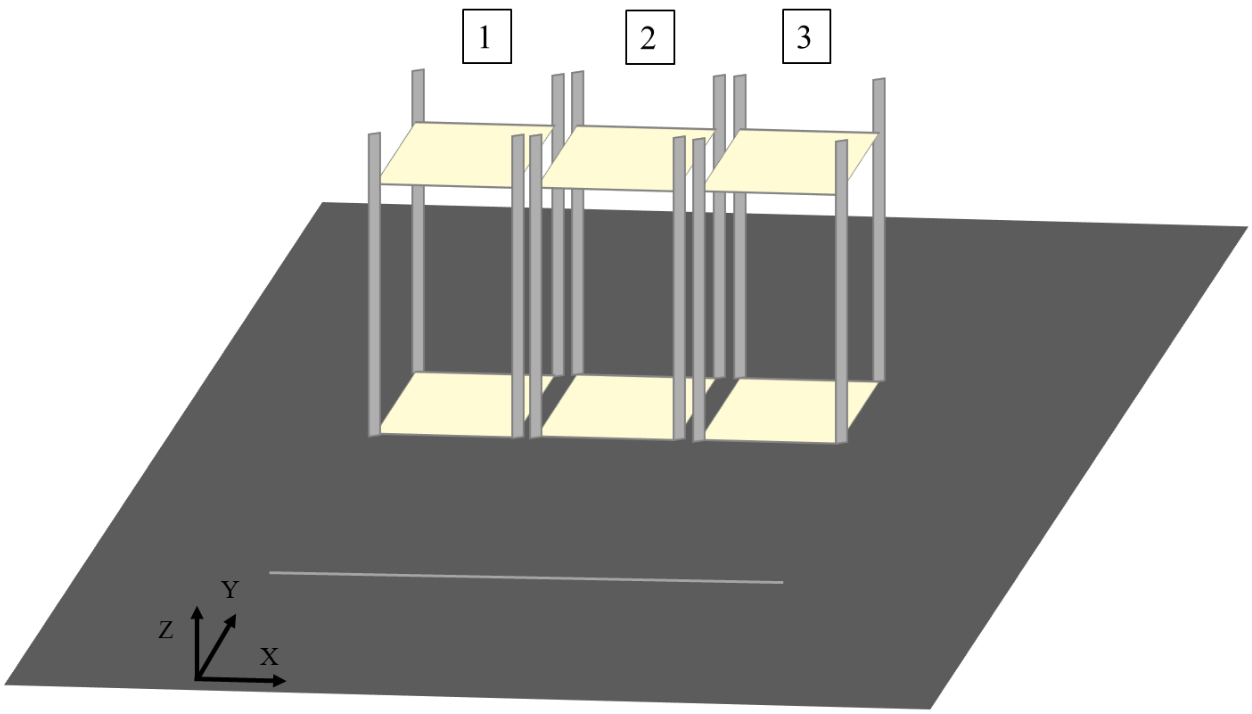

Figure 7.1: Three-shelf setup with the bottom shelf just above floor height and top shelf at shoulder height.

7.3.4 Procedures

Participants completed two data collection sessions 2-7 days apart which was deemed sufficient to recover any delayed-onset muscle soreness from the first session and to control for history as an internal bias to the individual's MV. In the first session participants completed a modified version of the Matheson's EPIC lifting capacity test (Matheson et al., 1995), to establish their maximum lifting capacity (Oomen et al., 2022). In the second session participants completed self-paced lifting for one short bout of 105 lifting cycles maximum (16 ± 4 minutes), using a load weight corresponding to 30% maximum capacity, and a prolonged bout until volutional fatigue or up to a maximum of 60 minutes (48 ± 19 minutes) using the same load mass (30% of maximum capacity). The 30% weight was justified for the prolonged lifting bout by the lifting duty cycle equation (Potvin, 2012). The duty cycle of this task was estimated at 31%, including estimates of time between trials. Based on a duty cycle of 31%, a maximal acceptable effort of 25% was estimated by use of the lifting duty cycle equation (Potvin, 2012). This equation is based on a duty cycle of an 8-h workday; however, this lifting protocol only took up to 1 hour. Therefore, the maximal acceptable effort for an hour protocol is probably closer to 30% and therefore was acceptable.

For both sessions, the possibility that participants were influencing their movement variability in a desirable manner based on the study purpose was prevented by deceiving participants about the true study purpose (Nichols & Maner, 2008). Participants were informed that the study aimed to estimate the optimal and safe number of repetitions during lifting in two scenarios. For the short lifting bout, participants were asked to perform as many repetitions as possible without inducing tiredness or strain at the end of the workday based on a 8-h workday. For prolonged lifting participants were also asked to perform as many repetitions as possible; however, they were expected to become tired and continue until they could no longer lift any crates. Although participants were aware of maximum time limits (i.e. 30 minutes for short bout and 60 minutes for prolonged bout) in each scenario, they were asked to perform as many repetitions as they could given the scenarios. More specifically, participants were not instructed on lifting technique, except for using both hands. Audio recordings and corresponding written transcripts were provided to ensure that all participants were exposed to the same instructions (Beach et al., 2018).

In the short lifting bout, participants approached each shelf of the three-shelf setup (see **Figure 7.1**) by walking from the 2.5-meter line to allow voluntary foot placement before lifting each crate. This lifting bout, which corresponds to the free high load lifting of Oomen et al. (2022), was performed for a maximum of seven sets of five trials, with one trial corresponding to three repetitions of the task (i.e. one repetition at each shelf). This lifting bout resulted in a maximum of 105 total repetitions each, if the participants completed all trials. After every set, participants were asked to report their RPE and, as part of the deception, asked if they could perform another set within an 8-h workday without feeling tired or experiencing strain at the end of the workday. Thus, some participants ended the short bout before the maximum amount of 105 repetitions was reached. The data from this bout represented lifting with only minimal development of fatigue, in contrast to prolonged lifting.

Before the prolonged lifting protocol participants were offered a 15-minute optional rest break. In agreement with the short lifting bout, participants were allowed voluntary foot placement and sets of five trials were performed after which RPE was reported. Also, in agreement with the short lifting bout, participants approached the first shelf by walking from the 2.5-meter line and after completing the lift at the third shelf walked back to the line. However, for prolonged lifting, participants were allowed to directly move to the next shelf in between shelf 1 and 2 and shelf 2 and 3 without walking back and forth between the line in between each lift. This removed four occasions of walking between the shelf and line when compared to the short bout, to increase the amount of active work relative to total time, which increased the duty cycle and thus would evoke fatigue mainly due to lifting rather than also walking. Participants were asked to perform as many sets as possible until volitional fatigue up to a maximum duration of 1 hour. The protocol was terminated if participants were unable to continue the protocol or if they completed 1 hour of lifting.

After completion of this session the participants were debriefed about the deception and the true purpose of the study was revealed by informing that their movement variability was studied rather than the number of repetitions. Participants signed another consent form after deception was lifted.

7.3.5 Data processing

Similarly, to Oomen et al. (2022), whole-body and crate kinematics were processed using best practices for gap filling (Howarth & Callaghan, 2010), padding and filtering (Howarth & Callaghan, 2008; Smith, 1989; Winter, 2009) and ISB recommendations were followed to create local coordinate systems that were used to derive three-dimensional joint angles (Wu et al., 2002, 2005). Then, the joint angles were segmented to lifting cycles based on the anterior-posterior crate marker velocity. This resulted in an average of 90 (± 21) and 333 (± 146) lifting cycles per participant for the short and prolonged lifting bouts, respectively.

Segmented lifting cycles were time-normalized to 101 data points corresponding to 0 to 100% of the task cycle (Graham et al., 2013). In agreement with Oomen et al. (2022), the number of cycles was further reduced by excluding outliers in sagittal joint angles that were outside of the ensemble average ± 3.75 standard deviations range. This resulted in an average of 79 (± 20) and 296 (± 127) lifting cycles per participant for the short and prolonged lifting bouts, respectively. Finally, the cycles of prolonged lifting were split into three equal parts to represent an early, middle and late phase, which resulted in 99 (± 42) lifting cycles per participants for each section.

