

The effects of manipulating task constraints on running economy and multi-segment spine kinematics: Utilising a constraints-led approach to understand the impact of fatigue on running performance

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Abstract

Running performance is shaped by the interaction between physiological demand, biomechanical organisation and the ability to adapt movement under changing task constraints. Although running biomechanics has been widely investigated, the trunk has often been modelled as a single rigid segment, which limits understanding of how the thoracic, lumbar and pelvic regions contribute to running economy, fatigue and performance. This thesis investigated spinal and whole-body biomechanical and physiological adaptations during treadmill running using a constraints-led framework, validated multi-segment kinematic modelling, waveform-based analysis and single-subject interpretation.

The thesis is structured as a progressive programme of methodological and applied studies. First, a systematic review examined how three-dimensional spine, back and pelvis kinematics have been quantified during running using marker-based motion capture systems. The review identified substantial methodological variation across the literature, particularly in marker configuration, segment definition, coordinate-system construction, pelvic reporting, reliability evidence and outcome presentation. These findings highlighted the need for direct model evaluation before multi-segment spine models are used to interpret adaptation during running.

A model-comparison study then evaluated a four-segment skin-marker-set model and a three-segment cluster-based model during treadmill running in sub-elite male runners. Both models demonstrated excellent static criterion validity across the sagittal, frontal and transverse planes. However, during running, the models were not interchangeable. Agreement was strongest in the sagittal plane, partial in the frontal plane and weakest in the transverse plane, particularly in the lumbar region. These findings showed that model choice can alter the magnitude, timing and regional distribution of measured spinal motion. A subsequent reliability study demonstrated that the selected skin-marker-set model produced acceptable between-session repeatability for most segment-plane combinations, supporting its use in repeated-measures running research, although lumbar sagittal range of motion and upper thoracic axial rotation required cautious interpretation.

The applied studies then used this model to examine how sub-elite male runners adapted to acute localised lower-limb fatigue and increased running intensity. Across these task constraints, runners generally preserved the global structure of gait, but reorganised local spinal behaviour through selective changes in segmental motion, waveform timing, segmental dominance and

coupling-angle variability. Acute fatigue did not produce a uniform breakdown in running mechanics. Instead, adaptation was region-, plane- and participant-specific, with the greatest sensitivity often observed in middle spinal couplings and around the lumbopelvic interface. Physiologically, fatigue and increased intensity altered oxygen cost and ventilatory demand, but these changes did not map onto one consistent biomechanical response across all runners.

Increased running intensity produced clearer temporal-spatial and transverse-plane demands, yet individual responses remained central to interpretation. Some runners showed relatively stable coordination patterns, whereas others demonstrated altered coupling behaviour and incomplete recovery when returning to the initial lower-intensity running condition. This suggests that adaptation to running constraints is not simply a linear shift from one stable pattern to another, but a dynamic process in which runners preserve task performance by reorganising local coordination strategies.

Overall, this thesis demonstrates that spinal behaviour during running is adaptive, relational and individual. The findings show that meaningful adaptation may be missed when the trunk is treated as a single rigid segment or when interpretation relies only on group-level discrete variables. By combining validated multi-segment modelling, waveform analysis, vector coding and single-subject interpretation, this thesis provides methodological evidence for reliability-informed spine analysis and empirical evidence that trained runners maintain global running performance through local reorganisation of spinal coordination. These findings contribute to a more nuanced understanding of running economy, fatigue and biomechanical adaptation under changing task constraints.

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Authors Declaration

I declare that this thesis is the result of my own work and has not previously been submitted for any other degree at Staffordshire University or another institution. Where material included in this thesis is the result of collaboration, this is made explicit within the thesis text.

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Publications Arising from the Thesis

Two manuscripts have been submitted for peer-review publication:

Hicks, C. A., Chockalingam, N., & Needham, R. A. Comparison of Two Multi-Segment Kinematic Spine Models During Treadmill Running (under review).

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List of Abbreviations

3D – Three-Dimensional

CAM – Coupling Angle Mapping

CAV – Coupling Angle Variability

CI – Confidence Interval

CRP – Continuous Relative Phase

CV – Coefficient of Variation

DST – Dynamical Systems Theory

GCS – Global Coordinate System

GRF – Ground Reaction Force

IC – Initial Contact

ICC – Intraclass Correlation Coefficient

IDP-ROM – Inter-Data Point Range of Motion

LL – Lower Lumbar

LR – Loading Response

LT – Lower Thoracic

MDC – Minimal Detectable Change

MDC₉₅ – Minimal Detectable Change at the 95% Confidence Level

MeSH – Medical Subject Headings

MS – Mid-Stance

NR – Not Reported

PAR-Q – Physical Activity Readiness Questionnaire

PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PS – Pre-Swing

RE – Running Economy

RER – Respiratory Exchange Ratio

ROM – Range of Motion

RPE – Rating of Perceived Exertion

SD – Standard Deviation

SEM – Standard Error of Measurement

SegDom – Segmental Dominancy

SkS – Skin-Mounted Marker Set

SPM – Statistical Parametric Mapping

SSA – Single-Subject Analysis

STA – Soft-Tissue Artefact

UL – Upper Lumbar

UT – Upper Thoracic

VE/VCO₂ – Ventilatory Equivalent for Carbon Dioxide

VE/VO₂ – Ventilatory Equivalent for Oxygen

VO₂ – Oxygen Uptake

VO₂max – Maximal Oxygen Uptake

VT – Ventilatory Threshold

VT1 – First Ventilatory Threshold

VT2 – Second Ventilatory Threshold

Chapter 1

Introduction

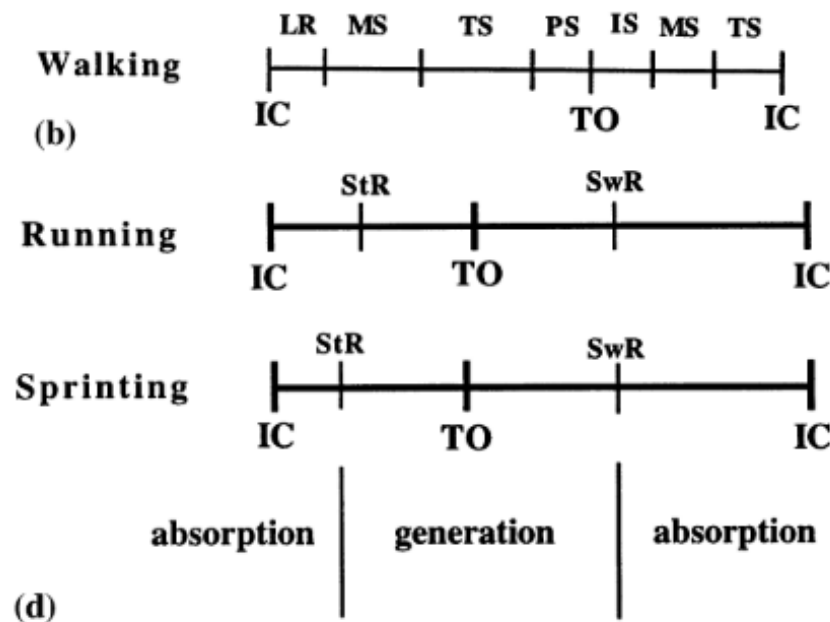
1.1 Background and rationale

Long-distance running is one of the most widely practised forms of physical activity, spanning organised competition, recreational training, and mass-participation community events. Alongside this growth in participation, there has also been increasing scientific and applied interest in understanding how running technique interacts with physiology, particularly because even small changes in movement strategy can influence performance outcomes and potentially alter tissue loading. Running economy is central to this discussion and is commonly defined as the steady-state metabolic demand, usually assessed through oxygen consumption, at a given submaximal running speed (Barnes & Kilding, 2015; Costill, 1967).

The gait cycle provides the biomechanical framework through which running movement is typically described. It is a cyclical process extending from foot strike to the next foot strike of the same limb, and as running velocity increases, the temporal structure of that cycle changes, with shorter support phases and distinct flight periods emerging when compared with walking (Novacheck, 1998). This is important because running performance is not simply determined by isolated segments acting independently; rather, it depends on how body segments interact and coordinate across the stride cycle (see Figure 1.1).

Within running, inter-individual differences in gait are common. Previous evidence indicates that technique contributes meaningfully to between-runner differences in running economy and performance, and that there is no single ideal pattern that applies to all runners (Folland et al., 2017; Moore, 2016). Running economy is therefore better understood as a multifactorial construct that reflects the interaction of metabolic, cardiopulmonary, biomechanical, and neuromuscular systems rather than a purely physiological descriptor (Barnes & Kilding, 2015; Moore et al., 2012).

Figure 1.1. Comparison of walking, running and sprinting gait cycles. Adapted from Novacheck (1998).

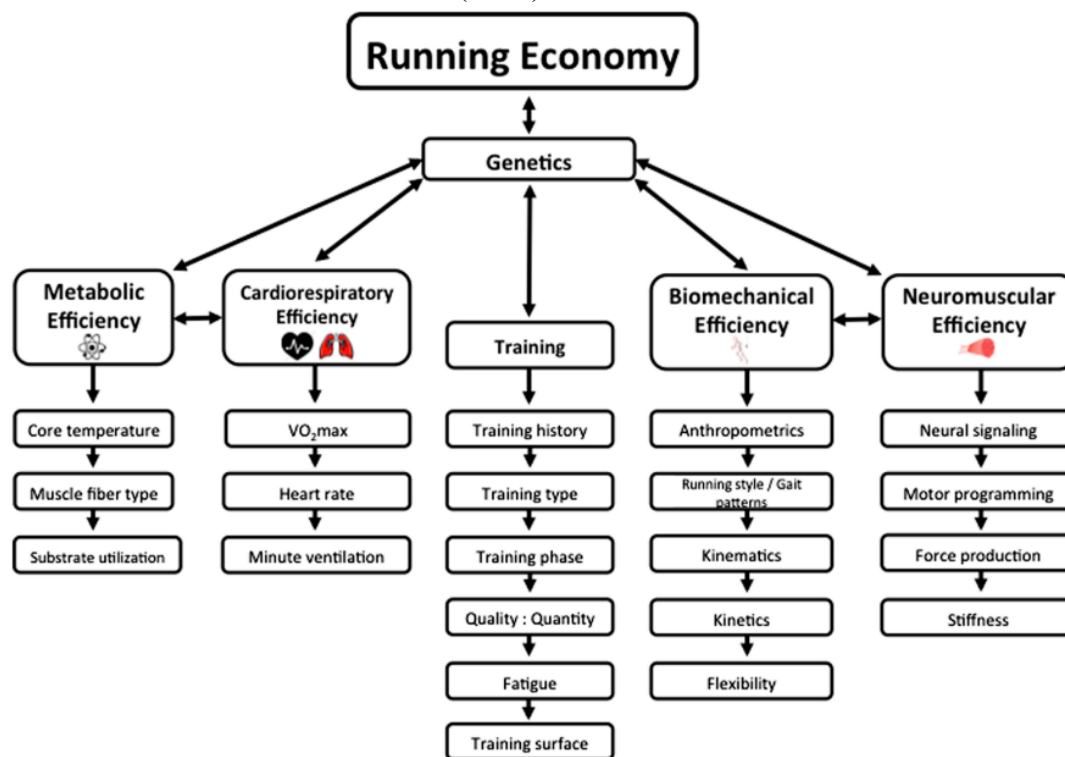


Biomechanically, the trunk and spine are particularly important because they contribute to whole-body coordination, regulation of centre of mass motion, and transmission of forces between the upper and lower body. The relationship between the pelvis and thorax has been suggested to influence running economy and performance, while axial coordination between these regions is also important for controlling postural stability during running (Folland et al., 2017; Preece et al., 2016; Seay et al., 2011). Despite this, much of the running literature has historically simplified the trunk as a single rigid segment, limiting insight into how the thoracic and lumbar regions contribute to movement control.

Running economy is affected by a wide range of interacting determinants, including cardiorespiratory efficiency, neuromuscular characteristics, anthropometrics, and biomechanical strategy. The broad range of factors proposed to affect running economy is illustrated in Figure 1.2. This multifactorial view is important because it suggests that performance cannot be understood from physiology alone; researchers must also consider how movement organisation changes under different task demands (Barnes & Kilding, 2015; Saunders et al., 2004).

Long-distance running performance is also rarely executed in a fresh state. A typical 30-minute run may involve thousands of repeated foot strikes, and the cumulative loading associated with prolonged running can contribute to fatigue-related changes in movement and performance (Mizrahi et al., 2000). Reviews suggest that fatigue can alter running biomechanics, but the direction and magnitude of change are inconsistent across studies and appear to depend on the runner, the protocol used, and the variables measured (Abt et al., 2011; Apte et al., 2021; Dierks et al., 2010).

Figure 1.2. Factors affecting running economy. Figure reproduced from the source introduction draft and attributed there to Barnes et al. (2014).



An especially under-developed area concerns trunk and multi-segment spine kinematics and their coordination with the pelvis during running. Recent work has provided a biomechanical rationale for coordinated spine-pelvis motion during running and has shown that segmental spine and pelvis kinematics can be measured with acceptable reproducibility during faster running (Mason et al., 2016; Needham et al., 2015, 2020; Preece et al., 2016). However, the relationship between fatigue, multi-segment coordination, and running economy remains insufficiently

characterised, particularly in trained cohorts and under systematically manipulated task constraints.

To address this gap, this thesis adopts a constraints-led approach. From this perspective, movement emerges from the interaction of task, environmental, and individual constraints rather than from a single fixed template (Newell, 1986; Davids et al., 2008; Renshaw et al., 2019). In the context of running, this provides a useful framework for examining how speed and acute fatigue influence running economy and multi-segment spine kinematics, and for exploring whether runners self-organise different biomechanical solutions when task demands change.

1.2 Problem Statement

Several important gaps in the literature underpin this thesis. First, the spine is frequently represented as a single rigid trunk segment during running, which masks potentially meaningful inter-segmental motion within the thoracic and lumbar regions. Second, although multi-segment spine models are becoming more feasible, there is still no clear consensus on the most appropriate model for running research, particularly in relation to validity and reliability. Third, coordination and coordination variability of spinal segments during running remain underexplored when compared with lower-limb research. Finally, much of the existing evidence relies on group-based analyses, which may obscure meaningful individual adaptations in response to speed and acute fatigue. Together, these issues limit understanding of how spinal and whole-body biomechanics relate to running economy and performance.

1.3 Aim and Objectives

Overall aim: To investigate spinal and whole-body biomechanical and physiological adaptations during running using validated multi-segment kinematic models and single-subject analytical methods across a range of task constraints.

Objective 1. To critically review literature on running economy, biomechanics, coordination, coordination variability, dynamical systems theory, and single-subject analysis.

Objective 2. To systematically review existing multi-segment spine models used to assess spinal and back movement during running.

Objective 3. To validate and compare two multi-segment kinematic models during running.

Objective 4. To establish the reliability of both models and identify the model to be used in the applied studies.

Objective 5. To examine biomechanical and physiological adaptations to acute fatigue in sub-elite runners.

Objective 6. To examine biomechanical and physiological adaptations to changes in speed in sub-elite runners.

1.4 Research Questions

RQ1. Which multi-segment kinematic spine model demonstrates superior validity and reliability during running?

RQ2. How do biomechanical and physiological variables adapt in response to acute fatigue in sub-elite runners at the individual level?

RQ3. How does increasing running speed alter spinal kinematics, coordination, and physiological responses in sub-elite runners?

1.5 Scope and Delimitations

This thesis focuses on sub-elite runners performing treadmill-based running tasks under controlled laboratory conditions. All empirical studies use optical motion capture to quantify multi-segment spinal and whole-body kinematics alongside physiological measures relevant to running economy and fatigue. Applied studies use a single-subject analytical framework to remain sensitive to individual adaptation patterns under different task constraints. The scope of the thesis is therefore intentionally limited and does not extend to clinical populations, overground running, or long-term intervention designs.

The empirical findings are also specific to male sub-elite runners. Although the methodological and theoretical framework developed within the thesis may be applicable more broadly, the magnitude and pattern of biomechanical and physiological adaptations identified should not be assumed to represent female runners. Sex may act as an individual constraint on running behaviour, and the transferability of the present findings to female runners therefore requires direct investigation.

1.6 Contributions to Knowledge

This thesis makes several original contributions to knowledge. It synthesises the existing evidence on the use of multi-segment spine models in running, provides validity and reliability data to support evidence-based model selection, and extends current understanding of how spinal kinematics and coordination respond to manipulated task constraints. It also demonstrates the value of single-subject analysis for identifying individual biomechanical and physiological adaptations that may be obscured by group means alone.

1.7 Thesis Structure

Chapter 2 presents a critical literature review on running economy, running biomechanics, coordination and coordination variability, dynamical systems theory, and single-subject analysis.

Chapter 3 reports a systematic review of multi-segment spine models used to assess spinal and back movement during running.

Chapter 4 outlines the general methodological framework that underpins the empirical programme.

Chapter 5 presents Study 1, which validates and compares two multi-segment kinematic models during running.

Chapter 6 presents Study 2, which evaluates the reliability of those models and supports final model selection.

Chapter 7 presents Study 3 on biomechanical and physiological adaptation to acute fatigue in sub-elite runners.

Chapter 8 presents Study 4 on biomechanical and physiological adaptation to changes in speed in sub-elite runners.

Chapter 9 provides the general discussion, original contributions to knowledge, limitations, recommendations for future research, and overall conclusions.

Chapter 2

Literature Review

2.1 Introduction

This chapter reviews the literature that underpins the empirical programme of work presented in this thesis. The discussion focuses on running economy, running biomechanics, the role of the trunk and multi-segment spine during running, dynamical systems theory, the constraints-led approach, coordination and coordination variability, and the value of single-subject analysis in sport and exercise science. Throughout the chapter, emphasis is placed on how these areas relate to running performance and on why manipulated task constraints such as speed and fatigue provide a useful framework for exploring biomechanical and physiological adaptation in trained runners.

Long-distance running performance depends on the ability to sustain speed while limiting energetic cost and maintaining effective movement organisation over time. For this reason, the chapter begins by considering running economy as a key performance construct, before moving to the biomechanical demands of running and the increasingly recognised role of the trunk and spine in whole-body control (Barnes & Kilding, 2015; Costill, 1967; Saunders et al., 2004). The chapter then introduces dynamical systems theory as the overarching theoretical perspective through which movement adaptation is interpreted (Bernstein, 1967; Glazier et al., 2003). This is followed by the constraints-led approach, which is presented as the practical experimental framework used in this thesis to examine how running behaviour changes when task demands are manipulated (Davids et al., 2008; Newell, 1986; Renshaw et al., 2019). The discussion then moves to coordination and coordination variability, before concluding with the rationale for adopting a single-subject analytical perspective (Bates, 1996; Needham et al., 2015; Seay et al., 2011).

Although running has been studied extensively, much of the existing literature remains centred on lower-limb variables, global physiological outcomes, or simplified representations of the trunk. Comparatively less attention has been given to how the spine functions as a coordinated multi-segment structure during running, how thorax-pelvis relationships may contribute to running economy, and how these behaviours may reorganise under changing task constraints (Mason et al., 2016; Needham et al., 2015, 2020; Preece et al., 2016; Tojima et al., 2019). This represents an important omission because running technique is unlikely to be adequately explained by isolated segments acting independently. Rather, performance appears to emerge from the interaction of multiple biomechanical and physiological systems working together under the specific demands of the task (Barnes & Kilding, 2015; Folland et al., 2017; Moore et al., 2012).

2.2 Running Economy

2.2.1 Defining and measuring running economy

Running economy is commonly defined as the steady-state metabolic demand required to run at a given submaximal speed, most often quantified through oxygen uptake (Barnes & Kilding, 2015; Costill, 1967; Saunders et al., 2004). It is one of the key determinants of endurance performance because runners with similar maximal oxygen uptake can still differ substantially in the energetic cost of maintaining the same running speed (Barnes & Kilding, 2015; Daniels, 1985). As a result, running economy is often used to explain performance differences that cannot be accounted for by aerobic capacity alone.

Despite its apparent simplicity, the measurement of running economy is methodologically sensitive. Treadmill versus overground testing, gradient selection, stage duration, speed prescription, and the time window used to determine steady-state metabolism can all influence the resulting value (Barnes & Kilding, 2015; Fletcher & MacIntosh, 2017; Saunders et al., 2004). This is especially important when physiological variables are interpreted alongside biomechanical measures, because apparently small protocol differences may alter conclusions about what constitutes efficient or economical running. Running economy should therefore be viewed as a valid but protocol-sensitive construct rather than as a single fixed physiological property.

A further issue is that running economy is sometimes interpreted too narrowly as an oxygen-consumption measure alone. In practice, the energetic cost of running is closely related to the movement strategy used to achieve the task. The metabolic demand of running cannot be separated fully from biomechanics, because the way the body organises itself mechanically influences how efficiently force is produced, transferred, and controlled across the stride cycle (Folland et al., 2017; Moore, 2016).

2.2.2 Determinants of running economy

Running economy is now widely accepted as a multifactorial construct rather than a purely physiological one. Major reviews have described interacting determinants including cardiorespiratory efficiency, neuromuscular function, anthropometrics, lower-limb stiffness, tendon behaviour, and biomechanical strategy (Barnes & Kilding, 2015; Fletcher & MacIntosh, 2017; Moore, 2016; Saunders et al., 2004). This means that running economy should not be considered in isolation from movement. Rather, it reflects the interaction of multiple systems that together determine the energetic cost of locomotion.

From a physiological perspective, variables such as ventilation, substrate utilisation, aerobic efficiency, and muscle recruitment patterns contribute to the oxygen cost of running (Barnes & Kilding, 2015; Saunders et al., 2004). From a biomechanical perspective, stride characteristics, vertical oscillation, joint stiffness, trunk posture, and segmental coordination may all influence how efficiently a runner moves (Folland et al., 2017; Moore, 2016; Moore et al., 2012; Williams & Cavanagh, 1987). These factors do not operate independently. Instead, they form part of a wider coordinative solution through which the runner manages propulsion, stability, and energy transfer.

Technique itself has been shown to explain a meaningful proportion of the variance in running economy and performance. Folland et al. (2017) demonstrated that technique is an important component of both economy and performance, reinforcing the argument that economy should not be understood as a metabolic property alone. This is particularly relevant to the present thesis, because it supports the idea that trunk and spinal behaviour may contribute to the energetic cost of running and therefore warrants direct investigation.

An alternative approach to prescribing exercise intensity is the critical power concept, or its running-specific equivalent, critical velocity or critical speed. Critical power represents the asymptote of the power–duration relationship and is commonly interpreted as the boundary between the heavy- and severe-intensity exercise domains, above which physiological variables such as $\dot{V}O_2$ and blood lactate are unable to stabilise (Jones et al., 2010; Poole et al., 2016). In running, the equivalent speed–duration relationship can be used to determine critical velocity, providing an individualised marker of sustainable exercise intensity and a useful predictor of endurance performance.

Although critical power or velocity and ventilatory thresholds are related, they should not be considered physiologically interchangeable, with evidence showing differences between critical power and commonly identified metabolic and ventilatory thresholds (Galán-Rioja et al., 2020). For the present thesis, VT1 and VT2 were selected because they could be identified directly from pulmonary gas-exchange responses during the same graded treadmill test used to determine $\dot{V}O_{2max}$. This allowed subsequent running speeds to be prescribed relative to each participant's physiological response while maintaining direct methodological alignment with the $\dot{V}O_2$, ventilatory-equivalent and respiratory-exchange measures examined in the applied studies. In

contrast, conventional determination of critical power or critical velocity generally requires multiple exhaustive performance trials or a separate dedicated maximal test to establish the power- or speed-duration relationship (Jones et al., 2010; Poole et al., 2016). The purpose of the present studies was not to establish the maximal metabolic steady state or predict endurance performance, but to manipulate running intensity systematically and examine the associated biomechanical and physiological adaptation. Ventilatory thresholds were therefore considered the most appropriate and practically consistent method of individualising the running-intensity constraints used throughout the thesis.

2.2.3 Is there an economical running technique?

A recurring theme in the literature is that there is no single universally optimal running technique (Moore, 2016; Williams & Cavanagh, 1987). Economical movement solutions may differ according to a runner's morphology, tissue properties, stiffness profile, training background, and habitual coordination tendencies (Folland et al., 2017; Moore, 2016). This is important because it challenges attempts to define one ideal technique that all runners should reproduce.

In applied terms, two runners may achieve similar performance outcomes through different coordinative solutions. One athlete may rely more on elastic return and stiffness, whereas another may achieve similar economy through a different segmental arrangement or postural strategy. Variation from one runner to another should therefore not automatically be interpreted as error. Instead, it may reflect athlete-specific solutions to the same movement problem.

This idea is particularly important for the present thesis because the empirical work focuses on spinal coordination and individual adaptation. If economical running is not universal, then the investigation of trunk and spine biomechanics must remain sensitive to individual-specific movement strategies rather than assuming that one global pattern is optimal for all performers.

2.3 Running Biomechanics

2.3.1 The biomechanical demands of running

Running is a cyclic locomotor task that requires coordinated control of the lower limbs, pelvis, trunk, and upper limbs across repeated stance and flight phases (Novacheck, 1998). Much

of the existing literature has focused on lower-limb kinematics and kinetics because of their obvious role in propulsion, impact attenuation, and injury mechanisms. However, whole-body running mechanics cannot be fully understood by examining the legs alone. Segmental interactions across the body contribute to balance, angular momentum regulation, force transfer, and centre-of-mass control, all of which are relevant to both performance and injury risk (Folland et al., 2017; Moore, 2016; Novacheck, 1998).

The trunk and pelvis are particularly important in this respect because they act as the mechanical link between the upper and lower body. Their behaviour influences how motion is distributed through the system and how the runner maintains stability and orientation throughout the stride cycle (Preece et al., 2016; Seay et al., 2011). Despite this, many running studies have simplified the trunk as a single rigid segment, limiting the ability to examine how thoracic and lumbar regions contribute independently to movement control. A broader biomechanical perspective is therefore necessary when the goal is not simply to describe movement, but to understand how runners adapt when demands change. This is especially relevant when task constraints such as speed and fatigue are manipulated.

2.3.2 Fatigue in running

Fatigue in running can involve both central and peripheral mechanisms and may alter force-generating capacity, muscular efficiency, timing, stiffness regulation, and movement organisation. In endurance contexts, fatigue may present as a reduced ability to maintain performance output or as an increased energetic cost required to sustain a given speed. Prolonged running has been associated with changes in running economy and running kinematics over time, which has led to growing interest in the concept of economy durability, that is, the ability to preserve economical movement as fatigue accumulates (Giandolini et al., 2016; Kyröläinen et al., 2000).

The biomechanical effects of fatigue remain inconsistent. Reviews suggest that fatigue can alter a wide range of biomechanical variables, but the direction and magnitude of change depend on the fatigue protocol employed, the participant group studied, and the variables selected for analysis (Apte et al., 2021; Derrick et al., 2002; Dierks et al., 2010). Some studies have reported fatigue-related changes in mechanics associated with injury-related variables, whereas others have shown comparatively stable kinematics even after exhaustive exercise (Abt et al., 2011; Clansey

et al., 2012). This suggests that fatigue should not be viewed as producing one uniform biomechanical response across all runners.

Fatigue is particularly important to the present thesis because long-distance running is rarely performed in a genuinely fresh state. A typical run may involve thousands of repeated foot strikes, and this accumulated loading may challenge the stability of coordinative patterns over time (Mizrahi et al., 2000a, 2000b). In that context, fatigue may reveal whether spinal coordination remains stable under increasing demand or whether runners reorganise movement in order to preserve performance.

2.3.3 Speed in running

Running speed is a major task constraint because increasing speed changes both the mechanical and physiological demands of locomotion. As speed increases, runners must reorganise stride mechanics, segmental posture, and whole-body coordination in order to maintain forward progression efficiently. These changes are not confined to the lower limbs. Previous work has shown that thoracic, lumbar, and pelvis motion can also change with increasing speed, suggesting that faster running requires broader segmental reorganisation across the body (Preece et al., 2016; Saunders et al., 2005; Tojima et al., 2019).

Speed-related increases in spinal motion appear especially evident in the transverse plane. Tojima et al. (2019) reported progressive increases in thoracic and lumbar motion as treadmill speed increased, with lumbar axial rotation showing particularly notable changes. Preece et al. (2016) also reported increases in trunk inclination and regional spinal behaviour with increasing speed. These findings suggest that faster running is not simply a matter of increasing stride frequency or stride length, but involves a wider reorganisation of how movement is distributed across the trunk and spine. For the present thesis, speed manipulation provides a practical and physiologically meaningful way of probing whether spinal coordination remains stable under greater demand or reorganises in response to increasing task intensity.

2.3.4 Trunk and spine biomechanics during running

The morphology and function of the human spine should also be considered within the context of its evolutionary development. The transition to habitual bipedalism required the axial skeleton to support an upright trunk while maintaining the body's centre of mass over the pelvis and lower limbs. Compared with non-human apes, the evolution of the human vertebral column involved a relatively elongated and mobile lumbar region and the development of lumbar lordosis, alongside the characteristic thoracic and lumbar spinal curvatures associated with upright posture (Lovejoy, 2005; Whitcome et al., 2007). Lumbar lordosis is particularly important because it positions the trunk over the hips, contributing to balance and reducing the muscular demand required to maintain an upright posture during bipedal locomotion (Whitcome et al., 2007). The later evolution of endurance-running capabilities within *Homo* placed further demands on postural control and stabilisation of the trunk during locomotion, with anatomical adaptations associated with sustained running proposed to have contributed to the evolution of the modern human body form (Bramble & Lieberman, 2004).

Functionally, the vertebral column is not a continuous rigid structure but consists of a series of individual motion segments. Each functional spinal unit comprises adjacent vertebrae connected through an intervertebral disc anteriorly and paired zygapophyseal, or facet, joints posteriorly, together with surrounding ligamentous and muscular structures. The facet joints are synovial articulations whose orientation helps to guide and constrain movement between adjacent vertebrae, while the intervertebral discs permit controlled movement and contribute to the transmission and distribution of compressive load (Jaumard et al., 2011; Inoue et al., 2020). Importantly, facet-joint orientation is not uniform throughout the vertebral column. Masharawi et al. (2004) demonstrated progressive regional variation in facet orientation throughout the thoracolumbar spine, including considerable anatomical variability around the thoracolumbar junction. These regional differences contribute to the different mechanical functions of the thoracic and lumbar spine. Within the thoracic region, facet orientation permits multi-planar movement, including axial rotation and lateral flexion, although movement is additionally constrained by the ribs, sternum and costovertebral articulations. The rib cage therefore forms a biomechanical unit with the thoracic spine and contributes substantially to thoracic stiffness and stability across all three planes of

motion (Liebsch & Wilke, 2022). In contrast, the orientation of the lumbar facet joints, together with the larger vertebral bodies and intervertebral discs, reflects the greater load-bearing requirements of this region. Lumbar anatomy facilitates flexion and extension while providing greater structural resistance to axial rotation, meaning that thoracic and lumbar regions should not be expected to demonstrate equivalent movement behaviour (Masharawi et al., 2004; Inoue et al., 2020).

A further consequence of this anatomy is that spinal movement rarely occurs independently within a single anatomical plane. Coupled motion describes secondary movement occurring in a plane other than that of the primary movement and is influenced by the geometry of the facet joints, intervertebral discs, ligamentous restraints, spinal posture and, within the thoracic region, the rib cage. For example, lateral flexion may occur alongside axial rotation rather than as an isolated frontal-plane movement. However, the direction and magnitude of this coupling should not be assumed to follow one fixed pattern. Sizer et al. (2007) systematically reviewed thoracic spinal coupling and found ipsilateral, contralateral and mixed patterns across the available literature, with no consistent universal coupling behaviour identified. Similarly, Legaspi and Edmond (2007) reported evidence that coupled motion occurs within the lumbar spine but found limited agreement regarding the specific direction or characteristics of the relationship between lateral bending and rotation. More recent evidence obtained under standardised in-vitro loading conditions has provided greater evidence of a relationship between lateral bending and axial rotation. Liebsch and Wilke (2025), for example, identified moderate-to-high ipsilateral axial rotation during thoracic lateral bending and low-to-moderate contralateral lateral bending during primary thoracic axial rotation. However, these findings were obtained under controlled passive loading and should not be assumed to describe the behaviour of the spine during dynamic tasks such as running, where muscular control, impact loading and whole-body coordination contribute to the movement solution.

These anatomical and biomechanical characteristics are particularly relevant to running because the spine is required simultaneously to transmit load, regulate trunk position and allow multi-planar movement between the pelvis and upper body. Regional differences in facet orientation, spinal curvature and external constraint from the rib cage mean that the thoracic and

lumbar regions have different available movement capacities, while coupled motion means that adaptation in one plane may be accompanied by changes in another. The spine should therefore be considered a coordinated multi-segment and multi-planar structure rather than a series of independent hinges or a single rigid trunk. This is consistent with evidence from running showing different thoracic and lumbar contributions to spinal movement, particularly within the transverse plane (Preece et al., 2016; Tojima et al., 2019). It also provides an anatomical rationale for the multi-segment approach adopted within the present thesis, in which upper thoracic, lower thoracic, upper lumbar and lower lumbar regions were examined separately and their coordination with neighbouring regions and the pelvis was quantified across the running gait cycle. An area that remains comparatively under-developed within running biomechanics is the role of the trunk and spine. The trunk contributes to whole-body coordination, centre-of-mass regulation, and the transmission of forces between the upper and lower body. Despite this, many running studies have historically simplified the trunk as a single rigid segment, limiting insight into how thoracic and lumbar regions behave during locomotion.

More recent work has challenged that simplification. Trunk and pelvis posture have been linked to running economy and movement efficiency, while coordinated thorax-pelvis motion has been proposed as a meaningful feature of whole-body running control (Folland et al., 2017; Moore, 2016; Preece et al., 2016). Seay et al. (2011) also demonstrated that pelvis-trunk coordination is relevant to postural control and movement variability. These findings suggest that trunk and spinal behaviour may have implications not only for injury-related questions but also for economy and performance.

Sex represents an additional individual characteristic that may influence the biomechanical organisation of running. Previous research has identified sex-related differences in lumbo-pelvic motion during treadmill running (Schache et al., 2003), while differences in coordination variability have also been reported between male and female runners (Boyer et al., 2017). More specifically to the trunk, Fisher et al. (2018) identified sex-related differences in thoracic kinematics across changes in running speed, indicating that the response of the trunk to increasing task demand may not be identical between males and females. Female runners have also been reported to demonstrate differences in pelvic mechanics, including greater pelvic obliquity, which may influence movement organisation further along the kinetic chain (Willson et al., 2015). These findings are relevant to the present thesis because sex can be considered an individual constraint

within a dynamical systems framework. Consequently, although common principles of spinal coordination and adaptation may exist across runners, the magnitude, timing and regional distribution of these adaptations may differ between males and females. This reinforces the need for sex-specific investigation rather than assuming that findings obtained from one sex can be directly generalised to the other.

The present thesis therefore treats the trunk and spine as active contributors to running behaviour rather than passive structures carried by the limbs. This is especially important when examining adaptation under altered task demands.

2.3.5 Measuring the spine during running

The measurement of spinal motion during running has historically been limited by methodological difficulties. Soft-tissue artefact, marker-placement uncertainty, surface deformation, and the challenge of defining anatomically meaningful spinal segments all complicate the use of marker-based motion capture for spinal analysis. As a result, many earlier running studies used rigid-trunk or lumbo-pelvic models rather than more anatomically differentiated approaches.

Advances in motion capture and modelling now allow the spine to be represented as multiple segments, improving the ability to examine regional motion and inter-segment coordination. Previous work has shown that thoracic spine, lumbar spine, and pelvis kinematics can be quantified with acceptable reproducibility during faster running, supporting the feasibility of multi-segment modelling in both research and applied contexts (Mason et al., 2016; Needham et al., 2015, 2020; Preece et al., 2016; Tojima et al., 2019).

Even so, substantial methodological variation remains. Studies differ in marker placement, coordinate-system definition, segment construction, reference frames, and rotation sequences, making cross-study comparison difficult (Benedetti et al., 2017; Leardini et al., 2009; Simon, 2004). This is especially relevant to the present thesis because it reinforces the need for model validation and reliability assessment before a multi-segment spine model can be used confidently to examine adaptation in running.

2.4 Dynamical Systems Theory, Constraints-Led Approach, Coordination Variability, and Single-Subject Analysis

2.4.1 Dynamical systems theory

Dynamical systems theory provides a useful framework for understanding movement because it emphasises coordination, control, stability, and non-linear adaptation rather than fixed templates of technique (Bernstein, 1967; Glazier et al., 2003). From this perspective, movement emerges from the interaction of many components within a complex system, rather than from the repetition of one stored motor programme. This aligns with Bernstein's (1967) degrees of freedom problem, which highlights that the motor system has many interacting parts and therefore many possible solutions for achieving the same task outcome.

For running biomechanics, this has several important implications. It suggests that there may not be one universal optimal running technique, that stable movement patterns may re-organise when constraints change, and that inter-individual differences should be expected rather than treated as noise (Glazier, 2019; Glazier et al., 2003). In other words, technique is better understood as a functional and adaptable solution than as a fixed ideal. This perspective is central to the present thesis because it provides the theoretical basis for examining how runners re-organise spinal and whole-body coordination under speed and fatigue manipulations.

2.4.2 Constraints-led approach as an experimental framework

The constraints-led approach builds on this theoretical foundation by offering a practical framework through which movement can be studied experimentally. Closely linked to ecological dynamics, it proposes that movement emerges from the interaction of individual, environmental, and task constraints (Davids et al., 2008; Newell, 1986; Renshaw et al., 2019). In this view, technique is best understood as a functional solution to a movement problem rather than as a rigid pattern that should be identical across performers.

This is particularly useful in running because constraints can be manipulated in a controlled and meaningful way. Speed, cadence prescription, time-on-task, and fatigue can all be viewed as constraints capable of reshaping coordination. Importantly, they do not operate independently. Rather, they interact with the runner's structural, physiological, and coordinative characteristics to

influence the movement solution that emerges. For the present thesis, the constraints-led approach is valuable both conceptually and methodologically. It provides the rationale for treating speed and fatigue as meaningful manipulations through which to examine adaptation in running economy and spinal coordination.

2.4.3 Coordination and coordination variability

Coordination refers to the way body segments are organised relative to one another in order to achieve a movement outcome. In running, this includes the timing and sequencing of motion between adjacent spinal regions, between the thorax and pelvis, and across the wider kinetic chain. Measures such as continuous relative phase and vector coding are particularly useful because they move beyond isolated joint angles and instead describe the relationship between segments over time (Needham et al., 2015; Seay et al., 2011). This is especially important for the spine, where the motion of one region may only be meaningful when interpreted relative to neighbouring segments or the pelvis.

Coordination variability has historically been interpreted in two contrasting ways. Traditionally, variability was viewed as undesirable noise around an ideal movement pattern. More contemporary interpretations, informed by dynamical systems theory, suggest that some variability is functional because it reflects adaptability and the capacity of the system to re-organise under changing demands (Davids et al., 2008; Glazier et al., 2003). From this perspective, variability is not inherently positive or negative. Its interpretation depends on the task, the performer, and whether it appears to support or disrupt performance.

In running, this is particularly important because movement patterns that appear variable at the group level may actually represent individual-specific solutions. The literature on coordination variability has focused predominantly on the lower limbs, while spinal coordination and its variability remain underexplored, particularly in trained runners and under manipulated task constraints (Preece et al., 2016; Seay et al., 2011). Yet thorax-pelvis and inter-segmental spinal relationships are likely to be important for postural control, centre-of-mass regulation, and efficient force transmission.

2.4.4 Single-subject analysis

Group-based statistical approaches remain valuable in biomechanics, but they can also obscure meaningful individual responses when substantial inter-individual variability is present. This is especially relevant for running, where different athletes may achieve similar outcomes through different coordinative strategies. A single-subject approach is therefore useful because it allows the researcher to examine how each runner responds to manipulated task constraints rather than assuming that the group mean adequately represents every participant (Bates, 1996).

This analytical position is well aligned with the theoretical framework adopted in this thesis. If movement emerges from the interaction of individual, environmental, and task constraints, then meaningful adaptation is likely to vary between runners. A given change in speed or fatigue may destabilise one runner's coordinative solution while leaving another's relatively unchanged.

Single-subject analysis therefore provides a more sensitive way of examining athlete-specific changes in biomechanics, coordination, and physiology. In the present thesis, this is particularly important because the aim is not only to identify whether adaptation occurs, but to understand how that adaptation may differ between individuals under different running constraints.

2.5 Summary of Gaps

The literature reviewed in this chapter shows that running economy is a key determinant of endurance performance and is shaped by both physiological and biomechanical factors. It also shows that fatigue and speed can alter running mechanics and energetic cost, although these responses are highly dependent on the runner and the demands of the task. At the same time, the trunk and multi-segment spine appear to play an important role in whole-body control, yet they remain comparatively underrepresented in running research when compared with lower-limb variables.

Several gaps therefore remain. First, there is limited evidence describing multi-segment spinal motion and thorax-pelvis coordination during running. Second, the relationship between these variables and running economy is still poorly characterised, particularly under systematically manipulated task constraints. Third, although fatigue and speed are likely to alter coordination in

meaningful and condition-specific ways, much of the literature remains centred on group-level analysis and therefore offers limited insight into individual adaptation. Finally, although advances in modelling have improved the feasibility of spinal analysis during running, methodological inconsistency remains an important limitation and reinforces the need for validation and reliability assessment. Together, these issues provide the rationale for the empirical studies that follow. They support the need for validated and reliable multi-segment kinematic models, the examination of spinal and whole-body adaptation under manipulated task constraints, and the use of a constraint-led and single-subject framework within this thesis.

Chapter 3

Comparing kinematic models to quantify three-dimensional spine, back and pelvis movement during running using marker-based systems: A systematic review

3.1. Introduction

Running economy (RE) describes the energy cost of running at a given submaximal speed and is a key determinant of distance-running performance. However, runners with similar maximal oxygen uptake can still differ substantially in RE, suggesting that performance is influenced by more than cardiorespiratory capacity alone (Daniels, 1985; Folland et al., 2017). Metabolic, neuromuscular, biomechanical and training-related factors have all been proposed as contributors to these between-runner differences (Barnes & Kilding, 2015).

From a biomechanical perspective, coordination between the trunk and pelvis during running may influence both economy and performance. Greater excursion in forward and backward trunk lean has been associated with higher energy cost, while greater pelvic transverse-plane rotation has been linked to both higher energy cost and poorer performance (Folland et al., 2017). In addition, coordinated thorax–pelvis motion has been proposed as a mechanism for reducing unnecessary centre-of-mass motion during running (Preece et al., 2016c). These findings support the need to quantify spine, back and pelvis motion in three dimensions.

Although optoelectronic marker-based motion capture systems are widely regarded as the reference standard for gait analysis, variability in three-dimensional kinematic modelling approaches makes interpretation and comparison across studies difficult (Benedetti et al., 2017; Simon, 2004). In running research, the trunk has often been modelled as a single rigid segment, or thorax motion has been analysed relative to the pelvis, but more detailed multi-segment approaches have also been proposed (Preece et al., 2016a; Tojima et al., 2019).

Interpretation of these models is further complicated by differences in marker application, including the use of rigid three-dimensional clusters and skin-mounted marker sets. In addition, pelvic kinematics are defined differently between studies, yet pelvic motion is fundamental to the interpretation of relative spinal motion. Taken together, these issues justify a review of how current marker-based models quantify spine, back and pelvis movement during running, and whether a more standardised methodological approach can be identified (Leardini et al., 2005; Needham et al., 2016).

This systematic review aimed to critically evaluate published literature on kinematic modelling techniques used to assess three-dimensional movement of the spine, back and pelvis during running using marker-based motion capture systems.

3.2. Methods

This systematic review was conducted in accordance with PRISMA guidelines. This review was not prospectively registered, and a separate protocol was not published.

3.2.1 Scope and boundaries

The review focused on the use of optoelectronic marker-based systems to quantify spine and back movement during running. Areas of interest included participant characteristics, kinematic modelling techniques and methodological considerations such as validity, reliability, data collection procedures, data analysis approaches and outcome measures (for example, range of motion, peak angle, relative and segment angles, and angle–time waveforms). Three-dimensional pelvic kinematics were included when reported alongside spine or back models.

3.2.2 Search strategy and review process

Searches were completed between April 2025 and May 2025 using SPORTDiscus, PubMed, MEDLINE, ScienceDirect, CINAHL and Scopus. MeSH terms and free-text terms were searched within title, abstract and keyword fields. Database filters included human, journal article, English language and full text where available. Reference lists of included papers were also screened to identify additional relevant studies.

Titles and abstracts were screened independently by two reviewers (CH and RN). Where insufficient information was available from the title or abstract, the full text was reviewed.

Search terms: running OR run OR sprint OR sprinting; AND ((pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral) AND (three dimensional OR 3D OR two dimensional OR 2D OR motion analysis OR non-invasive OR body mounted OR skin mounted OR cluster)).

3.2.3 Inclusion and exclusion criteria

Studies were included if they: (1) recruited human participants, with no restrictions on age, sex or health status; (2) quantified three-dimensional spine or back kinematics during running using a marker-based motion capture system; (3) reported numerical data and/or angle–time kinematic waveforms; and (4) were published in English as full-text articles.

Studies were excluded if they: (1) examined sports other than running or reported only walking or jogging speeds below 2.0 m/s; (2) used video-based recording technology only; or (3) reported only pelvic and lower-limb kinematics without spine or back outcomes.

3.2.4 Data extraction and methodological quality appraisal

Data extraction was guided by a quality appraisal tool adapted from previous systematic reviews of marker-based systems and kinematic modelling (Bishop et al., 2012; Needham et al., 2016). The tool comprised 15 questions related to research aims, participant description, laboratory setup, marker placement, segment definition, coordinate systems, rotation sequences, validity, reliability, data processing, outcome presentation and study limitations. Each item was scored as 2 (yes), 1 (limited detail) or 0 (no)

Table 3.1. Assessment of research quality tool

1. Are the research objectives or aims clearly stated?
 2. Are appropriate participant information and anthropometric details provided?
 3. Is the calibration and equipment set-up of the marker-based system stated?
 4. Are the marker locations and/or structural dimensions of the 3d cluster clearly described?
 5. Are the spine and/or back segment/s clearly defined?
 6. Is the segment/cluster coordinate system clearly defined?
 7. Are the methods used to describe the axes and order of rotations clearly described or referenced?
 8. Are appropriate validation procedures documented and reported?
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9. Are the appropriate reliability procedures documented and reported?
 10. Are data processing techniques reported?
 11. Are numerical data representing segment information presented?
 12. Are numerical data representing relative information presented?
 13. Are waveform data representing segment information presented?
 14. Are waveform data representing relative information presented?
 15. Are the limitations of the study clearly described?
-

Items were scored as 2 = yes; 1 = limited detail; 0 = no (adapted from Bishop et al., 2012; Needham et al., 2016).

3.2.5 Support and competing interests

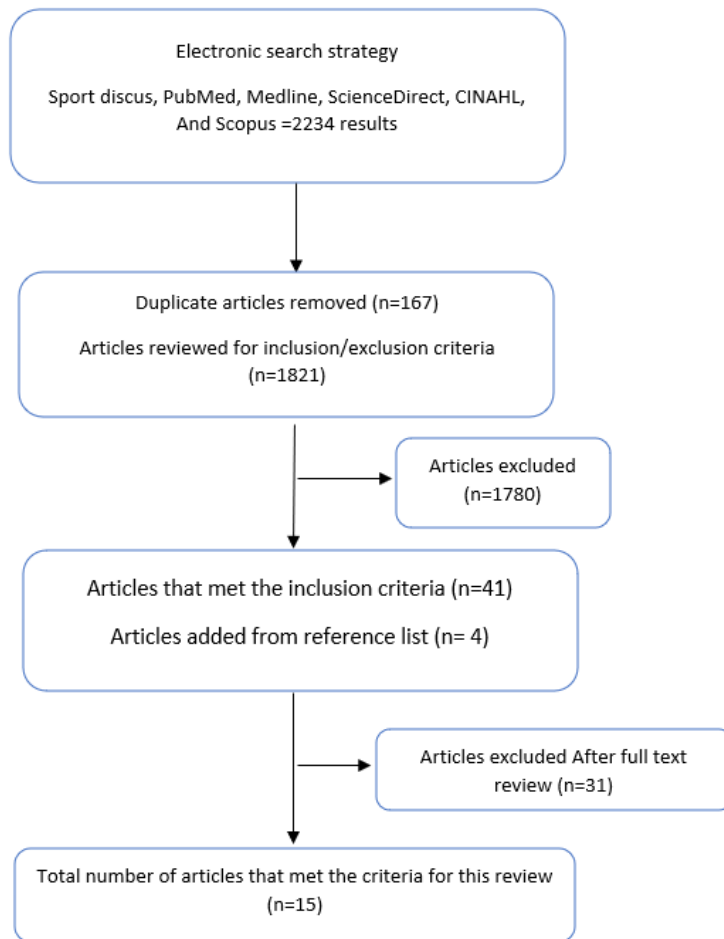
No external funding was received specifically for this systematic review. The review was completed as part of the author's doctoral research at the University of Staffordshire. The author declares no competing interests in relation to this review.

3.3 Results

3.3.1 Search results

The systematic search strategy identified 2234 records across the selected databases. After title and abstract screening, 37 articles were retained for full-text review. Screening of reference lists identified a further four potentially relevant studies. Following full-text review, 13 studies were included. During final manuscript preparation, two additional eligible studies (Tojima et al., 2019; Fisher et al., 2018) were identified and met the predefined inclusion criteria. The final narrative synthesis therefore reflects 15 included studies.

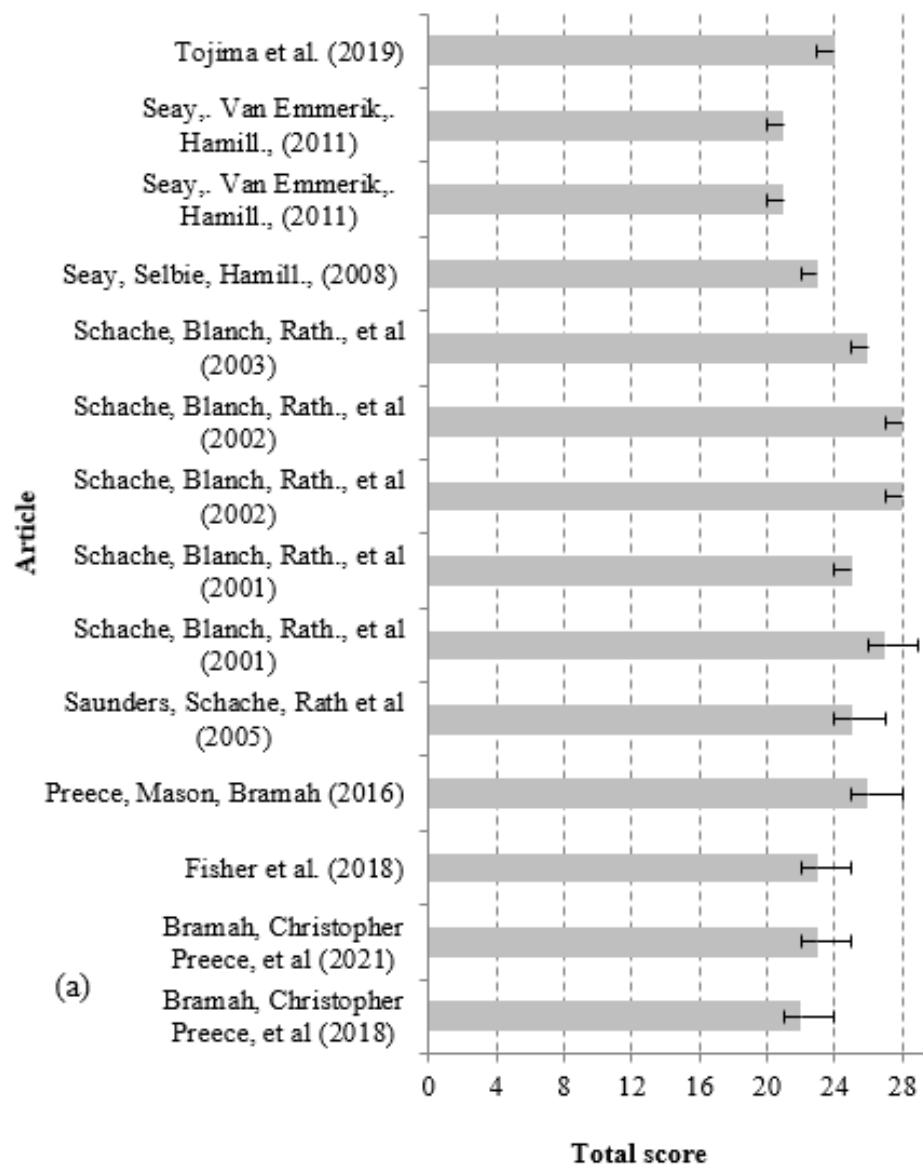
Figure 3.1. Flowchart describing the systematic search strategy used to identify the articles included in this review.



3.3.2 Quality assessment

A summary of study quality is presented in Figure 3.2. Based on the adapted scoring system, the median quality score across the included studies was 1.8 out of 2 per item. Most included studies were of moderate to high methodological quality, although completeness of reporting varied across studies.

Figure 3.2. Quality assessment results for the studies reviewed.



3.3.3 Reliability and validity measures

Most included studies reported laboratory setup and calibration procedures, although the strength of validity and reliability evidence varied substantially across the included literature (Table 3.6). Direct reliability or measurement-error evidence was reported most clearly by Bramah et al. (2021), who quantified between-day repeatability, standard error of measurement and minimal detectable change for discrete running kinematic variables, and by Schache et al. (2002b), who assessed intra-subject repeatability of lumbo-pelvic-hip kinematics. Preece et al. (2016a) also provided model-development evidence by comparing agreement and variability

between thoracic and lumbar marker-set configurations. In contrast, many other studies relied on established marker protocols, methodological rationale or citations to previous work rather than reporting study-specific validity or reliability testing. No included study directly validated measured spinal motion against an anatomical gold standard during running. Therefore, reliability evidence was strongest for selected applied trunk/pelvis and lumbo-pelvic outcomes but remained limited for several regional spine and coordination models.

3.3.4 Participant characteristics

The included studies recruited either healthy runners or mixed samples comprising healthy runners and runners with pathology. Reported pathology groups included low back pain, iliotibial band syndrome, medial tibial stress syndrome and Achilles tendinopathy. Participant classification varied considerably between studies, with terms such as general population, recreational runners, active runners, experienced runners, collegiate athletes and elite runners used inconsistently. Tojima et al. (2019) examined seven healthy female runners, described as collegiate track-and-field athletes, whereas Fisher et al. (2018) assessed 19 healthy runners during overground running and examined sex-related differences in thorax kinematics across speeds. In several studies, training status was not clearly reported.

Sex reporting was also inconsistent. Some studies recruited single-sex cohorts, whereas others pooled male and female data or did not clearly state sex distribution. Tojima et al. (2019) included only female participants, whereas Fisher et al. (2018) analysed male and female runners and reported sex-related differences in thoracic kinematic responses to speed. This inconsistency limits direct comparison between studies and supports the case for clearer sex-specific reporting.

Table 3.2. Participant characteristics

Study	Population/h ealth status	Training status/runner classification	Number of participants	Sex	Age	Height (cm)	Mass (kg)	Footwear
Bramah et al. (2018)	Mixed cohort including common soft tissue running injuries	Runners	108, 36 healthy & 72 pathology	Male (15 healthy, 28 pathology) & Female (21 healthy, 44 pathology)	Healthy 33.2±8.4 Pathology 34.8±9.9	Healthy 171.6±7.3 Pathology 170.7±8.6	Healthy 60.8±8.4 pathology 63.4±10.5	Own footwe ar
Bramah et al. (2021)	Healthy runners	Experienced runners >2yrs, 3x week	16	Male 6 & female 10 pooled	30.4±10.2	169.1±9.4	59.7±10.8	Own footwe ar
Fisher et al. (2018)	Healthy runners	Recreational runners 35-60 min 10km time	19	Male 9 & Female 10	M 36.7 23- 44 F 31.9 22-44	M 181 170- 190 F 170 150-180	M 85.9 58.4- 108.9 F 60.1 49.3-89.3	NR
Preece et al. (2016a)	Healthy runners	Healthy runners	15	Male	25±5	178±6.89	63.1±6.1	NR

Preece et al. (2016b)	Healthy runners	recreational 40-47 min 10km & elite runners 30-35 min 10km	28, 14 Rec 14 elite	Male pooled	28±3	175±0.09	63±9	NR
Saunders et al. (2005)	Healthy runners	Active runners> 20 km a week	7	6M 1F pooled	33, 31-37	NR	NR	Own footwear
Schache et al. (2001a)	Healthy runners	Active runners >20km a week	10	9M 1F pooled	28.3±4.7	177.8±5.3	77.1±8.2	Own footwear
Schache et al. (2001b)	Healthy runners	Active runners >20km a week	4	Male	27 21-34	180 175-185	78 76-82	Own footwear
Schache et al. (2002a)	Healthy runners	Active runners> 20 km a week	20	Male	32.7±7.3	178.3±4.6	75.1±6.8	Own footwear

Schache et al. (2002b)	Healthy runners	Active runners > 20 km a week	14	11 male, 3 Female pooled	29.8±4.8	176.5±8.5	73.2±5.8	Own footwear
Schache et al. (2003)	Healthy runners	Recreational and elite runners > 20 km a week	44	Male 22 & female 22	M 34.6±7.3 F 34.7±6.1	M 177±0.05 F 167±0.09	M 72.7±6.9 F 60.8±6.4	Own footwear
Seay et al. (2008)	General population	General population	10	NR	26.2±2.9	172±0.14	66.2±10.2	Own footwear
Seay et al. (2011a)	Runners with and without low back pain	Recreational runners	42	Male GP1 8, GP2 9, GP3 6 and female GP1 6, GP2 5, GP3 8 over 3 groups pooled M & F	GP1 35.71±10.9 0 GP2 32.56±9.42 GP3 29.90±0.36	GP1 171±0.12 GP2 172±0.10 GP3 169±0.10	GP1 73.94±13.42 GP2 71.43±9.75 GP3 63.94±10.06	NR

Seay et al. (2011b)	Runners with and without low back pain	Recreational runners	42	Male GP1 8, GP2 9, GP3 6 and female GP1 6, GP2 5, GP3 8 over 3 groups pooled M & F	GP1 35.71±10.9 0 GP2 32.56±9.42 GP3 29.90±0.36	GP1 171±0.12 GP2 172±0.10 GP3 169±0.10	GP1 73.94±13.42 GP2 71.43±9.75 GP3 63.94±10.06	NR
Tojima et al. (2019)	Healthy runners	Collegiate track-and-field athletes	7	Female only	19.4±1.4	159±5.7	47.8±4.1	NR

Abbreviations: NR = not reported in the source; N/A = not applicable. In the Cluster makeup column, material and fixation details are only stated when reported clearly; otherwise they are recorded as NR.

3.3.5 Running conditions and speeds

Running trials were conducted overground, on a treadmill, or in both conditions. Most studies used treadmill running, while fewer examined overground running alone. One study directly compared overground and treadmill running and reported minimal differences in spine and pelvic angular kinematics between the two conditions (Schache et al., 2001b). Tojima et al. (2019) used fixed treadmill speeds of 6, 9 and 12 km/h, whereas Fisher et al. (2018) compared thorax kinematics during slower-than-self-selected, self-selected and faster-than-self-selected overground running. Across the review, running speeds ranged from approximately 2.0 m/s to sprint-like conditions, with several studies assessing more than one speed.

3.3.6 Footwear

Footwear is known to influence running mechanics and performance; however, footwear control was limited across the included studies. Several studies allowed participants to wear their own preferred shoes, and others did not report footwear at all. No study clearly stated that footwear was standardised for all participants.

3.3.7 Kinematic modelling procedures

Both cluster-based and skin-mounted marker models were used. Most studies used either a rigid cluster combined with skin-mounted markers or an established lumbo–pelvic marker set. Four studies used the thoracic/lumbar cluster described by Preece et al. (2016a). Several other studies used the lumbo–pelvic marker configuration described by Schache and colleagues. Tojima et al. (2019) used a skin-mounted whole-body marker set to examine thoracic spine, lumbar spine and hip motion, whereas Fisher et al. (2018) used an optical marker-based approach focused specifically on thorax kinematics during overground running.

Model definitions differed substantially. Some studies treated the trunk as a single rigid segment, others focused specifically on the thorax, and others modelled the lumbar spine or combined thoracic and lumbar segments. Table 3.3 makes these modelling differences more explicit by separating the general marker/model approach from the specific construction of any rigid cluster or wand. This showed that cluster use was not uniform across the reviewed literature. Bramah et al. (2018, 2021) used a rigid trunk cluster, Preece et al. (2016a, 2016b) used a mixed model combining a sternum-mounted rigid cluster with skin-mounted lumbar markers,

and the Schache/Saunders lumbo-pelvic studies used a mixed skin-mounted approach with a three-marker posterior lumbar wand/cluster projecting from the lumbar region. By contrast, Fisher et al. (2018), Seay et al. (2008, 2011a, 2011b) and Tojima et al. (2019) did not report a rigid body cluster and relied on skin-mounted marker sets. Reporting of cluster materials and fixation methods was inconsistent, with several studies failing to state the material used or how the cluster/wand was secured to the body.

3.3.8 Data processing

All included studies reported at least some data processing procedures. Most studies used a low-pass Butterworth filter, with cut-off frequencies typically between 5 and 10 Hz, although several studies did not clearly report filtering details. All studies normalised data to the running gait cycle to facilitate comparison across participants and conditions.

3.3.9 Data reporting

Outcome reporting varied considerably. Some studies reported only range-of-motion values, others reported peak angles, and a smaller number reported both. Many studies presented both numerical and graphical outputs, including bar charts, scatter plots or kinematic waveforms, whereas others presented graphical data only. Tojima et al. (2019) and Fisher et al. (2018) provided useful speed-based comparisons by reporting regional spinal or thoracic outcomes across multiple speeds; however, their reporting differed in the exact variables emphasised and in whether pelvic outcomes were available.

Most studies also reported pelvic kinematics, although not always in the same way. In some cases, pelvic angles were reported relative to the spine and the laboratory coordinate system, whereas in others pelvic motion was reported relative to the laboratory only. A small number of studies did not report pelvic outcomes despite including a trunk or spine model; this group included Tojima et al. (2019) and Fisher et al. (2018), limiting interpretation of spine–pelvis coupling.

Table 3.3. Software and methods details

Study	Running condition	Speed (m/s)	System used	Marker/model approach	Cluster construction	Calibration methodology	Segment(s) modelled	Study type
Bramah et al. (2018)	Treadmill	3.2	12-camera Qualysis Oqus (Gothenburg , Sweden) & 3 AMTI force plates	Cluster-based trunk/spine model	Cluster-based. Rigid reflective-marker trunk cluster used with skin-mounted pelvic/anatomical markers.	Static calibration of each participant	Rigid trunk segment	Pathologies included iliotibial band syndrome, medial tibial stress syndrome and Achilles tendinopathy.
Bramah et al. (2021)	Treadmill	3.2	12-camera Qualysis Oqus (Gothenburg , Sweden) & 3 AMTI force plates	Cluster-based trunk/spine model	Same as Bramah et al. (2018)	Static calibration of each participant	Rigid trunk segment	Repeatability study
Fisher et al. (2018)	Overground	Male: 2.4±0.2, 3.0±0.3, 3.7±0.5. Female: 2.7±0.4, 3.1±0.5, 3.8± 0.5	8 Camera thorax model Vicon (Vicon Motion Systems Ltd)	No rigid body cluster reported. Skin-mounted marker set used	Vicon 5 marker wand & static calibration of each participant	Thorax and pelvis	Overground thorax study with sex-specific speed analysis	

Preece et al. (2016a)	Overground	5.2 ($\pm 2.5\%$)	12 camera Qualysis Oqus (Gothenburg, Sweden) & 2 AMTI force plate	Rigid kite-shaped sternum cluster	Mixed cluster/skin-mounted. Thorax tracked using a rigid kite-shaped sternum plate/cluster, Lumbar spine tracked with skin-mounted markers.	Static calibration of each participant	Thoracic and lumbar spine	Technical note / marker-set paper
Preece et al. (2016b)	Overground	3.3, 3.9, 4.8, 5.6 ($\pm 2.5\%$)	12 camera Qualysis Oqus (Gothenburg, Sweden) & 2 AMTI force plates	Rigid kite-shaped sternum cluster	Same as Preece et al. (2016a)	Static calibration of each participant	Thoracic and lumbar spine with pelvis	Speed progression study
Saunders et al. (2005)	Treadmill	1,2,3,4,5	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo– pelvic marker set/cluster	Same as Schache et al. (2001a)	Static calibration of each participant	Trunk and lumbar spine	Compared locomotor mode and speed
Schache et al. (2001a)	Treadmill	4.2	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo– pelvic marker set/cluster	Mixed/skin-mounted wand cluster. Lumbar 3 marker wand projecting from the back, with reflective skin markers for pelvis/trunk.	Static calibration of each participant	Lumbar spine and pelvis	Cardan sequence study

Schache et al. (2001b)	overground & treadmill	3.99±0.50 OG, 3.98±0.47 TM	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo–pelvic marker set/cluster	Same as Schache et al. (2001a)	Static calibration of each participant	Lumbar spine and pelvis	3D lumbar–pelvic kinematics
Schache et al. (2002a)	Treadmill	4	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo–pelvic marker set/cluster	Same as Schache et al. (2001a)	Static calibration of each participant	Lumbar spine and pelvis	Intra-subject repeatability study
Schache et al. (2002b)	Treadmill	3.9 ±0.5	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo–pelvic marker set/cluster	Same as Schache et al. (2001a)	Static calibration of each participant	Lumbar spine and pelvis	Overground vs treadmill comparison
Schache et al. (2003)	Treadmill	4	6 Camera Vicon (Vicon Motion Systems Ltd)	Lumbo–pelvic marker set/cluster	Same as Schache et al. (2001a)	Static calibration of each participant	Lumbar spine and pelvis	Sex comparison study
Seay et al. (2008)	Overground	Constant speed with	8-camera Qualysis Oqus	Skin-mounted	No rigid body cluster reported. Skin-mounted marker set used	Static calibration of	Lumbo-sacral / trunk–pelvis	Stride-length manipulation study

		stride-length manipulation	(Gothenburg, Sweden)	lumbo-sacral model		each participant		
Seay et al. (2011a)	Treadmill	0.8-3.8 (0.5 increments)	8 camera system (Notion Analysis Corp)	Skin-mounted markers	No rigid body cluster reported. Skin-mounted marker set used	Static calibration of each participant	Trunk–pelvis coordination	Low back pain comparison
Seay et al. (2011b)	Treadmill	0.8-3.8 (0.5 increments)	8 camera system (Notion Analysis Corp)	Skin-mounted markers	No rigid body cluster reported. Skin-mounted marker set used	Static calibration of each participant	Trunk–pelvis coordination and variability	Coordination variability study
Tojima et al. (2019)	Treadmill	6, 9 and 12 km/h	8-camera Qualysis Oqus (Gothenburg, Sweden)	Skin-mounted whole-body marker set	No rigid body cluster reported. Skin-mounted marker set used	Static calibration of each participant	Thoracic spine, lumbar spine and hip	Speed-comparison study (6, 9 and 12 km/h)

Abbreviation: NR = not reported in the source

Table 3.4. Outcome measures

Study	Primary kinematic region	Outcome type(s)	Pelvis reported?	Reference frame	Main reporting format
Bramah et al. (2018)	Trunk/pelvis	Peak angles	Yes	Pelvis relative to laboratory	Numerical + graphical
Bramah et al. (2021)	Trunk/pelvis	Peak angles	Yes	Pelvis relative to laboratory	Numerical + graphical
Fisher et al. (2018)	Thorax	Peak angles and ROM across speeds	No	Thorax relative to laboratory	Numerical + graphical
Preece et al. (2016a)	Thoracic and lumbar spine	Peak angles / technical outputs	No	Segment-based from cluster	Numerical + graphical
Preece et al. (2016b)	Spine and pelvis across speeds	ROM	Yes	Pelvis relative to laboratory	Numerical + graphical
Saunders et al. (2005)	Trunk and lumbar spine	ROM and peak angles	Yes	Pelvis relative to spine and laboratory	Graphical + numerical
Schache et al. (2001a)	Lumbar spine and pelvis	ROM	Yes	Pelvis relative to laboratory	Numerical + graphical
Schache et al. (2001b)	Lumbar spine and pelvis	Peak angles	Yes	Pelvis relative to spine and laboratory	Numerical + graphical
Schache et al. (2002a)	Lumbar spine and pelvis	Peak angles	Yes	Pelvis relative to spine and laboratory	Numerical + graphical
Schache et al. (2002b)	Lumbar spine and pelvis	ROM	Yes	Pelvis relative to laboratory	Numerical + graphical
Schache et al. (2003)	Lumbar spine and pelvis	Peak angles	Yes	Pelvis relative to laboratory	Numerical + graphical
Seay et al. (2008)	Lumbo-sacral loading/trunk–pelvis	Peak angles	Yes	Pelvis relative to laboratory	Numerical + graphical
Seay et al. (2011a)	Pelvis–trunk coordination	ROM	Yes	Pelvis relative to laboratory	Graphical
Seay et al. (2011b)	Pelvis–trunk coordination and variability	ROM	Yes	Pelvis relative to laboratory	Graphical

Tojima et al. (2019)	Thoracic spine, lumbar spine and hip/pelvis	Peak angles, ROM, waveforms	Yes	Segment-based angles	Numerical + graphical
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Abbreviations: NR = not reported in the source details provided in this manuscript draft; N/A = not applicable. In the Cluster makeup column, material and fixation details are only stated when reported clearly; otherwise they are recorded as NR.

