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Towards Real-world Biomechanical Detection of Fatigue, Energy, and Injury in Runners using Wearable Trunk Accelerometry



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Dissertation presented in partial fulfillment
of the requirements for the joint degree of
Doctor of Biomedical Sciences (KU Leuven) &
PhD in Sport Science (Stellenbosch University)

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Declaration

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Running can be considered both simple and difficult - simple because it is an instinctive, habitual skill, performed at some time by all but the most unfortunate - difficult in its mechanical complexity.

GEOFFREY DYSON- THE MECHANICS OF ATHLETICS 1962

Be careful and be critical of technology given as a black box...just a warning.

GERT-PETER BRÜGGEMANN - TECHNOLOGY IN SPORTS AND
EXERCISE, ISBS 2017

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Abstract

Running continues to be an extremely popular form of exercise and sport. Unfortunately, many runners, both recreational and competitive, fail to meet their fitness and performance goals due to sustaining an overuse injury. Such overuse injuries can be due to numerous environmental factors and internal factors. Therefore, any approach to identifying and minimizing these risk factors in real-life running conditions will help runners to reach their training goals while also to regain running's numerous health benefits.

Running requires minimal equipment and can be performed on practically any terrain. Ideally, measurements of a runner's mechanics should follow the runner through his or her typical training environment and be unrestricted to location. However, such measurements may require a totally different experimental approach compared to those traditionally performed in the laboratory (i.e. capture and analyse every stride of the runner outdoors rather than providing only a 'snapshot' view).

Over two decades ago it was acknowledged that obtaining objective data in real-life environments using wearable technology is of high priority with potential to advance running performance while also reducing injury risk. Even with recent and rapid technology advancements, there remains a paucity of literature linking the fields of wearable technology with running related performance and injury risk. Thus, **the global objective of this thesis is to expand understanding with regards to detecting fatigue-, energy-, and injury-related dynamic instability and dynamic loading in runners using wearable trunk accelerometry (WTA), with transferability to 'real-world' ecologically valid settings.**

In the **first part** of this thesis, we performed two indoor laboratory studies focusing firstly on the biomechanical, and secondly on the energetic aspects of running. **Study I (chapter 2)** biomechanically confirmed a fatigue-ability hypothesis, showing that runners incur a loss of stability from running-induced fatigue specific to laboratory-controlled treadmill running conditions at fixed speeds. **Study II (chapter 3)** physiologically confirmed a cost of instability hypothesis, revealing that certain aspects of dynamic stability are energetically advantageous to endurance running.

In the **second part** of this thesis we performed two outdoor over-ground running experiments. **Study III (chapter 4)** experimentally showed that running on an irregular outdoor surface such as wood-chip trails disrupts aspects of stability specific to the mediolateral direction. **Study IV (chapter 5)** partially confirmed a fatigue-ability and injury hypothesis, showing that runners with history of medial tibial stress syndrome (MTSS) incur a loss of stability in the mediolateral direction from outdoor track-running at self-selected speeds.

Finally, the **general discussion (chapter 6)** brings together findings with practical implications directed at runners, researchers, and practitioners. In addition, some preliminary data with regards to running stability before, during, and after an endurance training program are provided, with potential insights and future directions aimed at performance and injury detection. **Overall, this doctoral thesis contributes to a better understanding of a runner's dynamic stability and loading in relation to fatigue, energy and injury using wearable trunk accelerometry.**

Samenvatting (Nederlands)

Lopen is nog steeds een uiterst populaire vorm van lichaamsbeweging en sport. Jammer genoeg bereiken veel lopers, zowel recreatieve als competitieve, hun fitness- en prestatiedoelstellingen niet omwille van overbelastingsblessures. Dergelijke overbelastingsblessures kunnen het gevolg zijn van tal van omgevings en interne risicofactoren. Daarom zal elke aanpak om deze risicofactoren te identificeren en te verminderen in reële loopomstandigheden, lopers in staat stellen om hun trainingsdoelen te bereiken en tegelijk de talrijke voordelen voor de gezondheid te herwinnen.

Lopen vergt een minimale uitrusting en kan op vrijwel elk terrein worden beoefend. Ideaal gezien moeten metingen van de mechanica van het lopen de loper volgen in zijn of haar typische trainingsomgeving en zijn ze niet aan een locatie gebonden. Maar zulke metingen kunnen een totaal verschillende experimentele aanpak vereisen, in vergelijking met de metingen die traditioneel in het laboratorium worden uitgevoerd. Deze metingen registreren en analyseren elke stap die de loper buiten zet in plaats van enkel een momentopname te geven.

Meer dan twee decennia geleden werd erkend dat het verkrijgen van objectieve gegevens in levensechte omgevingen met gebruik van draagbare technologie sterk kan bijdragen tot het verbeteren van de loopprestatie en het verminderen van het letselrisico. Ondanks recente en snelle technologische ontwikkelingen is er nog steeds een gebrek aan literatuur die het domein van draagbare technologie verbindt met loopprestaties en letselrisico. **Dus, de algemene doelstelling van dit doctoraat is een beter inzicht te krijgen in de detectie van vermoeidheids-, energie- en letselgerelateerde dynamische instabiliteit en dynamische belasting bij lopers, gebruikmakend van draagbare romp accelerometers en transfereerbaar naar ecologisch valide situaties.**

In het **eerste gedeelte** van dit proefschrift hebben we twee laboratoriumstudies uitgevoerd die gericht waren op, ten eerste, de biomechanische en, ten tweede, de energetische aspecten van het lopen. **Studie I (hoofdstuk 2)** bevestigt biomechanisch een vermoeidheidshypothese: lopers ondergaan een verlies aan stabiliteit door vermoeidheid veroorzaakt door het lopen, specifiek voor laboratorium gecontroleerde conditie waarbij lopers lopen op een loopband aan vaste snelheden. **Studie II (hoofdstuk 3)** bevestigt fysiologisch een hypothese van verlies aan stabiliteit. Het blijkt namelijk dat bepaalde aspecten van dynamische stabiliteit energetisch voordelig zijn voor het uithoudingsvermogen bij het lopen.

Voor het **tweede deel** van dit proefschrift deden we twee experimenten op het terrein. **Studie III (hoofdstuk 4)** toont experimenteel aan dat lopen buiten op een hobbelige ondergrond, zoals bv. op de finse piste, aspecten van stabiliteit die typisch zijn voor de mediolaterale richting verstoort.

Studie IV (hoofdstuk 5) bevestigt gedeeltelijk een vermoeidheids- en letselhypothese waarbij blijkt dat lopers met een geschiedenis van het Mediaal Tibiaal Stress Syndroom (MTSS), een verlies aan stabiliteit in de mediolaterale richting ondervinden bij het lopen op de piste aan zelfgeselecteerde snelheden. Bovendien worden er in studie IV draagbare romp accelerometers gebruikt in combinatie met draagbare tibiale accelerometers. De resultaten suggereren dat proximale instabiliteit in plaats van dynamische belasting of schokdemping wordt beïnvloed bij lopers met een geschiedenis van MTSS tijdens een vermoeidheidstest op de looppiste.

Ten slotte brengt de **algemene discussie (hoofdstuk 6)** bevindingen samen met praktische consequenties voor lopers, onderzoekers en beoefenaars. Daarnaast worden enkele voorlopige gegevens verstrekt met betrekking tot loopstabiliteit voor, tijdens en na een uithoudingsprogramma, met mogelijke inzichten en toekomstige richting voor verder onderzoek gericht op prestatie en letselopsporing. **Over het algemeen draagt dit proefschrift bij tot een beter inzicht in de dynamische stabiliteit en belasting van een loper in verhouding tot vermoeidheid, energie en letsels gebruikmakend van draagbare romp accelerometrie (versnelling).**

Opsomming (Afrikaans)

Hardloop bly 'n uiters populêre manier van oefen, asook 'n sportaktiwiteit. Ongelukkig is daar baie hardlopers, rekreatief en kompetend, wat nie hul fiksheids- en prestasiedoelwitte bereik nie as gevolg van die feit dat hulle 'n oorgebruiksbesering opdoen. Sulke oorgebruiksbeserings kan die gevolg wees van verskeie omgewings- (ekstrinsiek) en interne (intrinsieke) faktore. Gevolglik sal enige benadering om hierdie risikofaktore in hardlooptoestande onder werklike lewensgetroue omstandighede te identifiseer en te verminder, hardlopers instaat stel om hul oefendoelwitte te bereik en die verskillende gesondheidsvoordele te herwin.

Hardloop vereis minimale toerusting en kan bykans op enige terrein beoefen word. Ideaalgesproke behoort metings van die hardloper se meganika die hardloper "te volg" in sy of haar tipiese oefen-omgewing en nie gebonde te wees aan 'n spesifieke plek nie. Sulke metings kan 'n totale andersoortige benadering en metingstoerusting vereis as wat tradisioneel in 'n laboratorium-opset gedoen word. Dus, in plaas daarvan dat 'n enkele oombliklike weergawe verkry word, behoort elke tree vasgevang en ontleed te word, retrospektief of in werklike tyd.

Meer as twee dekades gelede is dit al gestel dat die verkryging van objektiewe data in lewensgetroue omgewings deur middel van draagbare tegnologie, hoë prioriteit is, met die potensiaal om hardlopprestasie te verbeter, asook die risiko op beserings te verminder. Selfs met die onlangse en vinnige ontwikkeling in tegnologie, is daar steeds 'n leemte in die literatuur wat draagbare tegnologie en hardloopverwante prestasie en beseringsrisiko verbind. **Die oorkoepelende doel van hierdie tesis is gevolglik om begrip in terme van die bepaling van vermoënis-, energie-, en beseringsverwante dinamiese onstabieliteit met die gebruik van draagbare rompversnellingstegnologie uit te brei, met oordraagbaarheid na "regte-wêreld" ekologies geldige omgewings.**

In die **eerste deel** van die tesis is twee binnenshuise laboratoriumstudies gedoen wat eerstens op die biomeganiese, en tweedens op energie-aspekte, van hardloopmeganika gefokus het. **Studie I (hoofstuk 2)** het biomeganies 'n vermoënis hipotese bevestig wat aandui dat hardlopers 'n verlies van stabiliteit ervaar deur hardloop-geïnduseerde vermoënis, spesifiek aan laboratoriumbeheerde trapmeul hardlooptoestande teen 'n vasgestelde spoed. **Studie II (hoofstuk 3)** het fisiologies 'n koste van onstabiliteit hipotese bevestig, wat aangedui het dat sekere aspekte van dinamiese stabiliteit voordele in terme van energie vir uithouvermoë hardlopers inhou.

In die **tweede deel** van hierdie tesis het ons twee eksperimente in situasies buite die laboratorium uitgevoer. **Studie III (hoofstuk 4)** het eksperimenteel getoon dat om op 'n ongelyke oppervlakte soos houtsplinterpaaie te hardloop, aspekte van stabiliteit in spesifiek die medio-laterale rigting ontwig. **Studie IV (hoofstuk 5)** het gedeeltelik 'n vermoënis-oorgebruik-beseringshipotese bevestig. Hardlopers met 'n geskiedenis van mediale stres sindroom het 'n verlies aan stabiliteit in die medio-laterale rigting getoon wanneer hulle teen 'n self gekose spoed op 'n atletiekbaan buite gehardloop het. Ook in Hoofstuk 5 is draagbare rompversnellingstegnologie saam met tibiale versnellingstegnologie gebruik om voor te stel dat proksimale onstabiliteit, eerder as lading of skokverspreiding, retrospektief beïnvloed word deur mediale tibiale stressindroom tydens 'n toestand van hardloopvermoënis.

Laastens gee die **algemene bespreking (hoofstuk 6)** 'n samevatting van die bevindings met praktiese implikasies vir hardlopers, asook voorlopige data van hardlopers se stabiliteit voor, gedurende en na 'n uithouvermoë oefenprogram. **In geheel lewer hierdie doktrale tesis 'n bydrae tot 'n beter begrip van vermoënis-, energie-, asook beseringsverwante hardloopstabiliteit.**

Chapter 1

General introduction

There has been an explosion of interest in the use of wearable systems for running. Recent technology advancements in wearables include accelerometry, global positioning system (GPS), and photoplethysmography (heart rate (HR) via light reflected from skin). These systems have added value to a runner's training by answering the 'how much?', i.e. quantitatively-related questions, such as:

1. *How long was I running for?*
2. *How many steps were counted?*
3. *What was my average HR or running pace?*

However, wearable systems that answer 'how well' a runner is training appear to be largely ignored. Runners continue to sustain overuse injuries at a remarkable rate (29% to 79% annually) [89]. In addition, running form can deteriorate with fatigue which can influence both injury risk and economy. Thus, wearable systems are needed to add value to a runner's injury risk and performance by answering more *qualitative* questions such as:

1. *How/when am I **compensating due to fatigue**?*
2. *How/when is my **running economy optimal**?*
3. *How/when am I at **higher injury risk**?*

Answering these three qualitative questions may require wearable systems that integrate biomechanical principles, and, ironically, require collection of quantitative data. Thus, I start this chapter by broadly establishing a conceptual basis for biomechanical mechanisms underpinning running in relation to fatigue, energy, and injury.

Next, I draw attention to the experimental design of running biomechanics research over the past few decades and thereafter introduce wearable trunk accelerometry (WTA) as a potential tool to unobtrusively quantify running mechanics in ecologically valid settings. I provide a brief introduction on how WTA can be used to detect instability and quantify loading in runners related to fatigue, energy, and injury.

Subsequently, I outline the research gaps and specific aims of this doctoral project together with an overview of the different chapters. Finally, I describe the global methodology used in the various experimental studies of this doctoral project.

1.1 Biomechanical basis for running fatigue

A common objective of an athlete is to 'minimise fatigue' while at the same time 'maintain positive physiological adaptations' [98]. However, fatigue is a multi-faceted phenomenon that on the one hand is well known, but on the other hand difficult to define. Muscle fatigue specifically is known to be influenced by a multitude of factors including the type of contraction (isometric, isotonic, or intermittent), the duration, frequency, or intensity of the exercise, as well as the type of muscle [35]. As such, fatigue can also occur anywhere along the '*chain of command*' [31]. This command or continuum consists of both electrical and metabolic factors anatomically ranging from *peripheral* (below the neuro-muscular junction and all contractile mechanisms involved) to *central* (above the neuro-muscular junction and all processes involved to the brain). **For these reasons above, fatigue can be a cloudy construct that may require a more practical or operational definition.**

Practically, fatigue can be defined as either '*the deterioration of performance*' [9], '*an inability to complete a task that was once achievable within a recent time-frame*' [35] or '*negative consequences associated with training, temporarily causing decreased capacity in modifiable internal risk factors, such as tissue resilience or neuro-muscular control*' [98]. For the runner, the first definition proposed by Bartlett [9] implies an increase in completed time, i.e., slower average running speed. The second definition proposed by Halson [35] suggests that fatigue is history dependent and over time is a limitation to a runner's performance. The third definition described by Windt and Gabbett [98] takes into account that fatigue is a side effect of acute training workload that can negatively modify a runner's injury risk and health.

Yet how does one directly evaluate or quantify running fatigue? Forcing a runner to structural failure, as has been performed in rabbits [77], is neither plausible nor ethical. Unfortunately, the absence of data relating maximal human tolerance to repetitive impact loading incurred while running makes it extremely challenging to establish evidence-based methods for injury prevention, a fact acknowledged for a few decades already [17]. In addition, athletes asked to perform maximal testing close to competition phases are problematic as it can add to existing fatigue [35].

Thus, many alternative approaches are used to indirectly evaluate voluntary maximal effort. Although runners rarely run to a point of maximum fatigue or exhaustion due to anticipatory regulation or 'central governor' control [88], over the past 40 years researchers have sought several ways to assess a runner as close to his or her point of maximum tolerance for fatigue or exhaustion as possible. Sport scientists and practitioners have used a host of markers of fatigue, or at least tried to find proxies related to it. These markers or proxies generally represent some form of 'internal loads'. These internal loads can be physiological (e.g., HR), psychological (e.g., rating of perceived exertion (RPE)), or biomechanical (e.g., internal joint loads or stress imposed) [35, 90, 98].

Nevertheless, how fatigue is detected, monitored, and interpreted may depend entirely on the domain 'lens' through which it is being viewed - ranging from biomechanical, neuro-muscular, physiological, psychological, biochemical as well as sports performance perspectives. **Thus, throughout this thesis, the question of running fatigue (or exhaustion) is viewed primarily through the biomechanical lens, and, defined as:**

biomechanical compensations, alterations, manifestations, symptoms or the 'phenotype' to fatigue induced by running.

1.1.1 Kinetic and kinematic compensations

In terms of external **kinetics**, biomechanical fatigue has been defined as '*fatigue that causes the transient inability to maintain power output or force during repeated muscle contractions*' [4, 31]. The muscle's transient inability to perform is said to place other structures such as articular cartilage and ligaments at higher risk and more vulnerable to dynamic loading [65].