The linear measure of cycle-to-cycle variability was determined as the standard deviation between cycles at each normalized time point (i.e. point-by-point standard deviation), and the mean of the point-by-point standard deviation values was calculated resulting in meanSD. MeanSD was summed for left and right ankle, knee, and hip joints for a lower extremity measure, and for left and right wrist, elbow and shoulder joints for an upper extremity measure, while low back meanSD was considered separately. Also, meanSD was summed across all joints for a linear whole-body variability measure.

Nonlinear CRP was determined using a Hilbert approach applied to time-normalized joint angle couplings in the sagittal plane in agreement with Chapter 4. This resulted in 12 joint couplings, left and right ankle-knee, knee-hip, and hip-low back, and left and right wrist-elbow, elbow-shoulder and shoulder-low back couplings. Cycle-to-cycle variability of time-normalized CRP was defined similarly to meanSD of joint angles. The point-by-point standard deviation was determined and averaged across all 101 data points to obtain average cycle-to-cycle CRP variability (Hamill et al., 2000). Then, CRP variability was summed for left and right ankle-knee, knee-hip and hip-low back couplings for a lower extremity measure, for left and right wrist-elbow, elbow-shoulder and shoulder-low back couplings for an upper extremity measure. In addition, all joint couplings were summed to obtain a nonlinear whole-body variability measure.

Three measures based on RPE were defined as indicators of fatigue. First, the number of sets completed in the prolonged protocol until a RPE of 15 was reached for the first time, as a measure of endurance. This boundary of RPE was based on the average RPE at the end of a prolonged lifting protocol that also demonstrated expected reductions in isometric force indicative of fatigue development (Fischer et al., 2015). For the other two measures, a linear regression line was determined between RPE and number of sets for each individual throughout the prolonged lifting bout. Then, the second indicator of fatigue was defined as the slope of the regression line as a measure of the rate of fatigue development. Lastly, the third indicator of fatigue was defined as the intercept of the regression line which reflects initial differences in fatigue development. Using regression line characteristics of fatigue measure over time is similar to common practice in mean power frequency analysis of EMG as fatigue indicator (Falla et al., 2006, 2007; Falla & Farina, 2005).

7.3.6 Statistical analysis

All statistical analyses were conducted in R 4.0. Assessment of normality was performed using statistics of skewness, kurtosis and Shapiro-Wilks test and by visual inspection of histograms, Q-Q plots and box plots. The assumption of normality could not be confirmed for RPE values of the last set of each lifting bout, for linear variability of each body region, and for the three indicators of fatigue and thus nonparametric tests were performed.

To confirm the assumption of fatigue development with subsequent lifting bouts as part of research question 1 and 2, the effect of lifting bout on RPE indicated in the last set of each bout were compared using one-way Friedman's ANOVA. If a significant main effect was found, pairwise Wilcoxon signed-rank tests with Bonferroni corrections for the number of comparisons were performed. The direction of the differences were determined using group medians of each bout.

For body-region specific linear variability, differences between lifting bouts were assessed using a one-way Friedman's ANOVA. Since this resulted in nine different comparisons (i.e. 3 body regions by 3 movement planes), a Bonferroni correction was applied to control for familywise error rate and thus a critical significance level of $\alpha = .006$ was used. If significant main effects were found, to determine where differences between specific lifting bouts occurred Wilcoxon signed-rank tests with Bonferroni corrections were performed with the short lifting bout as a reference condition. Also, the direction of differences were determined by group medians.

For body-region specific nonlinear variability, differences between lifting bouts were assessed using a one-way repeated measures ANOVA. A Bonferroni correction resulting from two body regions imposed a critical level of significance of $\alpha = .025$. The assumption of sphericity was checked according to Girden (1992), if the Greenhouse-Geisser epsilon ≥ 0.75, the Huynh-Feldt correction was used, otherwise the Greenhouse-Geisser correction was used. If significant main effects were found, differences between lifting bouts were determined using dependent t-tests with Bonferroni corrections between the short lifting bout as a reference condition. Also, the direction of differences were determined by group means.

The consistency of whole-body linear and nonlinear variability across the four lifting bouts (one short and three sections of prolonged bout) was assessed using intraclass correlation (ICC) using a two-way mixed model for average measures (i.e. ICC(3,k) consistency model).

Association between body-region specific linear and nonlinear variability during the short bout with the three indicators of fatigue was determined by spearman's correlation coefficient for each indicator and variability measure. Since specific relationships between variability and fatigue indicators were expected, one-tailed tests were used with a confidence level of 95%. Specifically, a positive relationship was expected between variability and endurance; while, negative relationships between variability and the rate of fatigue and initial fatigue were expected.

7.4 Results

One participant was removed from the analysis as they were unable to follow lifting instructions, which resulted in final analyses with 10 females and 8 males.

A main effect of lifting bout was found in RPE of the last set ($\chi 2(3)$= 39.5, $p<.001$, W= 0.731). Post hoc analysis indicated significant differences for each pairwise comparison of lifting bout (all $p<.05$), except for the short lifting bout and the early phase of the prolonged lifting bout (p=0.07) (**Figure 7.2**). Overall, group medians indicated an increase in RPE with subsequent lifting bout (short: *Mdn*=13, prolonged early: *Mdn* =14.5, prolonged middle: *Mdn* =16, prolonged late: *Mdn* =17).

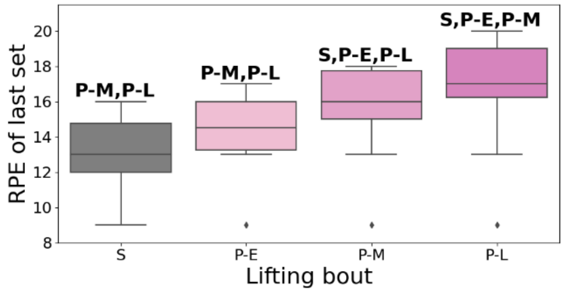

Figure 7.2: Boxplots of RPE of the last set for each lifting bout. S: short; P-E: prolonged early; P-M: prolonged middle; P-L: prolonged late. Each individual boxplot shows the quartiles (box), 1.5 interquartile range (whiskers) and values outside this range (diamonds). Significant differences between lifting bouts were based on Wilcoxon signed-rank tests and are indicated using abbreviations of lifting bouts.

No main effects of lifting bout were found across body regions and movement planes for linear variability (**Table 7.1**). However, sagittal lower extremity variability showed a trend for a main effect of lifting bout (*W*=0.223) (**Figure 7.3**). Possibly, this trend can be explained by a higher median in the early lifting phase (*Mdn* =48.12°) compared to the other lifting bouts (short: *Mdn* =39.62°, prolonged middle: *Mdn* =37.87°, prolonged late: *Mdn* =39.79°).

Table 7.1: Results of Friedman's ANOVA for linear variability of three body regions in three movement planes with lifting bout as within-subjects factor.

		Lifting bout		
Body region	**Plane**	χ2(3)	p	W
Lower extremity	Sagittal	12.100	0.007	0.223
	Frontal	0.333	0.954	0.006
	Transverse	2.070	0.559	0.038
Low back	Sagittal	4.070	0.254	0.075
	Frontal	8.270	0.041	0.153
	Transverse	2.200	0.532	0.041
Upper extremity	Sagittal	1.870	0.601	0.035
	Frontal	4.870	0.182	0.090
	Transverse	9.530	0.023	0.177