Table 3.5. Comparison of reported angle outputs across included studies by plane of movement

Study	Segment/reference definition and running condition	Sagittal-plane outputs	Frontal-plane outputs	Transverse-plane outputs
Bramah et al. (2018)	Rigid trunk and pelvis relative to the laboratory coordinate system. Treadmill running at 3.2 m/s; healthy controls vs injured runners.	Initial contact: trunk forward lean $3.9 \pm 2.9^\circ$ controls vs $5.7 \pm 3.9^\circ$ injured; pelvis anterior tilt $5.9 \pm 3.3^\circ$ vs $7.0 \pm 3.8^\circ$. Mid-stance: trunk forward lean $9.5 \pm 2.9^\circ$ vs $12.0 \pm 4.9^\circ$; pelvis anterior tilt $5.0 \pm 2.9^\circ$ vs $5.7 \pm 3.8^\circ$.	Initial contact: trunk ipsilateral lean $2.5 \pm 1.8^\circ$ controls vs $3.1 \pm 2.2^\circ$ injured. Mid-stance: trunk ipsilateral lean $3.6 \pm 1.8^\circ$ vs $4.3 \pm 2.6^\circ$; contralateral pelvic drop $3.7 \pm 1.9^\circ$ vs $6.4 \pm 2.1^\circ$. Each 1° increase in pelvic drop increased odds of injury classification by approximately 80%.	Mid-stance hip internal rotation was reported as $4.4 \pm 6.8^\circ$ in controls vs $4.2 \pm 8.0^\circ$ in injured. Specific transverse-plane trunk/pelvis numerical values were not clearly extractable from the available table outputs.
Bramah et al. (2021)	Rigid trunk and pelvis relative to the laboratory coordinate system. Repeatability study during treadmill running at 3.2 m/s.	Sagittal/frontal initial-contact and peak-stance parameters showed ICC 0.829-0.941, SEM 0.6-2.6°, MDC 1.5-7.2°. At toe-off, sagittal trunk and pelvis angles showed good repeatability, but sagittal hip and knee angles had low ICC values.	Peak trunk ipsilateral flexion, anterior pelvic tilt and contralateral pelvic drop showed excellent repeatability, with SEM values 0.6-1.1° for several peak stance variables. Frontal-plane pelvis excursion had SEM 0.6° and MDC 1.6° .	Transverse-plane trunk and pelvis kinematics at initial contact showed good repeatability (ICC 0.882 and 0.896). Peak hip internal rotation had SEM 3.2° and MDC 8.7° ; peak knee external rotation had SEM 3.0° and MDC 8.4° .

Study	Segment/reference definition and running condition	Sagittal-plane outputs	Frontal-plane outputs	Transverse-plane outputs
Fisher et al. (2018)	Thorax segment relative to the laboratory coordinate system. Overground running at slower-than-self-selected, self-selected and faster-than-self-selected speeds.	Thorax flexion-extension peak angles and ROM were reported across speed conditions; exact numerical values were not extractable from the current manuscript text.	Thorax lateral flexion/side-bending peak angles and ROM were reported; exact numerical values were not extractable from the current manuscript text.	Thorax axial rotation peak angles and ROM were reported; sex-specific differences were identified, but exact numerical values were not extractable from the current manuscript text.
Preece et al. (2016a)	Cluster-based thoracic and lumbar spine marker-set technical note. Overground running at 5.2 m/s $\pm$ 2.5%.	Thoracic and lumbar flexion-extension outputs were available as technical/model outputs; exact running angle means were not the primary comparative result.	Thoracic and lumbar lateral-flexion outputs were available as technical/model outputs; exact running angle means were not extractable from the current manuscript text.	Thoracic and lumbar axial-rotation outputs were available as technical/model outputs; exact running angle means were not extractable from the current manuscript text.
Preece et al. (2016b)	Thoracic spine, lumbar spine and pelvis during overground running at 3.3, 3.9, 4.8 and 5.6 m/s.	Mean forward trunk inclination increased from approximately 6° to approximately 13° as running speed increased. Forward-backwards trunk inclination ROM increased by up to approximately 5°.	Frontal-plane net trunk tilt increased from approximately 3° to approximately 10° with increasing speed.	Speed-related transverse-plane spine and pelvis changes were reported, but exact numerical values were not extractable from the current manuscript text.
Saunders et al. (2005)	Lumbo-pelvic model during treadmill locomotion. Walking/running speeds from 1 to 5 m/s.	Lumbar/trunk flexion-extension and pelvic tilt ROM/peak values were reported across mode and speed; exact values were not extractable from the current manuscript text.	Lumbar lateral-bending ROM increased from approximately 8° to 14° as speed increased from 7.2 to 18.0 km/h, as summarised by Tojima et al. (2019).	Lumbar rotation ROM increased from approximately 10° to 19° as speed increased from 7.2 to 18.0 km/h, as summarised by Tojima et al. (2019).

Study	Segment/reference definition and running condition	Sagittal-plane outputs	Frontal-plane outputs	Transverse-plane outputs
Schache et al. (2001a)	Lumbar spine and pelvis; Cardan angle sequence comparison during treadmill running at 4.2 m/s.	Sequence-dependent sagittal-plane lumbar/pelvic angles were reported; exact numerical values were not extractable from the current manuscript text.	Sequence-dependent frontal-plane lumbar/pelvic angles were reported; exact numerical values were not extractable from the current manuscript text.	Sequence-dependent transverse-plane lumbar/pelvic angles were reported; exact numerical values were not extractable from the current manuscript text.
Schache et al. (2001b)	Lumbar spine and pelvis during overground and treadmill running at approximately 4.0 m/s.	Overground and treadmill sagittal-plane lumbo-pelvic angular values were reported; exact numerical values should be verified from the full text.	Overground and treadmill frontal-plane lumbo-pelvic angular values were reported; exact numerical values should be verified from the full text.	Overground and treadmill transverse-plane lumbo-pelvic angular values were reported; exact numerical values should be verified from the full text.
Schache et al. (2002a)	Lumbar spine relative to pelvis; pelvis relative to laboratory. Treadmill running at 14.4 km/h.	Lumbar flexion-extension ROM approximately 13°, as summarised by Tojima et al. (2019).	Lumbar lateral-bending ROM approximately 19°, as summarised by Tojima et al. (2019).	Lumbar axial-rotation ROM approximately 23°, as summarised by Tojima et al. (2019).
Schache et al. (2002b)	Lumbar spine relative to pelvis; pelvis relative to laboratory. Treadmill running at 14.0 km/h.	Lumbar flexion-extension ROM approximately 15°, as summarised by Tojima et al. (2019).	Lumbar lateral-bending ROM approximately 23°, as summarised by Tojima et al. (2019).	Lumbar axial-rotation ROM approximately 24°, as summarised by Tojima et al. (2019).
Schache et al. (2003)	Lumbar spine and pelvis; sex comparison during treadmill running at 4.0 m/s.	Sex differences in sagittal-plane lumbo-pelvic angular rotations were reported; exact numerical values were not extractable from the current manuscript text.	Sex differences in frontal-plane lumbo-pelvic angular rotations were reported; exact numerical values were not extractable from the current manuscript text.	Sex differences in transverse-plane lumbo-pelvic angular rotations were reported; exact numerical values were not extractable from the current manuscript text.
Seay et al. (2008)	Lumbo-sacral / trunk-pelvis model during	Sagittal trunk-pelvis angles contributed to	Frontal trunk-pelvis angles contributed to	Transverse trunk-pelvis angles

Study	Segment/reference definition and running condition	Sagittal-plane outputs	Frontal-plane outputs	Transverse-plane outputs
	overground running with stride-length manipulation.	lumbosacral force/moment estimates; exact discrete angle values were not extractable from the current manuscript text.	lateral-bending/loading estimates; exact discrete angle values were not extractable from the current manuscript text.	contributed to rotational loading estimates; exact discrete angle values were not extractable from the current manuscript text.
Seay et al. (2011a)	Pelvis-trunk coordination model in runners with and without low back pain across treadmill speeds of 0.8-3.8 m/s.	Sagittal pelvis-trunk coordination patterns were reported, but not as directly comparable discrete angle magnitudes.	Frontal pelvis-trunk coordination patterns were reported, but not as directly comparable discrete angle magnitudes.	Transverse pelvis-trunk coordination patterns were reported, but not as directly comparable discrete angle magnitudes.
Seay et al. (2011b)	Pelvis-trunk coordination and variability model in runners with and without low back pain across treadmill speeds of 0.8-3.8 m/s.	Sagittal coordination variability was reported, but not as directly comparable peak or ROM angle values.	Frontal coordination variability was reported, but not as directly comparable peak or ROM angle values.	Transverse coordination variability was reported, but not as directly comparable peak or ROM angle values.
Tojima et al. (2019)	Thoracic spine: upper thoracic segment relative to thoracolumbar segment. Lumbar spine: thoracolumbar segment relative to pelvis. Treadmill running at 6, 9 and 12 km/h.	Thoracic flexion-extension ROM: $7.5 \pm 5.1^\circ$, $8.5 \pm 7.5^\circ$, $9.5 \pm 8.1^\circ$. Lumbar flexion-extension ROM: $8.7 \pm 3.6^\circ$, $10.8 \pm 4.6^\circ$, $11.6 \pm 4.8^\circ$. Lumbar extension: $18.3 \pm 5.4^\circ$, $20.3 \pm 5.4^\circ$, $22.4 \pm 6.1^\circ$.	Thoracic lateral-bending ROM: $4.6 \pm 3.7^\circ$, $5.4 \pm 3.2^\circ$, $6.2 \pm 3.3^\circ$. Lumbar lateral-bending ROM: $12.5 \pm 2.9^\circ$, $14.0 \pm 3.5^\circ$, $14.8 \pm 4.4^\circ$.	Thoracic rotation ROM: $6.5 \pm 3.9^\circ$, $8.0 \pm 4.2^\circ$, $8.7 \pm 4.1^\circ$. Lumbar rotation ROM: $17.6 \pm 6.9^\circ$, $21.4 \pm 8.4^\circ$, $24.7 \pm 9.1^\circ$.

Abbreviations: ROM = range of motion. Sagittal plane = flexion/extension, forward/backward trunk lean, and anterior/posterior pelvic tilt. Frontal plane = lateral bending, ipsilateral/contralateral trunk lean, pelvic obliquity and pelvic drop/elevation. Transverse plane = axial rotation, trunk rotation, pelvic rotation and segment rotation. Values are reported in degrees unless otherwise stated. NR/not extractable indicates that the study included the variable, but an exact numerical value was not available from the reviewed manuscript text or accessible summary tables.

3.3.10 Angle-output comparison

A comparison of reported angle outputs by plane of movement is presented in Table 3.5. Across the 15 included studies, numerical angle reporting was inconsistent. Some studies reported discrete peak angles, others reported range of motion, and others presented graphical waveforms or coordination variables without directly comparable numerical values. Therefore, a full comparison analysis was not possible. However, plane-specific comparison showed several important patterns.

Sagittal-plane outputs were commonly reported in applied trunk and pelvis studies. Bramah et al. (2018) reported that injured runners demonstrated greater trunk forward lean than controls at both initial contact and mid-stance. At initial contact, trunk forward lean was $5.7 \pm 3.9^\circ$ in injured runners compared with $3.9 \pm 2.9^\circ$ in controls. At mid-stance, trunk forward lean increased to $12.0 \pm 4.9^\circ$ in injured runners and $9.5 \pm 2.9^\circ$ in controls. Pelvic anterior tilt was also slightly greater in injured runners, although the difference was smaller, with values of $7.0 \pm 3.8^\circ$ versus $5.9 \pm 3.3^\circ$ at initial contact and $5.7 \pm 3.8^\circ$ versus $5.0 \pm 2.9^\circ$ at mid-stance.

Frontal-plane outputs appeared particularly relevant when pelvic motion was reported. In Bramah et al. (2018), injured runners had greater contralateral pelvic drop at mid-stance than controls, with values of $6.4 \pm 2.1^\circ$ compared with $3.7 \pm 1.9^\circ$. This represented a between-group difference of 2.7° . The same study reported that each 1° increase in contralateral pelvic drop increased the odds of being classified as injured by approximately 80%. Bramah et al. (2021) also showed that frontal- and sagittal-plane initial-contact and peak-stance variables generally had good to excellent repeatability, with SEM values between 0.6° and 2.6° and MDC values between 1.5° and 7.2° .

The clearest transverse-plane findings came from studies that reported regional spinal ROM. Tojima et al. (2019) showed that lumbar rotation ROM increased from $17.6 \pm 6.9^\circ$ at 6 km/h to $21.4 \pm 8.4^\circ$ at 9 km/h and $24.7 \pm 9.1^\circ$ at 12 km/h. Thoracic rotation ROM was smaller, increasing from $6.5 \pm 3.9^\circ$ to $8.0 \pm 4.2^\circ$ and $8.7 \pm 4.1^\circ$ across the same speeds. This indicates that lumbar transverse-plane motion was approximately two to three times greater than thoracic transverse-plane motion in that study.

The magnitude of angle outputs differed substantially by plane. In Tojima et al. (2019), lumbar flexion/extension ROM increased from $8.7 \pm 3.6^\circ$ to $11.6 \pm 4.8^\circ$ between 6 and 12 km/h, an increase of 2.9° . Lumbar lateral-bending ROM increased from $12.5 \pm 2.9^\circ$ to $14.8 \pm 4.4^\circ$, an increase of 2.3° . Lumbar rotation ROM increased

from $17.6 \pm 6.9^\circ$ to $24.7 \pm 9.1^\circ$, an increase of 7.1° . Therefore, the largest speed-related change was observed in the transverse plane.

Comparative values from previous lumbo-pelvic studies support this pattern. Schache et al. reported lumbar ROM values of approximately $13\text{-}15^\circ$ in flexion/extension, $19\text{-}23^\circ$ in lateral bending and $23\text{-}24^\circ$ in axial rotation during treadmill running at approximately $14.0\text{-}14.4$ km/h. Saunders et al. reported that lumbar lateral-bending ROM increased from approximately 8° to 14° and lumbar rotation ROM increased from approximately 10° to 19° as treadmill speed increased from 7.2 to 18.0 km/h. Taken together, these findings suggest that frontal- and transverse-plane lumbar ROM are generally larger than sagittal-plane lumbar ROM during running, particularly as speed increases.

Several studies could not be compared numerically because the relevant outputs were presented as waveforms, methodological comparisons or coordination variables rather than discrete peak or ROM values. This was particularly evident in the studies by Seay et al., which focused on pelvis-trunk coordination and variability, and in Schache et al. (2001a), which examined the effect of Cardan angle sequence on reported lumbo-pelvic kinematics. These studies remain important for interpreting movement coordination and methodological sensitivity, but their outputs are not directly comparable with studies reporting mean peak angles or ROM values.

Table 3.6. Reliability and validity measures

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Bramah et al. (2018)	Yes; treadmill, 12-camera Qualisys and force-platform setup described.	Used an established 3D running gait model/protocol to compare injured and healthy runners; no independent validation of the trunk/spine model against an anatomical gold standard was reported in this study.	No study-specific reliability or measurement-error testing reported; repeatability support comes from later/related protocol work rather than this injury-comparison paper.	Useful applied clinical dataset, but validity/reliability evidence is indirect.

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Bramah et al. (2021)	Yes; treadmill, 12-camera Qualisys and force-platform setup described.	Used the same established discrete running-kinematics protocol as previous Bramah work; no new anatomical validity study was performed.	Direct between-day repeatability reported using ICC, SEM and MDC for discrete trunk, pelvis and lower-limb variables during treadmill running.	Strongest study-specific reliability evidence for applied trunk/pelvis discrete variables.
Fisher et al. (2018)	Yes; overground Vicon setup and static calibration reported.	Thorax model rationale and optical 3D capture approach described; thoracic variables treated as proxy measures of thoracic neuromotor control; no direct validation against anatomical thoracic motion was reported.	No study-specific repeatability, SEM, MDC or ICC values reported for the thorax model.	Useful regional thorax study, but measurement-error evidence is limited.
Preece et al. (2016a)	Yes; laboratory setup and calibration reported as part of marker-set technical note.	Direct model-development evidence reported by comparing thoracic and lumbar marker-set configurations; lumbar seven-marker and reduced four-marker sets were assessed for agreement/variability.	No conventional between-day test-retest reliability reported; agreement/variability between marker configurations was reported.	Provides important marker-set evidence, but not full test-retest reliability.

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Preece et al. (2016b)	Yes; overground Qualisys and force-platform setup reported.	Used the previously developed Preece et al. (2016a) thoracic/lumbar marker set; no new validation study was reported.	No new study-specific reliability statistics reported; reliability support is indirect via the established marker-set/protocol literature.	Interpretable speed-comparison study, but model measurement error is not quantified within this sample.
Saunders et al. (2005)	Yes; treadmill Vicon setup and calibration procedures reported.	Used established lumbo-pelvic methods to examine kinematics and trunk muscle activity across speed/mode; no independent anatomical validation was reported.	No study-specific reliability statistics reported.	Strong physiological/kinematic comparison, but reliability evidence is indirect.
Schache et al. (2001a)	Yes; Vicon setup and calibration procedures reported.	Methodological evidence reported by examining the effect of different Cardan angle sequences on lumbo-pelvic angular outputs; this evaluates analytical sensitivity rather than anatomical validity.	No study-specific reliability statistics reported.	Important for interpreting rotation-sequence effects, but not a reliability study.

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Schache et al. (2001b)	Yes; overground and treadmill Vicon setup reported.	Compared overground and treadmill running to examine whether lumbo-pelvic-hip kinematics differed between testing modes; this supports ecological/mode comparison rather than anatomical validation.	No formal repeatability, SEM, MDC or ICC values reported.	Useful for testing-condition interpretation, but not direct reliability evidence.
Schache et al. (2002a)	Yes; treadmill Vicon setup and calibration reported.	Described typical 3D lumbar spine and pelvis kinematics and coordination using the established lumbo-pelvic-hip model; no independent validation was reported.	No formal reliability statistics reported in this descriptive kinematic paper.	Key descriptive reference, but reliability evidence should be taken from Schache et al. (2002b).
Schache et al. (2002b)	Yes; treadmill Vicon setup and calibration reported.	Used the established lumbo-pelvic-hip model; no separate anatomical validation was reported.	Direct intra-subject repeatability reported for 3D lumbo-pelvic-hip angular kinematics during running; time-distance and angular variables were reported as repeatable within session.	Key reliability paper for the Schache/Saunders lumbo-pelvic model family.

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Schache et al. (2003)	Yes; treadmill Vicon setup and calibration reported.	Used the established lumbo-pelvic-hip model to compare sex differences; no new validation was reported.	No study-specific reliability statistics reported.	Sex-comparison evidence is useful, but measurement error is not reported in this study.
Seay et al. (2008)	Yes; overground Qualisys setup reported.	Used prior trunk-pelvis/lumbo-sacral modelling methods for stride-length/loading analysis; no independent anatomical validation was reported.	No study-specific reliability statistics reported.	Kinematic/loading interpretation is limited by lack of direct reliability data.
Seay et al. (2011a)	Yes; treadmill motion-analysis setup and calibration reported.	Used prior pelvis-trunk coordination/vector-coding methods to compare low-back-pain status; no direct validation of segmental spine motion was reported.	No study-specific reliability statistics reported.	Coordination findings are clinically relevant, but measurement-error evidence is not quantified.
Seay et al. (2011b)	Yes; treadmill motion-analysis setup and calibration reported.	Used the same pelvis-trunk coordination approach to examine coordination variability; no direct anatomical validation was reported.	No study-specific reliability statistics reported for coordination variability outcomes.	Useful variability study, but reliability of coordination metrics is not directly reported.

Study	Calibration/lab setup reported?	Validity evidence reported	Reliability evidence reported	Interpretive comment
Tojima et al. (2019)	Yes; treadmill Qualisys setup and static calibration reported.	Used a skin-mounted whole-body marker set with additional spine markers to examine thoracic, lumbar and hip motion; no direct validation against anatomical spinal motion was reported.	No study-specific reliability, SEM, MDC or ICC values reported.	Provides valuable speed-related regional data, but reliability/validity evidence is limited.

Abbreviations: NR = not reported in the source details provided in this manuscript draft; N/A = not applicable. In the Cluster makeup column, material and fixation details are only stated when reported clearly; otherwise they are recorded as NR.

3.4. Discussion

This systematic review evaluated published literature on the methods used to assess three-dimensional spine, back and pelvis motion during running with marker-based motion capture systems. The main findings were: (1) substantial diversity in participant classification and reporting; (2) footwear and testing conditions were often poorly controlled or insufficiently described; (3) kinematic models differed markedly in marker configuration, segment definition, coordinate system construction and reporting strategy; and (4) these methodological differences limited meaningful comparison across studies. Taken together, the evidence suggests that although marker-based motion capture remains the reference standard for the assessment of running kinematics, the literature relating specifically to spine, back and pelvis motion remains methodologically fragmented.

A central issue arising from this review is that the spine was not conceptualised consistently across studies. In some investigations, the trunk was treated as a single rigid segment, whereas others focused on the thorax, lumbar spine or lumbo-pelvic region in isolation, and a smaller number adopted multi-segment approaches. These distinctions are important because they influence not only the variables reported, but also the extent to which regional spinal behaviour and inter-segment coordination can be interpreted. Consequently, differences in reported kinematic findings across studies may reflect true biomechanical variation but may equally reflect differences in modelling assumptions and analytical procedures.

3.4.1 Participant characteristics

Participant description was inconsistent across the reviewed literature. Labels such as recreational, active, experienced and elite runner were used across studies but were not applied consistently, with classification based variously on weekly mileage, race performance, years of experience or competition level. For example, Preece et al. (2016b) differentiated recreational and elite runners on the basis of 10 km performance, whereas Bramah et al. (2021) described participants as experienced runners according to years of running and training frequency. Several studies by Schache and colleagues used weekly running volume as an inclusion criterion. While each of these approaches may be appropriate within the context of an individual study, the absence of a common framework limits comparison between studies and reduces confidence in whether observed kinematic differences reflect methodological factors, population characteristics or both.

This inconsistency is important because running economy and performance are influenced by multiple factors beyond aerobic capacity alone, including neuromuscular, biomechanical and training-related characteristics (Daniels, 1985; Barnes, 2014; Folland et al., 2017). It is therefore plausible that spinal and pelvic movement patterns differ according to training status or performance level. However, the current literature does not describe runner populations consistently enough to establish this clearly. As a result, the evidence base remains limited in its capacity to support normative interpretation of spine and pelvis kinematics across runner subgroups.

Sex reporting was also inconsistent. Some studies included only male or only female participants, whereas others pooled male and female data or did not clearly report sex distribution. This is a notable limitation because sex-related differences in running mechanics have been reported previously, including differences in lumbo-pelvic motion during treadmill running (Schache et al., 2003) and broader differences in coordination variability (Boyer et al., 2017). Fisher et al. (2018) is particularly important in this regard, as the authors reported sex-related differences in thorax kinematics across running speeds. Their findings suggest that thoracic motion may respond differently to changes in running demand in male and female runners, reinforcing the need for sex-specific reporting or a clear rationale when data are pooled. Without this, potentially meaningful differences may be obscured.

Sample size should also be considered when interpreting the reviewed evidence. Several studies were based on relatively small cohorts, which is common in running biomechanics research but nonetheless limits generalisability. For example, Tojima et al. (2019) examined only seven healthy female collegiate track-and-field athletes. Although the

study provided useful speed-related information regarding thoracic and lumbar motion, the small and highly specific sample limits wider application of the findings. More broadly, many of the included studies appear to have been designed to address methodological or exploratory biomechanical questions rather than to establish broadly applicable normative values.

3.4.2 Footwear

Footwear was rarely standardised across the included studies. Several studies permitted participants to wear their own shoes, while others did not report footwear characteristics at all. This represents an important methodological limitation because footwear can influence running mechanics, comfort and energy cost (Kong et al., 2009; Luo et al., 2009; Worobets et al., 2013; Hunter et al., 2019). Although much of this evidence relates primarily to lower-limb biomechanics and running economy, it is unlikely that such effects are entirely isolated from more proximal segments. Running is a whole-body movement task, and changes in foot–ground interaction may alter pelvis and trunk motion through compensatory or coordinative adaptations.

The absence of footwear control therefore introduces a potential source of unexplained variance across studies. This is particularly relevant when comparing investigations that sought to identify relatively subtle differences in spinal or pelvic kinematics between groups or conditions. Future studies should standardise footwear where feasible or, at minimum, report footwear type and relevant characteristics clearly. Where standardised footwear is used, an appropriate familiarisation period should also be provided to reduce the likelihood that findings are influenced by short-term adaptation rather than habitual running mechanics.

3.4.3 Methodological considerations

Across studies, differences in marker placement, segment definition, coordinate systems and rotation sequences limited direct comparison of outcomes. This was the most consistent and important finding of the review. Table 3.6 further shows that validity and reliability evidence were not reported at the same level across studies. Some papers provided direct reliability or model-development evidence, such as Bramah et al. (2021), Schache et al. (2002b) and Preece et al. (2016a), whereas many others relied on established protocols or citations to previous methods without reporting study-specific measurement error. These approaches should not be interpreted as equivalent. A model that has been cited previously

may be methodologically defensible, but it does not provide the same level of evidence as direct repeatability statistics, minimal detectable change values, or explicit agreement testing within the population and running condition being analysed. This concern is consistent with previous discussions in the wider gait and motion analysis literature, which have highlighted how differences in model construction and reporting can compromise interpretability and reproducibility (Simon, 2004; Leardini et al., 2005; Benedetti et al., 2017).

A more consistent methodological framework and reporting checklist would therefore improve both interpretability and reproducibility in future studies. At present, the literature provides useful insight into running-related spine and pelvis motion but does so through parallel modelling approaches rather than through a clearly cumulative body of evidence. Future studies should distinguish clearly between validation evidence, reliability evidence and simple use of a previously published protocol, because each provides a different level of confidence in the resulting kinematic outputs. This gap provides the methodological rationale for the first empirical study in this thesis. Before a multi-segment spine model can be used confidently in subsequent running studies, it is necessary to test whether candidate skin-mounted and cluster-based models are valid, reliable and sufficiently comparable under running-specific conditions, rather than assuming that findings from walking, sit-to-stand or single-model running studies can be transferred directly to running gait.

3.4.4 Spine kinematics and kinematic models

The spine functions as a multi-segment structure, and its motion during running is likely to reflect coordinated interaction between thoracic, lumbar and pelvic segments rather than movement of a single rigid block (Moore, 2016; Novacheck, 1998). This review identified rigid trunk models, single-region models (thorax- or lumbar-only) and multi-segment thoracic–lumbar models. These different approaches do not simply vary in complexity; they also differ in the type of biomechanical question they are able to address.

Rigid trunk models may be useful where the aim is to quantify overall trunk orientation or derive clinically accessible variables. For example, Bramah et al. (2018) used a cluster-based trunk model in runners with and without common soft-tissue injuries, while Bramah et al. (2021) demonstrated acceptable between-day repeatability, standard error of measurement and minimal detectable change for discrete treadmill running kinematics. These studies indicate that simplified models can be practical and repeatable, particularly in applied settings. However, rigid trunk models are inherently limited in their ability to distinguish

thoracic from lumbar contributions and therefore cannot fully represent regional spinal behaviour.

By contrast, more anatomically differentiated models may provide greater insight when the aim is to understand regional motion or inter-segment coordination. Preece et al. (2016a) proposed a marker set specifically designed to quantify thoracic and lumbar spine kinematics during running, and Preece et al. (2016b) subsequently used this model to show that spine and pelvis motion changed as running speed increased. Similarly, Tojima et al. (2019) reported speed-related changes in thoracic rotation, lumbar rotation and lumbar extension, indicating that the thoracic and lumbar regions do not necessarily respond in the same way to increasing running demand. These findings support the view that the spine should not automatically be treated as a single rigid segment during running.

Fisher et al. (2018) provide a further example of the value of regional analysis. The authors examined thorax motion during overground running and reported that thorax peak angles and range of motion changed when runners moved slower or faster than self-selected speed. They also reported sex-related differences in thoracic kinematic responses. This suggests that thorax motion is sensitive to both task demand and participant characteristics. However, because lumbar and more detailed pelvic measures were not central to the model, the study provides less insight into spine–pelvis coordination than multi-segment or lumbo-pelvic approaches.

Cluster-based approaches may therefore be useful when the aim is to characterise regional spinal motion while reducing some limitations associated with extensive skin-mounted marker sets, although carefully applied skin-mounted regional models can also provide clinically useful information (Leardini et al., 2005; Preece et al., 2016a). However, the Cluster construction column (Table 3.3) demonstrates that cluster-based models should not be treated as equivalent simply because they include a cluster. Some studies used rigid trunk or sternum-mounted clusters, whereas the Schache/Saunders lumbo-pelvic studies used a mixed approach involving skin-mounted markers and a posterior lumbar wand/cluster. A rigid cluster may reduce independent movement between markers on the cluster itself, but it does not remove all measurement error, particularly where the cluster is attached to soft tissue or projects away from the body. Conversely, fully skin-mounted models may be easier to apply and less obtrusive, but are more directly exposed to soft-tissue artefact. Therefore, apparent differences in thoracic, lumbar or pelvic motion may partly reflect model construction, fixation method and anatomical calibration rather than true differences in spinal kinematics.

3.4.5 Pelvic kinematics

Interpretation of spinal motion is strongly influenced by how the pelvis is modelled and whether outcomes are reported relative to the pelvis, the laboratory coordinate system, or both. This review showed that several studies reported spinal kinematics relative to the pelvis, whereas others reported pelvic motion only in the laboratory frame or did not report pelvic outcomes in sufficient detail. This inconsistency is important because the pelvis forms the mechanical base for the lumbar spine and trunk, and without clear pelvic reporting it becomes difficult to determine whether observed spinal motion reflects true inter-segment movement or broader segment reorientation relative to the laboratory.

Studies using lumbo-pelvic models generally addressed this issue more effectively. Saunders et al. (2005) and the series of studies by Schache and colleagues provided both lumbar and pelvic outcomes, allowing more complete interpretation of movement within the lumbo-pelvic complex. These studies therefore offer a clearer account of the relative contributions of pelvic and lumbar motion during running. In contrast, Tojima et al. (2019) and Fisher et al. (2018) provided useful regional spine or thorax information but did not substantially extend evidence for spine–pelvis coupling because pelvic outcomes were either not emphasised or not reported in sufficient detail to allow direct comparison with lumbo-pelvic models.

Given the central role of lumbo-pelvic coordination in running mechanics, future studies should report pelvic kinematics alongside spinal outcomes wherever possible (Saunders et al., 2005; Schache et al., 2002a, 2002b). This is particularly relevant in light of previous work suggesting that coordinated thorax–pelvis motion may reduce unnecessary centre-of-mass motion during running (Preece et al., 2016c), and evidence linking greater trunk lean excursion and pelvic transverse-plane rotation with poorer running economy and performance (Folland et al., 2017). Without adequate pelvic reporting, the functional interpretation of spinal motion remains incomplete.

3.4.6 Data analysis and reporting

Outcome reporting varied across studies, with differences in whether range of motion, peak angles and/or waveform data were presented. Some studies reported only discrete variables, whereas others included waveform data across the gait cycle. This variation limits comparison because discrete and continuous measures provide different forms of information. Peak angles and range of motion may be clinically intuitive and useful in repeatability studies, but they do not capture the temporal organisation of movement across

the running cycle. Conversely, waveform data without sufficient summary statistics can be difficult to compare across studies, especially when sample sizes are small, or variability is not clearly reported.

This issue is particularly relevant for studies of coordination. Seay et al. (2011a) and Seay et al. (2011b) examined pelvis–trunk coordination and coordination variability in runners with and without low back pain, demonstrating that pain status influenced not only movement magnitude but also coordinative organisation. Such findings are unlikely to be fully captured through isolated peak values alone. The implication is that discrete variables, while useful, may not always be sufficient to characterise clinically or functionally relevant movement behaviour.

Future work should therefore, where feasible, report peak angles and range of motion, specify reference frames clearly for each variable, provide waveform data across the gait cycle, and include measurement error or repeatability metrics for the chosen model. This has direct relevance for Study 1, because a comparison of skin-mounted and cluster-based spine models requires more than isolated peak or ROM values. Discrete variables can indicate whether models differ in magnitude, but waveform-level agreement is needed to determine whether differences are consistent across the running cycle or concentrated within specific phases. More consistent reporting of both discrete and continuous outcomes would strengthen comparison across studies and improve the interpretive value of the literature.

3.4.7 Angle-output synthesis

The plane-specific angle comparison provides a clearer understanding of how spine, trunk and pelvis outputs differ across the reviewed literature. Although direct comparison remains limited by differences in marker sets, segment definitions, reference frames and speed protocols, the numerical values indicate that sagittal-, frontal- and transverse-plane outputs do not contribute equally to interpretation.

Sagittal-plane outputs were clinically intuitive and commonly reported, particularly in studies using rigid trunk models. Bramah et al. (2018) showed that injured runners ran with approximately 1.8° more forward trunk lean than controls at initial contact and 2.5° more forward trunk lean at mid-stance. Although these differences are relatively small in absolute terms, they may still be meaningful when interpreted alongside other proximal variables. Bramah et al. (2021) reported similar sagittal-plane values across repeated test days, with peak stance trunk forward lean of $11.2 \pm 6.3^\circ$ and $10.1 \pm 5.2^\circ$, suggesting that sagittal-plane trunk lean can be measured with reasonable consistency using a simplified applied model.

Frontal-plane pelvic motion appears especially important in clinical and injury-related running studies. The clearest example is contralateral pelvic drop. Bramah et al. (2018) reported a 2.7° greater contralateral pelvic drop in injured runners compared with controls at mid-stance. Importantly, this was not only a descriptive difference: every 1° increase in pelvic drop increased the odds of injury classification by approximately 80%. This suggests that frontal-plane pelvic mechanics may have stronger clinical relevance than some sagittal-plane trunk or pelvis variables, at least within the context of common soft-tissue running injuries.

Transverse-plane spinal motion appeared particularly sensitive to running speed. Tojima et al. (2019) reported that lumbar rotation ROM increased by 7.1° from 6 to 12 km/h, whereas lumbar flexion/extension ROM increased by only 2.9° and lumbar lateral-bending ROM increased by 2.3° . This suggests that increasing running speed produces a larger adaptation in axial rotation than in flexion/extension or lateral bending. The comparative values from Schache et al. and Saunders et al. support this interpretation, with lumbar axial rotation generally reported at approximately $19\text{--}24^\circ$ during faster treadmill running conditions.

The regional comparison between thoracic and lumbar motion also supports the use of multi-segment spine models. In Tojima et al. (2019), thoracic rotation ROM at 12 km/h was $8.7 \pm 4.1^\circ$, whereas lumbar rotation ROM was $24.7 \pm 9.1^\circ$. Similarly, thoracic lateral-bending ROM was $6.2 \pm 3.3^\circ$, whereas lumbar lateral-bending ROM was $14.8 \pm 4.4^\circ$. These differences show that the thoracic and lumbar regions do not behave as a single rigid unit during running. If only a single trunk segment were modelled, these regional differences would be lost.

However, the table also demonstrates why a meta-analysis of angle outputs is not currently appropriate. Even when studies reported the same plane of movement, the actual construct differed between studies. For example, sagittal-plane outputs included trunk forward lean relative to the laboratory, pelvis anterior tilt relative to the laboratory, thoracic flexion/extension ROM and lumbar flexion/extension relative to the pelvis. These are not interchangeable variables. Similarly, transverse-plane outputs could refer to trunk rotation, pelvic rotation, thoracic rotation or lumbar axial rotation depending on the model used.

The main implication is that future running studies should not only report whether angles were measured in the sagittal, frontal and transverse planes, but should define the exact segment relationship for each angle. At minimum, studies should report the proximal and distal segments, reference frame, plane of movement, gait event or phase, whether the

value represents a peak angle or ROM, and mean $\pm$ SD values. However, reporting alone cannot resolve whether different multi-segment models produce equivalent outputs. The review therefore leads directly to the need for Study 1, which compares two candidate multi-segment spine models within the same participants and running condition. This approach is necessary because the largest interpretive uncertainty identified here is not simply whether spinal motion can be measured, but whether model-dependent differences alter the magnitude, timing or regional distribution of reported thoracic and lumbar motion.

3.5 Recommendations

Based on the findings of this review, several recommendations can be made for future research. Participant characteristics should be reported using more objective and standardised descriptors, such as weekly mileage, years of running and recent performance level. Sex distribution should be reported clearly, and analyses should be stratified by sex or accompanied by a rationale for pooling data where appropriate. Footwear and familiarisation procedures should be controlled or described in greater detail, particularly where subtle kinematic differences are under investigation.

Methodologically, future studies should provide explicit descriptions of marker placement, segment definitions, coordinate systems, rotation sequences and cluster construction, including cluster material, marker number and fixation method where applicable. Pelvic kinematics should be reported alongside spinal outcomes, including relative and laboratory-referenced measures where appropriate. Running speed should be clearly stated as fixed or self-selected and justified in relation to the study aim. Finally, reporting should include both discrete variables and waveform data where possible, together with validity evidence, reliability statistics, measurement error metrics and, where more than one model is available, direct between-model agreement testing.

Overall, the main need in this field is not necessarily the development of a further untested kinematic model, but the systematic evaluation of existing candidate models under running-specific conditions. The first empirical study in this thesis responds to this need by assessing whether skin-mounted and cluster-based multi-segment spine models provide valid, reliable and comparable outputs during running. Without this step, future studies are likely to continue generating valuable but only partially comparable findings.

3.6 Conclusion

This systematic review identified substantial methodological variation in the way three-dimensional spine, back and pelvis motion is quantified during running using marker-based motion capture systems. The inclusion of Tojima et al. (2019) and Fisher et al. (2018) further emphasised that speed selection, segment definition and sex-specific reporting can materially affect interpretation of spinal and thoracic kinematics. Although optoelectronic systems remain the reference standard for kinematic analysis, differences in marker configuration, segment definition, reference frames, data processing and outcome reporting make direct comparison between studies difficult.

Overall, the evidence suggests that spinal motion during running is more appropriately considered as a coordinated multi-segment phenomenon than as movement of a single rigid trunk. Studies using regional or multi-segment approaches, particularly Preece et al. (2016a, 2016b) and Tojima et al. (2019), indicate that thoracic and lumbar segments may respond differently to increasing running speed. Fisher et al. (2018) further suggest that thoracic motion is influenced by both running speed and sex. Together, these findings support the value of more anatomically differentiated models where the aim is to understand regional spinal behaviour.

However, the current evidence does not support the recommendation of one universal kinematic model. Rigid trunk models may remain appropriate in some clinical or applied contexts, particularly where feasibility and repeatability of discrete outcomes are prioritised. In contrast, cluster-based and multi-segment approaches appear to offer greater interpretive value when the aim is to investigate regional spinal motion, spine–pelvis coordination or speed-related adaptation. The key limitation is that validation, repeatability and reporting are not yet sufficiently consistent across studies to establish a single preferred approach. Direct reliability evidence was concentrated in a small number of studies, whereas several papers relied on established protocols without reporting study-specific validity or reliability data. This limits confidence when comparing outputs across models, particularly where small differences in spinal or pelvic angles are interpreted as meaningful.

A further important conclusion is that pelvic kinematics are fundamental to the interpretation of spinal motion. Studies that reported both spinal and pelvic outcomes provided a more complete and interpretable account of running mechanics than those in which pelvic motion was limited or absent. Future work should therefore report pelvic kinematics routinely alongside spinal measures and clearly state the reference frame used for each variable.

The strongest recommendation arising from this review is therefore the adoption of more consistent methodological and reporting standards, alongside direct empirical testing of candidate models. More standardised reporting of participant characteristics, footwear, running condition, speed protocol, marker placement, segment definitions, coordinate systems, rotation sequence, reference frames, outcome variables and measurement error would improve reproducibility and support cross-study comparison. However, the review also shows that reporting improvements alone are insufficient unless model validity, reliability and between-model agreement are examined directly. This provides the direct rationale for Study 1, which evaluates and compares skin-mounted and cluster-based multi-segment spine models during running before these approaches are applied in later thesis studies.

Chapter 4

General Methodological Framework

4.1 Purpose of this Chapter

This chapter provides a concise methodological framework for the empirical programme. Its purpose is not to repeat each study method in full, but to identify the procedures that were shared across the thesis and to explain how the studies were linked. Detailed study-specific procedures, analyses and outcomes are reported in Chapters 5-8.

The chapter is retained because several core procedures underpin more than one empirical study: participant recruitment and ethics, speed-based VO_2max and ventilatory-threshold testing, biomechanics laboratory preparation, marker placement, motion capture, physiological recording and the multi-segment spine model. Presenting these shared procedures here reduces unnecessary repetition while allowing later chapters to focus on study-specific manipulations and analyses.

4.2 Empirical Study Sequence and Shared Design Logic

The empirical programme was organised in two phases. Phase one established the methodological basis for measuring multi-segment spinal motion during running by validating, comparing and assessing the reliability of candidate kinematic models. Phase two applied the selected model to examine adaptation to increased running speed and acute localised fatigue.

Across the applied studies, running speeds were prescribed from each participant's physiological thresholds rather than from one absolute speed. This allowed experimental intensity to be standardised relative to individual capacity, which was important given the thesis focus on running economy, coordination and individual adaptation. Procedures unique to each empirical study are therefore reported within the relevant chapter, while the shared methodological foundation is summarised here.

4.3 Participants and Ethical Approval

Participants were recruited from a sub-elite running population. Sub-elite runners were defined as highly trained competitive runners performing above recreational standard but below international elite level, consistent with Tier 3 of the participant classification framework proposed by McKay et al. (2022). This cohort was selected because trained runners were

expected to demonstrate more consistent running mechanics than a heterogeneous recreational sample, improving sensitivity to detect subtle biomechanical and physiological adaptations.

Sample sizes differed according to study purpose. The model-comparison, reliability and fatigue studies included ten sub-elite non-pathological male runners. The speed study included five sub-elite male runners. Participant characteristics are reported in the individual study chapters.

Common inclusion criteria were: male sex; age 18 years or older; regular endurance-running training; current participation at a sub-elite or highly trained standard; ability to complete treadmill running based on ventilatory-threshold speeds; and no current injury or pathology affecting normal running. Common exclusion criteria were current musculoskeletal injury, lower back pain or spinal pathology, contraindications to maximal or submaximal exercise testing, recent surgery, inability to complete the Physical Activity Readiness Questionnaire, inability to provide informed consent, or inability to complete the treadmill protocols.

Male participants were recruited to reduce biological heterogeneity and support direct comparison between individuals across the relatively small samples used within the empirical programme. This was particularly important given the single-subject analytical approach, where the primary aim was to identify individual adaptation rather than to estimate population-level sex differences. Restricting recruitment to males therefore strengthened internal consistency but was a deliberate methodological delimitation rather than an assumption that male and female running mechanics are equivalent. Previous evidence indicates that sex-related differences may occur in lumbo-pelvic and thoracic kinematics during running (Schache et al., 2003; Fisher et al., 2018), and female runners may therefore demonstrate different regional or coordinative responses to the task constraints examined in this thesis. The methodological framework and underlying principle that runners adapt spinal coordination in response to changing task demands may be relevant to both sexes; however, the specific magnitudes, timing and individual response profiles identified within the present studies should be interpreted as representative of the male runners tested and require validation in female cohorts.

Ethical approval was granted by the University of Staffordshire Ethics Committee (approved on 12/08/2022; see Appendix D). Before testing, participants received written

information describing the study aims, procedures, risks, benefits and right to withdraw. Written informed consent was obtained before data collection. At each visit, participants completed a Physical Activity Readiness Questionnaire and confirmed that there had been no relevant change in health, medication, injury status or training status (Appendices E-G). Participant data were anonymised using coded identifiers in processing files, figures and thesis chapters. Data were stored securely in accordance with university procedures. Maximal or submaximal testing would have been stopped if an adverse response occurred.

4.4 Speed-Based VO_2max and Ventilatory-Threshold Testing

A maximal treadmill test was required for all running studies because the subsequent experimental speeds were prescribed from individual ventilatory thresholds. Testing was completed in the Physiology Laboratory after measurement of stature, body mass and training history, and after exercise-readiness screening.

VO_2max was assessed using a direct gas-analysis graded treadmill test, which is considered the criterion method because oxygen uptake is measured directly during progressive exercise to volitional exhaustion rather than estimated from field performance or prediction equations (Bassett & Howley, 2000; Midgley et al., 2007). A speed-based protocol was used because the later studies required treadmill speeds corresponding to VT1 and VT2.

Before each test, the Metalyzer 3B metabolic cart (Cortex Biophysik GmbH, Leipzig, Germany) was calibrated according to manufacturer procedures using known calibration gases and volume/flow calibration. Participants wore a facemask and sampling apparatus throughout the test. Heart rate and rating of perceived exertion were recorded where available to support interpretation of maximal effort.

The treadmill was set to a 1% gradient to better approximate outdoor running energetic cost (Jones & Doust, 1996). After a short warm-up and familiarisation period, the test began at an individually selected submaximal running speed below expected VT1. Speed then increased by $1 \text{ km} \cdot \text{h}^{-1}$ every 60 s until volitional exhaustion or inability to maintain the required speed despite verbal encouragement.

$\dot{V}O_{2\max}$ was taken as the highest 30-s average oxygen uptake. Achievement of maximal effort was supported by established secondary criteria, including a plateau or levelling-off in oxygen uptake despite increasing workload, respiratory exchange ratio close to or greater than 1.10, heart rate close to age-predicted maximum and high perceived exertion (Bassett & Howley, 2000; Howley et al., 1995; Midgley et al., 2007).

VT1 was identified using the V-slope method and ventilatory-equivalent method, specifically the first disproportionate rise in $\dot{V}CO_2$ relative to $\dot{V}O_2$ and an increase in $\dot{V}E/\dot{V}O_2$ without a simultaneous increase in $\dot{V}E/\dot{V}CO_2$ (Beaver et al., 1986; Binder et al., 2008). VT2, where required, was identified as the second ventilatory breakpoint, characterised by a further disproportionate rise in ventilation and an increase in $\dot{V}E/\dot{V}CO_2$. The treadmill speeds corresponding to VT1 and VT2 were then used in the subsequent running protocols.

4.5 Biomechanics Preparation, Marker Placement and Dynamic Capture

Before each biomechanics session, participants confirmed no relevant change in health, medication, injury or training status. Participants wore their own running footwear to preserve habitual running mechanics, acknowledging that footwear may contribute to between-participant variation (Willwacher et al., 2020; Van der Meulen et al., 2024). Participants completed a 6-min treadmill familiarisation period before formal data collection (Lavcanska et al., 2005). Environmental conditions were recorded during the applied studies; temperature ranged from 21-24°C, relative humidity from 55-56% and barometric pressure from 1100-1200 mb.

Reflective markers and, where required, rigid or semi-rigid clusters were attached to the spine, back, pelvis and lower limbs using double-sided adhesive tape. Markers were 14 mm in diameter. Marker placement followed the skin-marker-set and cluster approaches described by Christe et al. (2016) and Needham et al. (2016), with lower-limb conventions informed by Cappozzo et al. (1995) and Leardini et al. (2007, 2011).

A static calibration trial was collected with the participant standing upright in the anatomical position. This defined marker positions, segment coordinate systems and the reference posture for dynamic angles. Standing posture was not forced into a standardised neutral alignment because runners differed naturally in spinal curvature and habitual posture. This

preserved ecological validity but may have influenced absolute segment-angle values, particularly in the lumbar region.

During running, motion-capture data were collected in repeated 15-s blocks, generally twice per minute. Where physiological outcomes were required, breath-by-breath data were recorded continuously and later averaged over 10-s epochs, with three consecutive epochs sampled per minute and averaged for analysis.

4.6 Laboratory Setting and Equipment

Physiological testing was conducted in the Physiology Laboratory using a Metalyzer 3B metabolic cart (Cortex Biophysik GmbH, Leipzig, Germany). The system provided $\dot{V}O_2$, $\dot{V}CO_2$, $\dot{V}E$, $\dot{V}E/\dot{V}O_2$, $\dot{V}E/\dot{V}CO_2$ and respiratory exchange ratio for $\dot{V}O_{2max}$ testing, ventilatory-threshold identification and applied-study physiological analysis. The treadmill used in the physiology laboratory was the HP Cosmos Venus 200/75 (Munich, Germany).

Biomechanical data were collected in the Biomechanics Laboratory using an 18-camera Vicon motion-capture system (Vicon, Oxford, UK), with marker coordinate data recorded at 200 Hz. Two Vue high-speed video cameras were available for supplementary visual reference. The laboratory setting allowed speed, gradient, instrumentation and data-capture procedures to be controlled across repeated sessions. The treadmill used in the biomechanics laboratory was the Vision Fitness TY700HRT; 1600 Landmark Dr, Cottage Grove, WI 5352.

4.7 Multi-Segment Kinematic Model Framework

Two spine/back models were evaluated: a four-segment skin-marker-set model and a cluster-based model. They were compared because marker configuration can influence spinal kinematic estimates during running, particularly through soft-tissue artefact, local skin deformation and coordinate-system definition. Importantly, both models were tracked from skin-mounted markers during running; the key difference was whether segment motion was represented by individual skin markers or by a rigid marker cluster attached to the skin.

For both models, the underlying segment definitions were based on spinal levels. Six central markers were placed on the spinous processes of T1, T6, T12, L1, L3 and L5. These

markers defined the upper thoracic region from T1-T6, the lower thoracic region from T6-T12, the upper lumbar region from L1-L3 and the lower lumbar region from L3-L5. Eight lateral markers were placed bilaterally between the central markers, approximately 5 cm from the spine, at the T3, T9, L2 and L4 levels. Rigid or semi-rigid three-dimensional clusters attached at T3, T8 and L3 tracked upper thoracic, lower thoracic and lumbar motion, respectively. This marker arrangement allowed regional spine and back motion to be described and provided the basis for examining adjacent segment couplings.

4.8 Summary

This chapter has been reduced to a methodological framework rather than a full repeated methods chapter. It identifies the shared procedures that link the empirical studies while retaining the detailed ethical, physiological, marker-placement and equipment information that is not fully reproduced elsewhere. The empirical chapters then report the study-specific protocols, analysis decisions and findings required to interpret each research question.

Chapter 5

Comparison of Two Multi-Segment Kinematic Spine Models During Treadmill Running

Aspects of this chapter have been submitted for peer-review publication:

Hicks, CA., Chockalingam, N., & Needham, R.A. Comparison of Two Multi-Segment Kinematic Spine Models During Treadmill Running (under review).

5.1 Introduction

The spine and trunk region is a complex, multi-articulated structure that plays an integral role during human running. Although the legs generate propulsion, the trunk comprises the largest proportion of body mass, and its movement aids in regulating whole-body momentum and dynamic stability (Folland et al 2017, Moore et al 2016). For example, coordinated movement between the lumbar spine and pelvis adjusts with changes in speed and step mechanics to help manage spinal loading (Seay et al., 2011; Schache et al., 2002). At the thoracic level, rotation and lateral bending are coordinated with pelvic rotation and arm swing to control the body's centre of mass (Pontzer et al., 2009; Bruijn et al., 2008). Furthermore, trunk and spine kinematics have been associated with running economy and with the development and management of low-back pain in runners (Seay et al., 2011b, 2011a). Therefore, understanding how each spinal region contributes to running gait and how it interacts with neighbouring structures such as the pelvis may advance our understanding of performance and injury risk, and help guide rehabilitation strategies (Moore, 2016; Moore et al., 2012; Preece, Mason, et al., 2016; Schache et al., 2002; Tojima et al., 2019).

Marker-based motion capture remains the benchmark technique for quantifying human movement in both research and clinical settings (Michellini et al., 2020; Ugbohue et al., 2013). However, the trunk has frequently been represented in gait and running analyses as a single rigid segment spanning the pelvis to the upper thorax (Mason et al., 2016; Novacheck, 1998; Preece, Bramah, et al., 2016; Riley et al., 2008; Seay et al., 2011b, 2011a). This kinematic modelling approach cannot capture differential motion in the lower thoracic and lumbar regions. Consequently, multi-segment kinematic models have been developed that subdivide the trunk into two or more segments, typically representing the thoracic and lumbar regions as upper and lower segments.

Although these models may share common segmental definitions (Christe et al., 2016; Needham et al., 2016), they can differ significantly in how segment movement is tracked, with meaningful consequences for the angles reported. Individual skin marker models place discrete markers directly on spinous processes and the surrounding back surface. Yet this approach makes segment pose estimation susceptible to the independent movement of each marker relative to the underlying bone or landmark. By contrast, 3D rigid cluster models attach a structured three-dimensional array to the spinous process, applying a common rigid body assumption across the

cluster and potentially reducing inter-marker variability. Since both approaches remain skin-mounted, however, neither eliminates soft tissue artefact. The differences in their kinematic outputs during running likely reflect, at least in part, the differential influence of soft tissue artefact between tracking strategies. Comparing these two models therefore provides insight into how tracking methodology shapes measured spinal kinematics, rather than offering a direct quantification of soft tissue artefact itself.

This study aimed to compare the kinematic outputs of two multi-segment spinal models: a four-segment skin-marker model and a three-segment rigid-cluster model during treadmill running in sub-elite runners. This may allow an evaluation of how tracking methodology influences measured spinal kinematics independent of true spinal motion. Two complementary analyses were conducted. A between-model analysis evaluated whether the two models produced interchangeable estimates of segmental spine motion across the sagittal, frontal, and transverse planes. A within-model analysis evaluated whether each model resolved adjacent spinal segments as kinematically distinct.

5.2 Methods

5.2.1 Participants

Ethical approval was granted by the University of Staffordshire Ethics Committee. Ten male sub-elite runners participated in the study (age 45.8 ± 9.2 years; height 178.7 ± 4.13 cm; mass 73.22 ± 5.4 kg), all of whom were free from current musculoskeletal impairment. Participants were classified according to the Participant Classification Framework proposed by McKay et al. (2022). The cohort was classified as Tier 3: Highly Trained/National Level, as participants identified running as their primary sport, completed structured endurance training, and typically ran 40–50 miles per week across regular weekly training sessions.

5.2.2 Kinematic models – defined segments, coordinate systems, and segment tracking

Two customised kinematic models were developed in Visual3D (HAS-Motion, Kingston, Ontario, Canada) with matching segment definitions. Six central markers were placed on the

spinous processes of T1, T6, T12, L1, L3 and L5 to define four segments; upper thoracic (UT) (T1-T6), lower thoracic (LT) (T6-T12), upper lumbar (UL) (L1-L3) and lower lumbar (LL) (L3-L5) (Christe et al., 2016; R. Needham, Naemi, et al., 2016). The Z-axis was defined as a line passing through two markers stated for each segment that represented posture in the sagittal plane (positive direction upwards from the distal marker). Eight lateral markers were placed between central markers on each side of the spine, at a distance of 5 cm, representing spinal levels T3, T9, L2 and L4 (Christe et al., 2016). The cross product of the Z-axis and a line connecting the two markers bilaterally for each segment defined the Y-axis (positive direction pointing to the left). The cross product of the Z- and Y-axis was used to define the X-axis (positive direction pointing forwards). For the individual skin marker model (SKS), the four markers used to define each segment were used to track motion (Christe et al., 2016). For the 3D rigid cluster model (CL), clusters attached at T3, T8, and L3 were assigned into segment coordinate systems to track motion in the UT, LT, and LL segments, respectively (Needham et al., 2016) (Figure 5.1).

Figure 5.1. Marker configurations used for the skin-marker-set (SKS) and cluster-based (CL) multi-segment spine models, adapted from Christe et al. (2016) and Needham et al. (2016).



Note. The SKS model defines four spinal regions: upper thoracic (UT; T1–T6), lower thoracic (LT; T6–T12), upper lumbar (UL; L1–L3), and lower lumbar (LL; L3–L5), using central spinous-process and bilateral skin-mounted markers. The CL model uses rigid three-dimensional clusters positioned at T3, T8, and L3 to track upper thoracic, lower thoracic, and lumbar segment motion, respectively. Both models were referenced to the same anatomical calibration procedure.

5.2.3 Segment parameters

Three-dimensional segment angles were calculated with respect to the normal standing position of the participant. Rotations about the global coordinate system (laboratory) were based on the right-hand rule convention. Angular kinematic data for all segments and both kinematic models were computed by measuring the relative movements between of the respective segment to the global coordinate system. Cardan angles were calculated using the YXZ convention with an order in the sagittal, frontal, and transverse plane (Grood & Suntay, 1983).

5.2.4 Instrumentation

Participants were required to run on a treadmill (Model TY700HRT; Vision Fitness, 1600 Landmark Dr, Cottage Grove, WI 5352) that was positioned in the centre of the laboratory. An 18-camera motion capture system (Vicon, Oxford, UK) was used to record three-dimensional marker coordinate data at 200 frames/s.

5.3 Experiment protocols

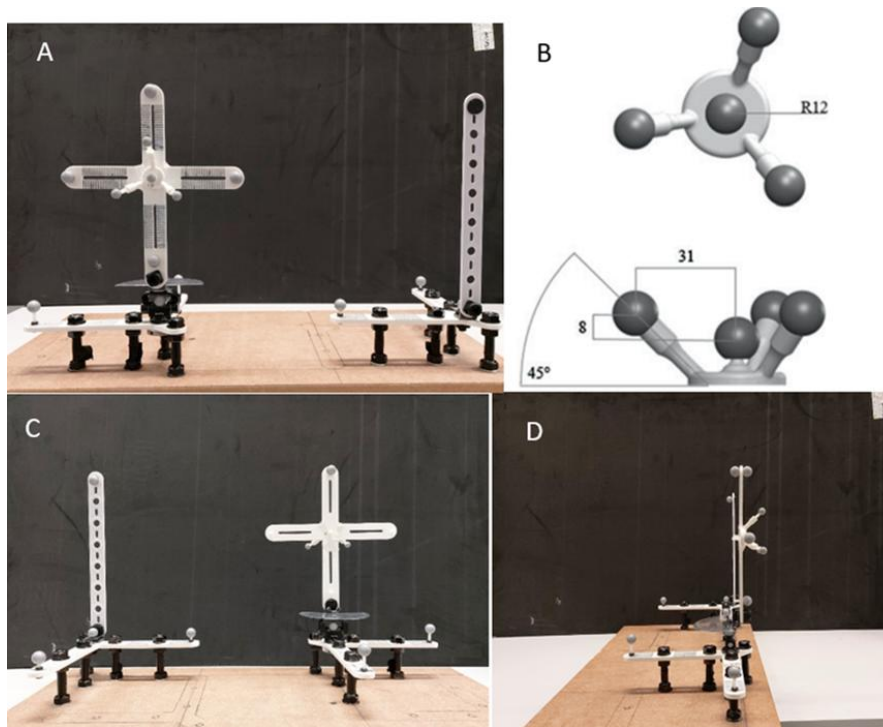
5.3.1 Part A – Defining and Validation of kinematic models

All model-derived segment angles were compared against the criterion angle (Vicon, Oxford, UK) at each designated reference position using a custom mechanical jig (SMALLRIG, Shenzhen, Guangdong, China) (Figure 5.2) set to static angles across the full measurement range. The skin-marker set (SKS) and 3D-cluster (CL) models were constructed in Visual3D (HAS-Motion, Kingston, Ontario, Canada) and evaluated independently.

Data were collected separately for each anatomical plane (sagittal, frontal, transverse) across designated angles of 5° to 40° in 5° increments in each rotation direction ($n = 16$ per model per plane). Using additional markers attached to the mechanical rig to create a global coordinate system, criterion reference angles were calculated using the “angle between” function in Nexus software (Vicon, OMG, Oxford, UK) to quantify the displacement from the 0° static reference position. The global coordinate system was defined with the X-axis aligned to the anterior–

posterior axis (positive X indicating forward progression), the Y-axis aligned to the medio-lateral axis (positive Y to the left), and the Z-axis aligned to the vertical axis (positive Z upwards).

Figure 5.2. A- Completed jig set up including lab XYZ coordinate markers, from the rear. B- 3D cluster structural dimensions (measurements are in millimetres). C- Completed jig set up including lab YXZ coordinate markers, from the front. D- Completed jig set up including lab YXZ coordinate markers, from the side.



Note. Panel A shows the completed mechanical jig and laboratory coordinate markers viewed from the rear. Panel B shows the dimensions and marker configuration of the three-dimensional cluster, with dimensions reported in millimetres. Panels C and D show the jig and laboratory coordinate system from the front and side, respectively. The jig was used to position both kinematic models at known criterion angles during static validation.

5.3.2 Part B- Application during running gait

Reflective markers and 3D-rigid clusters were applied to the spine and back using double-sided adhesive tape as described previously in accordance with the SKS model (Christe et al., 2016) and CL model (Needham et al., 2016). Additional markers were also applied to the pelvis and lower limbs (Cappozzo et al., 1995; Leardini et al., 2007).

Each participant was required to run on a treadmill at a speed representing their first ventilatory threshold, which was determined during a VO₂max test one week prior to data collection. All participants ran in their own footwear to preserve habitual running mechanics

(Willwacher et al., 2020; Van der Meulen et al., 2024) and were given a 6-minute familiarisation period (Lavcanska et al., 2005). Ten consecutive gait cycles from right heel to right heel strike were recorded within a 15-second trial. Heel strike was identified as the instant at which the distal heel marker reached its minimum vertical position, corresponding to the point at which its vertical velocity transitioned from negative to positive. This kinematic method has been validated for both treadmill and overground running, yielding absolute errors of 22.4–24.6 ms relative to force plate ground truth (Fellin et al., 2010). An equivalent criterion, in which heel strike is defined as the moment the calcaneus marker's vertical displacement shifts from a descending to an ascending trajectory, has also been widely applied and validated (Zeni et al., 2008).

5.4 Data Processing and Analysis

All data processing and analyses were performed in Python (Version 3.12.3) using NumPy (Version 2.4.4), SciPy (Version 1.17.1), Pandas (Version 3.0.2), and Matplotlib (Version 3.10.8).

5.4.1 Part A

Agreement between each model and the criterion was quantified using a complementary set of error, association, and reliability statistics. Systematic error (bias) was expressed as the mean signed difference between the model and the criterion (model – criterion). Positive values indicate model overestimation, and random error was expressed as the standard deviation (SD) of these differences. Overall absolute accuracy was summarised using the root-mean-square error (RMSE) and the mean absolute error (MAE). The strength of the linear association between each model and the criterion was assessed using the Pearson correlation coefficient (r) and the coefficient of determination (R^2), with model angles regressed on criterion angles using ordinary least-squares linear regression to quantify any fixed (intercept) or proportional (slope) offsets from perfect correspondence. Relative agreement was evaluated using the intraclass correlation coefficient, computed as a two-way random-effects model for absolute agreement, single measures [ICC(2,1)] (Needham et al., 2016). ICC values were interpreted as poor (< 0.50), moderate ($0.50–0.75$), good ($0.75–0.90$), or excellent (> 0.90), consistent with Koo and Li (2016).

5.4.2 Part B

5.4.3 Kinematic Data Processing

Three-dimensional segmental angles were computed from marker trajectories captured during a standardised movement task. Data were time-normalised to 101 data points representing 0–100% of the normalised running gait cycle, enabling comparison across participants. Angles were expressed in three planes of motion: sagittal (flexion–extension), frontal (lateral flexion), and transverse (axial rotation). Two kinematic models were compared: a back-surface skin marker model (SKS; four segments: upper thoracic [UT], lower thoracic [LT], upper lumbar [UL], and lower lumbar [LL]) and a cluster marker model (CL; three segments: UT, LT, and LL).

5.4.4 Comparison Structure

Between-model comparisons were conducted for four segmental pairs across all three planes: SKS UT versus CL UT, SKS LT versus CL LT, SKS LL versus CL LL, and SKS UL versus CL LL. The SKS UL versus CL LL comparison represents a cross-segment pairing in which the SKS upper lumbar segment is contrasted with the CL lumbar segment, acknowledging differences in segment definition between models. Within-model comparisons were additionally performed to characterise segmental differentiation within each model: SKS UT versus SKS LT, SKS UL versus SKS LL, and CL UT versus CL LT.

5.4.5 Discrete Kinematic Metrics

Three discrete kinematic metrics were extracted from each participant's normalised waveform: (1) range of motion (ROM), defined as the peak-to-peak amplitude (maximum minus minimum angle); (2) maximum angle; and (3) minimum angle. These metrics were computed independently for each participant, producing paired samples of $n = 10$ per model for each comparison and plane.

5.4.6 Waveform Agreement Metrics

For between-model comparisons, two additional per-participant waveform agreement metrics were computed. The root mean square difference (RMSD) was calculated as the square root of the mean squared difference between the SKS and CL waveforms at each time node, providing an overall measure of between-model waveform discrepancy. The mean bias was defined as the mean signed difference (SKS – CL) across the normalised cycle, reflecting the systematic directional offset between models. Both metrics were tested against zero using one-sample inference (see Statistical Analysis of Discrete Metrics below).

5.4.7 Statistical Analysis of Discrete Metrics

Prior to inferential testing, the Shapiro-Wilk test was applied to the paired differences (or single-sample values for agreement metrics) to assess the normality assumption. Parametric paired t-tests (degrees of freedom = 9) were used to compare SKS and CL discrete metrics. Wilcoxon signed-rank tests were conducted in parallel as the non-parametric alternative, providing inference that does not assume normality of differences. For RMSD and mean bias, one-sample versions of both tests were applied against a null value of zero. All tests were two-tailed with a significance level of $\alpha = .05$. Effect sizes were quantified using Hedge's g , a small-sample corrected version of Cohen's d computed as $g = d \times J$, where $J = 1 - 3/[4(n - 1) - 1]$. For $n = 10$, $J \approx 0.914$, producing an approximately unbiased estimate of the population effect size. Effect magnitudes were interpreted using conventional benchmarks: $|g| < 0.2 = \text{small}$, $0.5 = \text{medium}$, $0.8 = \text{large}$.

5.4.8 Time-series Waveform Analysis: SPM and SnPM

To complement the discrete metric analysis, time-series waveform-level inference was performed using Statistical Parametric Mapping (SPM) and non-parametric permutation-based SPM (SnPM), implemented via the *spm1d* package (v0.4.53; Pataky, 2012). Paired t-tests were conducted at every time node across the 0–100% normalised waveform, generating an $\text{SPM}\{t\}$ statistic continuum. This approach treats the entire waveform as a single statistical entity, avoiding

the multiple comparison problem inherent in node-wise testing and preserving the temporal structure of the data.