Force output in relation to running fatigue has also been examined externally using force plates or tibial-worn accelerometry. Force plates have been used to extract ground reaction force characteristics during stance, such as, peak impact force, peak impact loading rate, or peak active force during mid-stance. Tibial-worn accelerometry has been used to extract peak axial accelerations during impact or the frequency amplitude of accelerations over the entire stance phase. These characteristics typically generated by a rear-foot-striker, i.e., heel first are depicted in Figure 1.1.

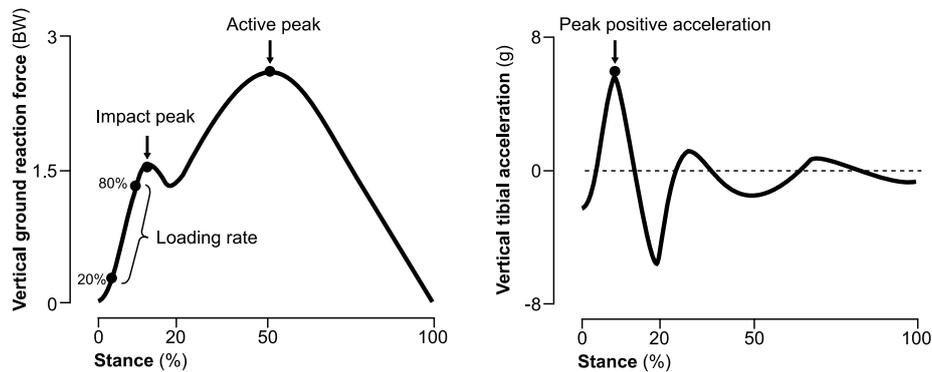


Figure 1.1: Characteristics of external vertical ground reaction force in body weight (left) and tibial acceleration in g (right).

In healthy runners, characteristics of the vertical ground reaction force profile have consistently been shown to decrease with fatigue, including the impact peak [29], impact loading rates [29], as well as active peaks [32, 71, 79, 80]. Kinetic changes to fatigue from the perspective of peak tibial accelerations and shock attenuation are less conclusive. For example, several studies [22, 65, 66, 94, 91] indeed have shown that tibial accelerations increase with running fatigue, yet other studies [1, 19, 62] have shown no changes.

In terms of **kinematics**, biomechanical fatigue can be characterised by a number of phrases, of which 'breakdown of technique', 'break-up of rhythm', 'disturbed or loss of coordination', 'loss of form', or 'compensatory movement' have been used to describe this phenomenon. Some researchers have provided more specific definitions of kinematic fatigue, such as '*fatigue that causes a breakdown or irregularity in the internal timing-layout of successive items of the performance which must be repeated*' [9]. This definition by Bartlett et al. [9] was soon after supported by the findings of Bates and Osternig [11], which demonstrated that relative relationships between the different phases of total stride time changed with running fatigue. Furthermore, recent work from our laboratory has demonstrated that fatigue can also disrupt several aspects of running kinematics during specific phases of the running gait cycle [56]. Interestingly, some of these aspects (i.e. increase in peak forward trunk lean and increase in hip abduction during mid-swing with fatigue) were more pronounced in novice runners compared to competitive runners. This suggests that training level or experience has an influence on the fatigue-ability of running kinematics.

Several theories exist around changes in movement variability with running fatigue. As put forth by Komi et al. [49], running fatigue '*causes problems to maintain constant angular displacement during ground contact*' and is a classical example of fatigue induced with repetitive stretch-shortening cycles. This definition [49] makes sense from a traditional motor control perspective in that fatigue may symptomatically reveal itself as an undesired increase in the movement trajectory, e.g., of joints, limbs, or body as a whole, thus increasing variability. One theory posited is that such undesirable movement patterns induced by fatigue will contribute to the muscles' inability to protect internal tissues from excessive shock waves [65].

Alternatively, if we consider the issue of movement variability from a *dynamical systems* perspective, adjustments in a runner's coordination or movement patterns may simply represent a context and task relevant adaptation. For example, an early definition of fatigue by Jones and Hanson 1966 [46] stated that running fatigue '*affects the organisation of movement that will be reflected by changes in the movement pattern*'. In other words, a runner's movement pattern must change with fatigue, whether the change is an increase, i.e., 'release' or a decrease, i.e., 'freezing' of degrees of freedom to realise the new specific task demand and metabolic requirements that occur over the course of a run.

Amidst a comprehensive list, Halson [35] included a 'technique' variable described as 'movement deviations' that can be used to monitor training load and subsequent fatigue. Vanrenterghem et al. [90] have recently acknowledged that the scientific literature to date has somewhat failed to differentiate between physiological and biomechanical monitoring of internal loads and markers of fatigue. Additionally, in contrast to physiological markers, few researchers have addressed the problem of monitoring a runner's kinematic or kinetic response to fatigue. This suggests that **there is room for research to further investigate novel biomechanical parameters that could be used to detect and monitor running fatigue. Hence, two chapters (chapter 2 and 4) are dedicated to detecting fatigue from a biomechanical perspective.**

1.2 Biomechanical basis for energy cost of running

There are three widely accepted primary determinants of endurance running performance [27], namely the maximal aerobic power (VO_{2max}), the ability to sustain a high percentage of VO_{2max} for an extended period of time, and running economy. Despite its importance, the latter determinant was termed 'the forgotten factor of elite performance' in a 2007 paper by Foster et al. [27] which reminded the research community of the importance to further investigate possible mechanisms and relationships between running economy and performance.

Although many forms of running economy exist, it can most appropriately be described as the energetic cost (E_c) (in joule or calorie) required to run at a given speed, or at a unit distance, provided speeds are sub-maximal and aerobic. As has been previously pointed out, the E_c to travel a given distance (i.e. per m or per km) has a specific ecological meaning, in contrast to simply the E_c to run at a particular speed for a particular time (i.e. per min). Regardless, the E_c of running is a complex, multi-factorial phenomenon with numerous anthropometrical, demographic, e.g., age- sex- and ethnic-related, physiological, biomechanical, and neuro-muscular determining factors [8, 51, 69]. Of these factors, establishing a biomechanical basis to running economy continues to be of interest to researchers and coaches. For example, using biomechanical principles such as drafting, lighter shoes, and course elevation drop has recently been proposed as quantifiable strategies needed to reduce energy cost and break the two-hour marathon barrier [41].

1.2.1 Kinetic and kinematic constituents

Movement economy - the link between a runner's mechanics and energy cost - is intuitive. Substantial early contributions to the link between running mechanics and running economy were made by Williams and Cavanagh [97], who found several kinetic and kinematic determinants of running economy, and concluded:

it appears that biomechanical factors of running style do have a substantial influence on energy expenditure during distance running.

Since then there has been a number of new papers investigating the mechanical-energetic link of running. In Moore's recent review titled 'is there an economical running technique?', she concluded that no general recommendations can be made, although there are some mechanical parameters during ground contact that have been linked to better running economy [69]. These parameters included less leg extension at toe-off, larger stride angles, and better alignment of the ground reaction forces with the leg axis (see Moore's [69] for a comprehensive list). It was further suggested [69] that a synergistic approach may be needed to understanding the role of mechanics in running economy.

Indeed, Arellano and Kram [3] have proposed a synergistic task-by-task approach to better understand the biomechanical constituents of running economy, as shown in Figure 1.2. Although the majority ($\sim 80\%$) of running economy is determined by the cost to support body mass and forward propulsion [3], there is an unexplained portion of energy cost likely due to several possible characteristics, including that of running mechanics.

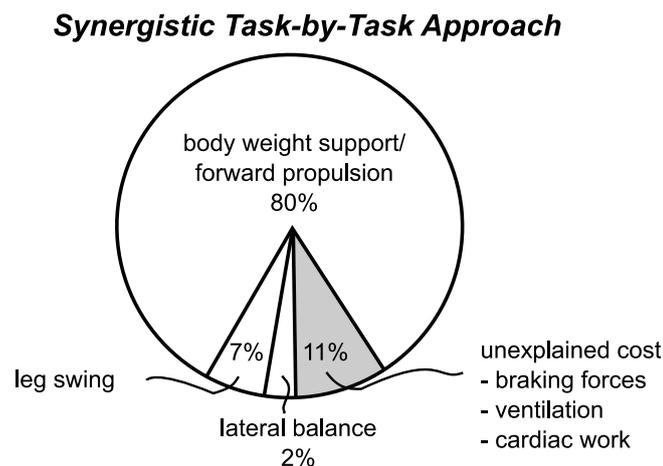


Figure 1.2: The synergistic task-by-task approach to partition the metabolic cost of running into its biomechanical constituents, adapted from Arellano and Kram with permission [3].

Traditionally there are two schools of thought when it comes to improving running economy. Stated formally, the first school of thought argues that deliberate efforts to make kinematic adjustments or alterations in movement patterns will lower the E_c of running and improve performance. Stated informally, running technique is like a tennis swing, with the help of a coach's instructions, slight tweaks here or there in form or posture can improve your economy. However, studies that have instructed runners to make alterations in running

technique have negatively affected economy [20, 59]. Specifically, Dallam et al. [20] found that runners who were instructed with the 'Pose Method' (i.e., 'vertically align body, then fall forwards using gravitational torque') impaired running economy significantly. In addition, McMahon et al. [59] showed that runners who were instructed to increase knee flexion during stance had a 50% increase in their E_c of running.

Advocates of the second school of thought argue that runners will naturally self-optimize their running pattern to an energetic optimum [69, 97]. Improvements in running economy are said to be most likely on a level that is subconscious, self-selected, and individual, requiring no instruction of changing technique [69]. In other words, go out and perform running training normally with no deliberate changes to your technique, and over time your running technique will naturally fine-tune to the most economical one.

Some evidence for the self-optimization theory has been provided acutely and in the short term. Acutely, self-optimization research has demonstrated that running at a preferred, rather than at an instructed stride frequency is most economical. Specifically, these studies typically show a quadratic or curvilinear response between stride rate and E_c , whereby deviations lower or higher than preferred are detrimental to running economy. With short term training, Moore et al. [70] showed that adaptations in running mechanics (a less extended knee at toe-off, peak dorsiflexion angle occurring later in stance, and slower ankle eversion velocity at touchdown) were able to explain 94.3% of variance in running economy improvement in novice runners undergoing a 10-week training program. Thus, it seems that simply through running training novice runners appear to improve their running economy.

Various factors related to motor control, specific training, or genetics are typically said to contribute, mediate, underlie, or be required for the improvements in running economy. For example, from a motor control standpoint, Bernstein [13] states that '*coordination develops slowly and as a result of experience and exercise, which gradually develops a greater economy of movement and a diminution of fatigue*'. In other words, long-term training can improve both movement economy and a resistance to fatigue. Or, to paraphrase Anderson [2], at higher levels of competition it is likely that through 'natural selection' the 'surviving athletes' have either 'inherited or developed the favourable characteristics for running economy'. Optimal movement economy could thus be viewed entirely at the individual level, i.e., 'one size does not fit all' with years of running experience. For example, elite marathon runner Paula Radcliff (holds current Women's marathon world record at 2hr 15 min 25s) is on the one hand known for her exceptional

running economy [45] but on the other hand is known for her unique running pattern characterised by awkward and inefficient head bobbing.

While several parameters have been identified in the literature, there is still an overall lack of consensus as to what constitutes an economical running technique. **Therefore, research is warranted to help identify which biomechanical aspects of running technique are economically advantageous. As such, chapter 3 of this work specifically attempts to detect novel biomechanical parameters that could help explain why some runners have superior running economy.**

1.3 Biomechanical basis for running-related injury

A runner cannot perform optimally if he or she is injured. While the lower limits to training benefits are well-known [78], the upper limits with respect to sustaining an injury from running, here forth defined as a **running-related injury (RRI)**, have yet to be established. Knowledge of biomechanical mechanisms that underpin these upper limits are therefore crucial to injury prevention from a recreational to an elite running level [6].

A RRI can generally be defined as a musculoskeletal ailment that is attributed to running and causes a restriction of running speed, distance, duration, or frequency for at least one week [42]. The most common site for RRI is the knee, attributed to patellofemoral pain, although other common injuries include Achilles tendinopathy, medial tibial stress syndrome (MTSS), patellofemoral knee pain and iliotibial band syndrome [89]. Of these prevalent injuries, MTSS is well known for its high rate of re-occurrence (i.e. relapse). **MTSS subjects therefore provide a good opportunity to evaluate biomechanical mechanisms related to RRI, which will be specifically addressed in chapter 5.**

A multi-factorial *injury Causation Model* proposed by Meeuwisse [61] provides a good basis for understanding the complexity and development of RRI (Figure 1.3). Firstly, the model begins with some athletes (runners in context) who are predisposed to RRI due to certain intrinsic factors (e.g. age, sex, experience, poor load tolerance or low fatigue resistance). Secondly, *predisposed* runners may become susceptible to RRI when they are exposed to certain extrinsic factors (e.g. harder running surfaces or worn-out shoes). Thirdly, *susceptible* runners become *injured* runners with the presence of an 'inciting event' which serves as the mechanism of injury, such as excessive increases in training loads, sustaining high intensities, or compensating biomechanically.

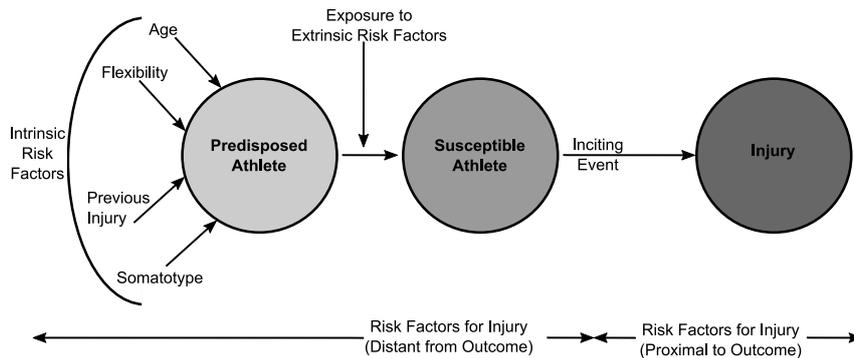


Figure 1.3: Multifactorial model of athletic injury etiology, adapted from Meeuwisse [61] with permission from Wolters Kluwer Health.

The inciting event of RRI, therefore, represents the final link in the mechanical chain that breaks, or in the words of Meeuwisse [61], 'the final straw that breaks the proverbial camel's back'. However, determining the inciting event or biomechanical mechanism leading up to RRI is not as easy as, for example, acute traumatic injury as highlighted by Bahr and Krosshaug [6]:

It should also be noted that — especially for overuse injuries — the inciting event can sometimes be distant from the outcome. For example, for a stress fracture in a long distance runner, the inciting event is not usually the single training session when pain became evident, but the training and competition programme he or she has followed over the previous weeks or months.

Therefore, this time discrepancy leading up to RRI makes it difficult to predict factors modifiable through intervention. By definition, a RRI can be termed 'overuse' when repetitive micro-trauma is incurred to tissue [37], or from the combined fatigue effect over a period of time beyond the capabilities of the specific structure that has been stressed [42]. Several biomechanical concepts can help elucidate on why RRIs are categorised as 'overuse' rather than 'acute', and why there could be several underlying mechanisms.

1.3.1 Kinetic and kinematic concepts

Some of the most prominent biomechanical concepts relating to RRI will be briefly discussed in terms of origin, mechanism, and supporting evidence where available. Kinetic concepts include the stress-frequency curve and measures of higher dynamic loading, while

kinematic concepts include some of the most well-known and well-cited concepts including excessive pronation, improper foot-strike pattern, and inadequate dynamic stability.

The stress-frequency curve. This concept, otherwise known as the 'fatigue curve' was designed to visualise the contrast between acute and overuse (i.e. accumulative) loads with respect to RRI development. An overuse RRI is said to occur once repetitive impact forces have accumulated and, importantly, with each force substantially less than the threshold needed to elicit an acute injury. Since the 'frequency of stress' can be ambiguous (e.g. frequency of steps, Hz, sessions etc.), the x axis of the stress-frequency curve has been modified to represent 'stress accumulation' rather than 'frequency' (Figure 1.4).

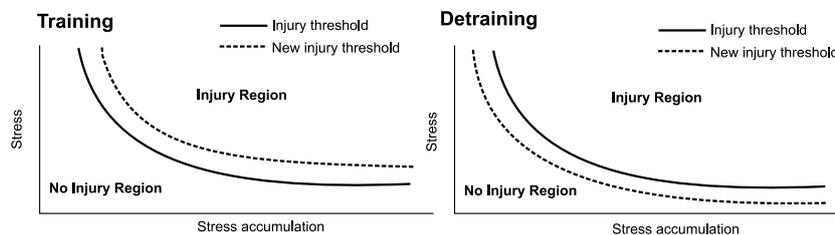


Figure 1.4: **The theoretical stress-accumulation curve** and its defining injury-threshold which shifts up and to the right with positive training effects (left) and down and to the left with negative de-training effects (right).