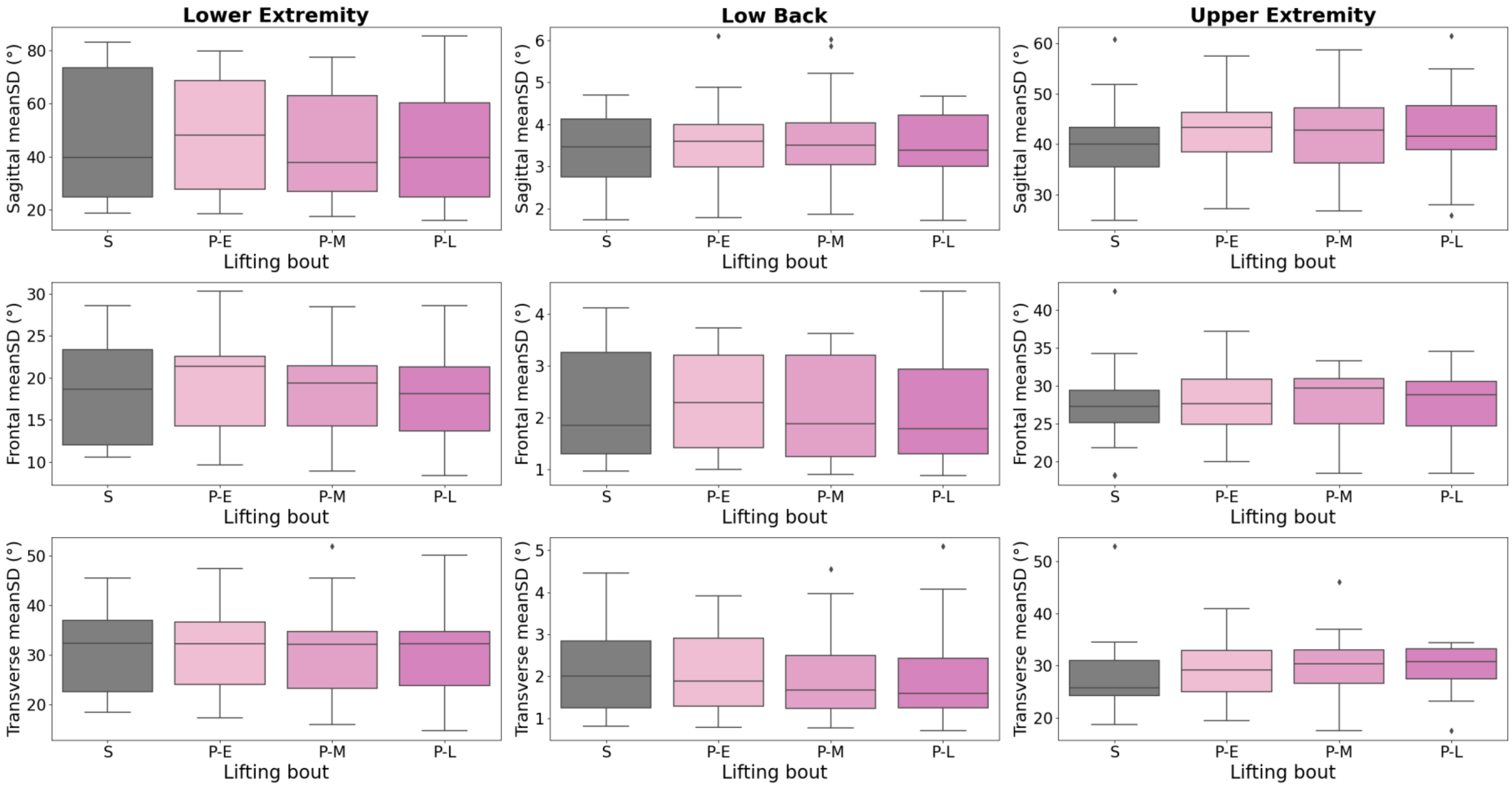

Figure 7.3: Boxplots of meanSD for each lifting bout in each movement plane (row) and for body area (column). S: short bout; P-E: prolonged early bout; P-M: prolonged middle bout; P-L: prolonged late bout. Each individual boxplot shows the quartiles (box), 1.5 interquartile range (whiskers) and values outside this range (diamonds).

Also, no main effect of lifting bout was shown for nonlinear sagittal CRP variability (**Table 7.2**). Although, sagittal upper extremity variability showed a trend for a main effect of lifting bout (η_p^2 = 0.139). When reviewing the corresponding graph (**Figure 7.4**), the median appeared to decrease with each subsequent lifting bout until the middle phase, while the late phase showed a slight increase relative to the middle phase (short: *Mdn*=160.08°, prolonged early: *Mdn* =157.51°, prolonged middle: *Mdn* =142.44°, prolonged late: *Mdn* =143.87°).

Table 7.2: Results of one-way repeated measures ANOVA for nonlinear continuous relative phase variability of sagittal plane lower and upper extremity variability with lifting bout as within-subjects factor.

		Lifting bout			
Body region	**Plane**	F	df	p	η_p^2
Lower extremity	Sagittal	1.223	1.65, 28.04	0.303	0.067
Upper extremity	Sagittal	2.751	1.81, 30.69	0.085	0.139

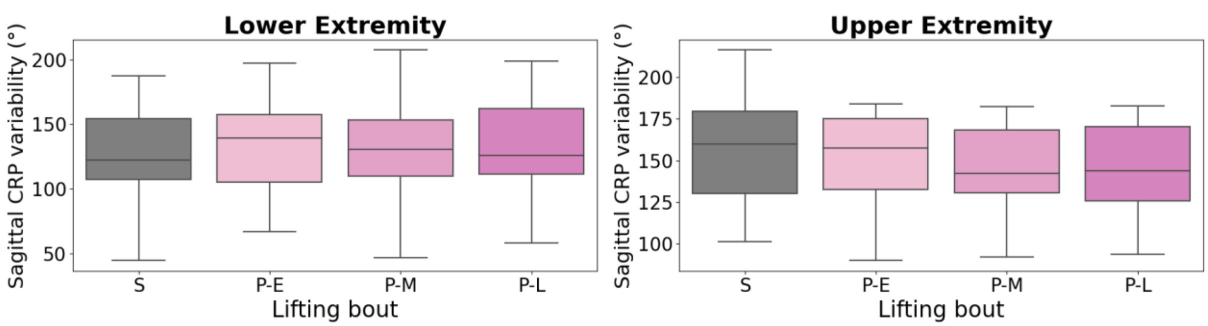

Figure 7.4: Boxplots of sagittal continuous relative phase (CRP) variability for each lifting bout and body area (column). S: short bout; P-E: prolonged early bout; P-M: prolonged middle bout; P-L: prolonged late bout. Each individual boxplot shows the quartiles (box), 1.5 interquartile range (whiskers) and values outside this range (diamonds).

Across lifting bouts significant ICCs (p < .001) were found for linear whole-body variability and for nonlinear whole-body CRP variability (**Table 7.3**). Across measures and movement planes, ICCs were reported between 0.95–0.97. These findings are supported by very similar individual variability across lifting bouts (**Figure 7.5** and **Figure 7.6**).

Table 7.3: Intraclass correlation (ICC) of whole-body variability using meanSD and continuous relative phase (CRP) as different measures in the listed planes across lifting bouts with corresponding p-value and 95% confidence interval (CI). Significant p-values are indicated in bold.

Measure	Plane	ICC	p	95% CI
MeanSD	Sagittal	0.97	**<.001**	0.95 - 0.98
	Frontal	0.95	**<.001**	0.91 - 0.98
	Transverse	0.96	**<.001**	0.93 - 0.98
CRP	Sagittal	0.96	**<.001**	0.92 - 0.98