For the parametric SPM, critical thresholds (t^*) were determined using random field theory (RFT), which accounts for the temporal smoothness of the $SPM\{t\}$ continuum. For SnPM, critical thresholds were estimated via sign-flip permutation testing (1,024 permutations), which makes no distributional assumptions and is particularly appropriate for small samples ($n = 10$). Both approaches were two-tailed at $\alpha = .05$. Significant clusters were defined as contiguous suprathreshold regions of the $SPM\{t\}$ continuum and are reported as percentage-cycle intervals. Where parametric and SnPM clusters diverge, the discrepancy reflects the difference in threshold sensitivity between the two methods; SnPM thresholds are typically lower for small samples, rendering it more sensitive. All between-model and within-model comparisons were analysed using SPM and SnPM across all three planes of motion

5.5 Results

5.5.1 Part A

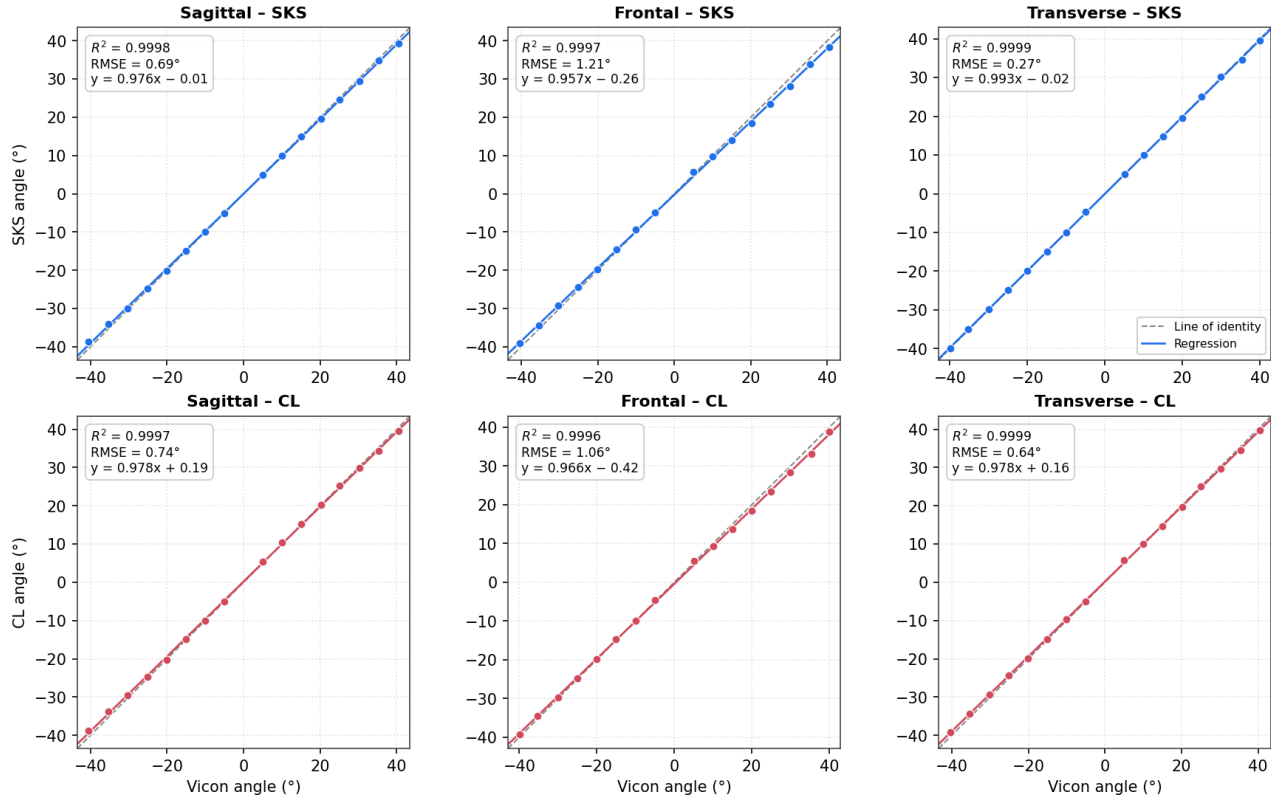
Both the SKS and CL models demonstrated excellent criterion validity across all three planes of motion ($ICC > 0.998$; Table 5.1). In the sagittal and transverse planes, both models achieved sub-degree accuracy ($RMSE \leq 0.74^\circ$), with the SKS model performing marginally better in both planes. The frontal plane returned the largest errors for both models ($RMSE$: SKS 1.21° , CL 1.06°), with the CL model showing a marginal advantage in this plane. As illustrated in Figure 5.3, data points in all conditions clustered tightly around the line of identity. However, regression slopes were slightly below unity across all conditions (range 0.957–0.994). This may indicate a small proportional underestimation that increased with angle magnitude.

Table 5.1. Agreement, Error, and Reliability of the Skin-Marker (SKS) and Cluster (CL) Kinematic Models Relative to the Criterion, by Plane.

Plane	Model	Bias (°)	SD (°)	RMS E (°)	MAE (°)	r	R^2	Slope	ICC(2,1)
Sagittal	SKS	-0.01	0.72	0.69	0.47	0.9999	0.9998	0.976	0.9996
Sagittal	CL	0.19	0.73	0.74	0.51	0.9999	0.9997	0.978	0.9996
Frontal	SKS	-0.26	1.22	1.21	1.04	0.9998	0.9997	0.957	0.9989
Frontal	CL	-0.42	1.00	1.06	0.85	0.9998	0.9996	0.966	0.9991
Transverse	SKS	-0.02	0.28	0.27	0.19	1.0000	0.9999	0.994	0.9999
Transverse	CL	0.16	0.63	0.64	0.53	0.9999	0.9999	0.978	0.9997

Note. SD = standard deviation of the differences; RMSE = root-mean-square error; MAE = mean absolute error; ICC = intraclass correlation coefficient [(2,1): two-way random effects, absolute agreement, single measures].

Figure 5.3. Model-estimated joint angle plotted against the criterion angle for each plane (columns) and model (rows: SKS, top; CL, bottom). The dashed line is the line of identity, and the solid line is the ordinary least-squares regression; R^2 , RMSE, and the regression equation are inset in each panel.



5.6 Part B

5.6.1 Sagittal Plane

In the sagittal plane, SKS UT produced significantly higher maximum angles (M difference = $+1.71^\circ$, $SD = 2.05$, $t(9) = 2.65$, $p = .026$, $g = 0.77$) and minimum angles ($p = .038$, $g = 0.70$) compared to CL UT, while ROM did not differ ($p = .927$). Waveform-level RMSD was significantly greater than zero ($M = 2.08^\circ$, $g = 1.13$), reflecting systematic positional offset throughout the cycle despite similar waveform shape.

For SKS LT versus CL LT, the ROM was significantly smaller in SKS ($M = 2.74^\circ$) compared to CL ($M = 4.08^\circ$), difference = -1.35° ($g = -1.27$, $p = .002$ for both tests). The minimum angle was significantly higher in SKS ($p = .007$, $g = 1.01$). RMSD was significantly greater than zero ($M = 1.48^\circ$, $g = 1.62$, $p < .001$).

For SKS LL versus CL LL, the minimum angle was significantly lower in SKS than CL (M difference = -3.27° , $p = .014$, $g = -0.88$). RMSD was large and significant ($M = 3.98^\circ$, $g = 2.35$, $p < .001$). For the cross-segment comparison SKS UL versus CL LL, no discrete kinematic metric reached significance in the sagittal plane (all $p > .30$), although RMSD remained significantly elevated ($M = 4.74^\circ$, $g = 1.50$, $p = .001$). Full statistics are presented in Table 5.2.

Table 5.2 Paired Comparison Statistics for Sagittal Plane Discrete Kinematic Metrics Between SKS and CL Models

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
SKS UT vs CL UT	ROM	4.40 (1.09)	4.38 (1.21)	0.02 (0.66)	0.09	.927	23	.695	0.03
	Maximum	30.21 (8.13)	28.49 (9.63)	1.71 (2.05)	2.65	.026*	8	.049*	0.77
	Minimum	25.81 (8.21)	24.11 (9.98)	1.69 (2.21)	2.43	.038*	8	.049*	0.70
	RMSD	2.08 (1.68)	—	2.08 (1.68)	3.91	.004*	0	.002*	1.13
	Mean bias	1.54 (2.10)	—	1.54 (2.10)	2.33	.045*	8	.049*	0.67
SKS LT vs CL LT	ROM	2.74 (0.60)	4.08 (0.81)	-1.35 (0.97)	-4.39	.002*	1	.004*	-1.27
	Maximum	4.53 (4.75)	4.57 (4.14)	-0.04 (1.39)	-0.08	.938	25	.846	-0.02
	Minimum	1.79 (4.81)	0.48 (4.07)	1.31 (1.19)	3.49	.007*	2	.006*	1.01
	RMSD	1.48 (0.84)	—	1.48 (0.84)	5.60	< .001*	0	.002*	1.62
	Mean bias	0.79 (1.18)	—	0.79 (1.18)	2.10	.065	11	.105	0.61

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
SKS LL vs CL LL	ROM	7.77 (3.62)	5.81 (2.70)	1.96 (2.96)	2.09	.066	11	.105	0.61
	Maximum	9.00 (7.59)	10.30 (8.56)	-1.30 (3.24)	-1.27	.235	16	.275	-0.37
	Minimum	1.22 (6.79)	4.49 (8.09)	-3.27 (3.39)	-3.05	.014*	5	.020*	-0.88
	RMSD	3.98 (1.55)	—	3.98 (1.55)	8.12	< .001*	0	.002*	2.35
	Mean bias	-2.17 (3.01)	—	-2.17 (3.01)	-2.27	.049*	11	.105	-0.66
SKS UL vs CL LL	ROM	5.26 (1.86)	5.81 (2.70)	-0.55 (2.99)	-0.58	.574	21	.557	-0.17
	Maximum	8.70 (8.57)	10.30 (8.56)	-1.60 (4.63)	-1.09	.303	18	.375	-0.32
	Minimum	3.44 (8.57)	4.49 (8.09)	-1.05 (5.76)	-0.58	.579	27	1.000	-0.17
	RMSD	4.74 (2.90)	—	4.74 (2.90)	5.18	< .001*	0	.002*	1.50
	Mean bias	-1.39 (5.16)	—	-1.39 (5.16)	-0.85	.415	20	.492	-0.25

Note. M = mean; SD = standard deviation; Diff = SKS – CL difference; t(9) = paired t-statistic (df = 9); W = Wilcoxon signed-rank statistic; g = Hedge's g effect size ($|g| < 0.2$ small, 0.5 medium, 0.8 large). RMSD and Mean bias are tested one-sample against zero (CL column shown as —). Asterisk (*) denotes $p < .05$.

5.6.2 Frontal Plane

In the frontal plane, SKS UT and CL UT did not differ significantly on any discrete kinematic metric (all $p > .13$). By contrast, SKS LT showed a significantly larger ROM than CL LT (M difference = $+1.08^\circ$, $p = .005$, $g = 1.08$) and a significantly lower minimum angle ($p = .035$, $g = -0.72$). For SKS LL versus CL LL, the ROM was significantly smaller in SKS (M difference = -2.40° , $p = .019$, $g = -0.83$) with a lower maximum (M difference = -1.55° , $p = .011$, $g = -0.92$). The cross-segment comparison (SKS UL vs CL LL) produced no significant frontal-plane differences on discrete metrics (all $p > .13$). Across all four comparisons, frontal-plane RMSD was consistently and significantly elevated above zero (all $p \leq .001$, $g = 1.63$ – 1.98), indicating persistent between-model waveform discrepancy in this plane. Full statistics are presented in Table 5.3.

Table 5.3. Paired Comparison Statistics for Frontal Plane Discrete Kinematic Metrics Between SKS and CL Models

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
SKS UT vs CL UT	ROM	15.22 (3.35)	14.81 (3.92)	0.41 (1.38)	0.94	.372	20	.492	0.27
	Maximum	9.42 (1.92)	9.47 (2.22)	-0.05 (1.40)	-0.12	.907	27	1.000	-0.03
	Minimum	-5.80 (2.60)	-5.34 (3.33)	-0.46 (0.90)	-1.63	.137	12	.131	-0.47
	RMSD	1.16 (0.65)	—	1.16 (0.65)	5.63	< .001*	0	.002*	1.63
	Mean bias	-0.32 (0.95)	—	-0.32 (0.95)	-1.08	.310	17	.322	-0.31
SKS LT vs CL LT	ROM	10.58 (2.43)	9.49 (2.14)	1.08 (0.92)	3.73	.005*	4	.014*	1.08

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
	Maximum	5.55 (2.45)	5.36 (2.29)	0.19 (1.24)	0.50	.630	23	.695	0.14
	Minimum	-5.02 (2.95)	-4.14 (3.24)	-0.89 (1.13)	-2.48	.035*	8	.049*	-0.72
	RMSD	1.70 (0.79)	—	1.70 (0.79)	6.83	< .001*	0	.002*	1.97
	Mean bias	-0.39 (1.23)	—	-0.39 (1.23)	-1.01	.340	16	.275	-0.29
SKS LL vs CL LL	ROM	6.57 (2.82)	8.98 (2.65)	-2.40 (2.66)	-2.86	.019*	4	.014*	-0.83
	Maximum	2.23 (3.46)	3.78 (3.57)	-1.55 (1.54)	-3.18	.011*	4	.014*	-0.92
	Minimum	-4.35 (3.29)	-5.20 (2.87)	0.86 (2.30)	1.18	.270	17	.322	0.34
	RMSD	2.01 (1.02)	—	2.01 (1.02)	6.26	< .001*	0	.002*	1.81
	Mean bias	-0.33 (1.61)	—	-0.33 (1.61)	-0.64	.539	24	.770	-0.18
SKS UL vs CL LL	ROM	7.41 (1.31)	8.98 (2.65)	-1.56 (2.97)	-1.67	.130	13	.160	-0.48
	Maximum	2.56 (3.32)	3.78 (3.57)	-1.21 (4.43)	-0.87	.409	19	.432	-0.25
	Minimum	-4.85 (3.20)	-5.20 (2.87)	0.35 (5.15)	0.22	.833	27	1.000	0.06

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
	RMSD	3.92 (2.42)	—	3.92 (2.42)	5.11	< .001*	0	.002*	1.48
	Mean bias	-0.38 (4.54)	—	-0.38 (4.54)	-0.26	.798	27	1.000	-0.08

Note. M = mean; SD = standard deviation; Diff = SKS – CL difference; t(9) = paired t-statistic (df = 9); W = Wilcoxon signed-rank statistic; g = Hedge's g effect size ($|g| < 0.2$ small, 0.5 medium, 0.8 large). RMSD and Mean bias are tested one-sample against zero (CL column shown as —). Asterisk (*) denotes $p < .05$.

5.6.3 Transverse Plane

The transverse plane revealed the largest between-model discrepancies. For SKS LT versus CL LT, the ROM was significantly larger in SKS than CL ($M = 29.54^\circ$ vs 20.48° , difference = $+9.07^\circ$, $p = .002$, $g = 1.26$), with significantly higher peak maximum ($p = .012$, $g = 0.91$) and lower peak minimum ($p = .010$, $g = -0.94$) angles. RMSD was very large ($M = 7.04^\circ$, $g = 4.06$, $p < .001$), the highest observed across all comparisons.

For SKS LL versus CL LL, all three amplitude metrics differed significantly: ROM (SKS $M = 18.45^\circ$ vs CL $M = 32.57^\circ$, difference = -14.11° , $p < .001$, $g = -1.78$), maximum (difference = -7.73° , $p < .001$, $g = -1.70$), and minimum (difference = $+6.38^\circ$, $p = .002$, $g = 1.25$). RMSD was also noticeably elevated ($M = 6.67^\circ$, $g = 3.52$). Similarly, for SKS UL versus CL LL, ROM (difference = -10.02° , $p = .001$, $g = -1.43$), maximum (difference = -5.99° , $p = .001$, $g = -1.53$), and minimum (difference = $+4.03^\circ$, $p = .034$, $g = 0.72$) all differed significantly. By contrast, the SKS UT versus CL UT comparison showed no significant differences in discrete transverse-plane metrics (all $p > .19$). Full statistics are presented in Table 5.4.

Table 5.4. Paired Comparison Statistics for Transverse Plane Discrete Kinematic Metrics Between SKS and CL Models

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
SKS UT vs CL UT	ROM	26.49 (2.99)	24.87 (3.68)	1.61 (3.58)	1.42	.188	16	.275	0.41
	Maximum	14.01 (3.61)	12.68 (4.06)	1.33 (4.66)	0.90	.390	15	.232	0.26
	Minimum	-12.48 (2.53)	-12.19 (4.32)	-0.28 (4.32)	-0.21	.840	25	.846	-0.06
	RMSD	4.15 (1.93)	—	4.15 (1.93)	6.82	< .001*	0	.002*	1.97
	Mean bias	0.72 (3.83)	—	0.72 (3.83)	0.59	.569	18	.375	0.17
SKS LT vs CL LT	ROM	29.54 (6.29)	20.48 (4.73)	9.07 (6.60)	4.34	.002*	2	.006*	1.26
	Maximum	14.56 (4.27)	11.58 (3.84)	2.97 (3.00)	3.13	.012*	1	.004*	0.90
	Minimum	-14.99 (3.23)	-8.89 (4.19)	-6.09 (5.91)	-3.26	.010*	4	.014*	-0.94
	RMSD	7.04 (1.58)	—	7.04 (1.58)	14.05	< .001*	0	.002*	4.06
	Mean bias	-1.41 (3.28)	—	-1.41 (3.28)	-1.36	.207	15	.232	-0.39
SKS LL vs CL LL	ROM	18.45 (2.28)	32.57 (8.97)	-14.11 (7.24)	-6.16	< .001*	0	.002*	-1.78

Comparison	Metric	SKS (SD)	M CL M (SD)	Diff (SD)	M t(9)	p	W	p	g
	Maximum	8.96 (2.71)	16.69 (5.97)	-7.73 (4.16)	-5.87	< .001*	1	.004*	-1.70
	Minimum	-9.49 (1.70)	-15.88 (4.87)	6.38 (4.68)	4.31	.002*	1	.004*	1.25
	RMSD	6.67 (1.73)	—	6.67 (1.73)	12.18	< .001*	0	.002*	3.52
	Mean bias	-1.15 (2.03)	—	-1.15 (2.03)	-1.80	.105	12	.131	-0.52
SKS UL vs CL LL	ROM	22.55 (3.97)	32.57 (8.97)	-10.02 (6.43)	-4.93	< .001*	0	.002*	-1.43
	Maximum	10.70 (3.46)	16.69 (5.97)	-5.99 (3.58)	-5.29	< .001*	1	.004*	-1.53
	Minimum	-11.85 (1.48)	-15.88 (4.87)	4.03 (5.09)	2.50	.034*	7	.037*	0.72
	RMSD	5.28 (1.56)	—	5.28 (1.56)	10.71	< .001*	0	.002*	3.10
	Mean bias	-1.12 (2.61)	—	-1.12 (2.61)	-1.36	.208	15	.232	-0.39

Note. M = mean; SD = standard deviation; Diff = SKS – CL difference; t(9) = paired t-statistic (df = 9); W = Wilcoxon signed-rank statistic; g = Hedge's g effect size ($|g| < 0.2$ small, 0.5 medium, 0.8 large). RMSD and Mean bias are tested one-sample against zero (CL column shown as —). Asterisk (*) denotes $p < .05$.

5.6.4 Between-Model Comparisons: SPM and SnPM Findings

Statistical Parametric Mapping (SPM) and non-parametric permutation-based inference (SnPM; 1,024 permutations) were applied as paired t-tests along the full normalised time-series waveform (0–100% cycle) for each between-model comparison across three planes of motion. The

SPM{t} statistic was computed at every time node, and critical thresholds (t^*) were established via random field theory (parametric) and permutation (SnPM). Significant clusters and contiguous regions exceeding t^* indicate time intervals at which the two models produce statistically different kinematic outputs. Significance was set at $\alpha = .05$ (two-tailed). Figures 5.4 and 5.5 display the angle waveforms with cluster overlays and the SPM{t} time-series, respectively.

5.6.5 SKS UT Versus CL UT

In the sagittal plane, parametric inference ($t^* = \pm 3.34$) identified no significant clusters. However, SnPM inference ($t^* = \pm 2.89$) detected two brief significant clusters at 9–13%, 67–76%, indicating that the lower non-parametric threshold captured transient differences not detected parametrically. No significant clusters were identified in the frontal (parametric $t^* = \pm 3.74$; SnPM $t^* = \pm 3.62$) or transverse (parametric $t^* = \pm 3.69$; SnPM $t^* = \pm 3.37$) planes by either method. Overall, these findings are consistent with the discrete metric results, where amplitude offsets (maximum and minimum angles) were detected in the sagittal plane, suggesting the two models track the same upper thoracic movement pattern with a small but consistent positional bias that is more sensitively detected by the non-parametric approach.

5.6.6 SKS LT Versus CL LT

Lower thoracic comparisons revealed no significant waveform-level differences in the sagittal ($t^* = \pm 3.89$) or frontal ($t^* = \pm 3.71$) planes via parametric inference. The SnPM identified a brief non-parametric cluster in the sagittal plane at 83–88% and a marginal cluster in the frontal plane at 42–45%, though these were not confirmed parametrically. In the transverse plane, both methods detected two substantial significant clusters: a parametric cluster at 29–44%, 70–98% ($t^* = \pm 3.94$) and corresponding SnPM clusters at 28–47%, 69–99% ($t^* = \pm 3.55$). These clusters, spanning the ascending and descending phases of the transverse waveform, coincide with the large ROM and amplitude differences identified in the discrete analysis (RMSD = 7.04°, $g = 4.06$).

5.6.7 SKS LL Versus CL LL

The lumbar comparison showed no significant clusters in the frontal plane (parametric $t^* = \pm 3.74$; SnPM $t^* = \pm 3.50$). A narrow parametric cluster was present in the sagittal plane at 96–98% ($t^* = \pm 3.86$), with SnPM extending this to 93–100% ($t^* = \pm 3.58$). The transverse plane exhibited the most extensive disagreement of all comparisons, with four significant parametric clusters spanning 0–3%, 13–57%, 65–83%, 95–100% ($t^* = \pm 4.09$) and corresponding SnPM clusters at 0–3%, 12–57%, 64–85%, 93–100% ($t^* = \pm 3.76$). Together, these clusters cover most of the gait cycle, indicating that the SKS and CL models produce fundamentally different transverse-plane lumbar waveforms (RMSD = 6.67° , $g = 3.52$).

5.6.8 SKS UL Versus CL LL

The cross-segment comparison between SKS upper lumbar (UL) and CL lumbar (LL) yielded no significant clusters in the sagittal ($t^* = \pm 3.47$) or frontal ($t^* = \pm 3.13$) planes via either method. In the transverse plane, both parametric and SnPM inference identified three significant clusters at 14–33%, 44–57%, 69–73% ($t^* = \pm 4.01$) and 13–35%, 43–57%, 67–75% ($t^* = \pm 3.43$), respectively. This pattern mirrors the SKS LL versus CL LL result and confirms that the transverse-plane disagreement between models persists regardless of whether the SKS LL or SKS UL segment is used as the comparator, consistent with the large discrete-metric differences observed (ROM difference = -10.02° , $g = -1.43$; RMSD = 5.28° , $g = 3.10$).

Figure 5.4. Segmental angle waveforms (mean $\pm$ SD) for between-model comparisons (SKS vs CL) with parametric (blue shading) and non-parametric (red shading) significant clusters. Rows represent segmental comparisons (UT, LT, LL, UL vs LL); columns represent planes of motion (Sagittal, Frontal, Transverse). The dashed vertical line indicates 40% of the movement cycle. $n = 10$, $\alpha = .05$, two-tailed.

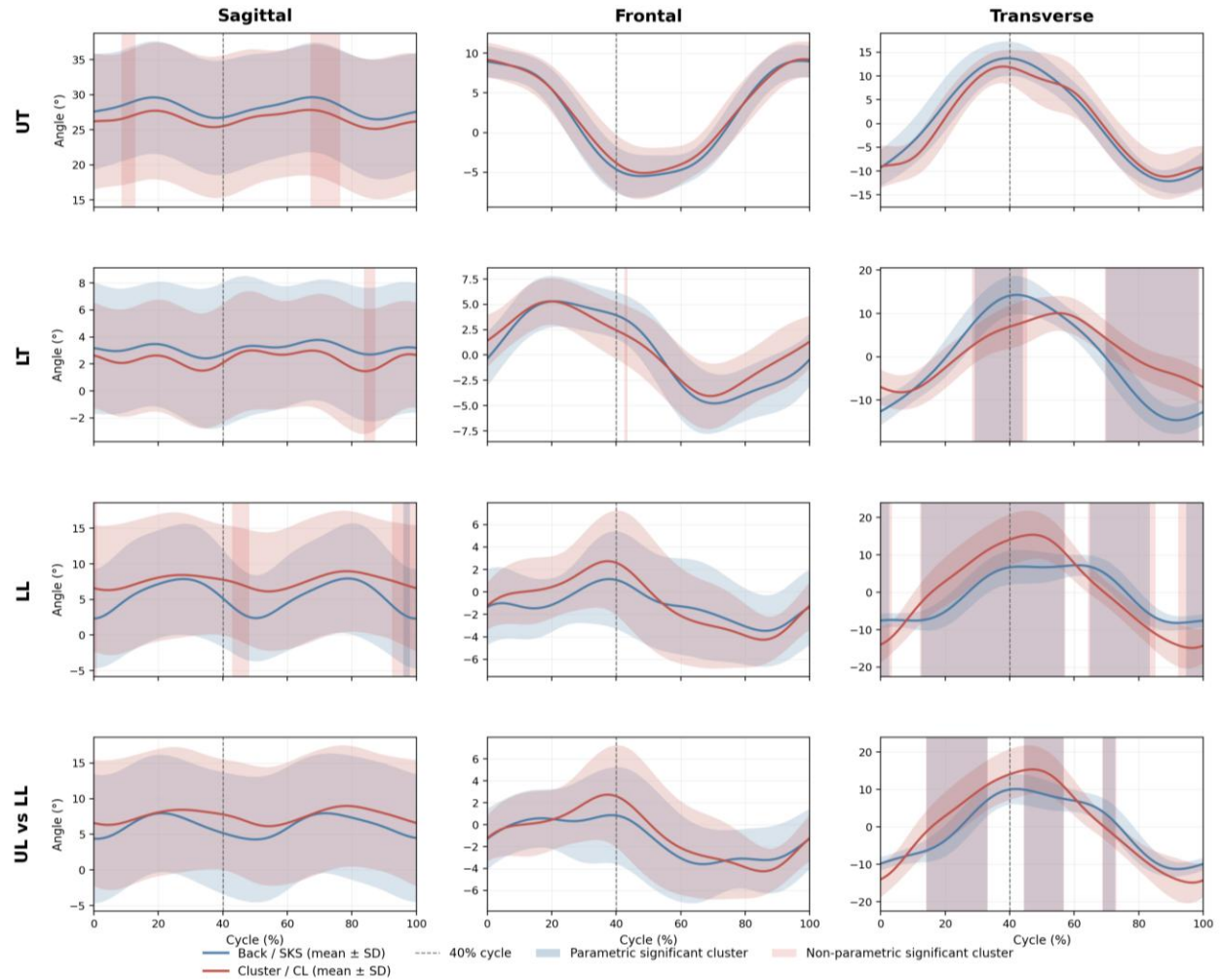


Figure 5.5. SPM{t} time-series for between-model comparisons. The solid black line denotes the SPM{t} statistic; dashed blue lines indicate the parametric critical threshold (t^*); dotted red lines indicate the non-parametric (SnPM) critical threshold. Shaded regions represent significant clusters. Parametric and SnPM t^* values are annotated in the upper-left of each panel. $n = 10$, $\alpha = .05$, two-tailed; 1,024-permutation SnPM inference.

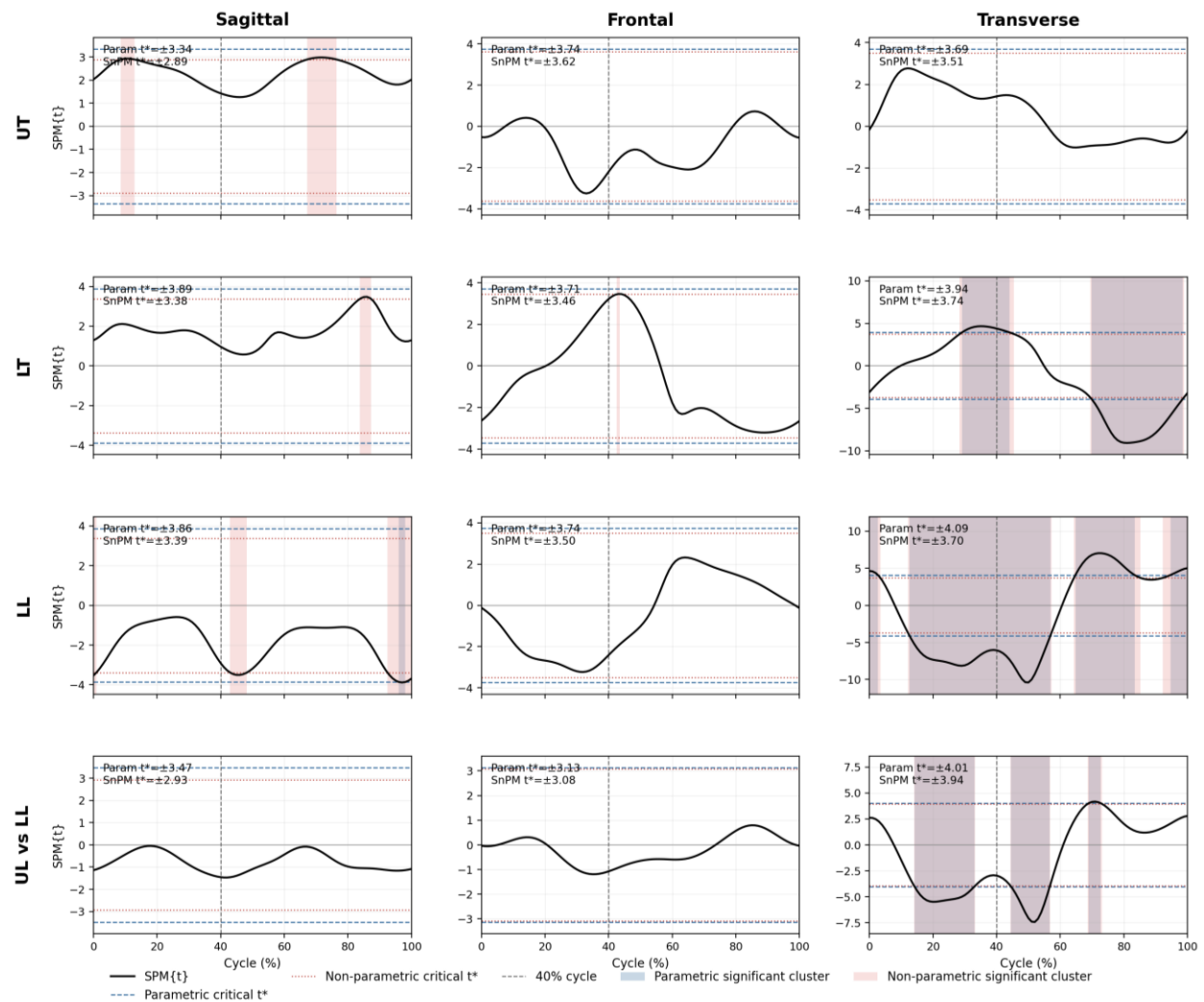


Figure 5.6. Strip plots of discrete kinematic metrics (ROM, maximum, and minimum angle) for between-model comparisons. Individual participant values (circles) are connected by grey lines to illustrate paired structure. Diamonds indicate group means; error bars represent ± 1 SD. Asterisk (*) indicates both parametric and Wilcoxon tests significant at $p < .05$; (*) indicates one test significant. Columns: Sag = sagittal, Fro = frontal, Tra = transverse.

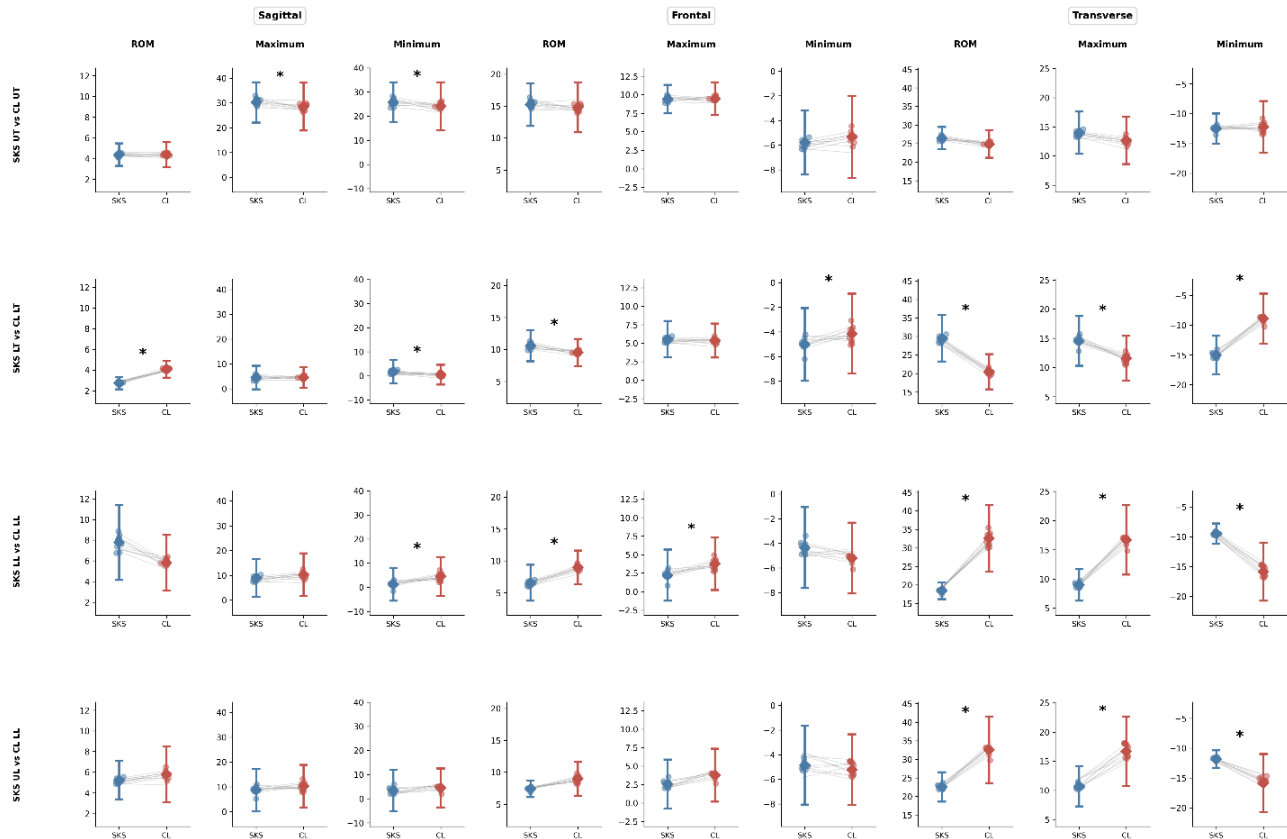
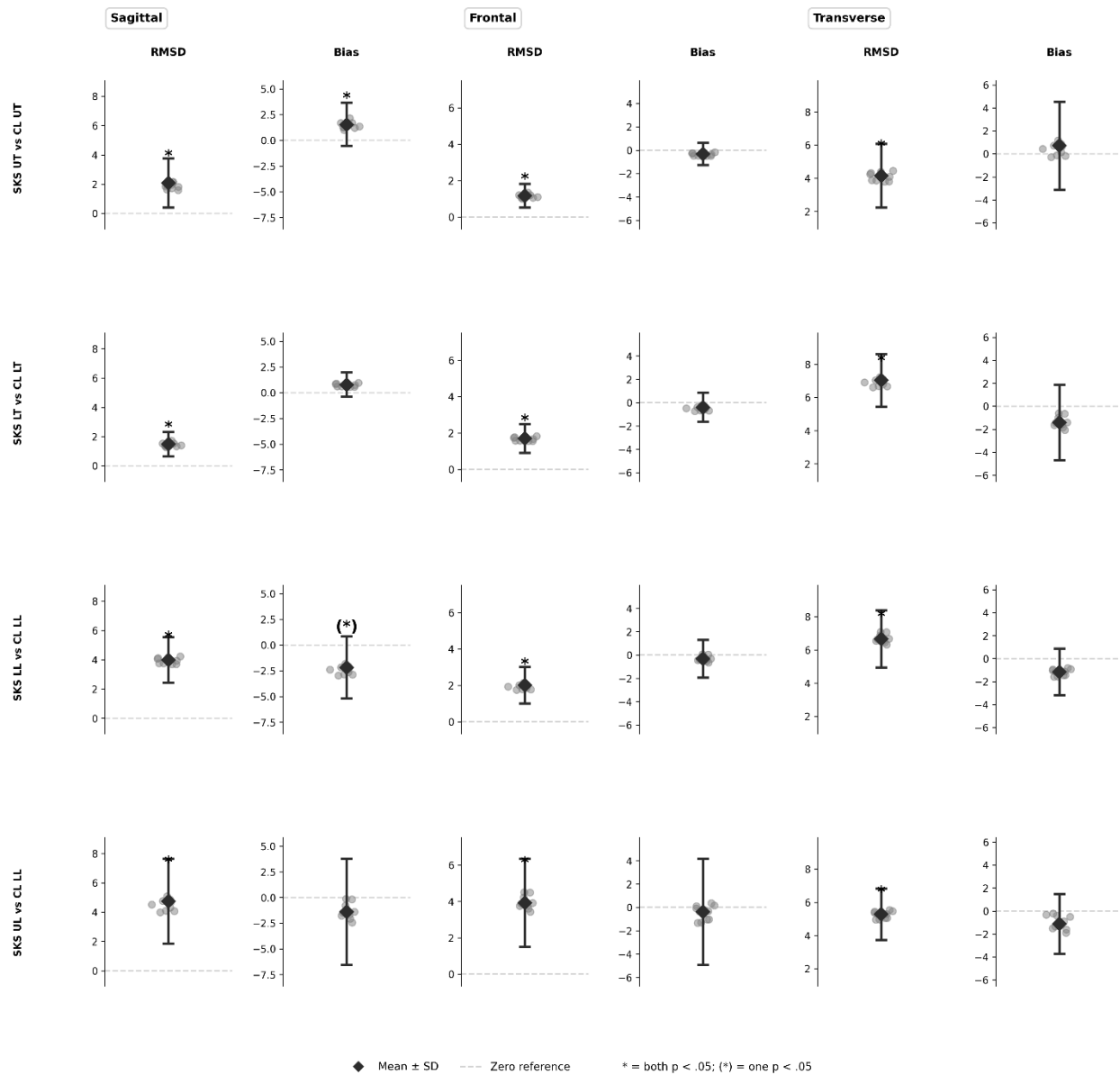


Figure 5.7. Strip plots of waveform agreement metrics (RMSD and mean bias [SKS – CL]) for between-model comparisons. Each value represents the per-participant summary computed across the full normalised waveform. Statistics are one-sample tests against zero. The dashed horizontal line denotes the zero reference.



5.6.9 Within-Model Comparisons: SPM and SnPM Findings

Within-model paired t-tests were conducted along the full normalised waveform (0–100% cycle) using SPM and SnPM (1,024 permutations, $\alpha = .05$, two-tailed) for three comparisons: SKS UT versus SKS LT, SKS UL versus SKS LL, and CL UT versus CL LT. These comparisons quantify the degree of segmental differentiation within each model across the three planes of motion. The SPM{t} difference is computed as the first-listed minus the second-listed segment. Figures 5.8 and 5.9 display the angle waveforms with cluster overlays and the SPM{t} time-series, respectively.

5.6.10 SKS UT Versus SKS LT

In the sagittal plane, both parametric ($t^* = \pm 2.78$) and SnPM ($t^* = \pm 2.12$) inference identified a significant cluster spanning the entire movement cycle (0–100%), indicating that SKS UT maintains a consistently greater sagittal angle than SKS LT throughout. In the frontal plane, both methods detected three significant clusters at 0–13%, 30–57%, 70–100% (parametric, $t^* = \pm 3.72$) and 0–13%, 29–57%, 69–100% (SnPM, $t^* = \pm 3.47$), together accounting for the majority of the gait cycle and reflecting substantial segmental differences in frontal-plane kinematics between UT and LT. In the transverse plane, a single significant cluster was identified at 9–29% by parametric inference ($t^* = \pm 3.82$) and 8–29% by SnPM ($t^* = \pm 3.71$), corresponding to the early-to-mid ascending phase of the waveform.

5.6.11 SKS UL Versus SKS LL

Neither the sagittal (parametric $t^* = \pm 3.48$; SnPM $t^* = \pm 3.31$) nor the frontal (parametric $t^* = \pm 3.10$; SnPM $t^* = \pm 3.00$) plane produced significant clusters, indicating that SKS UL and SKS LL produce statistically equivalent waveforms in these planes. In the transverse plane, however, both methods identified three significant clusters at 0–2%, 24–50%, 69–100% (parametric, $t^* = \pm 3.69$) and 0–2%, 23–51%, 68–100% (SnPM, $t^* = \pm 3.61$). The pattern of these clusters spanning the early cycle, mid-cycle ascending phase, and late-cycle descending phase indicates that the two lumbar segments differ substantially in transverse-plane rotation across most of the movement.

5.6.12 CL UT Versus CL LT

The CL model exhibited a similar pattern to SKS UT versus SKS LT. In the sagittal plane, a significant cluster spanning the full movement cycle (0–100%) was identified by both parametric ($t^* = \pm 2.92$) and SnPM ($t^* = \pm 2.17$) inference, confirming that CL UT and CL LT capture distinct sagittal positions throughout. In the frontal plane, three significant clusters were again detected at 0–13%, 33–55%, 69–100% (parametric, $t^* = \pm 3.75$) and 0–13%, 33–56%, 69–100% (SnPM, $t^* = \pm 3.67$), mirroring the SKS result closely. In the transverse plane, two significant clusters were found at 25–37%, 71–93% (parametric, $t^* = \pm 3.60$) and 23–39%, 69–94% (SnPM, $t^* = \pm 3.22$), indicating mid-cycle and late-cycle segmental deviation. The convergence of within-model results across both SKS and CL, particularly the whole-cycle sagittal significance and three-cluster frontal pattern, provides strong evidence that UT and LT are kinematically distinct segments regardless of the measurement model employed.

Figure 5.8. Within-model segmental angle waveforms (mean $\pm$ SD) with parametric (blue shading) and non-parametric (red shading) significant clusters. Rows represent within-model comparisons (SKS UT vs SKS LT, SKS UL vs SKS LL, CL UT vs CL LT); columns represent planes of motion (Sagittal, Frontal, Transverse). Blue lines denote the first-listed segment; red lines denote the second-listed segment. The dashed vertical line indicates 40% of the movement cycle. $n = 10$, $\alpha = .05$, two-tailed.

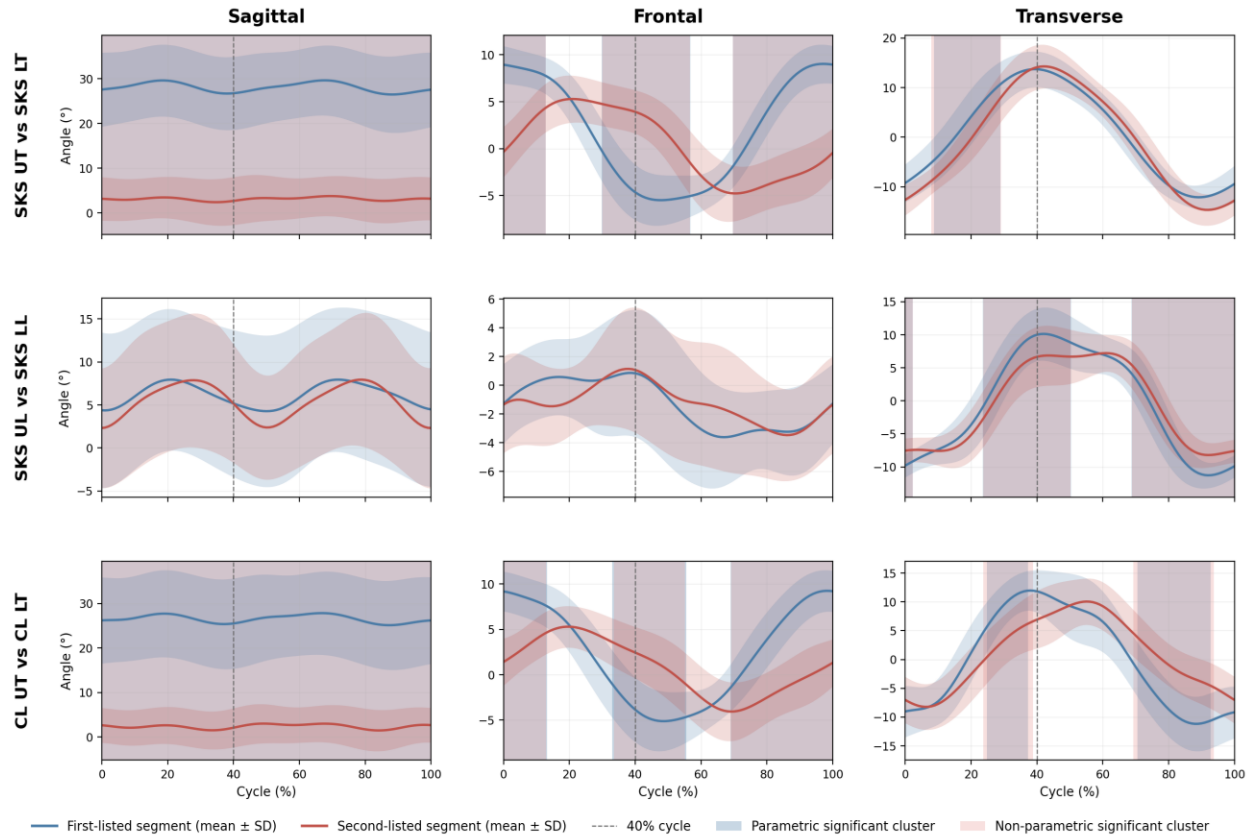
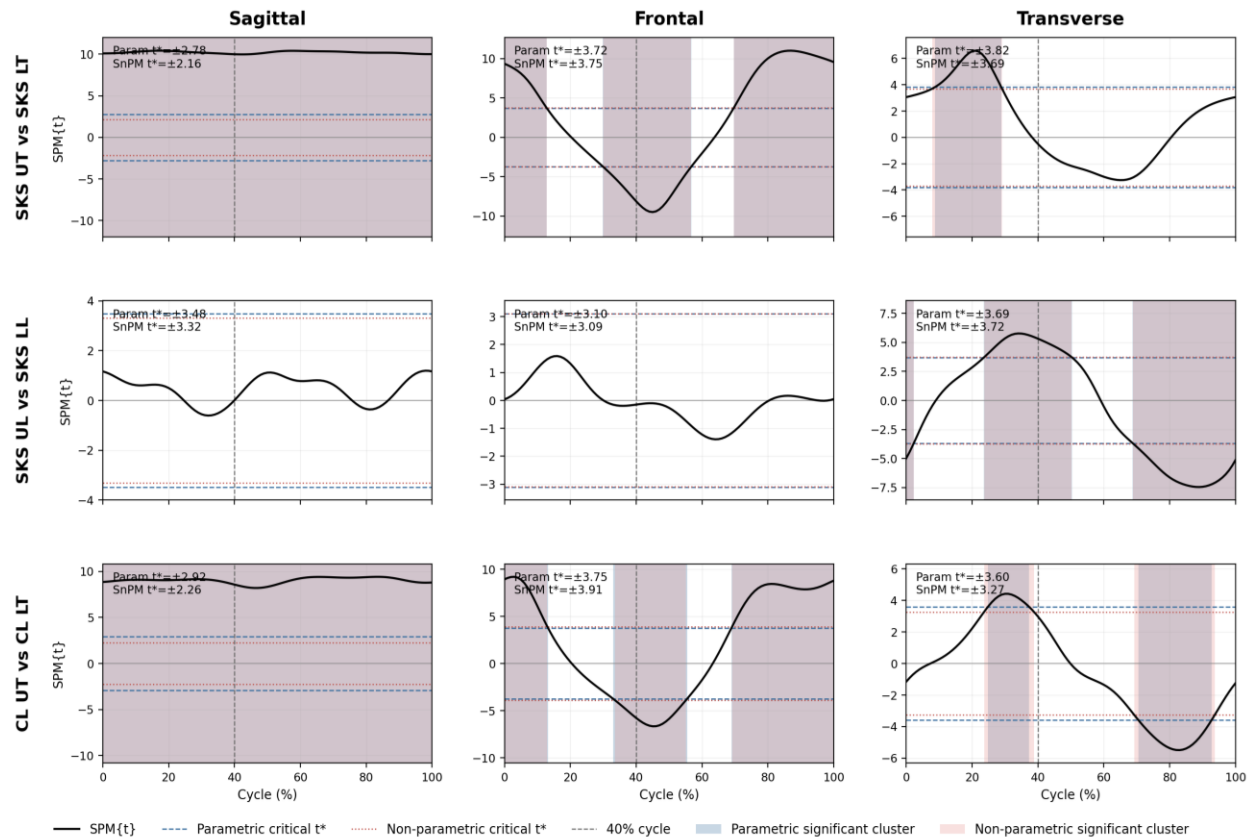


Figure 5.9. SPM{t} time-series for within-model comparisons (first-listed minus second-listed segment). The solid black line denotes the SPM{t} statistic; dashed blue lines indicate the parametric critical threshold (t^*); dotted red lines indicate the SnPM critical threshold. Shaded regions represent significant clusters. Parametric and SnPM t^* values are annotated in the upper-left of each panel. $n = 10$, $\alpha = .05$, two-tailed; 1,024-permutation SnPM inference.



5.7 Discussion

5.7.1 Part A

Both the SKS and CL models demonstrated excellent criterion validity across all three planes of motion, with intraclass correlation coefficients exceeding 0.998 in every condition. These values strongly satisfy the threshold for excellent agreement proposed by Needham et al. (2016). Root-mean-square errors remained below 0.75° for both models in the sagittal and transverse planes, indicating sub-degree accuracy that is unlikely to be of practical consequence in most biomechanical applications. Conversely, the frontal plane produced comparatively larger errors for both models (RMSE 1.06° – 1.21°). As illustrated in Figure 5.3, the data points in all conditions clustered tightly around the line of identity, with regression lines that were visually indistinguishable from perfect correspondence across most of the measured range.

However, a consistent and systematic departure was evident at larger angle magnitudes, reflected in regression slopes slightly below unity across all conditions (range 0.957–0.994; Table 5.1). Although modest across the tested range, this proportional underestimation may warrant consideration at the larger joint angles encountered during dynamic functional tasks such as running. Overall, these findings support the validity of both models under controlled laboratory conditions, though the degree to which this accuracy is maintained during unrestricted movement, where dynamic conditions introduce additional sources of error, remains to be established.

5.7.2 Part B

This study compared two multi-segment kinematic models of the spine: a back-surface skin-marker model (SKS; four segments) and a 3D rigid-cluster model (CL; three segments) during treadmill running in sub-elite runners, using both discrete waveform metrics and time-series statistical analysis (SPM and SnPM). Two complementary questions were addressed. The between-model analysis asked whether the two models produce interchangeable estimates of the same segmental motion. The within-model analysis tested whether each model could kinematically differentiate between adjacent spinal segments. The discussion is organised around these two questions in turn, before considering the implications for running biomechanics, the limitations of the work, and directions for future research.

5.7.3 Between-Model Comparison

The main finding of the between-model analysis was that agreement was strongly plane-dependent and region-dependent; the models were for the majority comparable for sagittal-plane motion, showed only partial agreement in the frontal plane, and diverged substantially in the transverse plane. There was substantial deviation in the transverse plane, where between-model differences in axial rotation reached up to 14° of ROM with very large effect sizes (Hedge's g up to 4.06). Transverse-plane disagreement increased more in the distal segments. The two models therefore cannot be treated as equivalent for transverse-plane or lumbar analyses.

In the sagittal plane, the two models tracked the same movement pattern. Range of motion did not differ at the upper thoracic segment (SKS UT vs CL UT, $p = .927$), and the time-series analysis identified no significant parametric clusters for this comparison, thus indicating closely matched waveform profiles. The differences that did emerge were positional: SKS UT produced significantly higher maximum (+1.71°, $g = 0.77$) and minimum (+1.69°, $g = 0.70$) angles, and the root mean square difference (RMSD) was significantly greater than zero (2.08°, $g = 1.13$). This pattern, equal ROM but offset peaks, accompanied by a non-zero mean bias, may suggest a near-constant inter-model offset rather than a difference in the underlying movement signal. The brief SnPM clusters detected at 9–13% and 67–76% of the gait cycle are in the absence of any parametric cluster. These are consistent with a small, temporally persistent offset that the more sensitive non-parametric threshold resolved but the random-field-theory threshold did not. This may be due to the difference in marker mounting site and the resulting anatomical reference for each segment (Johnson et al 2024, Leardini et al 2005, Kudo et al., 2017, Kiernan et al., 2014& 2015). Overall, a constant offset of this magnitude is unlikely to alter conclusions drawn from sagittal-plane ROM, but it would bias any comparison of absolute angular position between studies using different models.

Frontal-plane agreement sat between the sagittal and transverse extremes. Discrete differences were present but modest and localised to the lower thoracic and lumbar segments: SKS produced a larger lower-thoracic ROM than CL (+1.08°, $g = 1.08$) and a smaller lumbar ROM (−2.40°, $g = -0.83$), with a correspondingly lower lumbar maximum (−1.55°, $g = -0.92$). Importantly, however, the time-series analysis revealed no significant between-model clusters in the frontal plane for any segmental pair, even though RMSD was consistently elevated above zero

across all four comparisons ($g = 1.63\text{--}1.98$). The combination of significant RMSD with non-significant SPM clusters suggests that the frontal-plane discrepancy is largely one of amplitude scaling distributed across the gait cycle, rather than a phase-specific deviation large enough to exceed the waveform-level threshold. In practical terms, the models capture the same lateral-flexion waveform but partition its magnitude slightly differently between adjacent segments.

The transverse plane produced the largest and most consistent between-model differences, and these are the results that most strongly constrain interchangeability. At the lower thoracic segment, SKS produced a substantially larger axial-rotation ROM than CL (29.54° vs 20.48° ; $+9.07^\circ$, $g = 1.26$), with the highest RMSD observed in the entire dataset (7.04° , $g = 4.06$) and significant SPM clusters spanning much of the gait cycle (29–44% and 70–98%). At the lumbar level, the pattern reversed as SKS now produced a markedly smaller ROM than CL (18.45° vs 32.57° ; -14.11° , $g = -1.78$), with significant clusters covering most of the movement cycle. This reversal in bias, with SKS attributing more rotation than CL at the thoracic level but less at the lumbar level, indicates that the disagreement is not a simple uniform offset. It may be a redistribution of total trunk axial rotation across spinal levels, with the two models assigning rotation differently between the thorax and lumbar spine.

Two features of the data reinforce this interpretation. First, at the lower thoracic segment, the mean bias was not significantly different from zero ($p = .207$) despite the very large RMSD ($g = 4.06$). A signed mean close to zero combined with a large unsigned RMSD indicates a time-varying disagreement that changes sign across the running gait cycle rather than a constant directional offset. Second, the cross-segment comparison (SKS upper lumbar vs CL lumbar) reproduced the lumbar pattern closely (ROM difference -10.02° , $g = -1.43$; RMSD 5.28° , $g = 3.10$). This demonstrates that the transverse-plane lumbar discrepancy persists regardless of which SKS lumbar segment is used as the comparator. The disagreement is therefore intrinsic to how each model captures lumbar axial rotation, not an artefact of the segment pairing chosen. The most plausible mechanical explanations are the greater soft-tissue thickness and lordotic curvature over the lumbar spine. This may reduce skin-marker reliability in rotation, along with the structural difference that the CL model represents the lumbar region with a single segment whereas the SKS model subdivides it. (MacWilliams et al., 2014; Kudo et al., 2017).

A plausible explanation for the larger lumbar ROM observed in the CL model is that the cluster may have introduced additional movement artefact during running, rather than capturing greater true lumbar motion. The lumbar region is challenging for external marker tracking because of its concave surface, lordotic curvature, and surrounding paraspinal musculature (Needham et al., 2016a). Although the 3D-printed cluster base was designed for direct placement over the spinous process within the lumbar concavity, fit consistency across participants cannot be guaranteed. Minor variations in attachment, soft-tissue compression, or paraspinal muscle activity may consequently have altered cluster orientation during running. This may potentially explain why the CL model produced greater lumbar transverse-plane ROM than the SKS model, despite both demonstrating strong static validity.

The lumbar spine also contributes to shock attenuation during running (Castillo & Lieberman, 2018; Knight, 2018; Zemp et al., 2014). The repeated foot-ground impacts may therefore have induced small cluster oscillations relative to the skin, particularly in the transverse plane, where between-model discrepancies were greatest. These findings align with walking-based literature reporting greater inter-model disagreement in the transverse plane (Kiernan et al., 2015; Needham et al., 2020), and extend this evidence to running, where higher impact loading and trunk acceleration may amplify marker- or cluster-based artefact. This does not invalidate the CL model; rather, it suggests that lumbar tracking using a cluster is more sensitive to attachment stability and soft-tissue movement during dynamic tasks. Consequently, the two models should not be used interchangeably for lumbar transverse-plane analyses, and absolute axial-rotation values should only be compared across studies employing consistent model architectures and attachment strategies.

A recurring methodological message across the between-model comparisons is that agreement on discrete metrics did not guarantee agreement across the waveform. At the upper thoracic segment in the transverse plane, for example, no discrete metric differed significantly (all $p > .19$), yet RMSD remained large and significant (4.15° , $g = 1.97$). The same dissociation appeared in the cross-segment comparison in the sagittal and frontal planes. Reliance on peak or ROM extraction alone would therefore have understated the true level of between-model disagreement. This supports the use of time-series waveform analysis when evaluating model interchangeability. This is because SPM preserves the temporal structure of the full waveform and

avoids reducing continuous biomechanical data to isolated scalar values such as peaks or ROM (Pataky, 2010, 2012; Pataky et al., 2013). Relatedly, the SnPM analysis detected significant clusters that the parametric SPM did not, reflecting the lower critical thresholds of permutation inference at small sample sizes. For a sample of $n = 10$, the non-parametric approach is the more appropriate and more sensitive primary inference, and the parametric result is best read as the more conservative bound.

5.7.4 Within-Model Comparison

Whereas the between-model analysis tested whether the two models agree, the within-model analysis tested whether each model resolves adjacent spinal segment kinematics separately. Three contrasts were examined using SPM and SnPM: SKS UT versus SKS LT, SKS UL versus SKS LL, and CL UT versus CL LT. The results show that segmental differentiation is present and, where it occurs, is highly consistent across the two models.

In both models, the upper and lower thoracic segments differed significantly across the entire gait cycle, with the upper thoracic segment maintaining a consistently greater sagittal angle than the lower thoracic segment throughout. This whole-cycle separation confirms that UT and LT are genuinely distinct kinematic segments rather than a redundant subdivision, and that a multi-segment representation captures real intersegmental differentiation. The frontal plane reinforced this interpretation, as both models identified three significant clusters at almost identical phases of the cycle: SKS at approximately 0–13%, 30–57%, and 70–100%, and CL at approximately 0–13%, 33–55%, and 69–100%. Both models also identified more limited transverse-plane separation, with a single SKS cluster at 9–29% and two CL clusters at approximately 25–37% and 71–93%.

The close correspondence of these cluster patterns between the skin-marker and 3D-cluster models is an important finding, as it indicates that thoracic segmentation behaves consistently regardless of marker-mounting method. This supports the construct validity of the UT–LT segment definitions and suggests that the large between-model disagreement identified in the between-model analysis is specific to the lumbar region and transverse plane, rather than being a general limitation of the segmentation scheme.

The two SKS lumbar sub-segments showed a different pattern. SKS UL and SKS LL were statistically equivalent in both the sagittal and frontal planes, with no significant clusters identified in either plane. Differences were only evident in the transverse plane, where three significant clusters spanned the early, mid-ascending, and late-descending phases of the gait cycle: approximately 0–2%, 24–50%, and 69–100%. Subdividing the lumbar region into upper and lower segments therefore adds discriminative information almost exclusively for axial rotation; for sagittal and frontal motion, the two sub-segments appear to move as one. The additional lumbar segment that distinguishes the four-segment SKS model from the three-segment CL model appears most justified in the transverse plane. Interestingly, this is precisely the plane in which the between-model analysis showed the greatest disagreement, and the plane most vulnerable to soft-tissue artefact. Thus, the transverse plane is simultaneously where finer lumbar segmentation is most valuable and where the kinematic estimate is least robust. Studies seeking to exploit the additional lumbar segment for axial-rotation analysis should therefore weigh the gain in segmental resolution against the reduced measurement reliability in that plane and interpret finely segmented lumbar rotation with corresponding caution.

5.8 Implications for running biomechanics

The functional relevance of these findings is shaped by the demands of running. Transverse-plane trunk motion is central to running mechanics, where thoracic and lumbar axial rotation contribute to the regulation of whole-body angular momentum and to trunk–pelvis coordination during arm and leg swing (Preece et al., 2016; Li et al., 2018; Yang et al., 2013; Bruijn et al., 2008; Schache et al., 2002). The plane in which the two models disagree most is therefore precisely the plane of greatest functional interest for many running questions. Methodologically, the SKS and CL models can be used interchangeably for sagittal-plane trunk ROM, and with caution for frontal-plane motion, but they are not interchangeable for transverse-plane analyses, particularly at the lumbar level. For applied and clinical work, for example, studies relating trunk rotation to running economy, to low-back pain, or to trunk–pelvis coordination, the choice of spine model is not a neutral methodological detail but one that can change the magnitude and even the inter-segmental distribution of the reported rotation. Finally, because the between-model difference in lumbar transverse ROM exceeded 14°, pooling or directly comparing transverse-

plane spine kinematics across studies using different model architectures is not recommended. Authors should therefore report the model used explicitly and avoid cross-model comparison of absolute rotation values.

5.9 Methodological considerations and limitations

The classification of the present cohort as Tier 3: Highly Trained/National Level is an important contextual consideration when interpreting the findings. McKay et al. (2022) recommend defining participant ability through objective training and performance descriptors rather than subjective terms such as "trained", "well-trained", or "elite". The present runners were characterised by structured endurance training, running as their primary sport, and a typical weekly volume of 40–50 miles. This places them clearly above recreationally active or trained/developmental cohorts. Such a sample was appropriate for a model-comparison study, as highly trained runners tend to exhibit more consistent treadmill-running mechanics. Thereby reducing variability attributable to task unfamiliarity, irregular training exposure, or inconsistent self-selected pacing.

This sampling strategy carries inherent limitations for generalisability. The findings should be interpreted as model-specific evidence within the context of highly trained male runners, rather than as universal estimates of spinal kinematics during running. Recreational runners may exhibit greater movement variability because of lower training volumes and less stable running mechanics. Whereas elite runners may employ more refined trunk-control strategies not represented in the present sample (Folland et al. 2017; Moore et al. 2016). Accordingly, caution is warranted when extrapolating these findings beyond the population from which they were derived.

The male-only sample improves internal consistency but limits application to female runners, where sex-related differences in anthropometry, pelvic morphology, tissue distribution, and running mechanics may influence marker behaviour and measured spine motion. Future studies should therefore examine whether the same model-dependent differences are present across female, recreational, elite, and clinical running populations. As the model comparison was undertaken in male runners, the dynamic between-model findings should be considered specific to this cohort. Although the underlying measurement principles are not sex-specific, potential sex-

related differences in spinal and pelvic kinematics mean that the magnitude of between-model disagreement during running should be independently evaluated in female runners.

Several further limitations should be acknowledged. First, the sample comprised ten runners. Although many significant findings were supported by large effect sizes, the small sample limited statistical power to detect smaller model-dependent differences. Consequently, non-significant comparisons, such as the upper thoracic transverse metrics or sagittal and frontal lumbar sub-segment comparisons, should not be interpreted as evidence of equivalence. This is reinforced by the observation that RMSD was frequently elevated even where discrete metrics were non-significant.

Second, neither model was validated against a gold-standard reference, such as biplanar fluoroscopy. Therefore, although the present analysis establishes that the SKS and CL models produce different outputs during running, it cannot determine which model more accurately represents underlying vertebral motion (MacWilliams et al., 2014; Zemp et al., 2014; Frey et al., 2025). Third, soft-tissue artefact was not directly quantified, so its contribution to the transverse-plane disagreement remains inferred rather than measured. Fourth, the two models differed in segment number, with the SKS model using four segments and the CL model using three. The lumbar comparison therefore involved a definitional mismatch. The cross-segment analysis partly addressed this issue, and the persistence of transverse-plane disagreement across both lumbar pairings suggests that the finding was not solely an artefact of segment choice.

Finally, data were collected during treadmill running only. Generalisation to overground running, different running speeds, incline running, fatigue conditions, recreational or clinical populations, and runners with a history of low-back pain remains to be established. This is particularly important because treadmill and overground running can differ in trunk and lumbo-pelvic kinematics (Hafer & Boyer, 2017; Riley et al., 2007, 2008; Schache et al., 2001).

5.10 Future directions

Future work should validate both models against an imaging-based reference during running where feasible and should employ formal similarity testing against clinically or biomechanically meaningful thresholds rather than null-hypothesis significance testing alone.

Extending the comparison to overground running, to a range of running speeds, and to runners with low-back pain would clarify the generalisability of the plane- and region-dependent pattern reported here. A valuable further step would be to quantify how the between-model differences in transverse-plane lumbar rotation propagate into downstream outcomes, for example trunk–pelvis coordination metrics or model-estimated spinal loading.

5.11 Conclusion

A four-segment skin-marker model and a three-segment 3D-cluster model of the spine produced comparable sagittal-plane estimates during treadmill running but differed in a plane- and region-dependent manner. Disagreement was noted as segmental analysis moved distally, culminating in large, bidirectional differences in transverse-plane lumbar axial rotation. The within-model analysis confirmed that adjacent segments are genuinely distinct, consistently so across both models in the thoracic region, and that subdividing the lumbar spine is informative primarily for axial rotation. The two models are not interchangeable for transverse-plane or lumbar analyses, and model selection in spine running biomechanics should be guided explicitly by the plane of motion and the spinal region of interest. Where transverse-plane trunk rotation is the variable of interest, the choice of model should be reported and justified, and absolute rotation values should not be compared across studies using different model architectures.

Chapter 6

Reliability of a multi-segment spine skin-marker model during treadmill running

Aspects of this chapter have been submitted for peer-review publication:

Hicks, CA., Chockalingam, N., & Needham, R.A. Reliability of a multi-segment spine skin-marker model during treadmill running (under review).

6.1 Introduction

Running gait analysis is widely used to examine movement patterns associated with athletic performance, injury risk, and rehabilitation outcomes. Three-dimensional motion capture remains the predominant method for quantifying running biomechanics. However, the quality of the data derived from this approach depends heavily on the accuracy and consistency of reflective marker placement. Recent reporting guidelines for running biomechanics research have emphasised the need for a transparent and detailed description of marker placement protocols, biomechanical models, and measurement reliability. These methodological factors directly influence how findings are interpreted and compared across research laboratories (Hébert-Losier et al., 2023).

Although running biomechanics research has traditionally focused on the lower limbs, spinal and trunk motion are increasingly recognised as important components of running mechanics. The spine contributes to load transfer, postural control, and the storage and return of energy through coordinated multi-planar motion (Bruijn et al., 2008; Pontzer et al., 2009; Preece et al., 2016; Schache et al., 2002; Seay et al., 2011a, 2011b). Multi-segment kinematic models, which divide the spine into thoracic and lumbar regions, have been developed to provide a more anatomically representative description of segmental motion in the trunk region (Christe et al., 2016; Leardini et al., 2011; Mason et al., 2016; Needham et al., 2016; Preece et al., 2016). Yet despite the relevance of multi-segment spine models to running biomechanics, few studies have validated trunk marker reliability. Existing work typically reports measurement error for the entire thoracic or lumbar spine rather than for inter-segmental motion within these regions.