However, Hreljac [42] provides several reasons why predicting failure of particular biologic structures such as bones, joints, tendons, or muscles in response to dynamic loads incurred due to running per se is not so easy and straightforward. Perhaps the most important reasons provided is that the injury-threshold curve is dynamic and multi-directional, not static or two-dimensional as depicted [42].

Specifically, the injury-threshold curve shifts upward and to the right (thereby expanding the *No Injury Region*) when the applied stresses or training loads are optimal (e.g. appropriate training in no-injury region but maintained close to the theoretical curve), thus strengthening the structure via positive adaptation and remodelling [42] (see top dashed line in left panel of Figure 1.4).

In contrast, the injury-threshold curve shifts down and to the left when applied stresses are continuously low e.g. by bed rest or space-flight [42] and thus weakening the structure via negative adaptation or remodelling (see bottom dashed line in right panel of Figure 1.4).

Higher dynamic loading characteristics. Researchers have sought various methods to

quantify the *magnitude* and *rate* of dynamic loads incurred while running in an attempt to establish a link with RRI. For example, as emphasised by Milner et al. [64]:

stress fractures are thought to be related to some quantity, or 'dose' of loading, where dose may be a measure of some combination of peak shock, ground reaction force loading rates, peaks, and repetitions.

Despite these (higher) dynamic loading characteristics (see earlier Figure 1.1) being intuitively linked to higher incidence rates of RRI, research findings have been inconsistent. For example, some studies indeed have shown that higher impact forces, loading rates, or tibial shock are associated with runners with RRI history [43, 64, 100], while other studies have found no such link [5, 12, 14] compared to healthy runners. Moreover, one prospective study counter-intuitively revealed that lower impact force magnitudes and loading rates [72] were associated with higher RRI frequency. Although being substantially higher than impact magnitudes, peak active ground reaction forces have been given surprisingly little research attention. Hence, evidence relating higher external dynamic loads to RRI remains inconclusive. Several plausible explanations may exist.

One plausible reason is that all RRI investigations to date have been delimited to quantifying the magnitude of dynamic loads over a limited number of steps in controlled laboratory conditions (detailed in section on *ecological validity*). This has two implications. Firstly, the dynamic loads indoors on short laboratory runways or on motorised treadmills may not be completely representative of dynamic loads typically observed in more frequented conditions, i.e., on the road, track, or trail. Secondly, with the stress-frequency curve in mind, not only the magnitude should be addressed, as loading could change over the time period of an entire running session.

Another plausible reason could be that quantifying loading characteristics alone, ignores the fact that the body can compensate kinematically, shifting dynamic loads between biological structures. Indeed, over the past few decades several key **kinematic** concepts have emerged from various domains including clinical practice, evolutionary theory and dynamical systems theory. These concepts may offer various distal, proximal or combined mechanisms as to why runners sustain a RRI.

Excessive pronation. This is one of the earliest compensatory mechanisms thought to induce RRI. Pronation refers to the foot moving into an everted, adducted, and dorsiflexed position that occurs immediately after the foot strikes the ground until roughly about 70%

of stance [44]. The concept of excessive pronation originated from observations in clinical practice within orthopaedic context, as stated by James et al. [44]:

Some pronation is normal for the weight-bearing foot, but excessive pronation is a compensatory motion secondary to malalignment of the heel-foot or leg-foot alignment.

James et al. [44] further postulated in the late 1970s how prolonged pronation during the support phase is associated with RRI: higher applied stress to the supporting structures of the foot, obligatory tibial rotation, and disruptions in the tibial-femoral movement relationship. To date, three critical reviews have however concluded that there is no definitive RRI link to atypical foot-ankle pronation mechanics or alignment in either prospective or in epidemiological studies [18, 25, 73].

Improper foot-strike pattern. This is another 'bottom-up' theory implicated with running injury. Foot-strike pattern refers to the portion of the foot that contacts the running surface and is typically categorised as either rear-foot, mid-foot, or fore-foot first. Switching to a mid- or fore-foot strike is highly advocated among some running coaches due to being more 'natural' and due to an absence of the 'impact peak' typically observed in the ground reaction force curve. This 'natural' notion stemmed mostly from the findings of an evolutionary-directed paper by Lieberman and colleagues [53], where they conclude:

Fore-foot- and mid-foot-strike gaits were probably more common when humans ran barefoot or in minimal shoes, and may protect the feet and lower-limbs from some of the impact-related injuries now experienced by a high percentage of runners.

However, a recent research paper revealed that both rear-foot and non-rear-foot strike patterns generate similar impact in the frequency domain [33], indicating that landing with the fore-foot likely does not actually reduce impact. Despite one retrospective report [21] of lower incidence RRI in fore-foot collegiate runners, a recent review [36] concluded that changing to a mid- or fore-foot strike pattern does not reduce the risk of RRI.

Inadequate dynamic stability. This theory posits that proximal, rather than distal movements contribute to RRI. However, the notion of dynamic stability is not trivial and various operational definitions have been used in the literature depending on the context (Table 1.1).

Table 1.1: Operational definitions of dynamic stability identified in the literature.

Study	Definition: 'The ability of the ...
Baratta et al. [7]	(muscle system) to minimise unwanted joint displacement to aid stress absorption and generally prolong the cartilage serving time'.
Butcher et al. [15]	(trunk) to maintain active control of spinal and pelvic posture <i>during dynamic loading and movement conditions</i> '.
Kibler et al. [47]	(core muscles) to stabilise the spine <i>through muscle contraction</i> .
Verrelst et al. [93]	(joint) to maintain position or the intended trajectory '.
White and Panjabi [96]	(spine) to limit patterns of displacement <i>under physiologic loads</i> so as not to damage or irritate the spinal cord or nerve roots '.
Zazulak et al. [99]	(joint) to maintain intended trajectory <i>after internal or external disturbance or perturbation</i> '.

Clearly, as seen in Table 1.1, the operational definition of dynamic stability depends on the structure (e.g. muscle, joint, spine, trunk), the desired function or outcome (e.g. either maintaining desired motion or minimising undesired motion), and the intended context condition (e.g. during dynamic or physiological loads or after a perturbation) in question. Some definitions explicitly include an end goal to dynamic stability, such as to prevent damage [96] or prolong the life-time of the structure [7]. Regardless, the inadequacy or dysfunction of dynamic stability has recently gained more research attention and, refers to either neuro-muscular dysfunction or hip muscle weakness that may cause unsolicited accessory movements of the hips and trunk [18, 25, 55, 92].

Two operational definitions could be employed to understand how lower-limb injury may originate from inadequate dynamic stability. Firstly, Loudon et al. [55] points out that '*proximal mechanical faults will affect lower-limb loading which may cause tissue breakdown*'. Secondly, Verrelst et al. [92] elaborates that '*impaired function of the lumbopelvic-hip complex is believed to increase vulnerability to uncontrolled joint displacements or accessory movements throughout the lower kinetic chain*'.

Hence, RRI is thought also to develop when poor proximal dynamic stability inappropriately redistribute loads to distal structures throughout the kinetic chain. There is a growing body of prospective evidence supporting the role of these proximal dysfunction mechanisms in RRI [18, 25, 55, 92], and how such loads could be translated distally to various lower-limb structures:

- increased passive restraint on the iliotibial band - in the case of iliotibial band syndrome.

- higher frontal plane knee valgus moments at the knee - in the case of patellofemoral pain syndrome.
- increased stress on the lower-limb - in the case of medial tibial stress syndrome.

Sub-optimal coordinative variability. This is a dynamical systems approach to understand how the interaction of joint movements change with RRI. Coordinative variability refers to the multiple degrees of freedom involved in the coordination and control of human movement [37]. The theory postulates that RRIs result from too low variability that causes forces to be distributed across small surface areas. Thus, when the number of available movement patterns becomes reduced the system becomes less flexible to respond appropriately to an external perturbation, as explained by Hamill et al. [37]

Over time, reductions in effective degrees of freedom, interacting components and synergies involved in the control of the biological system may become associated with a loss of variability or complexity. When these reductions in degrees of freedom and variability reach a critical threshold, injury or disease emerge.

This decline in variability or complexity could provide insights into the progression of disease from a RRI perspective, and not only from a frailty perspective [54] as originally conceptualised (Figure 1.5). While this loss of complexity theory has made substantial contributions to our understanding of cardiovascular or neurological disease and frailty, this hypothesis warrants research in the domain of RRI. For example, lower coordinative variability has been observed in runners with patello-femoral pain syndrome [38].

Some studies have addressed RRI from a multi-factorial standpoint by investigating how runners with history of RRI may compensate differently with fatigue (i.e. an interaction between RRI and fatigue) compared to healthy runners. Firstly, a kinematic study performed by Miller et al. [63] found that runners with history of iliotibial band syndrome (ITBS) had different kinematic patterns such as greater knee-flexion at heel-strike, maximum knee internal rotation, and maximum foot inversion when exhausted at the end of a treadmill fatigue protocol compared to uninjured controls. Secondly, a kinetic study performed by Gerlach and colleagues [29] reported that decreases in impact loading rates with treadmill running fatigue were significantly less in previously injured runners compared to non-injured controls. **Therefore, how running fatigue and running injury**

interact is a crucial area for future research. Indeed, chapter 5 later on attempts to further this line of research.

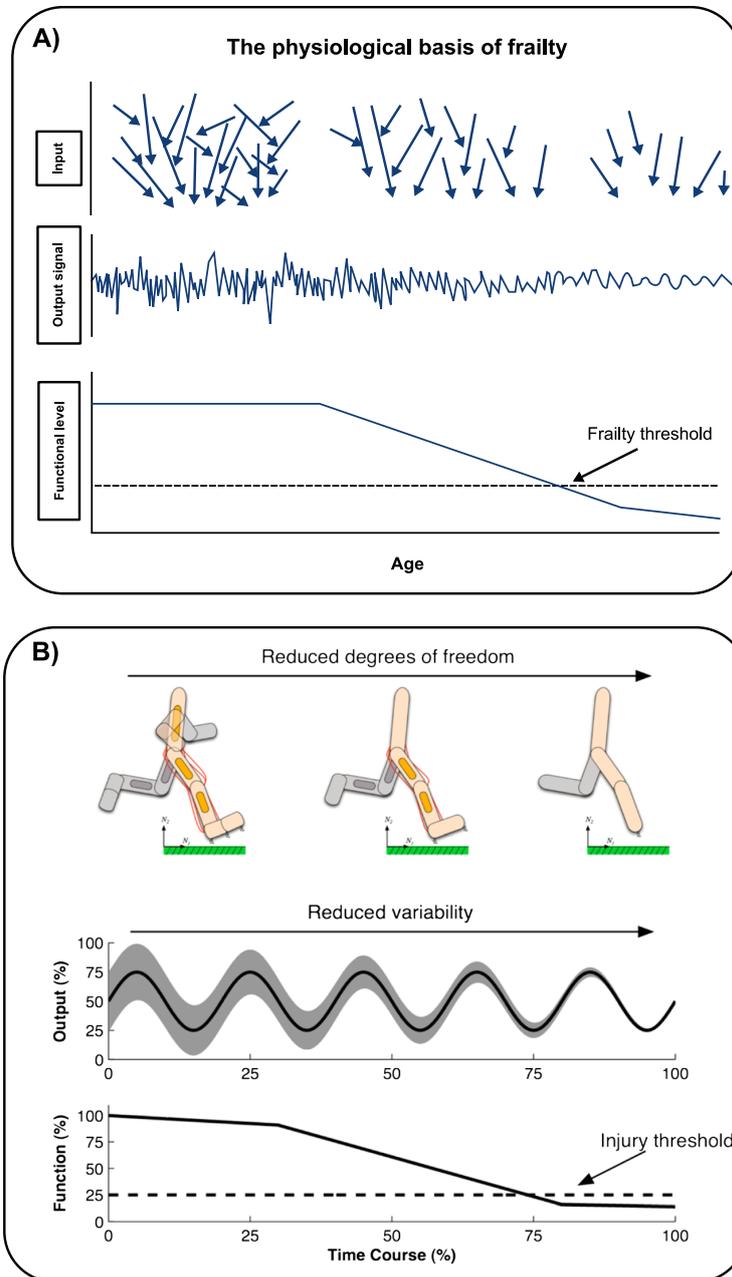


Figure 1.5: Loss of complexity hypothesis in ageing proposed by Lipsitz [54] (A) adapted with permission from Oxford University Press, and later applied to RRI (B), adapted with permission from Hamill et al. [37].

In summary, it appears necessary to **explore kinematic concepts and compensatory movement mechanics beyond those used traditionally to fully understand mechanisms related to RRI**. Of these concepts, proximal dynamic instability shows promising results. This concept, in combination with a sound hypothesis (e.g. the loss of complexity hypothesis) could shed more light into the development of RRI, and hence forms a theoretical basis for some of the running biomechanics measures (e.g. sample entropy of proximal trunk movements) used in this PhD work. Clearly, researchers should design appropriate protocols to experimentally test these concepts.

1.4 Ecological validity of running biomechanics research

Ecological validity commonly refers to the extent to which research findings can generalise to settings of everyday life. In the context of running research, generalising to everyday running conditions may constitute several different terms (see Table 1.2). In theory, ecological validity is reduced when running research is constricted or restricted to the testing environment. This section reviews some issues within running biomechanics research that poses threats to ecological validity, including experimental setting, running speed, and the number of running steps analysed.

Table 1.2: Terms related to ecological validity in running biomechanics research

Increased ecological validity	Reduced ecological validity
over-ground	treadmill
outdoors	indoor laboratory
appropriate place (in situ)	inappropriate place
representative (multiple strides collected)	unrepresentative (few strides collected)
multiple terrain	single surface
uncontrolled	controlled
unsupervised	supervised
mobile monitoring	immobile or fixed measurement area
self-selected speeds	controlled or fixed running speeds
unconstrained conditions	constrained conditions
real-time	significant post-processing
real-world	simulated conditions
typical environment	atypical environment

Experimental setting. In the 1920s Hill [40] evaluated outdoor sprinting by using a combination of wearable magnetic chest bands and galvanic responses recorded on wired coils as the runner passed by (see Figure 1.6). Running velocity profiles could be computed by dividing the distance between each coil and the elapsed time between

galvanic deflections. As highlighted by Bassett [10], this technique was the forerunner for the modern technique of using high-speed cameras.

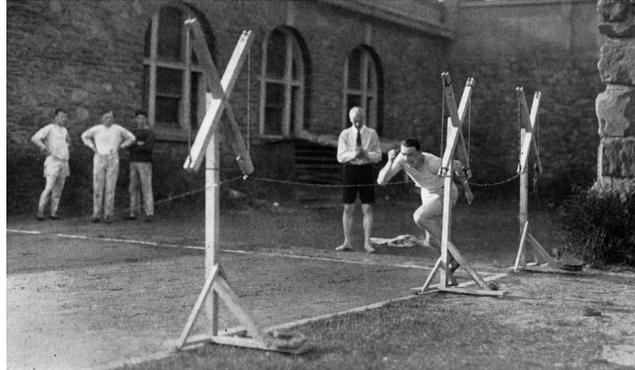


Figure 1.6: In 1927, outdoor over-ground sprinting acceleration was derived from wearable magnetic bands around the chest which created galvanic deflections as runners passed by coiled wires at known distances [40].

In general, to date very few studies have examined running biomechanics outside the laboratory ($n = 4$; Table 1.3). Studies conducted in the 1970s and 80s often used 2D cameras to analyse 2-4 consecutive running steps per lap on an athletics track [11, 24]. One particular study in the 90s analysed 193 consecutive running steps during a 400m time trial on an athletics track using foot-switches inserted in the shoes [75]. This highlights how being able to wear equipment can permit a ten-fold increase or more in the number of steps captured. However, their [75] study was limited to shorter track conditions given the need to simultaneously wear a heavy waist-worn transmitter (1.8 kg) to receive and store the data. A more recent outdoor study [30] used lightweight wireless accelerometers with on-board storage to capture up to 5530 consecutive running steps during a trail running race. This highlights the importance of using light-weight and unobtrusive equipment with potential for on-board storage. Thus, it appears that the setting and the number of consecutive running steps used in the biomechanics literature appear to be related to the nature of the equipment and technology restrictions of the time.