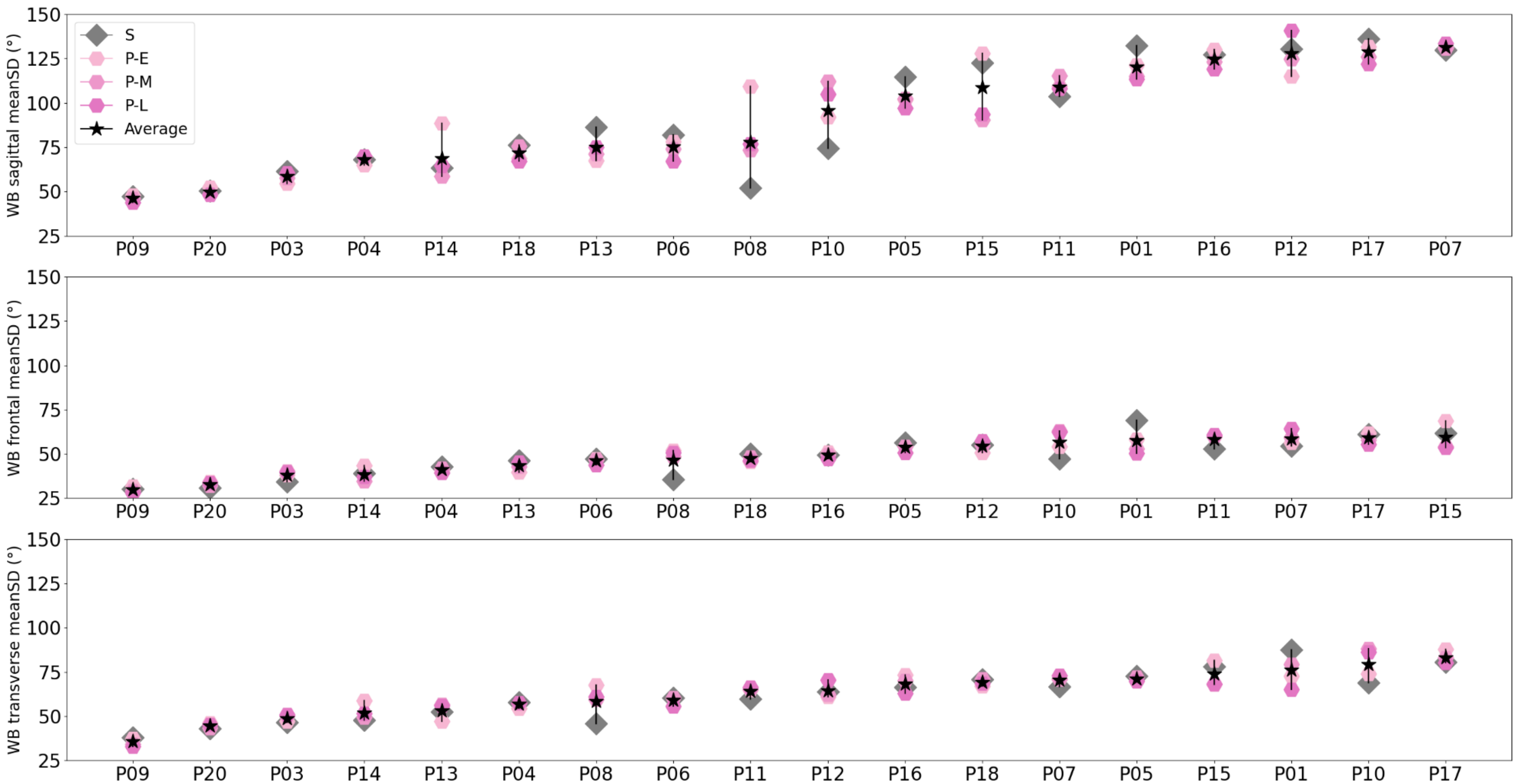

Figure 7.5: Whole-body (WB) meanSD for each lifting block with each participant ranked on average variability across lifting bouts on the abscissa with each plot showing a different movement axis. S: short bout; P-E: prolonged early bout; P-M: prolonged middle bout; P-L: prolonged late bout.

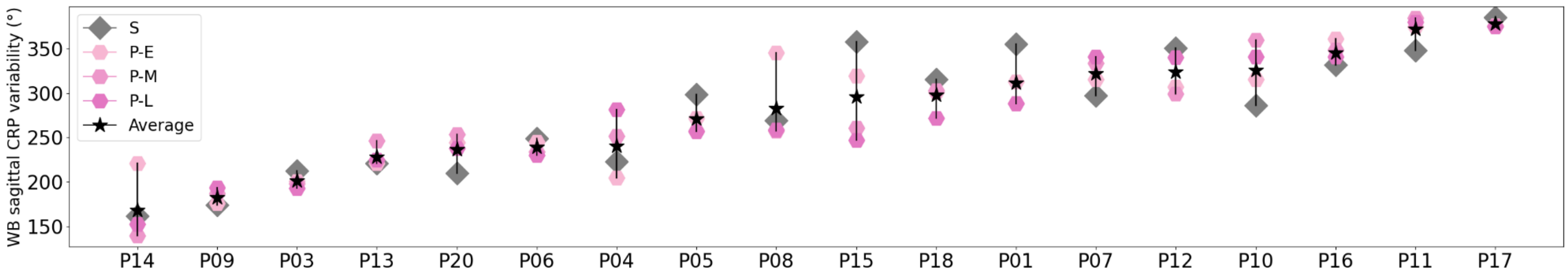

Figure 7.6: Whole-body (WB) sagittal continuous relative phase (CRP) variability for each lifting block with each participant ranked on average variability across lifting blocks on the abscissa. S: short bout; P-E: prolonged early bout; P-M: prolonged middle bout; P-L: prolonged late bout.

Correlations between short bout linear variability and indicators of fatigue derived from RPE showed significant correlations for low back sagittal plane variability with endurance and initial fatigue (**Table 7.4**). With respect to nonlinear variability, only lower extremity variability showed a significant correlation with initial fatigue (**Table 7.5**). Both linear and nonlinear variability demonstrated consistent negative coefficients for initial fatigue, while for other fatigue indicators both positive and negative coefficients were reported. An exemplar scatter plot of each fatigue indicator with low back sagittal plane linear variability is demonstrated in **Figure 7.7**.

Table 7.4: Spearman's correlation coefficient (r_s) of linear variability in three body regions and three movement planes during the short bout with endurance based on the number of sets performed until a RPE of 15, rate of fatigue and initial fatigue based on the slope and intercept from regression of RPE across sets respectively. Significant p-values are indicated in bold.

		Endurance		Rate of fatigue		Initial fatigue	
Body region	**Plane**	r_s	p	r_s	p	r_s	p
Lower extremity	Sagittal	-0.03	0.55	-0.15	0.28	-0.05	0.43
	Frontal	0.11	0.34	-0.01	0.48	-0.15	0.27
	Transverse	0.08	0.38	0.23	0.82	-0.25	0.16
Low back	Sagittal	0.46	**0.03**	0.18	0.76	-0.51	**0.02**
	Frontal	0.04	0.44	-0.31	0.10	-0.12	0.32
	Transverse	-0.09	0.64	-0.14	0.29	-0.14	0.29
Upper extremity	Sagittal	0.06	0.40	-0.22	0.19	-0.05	0.42
	Frontal	0.33	0.09	0.18	0.77	-0.40	0.05
	Transverse	0.23	0.18	0.19	0.78	-0.09	0.36

Table 7.5: Spearman's correlation coefficient (r_s) of continuous relative phase variability in sagittal movement plane of lower and upper extremity during the short bout with endurance based on the number of sets performed until a RPE of 15, rate of fatigue and initial fatigue based on the slope and intercept from regression of RPE across sets respectively. Significant p-values are indicated in bold.

		Endurance		Rate of fatigue		Initial fatigue	
Body region	**Plane**	r_s	p	r_s	p	r_s	p
Lower extremity	Sagittal	-0.09	0.64	0.00	0.50	-0.48	**0.02**
Upper extremity	Sagittal	0.07	0.39	0.10	0.65	-0.10	0.35

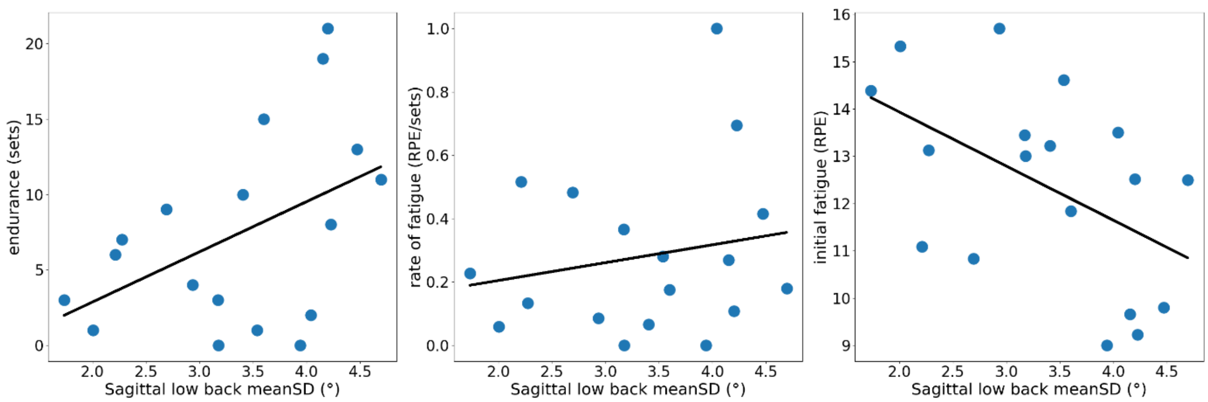

Figure 7.7: Scatter plots of each fatigue indicator with sagittal plane low back linear variability.