The practicality of any multi-segment model depends, however, on the quality of the underlying marker data. Skin-marker sets (SKS) for the trunk region typically comprise individual markers attached to palpable anatomical landmarks such as the spinous processes and/or onto the back surface. While manual marker placement introduces variability between applications, soft-tissue artefact, the movement of markers relative to underlying bone structures, poses a greater concern. This displacement is particularly problematic during running, where high accelerations and repetitive impacts may amplify translational movement of a marker. Since these error sources accumulate across testing sessions, the reproducibility of SKS multi-segment spine models must be empirically validated rather than assumed.

This study aimed to assess the test-retest reliability of a SKS multi-segment spine model for running gait analysis and establish whether measurement error is acceptable for research applications.

6.2 Methods

6.2.1 Participants

Ethical approval was granted by the University of Staffordshire Ethics Committee. Ten male sub-elite runners participated in the study (age 45.8 ± 9.2 years; height 178.7 ± 4.13 cm; mass 73.22 ± 5.4 kg), all of whom were free from current musculoskeletal impairment. Participants were classified according to the Participant Classification Framework proposed by McKay et al. (2022). The cohort was classified as Tier 3: Highly Trained/National Level, as participants identified running as their primary sport, completed structured endurance training, and typically ran 40–50 miles per week across regular weekly training sessions.

6.2.2 Kinematic model – defined segments, coordinate systems, and segment tracking

Six central markers were placed on the spinous processes of T1, T6, T12, L1, L3 and L5 to define four segments: upper thoracic (UT) (T1-T6), lower thoracic (LT) (T6-T12), upper lumbar (UL) (L1-L3) and lower lumbar (LL) (L3-L5) (Christe et al., 2016). The Z-axis was defined as a line passing through two markers stated for each segment that represented posture in the sagittal plane (positive direction upwards from the distal marker). Eight lateral markers were placed between central markers on each side of the spine, at a distance of 5 cm, representing spinal levels T3, T9, L2 and L4. The cross product of the Z-axis and a line connecting the two markers bilaterally for each segment defined the Y-axis (positive direction pointing to the left). The cross product of the Z- and Y-axis was used to define the X-axis (positive direction pointing forwards). For the individual skin marker model (SKS), the four markers used to define each segment were used to track motion.

6.2.3 Segment parameters

Three-dimensional segment angles were calculated with respect to the normal standing position of the participant. Rotations about the global coordinate system (laboratory) were based on the right-hand rule convention. Angular kinematic data for all segments and both kinematic

models were computed by measuring the relative movements between of the respective segment to the global coordinate system. Cardan angles were calculated using the YXZ with an order in the sagittal, frontal, and transverse plane (Grood & Suntay, 1983).

6.2.4 Instrumentation

Participants were required to run on a treadmill (Model TY700HRT; Vision Fitness, 1600 Landmark Dr, Cottage Grove, WI 5352) that was positioned in the centre of the laboratory. An 18-camera motion capture system (Vicon, Oxford, UK) was used to record three-dimensional marker coordinate data at 200 frames/s.

6.2.5 Experiment protocols

Reflective markers were applied to the spine and back using double-sided adhesive tape as described previously in accordance with the multi-segment spine model (Christe et al., 2016). Additional markers were also applied to the pelvis and lower limbs (Cappozzo et al., 1995; Leardini et al., 2007).

Each participant was required to run on a treadmill at a speed representing their first ventilatory threshold, which was determined during a VO₂max test one week prior to data collection during session one. Participants were required to return one week later for session two. For both sessions, all participants ran in their own footwear to preserve habitual running mechanics (Willwacher et al., 2020; Van der Meulen et al., 2024) and were given a 6-minute familiarisation period (Lavcanska et al., 2005). Ten consecutive gait cycles from right heel to right heel strike were recorded within a 15-second trial. Heel strike was identified as the instant at which the distal heel marker reached its minimum vertical position, corresponding to the point at which its vertical velocity transitioned from negative to positive. This kinematic method has been validated for both treadmill and overground running, producing absolute errors of 22.4–24.6 ms relative to force plate ground truth (Fellin et al., 2010). An equivalent criterion, in which heel strike is defined as the moment the calcaneus marker's vertical displacement shifts from a descending to an ascending trajectory, has also been widely applied and validated (Zeni et al., 2008).

6.2.6 Data Processing and Analysis

All data processing and analyses were performed in Python (Version 3.12.3) using NumPy (Version 2.4.4), SciPy (Version 1.17.1), Pandas (Version 3.0.2), and Matplotlib (Version 3.10.8).

Three-dimensional segmental angles were computed from marker trajectories captured during a standardised movement task. Data were time-normalised to 101 data points representing 0–100% of the normalised running gait cycle, enabling comparison across participants. Angles were expressed in three planes of motion: sagittal (flexion–extension), frontal (lateral flexion), and transverse (axial rotation). Between-session comparisons (Session 1 vs. Session 2) were conducted across all three planes and for each segment: upper thoracic (UT), lower thoracic (LT), upper lumbar (UL), and lower lumbar (LL).

6.2.7 Discrete Kinematic Metrics

Three discrete kinematic metrics were extracted from each participant's normalised waveform: (a) range of motion (ROM), defined as the peak-to-peak amplitude (maximum minus minimum angle); (b) maximum angle; and (c) minimum angle. These metrics were computed independently for each participant.

6.2.8 Statistical Analysis of Discrete Metrics

Prior to inferential testing, the Shapiro–Wilk test was applied to each metric's paired difference scores (Session 1 – Session 2) to assess the normality assumption. Where differences were approximately normally distributed (Shapiro–Wilk $p > .05$), parametric paired t -tests ($df = 9$) were interpreted as the primary inferential result. Wilcoxon signed-rank tests were conducted in parallel throughout as the non-parametric alternative, and are the preferred inference where normality was violated ($p \leq .05$). All tests were two-tailed with a significance level of $\alpha = .05$. Effect sizes were quantified using Hedge's g , a small-sample-corrected version of Cohen's d ($J \approx 0.914$ for $n = 10$). Effect magnitudes were interpreted as $|g| < 0.2 = \text{small}$, $0.5 = \text{medium}$, $0.8 = \text{large}$.

6.2.9 Measurement Error and Minimal Detectable Change

The standard error of measurement (SEM) was computed as $SEM = SD_{\text{Diff}} / \sqrt{2}$, where SD_{Diff} is the standard deviation of the paired difference scores. The minimal detectable change at

95% confidence (MDC_{95}) was derived as $MDC_{95} = SEM \times 1.96 \times \sqrt{2}$, representing the smallest change in a kinematic metric that exceeds measurement noise with 95% confidence (Atkinson & Nevill, 1998; Weir, 2005).

6.2.10 Time-series Waveform Analysis: SPM and SnPM

Time-series waveform-level inference was performed using Statistical Parametric Mapping (SPM) and non-parametric permutation-based SPM (SnPM), implemented via the *spm1d* package (v0.4.53; Pataky, 2012). Paired t -tests were conducted at every time node across the 0–100% normalised gait cycle waveform, generating an $SPM\{t\}$ statistic continuum. Parametric critical thresholds (t^*) were determined using random field theory (RFT). SnPM thresholds were estimated via sign-flip permutation testing (1,024 permutations). Both approaches were two-tailed at $\alpha = .05$. Significant clusters are reported as percentage-cycle intervals.

6.3 Results

6.3.1 Sagittal Plane

For SKS UT and SKS LT, no sagittal-plane discrete metric reached significance (all $p > .05$). For SKS UL, ROM was significantly lower in Session 1 than Session 2 (M difference = -3.72 (4.16)°, $t(9) = -2.83$, $p = .020$, $g = -0.82$, $SEM = 2.94$ °, $MDC_{95} = 8.15$ °). Shapiro–Wilk testing indicated non-normal difference distributions for ROM ($p < .05$), supporting reliance on the Wilcoxon signed-rank test for this metric. For SKS LL, ROM was significantly lower in Session 1 than Session 2 (M difference = -4.05 (2.85)°, $t(9) = -4.49$, $p = .002$, $g = -1.30$, $SEM = 2.02$ °, $MDC_{95} = 5.59$ °).

Table 6.1- Paired Comparison Statistics for Sagittal Plane Discrete Kinematic Metrics, Session 1 Versus Session 2

Comparison	Metric	Session 1 <i>M (SD)</i>	Session 2 <i>M (SD)</i>	Difference <i>M (SD)</i>	Normality <i>W (p)</i>	<i>t(9)</i>	<i>p</i>	<i>W</i>	<i>p</i>	<i>g</i>	SE <i>M</i>	MDC ₉₅
SKS UT S1 vs S2	ROM	4.40 (1.09)	4.45 (1.60)	-0.05 (0.74)	0.76 (.005)*	$\bar{0.20}$	.849	2 1	.557	$\bar{0.06}$	0.52	1.45
	Maximum	30.21 (8.13)	31.18 (8.24)	-0.98 (3.45)	0.95 (.611)	$\bar{0.89}$	.395	1 9	.432	$\bar{0.26}$	2.44	6.76
	Minimum	25.81 (8.21)	26.74 (8.20)	-0.93 (3.64)	0.96 (.751)	$\bar{0.81}$	.441	1 8	.375	$\bar{0.23}$	2.58	7.14
SKS LT S1 vs S2	ROM	2.74 (0.60)	2.73 (0.96)	0.01 (0.66)	0.96 (.816)	0.0 6	.953	2 5	.846	0.0 2	0.47	1.30
	Maximum	4.53 (4.75)	5.65 (4.12)	-1.11 (2.20)	0.93 (.429)	$\bar{1.60}$	.144	1 2	.131	$\bar{0.46}$	1.56	4.31
	Minimum	1.79 (4.81)	2.92 (4.43)	-1.13 (2.32)	0.91 (.309)	$\bar{1.54}$	.158	1 3	.160	$\bar{0.44}$	1.64	4.54
SKS UL S1 vs S2	ROM	5.26 (1.86)	8.98 (4.30)	-3.72 (4.16)	0.84 (.042)*	$\bar{2.83}$	.020*	3	.010*	$\bar{0.82}$	2.94	8.15
	Maximum	8.70 (8.57)	11.14 (11.89)	-2.44 (11.68)	0.92 (.320)	$\bar{0.66}$	.526	2 3	.695	$\bar{0.19}$	8.26	22.89
	Minimum	3.44 (8.57)	2.16 (11.61)	1.29 (9.97)	0.99 (.999)	0.4 1	.693	2 2	.625	0.1 2	7.05	19.53
SKS LL S1 vs S2	ROM	7.77 (3.62)	11.82 (5.85)	-4.05 (2.85)	0.88 (.145)	$\bar{4.49}$	.002*	0	.002*	$\bar{1.30}$	2.02	5.59
	Maximum	9.00 (7.59)	15.45 (8.37)	-6.46 (9.15)	0.93 (.488)	$\bar{2.23}$	.053	9	.064	$\bar{0.65}$	6.47	17.93
	Minimum	1.22 (6.79)	3.63 (8.22)	-2.41 (8.80)	0.96 (.840)	$\bar{0.86}$	.410	1 9	.432	$\bar{0.25}$	6.22	17.25

Note. *M* = mean; *SD* = standard deviation; Diff = Session 1 – Session 2; Normality *W(p)* = Shapiro–Wilk statistic and *p*-value for the paired difference scores; *t(9)* = paired *t*-statistic (*df* = 9); *W* = Wilcoxon signed-rank statistic; *g* = Hedge’s *g* ($|g| < 0.2$ small, 0.5 medium, 0.8 large); SEM = standard error of measurement ($SD_{\text{Diff}} / \sqrt{2}$); MDC₉₅ = minimal detectable change at 95% confidence ($SEM \times 1.96 \times \sqrt{2}$). Asterisk (*) denotes $p < .05$.

6.3.2 Frontal Plane

For SKS UT, ROM was significantly lower in Session 1 than Session 2 (M difference = -0.95 (0.74)°, $t(9) = -4.07$, $p = .003$, $g = -1.18$, $SEM = 0.52$ °, $MDC_{95} = 1.44$ °). For SKS LT, SKS UL, and SKS LL, no frontal-plane discrete metric reached significance (all $p > .05$).

Table 6.2. Paired Comparison Statistics for Frontal Plane Discrete Kinematic Metrics, Session 1 Versus Session 2

Comparison	Metric	Session 1 M (SD)	Session 2 M (SD)	Difference M (SD)	Normality W (p)	$t(9)$	p	W	p	g	SEM	MDC_{95}
SKS UT S1 vs S2	ROM	15.22 (3.35)	16.17 (3.19)	-0.95 (0.74)	0.92 (.379)	$\bar{4.07}$	.003*	0	.002*	$\bar{1.18}$	0.52	1.44
	Maximum	9.42 (1.92)	9.34 (2.77)	0.08 (1.90)	0.94 (.567)	0.14	.894	27	.1000	0.04	1.34	3.73
	Minimum	-5.80 (2.60)	-6.83 (1.89)	1.03 (1.98)	0.95 (.727)	1.65	.134	12	.131	0.48	1.40	3.88
SKS LT S1 vs S2	ROM	10.58 (2.43)	11.09 (2.03)	-0.51 (0.97)	0.93 (.437)	$\bar{1.66}$	.132	11	.105	$\bar{0.48}$	0.69	1.91
	Maximum	5.55 (2.45)	6.24 (2.50)	-0.69 (1.12)	0.88 (.147)	$\bar{1.94}$	.085	10	.084	$\bar{0.56}$	0.79	2.20
	Minimum	-5.02 (2.95)	-4.84 (2.73)	-0.18 (1.75)	0.81 (.019)*	$\bar{0.32}$	.755	23	.695	$\bar{0.09}$	1.23	3.42
SKS UL S1 vs S2	ROM	7.41 (1.31)	8.38 (3.01)	-0.96 (2.83)	0.92 (.368)	$\bar{1.08}$	.309	20	.492	$\bar{0.31}$	2.00	5.55
	Maximum	2.56 (3.32)	1.53 (4.29)	1.03 (2.52)	0.89 (.159)	1.29	.228	20	.492	$\bar{0.37}$	1.78	4.95
	Minimum	-4.85 (3.20)	-6.85 (3.85)	2.00 (3.56)	0.93 (.404)	1.77	.110	11	.105	$\bar{0.51}$	2.52	6.98
SKS LL S1 vs S2	ROM	6.57 (2.82)	7.75 (3.80)	-1.17 (4.46)	0.92 (.364)	$\bar{0.83}$	.428	22	.625	$\bar{0.24}$	3.16	8.75
	Maximum	2.23 (3.46)	2.24 (4.69)	-0.01 (4.21)	0.92 (.367)	$\bar{0.01}$	.994	26	.922	$\bar{0.00}$	2.98	8.26
	Minimum	-4.35 (3.29)	-5.51 (4.26)	1.16 (3.28)	0.98 (.956)	1.12	.292	17	.322	$\bar{0.32}$	2.32	6.42

Note. M = mean; SD = standard deviation; Diff = Session 1 – Session 2; Normality $W(p)$ = Shapiro–Wilk statistic and p -value for the paired difference scores; $t(9)$ = paired t -statistic ($df = 9$); W = Wilcoxon signed-rank statistic; g = Hedge’s g ($|g| < 0.2$ small, 0.5 medium, 0.8 large); SEM = standard error of measurement ($SD_{Diff} / \sqrt{2}$); MDC_{95} = minimal detectable change at 95% confidence ($SEM \times 1.96 \times \sqrt{2}$). Asterisk (*) denotes $p < .05$.

6.3.3 Transverse Plane

For SKS UT, SKS LT, SKS UL, and SKS LL, no transverse-plane discrete metric reached significance (all $p > .05$).

Table 6.3. Paired Comparison Statistics for Transverse Plane Discrete Kinematic Metrics — Session 1 Versus Session 2

Comparison	Metric	Session 1 <i>M</i> (<i>SD</i>)	Session 2 <i>M</i> (<i>SD</i>)	Difference <i>M</i> (<i>SD</i>)	Normality <i>W</i> (<i>p</i>)	<i>t</i> (9)	<i>p</i>	<i>W</i>	<i>p</i>	<i>g</i>	SE <i>M</i>	MDC ₉₅
SKS UT S1 vs S2	ROM	26.49 (2.99)	28.44 (4.93)	-1.96 (3.30)	0.95 (.682)	-1.88	.093	11	.105	-0.54	2.33	6.46
	Maximum	14.01 (3.61)	14.12 (3.90)	-0.11 (1.23)	0.96 (.772)	-0.28	.786	27	.100	-0.08	0.87	2.41
	Minimum	-12.48 (2.53)	-14.33 (3.00)	1.85 (3.11)	0.98 (.940)	1.88	.093	11	.105	0.54	2.20	6.09
SKS LT S1 vs S2	ROM	29.54 (6.29)	27.80 (8.62)	1.74 (6.91)	0.91 (.253)	0.80	.445	24	.770	0.23	4.89	13.55
	Maximum	14.56 (4.27)	12.19 (4.93)	2.37 (4.45)	0.80 (.014)*	1.68	.127	10	.084	0.49	3.15	8.72
	Minimum	-14.99 (3.23)	-15.61 (6.05)	0.62 (3.98)	0.97 (.856)	0.49	.633	22	.625	0.14	2.82	7.81
SKS UL S1 vs S2	ROM	22.55 (3.97)	23.56 (5.85)	-1.01 (3.16)	0.95 (.724)	-1.01	.337	17	.322	-0.29	2.23	6.19
	Maximum	10.70 (3.46)	10.28 (3.16)	0.42 (2.11)	0.97 (.926)	0.63	.545	22	.625	0.18	1.49	4.13
	Minimum	-11.85 (1.48)	-13.28 (3.39)	1.43 (2.91)	0.89 (.170)	1.55	.155	17	.322	0.45	2.06	5.71
SKS LL S1 vs S2	ROM	18.45 (2.28)	19.11 (4.55)	-0.65 (2.98)	0.92 (.382)	-0.70	.504	24	.770	-0.20	2.10	5.83
	Maximum	8.96 (2.71)	8.55 (2.64)	0.41 (1.11)	0.93 (.423)	1.17	.273	18	.375	0.34	0.78	2.17
	Minimum	-9.49 (1.70)	-10.56 (3.09)	1.06 (3.11)	0.92 (.366)	1.08	.308	18	.375	0.31	2.20	6.10

Note. *M* = mean; *SD* = standard deviation; Diff = Session 1 – Session 2; Normality *W* (*p*) = Shapiro–Wilk statistic and *p*-value for the paired difference scores; *t*(9) = paired *t*-statistic (*df* = 9); *W* = Wilcoxon signed-rank statistic; *g* = Hedge’s *g* ($|g| < 0.2$ small, 0.5 medium, 0.8 large); SEM = standard error of measurement ($SD_{\text{Diff}} / \sqrt{2}$); MDC₉₅ = minimal detectable change at 95% confidence ($SEM \times 1.96 \times \sqrt{2}$). Asterisk (*) denotes $p < .05$.

6.3.4 Time-series Statistical Analysis: SPM and SnPM Findings

6.3.5 Upper Thoracic

In the sagittal and frontal planes, parametric and SnPM inference identified no significant clusters between Session 1 and Session 2. In the transverse plane, parametric inference ($t^* = \pm 3.75$)

and SnPM inference ($t^* = \pm 3.54$) detected a significant between-session difference in UT axial rotation at 65–68% and 63–71% of the gait cycle, respectively.

6.3.6 Lower Thoracic

In the sagittal, frontal plane, and transverse plane, parametric and SnPM inference identified no significant clusters between Session 1 and Session 2.

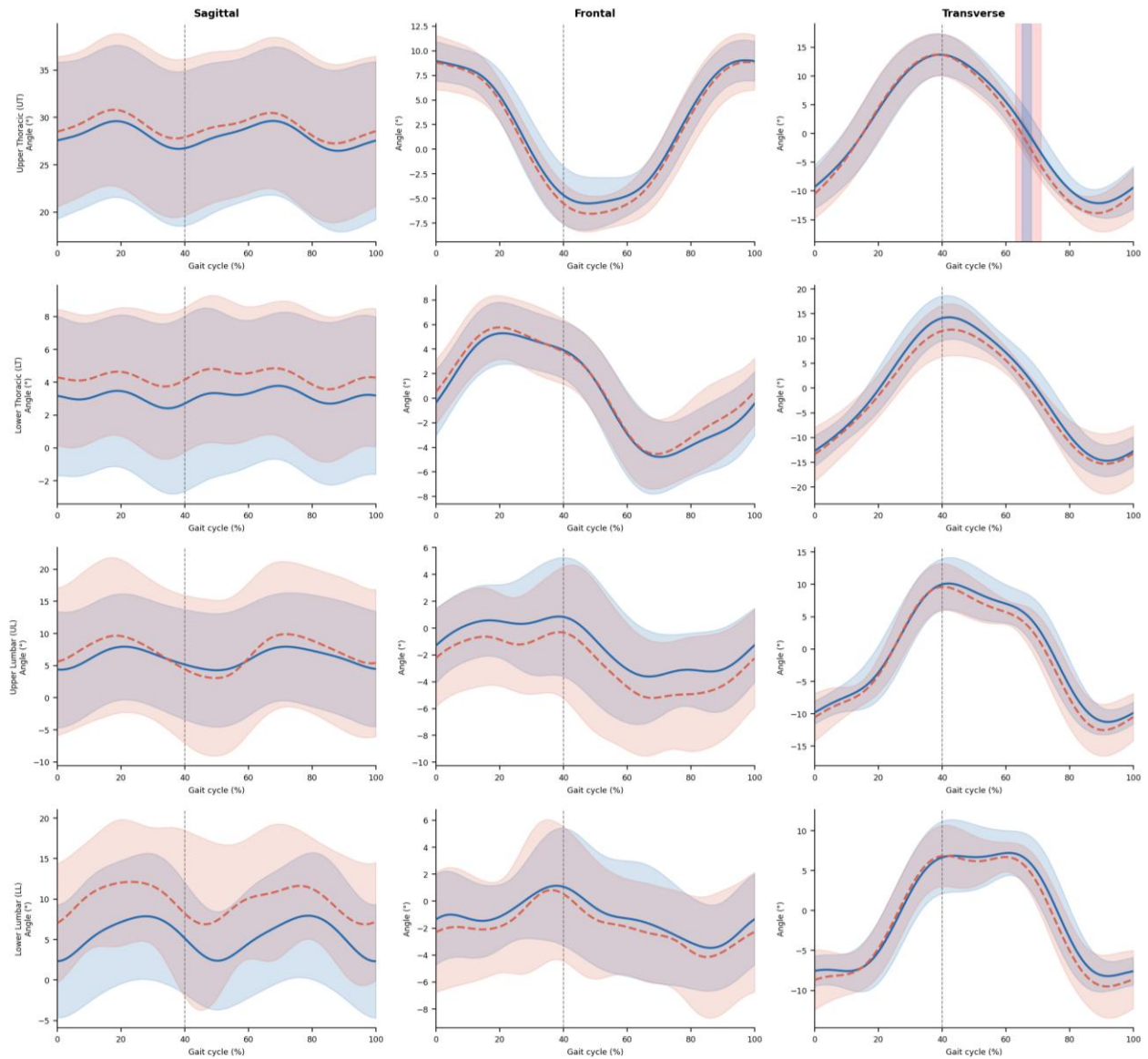
6.3.7 Upper Lumbar

In the sagittal, frontal plane, and transverse plane, parametric and SnPM inference identified no significant clusters between Session 1 and Session 2.

6.3.8 Lower Lumbar

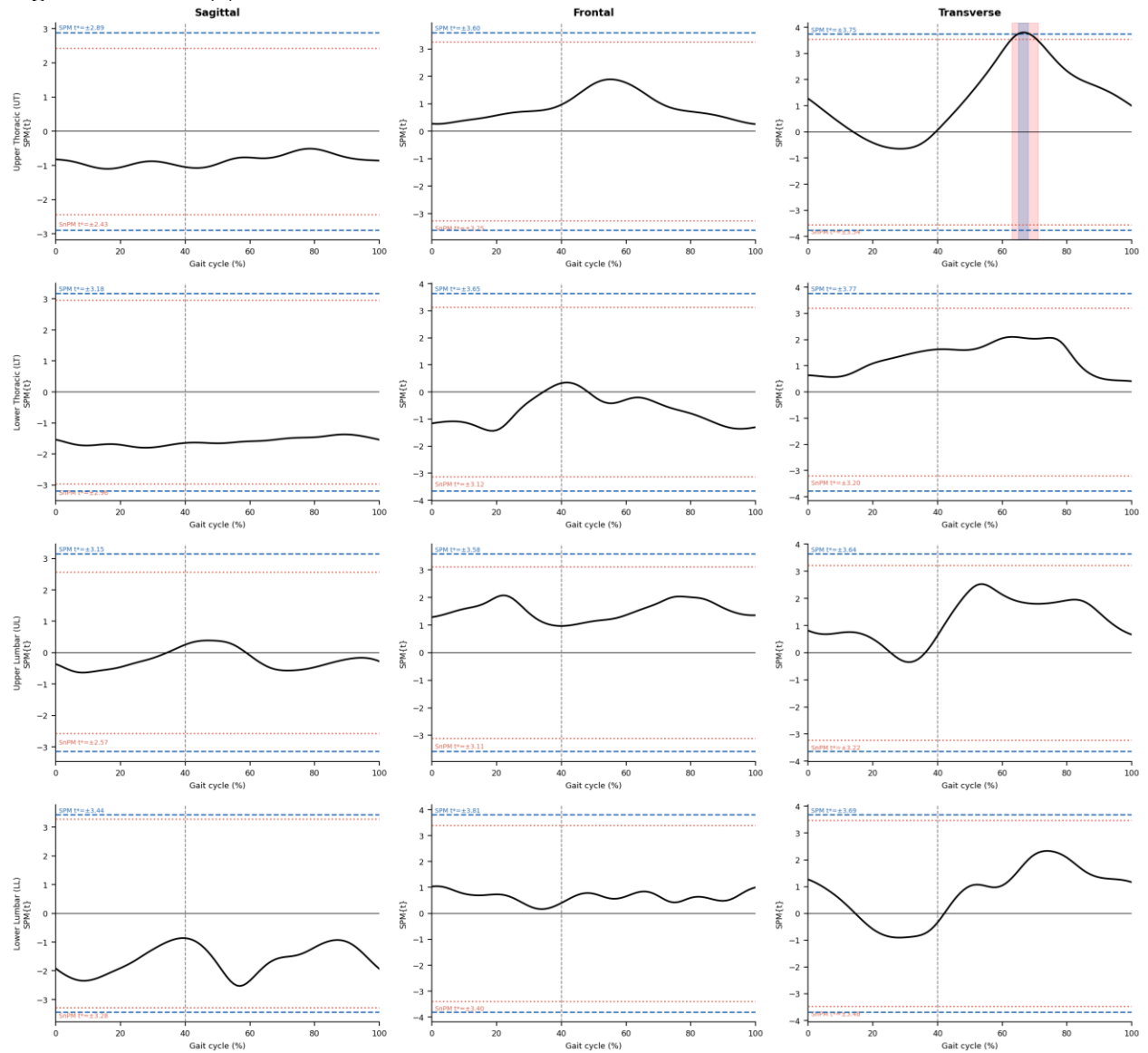
In the sagittal, frontal plane, and transverse plane, parametric and SnPM inference identified no significant clusters between Session 1 and Session 2.

Figure 6.1. Segmental Angle Waveforms (Mean $\pm$ SD), Session 1 Versus Session 2



Note. Rows represent segments (UT, LT, UL, LL); columns represent planes of motion (Sagittal, Frontal, Transverse). Blue solid lines = Session 1; red dashed lines = Session 2. Blue shading = SPM significant cluster; red shading = SnPM significant cluster. Dashed vertical line = 40% of gait cycle. $n = 10$, $\alpha = .05$, two-tailed.

Figure 6.2. SPM{t} Time-Series — Session 1 Versus Session 2



Note. Solid black line = SPM{t} statistic. Dashed blue lines = parametric critical threshold (t^*); dotted red lines = SnPM critical threshold. Shaded regions = significant clusters. t^* values annotated in each panel. $n = 10$, $\alpha = .05$, two-tailed; 1,024-permutation SnPM inference.

6.4 Discussion

The purpose of this study was to establish the between-session reliability of a SKS multi-segment kinematic model of the spine during treadmill running in sub-elite runners. Reproducibility was examined across four spinal segments in the sagittal, frontal, and transverse planes using both discrete metrics and time-series waveform analysis. The multi-segment model used in this study produced largely reproducible outputs between sessions. Of the 36 discrete comparisons examined, only three reached statistical significance, and time-series waveform-level inference identified only one significant cluster across all twelve segment-by-plane comparisons. Overall, the multi-segment model can be applied across separate testing sessions without introducing systematic differences in measured spinal kinematics during treadmill running.

The significant between-session differences observed are important and warrant careful interpretation. For LL sagittal ROM, the systematic bias (4.05°) was slightly below its minimal detectable change ($\text{MDC}_{95} = 5.59^\circ$), and for UL sagittal ROM the bias (3.72°) was well within the corresponding MDC_{95} of 8.15° . A comparable pattern was evident for the only significant frontal-plane finding, UT ROM (M difference = -0.95° , $g = -1.18$), where a large, standardised effect existed with a very small absolute bias (0.95°) that fell below the MDC_{95} of 1.44° . This evident difference reflects the distinction between group-level and individual-level reliability. For instance, a difference can be statistically robust and produce a large effect size because it is highly consistent across participants, while remaining smaller than the change required to be confident of a true difference in a single individual. The MDC_{95} values reported in the current study may provide a threshold for observing real change from measurement noise when the model is used to monitor individual runners.

The SEM and MDC_{95} values obtained in the present study are best interpreted in relation to the existing peer-reviewed literature on between-session reliability of optoelectronic spine kinematics during running. However, a direct comparison to current thresholds is limited since no published study has reported SEM or MDC_{95} for a four-region marker-based spine model during running. The available running-specific reliability evidence typically defines the spine into a single trunk segment or, at most, is reduced to thorax-versus-lumbar or lumbar-versus-pelvis analysis.

The closest threshold is Mason et al. (2016), who examined the between-day reproducibility of thoracic spine, lumbar spine, and pelvis kinematics during overground running at 5.6 m/s in 12 athletes. Reporting time-series waveform-level typical angular errors rather than

formal SEM or MDC⁹⁵ statistics, Mason et al. found good reproducibility in the frontal and transverse planes (typical angular errors 1.4–3°). With acceptable reproducibility in the sagittal plane (typical angular errors 1.9–3.5°).

The authors identified that the sagittal plane errors occurred not from an alteration of the time-series waveform shape between sessions, but from rigid offset shifts in the entire time-series waveform. This may be attributed to between-session variability in skin marker placement over the lumbar spinous processes. The curvature of the lumbar lordosis means that minor superior-inferior displacements of markers over individual spinous processes can alter the reference posture during static calibration. This offset mechanism is directly relevant to the lumbar sagittal plane systematic biases observed in the present study. This supports the interpretation that the significant between-session ROM differences in UL and LL reflect a marker re-placement artefact rather than genuine between-session change in dynamic movement patterns. This systematically shifts the entire waveform without altering its shape. Mason et al. also found no improvement in reproducibility when global optimisation joint constraints were applied over a six-degrees-of-freedom solution, suggesting that mathematical constraint approaches do not resolve the fundamental soft-tissue artefact problem at running speeds. Previous imaging-comparison and soft-tissue artefact studies have shown that skin markers can track spinal curvature change, but do not perfectly represent underlying vertebral motion, particularly when absolute angles are interpreted (Johnson et al., 2024; Leardini et al., 2005; Xi et al., 2022; Zemp et al., 2014). Therefore, the present lumbar ROM findings should not be interpreted as a failure of the SKS model, but as evidence that the lumbar sagittal plane is the most measurement-sensitive region for repeated assessment.

Bramah et al. (2021) provided the most directly comparable discrete-parameter SEM and MDC⁹⁵ estimates for treadmill running, examining trunk kinematics in 16 experienced runners across two sessions separated by two weeks. For sagittal and frontal plane variables at initial contact and peak stance, the authors reported SEM values of 0.6–2.6°, and MDC⁹⁵ values of 1.5–7.2°, reflecting good-to-excellent reliability. These values are generally consistent with the sagittal and frontal plane SEM and MDC⁹⁵ ranges obtained in the present study. This provides confirming evidence that marker-based spinal kinematics during treadmill running are sufficiently reproducible for detection of meaningful changes when those changes exceed individual-level noise. Bramah et al. also demonstrated that transverse-plane parameters and toe-off events were

substantially less reliable (MDC^{95} up to 15.7°), reinforcing the recommendation that transverse-plane spinal kinematics be interpreted with reference to segment-specific MDC^{95} values.

The time-series waveform analysis adds an important qualification. Eleven of the twelve segment-by-plane waveform comparisons showed no significant clusters under either SPM or SnPM inference, indicating that full gait-cycle profiles were highly reproducible. The only exception was UT axial rotation, where a significant transverse-plane cluster occurred at approximately 65–68% of the gait cycle by SPM and 63–71% by SnPM. The close agreement between the two inferential approaches strengthens confidence that this localised difference is real rather than an artefact of the parametric distributional assumptions. This region corresponds to the mid-swing phase of the gait cycle where the UT segment is particularly susceptible to marker movement associated with shoulder-girdle and arm motion during this phase. This may account for the reduced transverse-plane reproducibility at this single location (citations). Importantly, this difference was confined to a narrow portion of the cycle that was not evident as a significant difference in any discrete transverse-plane metric. This highlights the value of time-series waveform-level analysis for detecting phase-specific reliability limitations that summary measures can obscure.

The MDC^{95} represents the minimum change required at the individual level to exceed 95% of the measurement error distribution. By definition, MDC^{95} operates at the individual participant level; group-level inferential statistics assess whether mean differences are distinguishable from zero across participants, irrespective of the magnitude of individual-level noise. Consequently, it is entirely possible, and certainly observed in the present data, for a paired comparison to reach statistical significance whilst the mean difference remains smaller than the MDC^{95} . In the current dataset, the UT frontal ROM difference (mean 0.95°) showed this pattern: the difference was statistically significant yet substantially below its MDC^{95} of 2.61° . This emphasises the importance of reporting both inferential statistics and absolute reliability indices in reliability studies, and of interpreting significant findings within the context of their practical magnitude.

Another methodological strength of the present analysis was the parallel application of parametric and non-parametric procedures at both the discrete and continuous levels. Since none of these non-normal metrics produced a significant between-session difference, the violations did not alter the substantive conclusions. Nevertheless, the dual approach guards against the small-sample sensitivity of the paired t-test and increases confidence in the reported reliability profile.

The merging of SPM and SnPM at the time-series waveform level serves the same purpose, demonstrating that the conclusions are robust to the choice of statistical framework.

Several limitations should be acknowledged when interpreting these findings. First, the sample comprised ten sub-elite runners, which may limit the precision of the effect-size and measurement-error estimates and constrain generalisability to other populations such as recreational or elite runners or clinical groups. Second, reliability was assessed across a single pair of sessions; test–retest designs incorporating additional sessions or multiple raters would allow inter-rater reliability to be assessed. The findings are specific to treadmill running and to the SKS marker configuration; so the findings of the current study cannot be generalised to overground running and to alternative marker sets. Finally, Between-session reliability was established within a male sub-elite running cohort and should therefore not automatically be assumed to be equivalent in female runners. Future reliability work should reproduce the protocol in female athletes to determine whether comparable measurement error and MDC_{95} thresholds are observed.

6.5 Conclusion

In conclusion, the SKS multi-segment spine model demonstrated broadly acceptable between-session reliability during treadmill running across the majority of segment-plane combinations examined. Sagittal plane ROM and waveform kinematics were generally well-reproduced, with the exception of small but statistically significant between-session biases in the lumbar sagittal plane that did not reach individual-level detection thresholds. The UT transverse plane exhibited a localised region of time-series waveform difference in mid-swing phase that warrants caution in longitudinal applications. Frontal and transverse plane metrics across all segments should be interpreted with reference to segment-specific MDC_{95} values given the susceptibility of low-amplitude planes to soft-tissue artefact. These findings provide a quantitative reliability framework for the interpretation of SKS-derived spinal kinematics in future running biomechanics research.

Chapter 7

Multi-segment spine kinematics, coordination, and running economy under localised lower-limb fatigue: a dual linear and non-linear analysis

7.1 Introduction

Running economy is defined as the rate of submaximal oxygen consumption at a given speed. It is among the strongest predictors of distance-running performance independent of maximal oxygen uptake, explaining a substantial share of the variation in performance among athletes of similar aerobic power (Saunders et al., 2004; Barnes & Kilding, 2015). Despite this, the biomechanical determinants of economy that lie in the spine and trunk region have received far less attention than those of the lower limb. This is despite the axial skeleton constituting approximately half of body mass and is involved in transmitting forces between the thorax, pelvis, and legs (MacWilliams et al., 2014). During running, the spine performs an active, three-dimensional function. The thoracic counter-rotates against the pelvis to neutralise the angular momentum generated by the swinging legs, with frontal-plane lateral flexion dominating the lumbar contribution and transverse-plane rotation dominating the thoracic contribution (MacWilliams et al., 2014; Preece et al., 2016). Far from being a passive transmission, the spine is a coordinated, multi-segment kinetic chain whose behaviour bears directly on the mechanical and metabolic cost of locomotion (Folland et al., 2017; Moore, 2016; Preece et al., 2016c; Seay et al., 2011a, 2011b).

Fatigue represents the most consistent perturbation experienced by runners during prolonged endurance events, repeated intervals, and competition. It is conventionally differentiated into two categories that arise through distinct mechanisms and may influence movement in different ways. Central fatigue refers to an exercise-induced reduction in central drive, whereas peripheral fatigue indicates a decline in the maximal force-generating capacity of muscle. Existing literature has documented how running-induced fatigue alters trunk kinematics, most consistently reporting increased forward trunk lean, with greater changes observed in novice than in competitive runners (Koblbauer et al., 2014; Möhler et al., 2022). Fatigue has further been shown to alter frontal-plane trunk and pelvic control, including increased pelvic obliquity and impaired trunk–pelvis coordination (Maas et al., 2018; Tazji et al., 2023).

Two limitations constrain this body of work. First, the effect of fatigue on running has been investigated through opposing approaches across studies. Volitional exhaustion, fixed perceived-exertion thresholds, set distances, and heart-rate endpoints constitute protocols that produce distinct biomechanical signatures, conflating peripheral, central, and cardiovascular contributions. This leaves the specific role of peripheral lower-limb fatigue largely uncharacterised. Localised

trunk muscular fatigue is well established. Isolated lumbar paraspinal fatigue has been shown to increase forward trunk flexion during jogging (Hart et al., 2009), and experimentally reduced core stability alters stance-limb loading (Chaudhari et al., 2020). Whether an isolated peripheral deficit in the locomotor muscles of the leg reorganises the coordination of the spine above it, and whether such reorganisation carries a measurable energetic cost, has not been directly tested. Second, the dominant methodology models the entire trunk as a single rigid segment. This approach cannot quantify the intersegmental coupling, regional thoracic–lumbar behaviour, or counter-rotation that constitute the fundamental running function of the spine (MacWilliams et al., 2014; Preece et al., 2016; Seay et al., 2011a, 2011b; Tojima et al., 2019). The few studies employing multi-segment spine models have largely characterised unfatigued running. Consequently, the multi-segment behaviour of the spine under fatigue and its concurrent linkage to running economy remains essentially unexamined.

Dynamical systems theory, and specifically Newell's (1986) model of interacting constraints, offers a coherent theoretical framework for addressing these gaps. Within this model, coordinated movement is not specified by a fixed central motor programme but emerges from the confluence of three categories of constraint: organismic (the structural and functional properties of the performer), environmental (the surrounding physical conditions), and task (the goal and its associated rules) (Newell, 1986; Davids et al., 2008; Renshaw et al., 2019). Coordination thus constitutes an emergent, self-organising property of the interaction among these constraints. Dynamical systems theory further holds that rhythmic locomotion settles into stable coordination tendencies, such that a perturbation may either be absorbed within an existing tendency or, if sufficiently large, drive the system toward a reorganised and potentially less economical state. Within this framework, coordination variability is regarded as functional and informative rather than as error, reflecting the system's exploration of its available movement solutions. Intermediate variability has been proposed to indicate healthy function, whereas abnormally low or high variability is associated with pathology (Bernstein, 1967; Hamill et al., 2012). This perspective reconceptualises fatigue not as a global degradation of movement but as a single organismic constraint, the consequences of which may be observed as a reorganisation of the coordinative system. It further predicts that the spine need not respond uniformly. Regions occupying robust, stable coordination tendencies may absorb the perturbation while more adaptable regions

reorganise, and the variability of coordination may itself serve as a sensitive marker of where such reorganisation occurs.

The present study was designed to exploit this framework directly by employing a localised lower-limb fatigue protocol, which has been shown to reduce the maximal voluntary force of the locomotor musculature by approximately 18%, while minimising the metabolic and cardiovascular perturbations that accompany whole-body fatigue (Marcora et al., 2008). This approach permitted the manipulation of a single organismic constraint while holding constant both the environmental constraints (treadmill running at a fixed gradient under controlled conditions) and the task constraint (running at the first ventilatory threshold). Any resulting change in spinal coordination could therefore be attributed to the altered organismic constraint, with the remaining two categories experimentally controlled. Consequently, this study aimed to determine how multi-segment spine coordination, variability, and control adapt acutely to localised lower-limb muscle fatigue during treadmill running at the first ventilatory threshold, and to quantify the concurrent change in running economy. It was hypothesised that fatigue would produce measurable changes in spinal kinematics and coordination and, consistent with the dynamical systems framework, that these changes would be regionally specific rather than uniform.

7.2 Methods

7.2.1 Participants

Ethical approval was granted by the University of Staffordshire Ethics Committee. Ten male sub-elite runners participated in the study (age 45.8 ± 9.2 years; height 178.7 ± 4.13 cm; mass 73.22 ± 5.4 kg), all of whom were free from current musculoskeletal impairment. Participants were classified according to the Participant Classification Framework proposed by McKay et al. (2022). The cohort was classified as Tier 3: Highly Trained/National Level, as participants identified running as their primary sport, completed structured endurance training, and typically ran 40–50 miles per week across regular weekly training sessions.

7.2.2 Kinematic model – defined segments, coordinate systems, and segment tracking

Six central markers were placed on the spinous processes of T1, T6, T12, L1, L3 and L5 to define four segments: upper thoracic (UT) (T1-T6), lower thoracic (LT) (T6-T12), upper lumbar (UL) (L1-L3) and lower lumbar (LL) (L3-L5) (Christe et al., 2016). The Z-axis was defined as a

line passing through two markers stated for each segment that represented posture in the sagittal plane (positive direction upwards from the distal marker). Eight lateral markers were placed between central markers on each side of the spine, at a distance of 5 cm, representing spinal levels T3, T9, L2 and L4. The cross product of the Z-axis and a line connecting the two markers bilaterally for each segment defined the Y-axis (positive direction pointing to the left). The cross product of the Z- and Y-axis was used to define the X-axis (positive direction pointing forwards). For the individual skin marker model (SKS), the four markers used to define each segment were used to track motion.

7.2.3 Segment parameters

Three-dimensional segment angles were calculated with respect to the normal standing position of the participant. Rotations about the global coordinate system (laboratory) were based on the right-hand rule convention. Angular kinematic data for all segments and both kinematic models were computed by measuring the relative movements between of the respective segment to the global coordinate system. Cardan angles were calculated using the YXZ convention with an order in the sagittal, frontal, and transverse plane (Grood & Suntay, 1983).

7.2.4 Instrumentation

Each participant attended the university on two separate occasions and wore their own running footwear to preserve habitual running mechanics (Willwacher et al., 2020; Van der Meulen et al., 2024). The first session was conducted in the Physiology Laboratory, which involved a maximal $\text{VO}_{2\text{max}}$ test (Bassett & Howley, 2000; Midgley et al., 2007) on a treadmill (HP Cosmos Venus 200/75 (Munich, Germany). In the second session, participants were required to run on a treadmill (Model TY700HRT; Vision Fitness, 1600 Landmark Dr, Cottage Grove, WI 5352) that was positioned in the centre of the Biomechanics laboratory. Both treadmills were set to a 1% gradient to better approximate outdoor running energetic cost (Jones & Doust, 1996). An 18-camera motion capture system (Vicon, Oxford, UK) was used to record three-dimensional marker coordinate data at 200 frames/s. For both session one and two, pulmonary gas exchange and ventilatory variables were measured continuously on a breath-by-breath basis using a Metalyzer 3B metabolic cart (Cortex Biophysik GmbH, Leipzig, Germany). Environmental conditions in the Biomechanics lab were recorded each session and were as follows: temperature

ranged from 21-24 degrees; humidity ranged from 55-56%, and Barometric Pressure ranged from 1100-1200 mb.

7.2.5 Experiment protocols

The $\text{VO}_{2\text{max}}$ test during the first session was conducted to identify each participant's first ventilatory threshold (VT1), and the corresponding running speed required for the subsequent experimental trials in the second session. VT1 was identified using the V-slope method and ventilatory-equivalent method, specifically the first disproportionate rise in $\dot{V}\text{CO}_2$ relative to $\dot{V}\text{O}_2$ and an increase in $\dot{V}\text{E}/\dot{V}\text{O}_2$ without a simultaneous increase in $\dot{V}\text{E}/\dot{V}\text{CO}_2$ (Beaver et al., 1986; Binder et al., 2008).

The second session took place in the Biomechanics Laboratory. Reflective markers were applied to the spine and back using double-sided adhesive tape as described previously in accordance with the multi-segment spine model (Christe et al., 2016). Additional markers were also applied to the pelvis and lower limbs (Cappozzo et al., 1995; Leardini et al., 2007).

After a 6-minute treadmill familiarisation period (Lavcanska et al., 2005), a static calibration trial was collected requiring the participant to stand upright in the anatomical position. Participants then completed two 10-minute treadmill runs at the assigned VT1 speed. The 10-minute trial duration was chosen to provide sufficient time for participants to reach a steady-state physiological response, thereby allowing more stable assessment of ventilatory and metabolic measures while simultaneously capturing representative biomechanical data. Previous treadmill running-economy work has similarly employed 8–10-minute running bouts with analysis based on the steady-state period (Mercer et al., 2018).

Between the two 10-minute running bouts at VT1, participants completed a lower-limb localised fatigue protocol as described by Marcora et al. (2008). Participants performed 100 drop-jumps from a 40 cm platform, with one drop-jump executed every 20 seconds (total protocol duration of approximately 33 minutes). Participants were instructed to drop from the platform, land with knees flexed to approximately 90°, and immediately rebound with a maximal vertical jump. This protocol has previously been shown to reduce maximal voluntary force of the locomotor musculature by approximately 18% while minimising, rather than eliminating, the metabolic and cardiovascular perturbations typically associated with running-induced fatigue, thereby permitting the isolation of peripheral muscle fatigue from the metabolic and cardiovascular

perturbations that accompany running-induced fatigue. Following completion of the fatigue protocol, participants returned to the treadmill within 30 seconds and commenced the second 10-minute bout of running at VT1.

Fifteen consecutive gait cycles from right heel to right heel strike were recorded within a 15-second trial. Heel strike was identified as the instant at which the distal heel marker reached its minimum vertical position, corresponding to the point at which its vertical velocity transitioned from negative to positive. This kinematic method has been validated for both treadmill and overground running, producing absolute errors of 22.4–24.6 ms relative to force plate ground truth (Fellin et al., 2010). An equivalent criterion, in which heel strike is defined as the moment the calcaneus marker's vertical displacement shifts from a descending to an ascending trajectory, has also been widely applied and validated (Zeni et al., 2008).

7.2.6 Data Processing and Analysis

Three-dimensional kinematic data were processed in Visual3D (HAS-Motion, Kingston, Ontario, Canada). Spine segment angles were calculated relative to the laboratory coordinate system and low-pass filtered using a fourth-order Butterworth filter with a 10 Hz cut-off frequency (Schache et al., 2002b; Preece et al., 2016a; Bramah et al., 2021). Data were time-normalised to 101 data points representing 0–100% of the normalised running gait cycle, enabling comparison across participants.

Breath-by-breath pulmonary gas-exchange data were processed to derive oxygen uptake ($\dot{V}O_2$), carbon dioxide production ($\dot{V}CO_2$), minute ventilation ($\dot{V}E$), ventilatory equivalents for oxygen ($\dot{V}E/\dot{V}O_2$) and carbon dioxide ($\dot{V}E/\dot{V}CO_2$), and respiratory exchange ratio (RER). For running-economy analysis, $\dot{V}O_2$ data were time-averaged into 15-second epochs across each 10-minute running bout. Steady-state oxygen uptake was operationalised as the mean $\dot{V}O_2$ during the final five minutes of each bout (minutes 5–10), thereby avoiding any confound introduced by differing pre-bout physiological starting conditions. Running economy was consequently expressed as this steady-state $\dot{V}O_2$ ($\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$). The difference in steady-state $\dot{V}O_2$ between the post- and pre-fatigue bouts was calculated as an index of fatigue-induced change in running economy.

7.2.7 Calculation of Coupling Angle and Coupling Angle Variability

At each normalised time instant (i), the coupling angle (γ_i) was calculated from the proximal (θ_P) and distal (θ_D) segmental angles at consecutive data points using a non-linear modified vector coding approach (Needham et al., 2014). Specifically, the coupling angle was derived using the arctangent of the change in distal segment angle divided by the change in proximal segment angle across adjacent data points, with corrections applied to place the result within the full 0–360° range (Eq. 1 & 2).

$$\gamma_i = \text{Atan}\left(\frac{\theta_{D(i+1)} - \theta_{Di}}{\theta_{P(i+1)} - \theta_{Pi}}\right) \cdot \frac{180}{\pi} \quad \theta_{P(i+1)} - \theta_{Pi} > 0 \quad (1)$$

$$\gamma_i = \text{Atan}\left(\frac{\theta_{D(i+1)} - \theta_{Di}}{\theta_{P(i+1)} - \theta_{Pi}}\right) \cdot \frac{180}{\pi} + 180 \quad \theta_{P(i+1)} - \theta_{Pi} < 0 \quad (2)$$

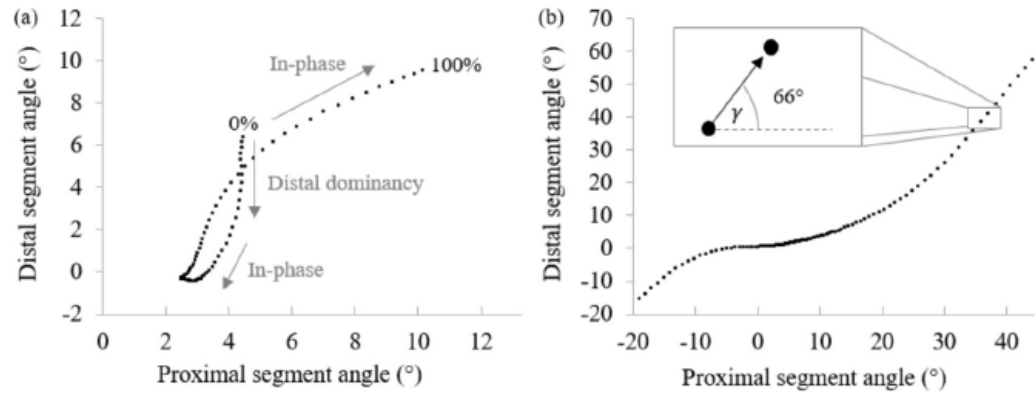
Additional boundary conditions (Eq. 3) were applied to handle special cases where one or both segmental angle changes equal zero:

$$\gamma_i = \begin{cases} \gamma_i = 90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} > 0 \\ \gamma_i = -90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} < 0 \\ \gamma_i = -180 & \theta_{P(i+1)} - \theta_{Pi} < 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} = 0 \\ \gamma_i = \text{Undefined} & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} = 0 \end{cases} \quad (3)$$

Following calculation, the coupling angle was corrected to ensure all values fell within the 0–360° range (Eq. 4). Where the raw coupling angle (γ_i) was negative, 360° was added; values already $\geq 0^\circ$ were retained as calculated:

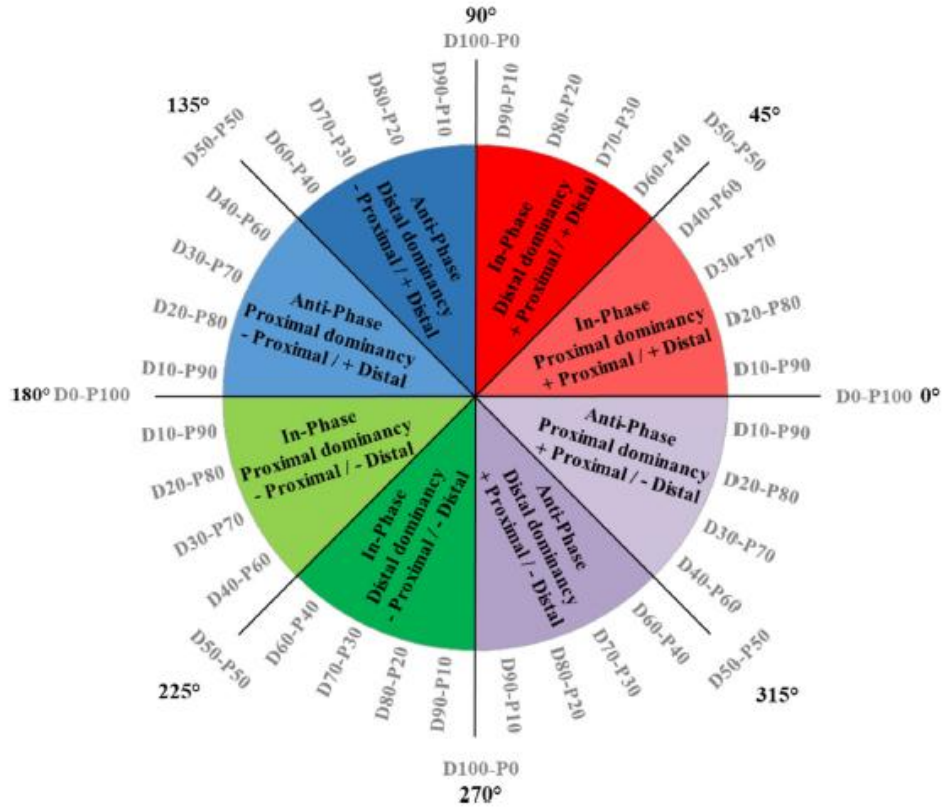
$$\gamma_i = \begin{cases} \gamma_i + 360 & \gamma_i < 0 \\ \gamma_i & \gamma_i \geq 0 \end{cases} \quad (4)$$

Figure 7.1. Angle–angle diagram of forefoot (distal) rearfoot (proximal) coordination during stance in the frontal plane; (b) Angle–angle diagram of foot (distal) shank (proximal) coordination during stance in the sagittal plane. Both figures represent mean data from 10 participants.



The resulting coupling angle values were then assigned to one of four coordination pattern classifications based on their angular position within the unit circle (Needham et al., 2015). These classifications distinguish between in-phase and anti-phase coordination (reflecting whether the two segments are rotating in the same or opposing directions), and between proximal and distal segment dominance (reflecting which segment is contributing the greater angular change at each instant). Each quadrant of the unit circle corresponds to 100 gradians, meaning that converting the coupling angle to gradians provides a direct percentage measure of segmental dominance. For example, a coupling angle of 45° equates to 50 gradians, indicating equal contribution from both segments (Needham et al., 2015).

Figure 7.2. Coordination pattern classification adapted from Needham et al. (2020) illustrating colour-scale for each classification. Segmental dominance (%) is shown around the circumference of the polar plot (grey text, D-distal/P-Proximal).



7.2.8 Averaging and Variability Calculation

Due to the directional (circular) nature of the coupling angle, standard arithmetic averaging is not appropriate. Instead, the mean coupling angle across a set of trials (n) was computed at each normalised time instant using circular statistics. The mean horizontal ($\bar{x}_i$) and vertical ($\bar{y}_i$) components of the unit vectors were calculated from the cosine and sine of each coupling angle, respectively (Eqs. 5 and 6):

$$\bar{x}_i = \frac{1}{n} \sum_{i=1}^n \cos \gamma_i \quad (5)$$

$$\bar{y}_i = \frac{1}{n} \sum_{i=1}^n \sin \gamma_i \quad (6)$$

The mean coupling angle ($\bar{\gamma}_i$) was then calculated from these mean vector components and corrected to fall within the 0–360° range according to the quadrant in which the resultant vector

resided (Eq. 7). The correction was based on the signs of $\bar{x}_i$ and $\bar{y}_i$, applying appropriate offsets of 0° , 180° , or 360° to the arctangent result to correctly place the angle in its respective quadrant:

$$\bar{\gamma}_i = \begin{cases} \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} & \bar{x}_i > 0, \bar{y}_i > 0 \\ \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} + 180 & \bar{x}_i < 0 \\ \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} + 360 & \bar{x}_i > 0, \bar{y}_i < 0 \\ 90 & \bar{x}_i = 0, \bar{y}_i > 0 \\ -90 & \bar{x}_i = 0, \bar{y}_i < 0 \\ \text{undefined} & \bar{x}_i = 0, \bar{y}_i = 0 \end{cases} \quad (7)$$

The length of the mean coupling angle vector (r_i) was then computed as the Euclidean magnitude of the mean horizontal and vertical components (Eq. 8). This value ranges from 0 to 1 and reflects the concentration of the coupling angles around the mean direction; a value of 1 indicates perfect agreement across trials, while a value approaching 0 indicates maximal dispersion:

$$\bar{r}_i = \sqrt{\bar{x}_i^2 + \bar{y}_i^2} \quad (8)$$

Coupling angle variability (CAVi) was calculated as the circular analogue of the standard deviation using the mean vector length, converted to degrees (Eq. 9). As the mean vector length decreases from 1 toward 0, the dispersion of the coupling angle across trials increases, and therefore CAVi increases. A mean vector length of 0 yields the maximum CAV value of approximately 81.07° :

$$CAV_i = \sqrt{2 \cdot (1 - \bar{r}_i)} \cdot \frac{180}{\pi} \quad (9)$$

Coupling angle variability is therefore the circular statistical equivalent of a standard deviation in linear statistics. The resulting CAV values were used alongside mean coupling angle data to characterise both the dominant coordination pattern and the consistency with which that pattern was expressed across repeated trials for each participant. All circular statistics were implemented following the approach described by Batschelet (1981).

7.2.9 Data and Statistical Analysis

7.2.10 Linear analysis

Spinal segment angles were analysed across three planes of motion (frontal, sagittal, and transverse), five spinal segments (upper thoracic [UT], lower thoracic [LT], upper lumbar [UL], lower lumbar [LL], and pelvis), and three discrete kinematic variables: maximum angle, minimum angle, and range of motion (ROM). Linear analysis was conducted at two complementary levels: (1) group-level inferential statistics to assess directional consistency of fatigue-related changes across participants, and (2) within-participant effect size analysis to quantify the magnitude and practical significance of individual responses. All analyses were performed in Python (Version 3.12.3) using NumPy (Version 2.4.4), SciPy (Version 1.17.1), Pandas (Version 3.0.2), and Matplotlib (Version 3.10.8). Statistical significance was set at $\alpha = .05$.

7.2.11 Group-level inferential statistics – discrete variables

For each plane–segment–metric combination, participant-level mean values were computed by averaging across the 12 trials within each condition (pre-fatigue [PRE] and post-fatigue [POST]). Normality of difference scores (POST – PRE participant means) was assessed using the Shapiro–Wilk test prior to test selection. A paired samples t-test and the Wilcoxon signed-rank test were conducted for all 45 combinations. Where the Shapiro–Wilk test indicated non-normally distributed difference scores ($p < .05$), the Wilcoxon signed-rank test was designated the primary statistic; both tests are reported in all cases. No correction for multiple comparisons was applied, consistent with the exploratory nature of this analysis and the small sample size. Group-level effect sizes are reported as Cohen’s d for paired samples ($d = \Delta M / SD_{diff}$). Group mean differences are reported with 95% confidence intervals (CIs) computed via the t-distribution.

7.2.12 Minimal detectable change

Within-participant measurement reliability was quantified using the minimal detectable change at the 95% confidence level (MDC95). The MDC95 was calculated as:

$$MDC_{95} = 1.96 \times \sqrt{2} \times SEM$$

where SEM (standard error of measurement) was calculated as the within-participant standard deviation divided by the square root of the number of trials ($SEM = SD / \sqrt{n}$, where $n = 12$

trials per condition). The more conservative of the PRE and POST MDC95 values was applied as the threshold for each combination. A mean difference ($\Delta = \text{POST} - \text{PRE}$) was considered to exceed measurement error when $|\Delta| > \text{MDC95}$.

7.2.13 Within-participant effect size: Hedges' g

To quantify the magnitude of fatigue-related changes at the individual level, Hedges' g was computed for each participant–segment–metric combination. Hedges' g is a pooled standard-deviation effect size with a small-sample correction factor, selected in preference to Cohen's d owing to the small number of trials per condition ($n = 12$; $df = 22$). Hedges' g was calculated as:

$$g = d \times J, \quad \text{where } J = 1 - 3 / (4df - 1) \quad \text{and} \quad d = (M_2 - M_1) / S_p$$

In this equation, M_1 and M_2 are the PRE and POST participant means, S_p is the pooled within-condition standard deviation, $df = n_1 + n_2 - 2 = 22$, and J is the small-sample correction factor that reduces the positive bias in Cohen's d for small degrees of freedom. Positive g values indicate a post-fatigue increase; negative values indicate a decrease. Effect sizes were interpreted as trivial ($|g| < 0.2$), small ($0.2 \leq |g| < 0.5$), medium ($0.5 \leq |g| < 0.8$), or large ($|g| \geq 0.8$; Cohen, 1988). A 95% CI was computed for each g estimate using the t-distribution ($df = 22$), with the standard error of g approximated as:

$$SE^G = J \times \sqrt{[(n_1 + n_2) / (n_1 \times n_2) + g^2 / (2df)]}$$

Given $n = 12$ trials per condition, 95% CIs were necessarily wide and are reported as indices of estimation precision rather than as independent inferential criteria.

7.2.14 Practical significance criterion

A dual criterion was applied to determine whether a fatigue-related change was practically significant at the individual level, requiring both: (a) the mean difference exceeding the within-participant MDC95, confirming the change was beyond measurement error; and (b) a large Hedges' g ($|g| \geq 0.8$), indicating the change was large relative to that individual's own within-condition movement consistency. This criterion was operationalised in the absence of established biomechanical thresholds for spinal segment angles during running, attaching practical significance to each participant's own signal-to-noise ratio rather than external population norms.

This approach is consistent with the need to distinguish statistically detectable change from change that exceeds measurement error, particularly in small-sample biomechanical designs where individual responses may be obscured by group-level summaries (Bates, 1996; Bramah et al., 2021; Koo & Li, 2016).

Participant–segment–metric combinations were classified into four categories: (a) practically meaningful, where MDC95 was exceeded and $|g| \geq 0.8$; (b) real but small-to-medium effect, where MDC95 was exceeded but $|g| < 0.8$; (c) large g within noise, where $|g| \geq 0.8$ but Δ ($= \text{POST} - \text{PRE}$ [absolute value]) was within MDC95, typically arising from very high within-participant movement consistency amplifying the standardised effect without the absolute change clearing the reliability threshold; and (d) neither criterion met. These classifications are displayed visually in heatmap figures for each kinematic variable, with distinct cell border colours encoding each category.

7.2.15 Visualisation

Results were presented as heatmaps in which each cell displays the within-participant mean Δ in degrees for one participant–segment combination. Cell colour translates the direction and magnitude of Δ using a diverging green–white–purple scale (green = post-fatigue decrease; purple = post-fatigue increase), clipped at $\pm 5^\circ$ for display clarity. Values beyond this range are printed in full within the relevant cells. Cell border colour encodes the practical significance classification: red-orange = practically meaningful; gold = real but small-to-medium effect; cyan = large g within noise; no border = neither criterion met.

7.2.16 Group-level inferential statistics – time-series waveforms.

Statistical Parametric Mapping (SPM1d; Pataky, 2010) was used to compare pre- and post-intervention segmental angle waveforms across the movement cycle. SPM1d evaluates one-dimensional biomechanical time-series data in their entirety, avoiding the loss of temporal information associated with discrete-point analyses (Pataky et al., 2013). For each participant ($n = 10$), trial-averaged segmental angle waveforms for five segments (upper thoracic, lower thoracic, upper lumbar, lower lumbar, and pelvis) were extracted in the frontal, sagittal, and transverse planes. All waveforms were time-normalised to 101 points (0–100% of the movement cycle).

A separate paired-samples t-test was conducted for each combination of plane and segment, yielding 15 tests in total. Inference was performed at $\alpha = 0.05$ (two-tailed) using Random Field Theory (RFT) to control the family-wise error rate across the entire waveform (Adler & Taylor, 2007; Pataky, 2010). For each test, the critical t-threshold was determined from the residual smoothness (FWHM) and degrees of freedom ($df = 9$). Supra-threshold clusters were reported with their cycle location, peak t-value, and cluster-level p-value.

The normality assumption underlying the paired t-test was assessed for each plane $\times$ segment combination using the D'Agostino-Pearson K^2 test implemented in SPM1d (Pataky, 2016). At each timepoint of the cycle, K^2 combines the standardised skewness and kurtosis of the paired differences (POST – PRE) and of each condition separately into a chi-square-distributed statistic, with Random Field Theory applied to control the family-wise error rate across the waveform ($\alpha = 0.05$). Where the K^2 test flagged a departure from normality in the paired differences, the validity of the parametric paired t-test cannot be assumed (Pataky et al., 2015). To assess whether such violations affected the substantive conclusions, all 15 paired comparisons were re-evaluated using statistical non-parametric mapping (SnPM), which does not require the paired differences to be normally distributed. All analyses were performed using the spm1d package (v0.4; www.spm1d.org).

7.2.17 Group and individual inference statistics - VO_2

To avoid the confound introduced by asymmetric pre-bout starting conditions, whereby PRE commenced from an active VT1 baseline, and POST commenced from near-resting VO_2 following the drop-jump protocol, steady-state oxygen uptake was operationalised as the mean VO_2 during the final five minutes of each bout (minutes 5–10). This window is independent of the cardio-dynamic phase and the rising primary component and is therefore comparable across bouts regardless of pre-exercise metabolic state (Bell et al., 2001; DiMenna et al., 2010). Breath-by-breath oxygen uptake relative to body mass (VO_2 ; $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) was recorded at 15-second intervals

7.2.18 Non-linear analysis

To address the limitations of traditional time-series representations of vector coding data, three complementary visualisation approaches were applied to display coupling angle and

movement control data across the normalised cycle: coupling angle mapping, segmental dominance profiling, and inter-data point range of motion (IDP-ROM) profiling. Coordination variability was visualised using two complementary presentation approaches applied within the same figure: coordination variability mapping and coordination variability profiling.

Coupling angle mapping refers to the colour-scale representation of the coupling angle time-series across the normalised movement cycle (Needham et al., 2020). At each normalised time instant, the calculated coupling angle was assigned a colour corresponding to its position within one of four coordination pattern classifications: in-phase proximal dominance (IPPD), in-phase distal dominance (IPDD), anti-phase proximal dominance (APPD), and anti-phase distal dominance (APDD). A distinct colour was assigned to each quadrant of the unit circle, such that four base colours represented the four classifications. Within each in-phase or anti-phase quadrant, a graduated two-shade colour scale was used to depict transitions between proximal and distal segmental dominance, providing a continuous representation of the coupling angle distribution throughout stance.

The coupling angle map for each participant was displayed as a horizontal colour bar spanning 0–100% of the stance phase, with each time point coloured according to the coordination pattern classification and degree of segmental dominance at that instant. Individual participant maps were stacked vertically to allow direct visual comparison across participants at each point in the movement cycle. A group mean coupling angle map was also included beneath the individual maps.

Segmental dominance profiling was used to quantify and display the relative contribution of the proximal and distal segments to the inter-segmental motion at each instant throughout the gait cycle. The coupling angle was converted to radians to express segmental dominance as a percentage, where 50% indicates equal contribution from both segments, and values approaching 100% indicate near-complete dominance of one segment. Segmental dominance was displayed as a series of vertical data bars plotted across the normalised cycle, with bar height corresponding to the percentage dominance of the dominant segment at each instant. The colour of each bar was matched to the coupling angle map colour-scale, preserving the coordination pattern classification information within the dominance profile.