Table 1.3: Overview of experimental approaches and technology used in the biomechanics literature

Study	Pub. Year	In/outdoors	Mode	Speed type	Intervals (n)	Steps analysed (n/interval)	Technology
Running-fatigue							
Bates & Osternig [11]	1977	out	OG track	self-paced	2	2	2D camera
Elliot & Ackland [24]	1981	out	OG track	self-paced	4	4	2D camera
Nummela et al. [75]	1996	out	OG track	self-paced	throughout	193	foot-switch
Verbitsky et al. [91]	1998	in	TM	standardised at physiological pace	7	30	wired 1D tibial ACC
Voloshin et al. [94]	1998	in	TM	standardised at physiological pace	7	27	wired 1D tibial ACC
Mizrahi et al. [65]	2000	in	TM	standardised at physiological pace	7	27	2D camera wired 1D tibial ACC
Derrick et al. [22]	2002	in	TM	standardised at 3.2-km performance pace	3	20	wired 1D tibial & head ACC; EGM
Mercer et al. [62]	2003	in	TM	standardised at 3.8 m ■ s ⁻¹	2	10	wired 1D tibial & head ACC
Le Bris et al. [52]	2006	in	OG track	standardised at physiological pace	3	32	wireless trunk ACC
Miller et al. [63]	2007	in	OG track	standardised at subjective pace	2	22	3D mocap
Girard et al. [32]	2010	in	OG track	self-paced	25	4	FP
Morin et al. [71]	2011	in	TM	standardised at physiological pace	over 10-second window	4	FP
Abt et al. [1]	2011	in	TM	standardised at physiological pace	2	6	wired 1D tibial & head ACC
Rabita et al. [80]	2011	in	OG track	standardised at physiological pace	4	4	FP
Meardon et al. [60]	2011	in	OG track	standardised at physiological pace	3	6.11	wireless 1D tibial ACC
Koblbauer et al. [48]	2013	in	TM	standardised at subjective pace	2	20	3D mocap
Rabita et al. [79]	2013	in	OG track	standardised at physiological pace	2	4	FP
Giandolini et al. [30]	2015	out	OG trail	self-selected	first 20km	5530	wireless 3D tibial and shoe ACC
Paquette et al. [76]	2017	in	TM	standardised at 75% 10-km performance pace	2	5	3D mocap
Energetic cost							
Williams & Cavanagh [97]	1987	in	OG runway	standardised at 3.57 m ■ s ⁻¹	1	1	FP; 3D cinematography
Heise et al. [39]	2001	in	OG runway	standardised at 3.35 m ■ s ⁻¹	1	?	FP
Kyröläinen et al. [50]	2001	in	OG track	standardised at 3.0 to 5.0 m ■ s ⁻¹	5	3	FP; 2D camera; EMG
Nummela et al. [74]	2007	in	OG track	standardised at 5.4 to 6.6 m ■ s ⁻¹	4	3 to 5	FP
Tartaruga et al. [86]	2012	in	TM	standardised at 4.4 m ■ s ⁻¹	1	6	3D mocap; EMG
Gruber et al. [34]	2013	in	TM	standardised at 3 to 4 m ■ s ⁻¹	3	20	3D mocap
Santos et al. [83]	2014	in	TM	standardised at 3.75 m ■ s ⁻¹	1	over 30-second window	2D camera; optical system
Moore et al. [70]	2016	in	OG runway	standardised at 2.53 m ■ s ⁻¹	1	10	FP; 3D mocap
Folland et al. [26]	2017	in	TM	standardised at 2.78 to 3.3 m ■ s ⁻¹	3	20	3D mocap
RRI							
Nigg et al. [73]	1995	in	OG runway	standardised at 4.0 m ■ s ⁻¹	1	7	FP
Hreljac et al. [43]	2000	in	OG runway	standardised at 4.0 m ■ s ⁻¹	1	2	FP
Bennell et al. [12]	2004	in	OG runway	standardised at 4.0 m ■ s ⁻¹	1	20	FP
Gerlach et al. [29]	2005	in	TM	standardised at 5-km performance pace	1	12	FP
Zifchock et al. [100]	2006	in	OG runway	standardised at 3.8 m ■ s ⁻¹	1	10	FP
Azevedo et al. [5]	2009	in	OG runway	self-paced at 3.0 m ■ s ⁻¹	1	5	FP; 3D mocap; wired EMG
Milner et al. [64]	2006	in	OG runway	self-paced at 3.7 m ■ s ⁻¹	1	5	FP; 3D mocap; wired 1D tibial ACC

OG: over-ground; TM: treadmill; FP: force plate; mocap: motion capture; EMG: electromyography; 1D/2D/3D: one-, two- or three-dimensional; ACC: accelerometer; EGM: electrogoniometer

Running speed. Running speed is well established as a primary determinant of running kinematics and kinetics variables and thus researchers have sought various ways to deal with it, either experimentally or statistically. Each strategy comes with its own advantages and disadvantages. Research seems mostly divided between the practice of self-paced and standardised pace protocols. The former allows runners to freely select their most comfortable running speed while the latter relies on various approaches to 'ecologically validate' fixed running speeds, such as:

1. **Standardised pace equivalent to outdoor performance**, e.g., at $\sim 100\%$ of 3200m speed [22] to simulate middle distance fatigue; or at $\sim 75\%$ of 10000m speed [76] to simulate fatigue at a comfortable running intensity.
2. **Standardised pace equivalent to a physiological threshold**, e.g., at \sim anaerobic threshold [65, 66, 91, 94], \sim lactate threshold [19]; or \sim ventilatory threshold [1] to simulate near long-distance race-pace fatigue; or at $\sim 100\%$ VO_{2max} , e.g., maximal aerobic speed [52] which are typically much shorter in duration of ~ 7 minutes to simulate middle-distance fatigue.
3. **Standardised pace equivalent to a self-perceived threshold**, e.g., a continuous speed at a start rating of perceived exertion RPE of "somewhat hard" (i.e. level 13 on the 6 to 20 scale) [48] to simulate a 'very hard' training session; or at a self-perceived pace that could be maintained for a duration of 20 minutes [63]; or a self-perceived intensity of $\sim 40\%$ VO_{2max} [71] which are much longer in duration of 24 hours to simulate ultra-marathon fatigue.

Speed standardisation mostly coincided with the advent of the motorised treadmill, which on the one hand improves consistency of results under tightly controlled conditions, but on the other hand leads to questions of ecological validity. Some studies [12, 43] for example, have acknowledged that the standardised running speeds chosen on their laboratory runways did not represent the typical running speeds experienced by their running study population. Indeed, a runner's kinematics can also change when comparing treadmill to overground running [82].

Although force plates have enabled over-ground self-paced running to be analysed they are also subject to limitation. Visual targeting of the force plate, stride-modification within the measurement zone, or insufficient runway length can all confound the biomechanical output and thus the ecological validity. Interestingly, most of the literature pertaining to

RRI and the energy cost of running have made use of laboratory force plates for their analysis, questioning the transferability of their results to the 'real-world' (see Table 1.3).

Nevertheless, real-world context or conditions can also provide low fidelity data with confounded results, reducing the internal validity of the research protocol. Acquiring accurate biomechanical information from ecologically valid settings, and attaining a technical trade-off between the two validity types remains a challenge. Ultimately, several steps in the research process should be taken to fully assess 'free-living' running mechanics in conditions that are unsupervised (i.e., without researcher) and uncontrolled (i.e., independent of context, situation, or terrain) (see Figure 1.7). **Thus, technology is needed to compliment the optimal experimental approach, moving towards research that is conducted in typical running settings, takes into account self-selected running speed, and enables analysis of a sufficient (representative) number of running steps.**

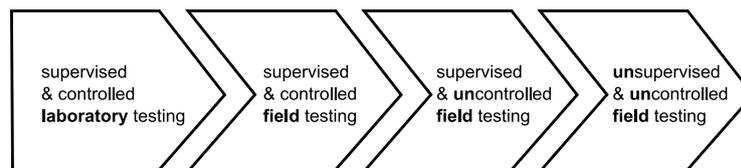


Figure 1.7: Model for research steps needed to move from laboratory to real-world experimental conditions, adapted from Caulfield and Pijnappels [16].

1.5 Wearable trunk accelerometry (WTA)

1.5.1 What is WTA?

A **wearable** can generally be defined as an object or product that interacts with the human body [28]. With rapid advances in technology and applications, this has recently been expanded more operationally as:

lightweight, sensor-based device which is worn close to and/or on the surface of the skin, where it detects, analyses, and transmits information concerning several internal and/or external variables to an external device and provide in some cases immediate biofeedback to the athlete [23].

Wearable technology has had an impact not only on industry but also on the research community - with the number of academic publications showing exponential growth over the past 10 years, as seen in Figure 1.8.

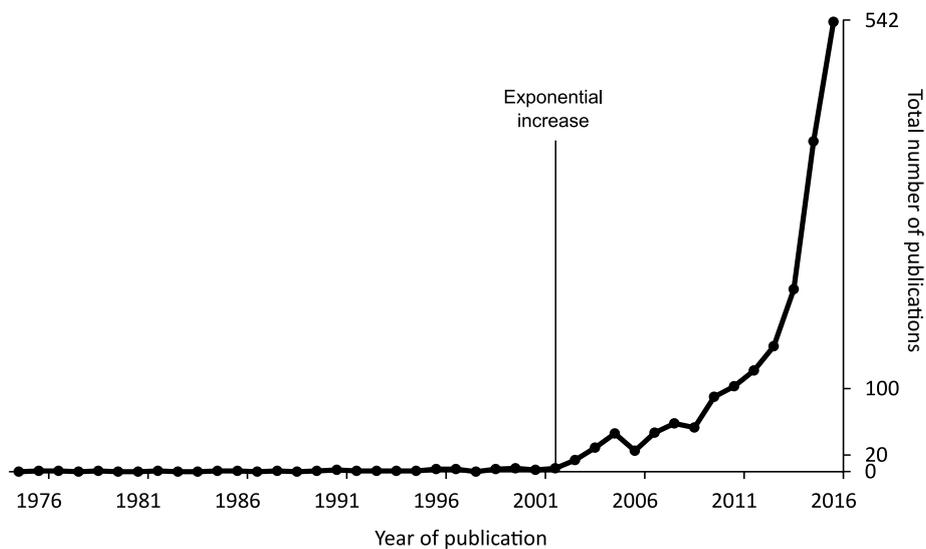


Figure 1.8: The number of publications listed on PubMed on 'Wearable Technology' has grown exponentially since 2002, data extracted from Alexandru Dan Corlan: URL:<http://dan.corlan.net/medline-trend.html>.

In the context of running, the definition of a wearable extends to a *dynamic wearable* that refers the human body *in motion* [28]. Wearables for running come in many shapes and sizes that change rapidly according to technological restraints or advancements. Wearables

have long been used to monitor physiological (e.g. HR) and training (e.g. GPS) aspects, but have only more recently started to provide the opportunity to monitor the activity- and biomechanically-related aspects of running.

Accelerometry refers to sensors that measure the applied acceleration acting along a sensing axis [57]. Although these accelerations can be measured by a variety of different types of transducers (e.g. piezoelectric crystals, piezoresistive sensors, variable capacitance accelerometers, etc.) they all conceptually use a variation of a spring-mass system (see Figure 1.9).

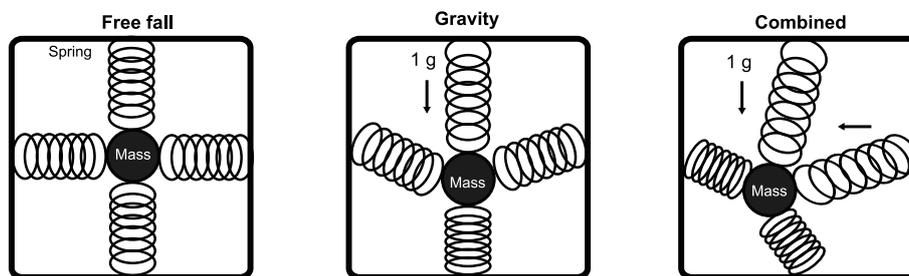


Figure 1.9: An accelerometer consists of a spring-mass system (left) that responds gravitational acceleration (middle) as well as various combinations of acceleration due to movement (right)

Low cost **inertial measurement unit (IMU)s** has been made possible due to the enhancement of **microelectromechanical systems (MEMS)** [57]. However, application of this technology is somewhat dictated by sensor specifications, accuracy, sensitivity and computing power - falling on a 'technology continuum'. For example, the most basic on the wearable accelerometry continuum are low resolution 'activity monitors' that sample every second (1 Hz), and are sufficient for quantifying and monitoring the *amount* of activity performed for a given period (e.g., training session, week, or month). On the high-end of the wearable accelerometry continuum are 'impact accelerometers' that sample more than one thousand times faster (> 1000 Hz) with larger sensing ranges (> 16 g) and that are better suited for quantifying the highly dynamic biomechanical aspects of running.

1.5.2 Why use WTA?

In the literature, WTA is a popular approach to quantifying the biomechanics of human walking gait. This section highlights numerous reasons why this approach is also well suited

for the application of quantifying and long-term monitoring of running biomechanics from a theoretical, technological, and practical standpoint.

1. **A single-sensor approach to estimate centre of mass (CoM) motion:** In running, CoM motion is typically estimated from a musculoskeletal model that is based on the position and magnitude of several body segments. However, methodological drawbacks acknowledged in musculoskeletal modeling are its dependency on accurate marker placement, camera positioning, and computer modeling software. WTA, in contrast, is a simple alternative approach that selects a single surface reference point in the proximity to where the CoM is expected to be, and estimates CoM motion relative to this reference point. Thus, as explained by Mo-Nilssen et al. [67], the error associated with choosing a specific surface reference point for the sensor is limited to changes in the reference point relative to the CoM. This error can be minimised by selecting a definitive position (e.g., over the L3 spinous process on the lower back) that minimises the effects of opposing axial rotations of the thorax and pelvis found during running. An attachment close to the proximity of the body's CoM also means that the weight of the sensor will have less of an inertial influence or hindrance on body movement.
2. **Suitable for *dynamic* wearability:** WTA meets important criteria or 'guidelines for dynamic wearability' devised by Gemperle et al. [28], given that WTA is positioned in an area that:
 - (a) is relatively the same size across adults
 - (b) has low movement or flexibility even when the body is in motion.
 - (c) is large in surface area
3. **Robustness of attachment:** Unlike wearable *tibial* accelerometry, WTA is more robust to coming loose and falling off. This is because vertical impact accelerations are much lower ($\sim 2\text{-}8$ **acceleration due to gravity (g)**) at the trunk compared to the tibia ($\sim 5\text{-}20$ g) due to high-frequency impact attenuation. This robustness also extends to greater suitability for *dynamic* wearability, since fixation at other distal locations (e.g. the tibia) often causes discomfort to the runner due to additional efforts required to improve fixation and maximise mechanical coupling with the limb. Moreover, attenuated accelerations at the trunk also means that there is a smaller chance of signal saturation, i.e., dynamic accelerations generated from running exceeding the sensing capacity of the sensor.

4. **Ability to evaluate different movement axes:** The site of attachment as well as tri-axial sensing ability within one casing opens up exploration into three movement axes relative to the body's **vertical (VT)**, **mediolateral (ML)**, and **anteroposterior (AP)** anatomical axes. However, measured accelerations are never perfectly aligned to the global coordinate reference due to alignment deviations caused by trunk posture or slight offsets in sensor placement. Therefore, deviations from the true coordinate system must be detected using the dispersion of the gravitational acceleration of $1g$, and measured dynamic tri-axial accelerations must be trigonometrically tilt-corrected. An example of tilt-corrected accelerations in the sagittal plane is shown in Fig 1.10, with Moe-Nilssen et al. [67] providing detailed equations and methods.

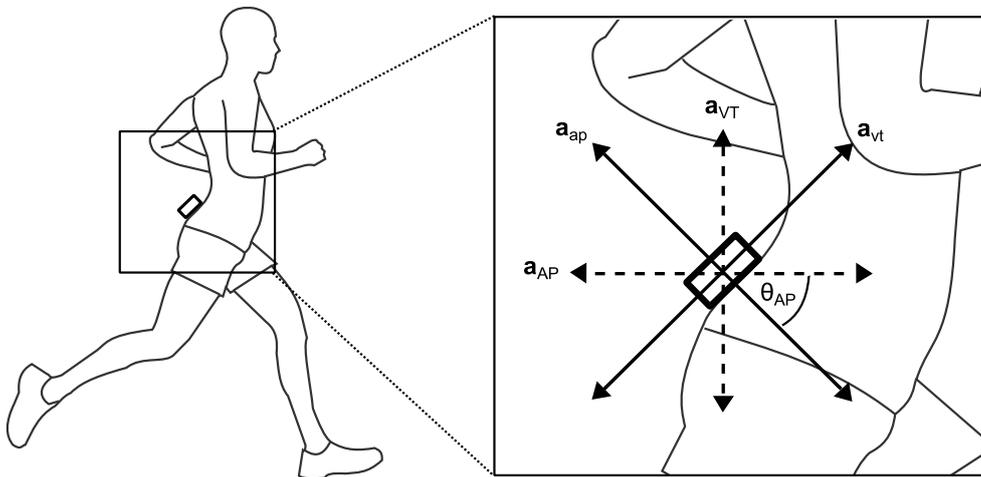


Figure 1.10: Converting measured vertical (a_{vt}) and anteroposterior (a_{ap}) accelerations in the sagittal plane to 'true' estimates of vertical (a_{vT}) and anteroposterior (a_{AP}) accelerations in an external global coordinate frame of reference.