7.5 Discussion

The purpose of this study was to assess differences in MV and individual MV consistency across lifting bouts as fatigue developed, and to investigate if lower between-trial variability at baseline was associated with increased fatigue. Self-reported fatigue increased with subsequent lifting bouts, confirming that fatigue was developed during the protocol, while no significant effect of lifting bout was found on variability in different body regions and planes when assessed with linear and CRP variability measures. For linear measures, a trend was found in sagittal lower extremity variability; although, this trend does not agree with the expected effect of an increase in variability with subsequent lifting bouts. Nonlinear CRP measures also showed a trend in sagittal upper extremity variability which demonstrated a decrease in variability with subsequent lifting bouts, opposite of the expected effect. Therefore, the first hypothesis could not be supported. Results for individual consistency showed excellent consistency (Koo & Li, 2016) across lifting bouts for each whole-body MV measure and movement plane. The consistency values across MV measures and movement planes were very similar. Therefore, the second hypothesis was supported. When three indicators of self-reported fatigue were related to baseline MV, some relationships between MV and fatigue development were found. Although the relationship was not observed for all body regions, this suggests some evidence for the third hypothesis specifically for the lower body in the sagittal plane. Collectively, we interpret these findings as strong support for the repeaters-replacers hypothesis and some support for the variability-risk hypothesis, at least when considering self-reported fatigue as a surrogate measure for WRMSD risk when specifically considering sagittal plane lower body MV.

In contrast to previous occupational research on fatigue development and kinematic variability, this study did not demonstrate differences in linear and nonlinear MV with fatigue development. With respect to linear MV and fatigue development, our results disagree with previous findings on occupational lifting and a pointing task. These previous studies indicated that linear MV increased with fatigue across the body parts involved in the task (i.e. for lifting at the whole-body level while for pointing only at measured shoulder and elbow joints) (Sedighi & Nussbaum, 2017; Yang et al., 2018). With respect to nonlinear MV and fatigue, our results agree with previous studies on lifting, while our results differ from evidence based on a pointing task (Sedighi & Nussbaum, 2017; Yang et al., 2018). In lifting no change was observed in whole-body movement complexity, while in pointing an increase in flexibility in shoulder-elbow coordination was observed with fatigue (Sedighi & Nussbaum, 2017; Yang et al., 2018). Possibly, our study does not indicate a similar finding because more freedom in task execution could have given participants more opportunity to exploit motor abundance and thus explore variability regardless of fatigue, while in restricted tasks variability may only increase during fatigue development to preserve task continuation. In previous lifting, task execution was constrained by external pacing, fixed foot placement and continuous holding of the lifting object (Sedighi & Nussbaum, 2017). In addition, in contrast to the previous pointing task performed with only the upper extremity specifically in one plane, whole-body movement in three planes during lifting could have further facilitated exploring different movement strategies to exploit motor abundance (Yang et al., 2018). Therefore, our lifting task may not have been sensitive enough to additional exploration of variability as a compensation strategy to limit further fatigue development that was found in restricted tasks (Farina et al., 2008; van Dieën, Oude Vrielink, & Toussaint, 1993; Yang et al., 2018) because possibly participants were already using motor abundance in completing the task. Furthermore, restricting tasks to improve internal validity could confound our understanding of MV during fatigue in less restricted tasks which could be more externally valid of performance in daily life.

In agreement with other occupational studies, this study supports MV as an individual trait which is an essential condition of the repeaters-replacers hypothesis (Jackson et al., 2020; Oomen et al., 2022; Sandlund et al., 2017). Until now, evidence demonstrated individual consistency when performing a fine motor task (Jackson et al., 2020), or gross motor lifting task (Oomen et al., 2022) across different task constraints, and also across different days when performing a fine motor task (Sandlund et al., 2017). This study adds evidence for individual consistency during fatigue development in a gross motor lifting task. Our previous work on individual consistency within occupational lifting across different task constraints using the same linear and nonlinear measures revealed ICCs of 0.71-0.84 and 0.88, respectively (Oomen et al., 2022; Chapter 4). In comparison, we observed ICCs of 0.95-0.97 while also performing lifting under one task constraint condition (i.e.

unrestricted foot movement, high load) of previous work, but when assessed across different levels of fatigue development in occupational lifting. Therefore, across different experimental conditions and variability measures, fatigue development represents the condition for which the highest consistency was demonstrated. This indicates that fatigue does not confound the assessment of individual MV magnitude relative to other individuals. In agreement with no differences in MV between lifting bouts during fatigue development, it is possible that repeaters and replacers respond to fatigue similarly by mostly maintaining their magnitude of MV.

In line with the variability-fatigue hypothesis, sagittal plane lower body MV was associated with some indicators of fatigue response. Thus, this study provides some support that repeaters are at higher risk than replacers based on self-reported RPE as a surrogate risk factor for WRMSD development in a repetitive lifting task. Possibly, only MV in the sagittal plane was related to the fatigue response because the sagittal plane represents the primary movement plane of the lifting task. In addition, only a relationship was found for variability at the low back and lower extremity indicating that potentially individuals can use lower body MV to mitigate fatigue development in the lifting task, rather than upper body MV. Across all fatigue indicators, two relationships were observed for initial fatigue, one relationship for endurance, and none for the rate of fatigue. Initial fatigue reflects an indicator of fatigue at the start of the prolonged protocol, which was performed shortly after the short bout. Possibly, fatigue experienced during the short bout remained present at the start of the prolonged protocol since fatigue can be considered a continuous process (Cowley & Gates, 2017). This idea could be supported by our average RPE intercept of 12.4 which is a bit higher than average RPE of 8.5 (Fischer et al., 2015) and 10 (Lotz et al., 2009) of previous work on prolonged repetitive lifting. More importantly, findings of relationships between MV and initial fatigue could be explained by the fact that initial fatigue represents a closer point in time to the MV it was related to at baseline. Similarly, the rate of fatigue could also be confounded by fatigue build up from the short bout and explain why no relationship with rate of fatigue was found. Although our average slope of RPE per set of 15 cycles was 0.32, while we determined a comparable value of 0.25 (Fischer et al., 2015) and 0.22 (Lotz et al., 2009) of previous work on prolonged repetitive lifting. Possibly, the collected rate of fatigue only represents a later part of the fatigue development process. For endurance, previous support for the variability-fatigue hypothesis was found for temporal and spatial EMG variability with endurance time in isometric tasks (Farina et al., 2008; van Dieën, Oude Vrielink, & Toussaint, 1993). Despite a different definition of endurance, another important difference to note with previous work is task type and related biomechanical variables. Isometric tasks do not provide muscle abundance and thus EMG variability is possibly more closely related to endurance of specific fatiguing musculature. However, dynamic tasks such as whole-body lifting offer muscle abundance that could help to sustain the task for longer since many muscles are involved with different levels of fatigue (Ferber & Pohl, 2011; Latash, 2012). Thus, endurance could be confounded by motor abundance at different levels of neuromuscular and musculoskeletal processes that result in the observed kinematics, and therefore only show a relationship with one of the eleven variability measures that were used in this study. In summary, the variability-fatigue hypothesis could only be supported for some kinematic MV measures and some fatigue indicators. The findings suggest that in our study variability is related to early perceptions of fatigue. Although a relationship was found with endurance for one variability measure, the relationship between variability and endurance may be limited to restricted tasks that have limited kinematic compensation due to motor abundance (Ferber & Pohl, 2011; Latash, 2012). Future research is recommended to also tease out if the variability-endurance relationship is only limited to EMG variability and does not translate to kinematic variability.