Inter-data point range of motion (IDP-ROM) profiling was introduced to provide an additional measure of movement control that complements the phase and dominance information

derived from vector coding. Vector coding captures only the relative angular change between adjacent data points and cannot independently quantify the absolute magnitude of segmental motion. IDP-ROM was therefore defined as the magnitude of the angular displacement of the dominant segment between consecutive normalised time points, calculated at each instant across the movement cycle. This measure was applied specifically to the dominant segment at each instant, as identified through the segmental dominancy profile described above. IDP-ROM was superimposed over the coupling angle map and segmental dominancy profile as a continuous line, with values displayed on a secondary vertical axis on the right-hand side of the figure. Higher IDP-ROM values indicate that the dominant segment is undergoing a large angular change between adjacent time points.

Coordination variability mapping refers to the use of a continuous three-colour spectrum to represent the degree of coupling angle variability at each normalised time instant across the movement cycle (Needham et al., 2020). The colour spectrum ranged from green, representing low coordination variability (0°), through amber, representing moderate variability, to red, representing high coordination variability (80°). This range was selected to encompass the full practical extent of CAV values, noting that the theoretical maximum of approximately 81.07° corresponds to a mean vector length of zero, indicating complete dispersion of coupling angles across trials. The coordination variability map for each participant was displayed as a horizontal colour bar spanning 0–100%. Coordination variability profiling presents the same CAV data as the colour map but in the form of vertical data bars plotted across the normalised stance phase, with bar height directly proportional to the CAV value in degrees at each time instant. The vertical axis of the variability profile was scaled from 0° to 80° , corresponding to the colour range of the variability map, and each bar was coloured using the same green–amber–red spectrum so that the two representations remain visually consistent and mutually interpretable.

7.3 Results

Linear analysis

7.3.1 Group-Level Inference: Normality, Paired t-Test, and Wilcoxon Signed-Rank Test

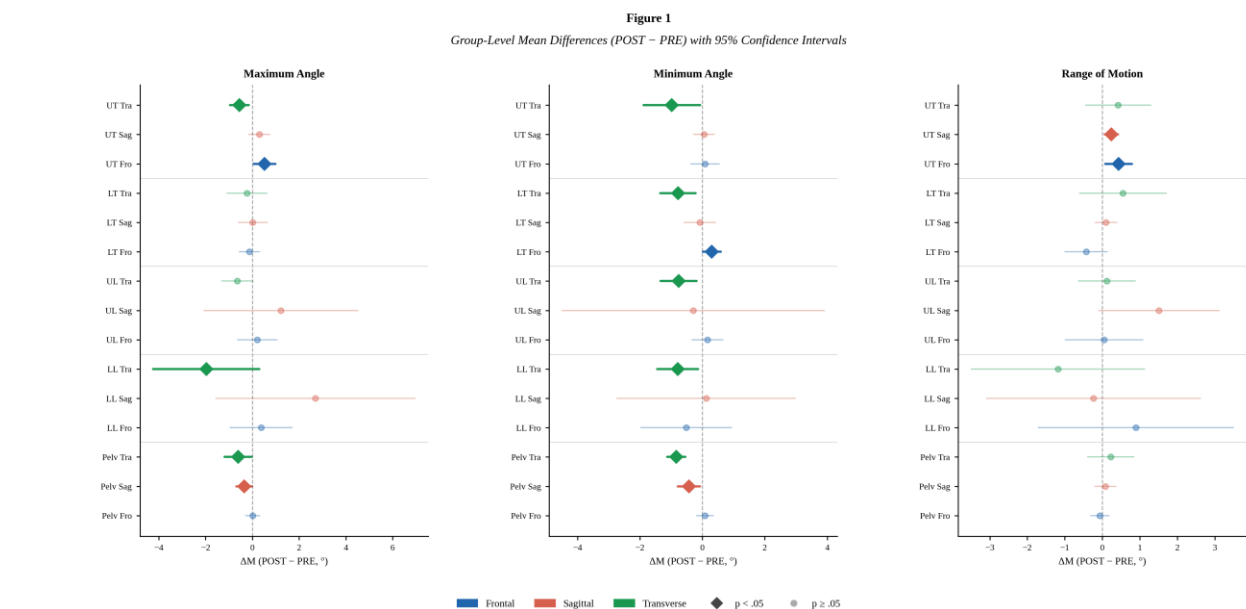
Group-level differences in spinal segment angle between pre-fatigue (PRE) and post-fatigue (POST) conditions were examined on participant-mean values for each of 45 plane–

segment–metric combinations. Normality of difference scores (POST – PRE participant means) was assessed using the Shapiro–Wilk test. Both a paired samples t-test and Wilcoxon signed-rank test were conducted for all 45 combinations; where the Shapiro–Wilk test indicated non-normally distributed difference scores ($p < .05$), the Wilcoxon signed-rank test was designated the primary statistic. Effect sizes are reported as Cohen’s d for paired samples ($d = \Delta M / SD_{diff}$). Group mean differences with 95% confidence intervals are displayed in Figure 3; statistically significant results are detailed in Tables 1–3.

7.3.2 Normality assessment

Shapiro–Wilk tests on difference scores indicated normally distributed data for 42 of 45 combinations (93%), supporting use of the paired t-test as the primary statistic for most comparisons. Three combinations produced non-normal difference scores ($p < .05$): maximum angle at the transverse lower lumbar level, minimum angle at the frontal lower lumbar level, and minimum angle at the sagittal upper lumbar level. For these combinations, the Wilcoxon signed-rank test is the preferred statistic.

Figure 7.3. Group-Level Mean Differences (POST – PRE) with 95% Confidence Intervals by Plane, Segment, and Variable



Note. Points represent group mean differences ($\Delta = \text{POST} - \text{PRE}$) and horizontal error bars represent 95% confidence intervals. Blue represents frontal-plane outcomes, orange represents sagittal-plane outcomes, and green represents transverse-plane outcomes. Diamond markers indicate statistically significant differences ($p < .05$), whereas circular markers indicate non-significant differences ($p \geq .05$). Positive values indicate an increase following the fatigue

intervention and negative values indicate a decrease. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; Pelv = pelvis; Max = maximum angle; Min = minimum angle; ROM = range of motion; n = 10.

7.3.3 Maximum angle

Five of 15 plane–segment combinations reached statistical significance ($p < .05$ on at least one test; Table 1). A significant post-fatigue increase was observed at the frontal upper thoracic level, $t(9) = -2.49$, $p = .035$, $d = 0.79$, 95% CI [0.05, 0.99°]. Significant post-fatigue decreases occurred at the transverse upper thoracic, $t(9) = 3.16$, $p = .012$, $d = -1.00$, 95% CI [-0.96, -0.16]°; transverse pelvis, $t(9) = 2.39$, $p = .041$, $d = -0.75$, 95% CI [-1.19, -0.03]°; and sagittal pelvis, $t(9) = 2.36$, $p = .043$, $d = -0.75$, 95% CI [-0.69, -0.02]°, though the Wilcoxon was non-significant for the latter ($p = .064$). At the transverse lower lumbar, non-normal difference scores (SW $p < .001$) led to designation of the Wilcoxon as primary, which indicated a significant decrease, $W = 1.0$, $p = .004$, despite a non-significant paired t-test ($p = .081$).

Table 7.1 Significant Group-level results for maximum angle: paired t-test and Wilcoxon signed rank (PRE vs Post).

Plane	Segment	n	PRE M (SD)	POST M (SD)	ΔM (SD)	95% CI	SW p	t	t p	W	W p	d
Frontal	Upper Thoracic	10	9.30 (3.36)	9.81 (3.45)	+0.52 (0.66)	[0.05, 0.99]	.207	- 2.49	.035	8.0	.049	.79
Sagittal	Pelvis	10	14.25 (4.98)	13.90 (5.17)	-0.35 (0.47)	[-0.69, -0.02]	.507	2.36	.043†	9.0	.064	-.75
Transverse	Upper Thoracic	10	13.61 (3.34)	13.06 (3.48)	-0.56 (0.56)	[-0.96, -0.16]	.840	3.16	.012	4.0	.014	- 1.00
Transverse	Lower Lumbar	10	9.11 (2.59)	7.13 (4.82)	-1.97 (3.17)	[-4.24, 0.30]	<.001*	1.97	.081	1.0	.004	-.62
Transverse	Pelvis	10	8.80 (2.34)	8.19 (2.59)	-0.61 (0.81)	[-1.19, -0.03]	.179	2.39	.041	8.0	.049	-.75

Note. Values are M (SD) in degrees (°). SW p = Shapiro–Wilk p-value on difference scores. t = paired t-statistic (df = n - 1). W = Wilcoxon signed-rank statistic. d = Cohen's d ($\Delta M / SD_{diff}$). CI = 95% confidence interval around ΔM . †t p significant but W p $\geq .05$. * Non-normal difference scores; Wilcoxon is primary. Anomalous observation excluded: P7 (SAG LL).

7.3.4 Minimum angle

Seven of 15 combinations reached significance (Table 2), the highest number across all three variables. Six of the seven significant combinations were in the transverse plane. The largest effect was at the transverse pelvis, $t(9) = 6.47$, $p < .001$, $d = -2.05$, 95% CI [-1.13, -0.54°], with $W = 0.0$ indicating a unanimously negative response across all ten participants. Significant

decreases were also found at the transverse lower thoracic, $t(9)=3.10$, $p=.013$, $d=-0.98$; transverse upper lumbar, $t(9)=2.97$, $p=.016$, $d=-0.94$; transverse lower lumbar, $t(9)=2.72$, $p=.024$, $d=-0.86$; sagittal pelvis, $t(9)=2.76$, $p=.022$, $d=-0.87$; and frontal lower thoracic, $t(9)=-2.42$, $p=.039$, $d=0.76$. The transverse upper thoracic reached significance on the t-test ($p=.037$) but not the Wilcoxon ($p=.064$), indicating a borderline result.

Table 7.2. Significant Group-Level Results for Minimum Angle: Paired t-Test and Wilcoxon Signed-Rank (PRE vs. POST)

Plane	Segment	n	PRE M (SD)	POST M (SD)	Δ M (SD)	95% CI	SW p	t	t p	W	W p	d
Frontal	Lower Thoracic	10	-5.27 (2.41)	-4.96 (2.35)	+0.30 (0.40)	[0.02, 0.59]	.881	- 2.42	.039	7.0	.037	.76
Sagittal	Pelvis	10	8.86 (5.24)	8.43 (5.39)	-0.43 (0.50)	[-0.79, -0.08]	.531	2.76	.022	6.0	.027	-.87
Transverse	Upper Thoracic	10	-13.14 (3.68)	-14.11 (3.48)	-0.98 (1.27)	[-1.89, -0.07]	.742	2.44	.037†	9.0	.064	-.77
Transverse	Lower Thoracic	10	-14.21 (6.60)	-15.00 (6.74)	-0.78 (0.80)	[-1.35, -0.21]	.123	3.10	.013	6.0	.027	-.98
Transverse	Upper Lumbar	10	-11.34 (5.54)	-12.10 (5.21)	-0.76 (0.81)	[-1.34, -0.18]	.797	2.97	.016	3.0	.010	-.94
Transverse	Lower Lumbar	10	-8.85 (4.29)	-9.64 (4.22)	-0.79 (0.92)	[-1.45, -0.13]	.695	2.72	.024	5.0	.020	-.86
Transverse	Pelvis	10	-7.98 (2.95)	-8.81 (2.97)	-0.84 (0.41)	[-1.13, -0.54]	.466	6.47	< .001	0.0	.002	- 2.05

Note. Values are M (SD) in degrees (°). SW p = Shapiro–Wilk p-value on difference scores. t = paired t-statistic (df = n – 1). W = Wilcoxon signed-rank statistic. d = Cohen’s d (Δ M / SD_{diff}). †t p significant but W p $\geq .05$. Anomalous observations excluded: P5, P7 (SAG LL).

7.3.5 Range of motion

Two of 15 combinations reached significance (Table 3), consistent with the lower practical significance rates for ROM identified at the individual level. Frontal upper thoracic ROM increased significantly, $t(9)=-2.75$, $p=.023$, $d=0.87$, 95% CI [0.08, 0.79°] (Wilcoxon: $p=.037$). Sagittal upper thoracic ROM also increased significantly, $t(9)=-3.07$, $p=.013$, $d=0.97$, 95% CI [0.06, 0.42°] (Wilcoxon: $p=.020$). Difference scores were normally distributed for all 15 ROM combinations.

Table 7.3. Significant Group-Level Results for Range of Motion: Paired t-Test and Wilcoxon Signed-Rank (PRE vs. POST)

Plane	Segment	n	PRE M (SD)	POST M (SD)	Δ M (SD)	95% CI	SW p	t	t p	W	W p	d
Frontal	Upper Thoracic	10	16.36 (3.98)	16.80 (4.04)	+0.43 (0.50)	[0.08, 0.79]	.743	- 2.75	.023	7.0	.037	.87
Sagittal	Upper Thoracic	10	4.71 (1.92)	4.95 (2.08)	+0.24 (0.25)	[0.06, 0.42]	.678	- 3.07	.013	5.0	.020	.97

Note. Values are M (SD) in degrees ($^{\circ}$). All ROM difference scores were normally distributed (SW $p > .05$). t = paired t-statistic ($df = n - 1$). W = Wilcoxon signed-rank statistic. d = Cohen's d ($\Delta M / SD_{diff}$). CI = 95% confidence interval around ΔM .

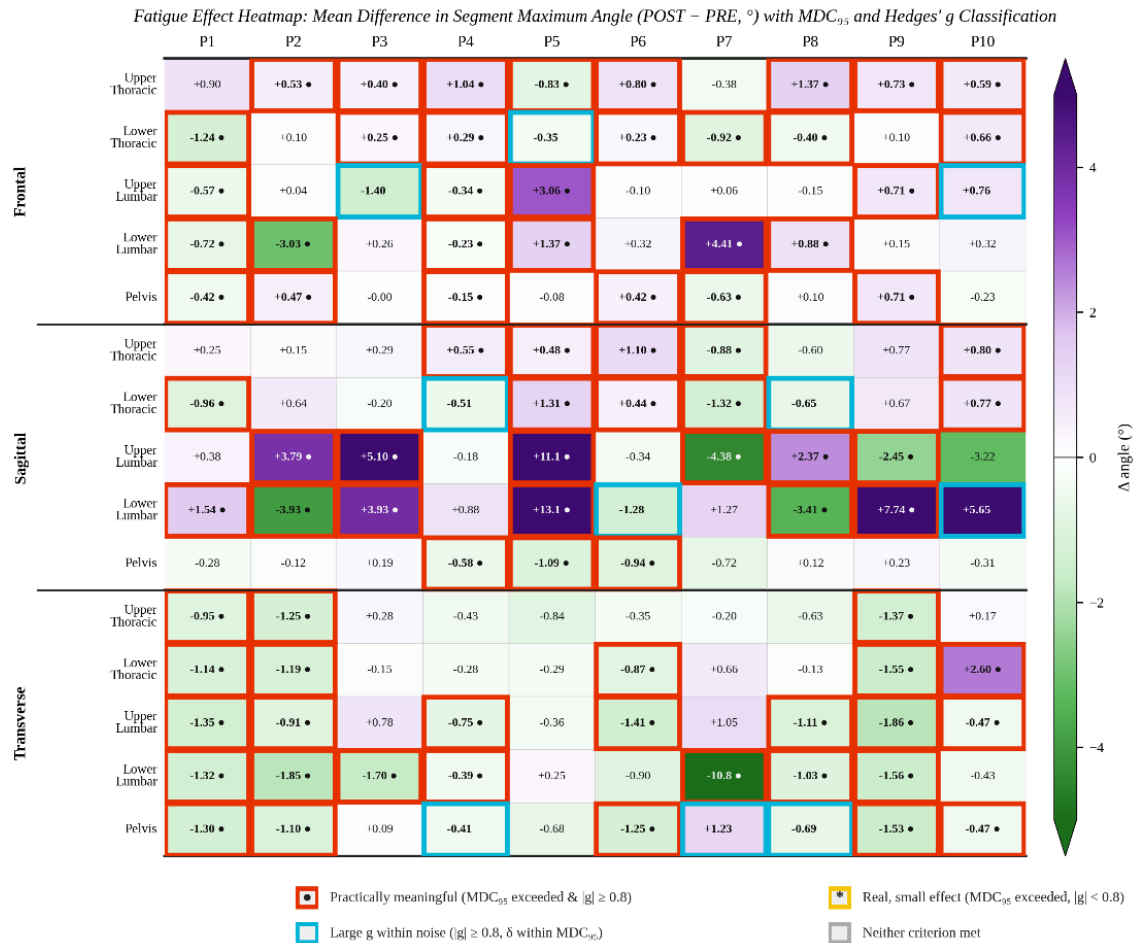
7.3.6 Within-Participant Effect Sizes: Hedges' g and Practical Significance

Figures 4-6 present heatmaps of the within-participant mean difference ($\Delta = \text{POST} - \text{PRE}$) in spinal segment angle in degrees for maximum angle, minimum angle, and range of motion (ROM), respectively.

7.3.7 Maximum angle

Practically meaningful post-fatigue changes in maximum segment angle were identified in 83 of 149 valid participant–segment combinations (56%), with a median within-participant effect size of $|g| = 1.05$ (Figure 4). Red-orange borders are distributed across all three planes, with the frontal plane showing the highest concentration (31 of 50; 62%), followed by the transverse (27 of 50; 54%) and sagittal (25 of 49; 51%) planes. In the transverse plane, bordered cells are predominantly green (41 of 50 negative Δ), reflecting a directionally consistent post-fatigue reduction in maximum transverse segment angle across participants and spinal levels. The sagittal plane displays the widest range of cell values, with large positive Δ values visible at the upper and lower lumbar levels for several participants (notably P5, $\Delta = +11.1^{\circ}$ and $+13.1^{\circ}$) alongside large negative values in others, illustrating marked inter-individual variability in the sagittal fatigue response. Ten cells (7%) show cyan borders indicating large g within noise, concentrated in the sagittal lumbar region where high within-participant movement consistency produced large, standardised effects from small absolute changes.

Figure 7.4. Within-participant mean difference in maximum segment angle following localised lower-limb fatigue across the frontal, sagittal, and transverse planes. Cell values represent POST – PRE change in degrees. Cell borders indicate practical-significance classification based on MDC₉₅ and Hedges' g.

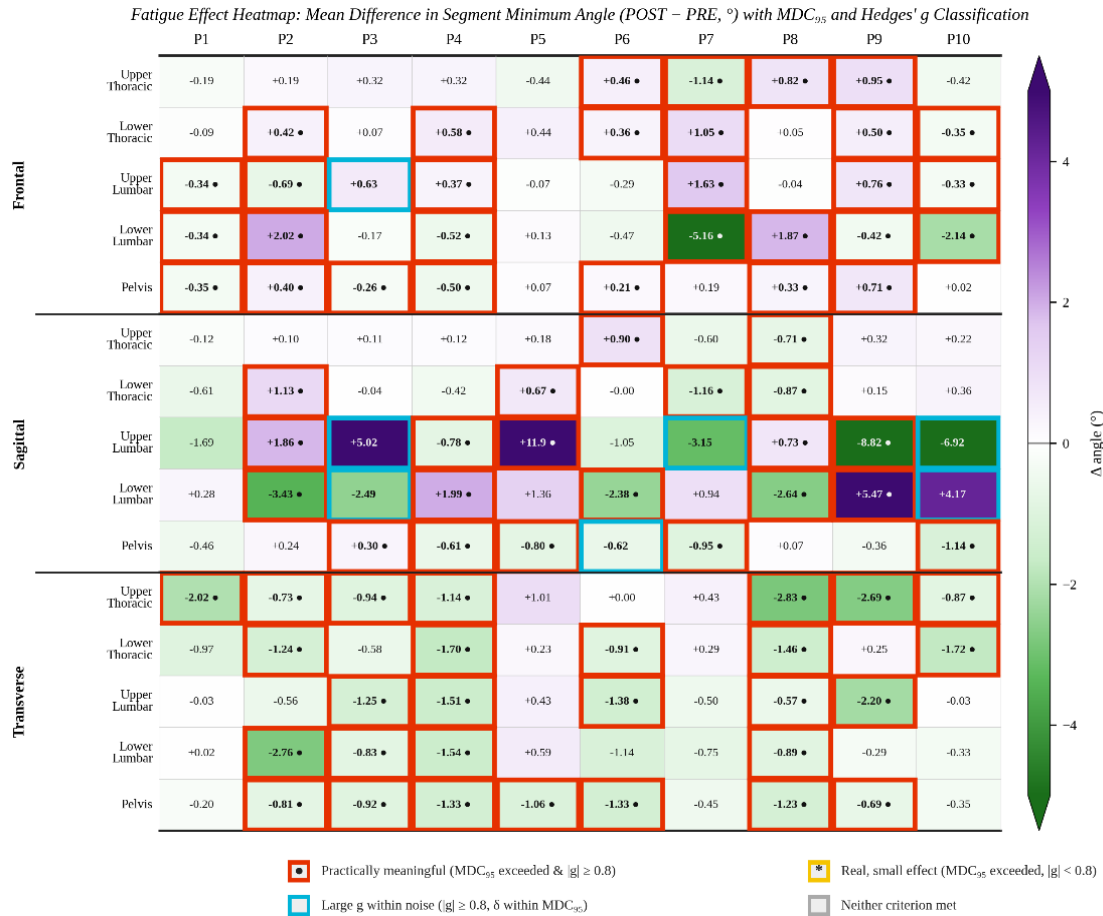


Note. Each cell represents the within-participant mean difference ($\Delta = \text{POST} - \text{PRE}$, °) for the relevant segment and participant. Cell fill colour represents the direction and magnitude of change using a green–white–purple scale: green indicates a post-fatigue decrease, white indicates little or no change, and purple indicates a post-fatigue increase. The colour scale is clipped at $\pm 5^\circ$ for visualisation, although numerical values exceeding this range are displayed in full within the cells. Border colour represents the practical-significance classification: red-orange = practically meaningful change, where MDC₉₅ was exceeded and $|\text{Hedges' } g| \geq 0.8$; gold = change exceeding MDC₉₅ but with a small-to-medium effect ($|g| < 0.8$); cyan = large effect ($|g| \geq 0.8$) occurring within measurement noise (change $\leq \text{MDC}_{95}$); no coloured border = neither criterion met. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; MDC₉₅ = minimal detectable change at the 95% confidence level; n = 10.

7.3.8 Minimum angle

Practically meaningful changes in minimum angle were identified in 79 of 148 valid combinations (53%; median $|g| = 1.04$) (Figure 5). The overall pattern closely mirrors Figure 1, with red-orange borders spread across all three planes. The transverse plane is particularly notable: bordered cells span all five segments and are almost uniformly green (41 of 50 negative Δ), indicating a consistent post-fatigue reduction in minimum transverse angle irrespective of spinal level. This directional uniformity is most pronounced at the pelvic level, where all ten participants decreased (visible as a fully bordered, uniformly green column in the transverse pelvis row). The frontal plane shows 30 practically significant combinations (60%), with the largest concentration of purple-bordered cells (positive Δ) at the lower thoracic and lower lumbar levels, reflecting post-fatigue increases in minimum frontal angle in some participants. Seven cells (5%) show cyan borders, primarily at the sagittal lumbar level.

Figure 7.5. Within-participant mean difference in minimum segment angle following localised lower-limb fatigue across the frontal, sagittal, and transverse planes. Cell values represent POST – PRE change in degrees. Cell borders indicate practical-significance classification based on MDC₉₅ and Hedges' g.

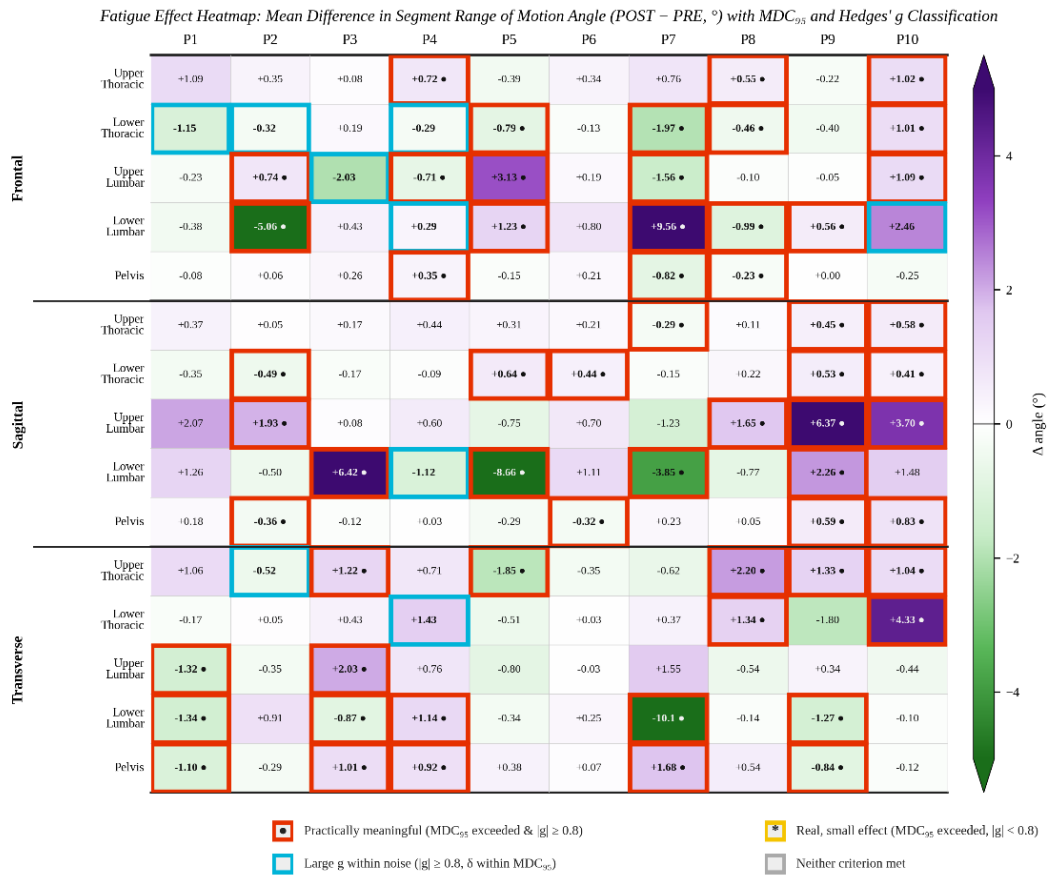


Note. Each cell represents the within-participant mean difference (Δ = POST – PRE, °) for the relevant segment and participant. Cell fill colour represents the direction and magnitude of change using a green–white–purple scale: green indicates a post-fatigue decrease, white indicates little or no change, and purple indicates a post-fatigue increase. The colour scale is clipped at $\pm 5^\circ$ for visualisation, although numerical values exceeding this range are displayed in full within the cells. Border colour represents the practical-significance classification: red-orange = practically meaningful change, where MDC₉₅ was exceeded and |Hedges' g| ≥ 0.8 ; gold = change exceeding MDC₉₅ but with a small-to-medium effect (|g| < 0.8); cyan = large effect (|g| ≥ 0.8) occurring within measurement noise (change $\leq$ MDC₉₅); no coloured border = neither criterion met. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; MDC₉₅ = minimal detectable change at the 95% confidence level; n = 10.

7.3.9 Range of motion

Practically meaningful changes in ROM were identified in 59 of 150 valid combinations (39%; median $|g| = 0.74$) (Figure 6). A lower rate than for the maximum and minimum metrics, consistent with the interpretation that fatigue primarily repositioned spinal segments within their operating range rather than substantially altering the total ROM. Red-orange borders are distributed more sparsely across Figure 3 relative to Figures 1 and 2, with mostly equal rates across frontal (20 of 50; 40%), sagittal (20 of 50; 40%), and transverse planes (19 of 50; 38%). The overall colour pattern is lighter and closer to white than in the preceding figures, reflecting the smaller absolute Δ values typical of ROM changes. Nine cells (6%) convey cyan borders, the highest proportion across the three figures, concentrated in the sagittal plane at the lumbar levels where large between-participant variability in ROM inflated standardised effects that nonetheless fell within individual measurement noise. The largest ROM changes visible in Figure 3 are at the lower lumbar level for P7 in the sagittal and transverse planes ($\Delta = -10.8^\circ$ and $+9.56^\circ$ respectively), where the cells appear as saturated green and purple.

Figure 7.6. Within-participant mean difference in segmental range of motion following localised lower-limb fatigue across the frontal, sagittal, and transverse planes. Cell values represent POST – PRE change in degrees. Cell borders indicate practical-significance classification based on MDC₉₅ and Hedges' g



Note. Δ = POST – PRE mean difference in degrees (°). Colour reflects Δ magnitude and direction (green = decrease, purple = increase); scale clipped at ±5° for display. MDC₉₅ = 1.96 × √2 × SEM (within-participant reliability threshold). Practical significance = MDC₉₅ exceeded AND |g| ≥ 0.8. PRE = pre-fatigue; POST = post-fatigue. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar.

Note. Each cell represents the within-participant mean difference (Δ = POST – PRE, °) for the relevant segment and participant. Cell fill colour represents the direction and magnitude of change using a green–white–purple scale: green indicates a post-fatigue decrease, white indicates little or no change, and purple indicates a post-fatigue increase. The colour scale is clipped at ±5° for visualisation, although numerical values exceeding this range are displayed in full within the cells. Border colour represents the practical-significance classification: red-orange = practically meaningful change, where MDC₉₅ was exceeded and |Hedges' g| ≥ 0.8; gold = change exceeding MDC₉₅ but with a small-to-medium effect (|g| < 0.8); cyan = large effect (|g| ≥ 0.8) occurring within measurement noise (change ≤ MDC₉₅); no coloured border = neither criterion met. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; MDC₉₅ = minimal detectable change at the 95% confidence level; n = 10.

7.3.10 Statistical parametric mapping of segment-angle waveforms

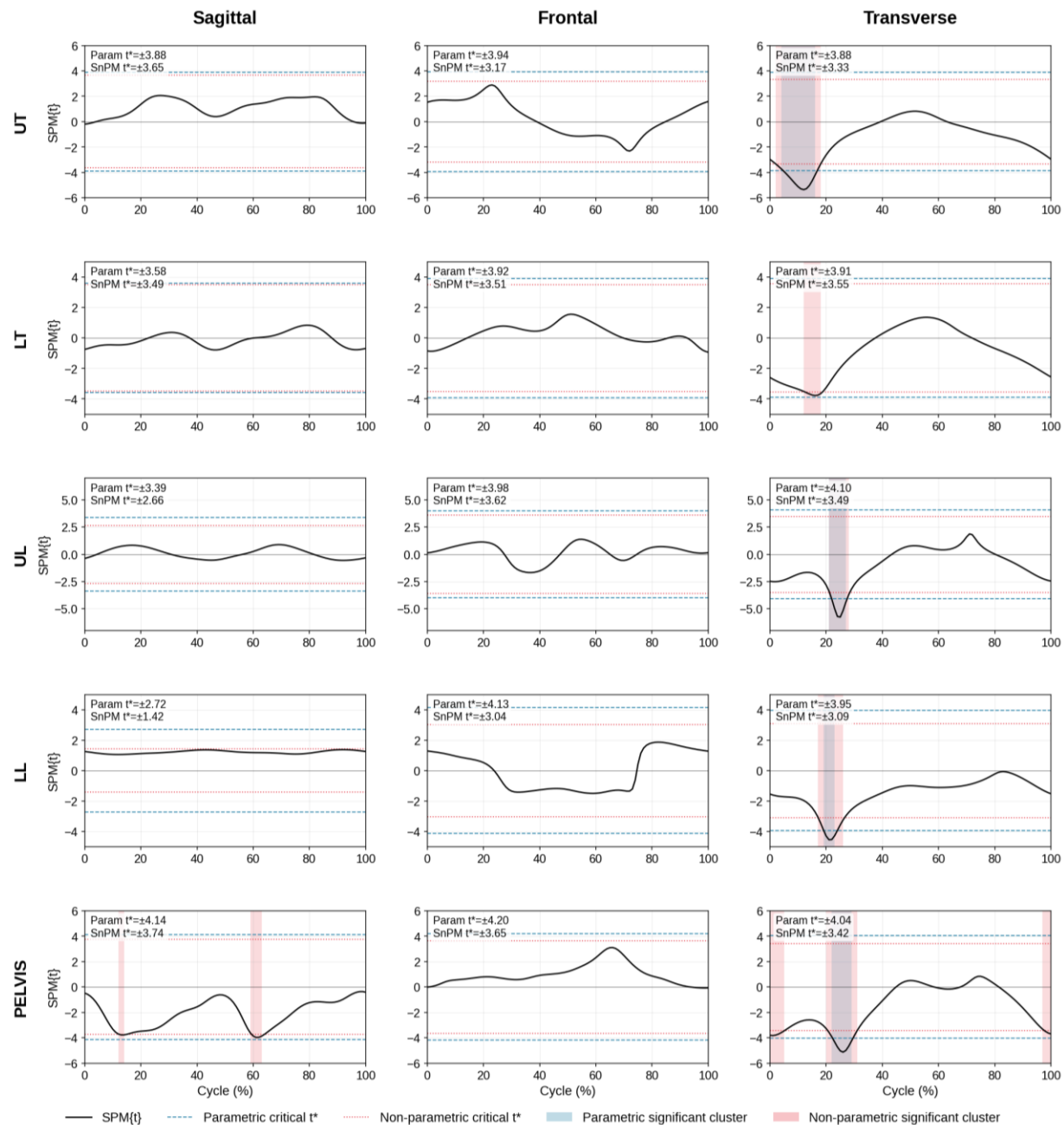
The D'Agostino–Pearson K^2 test identified non-normality in the paired differences for several plane $\times$ segment combinations. In the sagittal plane, non-normality was detected for the upper lumbar (16.8% of cycle), lower lumbar (60.3% of cycle), and pelvis (3.0%) segments; the upper thoracic and lower thoracic segments showed no departure from normality in the paired differences. In the frontal plane, K^2 exceeded the critical threshold for the upper thoracic (42.6% of cycle), lower thoracic (36.6%), upper lumbar (13.9%), lower lumbar (52.3%), and pelvis (5.9%) segments. In the transverse plane, non-normality was detected for the upper thoracic (8.9%), upper lumbar (12.9%), lower lumbar (40.6%), and pelvis (14.9%) segments.

All four significant clusters identified by the parametric test in the transverse plane were independently confirmed by SnPM, with comparable or expanded cycle ranges: upper thoracic (parametric 4–16%, $p = .009$; non-parametric 2–18%, $p = .002$), upper lumbar (parametric 21–27%, $p = .024$; non-parametric 21–28%, $p = .002$), lower lumbar (parametric 17–28%, $p < .01$; non-parametric similar range, $p = .002$), and pelvis (parametric 22–29%, $p = .017$; non-parametric 20–31%, $p = .002$). This concordance indicates that the K^2 -flagged normality violations in these segments did not affect the substantive inference; the parametric findings are robust.

The non-parametric analysis identified three significant clusters that the parametric test did not detect: transverse lower thoracic (12–18% of cycle, peak $t = -3.78$, $p = .008$), and sagittal pelvis at 12–14% (peak $t \approx -3.95$, $p < .05$) and 57–63% of the cycle (peak $t \approx -4.04$, $p < .05$). As these are cases where the two methods disagree, the parametric (null) finding cannot be considered robust, and the non-parametric result is taken as definitive. The additional clusters reflect the conservative bias of parametric inference under the small-sample, non-normal conditions identified by the K^2 screening. Two further non-parametric clusters were also identified in the transverse pelvis at 0–5% ($p = .008$) and 97–100% of the cycle ($p = .016$).

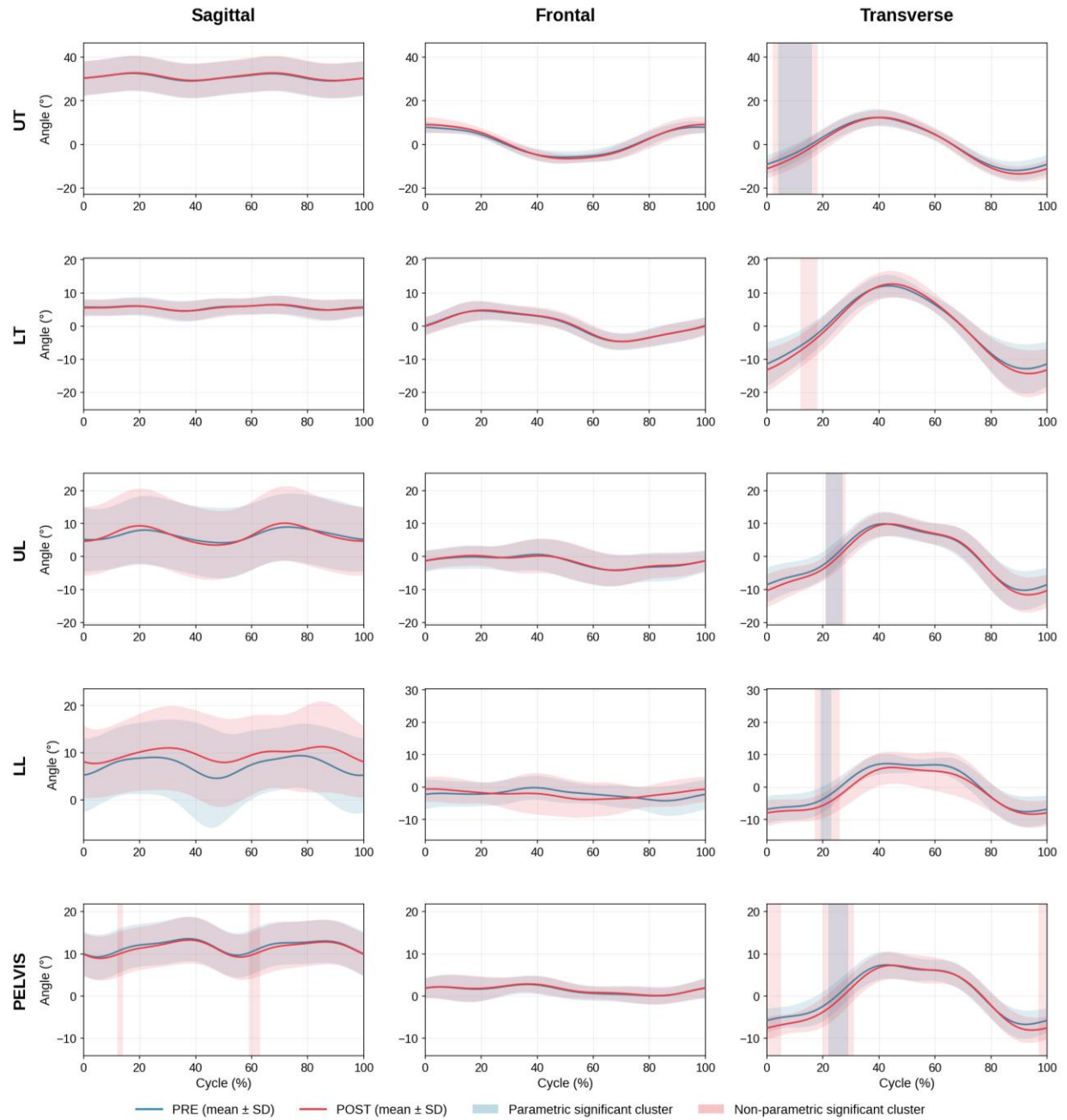
All frontal-plane comparisons and the remaining sagittal-plane comparisons (UT, LT, UL, LL) were non-significant under both methods, indicating that the K^2 -flagged normality violations in those segments did not mask hidden effects.

Figure 7.7 Statistical parametric mapping (SPM{t}) and non-parametric (SnPM) paired t-test results for segmental angle waveforms across the frontal, sagittal, and transverse planes (POST – PRE; $n = 10$, $\alpha = 0.05$, two-tailed).



Note. Blue dashed lines indicate parametric critical thresholds; red dotted lines indicate non-parametric critical thresholds derived from exhaustive permutation inference (2^n permutations). Blue and red shaded regions denote parametric and non-parametric significant clusters, respectively.

Figure 7.8. Group mean (± 1 SD) segmental angle waveforms for the pre- (blue) and post-intervention (red) conditions across the frontal, sagittal, and transverse planes.



Note. Blue and red shaded vertical bands denote regions of the movement cycle identified as statistically significant by the parametric and non-parametric paired t-tests, respectively ($n = 10$, $\alpha = 0.05$, two-tailed).

Non-linear analysis

7.3.11. Group-Level Coupling Angle Patterns and Coupling Angle Variability: Transverse Plane

Across all four segment pairs, the group mean coupling angle maps revealed a generally consistent coordination pattern in the transverse plane both pre- and post-fatigue. For UT–LT and LT–UL couplings, the group PRE profile was characterised by a clear bi-phasic pattern of in-phase coordination throughout the full gait cycle. During stance (0–40%), both segments rotated in a positive direction, with coordination progressing from in-phase proximal dominance (IPPD; light red) toward in-phase distal dominance (IPDD; dark red) across the stance phase, reflecting a proximal-to-distal sequencing of segmental dominance during positive rotation. Following the stance-to-swing transition (~40%), both segments reversed to a negative rotational direction, with coordination again progressing from IPPD (light green) toward IPDD (dark green) across swing. This indicates that the proximal-to-distal sequencing of dominance was preserved within negative rotation during swing. Bar height, reflecting the degree of segmental dominance (50–100%), was generally higher during mid-stance and mid-swing, consistent with the bi-phasic IDROM profile. This overall coordination pattern was mostly maintained POST-fatigue across both segment couplings, suggesting that the fundamental in-phase, direction-matched co-rotation with proximal-to-distal sequencing was not disrupted by the fatigue intervention.

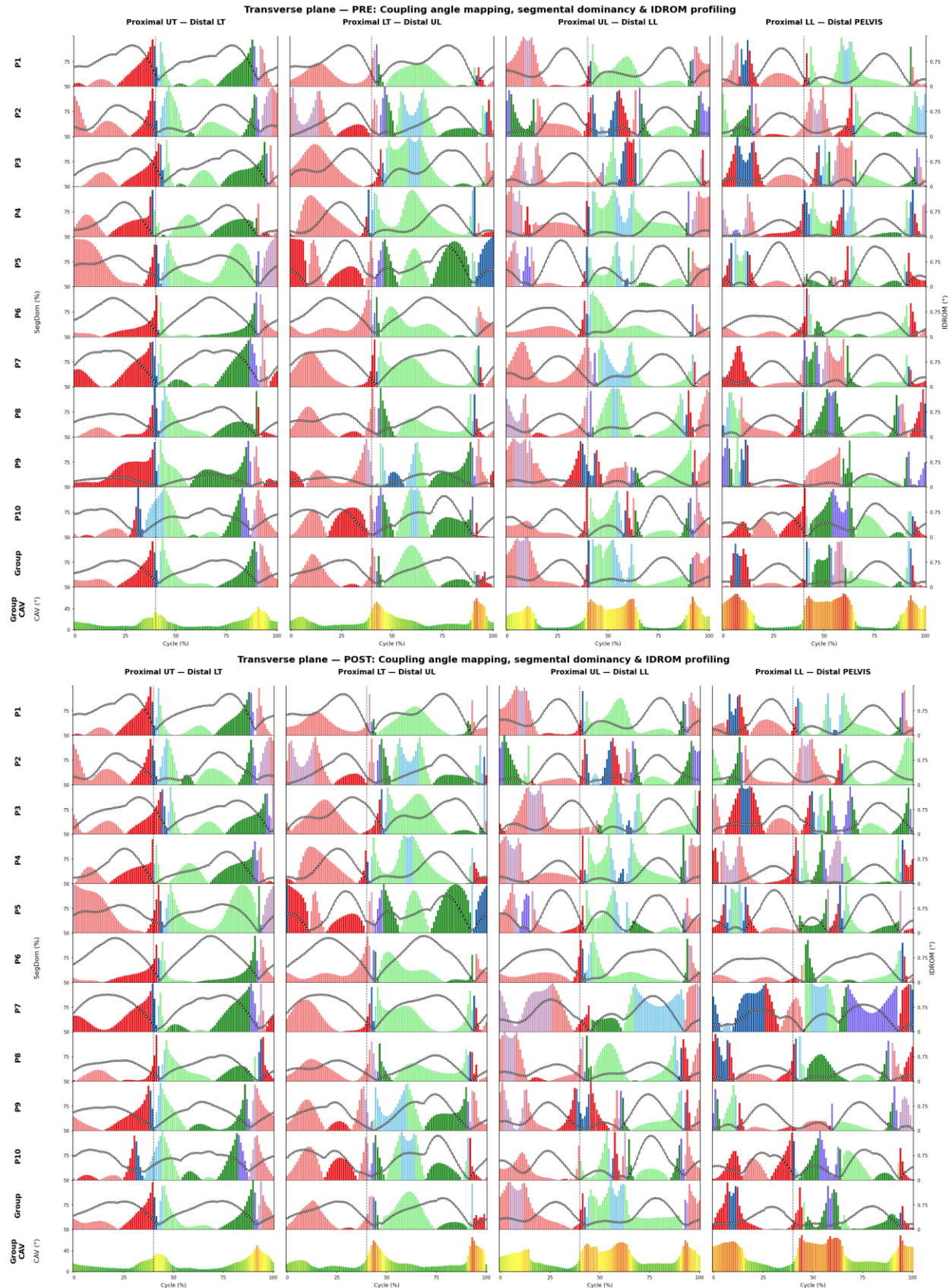
The UL–LL coupling showed a more heterogeneous group coordination pattern, with greater representation of anti-phase coordination occurrences scattered throughout the cycle relative to the UT–LT and LT–UL couplings. During early stance and early swing phase, occurrences of anti-phase proximal dominance (APPD; light purple) and anti-phase proximal dominance (APPD; light blue), reflecting the proximal segment rotating positively while the distal segment rotated negatively, were evident alongside periods of in-phase positive rotation. POST-fatigue, coordination patterns were maintained.

For LL–Pelvis coupling, the group PRE showed the most complex coordination profile across the cycle. During early stance (0–20%), coordination was characterised by in-phase distal dominance (IPDD; dark red). This indicates that the pelvis was the dominant contributor to positive co-rotation at initial ground contact, with the lumbar spine rotating in the same direction but to a lesser degree. As stance progressed, a transition toward proximal dominance (light red; IPPD) was apparent. At the onset of swing (~40%), in-phase distal dominance again emerged (dark

green; IPDD), suggesting that the pelvis continued to lead the rotational pattern as both segments reversed to negative rotation at the initiation of swing, before transitioning toward more proximal dominance (light green; IPPD) in the mid-to-late swing phase. This pattern of pelvic-led co-rotation at the onset of both stance and swing is notably distinct from the proximal-to-distal sequencing observed in the more cephalad UT–LT and LT–UL couplings. Additionally, a general trend toward increased pelvic dominance was apparent across the full cycle POST-fatigue, with a shift from lighter to darker colours observable during both mid-to-late stance (~20–40%) and mid-to-late swing (~60–100%), suggesting that the pelvis assumed a progressively greater role in driving transverse plane rotation between the LL and Pelvis segments following the fatigue intervention.

The Group CAV profiles revealed a clear proximal-to-distal gradient in inter-participant coordination variability across the transverse plane. In the UT–LT and LT–UL couplings, CAV was low across the majority of the gait cycle, indicating generally similar coordination patterns between participants throughout both stance and swing. Elevated CAV was confined predominantly to the region around the stance-to-swing transition (~40%), coinciding with toe-off and the reversal of rotational direction. This suggests that this directional transition point was the primary source of inter-participant variability in coordination pattern for the more cephalad segment couplings. In the UL–LL and LL–Pelvis couplings, elevated CAV again peaked around the stance-to-swing transition; however, the period of high variability extended across a considerably greater proportion of the cycle, encompassing substantial portions of both stance and swing. This implies that inter-participant consistency in coordination pattern decreased markedly for the more caudal couplings, with the lumbo-pelvic coordination (LL–Pelvis) exhibiting the greatest and most temporally extended variability of all four pairs. Taken together, these profiles indicate an incremental proximal-to-distal increase in CAV across the four segment couplings. Suggesting that transverse plane coordination becomes progressively less categorised between participants as one moves distally along the spine. For example, the thoracic segments exhibited a highly consistent inter-participant coordination strategy while lumbo-pelvic coordination exhibited the greatest individual variation. This CAV gradient was generally maintained POST-fatigue across all four segment couplings, though a general increase in CAV magnitude was apparent in the UL–LL and LL–Pelvis Couplings.

Figure 7.9. Transverse plane coupling angle mapping, segmental dominance profiling, and IDROM profiling for the PRE (upper panel) and POST (lower panel) conditions across all four segment pairs (Proximal UT–Distal LT, Proximal LT–Distal UL, Proximal UL–Distal LL, Proximal LL–Distal Pelvis). Individual participant (P1–P10), group mean, and Group CAV rows are displayed.



Note. Colour coding represents coordination pattern, direction of rotation and segmental dominance. Light red = in-phase proximal dominance (IPPD), positive rotation; dark red = in-phase distal dominance (IPDD), positive rotation; light green = IPPD, negative rotation; dark green = IPDD, negative rotation; light blue = anti-phase proximal dominance (APPD), proximal negative/distal positive; dark blue = anti-phase distal dominance (APDD), proximal negative/distal positive; light purple = APPD, proximal positive/distal negative; dark purple = APDD, proximal positive/distal negative. Within each colour family, lighter shades therefore indicate greater proximal-segment dominance and darker shades indicate greater distal-segment dominance. Bar height represents segmental dominance from 50% (equal proximal and distal contribution) to 100% (complete dominance of one segment). The dotted line represents inter-data point range of motion (IDP-ROM, °) of the dominant segment and is read from the right-hand vertical axis. PRE and POST represent running before and after the localised lower-limb fatigue intervention. UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; CAV = coupling angle variability.

7.3.12 Individual Participant Data: Commonalities and Differences

The most consistent feature across all ten participants was the bi-phasic in-phase coordination pattern in the UT–LT and LT–UL pairs, with positive co-rotation progressing from proximal-to-distal dominance (light-to-dark red) during stance and negative co-rotation again progressing from proximal-to-distal dominance (light-to-dark green) during swing. This pattern was robust to fatigue, being maintained PRE to POST across the majority of participants in both segment couplings. This is consistent with the group-level finding of an undisrupted bi-phasic in-phase coordination pattern. Correspondingly, the IDROM profile was bi-phasic in most participants, with peaks occurring within mid-stance and mid-swing, reflecting two periods of greater angular displacement by the dominant segment per cycle, again mirroring the group profile.

In the UL–LL and LL–Pelvis couplings, individual coordination patterns were more heterogeneous, consistent with the group-level observation. For the LL–Pelvis coupling specifically, the group-level pattern of pelvic-led distal dominance (dark red; dark green) at the onset of stance and swing was evident in several participants. The POST-fatigue trend toward increased pelvic dominance observed at group level was also apparent in several of these participants, with a visible shift from lighter to darker colours across mid-to-late stance and mid-to-late swing. The LL–Pelvis pair revealed the greatest inter-individual variability, with several participants not matching the group observation. For instance, P6, P7, and P10 showed uniform proximal dominance (light red; IPPD) throughout the entire stance phase, indicating that the lumbar spine rather than the pelvis was the dominant segment at this coupling during ground contact in these participants. The presence of these participants within the cohort, alongside those reflecting pelvic-led distal dominance in early stance, is likely a primary contributor to the elevated Group CAV observed across the stance phase for this pair.

Physiological responses: Steady-state $\dot{V}O_2$

7.3.13. Final 5-Minute Steady-State $\dot{V}O_2$ Comparison

Prior to inferential analysis, the normality of the difference scores (POST – PRE final 5-minute $\dot{V}O_2$) was assessed using the Shapiro–Wilk test. The test indicated no significant departure from normality ($W = 0.909$, $p = .276$), and inspection of the normal Q–Q plot confirmed that data points approximated the theoretical normal distribution without systematic deviation. A paired samples t -test was therefore selected as the appropriate inferential test. To address the positive bias in Cohen's d at small sample sizes, Hedges' g was computed as the bias-corrected effect size using the correction factor $J = 1 - 3/(4 \times df - 1)$, where $df = 9$, producing $J = 0.914$ (Hedges & Olkin, 1985).

The mean $\dot{V}O_2$ during the final five minutes of PRE ranged from 38.27 to 50.42 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ across participants (group mean $\pm$ SD : $41.52 \pm 4.00 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$). Following the drop-jump fatigue protocol, the mean $\dot{V}O_2$ during the final five minutes of POST ranged from 38.35 to 52.31 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ ($42.39 \pm 4.44 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$). A paired samples t -test indicated that the final 5-minute steady-state $\dot{V}O_2$ was significantly higher during POST than PRE ($t(9) = 3.215$, $p = .011$, 95% CI [$+0.26$, $+1.49$] $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, Hedges' $g = 0.930$, 95% CI [0.147 , 1.712]). Nine of ten participants demonstrated a higher steady-state $\dot{V}O_2$ during POST relative to PRE, with a group mean post-fatigue elevation of $+0.87 \pm 0.86 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ ($+2.1 \pm 2.0\%$). The effect size is classified as large (Cohen, 1988; Hedges & Olkin, 1985), indicating a practically meaningful, albeit modest in absolute terms, increase in the oxygen cost of level-ground VT1 running following lower-limb localised fatigue. The wide confidence interval for Hedges' g [0.147 , 1.712] reflects the sampling uncertainty inherent to $n = 10$ and should be interpreted accordingly, noting that the lower bound exceeds zero, confirming a reliably positive effect.

Individual responses were variable. The largest post-fatigue elevations were observed in P2 ($+2.06 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$; $+5.1\%$), P4 ($+1.89 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$; $+3.7\%$), P9 ($+1.79 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$; $+4.0\%$), and P8 ($+1.44 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$; $+3.7\%$). Smaller but positive elevations were observed in P7 ($+0.85 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), P6 ($+0.59 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), P10 ($+0.19 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), P1 ($+0.15 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), and P3 ($+0.09 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$). P5 was the sole participant to exhibit a marginally lower steady-state $\dot{V}O_2$ during con3 ($-0.30 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$; -0.7%), which is unlikely to reflect a genuine improvement in running economy and is most plausibly attributable to within-session measurement variability. The large SD relative to the mean difference (0.86 vs 0.87

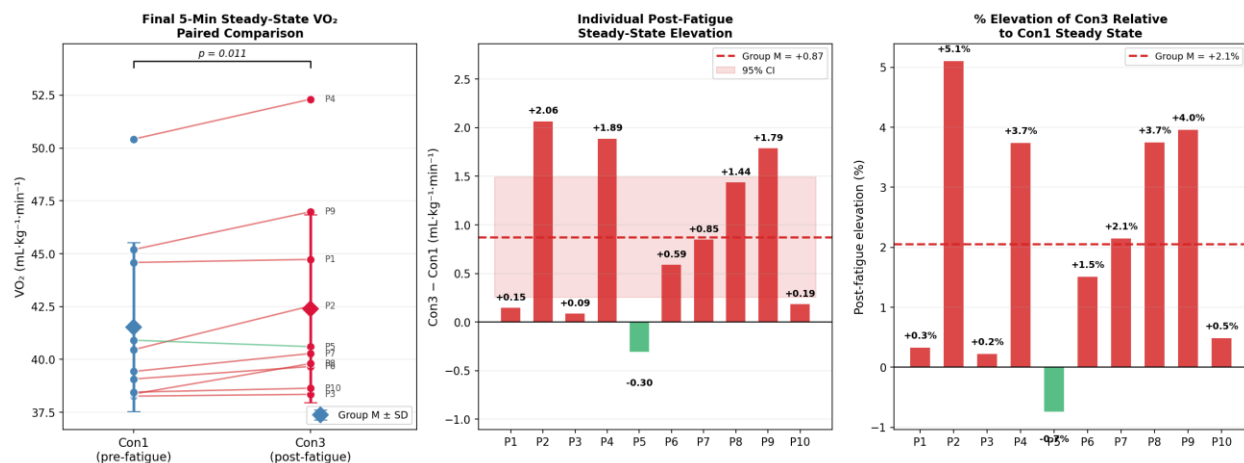
mL·kg⁻¹·min⁻¹) reflects considerable inter-individual variability in the magnitude of the post-fatigue effect, consistent with variation in the degree of neuromuscular fatigue sustained and the capacity of individual runners to compensate biomechanically.

Table 7.4. Final 5-Minute Steady-State VO₂ During Con1 and Con3 for Each Participant

Participant	Con1 M	SD	Con3 M	SD	Difference	% Change
	(mL·kg ⁻¹ ·min ⁻¹)		(mL·kg ⁻¹ ·min ⁻¹)		(mL·kg ⁻¹ ·min ⁻¹)	
P1	44.59	2.31	44.73	0.61	+0.15	+0.3%
P2	40.47	0.56	42.53	0.96	+2.06	+5.1%
P3	38.27	1.18	38.35	1.86	+0.09	+0.2%
P4	50.42	2.03	52.31	1.24	+1.89	+3.7%
P5	40.91	0.64	40.61	0.80	-0.30	-0.7%
P6	39.08	2.31	39.67	1.21	+0.59	+1.5%
P7	39.43	0.57	40.28	1.05	+0.85	+2.1%
P8	38.37	1.40	39.81	0.59	+1.44	+3.7%
P9	45.20	1.18	46.99	1.63	+1.79	+4.0%
P10	38.45	1.53	38.64	2.40	+0.19	+0.5%
M ± SD	41.52 ± 4.00		42.39 ± 4.44		+0.87 ± 0.86	+2.1 ± 2.0%

Note. Con1 = pre-fatigue VT1 bout. Con3 = post-fatigue VT1 bout. Final 5-min window = minutes 5–10 of each bout. Difference = Con3 M minus Con1 M. % Change = difference expressed as a percentage of Con1 M. Group statistics reflect all ten participants. VO₂ = oxygen uptake expressed relative to body mass (mL·kg⁻¹·min⁻¹). M = mean; SD = standard deviation.

Figure 7.10. Group-Level Final 5-Minute Steady-State VO₂ Comparison Between Con1 and Con3.



Note. CON1 represents the pre-fatigue VT1 running condition, and CON3 represents the post-fatigue VT1 running condition. Values represent the final 5-min steady-state $\dot{V}O_2$ response for each condition. Individual participant values are shown alongside the group summary. $\dot{V}O_2$ is expressed relative to body mass ($\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$). VT1 = first ventilatory threshold; $n = 10$.

7.3.14 Temporal-spatial gait parameters

Prior to conducting inferential analyses, the normality of difference scores between conditions was assessed for each gait parameter using the Shapiro-Wilk test. Results indicated that all difference scores were normally distributed: cycle time, $W(10) = 0.959$, $p = .769$; stance time, $W(10) = 0.956$, $p = .742$; swing time, $W(10) = 0.958$, $p = .767$; step rate, $W(10) = 0.936$, $p = .513$. The assumption of normality was therefore satisfied for all measures, supporting the use of paired samples t -tests.

Paired samples t -tests were conducted to examine differences in temporal-spatial gait parameters between PRE and POST in a sample of 10 participants. Descriptive statistics and inferential outcomes for all measures are presented in Table ?. No statistically significant difference was observed for cycle time between PRE ($M = 0.712$ s, $SD = 0.029$) and POST ($M = 0.708$ s, $SD = 0.026$), $t(9) = 1.06$, $p = .316$, mean difference = 0.004 s, 95% CI $[-0.005, 0.013]$. Stance time was significantly shorter in PRE ($M = 0.273$ s, $SD = 0.023$) compared with POST ($M = 0.283$ s, $SD = 0.030$), $t(9) = -3.13$, $p = .012$, mean difference = -0.009 s, 95% CI $[-0.016, -0.003]$, indicating that participants spent less time in the stance phase under PRE conditions. Swing time was significantly longer in PRE ($M = 0.439$ s, $SD = 0.025$) than in POST ($M = 0.426$ s, $SD = 0.030$), $t(9) = 3.29$, $p = .009$, mean difference = 0.013 s, 95% CI $[0.004, 0.023]$. This finding suggests that participants maintained a longer swing phase during PRE relative to POST. Step rate did not differ significantly between PRE ($M = 167.22$ steps/min, $SD = 9.93$) and POST ($M = 172.27$ steps/min, $SD = 7.71$), $t(9) = -2.24$, $p = .052$, mean difference = -5.049 steps/min, 95% CI $[-10.145, 0.047]$. Although this result approached the conventional threshold for statistical significance, it did not meet the criterion of $p < .05$.

Table 7.5. Paired Samples t-Test Results Comparing Temporal-Spatial Gait Parameters Between PRE and POST

Measure	PRE	POST	Mean Difference (95% CI)	<i>t</i>	<i>df</i>	<i>p</i>
	<i>M (SD)</i>	<i>M (SD)</i>				
Cycle Time (s)	0.712 (0.029)	0.708 (0.026)	0.004 [-0.005, 0.013]	1.06	9	.316
Stance Time (s)	0.273 (0.023)	0.283 (0.030)	-0.009 [-0.016, - 0.003]	- 3.13	9	.012*
Swing Time (s)	0.439 (0.025)	0.426 (0.030)	0.013 [0.004, 0.023]	3.29	9	.009*
Step Rate (steps/min)	167.22 (9.93)	172.27 (7.71)	-5.049 [-10.145, 0.047]	- 2.24	9	.052

Note. *n* = 10 participants. Normality of difference scores was confirmed for all measures using the Shapiro-Wilk test (all *W* ≥ 0.936, all *p* ≥ .513). Mean Difference = PRE – POST; positive values indicate PRE exceeded POST. 95% CI = 95% confidence interval of the mean difference. CT = Cycle Time; StaT = Stance Time; SwT = Swing Time; SR = Step Rate. Temporal measures are in seconds (s); SR is in steps per minute.

**p* < .05.

7.4 Discussion

This study examined how multi-segment spine coordination, variability, and control adapt acutely to localised lower-limb muscle fatigue during treadmill running at the first ventilatory threshold. This was achieved by combining discrete linear analysis across all three planes of motion with non-linear vector coding of transverse-plane coordination and concurrent measurement of running economy. The main findings were that fatigue produced (1) a plane-specific repositioning of the spine, (2) a directionally consistent reduction in transverse-plane angle, most uniform at the pelvis, alongside more localised frontal and sagittal change, (3) the transverse-plane coordination pattern of the thoracic spine was robust to fatigue while the lumbopelvic interface reorganised toward increased pelvic dominance and greater inter-individual variability, and (4) these adaptations were accompanied by a small but reliable rise in oxygen cost and a more conservative redistribution of temporal-spatial measures of the gait cycle. Together, these show that the spine does not degrade uniformly but reorganises in a regionally and planar-specific manner.

A defining methodological feature of this study is the use of a localised lower-limb fatigue protocol that isolates peripheral muscle fatigue from the central and cardiovascular perturbations that ordinarily accompany running-induced fatigue. By inducing a verified peripheral deficit, the present design attributes any change in spinal coordination to the altered force-generating capacity of the locomotor musculature rather than to a global reduction in central drive. This localised approach builds on prior work in which fatigue of specific trunk muscle groups has been shown to alter trunk kinematics. For example, Hart et al. (2009) demonstrated that isolated lumbar paraspinal fatigue produced a significant increase in forward trunk flexion during jogging, establishing a causal link between localised muscular fatigue and altered spinal posture. In addition, Chaudhari et al. (2020) showed that experimentally reduced core stability altered stance-limb loading, which may induce biomechanical changes that imply altered control of the trunk. The present data extend this reasoning to lower-limb fatigue, and suggest that a localised deficit in muscles below the spine reshaped how the trunk and pelvis coordinated movement above it. This interpretation is strengthened by the use of the Marcora et al. (2008) protocol, which was selected specifically because it induces lower-limb force loss while minimising the central and cardiovascular confounds associated with exhaustive running fatigue. This is relevant to the marked heterogeneity observed in the current study in the sagittal lumbar response and lumbopelvic strategies. Importantly, the finding that thoracic coordination was preserved while the lumbopelvic interface reorganised indicates peripheral fatigue acts selectively rather than degrading axial coordination uniformly. This observation refines the established narrative of generalised "forward postural collapse" (Koblbauer et al., 2014; Maas et al., 2018) into a regionally specific account.

The linear discrete analysis revealed that fatigue affected the three planes of motion differently, both in the consistency and in the anatomical distribution of change. The transverse plane showed the most directionally consistent response. Six of the seven significant minimum-angle reductions were transverse, spanning the UT, UL, LL, and pelvic segments. Furthermore, the within-participant heatmaps showed transverse bordered cells were almost uniformly green (post-fatigue decrease). The single largest effect in the entire dataset was the transverse pelvis minimum angle, where all ten participants decreased ($d = -2.05$; $W = 0.0$). This uniformity indicates that a reduction in axial rotation is a generalisable feature of the acute peripheral-fatigue response rather than an individual adjustment.

The frontal plane, by contrast, showed change that was significant but localised and bidirectional. The frontal UT segment increased significantly in both maximum angle ($d = 0.79$) and range of motion ($d = 0.87$). While the frontal LT minimum angle also increased ($d = 0.76$), the heatmaps showed the largest concentration of positive (purple) frontal cells at the LT and LL levels. This is consistent with bone-pin evidence that frontal-plane lateral flexion is an important contribution of the lumbar spine during running (MacWilliams et al., 2014) and with marker-based studies reporting meaningful frontal-plane lumbar and pelvic motion during treadmill running (Schache et al., 2002a; Saunders et al., 2005; Tojima et al., 2019). It has also been reported that pelvic obliquity and frontal-plane trunk control deteriorate under fatigue (Koblbauer et al., 2014; Maas et al., 2018; Möhler et al., 2022). The increased frontal UT motion observed in the present study may represent a compensatory lateral adjustment as transverse motion is reduced below it.

The sagittal plane showed the most heterogeneous response of the three planes. Although the sagittal pelvis decreased significantly in both maximum and minimum angle and the sagittal UT ROM increased significantly ($d = 0.97$), the participant-level data revealed the widest inter-individual range of any plane. For example, large positive lumbar shifts were noted in some runners (notably P5, $\Delta = +11.1^\circ$ and $+13.1^\circ$) alongside large negative shifts in others. The concentration of "large g within noise" classifications at the sagittal lumbar levels further indicates that several apparently large, standardised effects fell within individual measurement noise. This heterogeneity matches with the wider literature, in which the sagittal trunk response to fatigue, most often reported as increased forward lean, is highly individual and moderated by training status (Koblbauer et al., 2014; Maas et al., 2018; Möhler et al., 2022). The present sub-elite cohort showed no uniform sagittal lean increase, consistent with the proposition that more experienced runners better preserve trunk posture under exertion (Maas et al., 2018).

Critically, across all three planes the changes were dominated by repositioning rather than by a change in ROM. Range of motion reached significance at only two of fifteen combinations and showed the lowest rate of individually meaningful change (39%; median $|g| = 0.74$), distributed almost equally across the frontal, sagittal, and transverse planes. Fatigue therefore predominantly shifted the position of spinal segments within their available range. This is consistent with the documented MDC_{95} behaviour whereby absolute positional measures carry greater between-condition variability than ROM. Nevertheless, the positional shifts occurred consistently, which may strengthen the interpretation that they are genuine adaptive responses.

The SPM/SnPM analysis localised the linear findings in time and confirmed the planar pattern. In the transverse plane, all four significant clusters identified by parametric SPM (UT, UL, LL, pelvis) were independently confirmed by SnPM with comparable or expanded cycle ranges. All identified clusters were concentrated in early-to-mid stance and the stance-to-swing transition. This alignment between two methods making different distributional assumptions, rather than the re-running of a single test, is the substantive robustness check (Pataky et al., 2015). It confirms the transverse effects are real and not an artefact of the normality violations the D'Agostino–Pearson K^2 screening flagged in these segments. The variances are equally instructive. SnPM identified three clusters the parametric test missed: the transverse LT and two sagittal pelvis regions. This is precisely where K^2 had flagged non-normal paired differences, and additional transverse pelvis clusters at the cycle boundaries. Where the methods disagree, the parametric null cannot be considered robust. The non-parametric result is taken as definitive; these extra clusters reflect the conservative bias of parametric inference under small-sample, non-normal conditions. Particularly, all frontal-plane comparisons and the remaining sagittal comparisons were non-significant under both methods. This indicates the frontal and sagittal changes detected discretely were either too small or too temporally diffuse to form supra-threshold waveform clusters, and that the K^2 -flagged violations did not mask hidden effects in those planes.