Once accelerations axes align with the anatomical axis of the body, they can represent different functional qualities of running, dynamically related to:

- VT: bounce or stabilisation of body mass.
- ML: control or balance.
- AP: breaking and propulsive forces.

5. **Ability to quantify dynamic loading.** Albeit smaller in magnitude, impact 'shock' accelerations can be quantified by identifying the peak vertical or cranio-caudal

accelerations reaching the level of the trunk. Additionally, if the start and end events of stance phase (foot contact and toe-off) while running are identified, the entire acceleration waveform during ground contact can be converted to the frequency domain, as has been performed on tibial accelerometry [85]. Details on how contact time is derived from WTA and its validation are provided in APPENDIX II. Thereafter, the signal amplitude can be decomposed into low- and high-frequency accelerations that may provide clearer insights into both 'impact' and 'active' components [85].

Thus, throughout this PhD thesis, dynamic loading is defined operationally as:

the magnitude or attenuation of tri-axial trunk accelerations in the time and frequency domain during ground contact while running.

6. **Ability to evaluate aspects of inadequate dynamic stability.** Accelerometer patterns during running are repetitive and cyclical. There is a promising area of WTA research specifically to evaluate the inadequate proximal stabilisation theory (see earlier section on kinematic concepts). For example, WTA has been used to discriminate between populations with and without walking gait impairments using various measures that represent variability (e.g. root mean square (RMS) [84], step symmetry and stride regularity [68], or the waveform complexity [81, 87]). **Thus, throughout this PhD thesis, dynamic stability is defined operationally as:**

the ability to maintain optimal variability, symmetry, regularity or complexity of tri-axial trunk acceleration patterns while running.

1.6 Thesis overview

1.6.1 Research gaps and aims

The overall objective of this thesis is to expand the understanding with regards to detecting fatigue-, energy-, and injury-related dynamic instability and dynamic loading in runners using wearable trunk accelerometry with transferability to real-world ecologically valid settings. The following section critically reviews pertinent published work and the gaps between what has, and has not been done using high-end or high-spec WTA specifically for the application of detecting fatigue-, energy-, and injury-related aspects of instability and loading in runners.

1. One study to date conducted by Le Bris et al. [52] showed that WTA can be used to capture fatigue-ability aspects in loading and stability. However, their study was limited to a small sample of well-trained runners and used a protocol specific to high-intensity-short-duration ($VO_{2\max}$ speed) to elicit running fatigue. Therefore, there is still a large potential for WTA to identify instability and loading in various types of runners with different types of fatiguing protocols. **The first aim of this work was to detect fatigue-related instability and loading in runners using WTA.**
2. To the knowledge of the author only two studies [58, 95] have previously used trunk accelerometry to estimate energy expenditure while running. Unfortunately, neither of these studies investigated sub-maximal running economy specifically, by including running intensities beyond aerobic (e.g. ranging to maximal running intensity or aerobic capacity) in their regression analyses. Additionally, these studies either did not assess [95] or did not delineate [58] inter-subject variations in running economy. Biomechanical determinants of running economy are not well understood and it further remains unclear whether WTA can be used to distinguish runners with superior running economy. **The second aim of this work was to detect energy-related instability in runners using WTA.**
3. There are studies that have shown that inadequate proximal dynamic stability relates to RRI [18]. There are also studies that have shown that accelerometry can be used to detect RRI at the location of the tibia [64, 100]. However, it appears that there are no studies to date examining the link between RRI with dynamic instability

quantified using WTA at the trunk. **The third aim of this work was to detect RRI-related instability and loading in runners using WTA.**

4. Despite rapid advancements in wearable technology current solutions are inadequately addressing how it can apply to quantifying and monitoring a runner's biomechanics. Therefore, research is needed to expand on WTA as a potential solution to monitoring the biomechanical aspects of running in relation to injury and performance, while also covering several key issues with respect to technology barriers and ecological validity. Specifically, the importance of being able to perform continuous and *in situ* biomechanical monitoring appears to be the next necessary research step towards earlier detection and identification of fatigue-, energy-, and injury-related instability. **The fourth aim of this work was to address methodological and technical issues surrounding the ecological validity of running biomechanics using WTA.**

1.6.2 Outline

The following four chapters provide in-depth experiments and analysis to address the specific aims of this work. The first two experiments form part I: 'Indoor laboratory treadmill running', while the latter two experiments form part II: 'Outdoor over-ground running'. An overview of these experiments are provided in Table 1.4, and Figures 1.11, 1.12, and 1.13.

Table 1.4: Chapter overview

Part I: Indoor laboratory treadmill running				
Chapter	Aim	Hypothesis	Study design	Participants
2	To detect deviations in dynamic CoM motion in relation to running-induced fatigue using WTA	A fatigue-ability hypothesis, that WTA would be able to detect fatigue changes primarily occurring in the horizontal plane	Cross-sectional; indoor treadmill; pre-post fatigue; 20 steps analysed per interval	22 runners (ranging from novice to competitive)
3	To determine a link between a runner's stability and running economy using WTA	A cost of instability hypothesis that proposes a link between a runner's stability and running economy, and that this link can be assessed using measures derived from WTA	Cross-sectional; indoor treadmill; 20 steps analysed per interval	30 runners (all recreational)
Part II: Outdoor over-ground running				
Chapter	Aim	Hypothesis	Study design	Participants
4	To investigate outdoor surface effects on dynamic stability and dynamic loading during running using WTA	WTA measures of dynamic stability and loading would be minimally affected by outdoor running surface	Cross-sectional; repeated measures; outdoor over-ground running; 20 steps analysed per interval	28 runners (11 highly-trained; 17 recreational)
5	To determine the influence of outdoor running fatigue and medial tibial stress syndrome on both loading and stability derived from WTA and wearable tibial accelerometry	Runners with history of MTSS injury would reveal higher loading and dynamic instability with outdoor running fatigue compared to uninjured healthy controls	Cross-sectional; repeated measures; outdoor over-ground running; steps analysed throughout run	30 runners (14 with history of MTSS; 16 healthy recreational)



Figure 1.11: Study I (**chapter 2**) conducted at KU Leuven, biomechanically tested a fatigue-ability hypothesis during indoor treadmill running using WTA measures in relation to 3D motion capture.



Figure 1.12: Study II (**chapter 3**) conducted at Stellenbosch University, physiologically tested a cost of instability hypothesis during indoor treadmill running using WTA measures in relation to energy cost.



Figure 1.13: Study III (**chapter 4**) conducted at KU Leuven, tested the effects of running surfaces (concrete, synthetic and wood-chip for panels left to right) during outdoor over-ground running using WTA measures. Thereafter, study IV (**chapter 5**), also conducted at KU Leuven, returns to the fatigue-ability hypothesis, yet from an outdoor over-ground perspective on synthetic track (middle panel) and with the inclusion of runners with a history of MTSS overuse injury.

1.6.3 Methodology

Study design and participants. All four primary studies in this PhD work were cross-sectional in design. All of these studies obtained ethical clearance from the local ethics committees of KU Leuven and Stellenbosch University. The sample size included in the analyses totalled to 108 participants. These subjects were evenly distributed between men ($n = 56$) and women ($n = 52$), and ranged from mostly recreational ($n = 86$) to well-trained ($n = 22$) runners. Sample sizes per study were based on power calculations done in GPower software (GPower v3.1). Specifically, sample sizes needed to satisfy probability ($\alpha = 0.05$) and power ($1 - \beta = 0.8$) using effect sizes generated from relevant studies in the literature (i.e. studies that tested same hypothesis relating to fatigue, energy, or injury detection). Descriptive statistics for age, body weight, and running speeds used in this PhD project are shown Figure 1.14

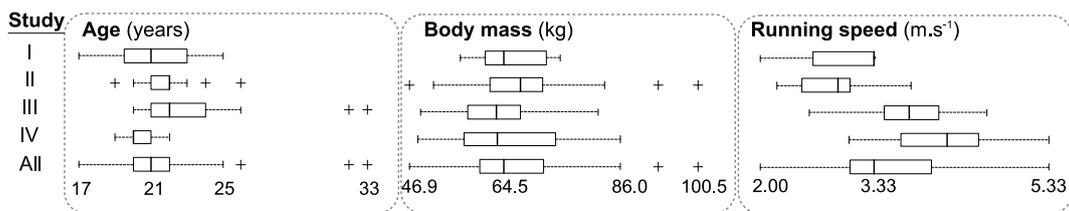


Figure 1.14: Participant cohorts used in this PhD thesis were mostly young adults of variable body mass categories, and were tested over running speeds ranging from 2 to 5.33 m · s⁻¹.

WTA specifications and attachment. Two high-end accelerometer brands (GCDC and Shimmer) with high sampling frequencies and sensing range were used in this thesis (Table 1.5). Slight differences in sensor choice between studies were due to state-of-the-art availability at the time each study was conducted. Additionally, attachment methods (e.g. on skin or in belt) differed slightly depending on experimental setting and practical issues such as dealing with sweating in outdoor conditions and providing additional support to improve mechanical coupling with the body (reduce wobbling mass effect of sensor). A deeper discussion is provided in the general discussion chapter.)

Table 1.5: Overview of which wearable accelerometers were included in which experiments along with associated specifications

	Study I		Study II		Study III		Study IV	
Brand	Gulf Coast Data	Concepts	Shimmer		Gulf Coast Data	Concepts	Gulf Coast Data	Concepts
Model	X-16-2		shimmer3		X-50-2		X-50-2	
Sampling frequency (Hz)	400		1024		1024		1024	
Sensing range ($\pm g$)	16		16		50		50	
Sensing resolution (bit)	15		16		13		13	
Weight (kg)	0.048		0.023		0.033		0.033	
Gyroscope capability	N		Y		N		N	
Magnetometer capability	N		Y		N		N	
Attachment type	against skin		in belt		against skin		in belt	

Accelerometer data: from collection to feature extraction. Several practical and pre-processing methodological steps are required before statistical analysis can be performed on WTA measures. A simplified version of these steps is schematically shown in Figure 1.15.

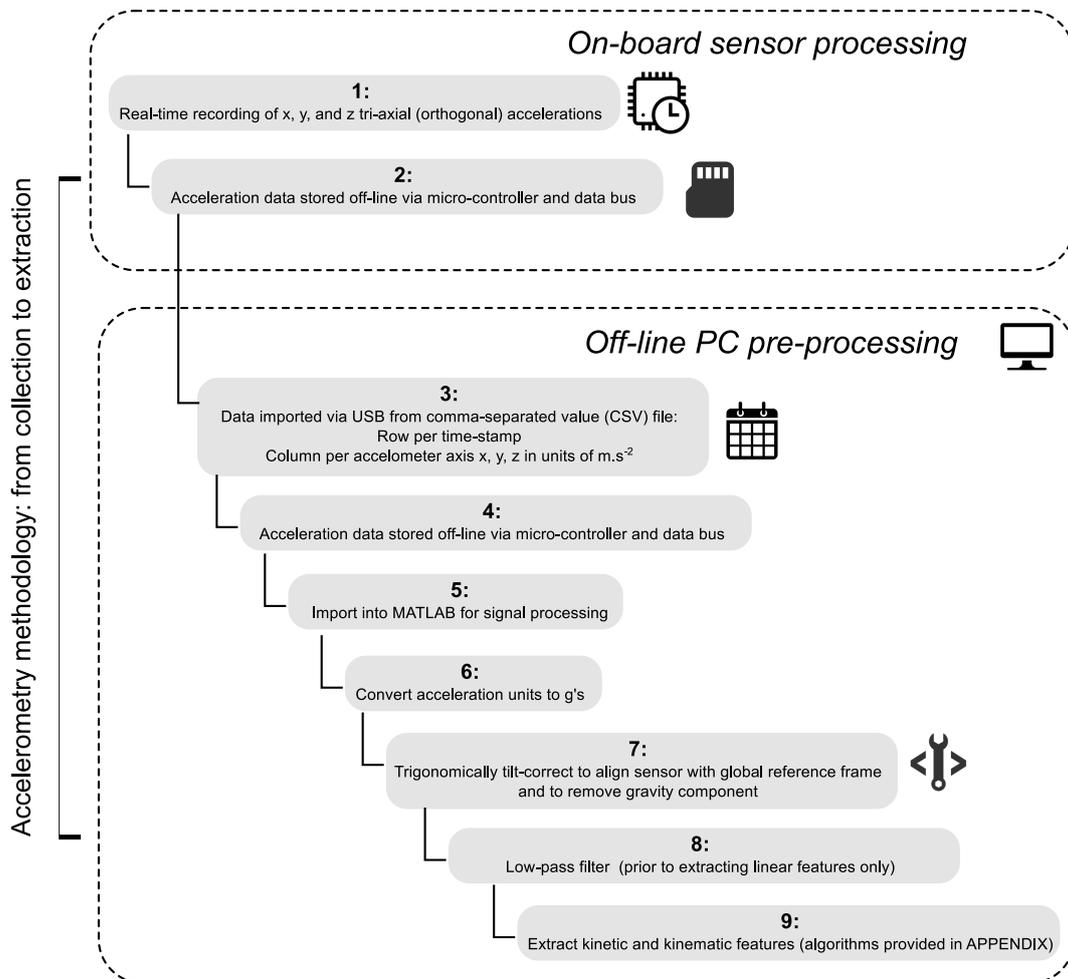


Figure 1.15: Accelerometer data: from collection to feature extraction

Kinetic and kinematic measures derived from WTA. A number of discrete and continuous measures were extracted from WTA to provide information on aspects of kinematics (spatio temporal and dynamic stability) as well as kinetics (impact shock and shock attenuation). A flow chart of these measures according to biomechanical division, type, and derived axes for studies I to IV (chapters two to five) are provided in Figure 1.16.

Although dynamic loading or kinetic related measures are additionally analysed in study III and IV, the central theme of this doctoral thesis relates to dynamic stability kinematic measures and therefore measures specific to dynamic stability were analysed in all studies. The methodology behind the accelerometry-based measures are mentioned in each subsequent chapter and full equations to the computation of each measure are provided in **Appendix I** to aid interpretation. Of note, many of the dynamic stability measures are unit less and depending on the specific journal requirements of each paper, were shown as either (unit less) or arbitrary units (a.u).

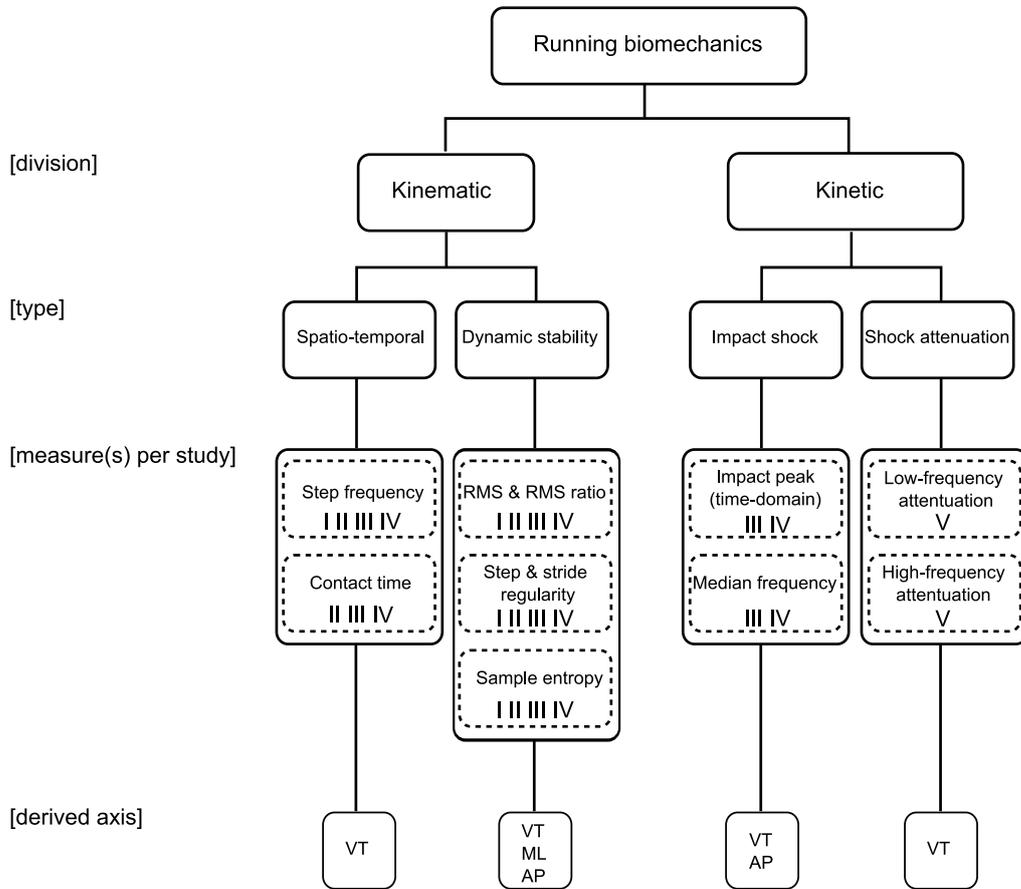


Figure 1.16: Overview of accelerometry-based kinematic and kinetic measures of running biomechanics used in this thesis, with I, II, III, and IV corresponding to the respective studies. VT: vertical; ML: mediolateral; AP: anteroposterior

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Part I

Indoor laboratory treadmill running

Chapter 2

Study I: Running-induced fatigue and dynamic instability

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Author Contributions

K.H.S, E.A.M and B.V conceived and designed research;

K.H.S, E.A.M and B.V performed experiments;

K.H.S analysed data;

K.H.S, E.A.M, B.V, V.E, R.V, and D.B interpreted results of experiments;

K.H.S drafted manuscript;

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Abstract

Small wireless trunk accelerometers have become a popular approach to unobtrusively quantify human locomotion and provide insights into both gait rehabilitation and sports performance. However, limited evidence exists as to which trunk accelerometry measures are suitable for the purpose of detecting movement compensations while running, and specifically in response to fatigue. The aim of this study was therefore to detect deviations in the dynamic center of mass (CoM) motion due to running-induced fatigue using tri-axial trunk accelerometry. Twenty runners aged 18-25 years completed an indoor treadmill running protocol to volitional exhaustion at speeds equivalent to their 3.2 km time trial performance. The following dependent measures were extracted from tri-axial trunk accelerations of 20 running steps before and after the treadmill fatigue protocol: the tri-axial ratio of acceleration root mean square (RMS) to the resultant vector RMS, step and stride regularity (autocorrelation procedure), and sample entropy. Running-induced fatigue increased mediolateral and anteroposterior ratios of acceleration RMS ($p < .05$), decreased the anteroposterior step regularity ($p < .05$), and increased the anteroposterior sample entropy ($p < .05$) of trunk accelerometry patterns. Our findings indicate that treadmill running-induced fatigue might reveal itself in a greater contribution of variability in horizontal plane trunk accelerations, with anteroposterior trunk accelerations that are less regular from step-to-step and are less predictable. It appears that trunk accelerometry parameters can be used to detect deviations in dynamic CoM motion induced by treadmill running fatigue, yet it is unknown how robust or generalizable these parameters are to outdoor running environments.