7.5.1 Limitations

The findings of this study should be considered within the following limitations. In this study fatigue was determined based on RPE and number of completed sets. It could be argued that assessing fatigue using more objective measures such as median power frequency of EMG or isometric force measurements could improve the determination of fatigue, despite strong relations of RPE with the perception of fatigue (Bonato et al., 2003; Enoka, 2012; Vøllestad, 1997). However, in agreement with previous studies on variability-fatigue our RPE measurements demonstrated that participants reached volitional fatigue. Previous work in motor variability used the criteria of reaching 8 or 9 out of 10 on the Borg CR-10 scale to define volitional fatigue (Cowley et al., 2014; Gates & Dingwell, 2008; Yang et al., 2018). When converting this finding to the Borg 6-20 scale, the criteria would be equivalent to 17-18 out of 20 (Borg, 1998). In our study sample thirteen out of eighteen participants reported at least 17 out of 20 on the RPE scale, three participants reported very close values of 15-16, while two participants reported lower values of 9 and 13. Therefore, most participants demonstrated volitional fatigue. In addition, previous work that used Borg CR-10 criteria also demonstrated changes in EMG related to volitional fatigue (Cowley et al., 2014; Gates & Dingwell, 2008; Yang et al., 2018) which makes it likely that similar changes occurred in our study based on the Borg scale alone.

7.6 Conclusion

When performing a repetitive lifting task, participants reported an increase in RPE over time, a surrogate measure of fatigue. However, MV did not change over time, regardless of MV measure and body region. Therefore, our results disagree with the consensus that MV increases with fatigue development. Perhaps, enhancing internal validity by imposing task restrictions confounds the understanding of MV and fatigue since it decreases the opportunity to exploit motor abundance as a compensation mechanism for task continuation during fatigue. At the individual level, consistent whole-body MV was shown across different lifting bouts with varying levels of fatigue. Thus, MV can be considered as an individual trait independent of the level of fatigue development, which provides an important piece of evidence in understanding the repeaters-replacers hypothesis. For the variability-fatigue hypothesis as part of the variability-risk hypothesis, some associations were found between baseline variability and indicators of fatigue. Possibly, our findings are mostly driven by early perceptions of fatigue development and earlier findings supporting relationships with endurance cannot be fully translated to a task performed with the whole-body and when characterizing MV using kinematics. Importantly, the findings for relationships between variability and fatigue in this study are affected by the preceding short bouts which could have led to higher initial fatigue and confounded rate of fatigue. Taking some support for the variability-fatigue hypothesis together with strong support for the repeaters-replacers hypothesis, this could suggest that for some fatigue and variability parameters repeaters have a higher early state of fatigue and less endurance compared to replacers.

Chapter 8: General Discussion

8.1 Summary of key findings

This dissertation aimed to assess between-trial kinematic motor variability (MV) during repetitive manual work tasks to test the repeaters-replacers and variability-fatigue hypotheses from both traditional and functional motor control perspectives. This collection of manuscripts provided quantitative evidence to support MV as an individual trait independent of task constraints, variability measures, and fatigue development in repetitive lifting. However, limited support was found for MV as an individual trait independent of task type. Thus, the fundamental condition that MV is genuinely an individual trait, underlying the repeaters-replacers hypothesis, is suggested to be task-specific rather than generalizable across tasks. Furthermore, some evidence indicated that baseline MV could be related to indicators of fatigue during fatigue development in repetitive lifting, which reflects some support for the variability-fatigue hypothesis.

8.2 Kinematic variability as an individual trait (repeaters-replacers hypothesis)

Evidence gathered in this dissertation supports that kinematic variability is an individual trait, as inferred by the repeaters-replacers hypothesis. In repetitive lifting, strong evidence was provided for whole-body kinematic variability as an individual trait independent of task constraints and fatigue development. However, in different tasks of carrying, lifting and simulated sawing, only moderate evidence was presented for upper body kinematic variability as an individual trait. Thus, findings of this dissertation support kinematic variability as an individual trait only within the context of the same task. Therefore, it is suggested that the repeaters-replacers hypothesis is task dependent.

Findings of this dissertation support earlier work on MV as an individual trait independent of task constraints, with novel contributions in investigating a gross motor task and physical task constraints. Previous work has presented evidence for MV as an individual trait in fine motor tasks performed with only the upper body (Jackson et al., 2020; Sandlund et al., 2017). Findings reported in this dissertation extends this existing evidence to gross motor tasks executed by whole-body movements. In the context of motor abundance, whole-body movement provides more opportunity to exploit MV and thus presents different task demands than fine motor tasks. Besides a different amount of degrees of freedom, gross motor tasks can differ from fine motor task in terms of scale of precision needed to complete the task and thus also reflect different task demands than fine motor tasks. Also, previous work investigated MV as an individual trait in four different temporal task constraints varying in pace (self-paced and imposed) and production process (batch and assembly-line), and on different measurement days (Jackson et al., 2020; Sandlund et al., 2017). Thus, the work presented in this dissertation contributes to the current body of literature by exploring physical task constraints as a different type of constraint. The physical task constraints used this dissertation restricted movement of the feet and changed the load weight of the crate in the lifting task. Compared to the physical task constraints, changing the pace and production process could increase task complexity, and could lead to dual tasking and different cognitive loads (Koch et al., 2018; Liu & Li, 2012). Both types of constraints affect mechanical task demands although temporal task constraints affected speed while physical task constraints affected range of motion and load and could therefore provoke different responses in MV. Thus, the evidence reported in this dissertation contributes to MV as an individual trait in a gross motor task which have different task characteristics than previous work focused on fine motor tasks in terms of motor abundance and precision. Also, the constraints investigated in this dissertation represent different types of constraints than earlier work that can affect how MV changes with constraints. Therefore, the findings of this dissertation further developed MV as an individual trait in terms of different type of constraints in a gross motor task.

More specifically, the findings of this dissertation on task constraints and MV showed a possible paradox. Task constraints that change the DOF of the task (i.e. restricting foot movement) affected how much MV an individual can exploit, and thus task DOF can be considered a determinant of MV. However, highly consistent MV across task constraints was observed for individuals, which suggests that MV of an individual relative to the study sample is not affected by constraints. Therefore, when comparing MV of different experiments it is important to consider task constraints because they could partially explain differences in MV. With respect to the repeaters-replacer hypothesis, the task constraints may not matter because a repeater in a highly constrained task is most likely also a repeater in a less constrained task due to findings of high consistency, despite possible absolute differences in MV in response to constraints.

One of the novel contributions of this dissertation is the investigation of MV as an individual trait during fatigue development. The body of literature on MV and fatigue has focused on exploring how fatigue affects MV (Farina et al., 2008; Sedighi & Nussbaum, 2017; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993; Yang et al., 2018). Fatigue is an important variable of interest for injury risk because it can serve as a surrogate risk factor for WRMSDs in healthy populations (Rempel et al., 1992; Sjøgaard & Søgaard, 1998). Therefore, fatigue also contributes to investigation of the variability-risk hypothesis (Côté, 2012; Madeleine, 2010; Mathiassen et al., 2003; Srinivasan & Mathiassen, 2012). However, until this dissertation, the repeaters-replacers hypothesis has not been connected to findings on MV and fatigue. Therefore, the evidence gathered in this dissertation provides the first piece of evidence on MV as an individual trait independent of fatigue, which is an important variable in the context of variability-risk hypotheses.

Furthermore, by exploring MV as an individual trait independent of tasks in this dissertation present a significant and novel contribution. The current body of literature on MV as an individual trait has only explored different task constraints and different measurement days within fine motor tasks (Jackson et al., 2020; Sandlund et al., 2017). Also, evidence provided in this dissertation supports MV as an individual trait across different task constraints within a gross motor task (Oomen et al., 2022). To investigate if previous finding can be generalized, the next step was to assess MV as an individual trait across both fine and gross motor tasks. This line of investigation has also been recommended as a future direction in previous work on MV as an individual trait and can be viewed as an extension of studying different constraints within the same task (Jackson et al., 2020; Sandlund et al., 2017). Despite promising results for different task constraints in repetitive lifting, only moderate support was established for MV as an individual trait across different tasks investigated in this work.

Now that more evidence has been added to support that hypothesis of MV as an individual trait, the question remains what determines whether an individual shows consistently low or high MV. In repetitive tasks, MV is a reflection of motor control (Latash et al., 2002; Newell & Corcos, 1993). From the perspective of motor abundance, individuals with higher MV could use a repertoire of task-specific synergies while individuals with lower MV could have limited task-specific synergies (Latash, 2008). An individual's movement repertoire is likely determined by individual-specific characteristics of their neuromusculoskeletal system such as sensory sensitivity or in cost functions of movement that could drive task execution, or even by differences in in cocontraction (Latash, 2008; Selen et al., 2007; Todorov & Jordan, 2002). Evidence in this dissertation demonstrated task-specific consistency in kinematic variability which reflects variability in task-specific movement repertoires. Thus, this work would support explanations that agree with task-specificity of MV as an individual trait, for example differences in optimal control laws where variability is regulated in a task specific manner (Todorov & Jordan, 2002).