Comparing this dual-inference approach with the two earlier fatigue studies that applied SPM to running helps clarify how the findings of the current study contribute to current literature. Maas et al. (2018) used SPM in 30 runners and found that their main trunk change was increased forward lean in the sagittal plane and most pronounced in novices. Whereas Möhler et al. (2022) found increased lumbar and thoracic ROM, again greatest in novices. In both cases, the dominant trunk effect was an increase in the amount of motion in the sagittal plane. By contrast, the present study's most robust effect was a shift in segment position in the transverse plane that occurred largely without any change in ROM. This difference may reflect the specific nature of the present fatigue stimulus. Since the drop-jump protocol fatigued the lower-limb musculature directly, the altered force output of the legs would be transmitted to the spine principally through the pelvis. The largest and most uniform effect in the current data, the reduction in transverse pelvis angle, is consistent with a pelvis-led reorganisation originating in the fatigued lower limb rather than with the trunk-driven sagittal changes reported under whole-body exhaustive protocols. Supporting this interpretation, the transverse pelvis effect was localised by both SPM and SnPM to early-to-mid

stance. This is the phase in which the loaded lower limb transmits force through the pelvis, rather than to swing, placing the kinematic change at precisely the point in the gait cycle where a lower-limb deficit would be expected to be shown. Also, the concurrent temporal-spatial adaptation, a longer stance and shorter swing phase, reasonably reflects the same lower-limb deficit, and the accompanying shift in pelvic kinematics may be an expression of this altered stance-phase mechanics rather than an independent trunk adjustment.

The earlier studies, by contrast, used whole-body protocols run to exhaustion, in which runners enlarge trunk motion to defend a failing pace. The present protocol instead held running speed constant at individualised first ventilatory threshold and isolated a peripheral lower-limb deficit, removing the pace-maintenance requirement. Furthermore, although Möhler et al. (2022) classified thoracic from lumbar ROM, this study did not divide the spine as finely as the present four-segment model. This advanced modelling approach allowed the detection of a specific transverse-plane adjustment localised to the LL–pelvis region that a rigid thoracic-versus-lumbar or trunk-versus-pelvis modelling approach would not have isolated.

The non-linear vector coding analysis was applied to the transverse plane alone, on the rationale that this is the plane of the spine's principal running function, counterrotation to neutralise the angular momentum of the swinging leg (MacWilliams et al., 2014; Preece et al., 2016). The upper couplings (UT–LT, LT–UL) showed bi-phasic, in-phase coordination progressing from proximal-to-distal dominance during stance and again during swing, maintained from PRE to POST at group and individual levels. This robustness suggests proximal-to-distal thoracic sequencing is a stable organisational principle resistant to acute peripheral perturbation. This is consistent with bone-pin evidence that the thoracic spine contributes the majority of transverse-plane motion and acts as a distinct functional unit during running (MacWilliams et al., 2014). Yet the LL–Pelvis coupling exhibited pelvic-led distal dominance at the onset of stance and swing, and a consistent post-fatigue shift toward increased pelvic dominance across the cycle. Since the lumbar spine normally opposes thoracic axial rotation, an increased pelvic contribution at this junction under fatigue possibly reflects the spine accommodating altered force transmission from the fatigued lower limb. The alignment of this observation with the discrete-level transverse pelvis result suggests the pelvis to be the principal point of adaptation.

The CAV data provides further supportive evidence. Variability showed a clear proximal-to-distal gradient, which was low and temporally confined in the thoracic couplings, and high and

extended variability for the UL-LL and LL-Pelvis couplings. The individual data explained the cause, as several participants showed the group-typical pelvic-led pattern, while others (P6, P7, P10) showed uniform lumbar proximal dominance through stance. The coexistence of qualitatively distinct strategies within one cohort highlights the elevated lumbopelvic CAV that would be obscured by group-mean analysis. The general CAV increase in UL-LL and LL-Pelvis following fatigue aligns with reports that fatigue increases trunk-to-pelvis coordination variability irrespective of running technique. That the increase was confined to the caudal couplings, leaving the thoracic strategy intact, indicates a regionally localised increase in coordinative exploration rather than a global loss of control. It is important to note that, because the non-linear analysis was restricted to the transverse plane, whether comparable coordinative reorganisation occurs in the frontal or sagittal planes, where the discrete analysis detected localised change, remains an open question that the present coupling-angle data cannot address.

The kinematic adaptations were accompanied by a small but reliable increase in steady-state VO_2 ($+0.87 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$; $+2.1\%$; Hedges' $g = 0.93$; nine of ten participants elevated). Although modest, an increase of this magnitude is meaningful given that running economy is among the strongest predictors of distance-running performance independent of $\text{VO}_{2\text{max}}$ (Saunders et al., 2004; Barnes & Kilding, 2015). Defining economy over the final five-minute steady-state window exploited a key property of the drop-jump protocol. It imposes no persistent metabolic or cardiovascular load, so the elevation reflects a change in the cost of running itself rather than a residual disturbance. The mechanism is supported, as trunk and core fatigue alone worsen economy through increased agonist-antagonist co-activation (Drum et al., 2019). The multi-planar reorganisation observed here- compensatory frontal and sagittal upper thoracic motion, reduced transverse rotation, a longer stance phase, and destabilised lumbopelvic coordination- plausibly represents the pathway through which this metabolic cost is incurred. The temporal-spatial data reinforce this: the significant shift toward longer stance and shorter swing, with a step-rate increase approaching significance ($p = .052$), indicates a more conservative gait consistent with the reduced stride frequency and increased duty factor widely reported under fatigue (Möhler et al., 2022; García-Pinillos et al., 2020), functioning as the behavioural intermediary linking the force deficit to the elevated oxygen cost. The sole participant showing a marginally reduced VO_2 (P5) is most reasonably attributable to within-session measurement variability.

These findings are most coherently interpreted through Newell's (1986) model of interacting constraints, in which coordination emerges from the interaction of organismic, environmental, and task constraints rather than from a prescribed motor programme. The present design maps onto this with unusual directness: environmental constraints (treadmill, fixed gradient, laboratory conditions) and the task constraint (running at the first ventilatory threshold) were held constant, while the intervention manipulated a single organismic constraint (induced lower-limb fatigue). Any change in coordination can therefore be read as the emergent reorganisation of the system in response to an altered organismic constraint. Dynamical systems theory holds that rhythmic locomotion is governed by attractors, and that perturbations such as fatigue can be absorbed within an existing attractor or, if large enough, drive a transition to a less efficient state (Hamill et al., 2012). The maintenance of thoracic coordination indicates the perturbation was absorbed within a robust attractor, whereas the lumbopelvic reorganisation indicates a region beginning to shift. The transverse-plane CAV findings fit naturally, the thoracic spine occupying a stereotyped, low-dimensional attractor shared across runners while the lumbopelvic region permits a wider range of coordination patterns between participants. The existence of pelvic-led and lumbar-led strategies is exactly the inter-individual exploration the model anticipates when a fixed task admits multiple solutions.

A central contribution is the integration of complementary analytical lenses on one dataset: discrete inferential statistics across all three planes, an individual-level practical-significance framework anchored to each participant's MDC₉₅, dual parametric and non-parametric waveform mapping, and non-linear vector coding of transverse-plane coordination and its variability. This directly answers the field's most-cited methodological criticism, that single-segment trunk models cannot resolve thoracic versus lumbar contributions or intersegmental coupling (MacWilliams et al., 2014).

Several limitations are noted. The sample of ten male sub-elite runners constrains generalisability, particularly given evidence that female runners show greater pelvic obliquity and may respond differently to fatigue (Willson et al., 2015; Chumanov et al., 2008). Accordingly, the regionally specific fatigue responses identified in the present study should not be assumed to occur with the same magnitude or coordinative organisation in female runners. The skin-marker model carries susceptibility to soft-tissue artefact, heightened during running and potentially confounded by fatigue-induced changes in trunk lean that alter skin-to-bone orientation (MacWilliams et al.,

2014); the consistency of the transverse findings across segments and use of a validated marker set mitigate but do not eliminate this. The non-linear analysis was restricted to the transverse plane, so the coordinative consequences of the localised frontal and sagittal changes detected discretely could not be characterised and warrant dedicated coupling-angle analysis in future work. The dynamical systems interpretation, while coherent, is interpretive: the analysis quantified coordination and its variability but did not compute direct attractor-stability metrics. The protocol induces a specific peripheral fatigue differing in mechanism and time course from the global fatigue of prolonged running, and fixed-velocity treadmill running may underestimate the kinematic adaptations runners adopt freely when fatigued (Strohrmann et al., 2012). Finally, only the acute response was captured; whether the regionally-graded, pelvis-focused adaptation persists, amplifies, or resolves across a prolonged bout, whether it generalises to mixed-fatigue conditions, and whether the distinct lumbopelvic strategies relate to running-related low-back pain or economy over time (Seay et al., 2011) are questions for future work.

7.5 Conclusion

This study characterised the acute response of the multi-segment spine to localised lower-limb muscle fatigue during treadmill running at the first ventilatory threshold, integrating discrete linear analysis across all three planes of motion, dual parametric and non-parametric waveform mapping, and non-linear vector coding of transverse-plane coordination, alongside concurrent measurement of running economy. The fatigued spine did not degrade uniformly. Instead, it underwent a regionally and planar-specific reorganisation. A directionally consistent reduction in transverse-plane segment angle, most pronounced and uniform at the pelvis, accompanied by localised frontal and sagittal change, with these adjustments reflecting a repositioning within the available range rather than an expansion of motion. The fundamental transverse-plane coordination pattern of the thoracic spine, bi-phasic, in-phase, proximal-to-distal co-rotation, was preserved under fatigue. While the lumbopelvic interface reorganised toward increased pelvic dominance and greater inter-individual coordination variability, identifying the pelvis as the main point of adaptation. Critically, this spinal reorganisation was accompanied by a small but reliable increase in the oxygen cost of running, linking the coordinative response to a meaningful deterioration in running economy.

Chapter 8

Multi-segment spine kinematics and coordination variability during treadmill running: individual adaptive responses to an acute increase in running intensity

8.1 Introduction

Long-distance running is one of the most widely practised forms of physical activity and is valued for its accessibility and health benefits (Lee et al., 2014). From a biomechanical perspective, running is usually described through lower-limb or single-trunk models, yet this can obscure independent movement within the thoracic and lumbar regions (Leardini et al., 2011). Multi-segment spine models show that the spine does not behave as one rigid unit during locomotion; instead, regional motion varies across the sagittal, frontal and transverse planes (Christe et al., 2016; Needham et al., 2016). This is especially relevant when running speed increases, because trunk and spine motion are known to change with locomotor demand (Preece et al., 2016a, 2016b; Schache et al., 2002; Saunders et al., 2005). However, most evidence remains group-based and provides limited insight into how individual runners achieve these adaptations.

The constraints-led framework used throughout this thesis views variability as a potential feature of adaptation rather than simply error. An increase in running intensity can therefore be interpreted as a task constraint that interacts with each runner's own anthropometrics, mobility and training history (Glazier, 2017; Glazier & Davids, 2009; Newell, 1986). Vector coding is well suited to this question because it describes both coordination pattern and coordination variability between adjacent segments (Needham et al., 2014, 2015, 2020). Despite this, few studies have applied vector coding to multi-segment spinal coordination during running, and fewer still have examined individual responses across a controlled speed manipulation.

The physiological response to increased intensity is also important. Heavy-intensity exercise above the second ventilatory threshold can produce a delayed rise in oxygen uptake ($\dot{V}O_2$), known as the slow component, partly reflecting progressive recruitment of less efficient motor units as fatigue develops (Burnley & Jones, 2007; Jones & Burnley, 2009; Poole et al., 1988). Recovery after heavy-intensity exercise is not immediate and varies between individuals (Jones et al., 2011; Rossiter et al., 2002). It is therefore plausible that incomplete physiological recovery may occur alongside incomplete biomechanical or coordinative recovery, but this has not yet been examined using multi-segment spinal kinematics and $\dot{V}O_2$ kinetics within the same running protocol.

A further limitation is that many running studies compare only two conditions. A two-condition design cannot distinguish a temporary adaptation from a persistent residual change, because the intermediate response is not observed. The present three-condition design, comprising

baseline VT1 running, VT2 running and a return to VT1, allows adaptation and recovery to be interpreted separately. This provides a stronger test of whether spinal coordination returns to baseline or remains altered after the higher-intensity bout.

The present study examined segmental spine range of motion, inter-segmental coordination, coordination variability and pulmonary $\dot{V}O_2$ kinetics in five sub-elite runners (McKay et al., 2022). It was hypothesised that the transition from CON1 to CON2 would increase segmental ROM and alter coordination pattern and variability; that the return from CON2 to CON3 would show partial but incomplete recovery; and that the CON1-versus-CON3 comparison would reveal residual, plane- and segment-specific effects. In line with the thesis framework, individual responses were expected to differ rather than follow a single uniform group pattern.

8.2 Methods

8.2.1 Study design

This study used a 30-minute continuous treadmill protocol comprising an initial first-ventilatory-threshold bout (CON1), a second-ventilatory-threshold bout (CON2), and a return to first-ventilatory-threshold running (CON3). Outcomes were evaluated at group and individual levels. A dual minimal detectable change (MDC_{95}) and Hedges' g criterion were used to distinguish changes that exceeded measurement noise from smaller fluctuations.

8.2.2 Participants

Ethical approval was granted by the University of Staffordshire Ethics Committee. Five sub-elite male runners were recruited (age, 47.4 ± 9.62 years; height, 178.8 ± 3.7 cm; mass, 75.04 ± 7.5 kg), all free from current musculoskeletal impairment. Using the Participant Classification Framework (McKay et al., 2022), the cohort was classified as Tier 3: Highly Trained/National Level because participants identified running as their primary sport, completed structured endurance training and typically ran 40–50 miles per week.

8.2.3 Kinematic model – defined segments, coordinate systems, and segment tracking

Six central markers were placed on the spinous processes of T1, T6, T12, L1, L3 and L5 to define four segments: upper thoracic (UT) (T1-T6), lower thoracic (LT) (T6-T12), upper lumbar (UL) (L1-L3) and lower lumbar (LL) (L3-L5) (Christe et al., 2016). The Z-axis was defined as a

line passing through two markers stated for each segment that represented posture in the sagittal plane (positive direction upwards from the distal marker). Eight lateral markers were placed between central markers on each side of the spine, at a distance of 5 cm, representing spinal levels T3, T9, L2 and L4. The cross product of the Z-axis and a line connecting the two markers bilaterally for each segment defined the Y-axis (positive direction pointing to the left). The cross product of the Z- and Y-axis was used to define the X-axis (positive direction pointing forwards). For the individual skin marker model (SKS), the four markers used to define each segment were used to track motion.

8.2.4 Segment parameters

Three-dimensional segment angles were calculated with respect to the normal standing position of the participant. Rotations about the global coordinate system (laboratory) were based on the right-hand rule convention. Angular kinematic data for all segments and both kinematic models were computed by measuring the relative movements between the respective segment and the global coordinate system. Cardan angles were calculated using the YXZ with an order in the sagittal, frontal, and transverse plane (Grood & Suntay, 1983).

8.2.5 Instrumentation

Participants attended two sessions and wore their own running footwear to preserve habitual running mechanics (Willwacher et al., 2020; Van der Meulen et al., 2024). Session one involved a maximal $\dot{V}O_{2\max}$ test in the Physiology Laboratory using an HP Cosmos Venus 200/75 treadmill and a Metalyzer 3B metabolic cart (Cortex Biophysik GmbH, Leipzig, Germany). Session two was completed in the Biomechanics Laboratory using a Vision Fitness TY700HRT treadmill positioned within an 18-camera Vicon motion-capture system (Vicon, Oxford, UK), sampling at 200 Hz. Both treadmills were set to a 1% gradient (Jones & Doust, 1996). Environmental conditions were recorded during testing (21-24°C, 55-56% humidity, 1100-1200 mb).

8.2.6 Experiment protocols

The $\dot{V}O_{2\max}$ test identified each participant's first ventilatory threshold (VT1), second ventilatory threshold (VT2), and the corresponding treadmill speeds for session two. VT1 and VT2 were identified using the V-slope and ventilatory-equivalent methods (Beaver et al., 1986; Binder et al., 2008).

The second session took place in the Biomechanics Laboratory. Reflective markers were applied to the spine and back using double-sided adhesive tape as described previously in accordance with the multi-segment spine model (Christe et al., 2016). Additional markers were also applied to the pelvis and lower limbs (Cappozzo et al., 1995; Leardini et al., 2007).

After a 6-minute treadmill familiarisation period (Lavcanska et al., 2005), a static calibration trial was collected in anatomical standing. Runners then completed three consecutive 10-minute stages: VT1 running (CON1; 0-10 min), VT2 running (CON2; 10-20 min), and a return to VT1 running (CON3; 20-30 min). Ten-minute stages were used to allow physiological stabilisation while also capturing representative biomechanical data, consistent with running-economy protocols using 8-10-minute bouts (Mercer et al., 2018).

Fifteen consecutive right-to-right gait cycles were recorded within each 15-second trial. Heel strike was identified from the distal heel marker's minimum vertical position and the transition of vertical velocity from negative to positive, a method validated against force-plate data during treadmill and overground running (Fellin et al., 2010; Zeni et al., 2008).

8.2.7 Data Processing and Analysis

Three-dimensional kinematic data were processed in Visual3D (HAS-Motion, Kingston, Ontario, Canada). Spine segment angles were calculated relative to the laboratory coordinate system and low-pass filtered using a fourth-order Butterworth filter with a 10 Hz cut-off frequency (Schache et al., 2002b; Preece et al., 2016a; Bramah et al., 2021). Data were time-normalised to 101 data points representing 0–100% of the normalised running gait cycle, enabling comparison across participants.

Breath-by-breath gas-exchange data were processed to derive $\dot{V}O_2$, $\dot{V}CO_2$, $\dot{V}E$, $\dot{V}E/\dot{V}O_2$, $\dot{V}E/\dot{V}CO_2$ and RER. $\dot{V}O_2$ data were averaged into 15-second epochs. Running economy was expressed as steady-state $\dot{V}O_2$ during the final five minutes of each 10-minute stage, reducing the influence of transient responses at the start of each bout.

8.2.8 Calculation of Coupling Angle and Coupling Angle Variability

At each normalised time instant (i), the coupling angle (γ_i) was calculated from the proximal (θ_P) and distal (θ_D) segmental angles at consecutive data points using a non-linear modified vector coding approach (Needham et al., 2014). Specifically, the coupling angle was derived using the arctangent of the change in distal segment angle divided by the change in proximal segment angle across adjacent data points, with corrections applied to place the result within the full 0–360° range (Eq. 1 & 2).

$$\gamma_i = \text{Atan}\left(\frac{\theta_{D(i+1)} - \theta_{Di}}{\theta_{P(i+1)} - \theta_{Pi}}\right) \cdot \frac{180}{\pi} \quad \theta_{P(i+1)} - \theta_{Pi} > 0 \quad (1)$$

$$\gamma_i = \text{Atan}\left(\frac{\theta_{D(i+1)} - \theta_{Di}}{\theta_{P(i+1)} - \theta_{Pi}}\right) \cdot \frac{180}{\pi} + 180 \quad \theta_{P(i+1)} - \theta_{Pi} < 0 \quad (2)$$

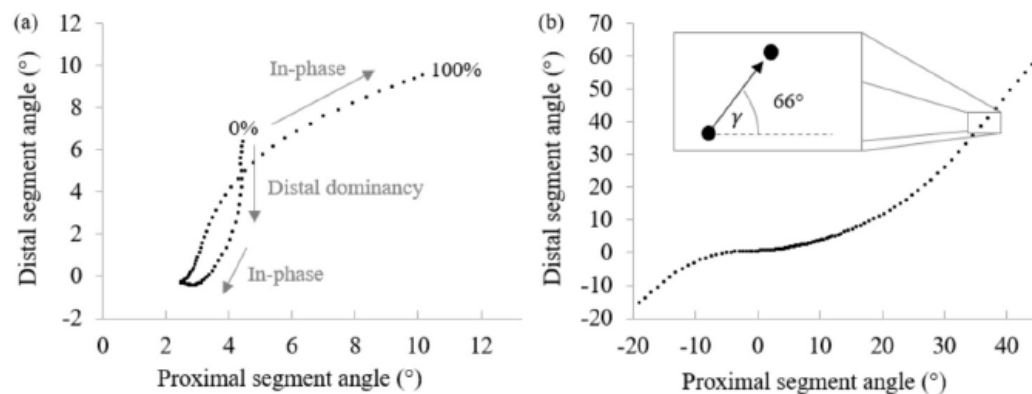
Additional boundary conditions (Eq. 3) were applied to handle special cases where one or both segmental angle changes equal zero:

$$\gamma_i = \begin{cases} \gamma_i = 90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} > 0 \\ \gamma_i = -90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} < 0 \\ \gamma_i = -180 & \theta_{P(i+1)} - \theta_{Pi} < 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} = 0 \\ \gamma_i = \text{Undefined} & \theta_{P(i+1)} - \theta_{Pi} = 0 \text{ and } \theta_{D(i+1)} - \theta_{Di} = 0 \end{cases} \quad (3)$$

Following calculation, the coupling angle was corrected to ensure all values fell within the 0–360° range (Eq. 4). Where the raw coupling angle (γ_i) was negative, 360° was added; values already $\geq 0^\circ$ were retained as calculated:

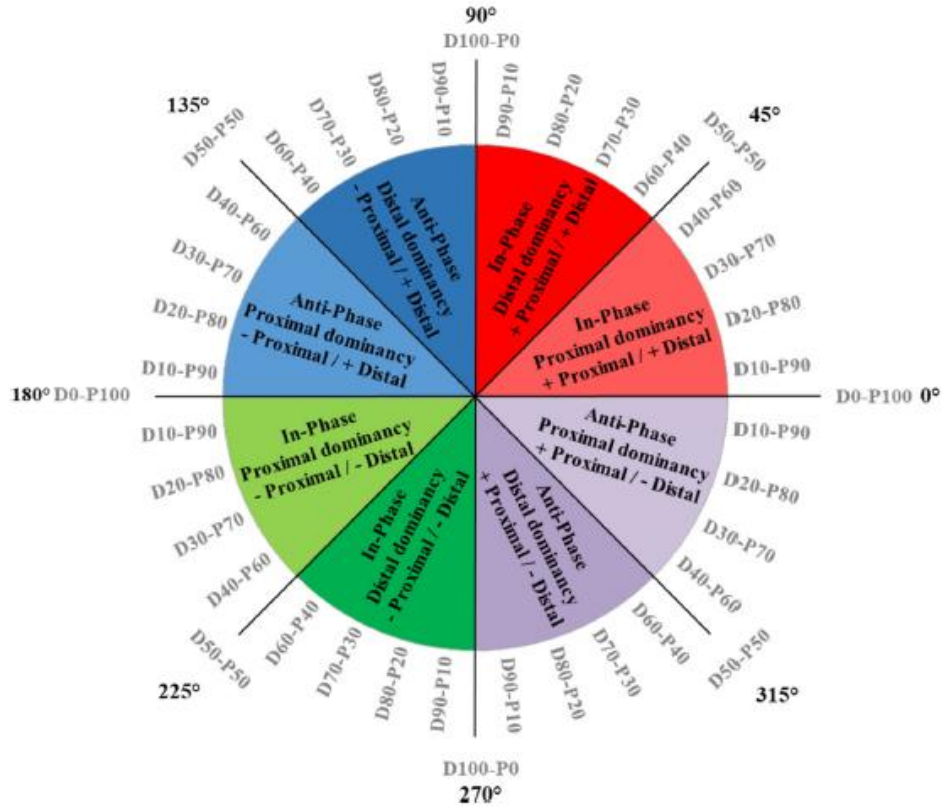
$$\gamma_i = \begin{cases} \gamma_i + 360 & \gamma_i < 0 \\ \gamma_i & \gamma_i \geq 0 \end{cases} \quad (4)$$

Figure 8.1. Angle–angle diagram of forefoot (distal) rearfoot (proximal) coordination during stance in the frontal plane; (b) Angle–angle diagram of foot (distal) shank (proximal) coordination during stance in the sagittal plane. Both figures represent mean data from 10 participants.



The resulting coupling angle values were then assigned to one of four coordination pattern classifications based on their angular position within the unit circle (Needham et al., 2015). These classifications distinguish between in-phase and anti-phase coordination (reflecting whether the two segments are rotating in the same or opposing directions), and between proximal and distal segment dominance (reflecting which segment is contributing the greater angular change at each instant). Each quadrant of the unit circle corresponds to 100 gradians, meaning that converting the coupling angle to gradians provides a direct percentage measure of segmental dominance. For example, a coupling angle of 45° equates to 50 gradians, indicating equal contribution from both segments (Needham et al., 2015).

Figure 8.2. Coordination pattern classification adapted from Needham et al. (2020) illustrating colour-scale for each classification. Segmental dominance (%) is shown around the circumference of the polar plot (grey text, D-distal/P-Proximal).



8.2.9 Averaging and Variability Calculation

Due to the directional (circular) nature of the coupling angle, standard arithmetic averaging is not appropriate. Instead, the mean coupling angle across a set of trials (n) was computed at each normalised time instant using circular statistics. The mean horizontal ($\bar{x}_i$) and vertical ($\bar{y}_i$) components of the unit vectors were calculated from the cosine and sine of each coupling angle, respectively (Eqs. 5 and 6):

$$\bar{x}_i = \frac{1}{n} \sum_{i=1}^n \cos \gamma_i \quad (5)$$

$$\bar{y}_i = \frac{1}{n} \sum_{i=1}^n \sin \gamma_i \quad (6)$$

The mean coupling angle ($\bar{\gamma}_i$) was then calculated from these mean vector components and corrected to fall within the 0–360° range according to the quadrant in which the resultant vector resided (Eq. 7). The correction was based on the signs of $\bar{x}_i$ and $\bar{y}_i$, applying appropriate offsets of 0°, 180°, or 360° to the arctangent result to correctly place the angle in its respective quadrant:

$$\bar{\gamma}_i = \begin{cases} \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} & \bar{x}_i > 0, \bar{y}_i > 0 \\ \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} + 180 & \bar{x}_i < 0 \\ \text{Atan} \left(\frac{\bar{y}_i}{\bar{x}_i} \right) \cdot \frac{180}{\pi} + 360 & \bar{x}_i > 0, \bar{y}_i < 0 \\ 90 & \bar{x}_i = 0, \bar{y}_i > 0 \\ -90 & \bar{x}_i = 0, \bar{y}_i < 0 \\ \text{undefined} & \bar{x}_i = 0, \bar{y}_i = 0 \end{cases} \quad (7)$$

The length of the mean coupling angle vector (r_i) was then computed as the Euclidean magnitude of the mean horizontal and vertical components (Eq. 8). This value ranges from 0 to 1 and reflects the concentration of the coupling angles around the mean direction; a value of 1 indicates perfect agreement across trials, while a value approaching 0 indicates maximal dispersion:

$$\bar{r}_i = \sqrt{\bar{x}_i^2 + \bar{y}_i^2} \quad (8)$$

Coupling angle variability (CAVi) was calculated as the circular analogue of the standard deviation using the mean vector length, converted to degrees (Eq. 9). As the mean vector length decreases from 1 toward 0, the dispersion of the coupling angle across trials increases, and therefore CAVi increases. A mean vector length of 0 yields the maximum CAV value of approximately 81.07°:

$$CAV_i = \sqrt{2 \cdot (1 - \bar{r}_i)} \cdot \frac{180}{\pi} \quad (9)$$

Coupling angle variability is therefore the circular statistical equivalent of a standard deviation in linear statistics. The resulting CAV values were used alongside mean coupling angle data to characterise both the dominant coordination pattern and the consistency with which that

pattern was expressed across repeated trials for each participant. All circular statistics were implemented following the approach described by Batschelet (1981).

8.2.10 Data and Statistical Analysis

8.2.11 Linear analysis

Spinal segment angles were analysed across three planes, five segments and three metrics: maximum angle, minimum angle and ROM. Participant-level means were calculated from 12 trials per condition. Analyses were performed in Python using NumPy, SciPy, Pandas and Matplotlib.

Three contrasts were examined: CON1 versus CON2, representing adaptation to increased speed; CON2 versus CON3, representing recovery; and CON1 versus CON3, representing the residual effect of the full protocol. Change was calculated as $\Delta = M_2 - M_1$.

8.2.12 Minimal Detectable Change

Within-participant measurement reliability was quantified using the minimal detectable change at the 95% confidence level (MDC_{95}), calculated as $MDC_{95} = 1.96 \times \sqrt{2} \times SEM$, where the standard error of measurement (SEM) was the within-participant standard deviation divided by the square root of the number of trials ($SEM = SD / \sqrt{n}$, with $n = 12$ trials per condition). For each contrast, the more conservative (larger) of the two condition MDC_{95} values was applied as the threshold. A mean difference was considered to exceed measurement error when $|\Delta| > MDC_{95}$.

8.2.13 Within-Participant Effect Size: Hedges' g

To quantify the magnitude of change at the individual level, Hedges' g was computed for each participant–segment–metric–contrast combination. Hedges' g is a pooled standard-deviation effect size incorporating a small-sample correction, selected in preference to Cohen's d owing to the small number of trials per condition ($n = 12$; $df = 22$). It was calculated as $g = d \times J$, where $d = (M_2 - M_1) / S_p$, S_p is the pooled within-condition standard deviation, $J = 1 - 3 / (4df - 1)$ is the small-sample correction factor, and $df = n_1 + n_2 - 2 = 22$. Positive g values indicate an increase in the later condition and negative values a decrease. Effect sizes were interpreted as trivial ($|g| < 0.2$), small ($0.2 \leq |g| < 0.5$), medium ($0.5 \leq |g| < 0.8$), or large ($|g| \geq 0.8$; Cohen, 1988). A 95% confidence interval was computed for each g using the t-distribution ($df = 22$), with the standard

error approximated as $SE_g = J \times \sqrt{[(n_1 + n_2) / (n_1 \times n_2) + g^2 / (2df)]}$. Given $n = 12$ trials per condition, confidence intervals were necessarily wide and are reported as indices of estimation precision rather than as independent inferential criteria.

8.2.14 Practical Significance Criterion

Practical significance required both the mean difference to exceed MDC_{95} and the effect size to be large ($|g| \geq 0.8$). This dual criterion was used because no established external threshold exists for meaningful spinal angle change during running. Changes were classified as practically meaningful, real but small-to-medium, large g within measurement noise, or neither criterion met.

8.2.15 VO₂ and Slow Component

The SC amplitude was calculated as the simple difference between the mean VO₂ during the final five minutes (minutes 15–20) and the mean VO₂ during the first three minutes (minutes 10–13) of the VT2 stage, consistent with established methods for quantifying primary and slow-phase VO₂ kinetics (Burnley et al., 2000; Jones & Burnley, 2009; Poole et al., 1988).

Recovery from the VT2 stage was assessed across the final 10-minute return-to-VT1 stage (minutes 20–30). The VT1 baseline was defined as the mean VO₂ during the first three minutes of the initial VT1 stage (minutes 0–3). The residual VO₂ deficit was calculated as the difference between the mean VO₂ during the final five minutes of the recovery stage (minutes 25–30) and the VT1 baseline, with a positive value indicating VO₂ remained elevated above the pre-exercise reference at stage end. Percentage recovery was calculated as the proportion of the VT2-induced VO₂ elevation (VT2 end minus VT1 baseline) that was recovered by the end of the 10-minute stage.

To evaluate whether the metabolic cost of running returned fully to initial baseline levels once VT1-intensity running resumed, whole-stage mean VO₂ during CON1 (minutes 0–10) was compared with whole-stage mean VO₂ during CON3 (minutes 20–30) for each participant.

8.2.16 Visualisation

Heatmaps displayed within-participant mean change (Δ) for each segment and participant. Colour indicated the direction and magnitude of change, while cell borders indicated whether the change met the practical-significance criteria.

8.2.17 Non-linear analysis

Five visualisation approaches were used for the non-linear analysis: coupling angle mapping, segmental dominance profiling, inter-data point range of motion (IDP-ROM), coordination variability mapping and coordination variability profiling.

Coupling angle mapping displayed the coordination pattern across the normalised gait cycle using the four vector-coding classifications: in-phase proximal dominance, in-phase distal dominance, anti-phase proximal dominance and anti-phase distal dominance (Needham et al., 2020).

Individual participant maps were stacked to allow direct comparison across participants, with a group mean map included beneath the individual traces.

Segmental dominance profiling expressed the relative proximal or distal contribution to each coupling as a percentage, where 50% indicated equal contribution and values approaching 100% indicated near-complete dominance of one segment.

IDP-ROM was used to indicate the magnitude of angular change in the dominant segment between consecutive time points, complementing the phase and dominance information provided by vector coding.

Coordination variability was displayed using both colour maps and bar profiles. CAV values ranged from low variability to the theoretical maximum of approximately 81.07°, allowing the consistency of each coordination pattern to be interpreted alongside its dominant phase relationship.

8.3 Results

Linear analysis

8.3.1 Temporal-Spatial Gait Parameters

Group temporal-spatial gait characteristics are presented in Table 1. As expected, the increase from VT1 (CON1) to VT2 (CON2) increased step rate in every participant, with the group mean rising from 163.9 to 179.6 steps/min. Cycle, stance and swing time decreased at CON2, reflecting the faster running speed. On return to VT1 (CON3), step rate decreased to 172.8 steps/min and cycle time returned close to CON1 values.

The CON1-versus-CON3 comparison showed small residual differences. Step rate remained modestly elevated and stance time was higher than CON1 in all five participants, suggesting substantial but incomplete reversal of the temporal-spatial response.

Table 8.1. Descriptive Statistics and Mean Differences for Temporal-Spatial Gait Parameters by Participant and Condition

Participant	Condition												Mean Difference											
	CON1				CON2				CON3				CON1 – CON2				CON1 – CON3				CON2 – CON3			
	CT (s)	StaT (s)	SwT (s)	SR (steps/min)	CT (s)	StaT (s)	SwT (s)	SR (steps/min)	CT (s)	StaT (s)	SwT (s)	SR (steps/min)	CT (s)	StaT (s)	SwT (s)	SR (steps/min)	CT (s)	StaT (s)	SwT (s)	SR (steps/min)	CT (s)	StaT (s)	SwT (s)	SR (steps/min)
01	0.674 (0.01 1)	0.231 (0.01 4)	0.443 (0.01 3)	176.5 6 (5.84)	0.663 (0.00 5)	0.226 (0.00 8)	0.437 (0.00 7)	187.7 5 (9.93)	0.685 (0.00 7)	0.249 (0.01 4)	0.436 (0.01 3)	181.6 1 (7.36)	+0.01 1	+0.00 5	+0.00 6	- 11.18	- 0.011	- 0.018	+0.00 7	-5.05	- 0.022	- 0.023	+0.00 1	+6.13
02	0.727 (0.00 5)	0.266 (0.01 1)	0.461 (0.00 8)	162.5 2 (6.23)	0.709 (0.00 4)	0.258 (0.00 8)	0.451 (0.01 1)	176.2 4 (7.15)	0.733 (0.00 5)	0.277 (0.00 8)	0.455 (0.00 8)	168.5 1 (3.63)	+0.01 8	+0.00 8	+0.01 0	- 13.73	- 0.006	- 0.011	+0.00 6	-6.00	- 0.024	- 0.019	- 0.004	+7.73
03	0.743 (0.00 4)	0.279 (0.00 9)	0.464 (0.00 9)	156.8 4 (3.27)	0.714 (0.00 3)	0.272 (0.01 2)	0.442 (0.01 3)	174.4 7 (4.83)	0.739 (0.00 5)	0.308 (0.01 3)	0.431 (0.01 2)	169.5 5 (6.12)	+0.02 9	+0.00 7	+0.02 2	- 17.63	+0.00 4	- 0.029	+0.03 3	- 12.71	- 0.025	- 0.036	+0.01 1	+4.92
04	0.742 (0.00 9)	0.291 (0.01 5)	0.451 (0.01 4)	158.1 2 (5.97)	0.700 (0.00 6)	0.274 (0.01 3)	0.425 (0.01 3)	181.7 0 (8.49)	0.727 (0.00 4)	0.303 (0.01 6)	0.424 (0.01 9)	171.8 3 (3.78)	+0.04 2	+0.01 7	+0.02 6	- 23.58	+0.01 5	- 0.012	+0.02 7	- 13.70	- 0.027	- 0.029	+0.00 1	+9.88
05	0.702 (0.00 9)	0.231 (0.01 3)	0.471 (0.01 7)	165.3 7 (6.24)	0.698 (0.00 8)	0.231 (0.01 4)	0.466 (0.01 5)	177.9 9 (5.16)	0.711 (0.01 6)	0.247 (0.01 9)	0.464 (0.02 8)	172.2 6 (5.44)	+0.00 4	0.000	+0.00 5	- 12.62	- 0.009	- 0.016	+0.00 7	-6.89	- 0.013	- 0.016	+0.00 2	+5.73

Note. Condition values are presented as M (SD) based on 12 trials per participant per condition. Mean Difference values are the signed difference between condition means (positive values indicate the first condition exceeded the second). CT = cycle time; StaT = stance time; SwT = swing time; SR = step rate. CON1, CON2, CON3 = the first VT1 bout, the VT2 bout, and the second VT1 bout, respectively. Temporal measures are in seconds (s); SR is in steps per minute.

8.3.2 Segmental Angles

Individual segmental angle maximum (Max), minimum (Min), and range of motion (ROM) for the five spine segments; upper thoracic (UT), lower thoracic (LT), upper lumbar (UL), lower lumbar (LL), and pelvis, are presented for each participant (P1–P5) across the three running conditions in Tables 2 through 4 (sagittal, frontal, and transverse planes, respectively).

Across planes, the general pattern was an increase from CON1 to CON2 followed by partial recovery from CON2 to CON3. Sagittal-plane changes were smallest and closest to full reversal, whereas frontal and transverse changes were larger and more likely to remain elevated at CON3.

8.3.3 Sagittal Plane

Sagittal-plane motion was the smallest of the three planes. Group-level ROM increased only modestly from CON1 to CON2 and then moved back toward CON1 at CON3. The UT segment remained the most flexed segment, while UL and LL generally showed the largest sagittal ROM.

Individual responses were not uniform. P4 maintained a more extended UL posture than the other participants across all conditions, indicating a stable individual characteristic rather than a speed-related change. P2 showed the largest pelvic ROM, whereas P1 showed the smallest. Most sagittal ROM changes were below 1°, supporting the interpretation that sagittal-plane adaptation was limited.

8.3.4 Frontal Plane

Frontal-plane ROM was larger at the upper spine and followed a proximal-to-distal decline. UT ROM increased from 15.32° at CON1 to 18.21° at CON2 before reducing to 16.73° at CON3, indicating partial recovery rather than full return to baseline.

At the individual level, all participants showed their greatest frontal ROM at the UT segment, although the magnitude differed considerably. P5 had the largest UT ROM, P3 the smallest, and P2 showed the largest CON1-to-CON2 increase. Most CON3 values sat between CON1 and CON2, again supporting partial recovery.

8.3.5 Transverse Plane

Transverse-plane motion was the largest and most speed-sensitive plane. Group ROM increased at every segment from CON1 to CON2, with the largest changes at LT, UL and LL, before declining at CON3 toward, but generally not fully to, CON1 values.

Individual transverse responses differed markedly. P1 was the most rotationally restricted participant, whereas P2 and P3 showed the largest excursions. P3 showed the steepest CON1-to-CON2 increases at UL, LL and pelvis, while P4 showed full or over-reversal at some segments by CON3. Thus, the group pattern was driven mainly by the participants with the largest rotational responses.

8.3.6 Within-Participant Effect Sizes: Hedges' *g* and Practical Significance

Across 675 participant-segment-metric-contrast combinations, 433 (64.1%) were practically meaningful, 222 (32.9%) met neither criterion, 19 (2.8%) reflected a large *g* within measurement noise, and 1 (0.1%) was real but small-to-medium. Practically meaningful changes were mostly increases for CON1-to-CON2 and mostly decreases for CON2-to-CON3, consistent with adaptation followed by partial recovery.

The transverse plane showed the clearest practical effects. Transverse ROM increased by a mean of 2.42° from CON1 to CON2 and decreased by 1.79° from CON2 to CON3, leaving only a small mean residual change of +0.62° from CON1 to CON3. P3 showed the largest individual rotational increases. Cases classified as large *g* within noise occurred mainly in the sagittal plane, where small absolute differences were amplified by high within-participant consistency.

Table 8.2. Individual Segmental Angle Maximum, Minimum, and Range of Motion (°) in the Sagittal Plane Across Conditions

Segment	Participant	CON1 (VT1)			CON2 (VT2)			CON3 (VT1)		
		Max	Min	ROM	Max	Min	ROM	Max	Min	ROM
Upper thoracic	P1	34.11	26.25	7.87	36.27	27.22	9.05	35.66	28.06	7.60
	P2	41.15	38.06	3.09	42.76	39.47	3.30	42.37	39.10	3.27
	P3	30.30	24.37	5.93	31.14	24.25	6.89	31.12	24.31	6.81
	P4	31.45	28.45	3.00	32.65	29.46	3.19	33.48	30.23	3.26
	P5	37.79	30.90	6.89	38.01	29.58	8.43	37.72	29.86	7.86
Lower thoracic	P1	6.90	2.29	4.61	8.90	3.38	5.52	8.07	3.68	4.39
	P2	9.86	6.24	3.63	11.47	7.73	3.74	10.84	6.44	4.39
	P3	-3.60	-6.03	2.43	-3.21	-6.00	2.79	-4.06	-6.45	2.39
	P4	6.49	4.03	2.46	7.35	4.59	2.76	8.18	5.74	2.43
	P5	4.94	0.44	4.51	4.35	-0.53	4.87	4.22	-0.38	4.60
Upper lumbar	P1	1.82	-4.89	6.71	4.33	-2.63	6.96	4.19	-3.13	7.32
	P2	10.86	6.05	4.81	11.76	8.28	3.48	11.30	7.63	3.67
	P3	-1.35	-9.05	7.71	-1.03	-9.11	8.09	-1.08	-9.57	8.49
	P4	22.85	16.91	5.95	23.02	17.40	5.62	24.11	19.64	4.47
	P5	6.26	-0.22	6.48	7.44	-0.12	7.56	7.12	0.15	6.97
Lower lumbar	P1	4.77	-1.16	5.93	6.25	0.69	5.56	4.82	-0.22	5.04
	P2	3.09	-5.14	8.22	3.17	-4.62	7.79	2.09	-6.26	8.35
	P3	7.37	0.33	7.04	7.01	0.09	6.92	5.27	-1.81	7.08
	P4	18.64	13.41	5.23	18.67	12.75	5.92	19.11	12.68	6.43
	P5	6.11	-0.60	6.71	6.80	-0.98	7.78	5.75	-0.84	6.59
Pelvis	P1	4.72	1.66	3.05	6.55	3.01	3.55	6.14	2.64	3.50
	P2	13.45	4.02	9.43	13.11	5.03	8.08	12.80	3.83	8.96
	P3	9.23	3.97	5.26	9.47	3.29	6.17	8.18	1.51	6.67
	P4	18.26	13.69	4.56	18.31	13.27	5.05	17.76	13.35	4.42
	P5	13.09	8.31	4.78	13.09	7.81	5.28	12.21	6.98	5.22

Note. Values are individual-participant means (N = 5). Max = maximum angle; Min = minimum angle; ROM = range of motion; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold. CON1 and CON3 = VT1 bouts (minutes 0–10 and 20–30); CON2 = VT2 bout (minutes 10–20).

Table 8.3 Individual Segmental Angle Maximum, Minimum, and Range of Motion (°) in the Frontal Plane Across Conditions

Segment	Participant	CON1 (VT1)			CON2 (VT2)			CON3 (VT1)		
		Max	Min	ROM	Max	Min	ROM	Max	Min	ROM
Upper thoracic	P1	5.24	-6.93	12.18	6.04	-8.90	14.95	5.26	-7.87	13.13
	P2	8.62	-10.04	18.66	10.89	-11.50	22.39	9.61	-11.45	21.06
	P3	9.17	-2.80	11.97	9.89	-4.54	14.43	9.48	-3.00	12.49
	P4	10.08	-2.69	12.77	11.66	-3.61	15.27	12.19	-2.22	14.42
	P5	12.18	-8.85	21.03	14.05	-9.98	24.03	13.14	-9.39	22.53
Lower thoracic	P1	5.29	-2.45	7.74	4.94	-3.58	8.52	4.39	-2.79	7.18
	P2	3.48	-7.36	10.84	3.57	-7.68	11.25	2.92	-7.22	10.14
	P3	6.85	-1.84	8.70	6.85	-1.70	8.55	6.88	-1.35	8.23
	P4	4.82	-3.81	8.63	5.68	-4.62	10.30	5.91	-3.83	9.74
	P5	4.33	-6.58	10.91	4.24	-6.92	11.16	4.18	-6.46	10.64
Upper lumbar	P1	4.25	-2.79	7.04	4.25	-2.99	7.24	3.36	-2.39	5.74
	P2	5.84	-2.37	8.20	6.19	-2.61	8.79	5.61	-2.82	8.44
	P3	-0.13	-7.25	7.12	-0.65	-7.40	6.75	-1.23	-6.96	5.73
	P4	-4.08	-11.14	7.06	-2.63	-11.48	8.85	-2.35	-10.64	8.29
	P5	3.26	-1.79	5.04	3.38	-2.49	5.87	3.26	-2.24	5.50
Lower lumbar	P1	-1.50	-6.44	4.94	-1.87	-6.51	4.65	-2.33	-6.37	4.04
	P2	4.95	-7.14	12.09	5.31	-7.88	13.20	4.36	-7.59	11.94
	P3	1.90	-6.23	8.12	2.32	-6.61	8.93	2.30	-6.40	8.70
	P4	3.65	-0.50	4.15	4.57	-0.94	5.52	4.78	-0.28	5.06
	P5	0.59	-3.83	4.42	0.46	-4.00	4.46	0.32	-3.23	3.55
Pelvis	P1	3.55	-1.00	4.55	3.67	-1.15	4.81	3.07	-1.07	4.13
	P2	4.01	-1.67	5.68	4.48	-2.33	6.81	3.71	-2.50	6.22
	P3	6.41	2.15	4.26	6.52	1.83	4.70	6.48	2.19	4.29
	P4	3.76	0.02	3.74	4.19	-0.27	4.46	4.53	-0.13	4.67
	P5	-0.20	-2.89	2.69	0.18	-3.13	3.31	0.27	-2.70	2.97

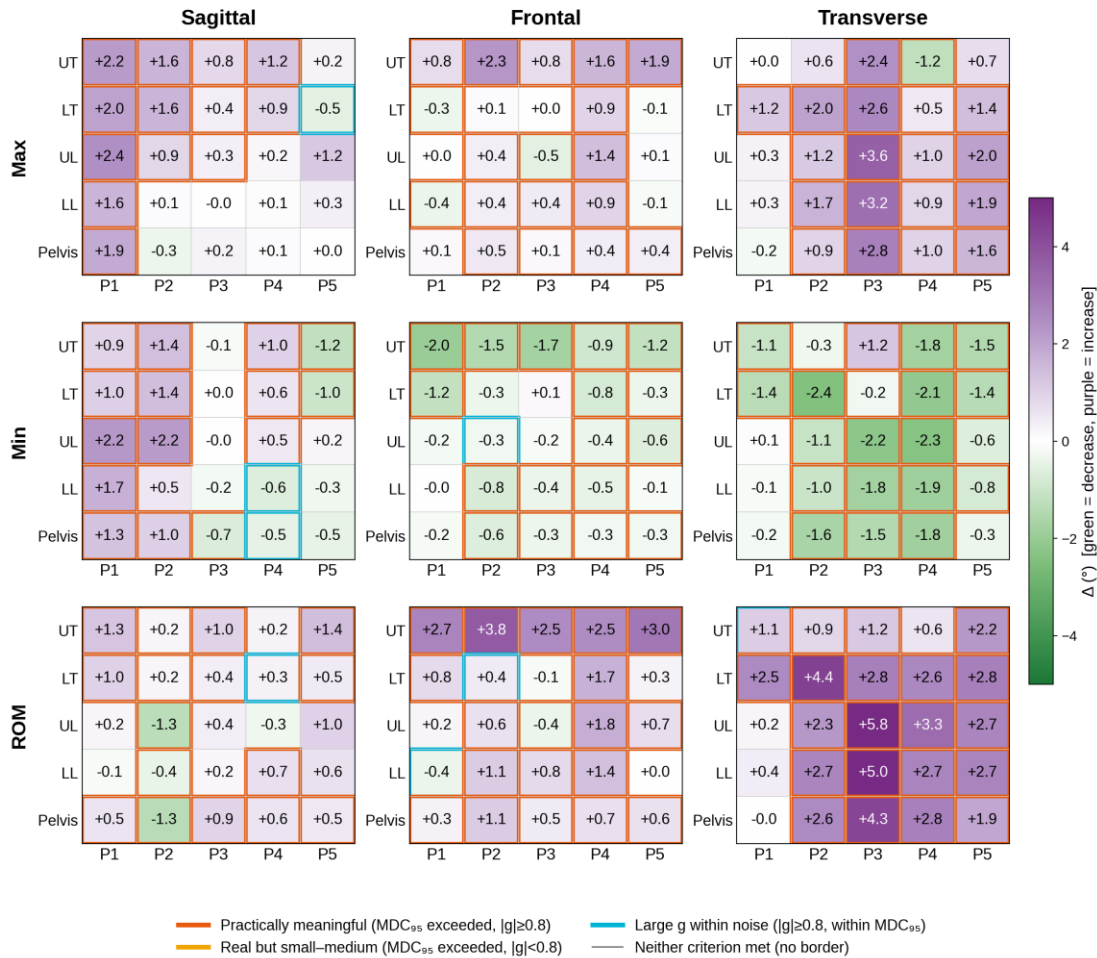
Note. Values are individual-participant means (N = 5). Max = maximum angle; Min = minimum angle; ROM = range of motion; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold. CON1 and CON3 = VT1 bouts (minutes 0–10 and 20–30); CON2 = VT2 bout (minutes 10–20).

Table 8.4 Individual Segmental Angle Maximum, Minimum, and Range of Motion (°) in the Transverse Plane Across Conditions

Segment	Participant	CON1 (VT1)			CON2 (VT2)			CON3 (VT1)		
		Max	Min	ROM	Max	Min	ROM	Max	Min	ROM
Upper thoracic	P1	12.92	-6.52	19.44	12.92	-7.56	20.48	12.00	-6.81	18.81
	P2	13.53	-11.00	24.53	14.11	-11.28	25.39	13.80	-10.68	24.47
	P3	9.66	-13.14	22.80	12.08	-11.90	23.98	12.59	-11.20	23.79
	P4	11.62	-14.81	26.43	10.35	-16.56	26.91	9.43	-15.92	25.35
	P5	9.73	-12.24	21.97	10.48	-13.75	24.23	9.99	-12.51	22.50
Lower thoracic	P1	16.01	-5.93	21.94	17.14	-7.25	24.39	15.83	-6.83	22.66
	P2	17.23	-17.64	34.87	19.21	-19.98	39.19	18.45	-18.49	36.94
	P3	8.53	-11.94	20.47	11.12	-12.19	23.31	10.03	-11.78	21.82
	P4	11.71	-14.92	26.63	12.20	-17.01	29.21	9.82	-16.35	26.18
	P5	14.96	-11.65	26.61	16.36	-13.05	29.41	15.29	-11.35	26.64
Upper lumbar	P1	13.72	0.72	13.01	13.98	0.87	13.10	13.47	0.14	13.32
	P2	12.49	-12.12	24.60	13.64	-13.17	26.80	13.09	-12.08	25.17
	P3	5.16	-9.04	14.20	8.71	-11.20	19.91	7.39	-9.04	16.43
	P4	10.82	-13.02	23.84	11.78	-15.30	27.09	9.40	-13.91	23.31
	P5	11.84	-10.51	22.35	13.83	-11.13	24.96	13.90	-10.48	24.38
Lower lumbar	P1	9.34	0.83	8.52	9.42	0.55	8.87	9.11	0.55	8.56
	P2	7.19	-9.59	16.78	8.83	-10.58	19.41	7.10	-10.02	17.12
	P3	5.78	-8.79	14.57	8.99	-10.57	19.55	7.02	-9.30	16.32
	P4	6.64	-10.00	16.64	7.48	-11.87	19.35	5.50	-10.78	16.28
	P5	11.86	-7.54	19.41	13.73	-8.29	22.02	13.87	-8.07	21.94
Pelvis	P1	8.68	-0.48	9.16	8.38	-0.85	9.23	8.09	-0.97	9.06
	P2	9.83	-9.19	19.02	10.73	-10.77	21.50	10.08	-9.44	19.51
	P3	1.91	-7.30	9.21	4.72	-8.77	13.49	3.22	-7.07	10.29
	P4	7.99	-8.45	16.43	8.94	-10.26	19.21	6.68	-9.45	16.13
	P5	10.76	-7.69	18.45	12.34	-8.00	20.34	12.30	-7.90	20.20

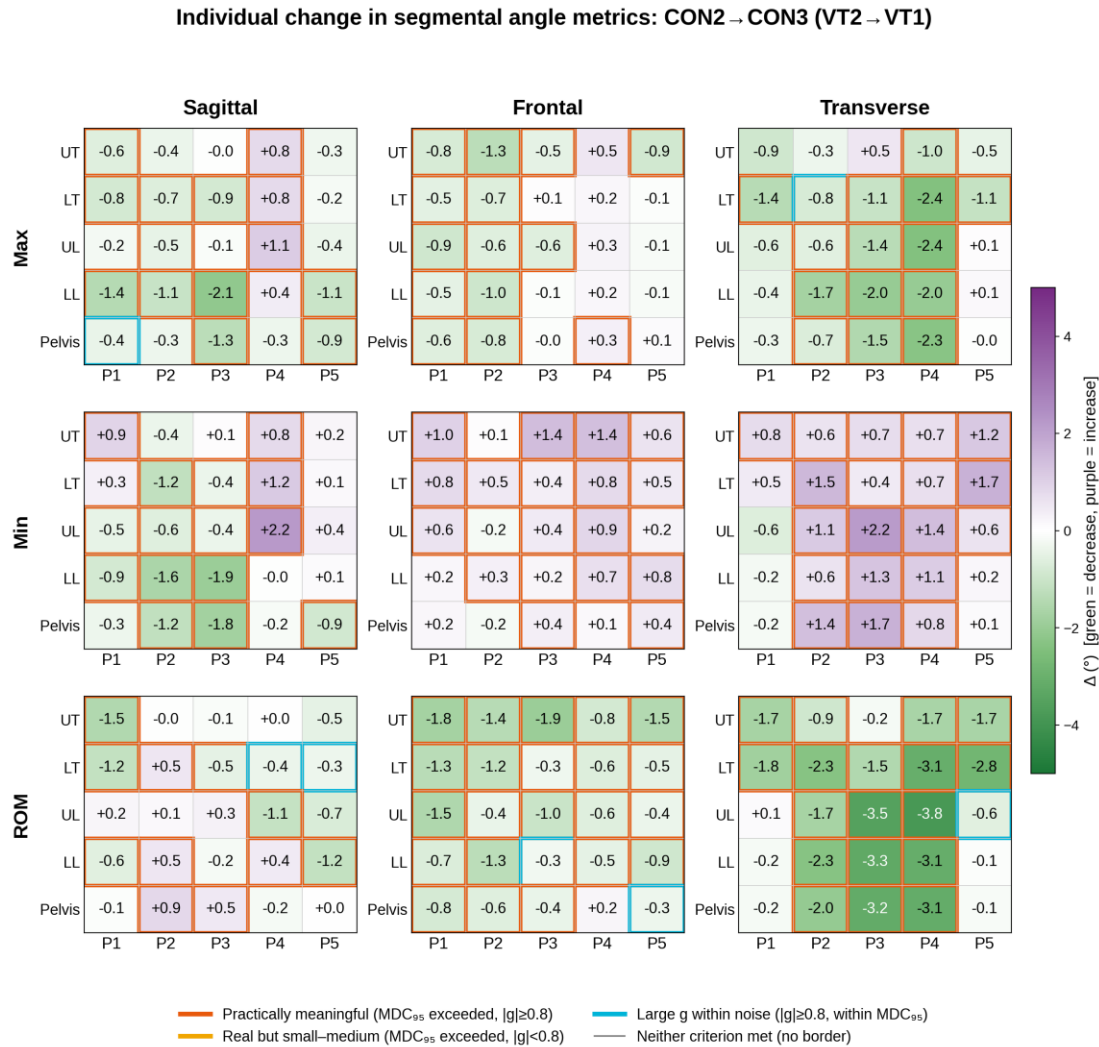
Note. Values are individual-participant means (N = 5). Max = maximum angle; Min = minimum angle; ROM = range of motion; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold. CON1 and CON3 = VT1 bouts (minutes 0–10 and 20–30); CON2 = VT2 bout (minutes 10–20).

Figure 8.3. Individual-Level Change in Segmental Angle Metrics for the CON1 to CON2 Contrast
Individual change in segmental angle metrics: CON1 → CON2 (VT1 → VT2)



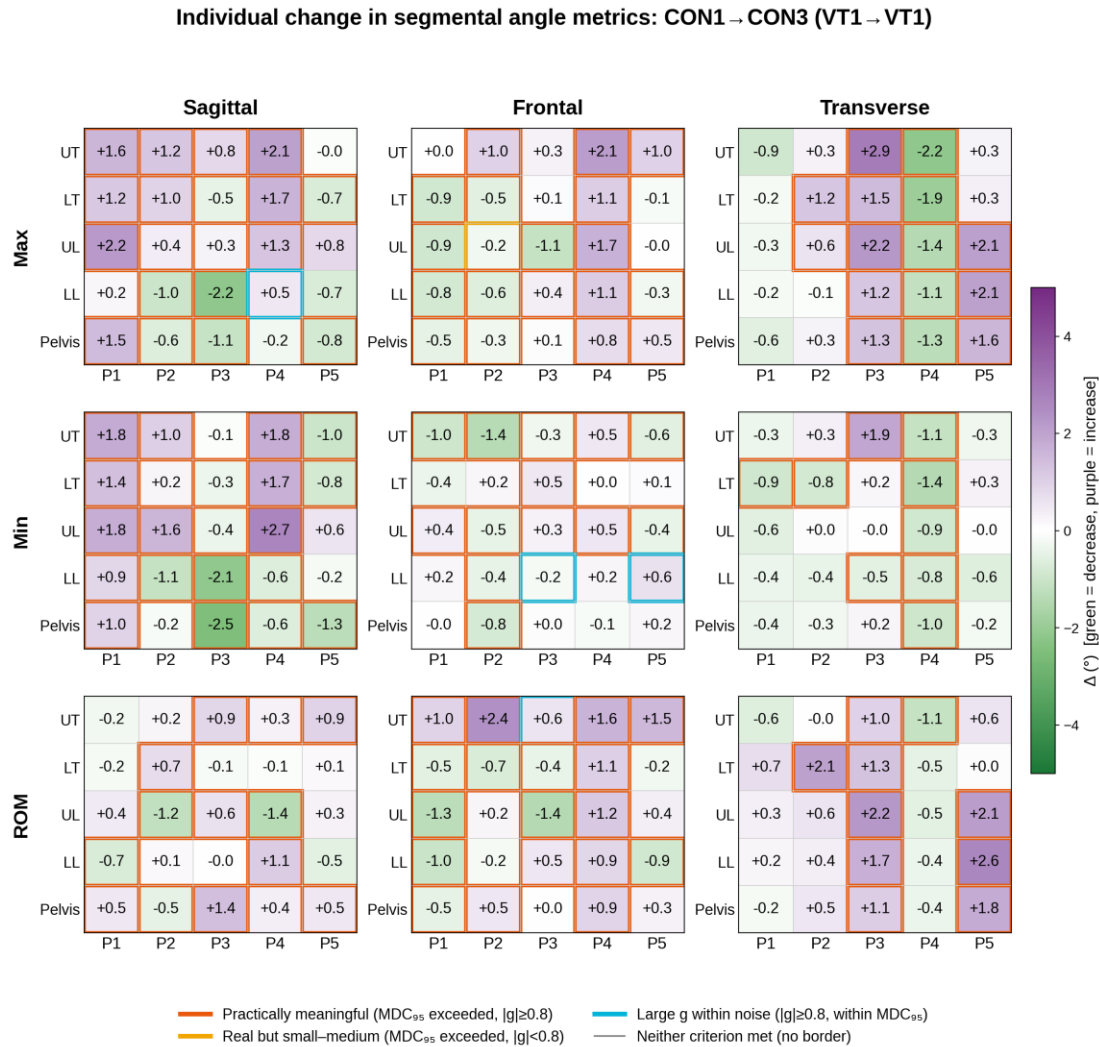
Note. Each cell shows the within-participant mean change ($\Delta = M_2 - M_1$, in degrees) for the CON1 to CON2 (VT1→VT2; adaptation to increased running speed) contrast, for one spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and participant (columns; P1–P5). Panel rows correspond to Max, Min, and ROM; panel columns to the sagittal, frontal, and transverse planes. Colour encodes Δ (green = decrease, purple = increase), clipped at $\pm 5^{\circ}$. Border colour encodes classification: red-orange = practically meaningful; gold = real but small-to-medium; cyan = large g within noise; no border = neither. $N = 5$.

Figure 8.4. Individual-Level Change in Segmental Angle Metrics for the CON2 to CON3 Contrast



Note. Each cell shows the within-participant mean change ($\Delta = M_2 - M_1$, in degrees) for the CON2 to CON3 (VT2→VT1; recovery) contrast, for one spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and participant (columns; P1–P5). Panel rows correspond to Max, Min, and ROM; panel columns to the sagittal, frontal, and transverse planes. Colour encodes Δ (green = decrease, purple = increase), clipped at $\pm 5^{\circ}$. Border colour encodes classification: red-orange = practically meaningful; gold = real but small-to-medium; cyan = large g within noise; no border = neither. N = 5.

Figure 8.5. Individual-Level Change in Segmental Angle Metrics for the CON1 to CON3 Contrast



Note. Each cell shows the within-participant mean change ($\Delta = M_2 - M_1$, in degrees) for the CON1 to CON3 (VT1 baseline versus final VT1 bout) contrast, for one spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and participant (columns; P1–P5). Panel rows correspond to Max, Min, and ROM; panel columns to the sagittal, frontal, and transverse planes. Colour encodes Δ (green = decrease, purple = increase), clipped at $\pm 5^{\circ}$. Border colour encodes classification: red-orange = practically meaningful; gold = real but small-to-medium; cyan = large g within noise; no border = neither. N = 5.

8.3.7 Segmental Angle Waveforms

Individual segmental angle time-series waveforms across the gait cycle are presented by segment and condition for the sagittal, frontal, and transverse planes in Figures 6, 7, and 8, respectively. Time-series waveform shape was generally sinusoidal in all three planes, with segment angle rising through stance and declining across swing, and this general pattern was preserved across CON1, CON2, and CON3 in every participant.

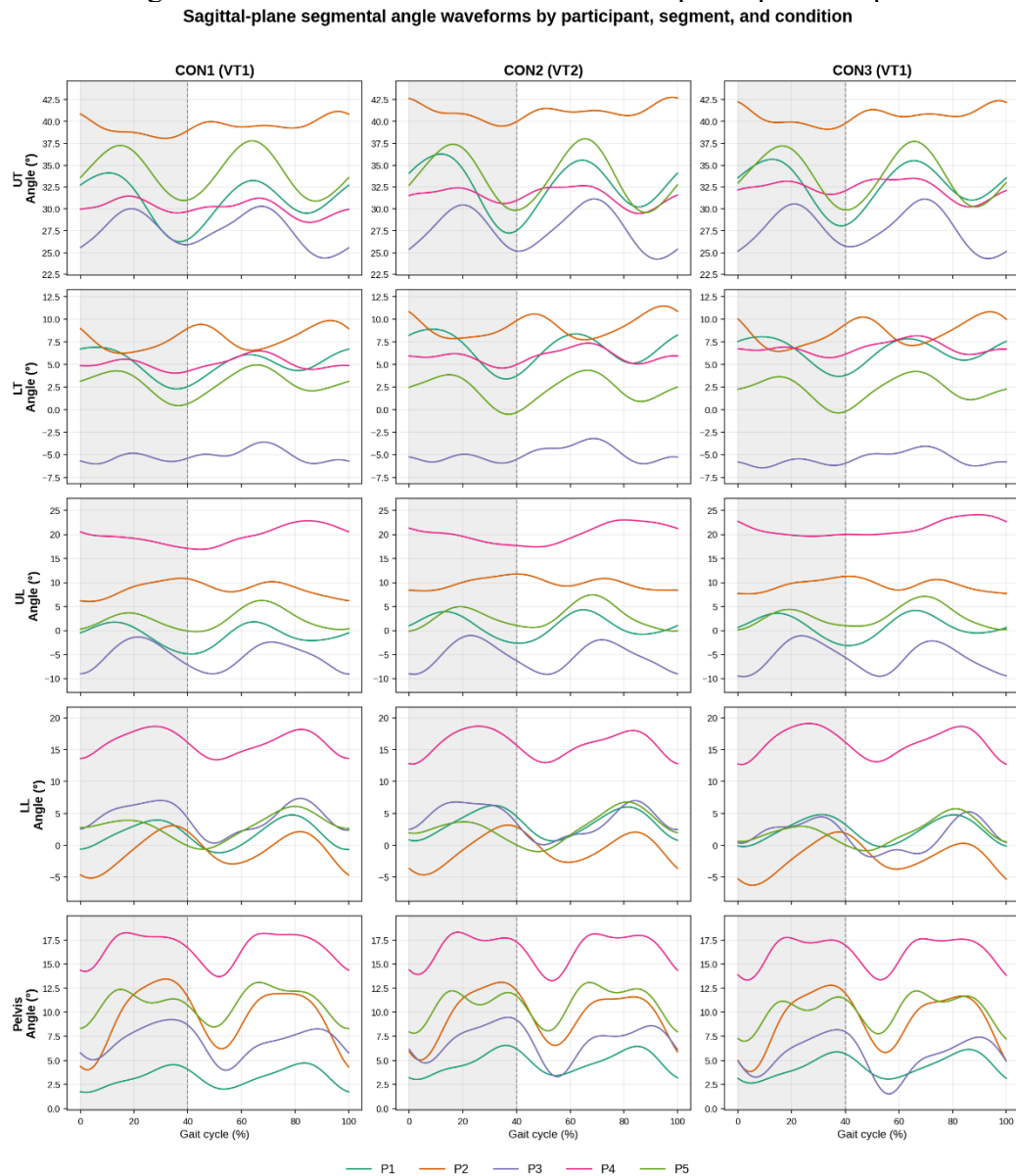
In the sagittal plane (Figure 6), waveforms were offset from one another primarily in vertical position rather than shape, consistent with between-participant differences in static posture; P4's UL and LL traces sat 10–20° above those of the other participants throughout the cycle at every condition, while P3's UL waveform occupied a comparably lower position. Time-series waveform amplitude and timing were visually stable across conditions within each participant.

In the frontal plane (Figure 7), time-series waveforms showed a clearer single-cycle oscillation with peak excursion occurring around the stance-to-swing transition at most segments, most pronounced at the UT segment. P3's LT waveform was visibly shifted relative to the other four participants across all three conditions, and P5's UT amplitude was consistently the largest of the group. Time-series waveform shape at CON2 mirrored that at CON1 and CON3 but with a modest increase in peak-to-trough amplitude, particularly at the UT segment.

In the transverse plane (Figure 8), waveforms displayed the largest peak-to-trough excursions of the three planes at every segment, with a single broad peak spanning the mid-to-late stance phase before declining through swing. P1's traces were consistently the most compressed in amplitude across all segments and conditions, while P2 and P3 showed the largest excursions, particularly at the LT and UL segments. The CON2 waveforms showed a visibly greater amplitude than CON1 or CON3 at most segments, with CON3 waveforms closely tracking the shape and magnitude of CON1, indicating that the intensity-related change in waveform amplitude was largely temporary.