Keywords: Running; Fatigue; Accelerometer; Variability; Unbiased Autocorrelation; Sample Entropy.

Introduction

Given the repetitive nature of running, it is generally recommended that a running bout be stopped at a point before an individual's typical level of fatigue causes adverse biomechanical effects and subsequent injury [5]. Indeed, runners in a fatigued state have shown to lose coordination and consistency over positioning of their lower extremities [14, 17, 25] and become less capable at attenuating tibial shock accelerations [23]. **Identifying and correcting deterioration in a runner's technique due to fatigue is of value to enhancing athletic performance and might have potential to prevent injuries** [4].

In contrast to the lower extremity which has been well studied [22, 23, 32], **the response of the trunk or whole body center of mass (CoM) to running-induced fatigue has received limited attention**. The trunk serves a number of functions beneficial during locomotion, such as to attenuate accelerations that reach the head [39] or to maintain upright posture [9]. Koblbauer et al.[11] showed for novice runners, that besides an increase in peak ankle eversion angles, the most pronounced compensation in kinematics due to running-induced fatigue was an increase in forward inclination of the trunk. Morin et al. [25] reported that along with increased leg stiffness, the vertical motion of the CoM significantly reduced with prolonged exhaustive running. Reducing energetic cost [1, 26, 27], self-preservation of musculoskeletal structures [25], and pain avoidance [25] have all been considered mechanisms to explain the deviations in CoM motion during running.

In comparison to traditional 3D motion capture methods, **a single tri-axial trunk accelerometer offers a valid [18, 40, 41] and reliable [21, 24] approach to measure trunk and CoM acceleration during human locomotion and facilitates unobtrusive data collection in various environments**. Trunk accelerometry measures of human gait that have shown to objectively detect deviations in dynamic CoM motion include: variability, represented as the root mean square (RMS) of accelerations contributing to each independent axis [21, 31], step and stride regularity, assessed by the unbiased autocorrelation procedure [10, 24, 37], and the sample entropy value [15]. The latter is a non-linear statistic that considers the complexity of movement variability which may be masked or ignored using traditional measures [29] .

Although CoM accelerometry measures have been well established for assessing walking

gait [8, 12, 16, 31, 37], **limited investigations exist for assessing running gait** [13, 17, 21]. Only two studies [17, 21] have specifically used trunk accelerometry measures to assess running-related fatigue. The former study [17] found a decrease in regularity of vertical CoM accelerations, and an increase in the impulse of mediolateral CoM accelerations when their sub-elite distance runners underwent a short but highly intensive track run to exhaustion. The latter study [21] showed that increases in vector RMS of trunk accelerations could accurately estimate increases in metabolic work (VO_2) during an incremental running protocol to exhaustion. However, they [21] additionally reported that the vector RMS of trunk accelerations was associated with increments in running speed. Thus, albeit large potential, limited evidence exists [17] as to which trunk accelerometry measures are suitable for the purpose of detecting compensations in dynamic CoM motion while running under steady-state conditions. Moreover, measures such as sample entropy that consider the complexity of movement patterns may reveal additional insights into CoM fatigue-related compensations that have previously been unexplored.

The aim of this study was to detect deviations in dynamic CoM motion in relation to running-induced fatigue using tri-axial accelerometry. We hypothesized that when runners were in a fatigued state, a single trunk-mounted accelerometer would be able to detect changes primarily occurring in the horizontal plane. More specifically, we expected mediolateral and anteroposterior trunk acceleration patterns of fatigued runners to demonstrate 1) a greater contribution of variability (larger ratio of acceleration RMS), 2) less step and stride regularity, and 3) less predictability (higher sample entropy values).

Methods

2.0.1 Participants

Twenty-two runners aged 18-25 years were recruited to participate in this study. Participants were recruited via social media, e-mails and flyers. Runners were eligible for the study if they ran at least 10 km per week and ranged in experience from novice to competitive. Exclusion criteria were pulmonary, neurological and cardiovascular diseases, muscle weakness and obesity, assessed through a questionnaire prior to study participation. Runners with overuse injuries in the previous six months were excluded, as well as runners with orthopedic devices, except insoles. The study was approved by the local ethics committee (Commissie Medische Ethiek KU Leuven). Written informed consent was

signed by participants or on behalf of a legal guardian prior to study participation in accordance with the Declaration of Helsinki.

2.0.2 Experimental protocol

On day one the participants performed a 3.2 km run at maximal effort on an outdoor track. The time was recorded to determine their average running speed to be subsequently used for the treadmill fatigue protocol. On day two, participants completed an exhaustive treadmill run, set at speeds equivalent to their 3.2 km time-trial track performance. The aim of the exhaustion protocol was to have participants run to voluntary exhaustion, or when the termination criteria was achieved (BORG-score of at least 17/20 [2]). There were a minimum of 7-and a maximum of 10-days between testing day one and two [3]. Participants were instructed to abstain from arduous exercise for the 24 hours prior to both testing days, and to maintain their regular running schedule between tests. Each participant had previous treadmill running experience.

On testing day two participants were given at least five minutes to acclimatize to the motorized treadmill of the laboratory where data collection took place. This also served as their warm-up. Some participants had time-trial speeds that exceeded the maximum speed of the laboratory instrumented treadmill ($3.33 \text{ m} \cdot \text{s}^{-1}$). For these participants, pre-fatigue and fatigued conditions were fixed at $3.33 \text{ m} \cdot \text{s}^{-1}$, and they had to perform the exhaustive run on a separate motorized treadmill that enabled time-trial speeds. Due to logistical reasons, this separate treadmill could not be placed within the capture volume of the motion analysis system, and thus sacral marker trajectory could not be recorded during the fatigue protocol. Since we felt it was imperative that participants' were fatigued at their time-trial speed, the primary scope of this study was delimited to a pre-post fatigue design. The pre-fatigue condition was defined as the first two minutes of the fatigue protocol, and the last 10-seconds of this period was extracted for processing (three dimensional motion analysis and trunk accelerometry measurements). The fatigued condition was defined as the last 10-seconds prior to the aforementioned fatigue-related termination criteria. For participants that were fatigued on a separate treadmill; their fatigued condition was defined as the last 10-seconds of the first minute upon re-transitioning to the laboratory treadmill. The post-fatigue period between treadmill transitioning was never more than 30 seconds. Standardized running shoes were provided for all participants (Asics Gel Landreth 7).

2.0.3 Three dimensional motion analysis

A ten camera Vicon system (Vicon®, Oxford, Metrics UK) was used to track the motion of the retro-reflective sacral marker sampled at 150 Hz. The sacral marker displacement method was used to represent the total body CoM displacement, a method that has shown to be accurate during walking [35] and running [6]. Three dimensional marker trajectory was recorded during the last 10 seconds of each test condition. Trials were deemed to be successful if at least 20 consecutive steps of sacral marker visibility could be obtained.

2.0.4 Accelerometry measurements

A single tri-axial accelerometer (X16-2 wireless accelerometer, range $\pm 16g$, resolution 15-bit, Gulf Coast Data Concepts, MS) sampling at 400 Hz and weighing 48 g was mounted over the L3-L5 spinous process of each runner with double-sided tape [24]. Additional elastic straps were used to secure the accelerometer and minimize unnecessary movement. Trials were discarded in the case that the investigators deemed the accelerometer to be “not securely fastened” upon its removal (after completion of the data collection). Trunk accelerometry signals were recorded throughout the pre-fatigue and fatigue conditions (on-board SD card).

2.0.5 Data reduction

All data processing and analyses were performed using customized MATLAB software version 8.3 (The Mathworks Inc., Natick, MA, USA). Dependent variables assessed in this study were derived from 3D sacral marker trajectories (mean displacement and range) and tri-axial trunk accelerations (acceleration RMS, ratio of acceleration RMS, step regularity, stride regularity, and sample entropy). From 10-seconds of signals (trajectories and accelerations), the first 20 running steps were extracted to calculate each dependent variable.

Vertical, mediolateral, and anteroposterior sacral marker trajectories were filtered using a zero-lag 4th order low-pass Butterworth filter with a cut-off frequency of 15 Hz. Vertical displacement was determined by averaging the peak-to-peak difference (maximum-minimum) [35] of exactly 20 consecutive running steps for each participant. Since anteroposterior and mediolateral trajectories depend to some extent on where the participant is positioned on the treadmill, the start and end points for each step are

not the same (each step thus results in a net gain or loss in displacement), rendering step-to-step displacements for these directions not as useful [7]. Rather, we used the procedure devised by Hinrichs et al. [7] to calculate anteroposterior and mediolateral displacement: by computing the total excursion per step (sum of the absolute displacements between samples (frames), and finally averaging over 20 steps. Steps were identified according to the locations of the peaks in the vertical trajectory. Additionally, we calculated the range, which was the maximum distance (absolute maximum-minimum) between any two points of each axis over the 20-step interval.

The raw vertical, mediolateral, and anteroposterior signals from the accelerometer were converted from counts to g's offline, trigonometrically corrected to remove the static gravitational component [24], and filtered using a zero-lag 4th order low-pass Butterworth filter with a cut-off frequency of 50 Hz. The sensing axis of the accelerometer may not be aligned with the axes of the horizontal-vertical coordinate system of the laboratory while running. Therefore, a trigonometric correction [24] of the acceleration signal was performed, a procedure consistently applied to CoM accelerations during walking [9, 24, 31] and running [12, 21, 41]. In this study, calculated deviations of accelerometer axes were between 3.5 degrees to 9.3 degrees (anterior tilt) and 0.1 to 1.2 degrees (laterolateral tilt) prior to axis transformation. This procedure also enabled accelerometer alignment with the axes of the sacral marker. Tri-axial trunk accelerometry measures were examined using the acceleration root mean square (RMS), the RMS ratio of each axis to the resultant vector [21], step regularity and stride regularity [24], and sample entropy [29] of accelerations.

The acceleration root mean square (RMS) was calculated for each axis independently and gives an overall indication of variability of acceleration dispersion [21, 24]. Next, the acceleration RMS ratio, an indicator of the proportion of accelerations in each axis contributing to the overall movement, was calculated as the RMS of each axis relative to the resultant vector RMS [21, 31].

Step and stride regularity of accelerations were computed using the unbiased autocorrelation procedure previously described by Moe Nilssen et al. [24]. Representative unbiased autocorrelation patterns of all three acceleration axes are shown in Figure 2.1. Step regularity, the first dominant autocorrelation peak (Ad1 in Figure 2.1), indicates a correlation between consecutive steps and is therefore considered the symmetry index. Since mediolateral trunk accelerations produce both positive and negative accelerations that represent left-to-right lateral trunk motion, step regularity values for the mediolateral direction are always negative (Ad1 in Figure 2.1 B). The absolute value for mediolateral

step regularity was therefore used for analysis.

Lastly, the sample entropy of accelerations was determined using the non-linear mathematical algorithms previously described in detail by Richman and Moorman [29] and quantifies the uncertainty or unpredictability of the accelerometry time series [42], with a larger value indicating a less periodic and less predictable or periodic pattern. In contrast to the aforementioned measures, sample entropy was analyzed from unfiltered accelerations so as not to mask or remove any dynamical properties or variability present within the system [29]. In the literature, there are two contrasting approaches in human gait analysis to select the data string length parameter for sample entropy, either according to a fixed number of samples (time) [34, 36], or according to a fixed number of gait cycles [28]. In contrast to its predecessor statistic (approximate entropy), sample entropy values are more robust to shorter data strings and become stable at data strings exceeding over 2000 samples [42] – all of our trials were beyond this length to acquire 20 consecutive running steps (minimum was 2700 samples). Thus, we selected the “fixed-step” approach, also enabling consistency in number of steps selected from the sacral marker trajectory. Therefore, input parameters for our sample entropy calculation were firstly, a time series sample length (N) equivalent to 20 running steps (typical data string between 2700 to 3300 data points), secondly, a series length (m) of 2 data points, and thirdly, a tolerance window (r) normalized to 0.2 times the standard deviation of individual time series [42].

Step frequency was computed from the vertical axis of the sequence of trunk accelerations using samples per dominant period of the autocorrelation peak and sampling frequency of the accelerometer as inputs [24] (D1 in Figure 2.1 A). Stride regularity (Ad2 in Figure 2.1), the second dominant autocorrelation peak, represents a correlation between consecutive strides and can be considered as a regularity index. After normalization to the zero lag component, the maximum value (most periodic, most regular) for both step regularity and stride regularity is one.

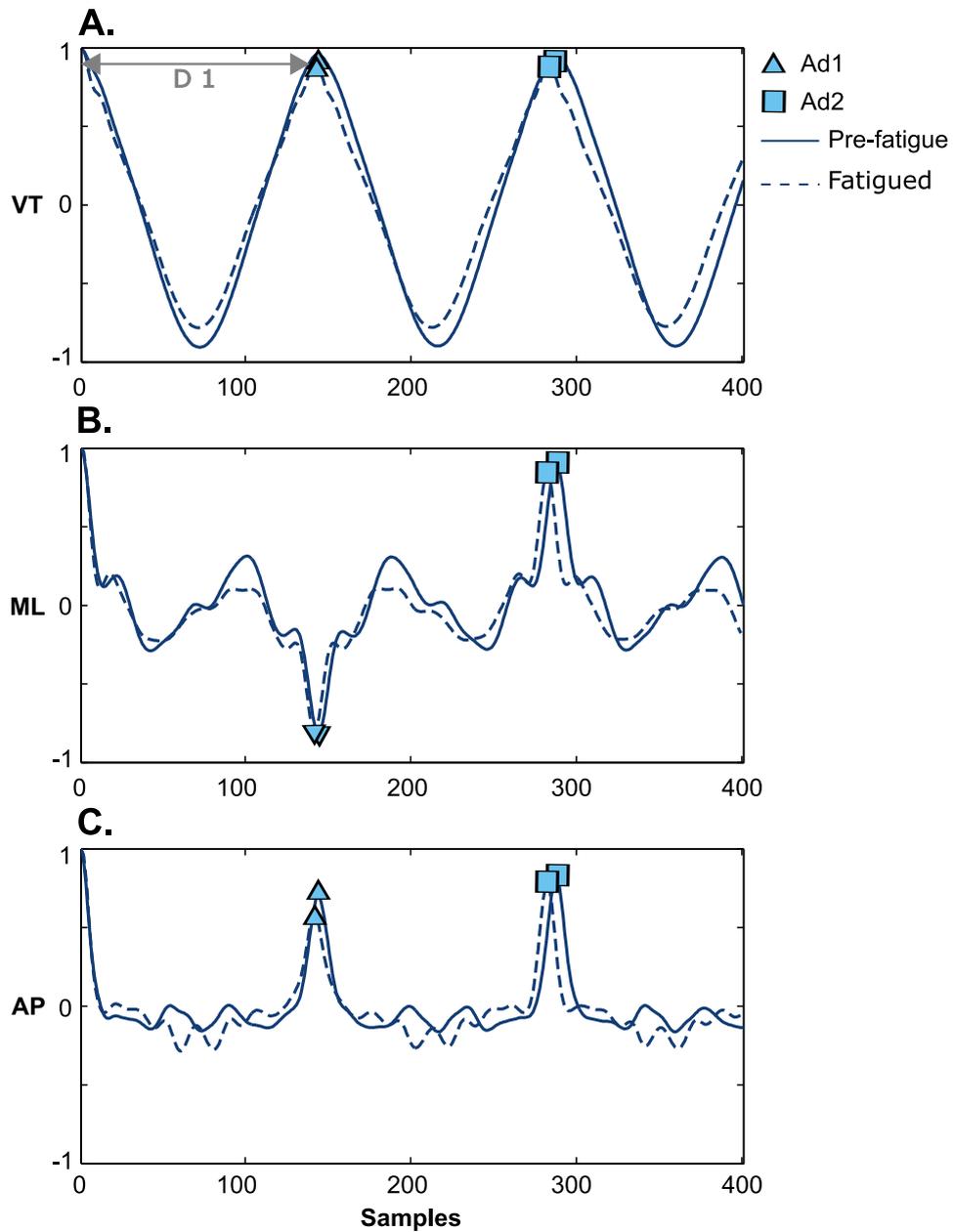


Figure 2.1: Unbiased autocorrelation patterns derived from vertical (A), mediolateral (B), and anteroposterior (C) acceleration signals of one representative subject running pre-fatigue (solid line) and fatigued (dashed line). The first (Ad1) and second (Ad2) dominant autocorrelation peaks represent step and stride regularity measures respectively. The distance (D1, grey arrow) from time zero shift to Ad1 in the vertical pattern is used to calculate step frequency.