8.3 Variability-fatigue hypothesis

In line with the variability-fatigue hypothesis, some associations between baseline MV and indicators of fatigue were found in this dissertation. Based on this investigation, some evidence was provided that baseline MV can predict characteristics of fatigue development. Furthermore, when fatigue is considered as a risk factor for WRMSDs, this work provides some support to the variability-risk hypothesis that repeaters are at higher risk than replacers.

The results of the dissertation contribute to the existing body of literature by showing some agreement with the variability-fatigue hypothesis. The variability-fatigue hypothesis has been supported in isometric tasks based on positive relationships between EMG variability and endurance time (Farina et al., 2008; van Dieën, Oude Vrielink, & Toussaint, 1993). The measure of endurance as defined using RPE in this dissertation could only be related to one kinematic variability measure during lifting as a dynamic task. Therefore, the relationship between variability and endurance is possibly affected by the combination of task and related motor variable used to assess MV (Fischer et al., 2015; Lotz et al., 2009). A lifting task involves whole-body movement, and when considering motor abundance, offers more opportunities to exploit variability as a compensation mechanism to sustain a fatiguing task (Ferber & Pohl, 2011; Latash, 2012). Since variability was assessed using kinematics of each body region in the lifting task and EMG of specifically fatiguing musculature in the isometric task, EMG of the specific muscle is more closely related to fatigue development than kinematics of body regions during whole-body fatigue and could thus explain why not more relationships in terms of body regions and movement planes were found for endurance in this dissertation. At a higher level, this highlights that studying the variability-fatigue hypothesis in a very controlled setting to increase internal validity could confound our understanding of variability and fatigue in more externally valid functional tasks that are present at the workplace.

Furthermore, this work presents a novel contribution in investigating the variability-fatigue hypothesis by exploring associations between individual MV and fatigue responses. To date, only one study has explicitly tested relationships between variability and fatigue (Farina et al., 2008) rather than inferred from effects of fatigue development on MV (Sedighi & Nussbaum, 2017; van Dieën et al., 2009; van Dieën, Oude Vrielink, & Toussaint, 1993; Yang et al., 2018). When comparing MV at different levels of fatigue, the outcomes reflect group averages and thus relationships between MV and fatigue at the individual level could be obscured when individuals have considerably different responses (i.e. both increase and decrease in MV which cancel out when averaging). Therefore, the approach of this dissertation offered a more robust investigation of the variability-fatigue hypothesis by relating changes in MV to change in fatigue indicators.

8.4 Assessment of kinematic variability using measures from different perspectives

For the three variability measures selected in this dissertation, linear, CRP and task-irrelevant variability, several important observations were made. The ability to detect changes in MV in response to changes in task constraints during lifting was only present in linear and CRP measures. However, detection of similar ranking of individual MV values within the study sample was confirmed for all measures. Furthermore, a more focused analysis across all measures within the same task condition of a lifting task revealed overall consistency across measures. However, linear and task-irrelevant measures showed the highest consistency, while CRP measures showed lower consistency with the other two measures. Therefore, future research could consider using both linear and CRP variability as a starting point when studying between-trial kinematic variability of repetitive lifting.

One of the major contributions of this dissertation is to compare different (sub)categories of between-trial kinematic MV measurements to address the lack of standardized techniques to assess MV, which exposes a larger problem in biomechanical waveform analysis (Deluzio et al., 2014). Specifically, the categories of measurements were chosen based on different underlying motor control perspectives, rather than following current practice of mostly focusing on the traditional perspective within ergonomics (Granata et al., 1999; Huysmans et al., 2008; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Madeleine & Madsen, 2009; Sedighi & Nussbaum, 2017). Furthermore, the functional perspectives were chosen based on their potential to connect variability to injury mechanisms in support of the variability-risk hypothesis, which has not received much attention in occupational MV research. The findings of this dissertation showed discrepancies between the different measures based on several criteria. The criterion of responsiveness to changing task constraints informed if the measurement was able to detect changes in DOF constraint and load weight. Since the DOF constraint reduced the amount of DOF available to perform the task, appropriate measurement of MV was assumed to decrease, which was only observed for linear and CRP variability. Furthermore, individual consistency across task constraints would indicate the repeaters-replacers hypothesis, and considerable evidence was found for this in all measurements. In addition, within a task constraint consistency between different measurements would indicate that measurements reflect the same construct of MV, which resulted in similarities between linear and task-irrelevant variability while CRP variability showed some difference. Thus, this work contributes to the larger body of MV literature in demonstrating that the choice of MV measurement can affect the findings of the experiment and thus support for variability-risk hypothesis. More generally, the approach of this dissertation challenges the status quo in ergonomics of describing MV by use of several measurements without considering underlying motor control theories and their potential to explain the underlying injury mechanism in variability-risk hypothesis. Currently, work on the variability-risk hypothesis has focused on the use of linear measurements, while nonlinear measurements of CRP and task-irrelevant variability are relatively understudied despite providing stronger rational on injury risk without sacrificing task performance. A possible disadvantage of using nonlinear measurements is that they are more analytically complex and therefore are hard to interpreter compared to linear measurements, which could be helpful to consider when having limited collection and processing resources.

In this dissertation a novel approach is presented in quantifying whole-body MV. For describing MV in lifting tasks, this work presents one of a few works that use whole-body measurements (Sedighi & Nussbaum, 2017). Although lifting is a whole-body task, previous work has focused on the low back and/or lower body (Granata et al., 1999; van Dieën et al., 1996). In this dissertation, MV was summed at the levels of upper or lower body regions and at the whole-body level. Thus, aggregate measures were chosen over detailed measures at joints, which makes our findings have lower resolution than previous work in lifting. However, the use of body regions still gives indication of regional effects. Furthermore, in studying MV as an individual trait during lifting local (i.e. joint) or regional (i.e. body region) variables of MV do not give a complete representation of consistency in MV due to the common phenomenon of MV compensation between body locations (Bartlett et al., 2007; Button et al., 2003). Therefore, whole-body summation of MV was used when investigating MV as an individual trait.

Another novel aspect of this dissertation is the quantification of individual consistency in MV. More broadly, by assessing individual consistency this work contributes to the larger biomechanics community by studying individual patterns rather than group averages that can obscure these individual patterns (Bartlett et al., 2007). Specifically, the approach of this dissertation was to quantify individual consistency in MV using ICC, while no consensus exists in the repeaters-replacers literature (Jackson et al., 2020; Sandlund et al., 2017). Furthermore, in determining consistency across different measures of MV, individuals were also ranked on MV. This approach of ranking individual on their MV follows the idea that individuals should rank consistently as an important element of the repeaters-replacers hypothesis (Sandlund et al., 2017). The findings of this work also confirm this idea.

A focused contribution is related to the broad use of CRP. Despite the fact that CRP variability is a frequently used variability measurement, we discovered that this method was not always feasible due to strong deviations from sinusoidal patterns (van Emmerik et al., 2014). In our case, carrying led to constant joint angles in the upper extremity and thus construction of the phase plane led to many zero crossings, which can be related to spurious oscillation as previously described (van Emmerik et al., 2014). Furthermore, since tasks were performed for many repetitions, the magnitude normalization was affected by the most extreme cycles, which should be avoided if these cycles deviated from the majority of cycles and therefore can also lead many zero crossings in the phase plane (van Emmerik et al., 2014). Therefore, we applied a method to remove the most extreme outliers. Thus, CRP should be used with caution when signals differ strongly from sinusoidal signals and when extreme cycles are present, where the latter is more likely with a large number of repetitions.