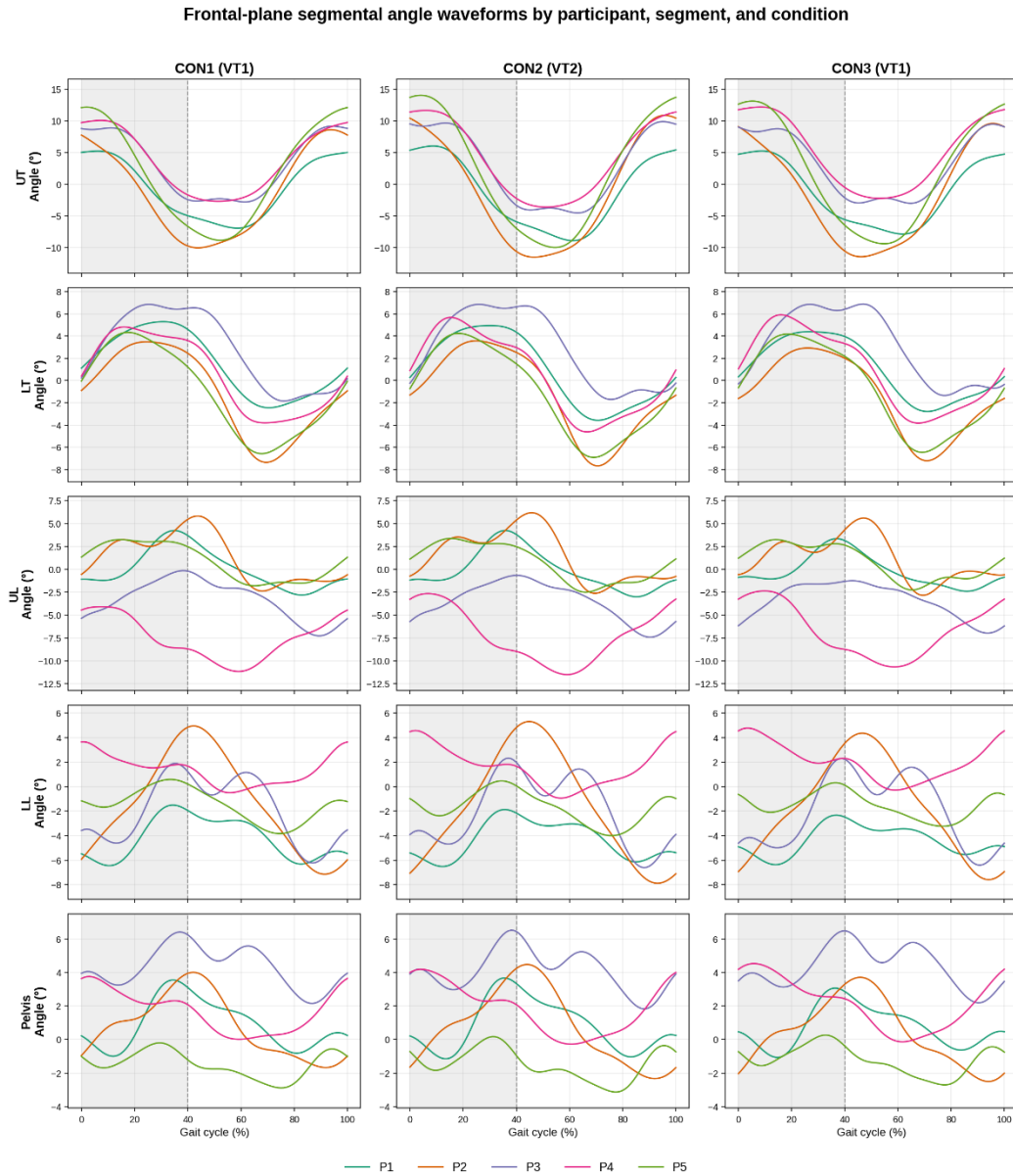
Across all three planes, time-series waveform shape was highly consistent within participants across conditions, whereas amplitude and vertical offset were the primary sources of both between-participant and between-condition variation.

Figure 8.6. Sagittal-Plane Segmental Angle Waveforms by Participant, Segment, and Condition. Line colour identifies the participant (P1–P5), with the same participant colour retained across segments and conditions to facilitate within-participant comparison.



Note. Lines show each participant's (P1–P5) mean sagittal-plane angle waveform (101 points, 0–100% of the gait cycle) for each spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and running condition (columns; CON1 and CON3 = running at the first ventilatory threshold [VT1], minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold [VT2], minutes 10–20). The shaded region (0–40%) denotes the stance phase and the dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle.

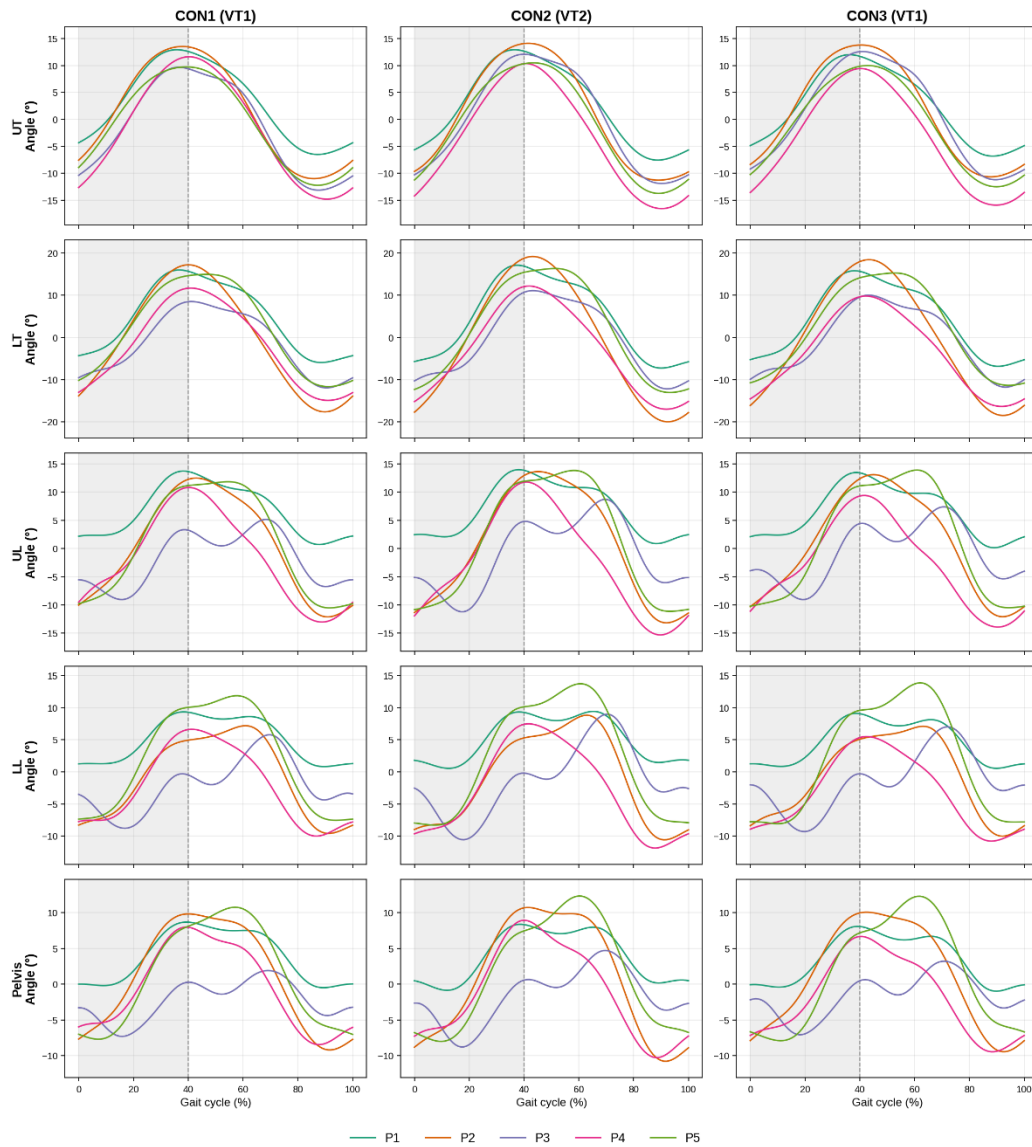
Figure 8.7. Frontal-Plane Segmental Angle Waveforms by Participant, Segment, and Condition. Line colour identifies the participant (P1–P5), with the same participant colour retained across segments and conditions to facilitate within-participant comparison.



Note. Lines show each participant's (P1–P5) mean frontal-plane angle waveform (101 points, 0–100% of the gait cycle) for each spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and running condition (columns; CON1 and CON3 = running at the first ventilatory threshold [VT1], minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold [VT2], minutes 10–20). Positive values indicate contralateral/ipsilateral orientation per the laboratory's segment coordinate convention. The shaded region (0–40%) denotes the stance phase, and the dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle.

Figure 8.8. Transverse-Plane Segmental Angle Waveforms by Participant, Segment, and Condition. Line colour identifies the participant (P1–P5), with the same participant colour retained across segments and conditions to facilitate within-participant comparison.

Transverse-plane segmental angle waveforms by participant, segment, and condition



Note. Lines show each participant's (P1–P5) mean transverse-plane angle waveform (101 points, 0–100% of the gait cycle) for each spine segment (rows; UT = upper thoracic; LT = lower thoracic; UL = upper lumbar; LL = lower lumbar) and running condition (columns; CON1 and CON3 = running at the first ventilatory threshold [VT1], minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold [VT2], minutes 10–20). The shaded region (0–40%) denotes the stance phase, and the dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle.

8.3.8 Physiological response

8.3.9 VO₂ Slow Component During the VT2 Stage

The mean VO₂ across the first three minutes of the VT2 stage ranged from 40.71 to 54.72 mL·kg⁻¹·min⁻¹ across participants (group mean ± SD: 47.96 ± 6.20 mL·kg⁻¹·min⁻¹), and the mean VO₂ during the final five minutes ranged from 43.82 to 57.17 mL·kg⁻¹·min⁻¹ (49.20 ± 5.07 mL·kg⁻¹·min⁻¹). The group mean SC amplitude was +1.23 ± 3.80 mL·kg⁻¹·min⁻¹. Four of five participants demonstrated a positive SC, consistent with the expected progressive increase in oxygen cost during sustained heavy-intensity exercise. P2 exhibited the largest SC (+5.64 mL·kg⁻¹·min⁻¹), followed by P1 (+2.45 mL·kg⁻¹·min⁻¹), P5 (+1.66 mL·kg⁻¹·min⁻¹), and P4 (+1.24 mL·kg⁻¹·min⁻¹). P3 was the only participant to exhibit a negative SC value (−4.82 mL·kg⁻¹·min⁻¹), which is likely attributable to elevated variability during the first three minutes of the VT2 stage (SD = 4.05 mL·kg⁻¹·min⁻¹), producing an inflated reference mean rather than a genuine physiological decrease in VO₂. Individual and group-level results are presented in Table 5.

Table 8.5. VO₂ Slow Component Amplitude for Each Participant During the VT2 Stage (Minutes 10–20)

Participant	M VO ₂ first 3 min	SD	M VO ₂ final 5 min	SD	SC amplitude
	(mL·kg ⁻¹ ·min ⁻¹)		(mL·kg ⁻¹ ·min ⁻¹)		(mL·kg ⁻¹ ·min ⁻¹)
P5	48.74	2.72	50.40	1.04	+1.66
P4	42.57	2.30	43.82	0.65	+1.24
P3	53.06	4.05	48.24	2.23	−4.82
P2	40.71	2.48	46.35	0.66	+5.64
P1	54.72	3.99	57.17	1.51	+2.45
M ± SD	47.96 ± 6.20		49.20 ± 5.07		+1.23 ± 3.80

Note. VO₂ = oxygen uptake relative to body mass (mL·kg⁻¹·min⁻¹). SC = slow component amplitude, calculated as mean VO₂ during the final five minutes minus mean VO₂ during the first three minutes of the VT2 stage. M = mean. SD = standard deviation. Data are derived from a single exercise bout per participant.

8.3.10 VO₂ Recovery During the Return-to-VT1 Stage

No participant fully returned to their VT1 baseline VO₂ within the 10-minute recovery window (group mean recovery: $73.1 \pm 14.4\%$), demonstrating that the VT2 stage produced a sustained metabolic perturbation extending beyond the stage duration. The group mean residual deficit was $+3.05 \pm 2.45 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$. Considerable inter-individual variability was observed: P4 and P3 achieved near-complete recovery (89.8% and 83.9%, respectively), with residual deficits within one baseline standard deviation ($+0.70$ and $+1.11 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$, respectively). In contrast, P2 and P1 demonstrated markedly incomplete recovery (60.0% and 57.0%, respectively), with residual deficits of $+4.29$ and $+6.64 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$, both exceeding their respective VT1 baseline standard deviations and consistent with persistent excess post-exercise oxygen consumption. Notably, P2 and P1 also exhibited the two largest positive SC amplitudes ($+5.64$ and $+2.45 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$, respectively). P3's VT1 baseline exhibited notably high variability ($\text{SD} = 11.28 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$), and its recovery classification should therefore be interpreted with caution. Individual and group results are presented in Table 6

Table 8.6. VO₂ Recovery Kinetics During the Return-to-VT1 Stage (Minutes 20–30)

Participant	VT1 baseline	VT2 end	Recovery start	Recovery final	Residual deficit	% Recovered
	M (SD) (0–3 min)	M (18–20 min)	M (SD) (20–23 min)	M (SD) (25–30 min)	M	
P5	40.08 (2.91)	50.09	45.02 (3.18)	42.60 (1.13)	+2.52	74.8
P4	36.73 (1.59)	43.57	41.11 (2.52)	37.43 (1.37)	+0.70	89.8
P3	41.72 (11.28)	48.59	45.29 (3.69)	42.83 (3.83)	+1.11	83.9
P2	35.93 (2.02)	46.65	43.27 (2.22)	40.21 (0.70)	+4.29	60.0
P1	41.44 (5.52)	56.90	50.93 (3.45)	48.08 (4.64)	+6.64	57.0
M $\pm$ SD					+3.05 $\pm$ 2.45	73.1 $\pm$ 14.4

Note. VO₂ = oxygen uptake relative to body mass ($\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$). VT1 baseline = mean VO₂ during minutes 0–3. VT2 end = mean VO₂ during minutes 18–20. Recovery start = mean VO₂ during minutes 20–23. Recovery final = mean VO₂ during minutes 25–30. Residual deficit = recovery final minus VT1 baseline. % Recovered = proportion of the VT2-induced elevation above VT1 baseline recovered by end of stage. All VO₂ values in $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$. M = mean; SD = standard deviation.

8.3.11 VO₂ Comparison Between CON1 and CON3

Group mean VO₂ was $42.03 \pm 4.57 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ during CON1 and $43.44 \pm 3.99 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ during CON3, a group mean difference of $+1.41 \pm 2.63 \text{ mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$. Four of five participants showed a modest elevation in whole-stage mean VO₂ at CON3 relative to CON1, consistent with a residual metabolic cost of the preceding VT2 stage: P2 showed the largest proportional increase (37.10 to 41.24 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, +11.2%), followed by P1 (46.25 to 49.59 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, +7.2%), P4 (37.70 to 38.89 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, +3.2%), and P5 (42.33 to 43.32 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, +2.3%). P3 was the sole participant to show a decrease at CON3 relative to CON1 (46.78 to 44.16 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, -5.6%), which is consistent with the elevated within-stage variability already noted for this participant's VT1 baseline (SD = 7.88 $\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ during CON1) and should therefore be interpreted with caution. Individual and group results are presented in Table 7.

Table 8.7. VO₂ Comparison Between CON1 (Minutes 0–10) and CON3 (Minutes 20–30)

Participant	M (SD) CON1 (0–10 min)	M (SD) CON3 (20–30 min)	Difference (CON3 – CON1)	% Change
P5	42.33 (2.47)	43.32 (2.36)	+0.99	+2.3
P4	37.70 (1.39)	38.89 (2.45)	+1.20	+3.2
P3	46.78 (7.88)	44.16 (3.22)	-2.63	-5.6
P2	37.10 (1.65)	41.24 (1.96)	+4.15	+11.2
P1	46.25 (4.61)	49.59 (2.74)	+3.33	+7.2
M ± SD	42.03 ± 4.57	43.44 ± 3.99	+1.41 ± 2.63	

Note. VO₂ = oxygen uptake relative to body mass ($\text{mL} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$). CON1 = mean VO₂ during minutes 0–10. CON3 = mean VO₂ during minutes 20–30. Difference = CON3 minus CON1. % Change = difference expressed as a percentage of the CON1 mean. M = mean; SD = standard deviation.

8.3.12 Non-linear analysis

8.3.13 Individual-Level Coordination Patterns: Sagittal Plane

In the sagittal plane, UT-LT coordination was mainly proximal-dominant and in-phase across participants and conditions, except for P2, who showed a mixed distal-dominant pattern. LT-UL and UL-LL showed greater individual variation, including C3-specific shifts in P2 and P4 and a persistent anti-phase component in P3. LL-Pelvis responses were also participant-specific: P2 and P3 drove the group shift toward proximal dominance, whereas P5 moved in the opposite direction. These findings indicate that sagittal coordination did not follow a single group response.

8.3.14 Individual-Level Coordination Patterns: Frontal Plane

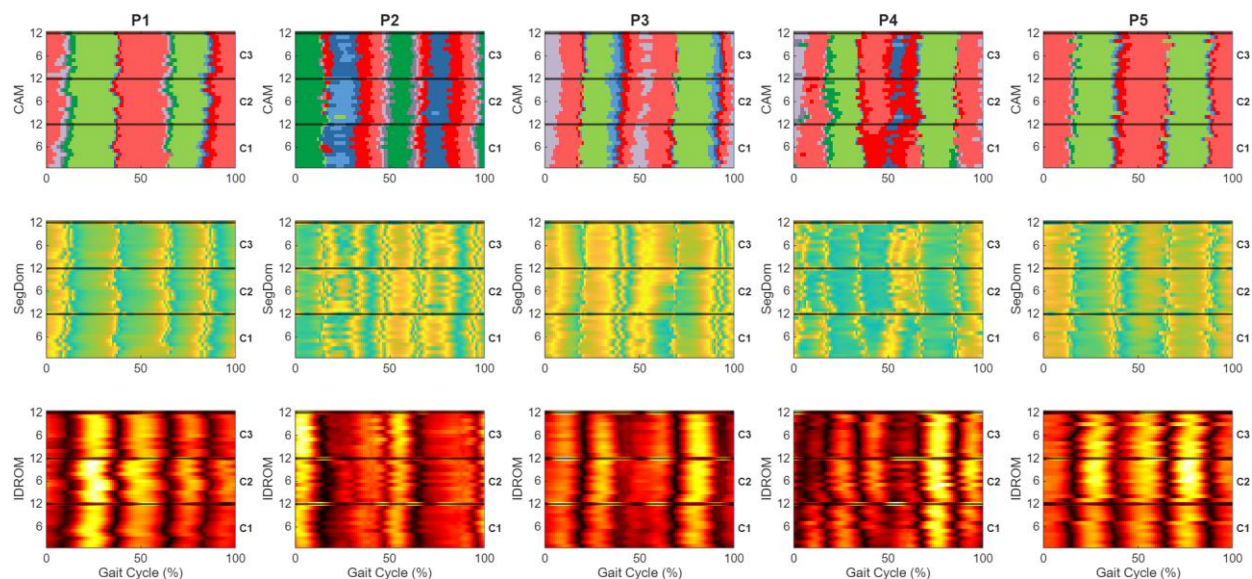
In the frontal plane, coordination was more heterogeneous. UT-LT split the cohort into anti-phase-dominant participants (P1-P3) and in-phase-dominant participants (P4-P5). LT-UL showed opposing individual trends, with P3 moving toward proximal dominance and P4 moving toward distal dominance. UL-LL and LL-Pelvis also showed distinct participant strategies, including near-total proximal-dominant coordination in P2 at LL-Pelvis. Overall, frontal-plane coordination highlighted the strongest individual differences.

8.3.15 Individual-Level Coordination Patterns: Transverse Plane

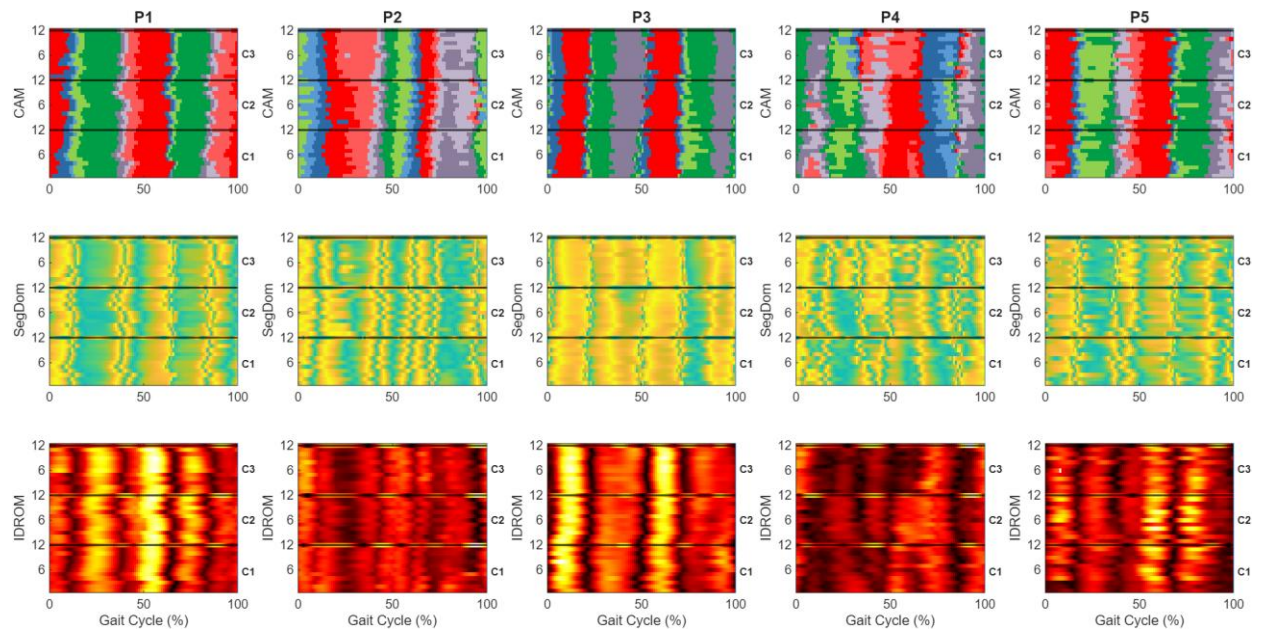
In the transverse plane, UT-LT was largely distal-dominant, driven mainly by P1, P2 and P5. LT-UL showed the clearest intensity-related trend, but this was participant-dependent: P2 and P4 accounted for most of the shift toward proximal dominance, whereas P3 remained distinct with a persistent anti-phase component. UL-LL showed high proximal dominance in four participants, while LL-Pelvis responses ranged from stable distal dominance in P2 to partial normalisation in P1. Thus, transverse coordination was organised but not uniform across runners.

Figure 8.9. Coupling-angle mapping (CAM), segmental dominance (SegDom), and inter-data point range of motion (IDP-ROM) for upper thoracic-lower thoracic, lower thoracic, upper lumbar, upper lumbar-lower lumbar and lower lumbar–pelvis coordination in the sagittal plane across the gait cycle in five participants (P1–P5) during three running conditions (C1 = VT1, C2 = VT2, and C3 = VT1 recovery).

Upper thoracic and lower thoracic coupling



Lower thoracic and upper lumbar coupling



Upper lumbar and lower lumbar coupling

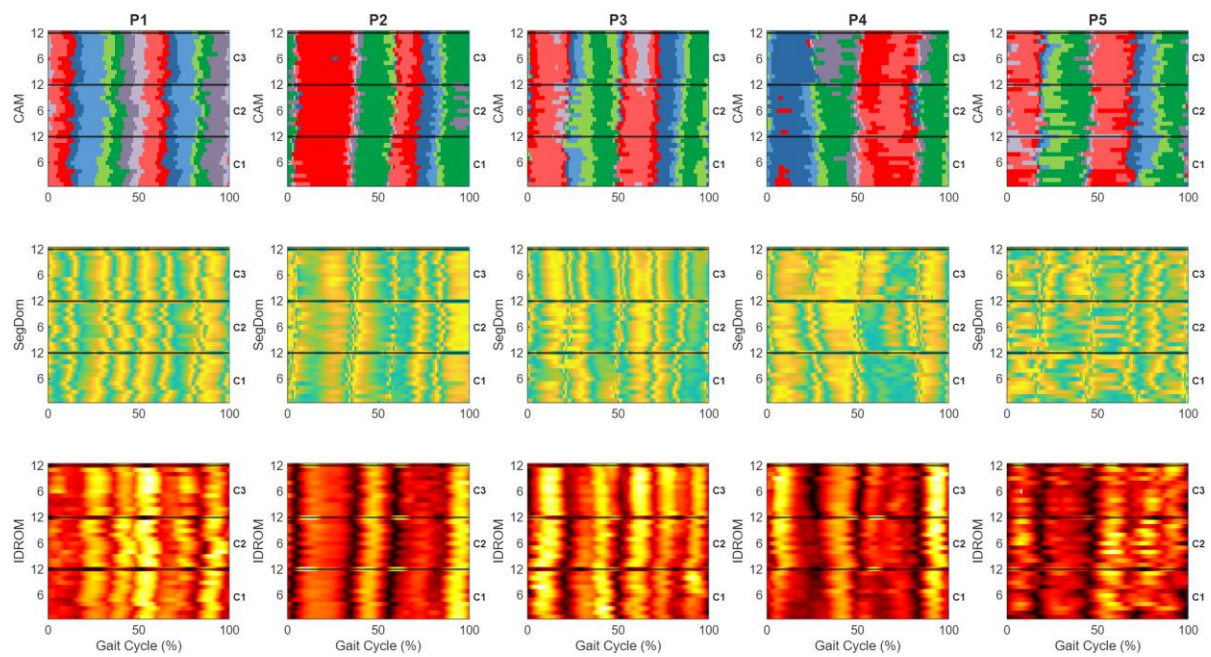
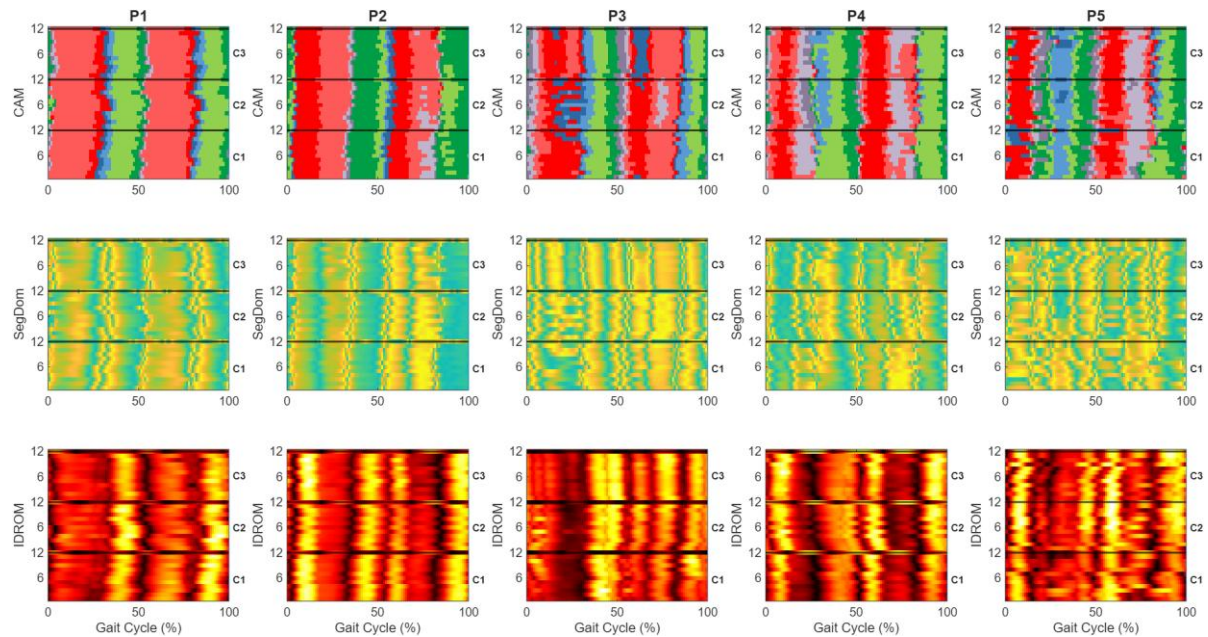


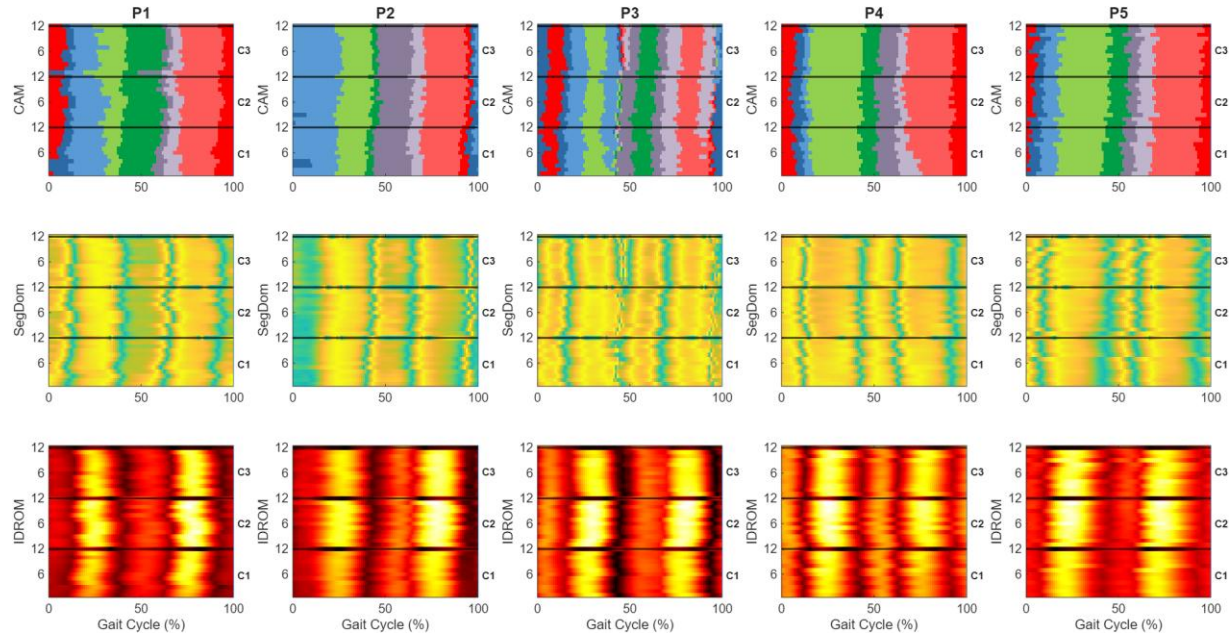
Figure 8.9 continued
Lower lumbar and pelvis coupling



Note. Each participant column (P1–P5) displays three complementary representations of upper thoracic–lower thoracic coordination across the normalised gait cycle (0–100%) for C1, C2 and C3. The upper panel shows coupling-angle mapping (CAM), where colour represents coordination pattern classification and rotational direction: light red = in-phase proximal dominance (IPPD), positive rotation; dark red = in-phase distal dominance (IPDD), positive rotation; light green = IPPD, negative rotation; dark green = IPDD, negative rotation; light blue = anti-phase proximal dominance (APPD), proximal negative/distal positive; dark blue = anti-phase distal dominance (APDD), proximal negative/distal positive; light purple = APPD, proximal positive/distal negative; and dark purple = APDD, proximal positive/distal negative. The middle panel shows segmental dominance (SegDom), expressing the relative contribution of the proximal and distal segments, where 50% represents equal contribution and values approaching 100% indicate near-complete dominance of one segment. The lower panel shows inter-data point range of motion (IDP-ROM), representing the magnitude of angular displacement of the dominant segment between consecutive normalised time points; higher values indicate greater angular change. C1 = VT1 baseline running; C2 = VT2 running; C3 = return to VT1 following the higher-intensity condition. P = participant; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold.

Figure 8.10. Coupling-angle mapping (CAM), segmental dominance (SegDom), and inter-data point range of motion (IDP-ROM) for upper thoracic-lower thoracic, lower thoracic, upper lumbar, upper lumbar-lower lumbar and lower lumbar–pelvis coordination in the frontal plane across the gait cycle in five participants (P1–P5) during three running conditions (C1 = VT1, C2 = VT2, and C3 = VT1 recovery).

Upper thoracic and lower thoracic coupling



Lower thoracic and upper lumbar coupling

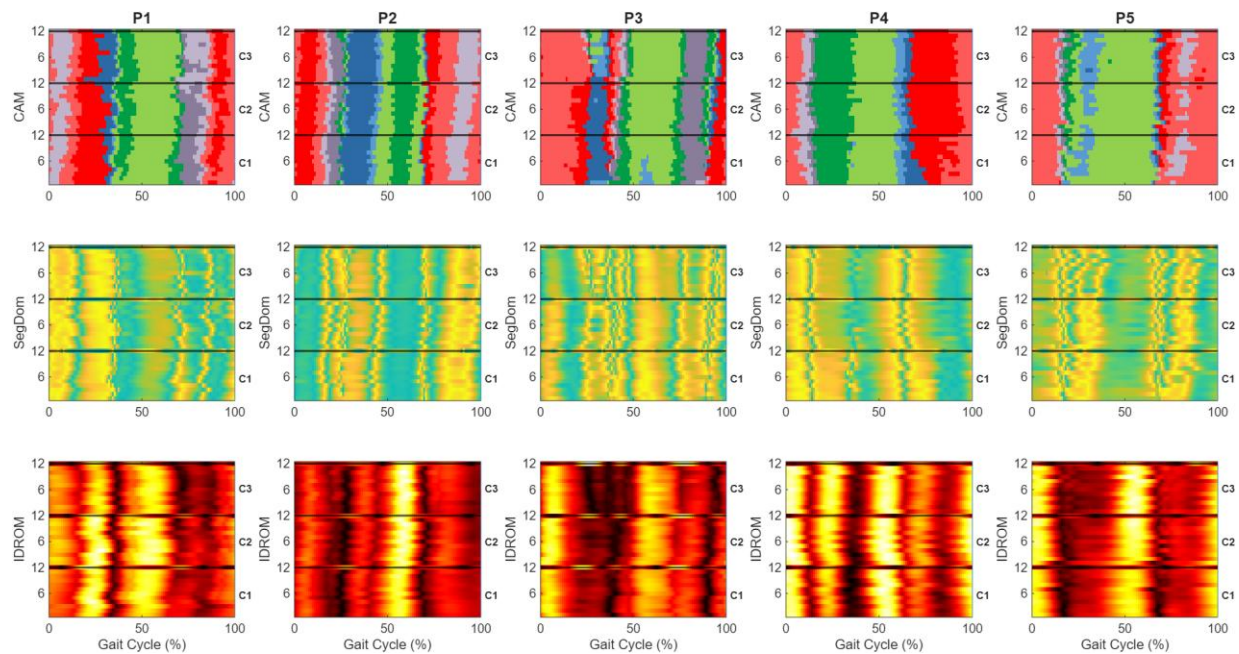
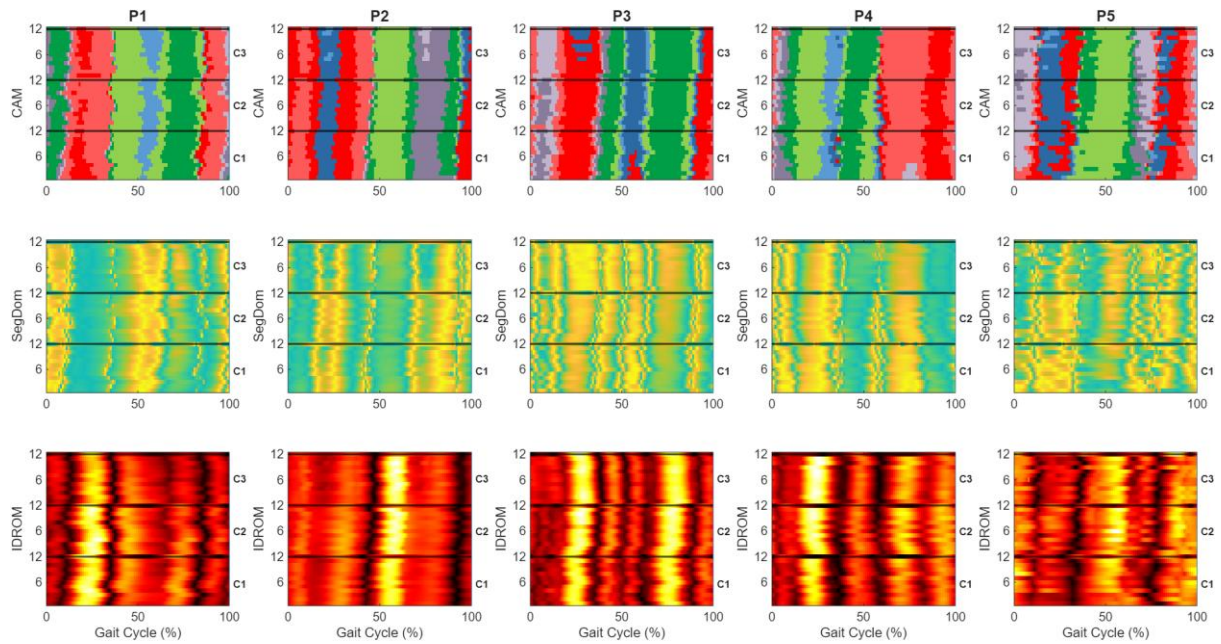
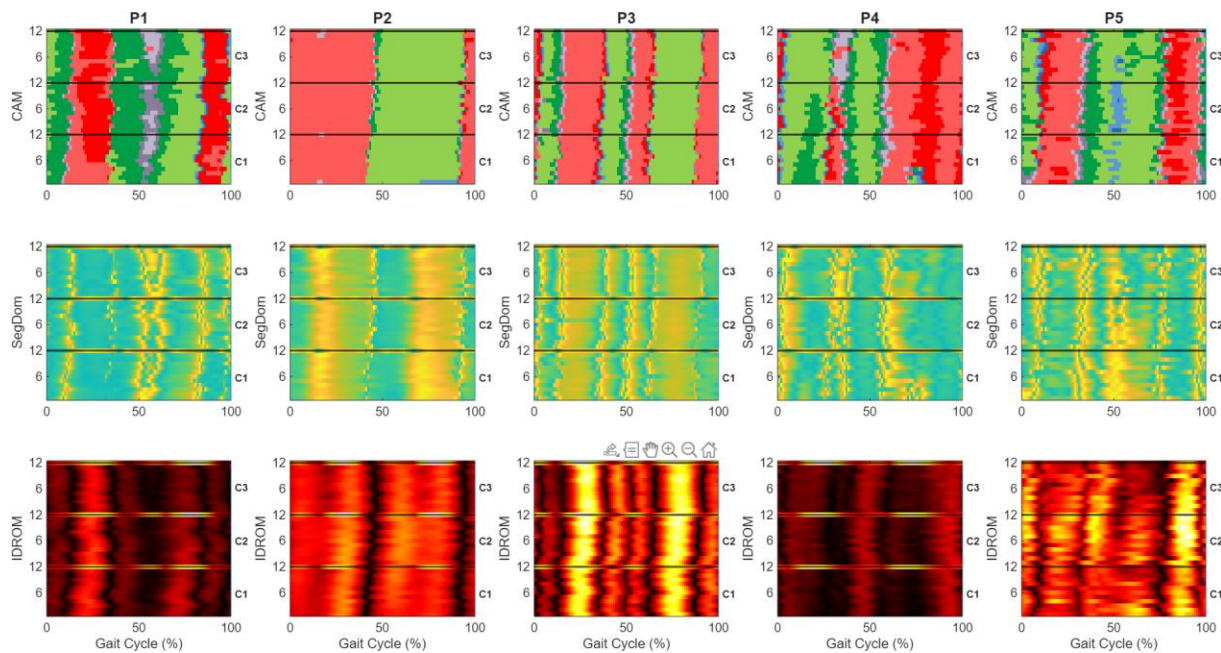


Figure 8.10. continued
Upper lumbar and lower lumbar coupling



Lower lumbar and pelvis coupling

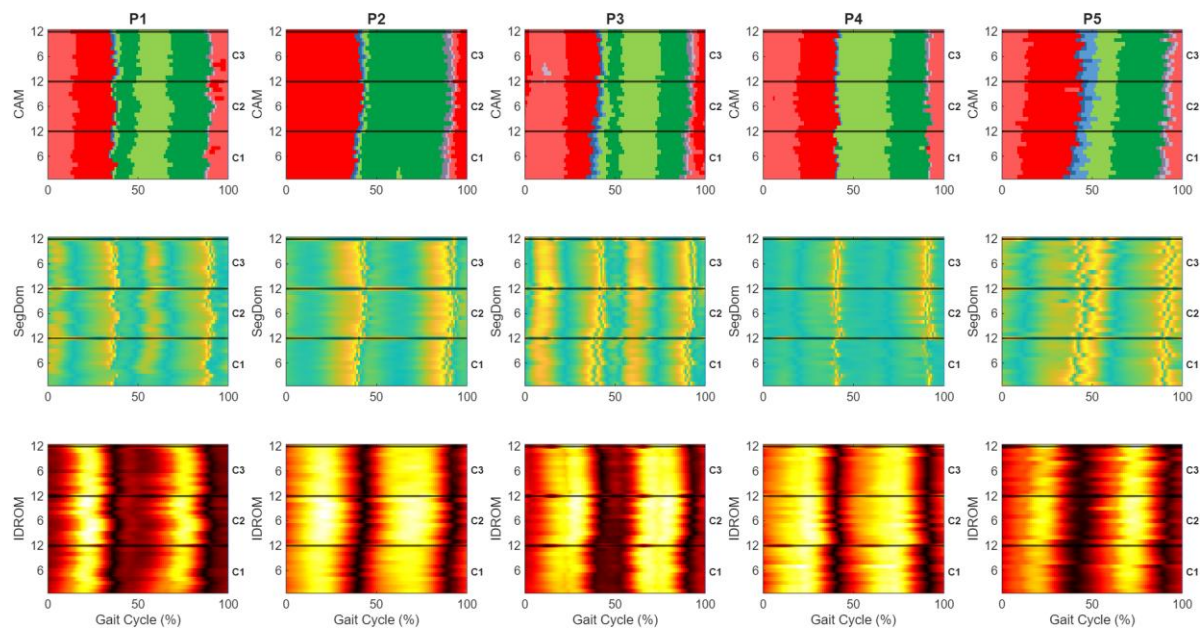


Note. Each participant column (P1–P5) displays three complementary representations of upper thoracic–lower thoracic coordination across the normalised gait cycle (0–100%) for C1, C2 and C3. The upper panel shows coupling-angle mapping (CAM), where colour represents coordination pattern classification and rotational direction: light red = in-phase proximal dominance (IPPD), positive rotation; dark red = in-phase distal dominance (IPDD), positive rotation; light green = IPPD, negative rotation; dark green = IPDD, negative rotation; light blue = anti-phase proximal dominance (APPD), proximal negative/distal positive; dark blue = anti-phase distal dominance (APDD), proximal negative/distal positive; light purple = APPD, proximal positive/distal negative; and dark purple = APDD, proximal positive/distal negative. The middle panel shows segmental dominancy (SegDom), expressing the relative contribution of the proximal and distal segments, where 50% represents equal contribution and values approaching 100% indicate near-complete dominance of one segment. The lower panel

shows inter-data point range of motion (IDP-ROM), representing the magnitude of angular displacement of the dominant segment between consecutive normalised time points; higher values indicate greater angular change. C1 = VT1 baseline running; C2 = VT2 running; C3 = return to VT1 following the higher-intensity condition. P = participant; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold.

Figure 8.11. Coupling-angle mapping (CAM), segmental dominance (SegDom), and inter-data point range of motion (IDP-ROM) for upper thoracic-lower thoracic, lower thoracic, upper lumbar, upper lumbar-lower lumbar and lower lumbar–pelvis coordination in the transverse plane across the gait cycle in five participants (P1–P5) during three running conditions (C1 = VT1, C2 = VT2, and C3 = VT1 recovery).

Upper thoracic and lower thoracic coupling



Lower thoracic and upper lumbar coupling

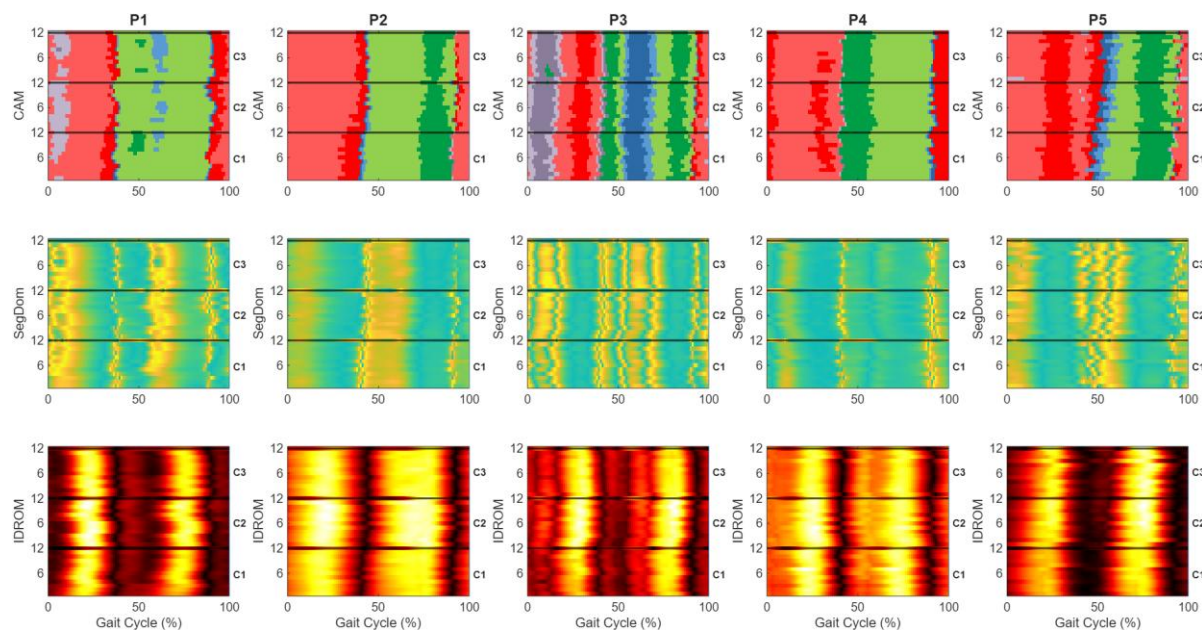
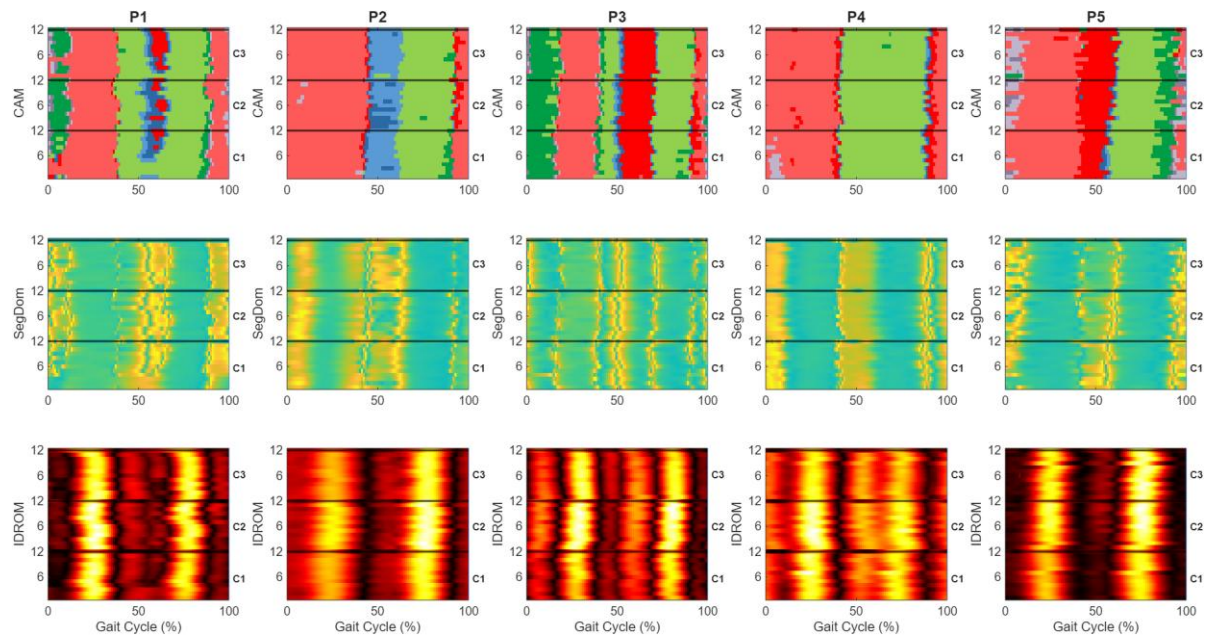
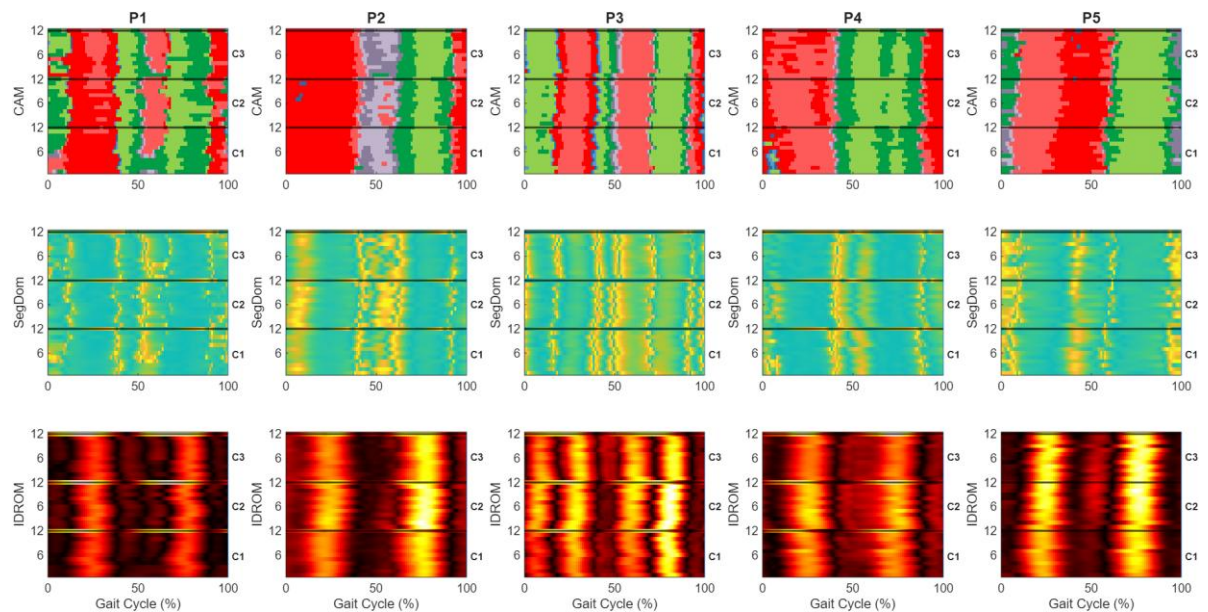


Figure 8.11. continued
Upper lumbar and lower lumbar coupling



Lower lumbar and pelvis coupling



Note. Each participant column (P1–P5) displays three complementary representations of upper thoracic–lower thoracic coordination across the normalised gait cycle (0–100%) for C1, C2 and C3. The upper panel shows coupling-angle mapping (CAM), where colour represents coordination pattern classification and rotational direction: light red = in-phase proximal dominance (IPPD), positive rotation; dark red = in-phase distal dominance (IPDD), positive rotation; light green = IPPD, negative rotation; dark green = IPDD, negative rotation; light blue = anti-phase proximal dominance (APPD), proximal negative/distal positive; dark blue = anti-phase distal

dominancy (APDD), proximal negative/distal positive; light purple = APPD, proximal positive/distal negative; and dark purple = APDD, proximal positive/distal negative. The middle panel shows segmental dominancy (SegDom), expressing the relative contribution of the proximal and distal segments, where 50% represents equal contribution and values approaching 100% indicate near-complete dominancy of one segment. The lower panel shows inter-data point range of motion (IDP-ROM), representing the magnitude of angular displacement of the dominant segment between consecutive normalised time points; higher values indicate greater angular change. C1 = VT1 baseline running; C2 = VT2 running; C3 = return to VT1 following the higher-intensity condition. P = participant; VT1 = first ventilatory threshold; VT2 = second ventilatory threshold.

8.3.16 Coupling Angle Variability

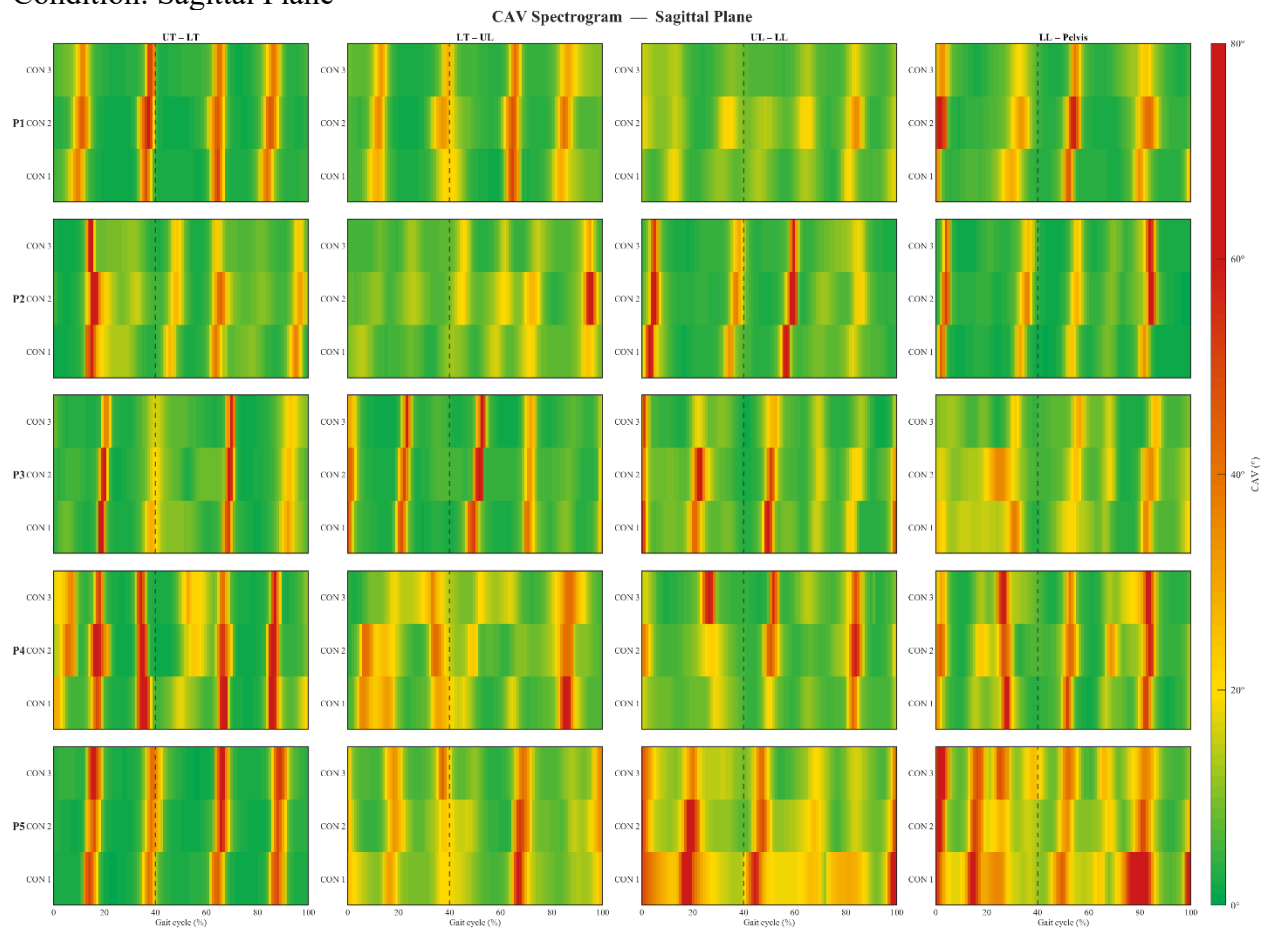
At group level, CAV generally increased from CON1 to CON2 and then decreased from CON2 to CON3. This recovery pattern was most consistent in the sagittal plane and was also evident in most frontal and transverse responses. However, P2 and P5 showed a positive CON1-to-CON3 net change in transverse CAV, indicating incomplete recovery in some participants.

Individual trajectories varied. P1 and P2 showed the clearest increase-then-recover sagittal pattern. P5 showed the largest single-condition change, with sagittal CAV decreasing from CON1 to CON2 rather than increasing, driven mainly by distal pairs. P5 also showed a reversed frontal-plane trajectory, decreasing from CON1 to CON2 before increasing at CON3. These responses show that changes in variability were not simply scaled versions of the group pattern.

Segment-pair specificity was also evident. In the transverse plane, P1 and P2 both increased CAV at proximal pairs, but differed at distal pairs: P1 decreased at UL-LL and LL-Pelvis, whereas P2 increased at every pair. P4 showed the most consistent CON2-to-CON3 decrease across planes. These findings support the interpretation that coordination variability was reorganised in a participant- and pair-specific manner.

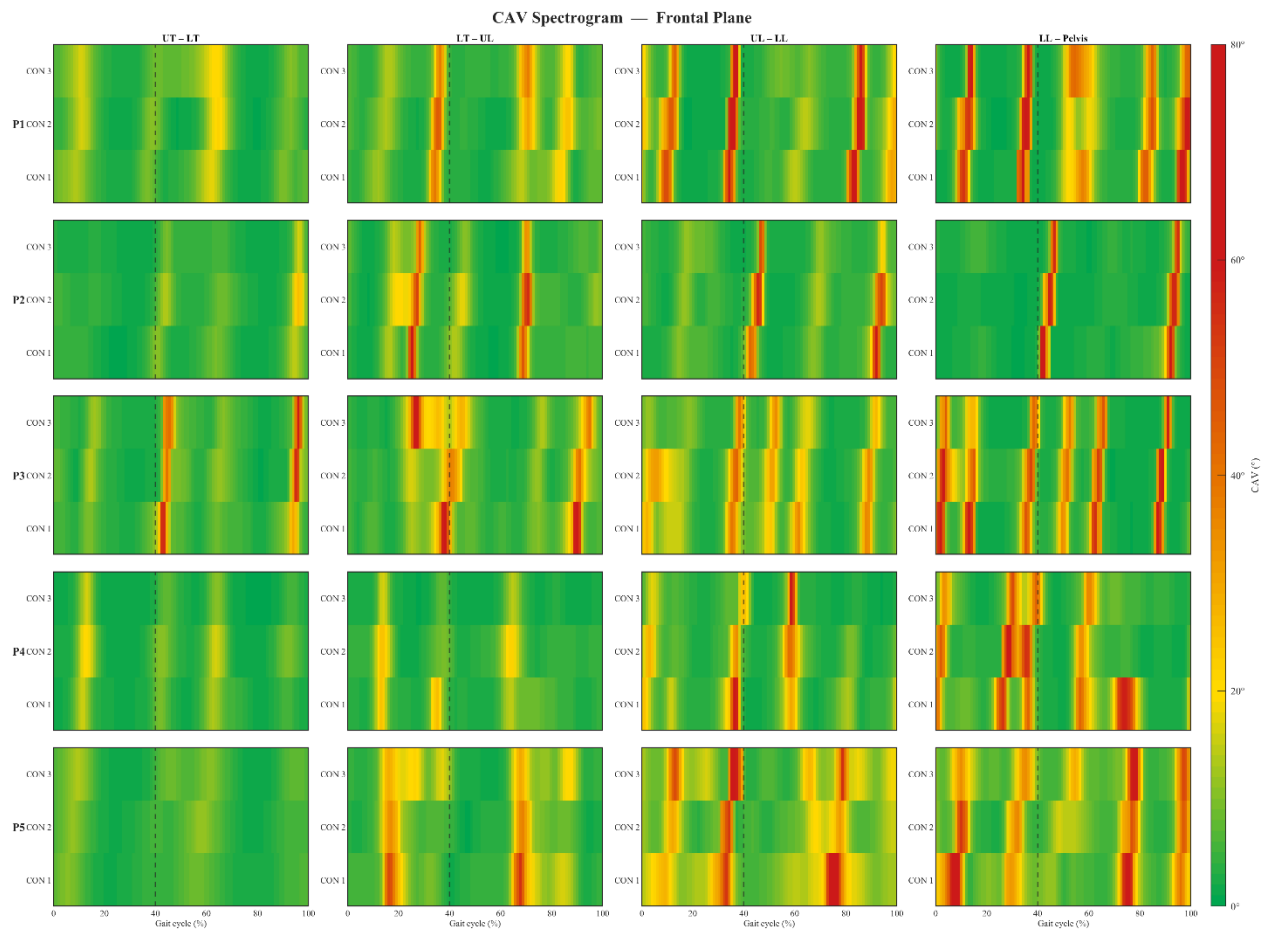
Overall, CAV supported a speed-related change in coordination consistency, but the direction and completeness of recovery differed between runners. This reinforces the value of interpreting group trends alongside individual response profiles.

Figure 8.12. Coupling Angle Variability Spectrogram by Participant, Segment Pair, and Condition: Sagittal Plane



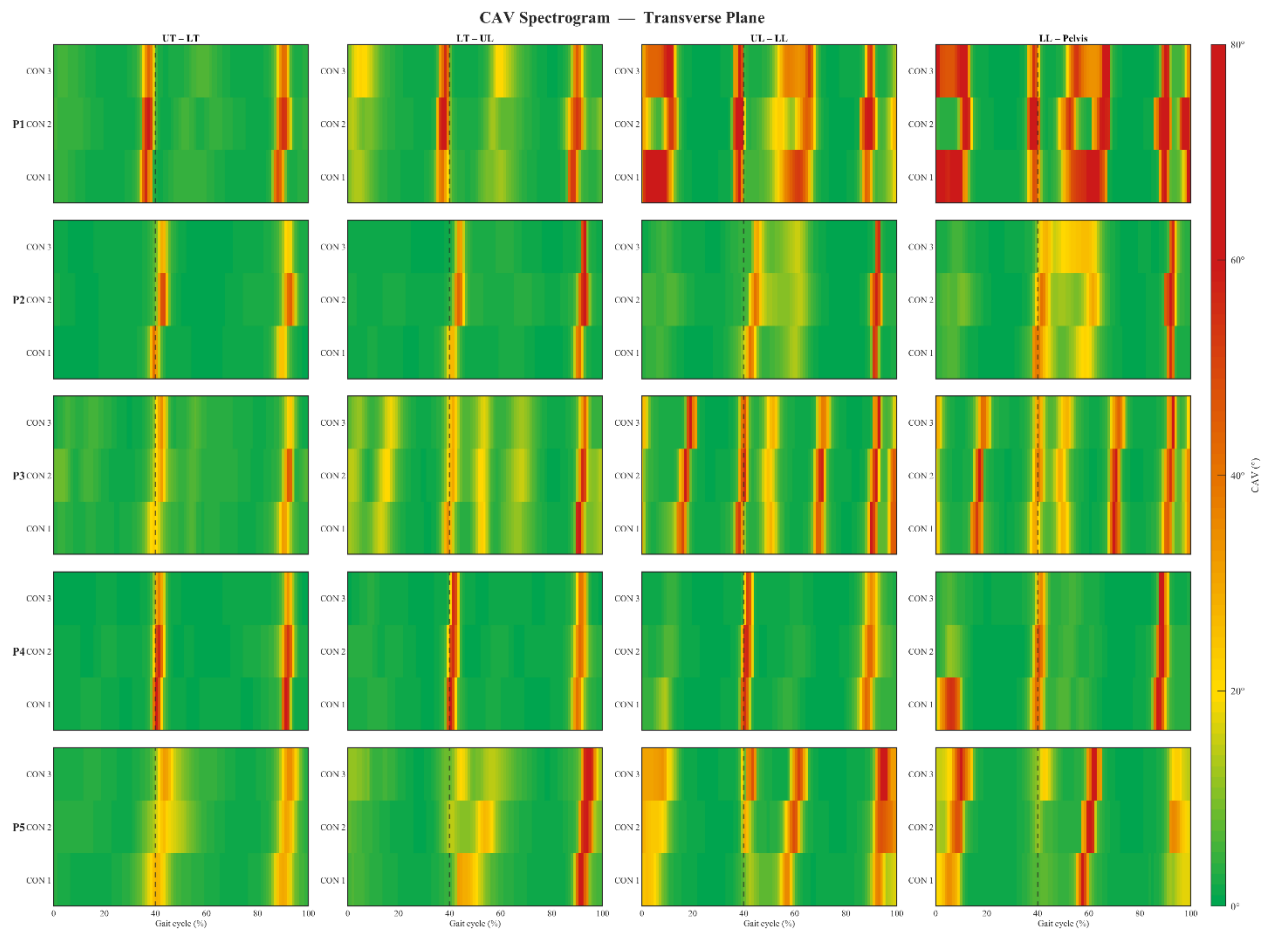
Note. Each row block shows one participant (P1–P5), with coupling angle variability (CAV, in degrees) plotted across the gait cycle (0–100%, x-axis) for CON1, CON2, and CON3 (stacked rows within each block, bottom to top). Columns correspond to the four adjacent spine segment pairs (UT–LT, LT–UL, UL–LL, LL–Pelvis; UT = upper thoracic, LT = lower thoracic, UL = upper lumbar, LL = lower lumbar). Colour encodes CAV magnitude on a continuous green–yellow–orange–red scale (0–80°), with green indicating low variability and red indicating high variability. The dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle. CON1 and CON3 = running at the first ventilatory threshold (VT1), minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold (VT2), minutes 10–20.

Figure 8.13. Coupling Angle Variability Spectrogram by Participant, Segment Pair, and Condition: Frontal Plane.



Note. Each row block shows one participant (P1–P5), with coupling angle variability (CAV, in degrees) plotted across the gait cycle (0–100%, x-axis) for CON1, CON2, and CON3 (stacked rows within each block, bottom to top). Columns correspond to the four adjacent spine segment pairs (UT–LT, LT–UL, UL–LL, LL–Pelvis; UT = upper thoracic, LT = lower thoracic, UL = upper lumbar, LL = lower lumbar). Colour encodes CAV magnitude on a continuous green–yellow–orange–red scale (0–80°), with green indicating low variability and red indicating high variability. The dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle. CON1 and CON3 = running at the first ventilatory threshold (VT1), minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold (VT2), minutes 10–20.

Figure 8.14. Coupling Angle Variability Spectrogram by Participant, Segment Pair, and Condition: Transverse Plane



Note. Each row block shows one participant (P1–P5), with coupling angle variability (CAV, in degrees) plotted across the gait cycle (0–100%, x-axis) for CON1, CON2, and CON3 (stacked rows within each block, bottom to top). Columns correspond to the four adjacent spine segment pairs (UT–LT, LT–UL, UL–LL, LL–Pelvis; UT = upper thoracic, LT = lower thoracic, UL = upper lumbar, LL = lower lumbar). Colour encodes CAV magnitude on a continuous green–yellow–orange–red scale (0–80°), with green indicating low variability and red indicating high variability. The dashed vertical line marks the stance-to-swing transition at 40% of the gait cycle. CON1 and CON3 = running at the first ventilatory threshold (VT1), minutes 0–10 and 20–30; CON2 = running at the second ventilatory threshold (VT2), minutes 10–20.

8.4 Discussion

This study examined multi-segment spine kinematics, inter-segmental coordination, coordination variability and pulmonary $\dot{V}O_2$ across a 30-minute treadmill protocol comprising baseline VT1 running (CON1), increased-intensity VT2 running (CON2), and a return to VT1 running (CON3). The discussion is organised around the three transitions embedded within the protocol: adaptation to increased running intensity, recovery after the higher-intensity bout, and the residual effect observed when the initial and final VT1 stages are compared. This structure is important because the study did not simply ask whether runners were different at the end of the protocol. Instead, it examined how the movement system changed when speed increased, how far that change reversed when speed was reduced, and whether any remaining biomechanical or physiological signature persisted at the final VT1 bout.