2.0.6 Statistical analysis

All statistical analyses were performed using SPSS (version 20.0; SPSS Inc, Chicago, IL). Descriptive statistics were computed for all participant characteristics. Changes between pre-and post-fatigued dependent measures were assessed using repeated measures ANOVA. All dependent variables that did not meet assumptions for normality (Kolmogorov-Smirnov test with Lilliefors significance correction) were transformed by taking their common based 10 log prior to statistical analysis. If a measure did not achieve normality after log transformation, a non-parametric Friedman's analysis was performed rather than the repeated measures ANOVA. The level of statistical significance for all tests was set at a value of 0.05.

Results

Two participants were excluded from analysis due to faulty equipment: one participant was excluded because the sacral marker lost visibility during recording of the fatigued condition (~12 complete steps could be identified); and the other participant was excluded since the investigators deemed the accelerometer to be “not securely fastened” upon its removal after data collection. For the latter participant, visual inspection of the vertical axis also revealed clipping (saturation) of peak accelerations beyond the 16 g threshold. The mean [range] of participant characteristics from the remaining 20 participants are represented in Table 2.1. Participants completed their treadmill exhaustion protocol in 20.54 (6.90) minutes and all achieved Borg RPE ratings greater than 17/20 at time of termination.

Table 2.1: Subject characteristics for N = 20 (12 males): mean, (SD) and range.

Age (years)	Height (m)	Weight (kg)	Training volume (km · wk ⁻¹)	3.2 km time trial speed (m · s ⁻¹)
21.05 (2.14)	1.77 (0.08)	66.12 (6.19)	48.28 (36.18)	3.89 (1.24)
17 – 25	1.61 - 1.90	56.4 – 74.9	10 – 110	2.03 – 5.69

The effect of running fatigue on sacral marker trajectory variables can be seen in Table 2.2. In the fatigued condition, runners significantly increased their CoM displacements and range for mediolateral and anteroposterior directions, but not for the vertical direction. An exemplary stabilogram of changes in horizontal sacral marker trajectory for one participant can be seen in Figure 2.2 A (pre-fatigue) and Figure 2.2 B (fatigued).

The effect of running fatigue on trunk acceleration variables can be seen in Table 2.3. RMS values increased significantly for all three axes with fatigue. In contrast, the RATIO of acceleration RMS increased in the mediolateral and anteroposterior directions but did not change in the vertical direction. A typical example of horizontal plane accelerations can be seen for the same aforementioned participant in Figure 2.2 C (pre-fatigue) and Figure 2.2 D (fatigued). Step regularity of accelerations decreased in the anteroposterior direction. No significant changes were detected for stride regularity of accelerations in any axis, or step frequency. Sample entropy of accelerations increased significantly in the anteroposterior direction.

Table 2.2: Sacral marker trajectory measures pre-fatigue and fatigued represented as mean (SD), along with pairwise comparisons for mean difference and 95% confidence limits of the difference.

Measure	Axis	Pre-fatigue (SD)	Fatigued (SD)	Mean-change [95% CI]	P Value
Trajectory displacement (cm)	VT	10.72 (1.32)	10.97 (1.44)	0.25 [-0.28, 0.79]	0.33
	ML	3.83 (1.36)	4.52 (1.39)	0.70 [0.09, 1.10]	0.002
	AP	7.09 (2.17)	8.54 (2.55)	1.44 [1.14, 1.28]	<0.001 [#]
Trajectory range (cm)	VT	13.04 (1.71)	12.95 (1.58)	-0.09 [-0.59, 0.51]	0.76
	ML	7.61 (2.09)	9.11 (2.50)	1.50 [0.40, 2.59]	0.006 [#]
	AP	9.92 (2.53)	11.73 (3.96)	1.81 [0.60, 3.02]	0.005

VT: vertical, ML: mediolateral, AP: anteroposterior; [#] Log base 10 transformed data

Table 2.3: Trunk accelerometry measures pre-fatigue and fatigued represented as mean (SD), along with pairwise comparisons for mean difference and 95% confidence limits of the difference.

Measure	Axis	Pre-fatigue (SD)	Fatigued (SD)	Mean-change [95% CI]	P Value
Acceleration RMS (g)	VT	1.39 (0.22)	1.48 (0.21)	0.09 [0.03, 0.15]	0.007
	ML	0.52 (0.15)	0.64 (0.15)	0.12 [0.08, 0.17]	<0.001
	AP	0.51 (0.18)	0.61 (0.20)	0.11 [0.06, 0.15]	< 0.001
Ratio of acceleration RMS (a.u)	VT	1.11 (0.10)	1.08 (0.09)	-0.03 [-0.05, -0.01]	0.18 [#]
	ML	0.41 (0.10)	0.46 (0.08)	0.05 [0.01, 0.09]	0.01
	AP	0.39 (0.07)	0.44 (0.10)	0.05 [0.02, 0.09]	0.01
Step regularity (a.u)	VT	0.88 (0.07)	0.87 (0.05)	-0.01 [-0.05, 0.03]	0.56
	ML	0.54 (0.16)	0.47 (0.17)	-0.04 [-0.12, 0.04]	0.28
	AP	0.57 (0.11)	0.45 (0.18)	-0.12 [-0.18, -0.07]	< 0.001
Step frequency (steps.min ⁻¹)	VT	162.44 (7.54)	162.88 (8.15)	0.44 [-2.29, 3.17]	0.74
Stride regularity (a.u)	VT	0.87 (0.08)	0.86 (0.05)	-0.01 [-0.05, 0.03]	0.58
	ML	0.69 (0.11)	0.70 (0.10)	0.02 [-0.03, 0.07]	0.42
	AP	0.65 (0.13)	0.62 (0.15)	-0.03 [-0.09, 0.02]	0.21
Sample entropy (a.u)	VT	0.17 (0.03)	0.18 (0.03)	0.01 [0.00, 0.02]	0.07
	ML	0.43 (0.08)	0.45 (0.09)	0.02 [-0.02, 0.06]	0.37
	AP	0.42 (0.11)	0.48 (0.12)	0.06 [0.03, 0.08]	<0.001

VT: vertical, ML: mediolateral, AP: anteroposterior; [#] Based on non-parametric Friedman test

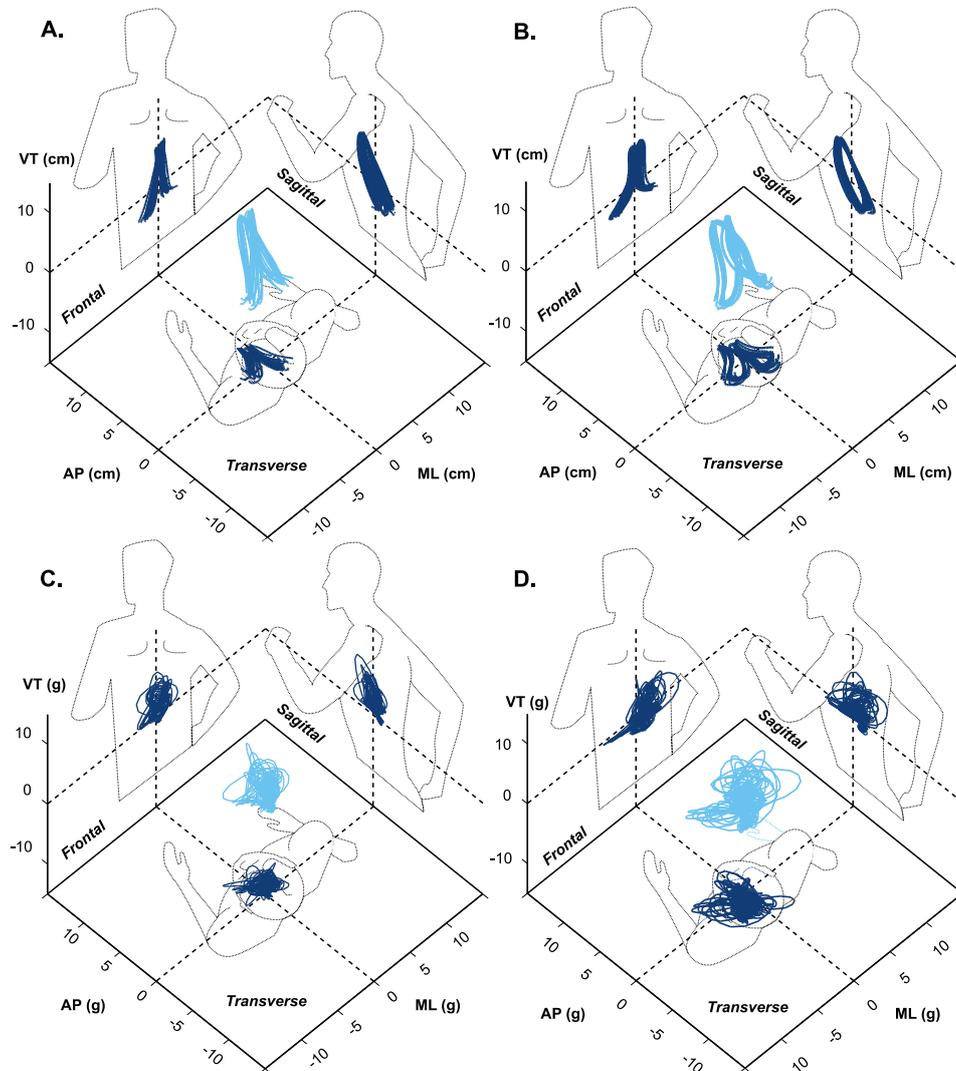


Figure 2.2: Sacral trajectory (A: pre-fatigue ; B: fatigued) and trunk accelerations (C: pre-fatigue ; D: fatigued) for 20 consecutive steps of treadmill running of one representative participant. Vertical (VT), anteroposterior (AP), and mediolateral (ML) axes are used to compute three dimensional (in dark blue) and two dimensional (in light blue) projections of CoM motion relative to the planes of movement. The outline of the human body is shown only for the purpose of indicating direction of running (positive AP).

Discussion

The purpose of the current study was to detect directional changes in dynamic CoM motion in relation to running-induced fatigue based on tri-axial accelerometry. We focused on extracting a select number of measures from a single trunk-mounted accelerometer during speed controlled running until volitional fatigue. Furthermore, the trunk accelerometry measures used in this study were chosen on the basis that 1) they have previously been used to successfully detect limitations in walking gait function, and 2) were calculated relatively easily that avoided algorithms for accurate peak detection or stride-to-stride partitioning. **In support of our hypothesis, our main findings indicate that running-induced fatigue resulted in a higher contribution of variability in horizontal plane trunk accelerations**, as evidenced by higher mediolateral and anteroposterior ratios of acceleration RMS. In partial support of our hypothesis, only anteroposterior acceleration patterns became less regular and less predictable once running fatigue was induced, as supported by lower step regularity and larger sample entropy values.

Running-induced fatigue greatly influenced the variability of horizontal plane trunk accelerations. This increase was expected, since running-induced fatigue may introduce horizontal compensations in trunk kinematics [11] that may manifest in increased variability of trunk acceleration signals. Additionally, the increase in mediolateral CoM displacements recorded from the sacral marker trajectory confirmed that our fatigue protocol induced greater mediolateral motion of the CoM. Increased trunk acceleration variability mediolaterally indicates an increase in postural sway and greater lateral trunk motion [15, 31], which may translate to higher mediolateral impulses during ground contact and expose soft tissue structures to higher strain rates [20]. Le Bris et al. [17] similarly found running-fatigue induced increases in mediolateral trunk accelerations when their runners underwent a highly intensive track running protocol to exhaustion. These researchers [17] speculated that excessive accelerations in the mediolateral direction represents a loss of coordination, with an increase in energy expenditure that is not useful for propulsion. Albeit mediolateral motions being relatively smaller in magnitude compared to the vertical, if reduced, they could act as an important mechanism to facilitate balance control and minimize the energetic cost of running [1, 27]. Interestingly, untrained runners have exhibited a higher proportion of horizontal plane (mediolateral and anteroposterior) accelerations of the trunk compared to trained runners [21].

Running-induced fatigue did not influence the step or stride regularity measures except

for the anteroposterior step regularity. Step regularity has more recently been used as a symmetry index [37] that represents a correlation of trunk accelerations between left and right steps. It is, therefore, possible that less regular anteroposterior step regularity detected during fatigue may resemble asymmetrical breaking and propulsive phases between left and right running steps. In line with previous investigations of walking gait [9], trunk accelerations were least regular in the horizontal plane. Highly regular vertical accelerations could partially be explained by the fact that the vertical direction of gait is continuously constrained to gravity [33] and thus less subjected to system “noise”.

Sample entropy of trunk accelerations was assessed to gain insight in the non-linearity of the acceleration waveforms. Sample entropy is a useful measure, since it examines every time point of the time-series being analyzed. To the best of our knowledge, sample entropy has never been used to elucidate on running movement patterns. We found that sample entropy values for trunk acceleration patterns were higher and thus less predictable in all three axes when runners were fatigued, although only significant for the anteroposterior direction. This may be partially substantiated by the findings of Meardon et al. [22] who found that runners' stride times become more unpredictable as they reached exhaustion. According to the “loss of complexity hypothesis”, lower sample entropy values relate to a more predictable physiological time series that is often represented by frailty, disability or disease due to an unhealthy biological steady-state [19, 29]. In line with this hypothesis, human locomotion studies have reported lower sample entropy values of populations with pathologically-related walking gait [34, 36]. Therefore, we hypothesize that our more variable and less predictable anteroposterior time-series (higher sample entropy) reveals an overall protective neuromuscular CoM control to preserve musculoskeletal structures and avoid pain [25] due to fatigue. A theory which therefore remains untested is whether runners with a history of overuse injuries fail to reduce regularity and predictability of trunk acceleration patterns when in a fatigued state.

The indoor treadmill protocol we selected was chosen on the basis of selecting a controlled steady-state environment. **An important question to ask is whether certain measures that changed with fatigue, such as anteroposterior step regularity for example would change even more in an overground situation.** Firstly, the speed of running is naturally more variable overground than compared to treadmill running, even under controlled conditions [30]. Secondly, we noticed that in a fatigued state, our runners were struggling to maintain anterior positioning on the treadmill belt at their individually constant speed. Therefore, had the fatigue protocol been performed overground, we

expect that our runners would have slowed down as a protective means [38], resulting in more variable trunk accelerations anteroposteriorly. Thus even greater changes in anteroposterior step regularity could be expected. To improve generalizability, further steps are aimed at determining the robustness of the current accelerometry measures to running related fatigue in self-paced outdoor environments, where runners would typically counter fatigue by reducing their running speed [38]. Therein lies large potential to monitor the biomechanical-aspects of running, with the aim of detecting early onset of excessive variability or irregularities of horizontal plane accelerations due to fatigue [17].

Conclusion

In conclusion, our findings indicate that **a single trunk-mounted accelerometer can be used to detect deviations in dynamic CoM motion induced by running-fatigue**. In light of our results, running-induced fatigue might reveal itself in a greater contribution of variability in horizontal plane trunk accelerations, and anteroposterior trunk accelerations that are less regular from step-to-step and less predictable.