8.5 Limitations and future directions

The sample size of the data collection in this dissertation was slightly lower than what was recommended for a within-subject design (i.e. 25 participants) (Srinivasan, Rudolfsson, et al., 2015). Several results of this work showed trends with considerable effect sizes and thus it is possible that future work with larger sample size could find additional differences due to higher statistical power. However, these trends were observed for effects of task constraints on different MV measurements and for the effect of lifting bout on MV, which do not change the main findings of this dissertations and thus do not change the overall interpretation and main conclusions. Furthermore, our study population was relatively homogenous in terms of age and main occupation. Since individuals were recruited from the student population the age range was fairly narrow (18-32 years) and studying was their main occupation. Thus, this exposes an opportunity for future work to extend our findings to more heterogenous population that better reflects the total population of manual material handling employees, for example by recruiting workers with manual material handling as main occupation and a broader age range. Lastly, a limitation specific to this work is lack of randomization. Since this work had multiple purposes, although not all of those were presented in this dissertation, randomization was not feasible. Possible negative consequences are most relevant to work on lifting constraints. However, in these studies participants were deceived to the study purpose which prevents explicit effects of presentation order on MV. In addition, the difference in MV between DOF constraints and load weight are most likely reflective of the constraints rather than presentation order or related learning effects due to the large magnitude of difference where for some variables comparison could be made with values previously reported in the literature (Graham et al., 2012; Granata et al., 1999; Norasi et al., 2019; Plamondon et al., 2014). Future work is recommended to randomize conditions to confirm our findings.

In studying MV as an individual trait, the approach of this dissertation relies heavily on the use of intraclass correlation (ICC). ICC consists of a ratio of between- and within-subject variance (McGraw & Wong, 1996; Shrout & Fleiss, 1979). Sandlund et al. (2017) critically reflected on this measurement by indicating that it does not share information on which subjects differ consistently due to the use of within-subject variance in ICC. However, in this dissertation a slightly different approach was followed, where the main interest was to quantify how consistently individuals performed in terms of MV across different task conditions, which was also raised as a future direction (Sandlund et al., 2017). This would support the necessary condition of the repeaters-replacer hypothesis where individuals are assumed to show consistent MV independent of task factors. Although the application of ICC in investigating MV as an individual trait does not follow the traditional use of ICCs for inter-rater reliability (Field et al., 2012). ICC can be defined as the proportion of a variance that is attributed to the objects of measurements (in this dissertation the participants) (McGraw & Wong, 1996). This definition justifies our use of ICC to quantify how consistent subjects' MV was shown across different task conditions and other variables. However, the ICC is limited by the between-individual variability which depends on the sample size. Since the investigation of MV as an individual trait is quite recent, future research could take up the challenge of exploring other measures to quantify the consistency aspect of individual MV. For example, new approaches could also try to quantify consistent ranking of individuals in a more direct or explicit way than by ICCs.

Another related limitation of this dissertation is the definition that was used for MV as an individual trait. The approach in this dissertation defined a trait as consistency in individual MV across different task constraints, tasks and fatigue states. However, to further distinguish between a trait and a state, evidence will have to be gathered for MV as a phenotype to be fully considered a trait. For example, by assessing MV across a long time interval, of a larger sample size and across a larger range of tasks.

Another future direction that this dissertation exposes is to connect findings of kinematic variability to non-kinematic variability, where non-kinematic variability is important to further understand the variability-risk hypothesis. More concretely, a hypothesis that can be pursued is whether an increase in kinematic MV translates to an increase in kinetic MV and/or MV in muscle activation. Higher kinematic variability could reflect the use of different movement strategies. Kinematic variability could be related to kinetic variability, where an increase in variability reflective of more distributed loads across multiple tissues that are subject to cumulative loading in repetitive tasks would agree with the variability-risk hypothesis (Bartlett et al., 2007; Hamill et al., 1999; Srinivasan & Mathiassen, 2012). Furthermore, kinematic variability could be related to muscle activation variability, where an increase in variability reflective of less continuously active motor units following the Cinderella hypothesis could provide evidence for the variability-risk hypothesis (Srinivasan & Mathiassen, 2012; Visser & van Dieën, 2006). Although this work does not support associations between variability and fatigue as a precursor for risk on WRMSDs among healthy individuals, the body of literature does support the variability-risk hypothesis. Therefore, future research could more directly investigate the relationship of distribution of muscle activation and kinematic MV and distribution of loading and kinematic MV by use of EMG and kinetics besides kinematics.

The assessment of between-trial kinematic variability is limited by the specific choices made in the analysis strategy of between-trial kinematic MV. An important element to consider as a limitation of this work is that between-trial kinematic MV is not only determined by the range of movement strategies, but also by initial and end positioning of both the body and the object, which can influence the chosen movement strategy on their own. Therefore, between-trial kinematic MV could be entangled with the effect of these initial and end states. This represents an important problem as it may not be possible to keep these states constant, although future research could develop a way to normalize for differences in these states. Furthermore, future work could also assess how much these states alone determine MV of the entire cycle, as initial and end states only represent the start and end of the cycle (i.e. at 0 and 100% cycle). Another limitation of this work is possible confounding effects of skill acquisition due to performing approximately 100 cycles of each task. It is possible that some training or learning effects occurred because of the amount of repetitions. Future work could check for these effects by comparing variability at the beginning and end of a protocol. However, MV is likely also a function of the number of cycles as with more cycles individuals have more opportunity to increase MV. Possibly, time evolution measures of MV such as detrended fluctuation analysis could quantify differences between groups of cycles without excluding cycles of the whole recording. Lastly, the results presented in this dissertation rely heavily on the use of meanSD as variability metric. The point-by-point standard deviation, as part of determining meanSD, is limited by the assumption of a normal distribution of cycles around the average cycle. Possibly, if this assumption is not met, point-by-point standard deviation could be driven by extreme cycles. Also, it is possible that similar values can be found for constant or regular exploration of variability throughout the protocol and intermittent exploration of variability, where few deviating cycles could drive the resulting point-by-point standard deviation.

Several limitations and future directions are to be reported around the use of variability measurements. A general future recommendation is to provide standardization of MV measurements based on study purposes. In line with the dissertation purpose, the work presented in this dissertation only investigated one measurement of three different concepts that indicate different meanings of variability. Although occupational MV research has created interesting evidence for several variability hypotheses, the approach of this dissertation contrasts the current practice of using many different variability measurements. Therefore, from the findings of this dissertation it is recommended to consider the underlying concept and thus potential meaning of variability. In addition, the specific measurements used in this work are aggregate measurements to reflect variability across multiple joints, which assume that the joints within each body region do not show any differences and thereby could have reduced the ability to detect differences. Eventually, each measurement was reduced to a discrete measurement for statistical analysis, and thereby information on specific phases of task execution is ignored which also could have reduced the ability to detect differences. Thus, future work could use a higher resolution by focusing on finding differences at the joint level that determine individuals' MV level at higher levels and potentially separate task phases to gain more resolution in the time domain of task execution. Also, future research could improve assessment of joint angle MV by assessing differences in range of motion and finding effective ways to take this into account, since joints with larger range of motion have a higher contribution to aggregate measures of MV. Future work on MV could consider maintaining temporal information of the kinematic waveforms, for example to explore which parts of the task cycle determine where an individual is positioned on the MV continuum (e.g. Yang et al. (2018)).

For an ergonomics standpoint, this work contributed from a more fundamental level and thus it has little contribution from an application perspective. However, a main barrier is to provide evidence that repeaters are at higher risk of WRMSDs than replacers, which is necessary before steps in more applied research can be undertaken. Thus, more work on variability-risk hypotheses is recommended, where there is currently a relative lack of longitudinal studies and based on the evidence presented in this dissertation the repeaters-replacers hypothesis should be considered.

8.6 Overall Conclusion

The finding of this dissertation demonstrated evidence for MV as an individual trait across different task constraint and different levels of fatigue development in repetitive lifting, in addition to several variability measurements from different motor control perspectives. Since this finding could not be extended to different tasks of lifting, carrying and simulated sawing, it was concluded that the repeaters-replacer hypothesis is task-specific. In investigating different task constraints and tasks, MV increased when the task allowed for more degrees of freedom which reflects exploitation of variability when more movement solutions are available. When MV was assessed using measurements of different perspectives, differences were found for the responsiveness to task constraints and fatigue development. This finding exemplifies that different variables expose different aspects of MV. When MV was related to indicators of fatigue, a few relationships were found between MV and fatigue development. Thus, this work provides some support for the variability-fatigue hypothesis as part of the general variability-risk hypothesis where a negative relationship is proposed between variability magnitude and risk of WRMSDs.

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