The central finding was that the response to increased running intensity was not a uniform increase in all outcomes, nor was recovery a simple mirror image of adaptation. Step rate, segmental ROM, coordination pattern, CAV and $\dot{V}O_2$ all changed across the protocol, but they did so at different rates and with different degrees of recovery. This indicates that the higher-intensity bout altered both the mechanical execution of running and the organisation of inter-segmental spinal coordination. The three-condition design was therefore essential. A comparison of CON1 and CON3 alone would have shown only the residual endpoint, whereas the inclusion of CON2 revealed that some variables changed substantially during the protocol and then only partially returned toward baseline.

8.4.1 CON1 to CON2: Adaptation to Increased Running Intensity

The transition from CON1 to CON2 produced a clear adaptation to the increased task demand. Step rate increased, cycle time shortened, and segmental ROM increased across the spine and pelvis. These changes are expected when running speed increases, because the runner must complete each stride more quickly while maintaining forward progression, balance and force transfer. In practical terms, the faster VT2 bout required a more rapid coordination of the trunk, pelvis and lower limbs. The temporal-spatial data therefore confirm that the experimental manipulation was effective: CON2 was not simply a metabolically harder condition, but a mechanically different running task.

The largest segmental changes occurred in the transverse plane, especially around the LT, UL and LL regions. This is important because axial rotation is one of the primary ways the trunk and pelvis help regulate angular momentum during running. When step rate

increases, the upper body must continue to counterbalance pelvic and lower-limb motion while allowing efficient arm swing and maintaining forward orientation. The increase in transverse ROM therefore likely reflects a greater requirement for axial motion distribution through the spine-pelvis system rather than a non-specific increase in movement. This interpretation is consistent with previous work showing that spinal and pelvic axial rotation are sensitive to changes in running speed (Preece et al., 2016a, 2016b; Schache et al., 2002; Saunders et al., 2005; Tojima et al., 2019).

However, the response was not simply that the spine moved more. The increase in CAV from CON1 to CON2 in many participant-pair combinations suggests that the consistency of inter-segmental coordination was also altered. This distinction matters. ROM describes how much a segment moved, whereas CAV describes how consistently adjacent segments were coordinated across repeated strides. An increase in CAV therefore suggests that the higher-intensity bout challenged the stability of some coordination patterns or required the system to operate with a broader range of stride-to-stride solutions. Under the constraints-led framework, this should not be interpreted automatically as error. It may reflect functional adaptability as the runner reorganises movement to meet the greater speed demand (Newell, 1986; Glazier & Davids, 2009; Glazier, 2017).

The coordination pattern data explain why this change in variability is meaningful. Several CON1-to-CON2 changes involved a shift in segmental dominance, particularly at the transverse LT-UL coupling. In P2 and P4, increased intensity was associated with stronger proximal dominance, suggesting that the lower thoracic region contributed more strongly to the coupled thoracolumbar motion. This may indicate that these runners relied more on upper trunk or thoracic control to manage the increased rotational demand at VT2. In contrast, P1 and P5 remained comparatively stable, while P3 retained a distinct anti-phase component. The same speed constraint therefore produced different coordination strategies across runners.

This finding is critical because it shows why a group-level increase in transverse ROM is not sufficient to explain the adaptation. At group level, the result could be described as a speed-related increase in axial motion. At the individual level, the mechanism appears more complex. Some runners increased movement magnitude while maintaining a similar coordination structure, whereas others changed which segment dominated the coupled motion. This means that increased running intensity affected spinal movement at three separable levels: the amount of motion, the consistency of coordination, and the pattern of

inter-segmental dominance. The adaptation to CON2 was therefore not simply biomechanical scaling; it was a reorganisation of movement control in several runners.

The physiological data provide an additional context for this interpretation. CON2 was performed at VT2, where oxygen uptake kinetics are expected to become less stable and where a slow component may emerge during sustained heavy-intensity exercise (Burnley & Jones, 2007; Jones & Burnley, 2009; Poole et al., 1988). Four of five participants showed a positive $\dot{V}O_2$ slow component, indicating that the higher-intensity stage imposed a progressive metabolic cost. It is plausible that this rising physiological demand contributed to the altered coordination response, either through increasing neuromuscular demand, changing muscle recruitment strategy or reducing the efficiency with which existing coordination patterns could be maintained. The present study cannot identify the exact neuromuscular mechanism, but the concurrent change in ROM, CAV and $\dot{V}O_2$ supports the interpretation that CON2 represented a meaningful cross-domain perturbation rather than an isolated change in speed.

8.4.2 CON2 to CON3: Recovery Following High-Intensity Running

The return from CON2 to CON3 showed partial recovery, but not full reversal. Step rate decreased and cycle time lengthened toward CON1 values, showing that participants mechanically responded to the lower VT1 speed. Frontal- and transverse-plane ROM also reduced from CON2 to CON3, and CAV decreased in many participant-pair combinations. These changes show that the system did begin to move back toward the original lower-intensity running pattern. However, the recovery was incomplete because several variables remained different from CON1, and $\dot{V}O_2$ did not return fully to baseline in any participant within the 10-minute CON3 window.

This incomplete recovery is important because it shows that reducing the treadmill speed did not immediately restore the initial movement state. The most likely explanation is that the preceding VT2 bout left a residual physiological and neuromuscular load that continued to influence the subsequent VT1 running. Heavy-intensity exercise can produce a delayed elevation in oxygen uptake and a prolonged recovery response after the workload is reduced (Jones et al., 2011; Rossiter et al., 2002). In the present study, the mean $\dot{V}O_2$ recovery was $73.1 \pm 14.4\%$, meaning that the runners were still operating above their initial metabolic baseline at the end of CON3. The biomechanical and coordination findings suggest that spinal movement may also carry this residual load, with some coordination patterns remaining altered or continuing to evolve during the recovery stage.

The key point is that CON3 was not merely a passive recovery period. It was a new running condition in which participants returned to the original speed while still carrying the effects of the VT2 bout. This helps explain why some coordination changes emerged at CON3 rather than at CON2. For example, sagittal LT-UL coordination in P2 and P4 changed specifically during C3, indicating that the recovery bout required a different coordinative solution from both the initial VT1 and the higher-intensity VT2 stage. Similarly, P4 showed a monotonic shift in frontal UL-LL coordination across all three conditions rather than a simple increase followed by reversal. These patterns suggest that recovery can involve active reorganisation, not simply the undoing of the previous adaptation.

This interpretation also clarifies why each subsection of the discussion needs to consider both direction and timing of change. A variable that decreases from CON2 to CON3 may appear to be recovering, but it may still remain above CON1. Conversely, a coordination pattern that changes most clearly at CON3 may represent a delayed response to the previous high-intensity bout rather than immediate adaptation to speed. The timing of change therefore matters. The present findings show that some outcomes responded directly to the speed increase, some began to reverse when speed was reduced, and others appeared to reorganise later during the return-to-VT1 stage.

CAV further supports this interpretation. At group level, CAV generally decreased from CON2 to CON3, suggesting improved consistency once the intensity was reduced. However, individual trajectories show that this was not a universal recovery response. P4 showed one of the clearest reductions in CAV across planes and segment pairs, suggesting that this participant may have stabilised coordination by the end of the protocol. P5, by contrast, reduced sagittal CAV from CON1 to CON2 and maintained this lower variability at CON3, especially at distal segment pairs. This suggests a different strategy: rather than becoming more variable under speed demand, P5 may have constrained distal spinal variability to maintain control. This response is important because it shows that a decrease in CAV is not always a sign of recovery; in some participants, it may be the primary adaptation strategy.

The physiological recovery profiles also help explain the participant-specific nature of CON3. P4 had the most complete $\dot{V}O_2$ recovery and also showed a relatively coherent reduction in CAV, which may indicate a runner whose physiological and coordinative systems were returning toward a stable lower-demand state. In contrast, P1 and P2 had larger residual $\dot{V}O_2$ deficits, suggesting that they remained under greater metabolic strain during CON3. Their coordination profiles also showed persistent or divergent pelvis-adjacent

patterns. Although causal conclusions cannot be drawn, the co-occurrence of incomplete $\dot{V}O_2$ recovery and persistent coordination differences suggests that physiological recovery and movement recovery should be interpreted together rather than separately.

Overall, the CON2-to-CON3 transition demonstrates that recovery was domain-specific and participant-specific. Temporal-spatial variables recovered most clearly because they were directly constrained by the treadmill speed. Physiological variables recovered least completely because metabolic perturbation persisted after the VT2 bout. Coordination variables sat between these two responses, with some returning toward baseline and others showing delayed or persistent reorganisation. This provides a stronger explanation than simply stating that recovery was incomplete: recovery was incomplete because each domain has a different time course and because each runner resolved the return-to-VT1 condition using a different coordination strategy.

8.4.3 CON1 versus CON3: Evidence of a Residual, Incompletely Reversed Effect

The CON1-versus-CON3 comparison is critical because both stages were performed at VT1. Any remaining difference at CON3 therefore reflects the residual influence of the preceding VT2 bout rather than a difference in prescribed speed. Step rate remained modestly elevated, frontal- and transverse-plane ROM remained above baseline in several segments, and whole-stage $\dot{V}O_2$ was higher at CON3 than CON1 in four of five participants. This shows that the final VT1 bout was not equivalent to the initial VT1 bout. The runners had returned to the same relative speed, but not to the same physiological or coordinative state.

The residual effect was plane-specific. Sagittal-plane motion showed the closest return to baseline, whereas frontal and transverse responses were more likely to remain elevated. This matters because sagittal motion in this protocol was relatively small and appeared less sensitive to the speed manipulation. Frontal and transverse planes, by contrast, are more closely related to lateral control, axial rotation and pelvis-spine coupling. These are the planes most likely to be challenged when runners increase speed and then attempt to stabilise movement after the higher-intensity bout. The residual frontal and transverse changes therefore suggest that the prior VT2 stage left a remaining coordination demand in the planes most involved in trunk-pelvis control.

The transverse residual is particularly important. Previous studies have shown that transverse-plane spine and pelvis motion increase with running speed (Preece et al., 2016a, 2016b; Saunders et al., 2005; Tojima et al., 2019). The present findings extend this by showing that the rotational response may not fully disappear when speed is reduced. This

suggests that axial trunk and pelvis control may have a short-term memory of the previous high-intensity state, either because the neuromuscular system has not fully recovered or because the runner adopts a slightly altered movement solution to manage residual fatigue or metabolic cost. This does not mean that runners were fatigued in a global sense, but it does indicate that their movement system had not fully returned to its initial state.

The residual coordination effects were also participant-specific. At the frontal LL-Pelvis pair, P1 shifted from proximal toward distal dominance and did not fully return, whereas P2 remained almost completely proximal-dominant across the protocol. At the transverse LL-Pelvis coupling, P2 remained a stable distal-dominant outlier, while P1 changed substantially. These examples are important because the pelvis-adjacent couplings represent the interface between spinal motion and whole-body running mechanics. A residual change at these couplings may indicate that the runner altered how motion was distributed between the lumbar spine and pelvis after the VT2 bout. This may be one way of maintaining running at VT1 when metabolic recovery is incomplete.

The physiological findings reinforce this interpretation. Whole-stage $\dot{V}O_2$ remained elevated at CON3 in most participants, which indicates a residual metabolic cost of the preceding heavy-intensity bout. P1 and P2 showed the largest residual deficits and also displayed notable pelvis-adjacent coordination features. This does not prove that elevated $\dot{V}O_2$ caused the coordination changes. However, it does show that incomplete metabolic recovery and altered coordination can co-exist within the same protocol and, in some cases, within the same participants. This cross-domain finding is important because running economy and biomechanics are often discussed separately, whereas the present study suggests that recovery from increased intensity may involve both systems simultaneously.

Therefore, the CON1-versus-CON3 comparison should not be treated as a simple pre-post test. It should be interpreted as the endpoint of a transition sequence. A small net residual change can hide a large response at CON2 followed by partial reversal, while a larger residual change can indicate either incomplete recovery or delayed reorganisation during CON3. This distinction is one of the main methodological contributions of the study. The three-condition design allowed the final VT1 bout to be interpreted in light of the preceding speed manipulation, rather than as an isolated comparison with baseline.

8.4.4 Individual Differences as a Unifying Theme Across Transitions

Across ROM, CAV, coordination dominance and $\dot{V}O_2$, the most consistent finding was inter-individual variation. This was not random noise around a single group response. Instead, several participants showed stable response profiles across multiple outcomes. This supports the constraints-led interpretation adopted throughout the thesis, where movement emerges from the interaction of task demands with individual constraints such as morphology, mobility, fitness, training history and habitual coordination tendencies (Newell, 1986; Glazier & Davids, 2009; Glazier, 2017). The same speed manipulation therefore created a common task demand, but each runner solved that demand differently.

P2 provides a clear example. This participant showed highly stereotyped frontal LL-Pelvis coordination, with near-total proximal-dominant coordination across conditions, yet also showed meaningful changes elsewhere and one of the largest $\dot{V}O_2$ slow components. This suggests that a stable strategy in one coupling does not mean the runner is globally rigid or unresponsive. Instead, P2 may have protected or maintained a preferred pelvis-adjacent coordination pattern while adapting at other regions. This is important because it shows that adaptation may be localised: runners can preserve some coordinative relationships while altering others.

P1 showed a different profile. This participant repeatedly diverged from the group at pelvis-adjacent couplings and showed the most incomplete $\dot{V}O_2$ recovery. One possible interpretation is that P1 had a less complete recovery from the VT2 perturbation and therefore required a different lumbar-pelvis coordination strategy during the final VT1 stage. Again, this cannot be treated as causal, but it provides an example of how physiological and coordinative responses may align at the individual level. P4, in contrast, showed relatively complete physiological recovery and a coherent reduction in CAV, suggesting a more stable return toward a lower-demand state. P5 showed another distinct strategy, reducing sagittal CAV during the higher-intensity bout and relying on an atypical distal sagittal pattern. These individual profiles explain why the group mean alone is insufficient.

The wider implication is that running adaptation cannot be fully understood by asking only whether the group increased or decreased a given variable. Two runners may show similar group-level ROM changes while achieving them through different segmental dominance patterns. Similarly, two runners may show similar $\dot{V}O_2$ responses while differing in whether spinal coordination becomes more or less variable. The present findings therefore support the single-subject approach because it identifies the form of adaptation, not only its average direction. This is particularly important for multi-segment spine analysis, where

adjacent regions can redistribute motion between one another in ways that are lost when data are collapsed into a single trunk measure or group mean.

8.4.5 Practical Significance Framework and Interpretation of Meaningful Change

The dual MDC₉₅/Hedges' *g* criterion strengthened the interpretation of individual change because it required each response to be evaluated against that participant's own variability. This was necessary because small angular differences can appear important when trial-to-trial variability is low, while larger differences may be less convincing if measurement noise is high. The approach therefore helped avoid two common problems: over-interpreting small but statistically amplified changes, and dismissing individual responses that were large enough to exceed measurement error.

This framework is especially important in the sagittal plane, where absolute changes were often small. Some sagittal effects reached large standardised values because the participant's movement was very consistent across trials. Without the MDC₉₅ criterion, these could be misread as functionally meaningful changes in spinal control. Conversely, by combining MDC₉₅ with Hedges' *g*, the analysis identified changes that were both large relative to within-participant variability and large enough to exceed measurement error. This better matches the central question of the study, which was not whether any numerical difference occurred, but whether the speed constraint produced a practically meaningful change in spinal movement organisation.

Interpreting practical significance alongside vector-coding outputs added a further layer of criticality. A meaningful ROM or CAV change was most persuasive when it coincided with a change in coordination pattern or dominance. For example, a shift in LT-UL dominance provides stronger evidence of reorganisation than a small ROM difference alone. Conversely, a large standardised effect within measurement noise may reflect a very stable pattern rather than a new coordinative state. This combined interpretation helped distinguish true movement reorganisation from numerical fluctuation. It also aligns with the thesis aim of understanding how runners adapt, rather than simply identifying whether variables differ.

8.5 Limitations

Several limitations should be considered. is that the study included only male runners. This is particularly relevant to the speed manipulation because previous evidence has identified sex-related differences in thoracic kinematic responses across running speeds (Fisher et al., 2018). Another limitation is the small sample size of five sub-elite male

runners. The adaptive patterns observed between VT1 and VT2 should therefore be interpreted as male-specific response profiles rather than assumed to represent female runners. The broader finding that increasing task demand can produce individual and region-specific spinal reorganisation may provide a framework for studying female runners, but the magnitude, timing, dominance and variability of those adaptations require direct investigation in female cohorts. This was appropriate for an individual-level analytical approach and for the thesis focus on trained runners, but it means that group-level findings should be interpreted as a summary of five cases rather than as population estimates. The participant-specific profiles identified here should therefore be treated as evidence of possible adaptive strategies, not definitive categories that can be generalised to all runners.

Second, the study used a single-session design. Although the reliability work elsewhere in the thesis supports the use of the skin-marker model, this study cannot confirm whether each participant would reproduce the same speed-recovery profile on another day. This is important because the most interesting findings are individual profiles, such as P4's coherent recovery pattern or P5's atypical reduction in sagittal variability. Future repeated-session work would be needed to determine whether these profiles reflect stable individual traits or session-specific responses.

Third, the 10-minute CON3 stage may not have been long enough to observe full recovery. $\dot{V}O_2$ remained elevated in all participants, and several coordination variables had not returned fully to baseline. A longer recovery window would help determine whether the residual differences observed here represent delayed recovery, persistent reorganisation or a new stable movement state after heavy-intensity running. Finally, vector coding describes coordination pattern, dominance and variability, but it cannot identify the neuromuscular mechanism responsible for those changes. Combining this approach with electromyography or trunk muscle fatigue measures would help determine whether changes in dominance reflect altered recruitment, mechanical coupling or threshold effects within the vector-coding classification.

8.6 Conclusion

This study showed that increased running intensity altered multi-segment spine kinematics, inter-segmental coordination, coordination variability and pulmonary $\dot{V}O_2$ in sub-elite runners. The transition from CON1 to CON2 increased mechanical and metabolic demand, which was expressed through increased step rate, greater segmental ROM, altered CAV and participant-specific shifts in coordination dominance. These changes indicate that

the higher-intensity bout affected not only how much the spine and pelvis moved, but also how adjacent segments were organised relative to one another.

Recovery from CON2 to CON3 was partial rather than complete. Although temporal-spatial variables and several kinematic outcomes moved back toward CON1, $\dot{V}O_2$ remained elevated in all participants, and some coordination patterns either persisted or emerged during the recovery bout. The CON1-versus-CON3 comparison therefore demonstrated a residual effect of the preceding VT2 stage, particularly in frontal and transverse plane variables and in pelvis-adjacent coordination. This supports the value of the three-condition design, because a simple pre-post comparison would have underestimated the adaptation that occurred at CON2 and would not have explained why CON3 differed from CON1.

Importantly, the group-level pattern was underpinned by distinct individual response profiles. Some runners appeared to adapt through increased movement magnitude, others through changes in coordination dominance or variability, and others showed more persistent physiological or coordinative residual effects. These findings support the single-subject and constraints-led approach used in this thesis and suggest that running adaptation should be interpreted as an individually organised response to task demand rather than as a single uniform group response. Future work should examine whether these cross-domain profiles are stable across repeated sessions and whether they reflect generalisable traits in movement adaptability.

Chapter 9

Overall discussion

Chapter 9. Overall Discussion

This chapter brings together the methodological and empirical findings of the thesis to explain what has been learned about multi-segment spinal motion, coordination variability and physiological demand during running. The purpose of the chapter is not to restate each empirical study, but to integrate the programme of work into a thesis-level explanation of how trained runners adapt when task demands change. The central argument developed across the thesis is that running is a whole-body coordinative task, and that the spine should not be reduced to a single rigid trunk segment when the research question concerns fatigue, speed, running economy or movement adaptation (Preece et al., 2016; Schache et al., 2002; Seay et al., 2011).

Across the thesis, adaptation was not expressed as a uniform increase or decrease in spinal motion. Instead, altered task demands were managed through selective changes in regional movement, waveform timing, segmental dominance and coupling-angle variability. The broad structure of gait was generally preserved, but the local organisation used to maintain that gait changed. This distinction is important because it shows that visible stability in running form can coexist with meaningful underlying reorganisation. In this sense, the thesis supports a constraints-led interpretation of running, where movement emerges from the interaction between the task, the performer and the environment rather than from one fixed ideal technique (Newell, 1986; Davids et al., 2008; Renshaw et al., 2019).

9.1 Thesis aim

The overall aim of the thesis was to investigate spinal and whole-body biomechanical and physiological adaptation during running using a validated and reliability-informed multi-segment kinematic approach. This aim developed from three related gaps in the literature. First, the systematic review showed that there was limited consistency in how spine, back and pelvis motion had been modelled and reported during running. Second, it was unclear whether different multi-segment marker approaches produced comparable dynamic outputs, particularly in the transverse plane and lumbar region. Third, many running studies relied on group-level or discrete kinematic outcomes, which may obscure individual coordinative solutions (Bates, 1996; Glazier & Mehdizadeh, 2019).

The thesis addressed these gaps through a progressive research programme. The systematic review established the methodological fragmentation of the running-spine literature.

The model-comparison and reliability studies then showed why model choice and measurement error must be considered before interpreting adaptation. The applied studies used acute localised fatigue and increased speed as manipulated constraints to examine whether trained runners preserved, modified or reorganised spinal coordination under changing demand. The thesis therefore moved from a methodological question, how spinal motion should be measured, to a functional question, how runners use regional spinal coordination to maintain running when constraints change.

9.2 Integrated finding 1: Methodological model choice shapes the interpretation of spinal adaptation

A primary finding of the thesis is that conclusions about spinal adaptation are shaped by the model used to measure it. The systematic review showed substantial variation in marker configuration, segment definition, coordinate-system construction, reference frame, rotation sequence, filtering, footwear control, speed prescription and outcome reporting. These are not minor reporting details. They determine what the measured variable represents. A value labelled as trunk, lumbar or pelvic motion may refer to a different anatomical construct, segment relationship or mathematical reference frame across studies. This problem is consistent with wider gait-analysis literature showing that model definition and reporting quality directly influence interpretability and reproducibility (Simon, 2004; Benedetti et al., 2017; Leardini et al., 2009).

The model-comparison study demonstrated this issue directly. Both the skin-marker-set and cluster models showed excellent static criterion validity, but their dynamic running outputs were not interchangeable. Agreement was strongest in the sagittal plane, partial in the frontal plane and weakest in the transverse plane. The most important finding was not simply that one model measured more movement than the other, but that the models redistributed axial rotation differently across spinal regions. The skin-marker-set model attributed more transverse motion to the lower thoracic region, whereas the cluster model attributed more motion to the lumbar region. Therefore, the same runner and the same running task could support different biological interpretations depending on the selected marker model.

This finding has important consequences for the applied chapters. The fatigue and speed studies repeatedly identified transverse-plane and middle-spinal responses as sensitive to altered constraints. These findings are meaningful, but they must be interpreted at the correct

methodological level. They show changes in model-derived regional spine and back behaviour, not direct vertebral motion. This distinction strengthens the thesis because it prevents overclaiming. The thesis does not argue that one model provides absolute anatomical truth during running. Rather, it argues that when a consistent and reliability-informed model is used, regional coordination patterns can be examined meaningfully within that model and across controlled constraints.

The reliability study provided the second part of this methodological foundation. The selected skin-marker-set model demonstrated acceptable between-session repeatability for most running variables, but not all planes and regions were equally stable. Lumbar sagittal range of motion and a phase-specific period of upper-thoracic axial rotation required particular caution. This is important because the applied studies often found their clearest effects in coordination pattern, dominance and variability rather than in small sagittal ROM changes. Reliability therefore shaped interpretation by identifying which changes were likely to exceed measurement sensitivity and which should be treated more conservatively. In this way, measurement error was not an afterthought; it was part of the logic used to interpret adaptation.

Taken together, the methodological studies show that model choice determines the biological story that can be told. A simplified trunk model may describe global posture, but it cannot show how thoracic and lumbar regions redistribute motion. A multi-segment model provides richer regional information, but it also requires careful reporting, direct reliability evidence and cautious anatomical interpretation. The first thesis-level contribution is therefore methodological: before spinal adaptation during running can be explained, the measurement model and its limitations must be made explicit (Bramah et al., 2021; Needham et al., 2016; Preece et al., 2016).

9.3 Integrated finding 2: Runners preserved global gait while reorganising local spinal coordination

Across acute fatigue and increased speed, the most consistent applied finding was preservation of global gait alongside selective reorganisation of local spinal coordination. The runners continued to complete the treadmill task and generally retained recognisable waveform structure, but the local organisation of spine-pelvis movement changed. This pattern fits the constraints-led framework underpinning the thesis. Movement stability does not mean that every component remains unchanged. A runner can preserve the task goal while redistributing

control across available degrees of freedom (Newell, 1986; Davids et al., 2008; Glazier & Davids, 2009).

The fatigue study illustrates this clearly. Acute localised lower-limb fatigue did not produce a widespread collapse in spinal mechanics. Instead, the clearest changes were concentrated around transverse-plane orientation, the stance-to-swing transition and the lumbopelvic interface. The thoracic transverse coordination pattern was comparatively robust, whereas the lumbopelvic region reorganised toward increased pelvic dominance and greater inter-individual coordination variability. This suggests that fatigue was not expressed primarily as a visible deterioration in running form. Rather, the system absorbed the perturbation through local changes in how the spine and pelvis shared motion, dominance and variability.

The meaning of this finding is that fatigue may affect the control of running before it produces obvious changes in gross technique. If analysis is limited to lower-limb variables, centre-of-mass outcomes or visual observation, the runner may appear relatively stable. However, the multi-segment coordination results show that the internal organisation of the movement changed. This helps explain why fatigue-running studies have sometimes reported inconsistent or modest changes in conventional kinematics: the response may be redistributed into axial coordination, phase timing or variability rather than appearing as a simple change in one discrete angle (Abt et al., 2011; Derrick et al., 2002; Dierks et al., 2010; Koblbauer et al., 2014).

The speed study provided a related but more transition-based example. Increasing intensity from VT1 to VT2 increased temporal and mechanical demand, including higher step rate, shorter cycle time and larger segmental motion, particularly in the transverse plane. These findings align with previous evidence that running speed changes lumbo-pelvic and trunk kinematics (Saunders et al., 2005; Schache et al., 2002; Preece et al., 2016; Tojima et al., 2019). However, the important thesis-level point is that faster running changed more than the amount of spinal motion. It also altered coupling-angle variability and segmental dominance, especially in middle spinal couplings. The speed constraint therefore changed how adjacent regions were coordinated, not simply how far they moved.

The return from VT2 to VT1 further strengthens this interpretation. If adaptation were only a direct response to treadmill speed, then reducing speed should have restored the original state. Instead, recovery was partial. Some temporal-spatial and kinematic variables moved back toward baseline, but oxygen uptake remained elevated, and some coordination patterns did not

fully return. This shows that the final VT1 condition was not equivalent to the initial VT1 condition. The external speed was the same, but the runner's internal physiological and coordinative state had changed. This aligns with the wider physiology literature showing that oxygen uptake recovery after higher-intensity exercise can be delayed and individually variable (Jones et al., 2011; Rossiter et al., 2002).

Taken together, the fatigue and speed studies show that different constraints can produce related but not identical adaptations. Fatigue altered the organismic state of the runner, while speed altered the external task demand and temporal organisation of gait. In both cases, the response was selective rather than global, and changes were often concentrated in coordination timing, dominance and variability within middle spinal couplings. These couplings may therefore act as an adaptive interface between the comparatively stable upper thoracic region and the pelvis-linked lumbar region. However, the participant-specific profiles show that this interface was not controlled in one uniform way.

Across the applied studies, adaptation should therefore not be equated automatically with deterioration. Some changes may reflect reduced stability or increased physiological cost, but others may represent functional reorganisation that allows the runner to preserve the task. This is why range of motion, waveform shape, vector-coding pattern and coupling-angle variability need to be interpreted together. A stable waveform can coexist with altered dominance. A small ROM change can sit alongside meaningful coordination reorganisation. Increased variability may reflect instability, but it may also reflect the exploration of alternative movement solutions. Its meaning depends on the region, plane, gait-cycle phase and physiological context (Hamill et al., 1999; van Emmerik et al., 2004; Needham et al., 2014, 2015).

9.4 Why these changes occurred: Mechanical, coordinative and physiological explanations

The changes observed across the thesis can be explained by considering how each manipulation altered the relationship between task demand, internal physiological state and available movement solutions. Increased speed changed the temporal organisation of running. Strides had to be completed more quickly, stance and swing durations shortened, and the trunk and pelvis had to coordinate over a shorter cycle. This likely increased the demand on axial rotation and counter-rotation because the upper body contributes to angular-momentum

regulation while the lower limbs and pelvis move more rapidly. The larger transverse-plane responses in the speed study are therefore biomechanically plausible rather than incidental (Saunders et al., 2005; Schache et al., 2002; Tojima et al., 2019).

The speed-related changes in dominancy also explain why adaptation was not simply a scaled version of baseline running. Some runners appeared to rely more heavily on proximal thoracolumbar contribution, whereas others preserved their original coupling strategy or retained anti-phase components. This suggests that when the temporal constraint increased, runners did not all solve the problem in the same way. Some increased movement magnitude, some changed which segment dominated the coupled motion, and some altered stride-to-stride consistency. The same increase in external demand therefore produced different internal coordination solutions.

Fatigue changed the organismic constraint rather than the treadmill condition. The box-jump protocol likely reduced or altered lower-limb force-production capacity and neuromuscular control. During the subsequent running bout, the same external task was performed by a runner whose internal state had changed. The spine may therefore have contributed to stabilising the task when the lower-limb system was perturbed. The fact that global gait remained largely preserved suggests compensation rather than collapse. This interpretation is consistent with previous work showing that locomotor muscle fatigue can increase cardiorespiratory demand independently of central metabolic stress, and that fatigue-related kinematic changes vary according to the protocol and athlete (Marcora et al., 2008; Clansey et al., 2012; Dierks et al., 2010).

Physiological demand helps explain why biomechanical recovery was incomplete in the speed study. Returning to VT1 speed restored the external condition but did not immediately restore the runner's internal state. Elevated oxygen uptake after the harder bout indicated a residual metabolic cost. Heavy-intensity exercise can produce a $\dot{V}O_2$ slow component and delayed recovery, partly associated with progressive recruitment of less efficient motor units and the time course of post-exercise metabolic restoration (Burnley & Jones, 2007; Jones & Burnley, 2009; Poole et al., 1988; Jones et al., 2011). It is therefore reasonable that some coordination patterns either persisted or continued to reorganise during recovery.

The thesis-level implication is that biomechanical and physiological responses should not be interpreted as separate systems. Increased $\dot{V}O_2$ and ventilatory demand indicate

increased internal cost, but the runner still has to organise movement mechanically. Conversely, altered coordination may help maintain the task, but it may also require greater internal effort. The present studies cannot determine the direction of causality. However, they show that mechanical and physiological changes co-occurred in participant-specific ways. Running economy, spinal coordination and movement variability should therefore be considered interacting features of adaptation rather than independent outcomes (Barnes & Kilding, 2015; Folland et al., 2017; Moore, 2016; Saunders et al., 2004).

9.5 Agreements, tensions and positioning within the wider literature

When the thesis findings are positioned within the wider literature, the clearest agreement is that running speed and fatigue do not affect the body through one isolated variable. Running economy is widely described as a multifactorial construct shaped by physiological, neuromuscular and biomechanical factors, while technique has been shown to contribute meaningfully to both economy and performance (Barnes & Kilding, 2015; Folland et al., 2017; Moore, 2016; Saunders et al., 2004; Williams & Cavanagh, 1987). The present thesis supports this view by showing that changes in oxygen cost and ventilatory demand occurred alongside changes in spinal coordination, but not through one consistent biomechanical pattern across all runners. This brings the thesis back to its central premise: running performance is maintained through interaction between systems, not through one isolated mechanical or physiological determinant.

The thesis also agrees with previous trunk and pelvis literature showing that speed changes lumbo-pelvic kinematics and trunk behaviour (Saunders et al., 2005; Schache et al., 2002; Preece et al., 2016; Tojima et al., 2019). However, it extends this work by separating the spine into upper thoracic, lower thoracic, upper lumbar and lower lumbar regions and by examining how adjacent segments coordinate through the gait cycle. Treating the trunk as one segment can be useful when the aim is to describe global posture, but it cannot reveal whether adaptation occurs through thoracic motion, lumbar motion, pelvis-linked change or altered dominance between regions. The present thesis therefore shows that meaningful adaptation can occur within the trunk, not only at the level of the trunk as a whole.

A further agreement is with coordination literature showing that movement variability should not be interpreted simply as error. Dynamical systems and constraints-led approaches view variability as part of how performers adapt to changing task demands (Hamill et al., 1999;

van Emmerik et al., 2004; Davids et al., 2008; Glazier, 2017). The thesis supports this position because increased CAV did not always indicate a failed pattern. In some runners, higher variability appeared to represent exploration or redistribution of control during a harder task. In others, persistent variability during recovery may have indicated that the original coordinative state had not yet been restored. Equally, a decrease in variability was not automatically positive; it could reflect a more constrained strategy used to maintain control. Variability therefore needs to be interpreted in relation to task preservation, physiological cost, region and gait-cycle phase.

The thesis extends previous coordination research by applying modified vector coding, segmental dominancy, IDP-ROM and CAV to multi-segment spine behaviour during running. Previous work has demonstrated the value of vector coding for lumbar-pelvis and gait coordination (Needham et al., 2014, 2015; Seay et al., 2011). This thesis builds on that foundation by showing that coupling pattern and variability reveal changes that are not apparent from ROM alone. The analytical emphasis therefore shifts from asking how much each spinal region moves to asking how neighbouring regions are organised relative to one another across the running cycle.

There is also an important methodological tension. The model-comparison study showed that transverse-plane outputs were model-sensitive, while the applied studies repeatedly identified transverse-plane responses as important. This tension should not be ignored. It means that exact transverse-plane angles should be interpreted cautiously and should not be treated as direct anatomical measurements. However, it does not mean that the transverse findings are unimportant. The repeated responsiveness of transverse-plane and middle-spinal coordination across different constraints suggests that these variables captured meaningful changes within the chosen model. The defensible conclusion is therefore balanced: transverse-plane values are model-derived, but their consistent responsiveness indicates that axial coordination is a key feature of running adaptation.

The fatigue findings refine previous literature in which fatigue has produced mixed or modest changes in lower-limb and trunk kinematics. Some studies have shown altered impact and kinematic adjustments after exhaustive running, whereas others have reported limited change in conventional running mechanics (Abt et al., 2011; Derrick et al., 2002; Dierks et al., 2010; Clansey et al., 2012). The present thesis suggests that limited visible change does not mean fatigue has little biomechanical effect. Instead, fatigue-related adaptation may be redistributed into axial coordination, lumbopelvic dominancy or variability while global gait

remains stable. This provides a possible explanation for inconsistent findings in fatigue-running studies: different methods may be detecting different levels of adaptation.

An unexpected finding was that recovery did not consistently mirror adaptation. In the speed study, returning to the original external condition did not immediately restore the original physiological or coordinative state. Some outcomes moved toward baseline, some remained elevated, and some changed most clearly during the recovery stage. This finding is important because it shows that adaptation has a history. The response at a given moment depends not only on the current treadmill speed, but also on the runner's preceding physiological and coordinative state. Two-condition designs can therefore miss the difference between immediate adaptation, residual effect and delayed recovery.

Finally, the thesis reinforces the value of individual analysis. Individual profiles were not random noise. Some runners showed coherent patterns across physiological and coordinative outcomes, whereas others solved the same task through different combinations of movement magnitude, dominance and variability. This supports the argument that group means can conceal meaningful movement solutions in biomechanics (Bates, 1996; Glazier & Mehdizadeh, 2019). The same group trend can be produced by different mechanisms across runners. A thesis concerned with adaptation must therefore retain the individual runner as a meaningful unit of analysis.

Overall, the thesis sits between two strands of literature: methodological work on how spine and trunk motion should be measured, and applied work on how runners adapt to changing constraints. Its contribution is to connect these strands. It shows that methodological choices influence what can be detected, and that when regional coordination is measured consistently, subtle but meaningful adaptation becomes visible beneath apparently stable running form. This is the main way in which the programme of studies comes together: measurement decisions shape interpretation, and interpretation becomes richer when spinal coordination, physiological demand and individual response profiles are considered as one adaptive system.

9.6 Theoretical and methodological contributions

This thesis contributes to the field in several ways. First, it demonstrates that multi-segment spinal adaptation during running is regional and relational. The spine should not be treated only as a passive extension of the pelvis or as a single rigid trunk when the research

question concerns coordination, fatigue or task constraints. Regional couplings can change even when whole-body gait appears stable. This supports the need for multi-segment models when the aim is to understand how running movement is organised rather than simply describe global trunk posture (Needham et al., 2016; Preece et al., 2016; Schache et al., 2002).

Second, the thesis provides a reliability-informed approach to interpreting running-spine kinematics. By combining model comparison, SEM, MDC95, waveform analysis and within-participant effect sizes, the research programme distinguishes measurement sensitivity from likely biological adaptation. This is especially important for small spinal angles and for transverse-plane variables where model architecture influences outputs. The approach responds directly to concerns in gait analysis that model construction, reliability evidence and reporting standards must be explicit before kinematic data can be interpreted confidently (Simon, 2004; Benedetti et al., 2017; Bramah et al., 2021).

Third, the thesis demonstrates the value of integrating discrete kinematics with coordination and variability analysis. ROM and waveform measures describe movement magnitude and timing, whereas vector coding describes phase relationship, segmental dominance and stride-to-stride consistency. These levels of analysis are complementary. None of them alone gives a complete account of adaptation. The combined approach was particularly important because some of the most meaningful thesis findings were coordinative rather than purely angular.

Fourth, the thesis contributes evidence for a constraints-led interpretation of running adaptation. Acute fatigue and increased speed did not produce one universal response. Instead, each runner reorganised selected degrees of freedom according to the interaction between the imposed constraint, their internal physiological state and their habitual coordination tendencies. This supports the view that variability and individual differences are central to understanding skilled running rather than errors to be averaged away (Newell, 1986; Davids et al., 2008; Renshaw et al., 2019).

Fifth, the thesis demonstrates the importance of transition-based designs. The speed study showed that returning to the original external condition does not necessarily restore the original physiological or coordinative state. Adaptation and recovery should therefore be studied as time-dependent processes rather than as static differences between isolated conditions. This is particularly important for endurance running, where fatigue, recovery and

economy are cumulative rather than momentary processes (Burnley & Jones, 2007; Jones et al., 2011).

Together, these contributions provide an analytical framework for future running-spine research: define the model clearly, test its reliability, interpret outputs at the correct anatomical and methodological level, examine both discrete and continuous outcomes, assess coordination between regions and preserve individual response profiles. This framework is one of the main outcomes of the thesis.

9.7 Practical and applied implications

For gait laboratories and researchers, the most immediate implication is that model choice must be matched to the research question. A simplified trunk model may be suitable when the aim is to capture global posture, but it is insufficient when the aim is to understand regional spinal coordination or spine-pelvis adaptation. Researchers should report segment definitions, marker placement, coordinate systems, rotation sequence, filtering, gait-event detection and reliability thresholds in enough detail for replication. Without this, comparison across studies may be misleading (Benedetti et al., 2017; Leardini et al., 2009; Simon, 2004).

For applied biomechanics and coaching, the findings caution against relying only on visible form or single kinematic variables when evaluating running adaptation. A runner may look stable while local coordination becomes more variable, more thoracic-dominant, more pelvis-dominant or more metabolically costly. This does not mean that every runner requires spinal coordination analysis in practice. Rather, it means that technique assessments should be interpreted with caution, especially after high-intensity running or fatigue exposure.

The findings also suggest that recovery following harder running bouts should not be assumed from pace alone. In the speed study, participants returned to the original external speed but retained elevated $\dot{V}O_2$ and, in some cases, altered coordination. For practitioners, this implies that an athlete may resume an easier pace while still carrying residual physiological and coordinative effects from the preceding bout. Training sessions that alternate intensity or fatigue exposure may therefore create adaptation during the transition periods as well as during the harder efforts themselves.

Finally, the individual response profiles suggest that coaching and rehabilitation decisions should avoid assuming one optimal spinal strategy. Some runners adapted through increased movement magnitude, others through changes in dominance or variability, and others

through preserving specific couplings while changing elsewhere. The applied implication is not to force all runners toward a single trunk pattern, but to understand whether an individual runner's strategy is repeatable, adaptable and sustainable for the task demands they face.

9.8 Overall strengths and limitations

A major strength of the thesis is its integrated methodological sequence. The applied findings were not interpreted in isolation; they were built on a systematic review, direct model comparison and reliability analysis. This strengthens the programme because it acknowledges that measurement choices influence interpretation. The use of multi-segment modelling, waveform analysis, vector coding, CAV, IDP-ROM, physiological measurement and individual-level analysis provided a richer account of adaptation than any single method could provide.

A second strength is the consistency of the participant group. Focusing on Tier 3 sub-elite male runners reduced heterogeneity related to training status, treadmill familiarity and running exposure. This was important because the thesis aimed to detect subtle spinal coordination responses rather than broad differences caused by inconsistent running experience. However, the same feature represents an important limitation to external validity. The findings cannot be assumed to generalise directly to female runners, particularly because sex-related differences have previously been reported in lumbo-pelvic mechanics, thoracic kinematics and coordination variability during running (Schache et al., 2003; Boyer et al., 2017; Fisher et al., 2018). From the constraints-led perspective adopted throughout this thesis, sex can be considered one of several individual constraints capable of influencing the movement solution that emerges when task demand changes. The central theoretical finding that runners preserve global task performance through local coordinative adaptation may therefore provide a relevant framework for both male and female runners; however, the specific regional changes, coordination patterns, segmental dominance and variability reported within this thesis should be considered specific to the male cohorts investigated. Direct replication in appropriately classified female running populations is required before the magnitude or direction of these responses can be generalised.

The small sample size in the speed study is another limitation. The individual-level approach was appropriate for exploring adaptation profiles, but the study was not powered to estimate population effects or test predictors of response. The results should therefore be

interpreted as evidence of possible adaptive mechanisms and individual strategies, rather than definitive prevalence estimates. Future work must determine whether the profiles observed here are stable across repeated sessions and larger cohorts.

A further thesis-level limitation is that all spinal outcomes were derived from external markers or clusters. Skin movement, soft-tissue artefact, marker-placement error and segment construction all influence the measured signals. Static criterion validity and between-session repeatability do not establish dynamic vertebral validity. This limitation is especially important because the thesis repeatedly identifies transverse-plane and middle-spinal variables as sensitive. The findings should therefore be interpreted as model-derived spinal and back segment behaviour, not direct measurement of vertebral motion.

The experimental designs also used controlled treadmill tasks. This improved standardisation and supported comparison across studies, but it limited ecological validity. Outdoor running includes terrain changes, pacing decisions, wind resistance, turns and naturally developing fatigue. The fatigue protocol was acute and localised rather than a prolonged endurance-fatigue model. Similarly, the fixed duration of the speed recovery stage may have captured only part of the recovery process. These limitations do not undermine the thesis findings, but they define the conditions under which they apply.

9.9 Future research directions

Future research should extend the methodological work by validating multi-segment spine models against dynamic reference methods where feasible. Dynamic imaging, fluoroscopy or other independent approaches may not be practical during running for all segments, but targeted validation would help determine how much of the observed regional motion reflects vertebral movement, soft-tissue artefact or model construction. Inter-rater and multi-session reliability should also be examined, particularly for the middle couplings and transverse-plane variables that emerged as sensitive across this thesis.

A second priority is to test whether the individual response profiles observed here are stable. Repeated exposure to the same fatigue and speed protocols would help determine whether runners have characteristic coordination signatures or whether the profiles vary substantially from day to day. Hierarchical or mixed-effects modelling could preserve individual trajectories while estimating population-level tendencies. Larger and more diverse

samples would also allow examination of sex, performance level, age, training history, strength, mobility and injury status as potential moderators of spinal adaptation.

Future studies should also examine longer and more ecologically valid running tasks. Prolonged runs, outdoor terrain, variable pacing and race-like demands would help establish whether the selective spinal coordination changes observed under controlled treadmill conditions also occur during natural training and competition. Longer recovery periods are particularly important. The present findings suggest residual physiological and coordinative effects after return to the original condition, but it remains unclear how long these effects persist and whether they resolve, stabilise or develop into new coordination states.

Finally, future research should model biomechanical and physiological responses jointly. Time-resolved analyses could test whether changes in CAV, dominance or waveform behaviour precede, accompany or follow changes in $\dot{V}O_2$, ventilatory equivalents, RER or perceived exertion. Adding electromyography would help determine whether changes in segmental dominance reflect altered trunk muscle recruitment, mechanical coupling or classification-threshold effects within vector coding. This work is needed before spinal coordination can be considered a modifiable determinant of running economy rather than an associated adaptive response.

9.10 Overall conclusion

This thesis established that multi-segment spinal behaviour during running is adaptive, region-specific and dependent on the constraint imposed. Acute fatigue and increased speed did not cause sub-elite runners to abandon their preferred running patterns. Instead, they altered selected features of spinal motion, coordination timing, segmental dominance and variability while preserving the broad structure of gait. These adaptations were often accompanied by increased or prolonged physiological cost, indicating that maintaining stable running form can require altered internal organisation.

The lower thoracic-upper lumbar, upper lumbar-lower lumbar and lower lumbar-pelvis relationships repeatedly emerged as sensitive interfaces across constraints, although they should be interpreted as model-derived segment behaviours rather than direct vertebral motions. The findings show that model choice, measurement reliability, plane of motion and gait-cycle phase all influence the conclusions that can be drawn. A single trunk segment or a

single discrete kinematic variable is therefore insufficient when the research question concerns regional adaptation, fatigue or the interaction between technique and physiology.

The natural conclusion of the thesis is that running performance is not maintained through one fixed ideal technique. It is maintained through the capacity to preserve the task goal while reorganising local coordination in response to changing constraints. By combining systematic review, model comparison, reliability thresholds, waveform analysis, modified vector coding, coordination variability, temporal-spatial analysis, physiological measurement and single-subject interpretation, the thesis shows that meaningful adaptation can occur beneath an apparently stable running pattern. This is the central contribution of the work: it provides a methodological and theoretical basis for understanding spinal coordination as part of the adaptive whole-body system that supports endurance running.

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Appendices

Appendix A. PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Chapter 3 title: Comparing kinematic models to quantify three-dimensional spine, back and pelvis movement during running using marker-based systems: A systematic review.
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Chapter 3 Abstract.
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	3.1 Introduction.
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Chapter 3 Abstract; 3.1 Introduction.
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	3.2.3 Inclusion and exclusion criteria.
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	3.2.2 Search strategy and review process; 3.3.1 Search results; Appendix B. Systematic Review Search Strings.
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	3.2.2 Search strategy and review process; Appendix B. Systematic Review Search Strings.

Section and Topic	Item #	Checklist item	Location where item is reported
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	3.2.2 Search strategy and review process.
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	3.2.4 Data extraction and methodological quality appraisal.
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	3.2.1 Scope and boundaries; 3.2.4 Data extraction and methodological quality appraisal; 3.3.7-3.3.10; Tables 3.3-3.5.
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	3.2.4 Data extraction and methodological quality appraisal; 3.3.4 Participant characteristics; 3.3.5 Running conditions and speeds; 3.3.6 Footwear; Tables 2, 3.3, 3.4 and 3.6.
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	3.2.4 Data extraction and methodological quality appraisal; Table 3.1; 3.3.2 Quality assessment; Figure 3.2; Table 3.6. This was a methodological quality appraisal rather than a formal risk-of-bias tool.

Section and Topic	Item #	Checklist item	Location where item is reported
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	3.3.10 Angle-output comparison; Table 3.5. No meta-analytic effect measures were used because the review used narrative synthesis of heterogeneous kinematic outcomes.
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	3.2.3 Inclusion and exclusion criteria; 3.3.4-3.3.10.
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	3.3.10 Angle-output comparison; Table 3.5. Non-extractable numerical values are identified in the table where applicable.
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Tables 2, 3.3, 3.4, 3.5 and 3.6; Figures 3.1 and 3.2.
	13d	Describe any methods used to synthesise results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	3.2.4 Data extraction and methodological quality appraisal; 3.3.10 Angle-output comparison. Narrative synthesis was used because marker models, outcomes, reference frames and reporting formats differed across studies.

Section and Topic	Item #	Checklist item	Location where item is reported
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	3.3.4-3.3.10; 3.4.1-3.4.7. Heterogeneity was explored narratively by participant characteristics, footwear, running conditions, kinematic model, pelvic reporting, data processing and outcome reporting.
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesised results.	Not applicable. Sensitivity analyses were not conducted because no meta-analysis or pooled statistical synthesis was performed.
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Not reported/not applicable. No formal assessment of reporting bias due to missing results was conducted.
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Not reported. No formal certainty or confidence assessment of the body of evidence was conducted.
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	3.3.1 Search results; Figure 3.1.
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	3.3.1 Search results report the

Section and Topic	Item #	Checklist item	Location where item is reported
			number retained and included. A list of excluded full-text studies with reasons is not reported.
Study characteristics	17	Cite each included study and present its characteristics.	3.3.4-3.3.10; Tables 2, 3.3, 3.4 and 3.5.
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	3.3.2 Quality assessment; Figure 3.2; Table 3.6. This is reported as methodological quality/reliability-validity evidence rather than formal risk of bias.
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	3.3.10 Angle-output comparison; Table 3.5.
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	3.3.2-3.3.10; Table 3.6.
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Not applicable. No meta-analysis or statistical synthesis was conducted.
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	3.3.4-3.3.10; 3.4.1-3.4.7.
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesised results.	Not applicable. Sensitivity analyses were not conducted.
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Not reported/not applicable. No reporting-bias assessment was conducted.

Section and Topic	Item #	Checklist item	Location where item is reported
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not reported. No formal certainty or confidence assessment was conducted.
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	3.4 Discussion; 3.4.3-3.4.7.
	23b	Discuss any limitations of the evidence included in the review.	3.4.1-3.4.7; 3.5 Recommendations; 3.6 Conclusion.
	23c	Discuss any limitations of the review processes used.	3.4.3 Methodological considerations; 3.4.6 Data analysis and reporting; 3.4.7 Angle-output synthesis; 3.5 Recommendations; 3.6 Conclusion.
	23d	Discuss implications of the results for practice, policy, and future research.	3.5 Recommendations; 3.6 Conclusion.
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	3.2 Methods. The review states that it was not prospectively registered.
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	3.2 Methods. The review states that a separate protocol was not published.
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable. No registration or published protocol was prepared, so no protocol amendments are reported.

Section and Topic	Item #	Checklist item	Location where item is reported
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	3.2 methods- 3.2.5, support and competing interests
Competing interests	26	Declare any competing interests of review authors.	3.2 methods Section 3.2.5, Support and competing interests
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Appendix B. Systematic Review Search Strings; Tables 2 and 3.3-3.6. No analytic code or separate data repository is reported.

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit <https://creativecommons.org/licenses/by/4.0/>

Appendix B. Systematic Review Search Strings

These search strings operationalise the search terms reported in the systematic review methods. They are formatted for the databases used in the review: SPORTDiscus, PubMed, MEDLINE, ScienceDirect, CINAHL and Scopus. Searches were reported as being completed between April and May 2025, with terms searched within title, abstract and keyword fields where available.

Core search structure

Concept	Terms
Running terms	(running OR run OR sprint OR sprinting)
Spine/back/pelvis terms	(pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral)
Measurement/model terms	("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster)

Database-specific search strings

SPORTDiscus (EBSCOhost)

(TI (running OR run OR sprint OR sprinting) OR AB (running OR run OR sprint OR sprinting) OR SU (running OR run OR sprint OR sprinting)) AND

(TI (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral) OR AB (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral) OR SU (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral)) AND

(TI ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster) OR AB ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster) OR SU ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster))

Limits/notes: Use title, abstract and subject terms to reflect the review method. Apply English language, human, journal article and full-text limits where available.

PubMed

((running[Title/Abstract] OR run[Title/Abstract] OR sprint[Title/Abstract] OR sprinting[Title/Abstract])

AND

(pelvis[Title/Abstract] OR spine[Title/Abstract] OR spinal[Title/Abstract] OR vertebrae[Title/Abstract] OR vertebral[Title/Abstract] OR back[Title/Abstract] OR cervical[Title/Abstract] OR thorax[Title/Abstract] OR trunk[Title/Abstract] OR thoracic[Title/Abstract] OR thoracolumbar[Title/Abstract] OR lumbar[Title/Abstract] OR lumbo[Title/Abstract] OR lumbosacral[Title/Abstract])

AND

("three dimensional"[Title/Abstract] OR 3D[Title/Abstract] OR "two dimensional"[Title/Abstract] OR 2D[Title/Abstract] OR "motion analysis"[Title/Abstract] OR "non-invasive"[Title/Abstract] OR "body mounted"[Title/Abstract] OR "skin mounted"[Title/Abstract] OR cluster[Title/Abstract]))

Limits/notes: PubMed does not use a separate keyword field in the same way as Scopus; Title/Abstract was used to reflect the stated title/abstract/keyword approach as closely as possible. Apply Humans, English and Journal Article filters.

MEDLINE (Ovid)

1. (running OR run OR sprint OR sprinting).ti, ab,kf.
2. (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral).ti, ab,kf.
3. ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster).ti, ab,kf.
4. 1 AND 2 AND 3
5. Limit 4 to English language, humans and journal articles.

Limits/notes: Uses .ti, ab,kf. Fields for title, abstract and keyword heading word. Apply human, English and journal article limits.

ScienceDirect

Title, abstract or author-specified keywords:
(running OR run OR sprint OR sprinting)

AND

(pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral)

AND

("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster)

Limits/notes: ScienceDirect field options vary by interface. Enter this in the Title, abstract or author-specified keywords search field and then apply English/full-text/article filters where available.

CINAHL (EBSCOhost)

(TI (running OR run OR sprint OR sprinting) OR AB (running OR run OR sprint OR sprinting) OR MW (running OR run OR sprint OR sprinting))

AND

(TI (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral) OR AB (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral) OR MW (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral))

AND

(TI ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster) OR AB ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster) OR MW ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster))

Limits/notes: Uses title, abstract and keyword/subject-word searching. Apply English language, human, journal article and full-text limits where available.

Scopus

TITLE-ABS-KEY (running OR run OR sprint OR sprinting)

AND

TITLE-ABS-KEY (pelvis OR spine OR spinal OR vertebrae OR vertebral OR back OR cervical OR thorax OR trunk OR thoracic OR thoracolumbar OR lumbar OR lumbo OR lumbosacral)

AND

TITLE-ABS-KEY ("three dimensional" OR 3D OR "two dimensional" OR 2D OR "motion analysis" OR "non-invasive" OR "body mounted" OR "skin mounted" OR cluster)

Limits/notes: TITLE-ABS-KEY searches title, abstract and keywords. Apply document type article and English language filters.

Appendix C. Quality Assessment Scores

Question	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Median	Total
Bramah, ChristopherPreece, et al (2018)	2	1	1	2	2	2	2	2	2	2	2	0	0	0	2	2	22
Bramah, ChristopherPreece, et al (2021)	2	2	1	2	2	2	2	2	2	2	2	0	0	0	2	2	23
Fisher et al. (2018)	2	1	1	2	2	2	2	2	2	2	1	2	0	0	2	2	23
Preece, Mason, Bramah (2016)	2	2	2	2	2	2	2	2	2	2	2	0	2	0	2	2	26
Saunders, Schache, Rath et al (2005)	2	1	2	2	2	2	2	2	2	0	2	2	2	2	0	2	25
Schache, Blanch, Rath., et al (2001)	2	2	2	2	2	2	2	2	2	0	1	2	2	2	2	2	27
Schache, Blanch, Rath., et al (2001)	2	1	2	2	2	2	2	2	2	0	2	2	2	2	0	2	25
Schache, Blanch, Rath., et al (2002)	2	2	2	2	2	2	2	2	2	0	2	2	2	2	2	2	28
Schache, Blanch, Rath., et al (2002)	2	2	2	2	2	2	2	2	2	0	2	2	2	2	2	2	28
Schache, Blanch, Rath., et al (2003)	2	2	2	2	2	2	2	2	2	0	2	2	2	2	0	2	26
Seay, Selbie, Hamill., (2008)	2	1	2	2	2	2	2	2	2	2	2	0	2	0	0	2	23
Seay, Van Emmerik.,Hamill., (2011)	2	1	2	2	2	2	2	2	2	2	0	0	2	0	0	2	21
Seay, Van Emmerik.,Hamill., (2011)	2	1	2	2	2	2	2	2	2	2	0	0	2	0	0	2	21
Tojima et al. (2019)	2	1	2	2	2	2	2	2	2	1	2	1	1	1	1	2	24
	2	1	2	2	2	2	2	2	2	2	2	2	2	1	2	1.86667	

Note. A score of 0 was given if no information was provided. A score of 1 was given if minimal details were provided or if parameters were missing. A score of 2 was given if all parameters were provided and clearly described

Appendix D. Ethics Approval Documentation



School of Health, Science and Wellbeing

ETHICAL APPROVAL FEEDBACK

Researcher name:	Craig Andrew Hicks
Title of Study:	The effects of manipulating task constraints on running economy and multi-segment spine kinematics: utilising a constraints led approach to understand the impact of fatigue on running performance
Status of approval:	Approved

Thank you for addressing the committee's comments. Your research proposal has now been approved by the Ethics Panel and you may commence the implementation phase of your study. You should note that any divergence from the approved procedures and research method will invalidate any insurance and liability cover from the University. You should, therefore, notify the Panel of any significant divergence from this approved proposal.

You should arrange to meet with your supervisor for support during the process of completing your study and writing your dissertation.

When your study is complete, please send the ethics committee an end of study report. A template can be found on the ethics BlackBoard site.

Signed:

Date: 12.08.2022

A handwritten signature in black ink, appearing to read 'R. Naemi'.

Prof. Roozbeh Naemi

Ethics Co-ordinator
Sport and Exercise
Biological Sciences
School of Health, Science and Wellbeing



INFORMATION SHEET FOR PARTICIPANTS

Title of study

The effects of manipulating task constraints on running economy and multi-segment spine kinematics: utilising a constraints-led approach to understand the impact of fatigue on running performance

Invitation Paragraph

I would like to invite you to participate in this research project which is trying to understand how manipulating task constraints while running impacts on reported spine and back movement when using two different marker set configurations. Before you decide whether you want to take part, it is important for you to understand why the research is being done and what your participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask me if there is anything that is not clear or if you would like more information.

What is the purpose of the study?

Marker-based motion capture systems are widely adopted in gait analysis laboratories worldwide and are the gold standard for movement analysis. To capture human movement retroreflective markers are attached onto specific anatomical landmarks to represent specific body parts. The method and selection of anatomical landmarks are termed a marker set. However, there are several markers sets that have been developed to assess movement in the trunk region during running gait. The difference in anatomical landmarks used to define and track movement of segments in the trunk region may produce different results regarding movement. Therefore, the purpose of this study (**study1**) is to examine the difference in reported angles from two marker sets when running on a treadmill at varying inclinations and speeds.

The coordination between the trunk and pelvis segments is one of several biomechanical variables that may contribute to running economy and performance. Previous research on this topic have mainly focused on defining the spine as a rigid segment or have analysed movement of the thorax segment in relation to the pelvis. Therefore, the purpose of this study (**study 2**) is to examine how sub-elite runners adjust their running technique regions following the manipulation of running on a treadmill at varying speeds and inclinations, and to see how adaptations on running technique affect running economy.

In addition, it has been reported that in a fatigue state changes in trunk posture can have a negative influence on running economy. Therefore, the purpose of this study (**Study 3**) is to investigate how induced fatigue affects running economy and the coordination and control between the multi-segment spine and pelvis during treadmill running in novice vs sub-elite runners.

Why have I been invited to take part?

As you are a healthy male ages 18+ and fit the criteria you have been invited to participate in this study

Do I have to take part?

It is up to you to decide whether or not you can take part. If you do decide to take part, you will be given this information sheet to keep. You are still free to withdraw at any time without giving a reason.

What will happen if I take part?

We ask that you come to Staffordshire University on three occasions.

On the first occasion, you will be in the lab for one hour and be asked to undertake a VO2 max test (maximal exhaustion treadmill test) in the physiology laboratory to establish your individualised ventilatory threshold.

On the second occasion you will be in the lab for two and a half hours, anthropometric information will be collected on height, mass, and leg length. Following this, reflective markers will be placed on the lower limbs and spine using double sided tape. You will then be asked to carry out 3 running trials on a treadmill. For the first condition, you will complete a 10-minute baseline run on the treadmill at 1 % incline at a speed that coincides with your individualised ventilatory threshold (VT1). Once completed you will continue Running and begin one of two randomised protocols, the 1st protocol is 10 minutes at 5% incline at the same threshold speed you ran at for the first 10. 2nd protocol is a 10-minute run at your respiratory compensation point (VT2) speed at 1% incline. For the third running condition, you will repeat the 1st baseline trial of a 10-minute run on the treadmill at 1 % incline at your ventilatory threshold. During the running conditions we will ask you to wear a mask so breath by breath data can be collected using the Metalyzer 3B cortex breath by breath analyser.

For the third session, you will be asked to complete a 10-minute baseline trial run on a treadmill at 1% incline at a speed that coincides with your individualised ventilatory threshold. You will then immediately perform a 100-box jump localised eccentric muscle fatigue protocol. The protocol will require you to jump down from a 40-cm box and land with a 90-degree knee angle before jumping upward as high as possible. A 20-second rest interval between each jump will be implemented to allow you sufficient recovery to ensure maximal effort for the next jump. We will then ask you to repeat the 10-minute run on the treadmill at 1 % incline at your ventilatory threshold. During the running conditions we will ask you to wear a mask so breath by breath data can be collected using the Metalyzer 3B cortex breath by breath analyser.

What to bring

We ask that you bring your habitual running trainers along with a pair of tight-fitting thermal/undershorts.

Incentives

You will have access to your individual VO2max data that can be used to guide your future exercise prescription.

What are the possible risks of taking part?

There are risks to taking part in this study, participation in the study will involve vigorous activity and may increase the risk of respiratory and heart failure. the study involves repetitive running that may expose the participants to higher risk of developing injuries such as knee and lower back pain. Furthermore, you may experience an allergic reaction to the adhesive tape used to attach the reflective markers to the skin.

What are the possible benefits of taking part?

Although there might not be a direct benefit to you, this project will provide us with a better understanding on the differences between reported angles from two marker sets. The results of this study will help future design of marker sets for the purpose of tracking movement in the trunk region during running.

Data handling and confidentiality

Your data will be processed in accordance with the data protection law and will comply with the General Data Protection Regulation 2018 (GDPR).

Data Protection Statement

The data controller for this project will be Staffordshire University. The University will process your personal data for the purpose of the research outlined above. The legal basis for processing your personal data for research purposes under the data protection law is a 'task in the public interest'. You can provide your consent for the use of your personal data in this study by completing the consent form that has been provided to you. The data will be kept for 10 years.

What if I change my mind about taking part?

You are free to withdraw at any point of the study, without having to give a reason. Withdrawing from the study will not affect you in any way. You are able to withdraw your data from the study up until 2 weeks post data collection. after which withdrawal of your data will no longer be possible due to the data being anonymised and incorporated into the wider data set. If you choose to withdraw from the study, please inform the principal investigator in writing (the details are provided below). We will not retain any information that you have provided us as a part of this study.

How is the project being funded?

This project is fully funded by Staffordshire university.

What will happen to the results of the study?

Any personal details will be kept confidential and anonymised and will not be shared with anyone at any time. Information will be kept on a password protected computer, and only the researchers will have access to this information. The results of the research will be used in research publications and the researcher will be able to advise you on how you can obtain a copy of any published research.



Version Number 1 11/02/23

Who should I contact for further information?

If you have any questions or require more information about this study, please use the following contact details:

Craig Hicks
Phone: 07964996621
Email: h010134g@student.staffs.ac.uk

What if I have further questions, or if something goes wrong?

If this study has harmed, you in any way or if you wish to make a complaint about the conduct of the study you can contact the study supervisor.

Craig Hicks
Phone: 07964996621
Email: h010134g@student.staffs.ac.uk

You can also contact the Chair of the Staffordshire University Ethics Committee who is independent of this study for further advice and information, and in case of complaints and concerns about the study:

Dr Tim Horne, Research, Innovation and Impact Services
Cadman Building, Staffordshire University, College Road Stoke-on-Trent
ST4 2DF
Tim.horne@staffs.ac.uk
+441782295722

Thank you for reading this information sheet and for considering taking part in this research.

Appendix F. Participant Consent Form



RESEARCH PROJECT CONSENT FORM

Title of Project: The effects of manipulating task constraints while running on multi-segment spine kinematics in novice and sub-elite runners: A comparison of two kinematic marker sets.

Researcher: Craig Hicks

I have read and understood the information sheet. Yes ☐ No ☐

I have been given the opportunity to ask questions, and I have had any questions answered satisfactorily. Yes ☐ No ☐

I understand that my participation in this study is entirely voluntary and that I can withdraw at any time without having to give an explanation Yes ☐ No ☐

I consent that data collected could be used for publication and understand that all data will be presented anonymously. Yes ☐ No ☐

All data will be stored safely on a password protected computer (electronic data), or locked away securely (hard copies of data) for 10 years before being destroyed Yes ☐ No ☐

I understand that I can withdraw my data from the project up to two weeks post data collection without having to give an explanation Yes ☐ No ☐

I Consider myself physically fit and able to participate in the study Yes ☐ No ☐

I hereby give consent to take part in this study Yes ☐ No ☐

Name Participant (print) Date Signature

Name Researcher (print) Date Signature

Appendix G. Pre-test Questionnaire

SPORT AND EXERCISE: PRE-TEST QUESTIONNAIRE & INFORMED CONSENT

Name: _____

D.O.B: ____ / ____ / ____ Age: ____

Required when maximal testing:

Resting blood pressure: ____ / ____

Resting heart rate: ____

For your health and safety please answer these questions truthfully and completely. The purpose of this questionnaire is to ensure that you are fit and healthy enough to participate in this laboratory practical/research project.

ALL INFORMATION YOU PROVIDE WILL REMAIN CONFIDENTIAL

- How often do you normally undertake vigorous physical activity?
 < once per week once per week 2-3 x per week 4-5 x per week > 5 x per week
- How would you describe your present level of fitness?
 Unfit Moderately Fit Trained Highly Trained
- Do you suffer, or have you suffered from any form of heart condition?
 Yes No
- Do you feel any pain in your chest when you exercise?
 Yes No
- Do you suffer, or have you suffered from any of the following?
 Asthma ☐ Diabetes ☐ Bronchitis ☐ Epilepsy ☐ High Blood Pressure ☐
- Do you ever feel dizzy, light headed, or suffer palpitations when exercising?
 Yes No
- Have you had to consult your doctor in the last six months?
 Yes (please give details below) No

- Are you currently taking any form of medication?
 Yes (please give details below) No

- Do you have any known allergies?
 Yes (please give details below) No

- Have you suffered any form of viral or bacterial infection in the last two weeks?
 Yes No

- Do you have any form of muscle, bone, or joint injury?
Yes (please give details below) No

- Have you taken part in any strenuous activity in the last 3 days?

Yes

No

- How many hours since your last meal? _____ hours.

- Do you have any skin allergies to adhesive materials such as plasters?

Yes

No

- Do you know of any other reason why you should not be able to complete the tests that have been outlined to you?

Yes (please give details below)

No

INFORMED CONSENT

I understand that the information provided on the pre-test questionnaire is confidential.

The full details of the tests have been explained to me. I am clear about what will be involved, and I am aware of the purpose of the tests and the potential risks.

Any questions that I have about the tests or my participation in them have been answered to my satisfaction.

I know that I am not obliged to complete the tests. I am free to stop the test at any time and for any reason.

I have no injury or illness that will affect my ability to successfully complete the tests.

The test results will only be communicated to members of my laboratory group for the purpose of demonstrating the physiological principles underlying the exercise protocol.

Having read the above I agree to participate in the testing.

Signature of Participant: _____ Date: ____ / ____ / ____

Signature of Supervisor: _____ Date: ____ / ____ / ____