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Chapter 3

Study II: The energy cost of dynamic instability

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Author Contributions

K.H.S, R.V and B.V conceived and designed research;
K.H.S, S.S and R.V performed experiments;
K.H.S analysed data;
K.H.S, S.S, R.V, and B.V interpreted results of experiments;
K.H.S drafted manuscript;
K.H.S prepared figures;
K.H.S, S.S, R.V and B.V revised manuscript;
K.H.S, S.S, R.V and B.V approved final manuscript.

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Abstract

Maintaining stability under dynamic conditions is an inherent challenge to bipedal running. This challenge may impose an energetic cost (E_c) thus hampering endurance running performance, yet the underlying mechanisms are not clear. Wireless tri-axial trunk accelerometry is a simple tool that could be used to unobtrusively evaluate these mechanisms. Here, we test a cost of instability hypothesis by examining the contribution of trunk accelerometry-based measures (tri-axial root mean square, step and stride regularity, and sample entropy) to inter-individual variance in E_c ($J \cdot m^{-1}$) during treadmill running. Accelerometry and indirect calorimetry data were collected concurrently from 30 recreational runners (16 men; 14 women) running at their highest steady-state running speed ($80.65 \pm 5.99\% \text{ VO}_{2\text{max}}$). After reducing dimensionality with factor analysis, the effect of dynamic stability features on E_c was evaluated using hierarchical multiple regression analysis. Three accelerometry-based measures could explain an additional 10.4% of inter-individual variance in E_c after controlling for body mass, attributed to anteroposterior stride regularity (5.2%), anteroposterior RMS ratio (3.2%), and mediolateral sample entropy (2.0%). Our results lend support to a cost of instability hypothesis, with trunk acceleration waveform signals that are 1) more consistent between strides anteroposteriorly, 2) larger in amplitude variability anteroposteriorly, and 3) more complex mediolaterally, are energetically advantageous to endurance running performance. This study shows that wearable trunk accelerometry is a useful tool for understanding the E_c of running, and that running stability is important for economy in recreational runners.

Keywords: Wearable technology; trunk accelerometer; energy cost; running instability; running economy.

New and noteworthy: This study evaluates and more directly lends support to a cost of instability hypothesis between runners. Moreover, this hypothesis was tested using a minimalist setup including a single tri-axial trunk mounted accelerometer, with potential transferability to biomechanical and performance analyses in typical outdoor settings.

Introduction

Running economy is widely accepted as a key determinant of endurance running performance. Running economy is also a complex, multifactorial phenomenon with numerous anthropometrical, demographic, i.e. age- sex- and ethnic-related, physiological, biomechanical, and neuromuscular determining factors [5, 22, 27]. Of these factors, establishing a biomechanical basis to running economy continues to be of interest to researchers and coaches. For example, using biomechanical principles such as drafting, lighter shoes, and course elevation drop has recently been proposed as quantifiable strategies needed to reduce energy cost and break the two-hour marathon barrier [16]. A biomechanical basis for running economy is also intuitive from a running 'technique' standpoint. Although the majority (~80%) of running economy is determined by the cost to support body mass [4], a most recent review has revealed that superior running economy has its strongest direct links to running technique characteristics such as less leg extension at toe-off, larger stride angles, alignment of the ground reaction force and leg axis, and low activation of the lower limb muscles [27].

Despite the plethora of studies examining biomechanical or running 'technique' links to economy [4, 13, 21, 29, 33, 36, 45, 50], **the upper extremity with respect to trunk control or dynamic postural stability has been largely ignored.** Evolutionary theory suggests that while structural adaptations have allowed humans to have a more stable and less energetically costly running gait, human running remains unwieldy and prone to instability [8, 24]. Indeed, trunk control has been identified as a critical component of locomotor efficiency [37]. During ground contact a runner must activate muscles sufficiently to ensure adequate stability while also maintaining forward momentum [13]. Electromyography has demonstrated that during human running, the back extensors activate early to control forward momentum during impact, while abdominal obliques' actively decelerate the thorax during second half of stance [34]. The increased activation of these trunk muscles could help explain earlier findings relating trunk lean to running economy [50]. For example, aside from a comprehensive set running gait characteristics, Williams and Cavanagh [50] showed that a group of distance runners with the best running economy exhibited greater mean forward trunk lean relative to the vertical compared to runners with middle and least economical groups. Other previous work indicates that larger horizontal plane lumbo-pelvic motion while running relates to augmented activity of both abdominal and the superficial multifidi muscles [37]. Therefore, it is plausible that

various characteristics of dynamic stability or trunk kinematics in 3D could influence the activation levels of these stabilizing muscles as well as running economy.

The effects of upper extremity posture on walking and running economy has been indirectly assessed by removing stability [2, 47]. For example, instability induced by suppressing arm swing increases energetic cost (E_c) by 7.7% and 7.6% while walking [47] and running [3] respectively. The maintenance of lateral balance, i.e. additional step width variability has been a primary yet refuted mechanism for this increase [3], reasoned that other unknown aspects of dynamic stability could account for this increased energetic cost. Alternative explanations may include compensatory strategies in torso rotation or increases in the free moment in the horizontal plane [3]. Moreover, dynamic instability as reflected by larger lateral and horizontal total excursions or exacerbated accelerations of the CoM could also account for increased energy cost without arm swing [14].

Wearable trunk accelerometers provide a new level of analysis for dynamic stability of human locomotion. Accelerometers have improved from an accuracy, sensitivity, and computing power standpoint and have enabled more sophisticated analyses of motion. When mounted to the lower trunk, accelerometry unobtrusively estimates CoM motion and thus allows for several aspects of dynamic stability to be captured. These stability aspects, whether it function vertically, i.e. body weight support, mediolaterally, i.e. side-to-side balance control, or anteroposteriorly, i.e. braking and propulsion could more directly test various biomechanical hypotheses underpinning running economy. To the knowledge of the authors only two studies [25, 48] and one pilot study [31] have previously used trunk accelerometry-based measures to estimate energy expenditure while running. Unfortunately, these studies [25, 48] did not investigate submaximal running economy specifically, by including running intensities beyond aerobic, i.e. ranging to maximal aerobic capacity in their regression analyses. Additionally, these studies either did not assess [31, 48] or did not delineate [25] inter-subject variations in running economy. Therefore, **it remains unclear which trunk-accelerometry based aspects of dynamic stability may be economically favourable for endurance running.** Several linear and non-linear stability aspects are worthy of investigation.

Firstly, higher amplitudes or variations of trunk accelerations expressed as the acceleration root mean square (RMS) could reflect excessive changes in momentum that are energetically wasteful [13]. Vertically, this is plausible since runners with poor economy often demonstrate larger vertical oscillation of the pelvis [11] and CoM [11, 45, 50], which may translate to larger vertical accelerations. Horizontally, this is plausible since

coordination patterns of the pelvis and spinal segments during running function to minimize both ML and AP changes in momentum [34, 37]. Indeed, Folland et al. [11] recently found that runners with greater minimum AP horizontal velocity of the pelvis, i.e. more deceleration/braking were more energetically costly. Poor trunk coordination could therefore increase energetic cost via larger changes in horizontal momentum [14]. In partial support, trunk accelerations in the ML and AP direction have shown to increase due to running induced fatigue [23, 39].

Secondly, the **dominant autocorrelations of acceleration waveforms** could empirically test whether the ability to maintain a global consistency either between steps or strides are influential on economy. Step regularity indicates bilateral (a)symmetry and could evaluate the notion that as occurring in cars, dynamic asymmetries could generate a higher energetic cost to travel a given distance [42]. Stride regularity indicates consistency between strides, and sticking with the car analogy, inconsistencies thereof could be synonymous to a driver rapidly and/or more frequently applying accelerations, i.e. “gas-brake-gas” that result in increased fuel consumption.

Thirdly, the **sample entropy of trunk accelerations** accounts for the complexity of the trunk acceleration signal waveform and could assess whether overall fluidity of a runner’s gait pattern is related to economy [1]. Sample entropy is a non-linear measure that might be sensitive enough to detect movement efficiencies masked by linear measures such as the RMS.

Here, we test a cost of instability hypothesis that proposes a link between a runner’s stability and running economy, and that this link can be assessed using measures derived from wearable tri-axial trunk accelerometry. Specifically, we hypothesize that runners running with less deviations in CoM motion such as 1) less amplitude variability (RMS); 2) higher symmetry; 3) higher consistency; and 4) less complexity have a running gait that is energetically advantageous. We experimentally evaluate these hypotheses using simple and non-linear measures including 1) the RMS; 2) inter-step 3) inter-stride regularity, and 4) the sample entropy of waveforms of each acceleration axis (vertical, ML, AP), each of which express unique aspects of dynamic stability during running. Additionally, since low-pass filtering of acceleration waveforms is a common, yet often questioned pre-processing approach, we further assessed whether leaving accelerations unfiltered prior to calculating stability measures would explain more inter-individual variance in E_c .

Methods

3.0.1 Participants

Thirty recreational to moderately trained runners including 16 men and 14 women (aged 19-26 years with running experience of 5 - 10 years) volunteered to be part of this study. To be included in the study runners had to be running regularly (2 – 4 sessions per week; 15 – 40 km/week) and have prior experience with treadmill running. All subjects were screened to have no known history of metabolic, neurological, cardiovascular disease, or surgery to the back or lower limbs, and were symptom-free of any lower extremity injury for at least six months prior to the study. All runners provided written informed consent prior to participation in accordance with the Declaration of Helsinki. The local ethics committee of Stellenbosch University approved the study (#SU-HSD-002032).

3.0.2 Experimental protocol

Incremental treadmill running speed test. Subjects were asked to refrain from alcohol, caffeine, and vigorous physical activity for 24 h before the session. They were also instructed not to consume any food or drink, other than water, during the 90 min before the testing session. All subjects indicated “excellent” as their self-reported motivation for exercise testing on the day. Subjects performed a maximal incremental running test to exhaustion at 1% slope on a motorized treadmill (Saturn h/p/cosmos, Nussdorf-Traunstein, Germany), starting at a running speed of 2.22 m⁻¹ or 2.5 m⁻¹ depending on individual comfort and previous experience. A warm-up of 4 minutes equivalent to starting speed was first provided, after which treadmill speed was increased discontinuously in increments of 0.42 m/s every four minutes interspersed by a one minute rest until volitional exhaustion. Participants could run in their own relatively new (within three months of use) conventional shod running shoes. Treadmill gradient was maintained at 1% throughout submaximal assessments to reflect the energetic cost of outdoor running. All tests were performed under similar laboratory conditions (20–25°C, 50–60% relative humidity at 130 m of altitude). Rating of perceived exertion scores on a 6 – 20 point scale (Borg GAV. 1982), as well as capillary blood samples from the finger (blood lactate (BLa) concentrations obtained with a portable lactate analyzer ; Lactate Pro 2 LT-1730, Japan) were obtained immediately after each stage. Heart rate (HR) was recorded by a heart rate monitor (Cosmed Quark CPET, Rome, Italy).

Participants were fitted with an adjustable safety harness during the entire treadmill test. Runners were considered to have achieved VO_2max when at least two of the following criteria were fulfilled: 1) A plateau in the oxygen consumption (VO_2), defined as an increase of less than $1.5 \text{ ml} \cdot \text{kg} \cdot \text{min}^{-1}$ in two consecutive workloads; 2) respiratory quotient (R- value) > 1.15 ; 3) maximal heart rate value (HR_{max}) $> 95\%$ of the age-predicted maximum ($220 - \text{age}$); and 4) rating of perceived exertion (RPE) ≥ 19 on the 6-20 Borg scale. Additionally, peak treadmill speed (V_{peak} ; in $\text{m} \cdot \text{s}^{-1}$) was calculated as follows, taking every second into account:

$$V_{\text{peak}} = \text{completed full intensity (m} \cdot \text{s}^{-1}) + [(\text{seconds at final speed} \times 240 \text{ s}^{-1}) \times 0.42 \text{ m} \cdot \text{s}^{-1}]$$

Running economy assessment. Pulmonary gas exchange was recorded through-out the incremental test using a breath-by-breath metabolic analyser (Cosmed Quark CPET, Rome, Italy). Gas analysers were calibrated before each session to 16% O_2 , 4% CO_2 , balance N_2 , and the turbine flow meter was calibrated with a 3L calibration syringe before each test. VO_2 data collected from the last two minutes of each stage were checked for steady-state. Specifically, linear regressions were performed on the final two minutes of each speed increment to determine whether the VO_2 profile was not statistically different ($p < 0.05$) from the horizontal flat line. In other words, no additional rise in the slow component of VO_2 was to be detected during steady-state. V_{OBLA} was determined using this VO_2 criterion in addition to the highest stage which elicited a post-stage BLa below the onset of blood lactate accumulation (OBLA) ($\text{BLa} < 4 \text{ mmol} \cdot \text{L}^{-1}$) (Figure 3.1).

VO_2 , V_{CO_2} and respiratory exchange ratio (RER) were averaged during the final minute of V_{OBLA} . Updated non-protein respiratory equations were used to estimate substrate use ($\text{grams} \cdot \text{min}^{-1}$) and the relative energy derived from fat and carbohydrate was calculated by multiplying by 9.75 and 4.07 respectively [18]. Running economy was defined as gross absolute E_c (expressed as joules per meter), quantified as the sum of these values to reflect the mean energy content of the metabolized substrates during moderate to high-intensity exercise [18]. This definition was chosen firstly to account for variations in substrate use when running at submaximal speeds, i.e. energetic, rather than oxygen cost [43], and secondly to enable normalization and comparison between runners with different speed thresholds often determined by individual training level and/or sex, e.g. running at similar relative intensity (different absolute speeds) rather than at a single fixed speed for all runners [10]. Resting metabolic rate was not subtracted since it cannot be ascertained if resting metabolic demand continues at the same rate during the running [44].

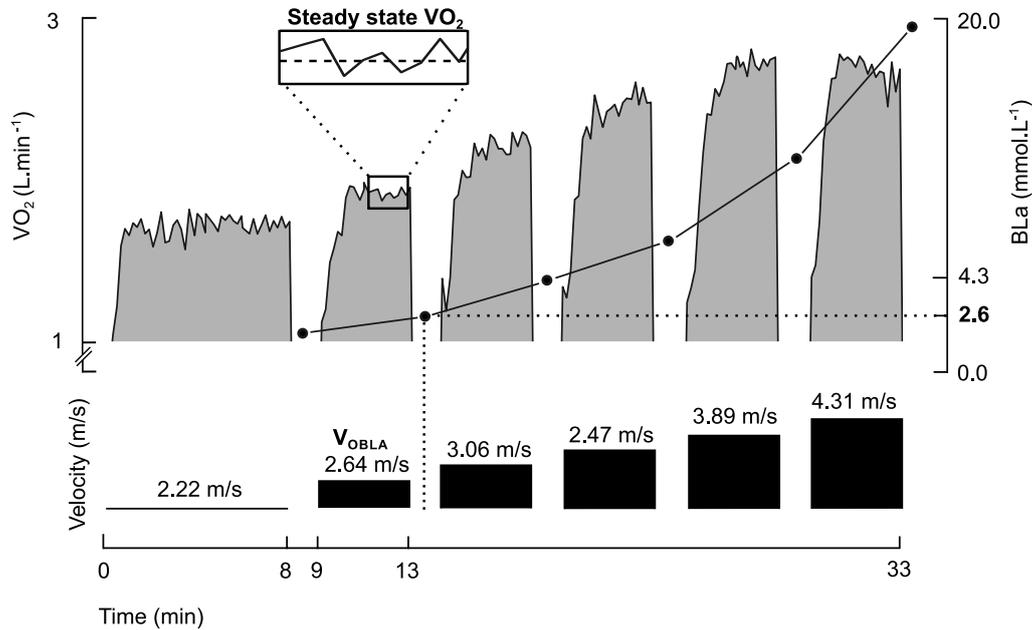


Figure 3.1: Representative example of determining the highest sub-maximal steady-state stage for estimating energetic cost (E_c) of running. E_c was extracted from the final two minutes of stage two (here 2.64 m/s), which demonstrated a running velocity at which 1) the oxygen uptake (VO_2) curve was not drifting, i.e. not statistically significant ($p > 0.05$) from the horizontal (flat dashed line shown in steady-state VO_2 box), and 2) a post stage blood lactate (BLa) that was less than the velocity required to elicit onset of blood lactate accumulation (V_{OBLA} ; $BLa < 4 \text{ mmol.L}^{-1}$), here 2.6 mmol.L^{-1} .

3.0.3 Accelerometry measurements

Tri-axial accelerometry was acquired during the entire running test using a Shimmer3 wireless device ($\pm 16 \text{ g}$ range, sampling at 1024 Hz, 16-bit resolution, 0.023 kg weight, Shimmer Sensing, Dublin, Ireland). The accelerometer was securely positioned over the L3 spinous process of the trunk and directly mounted to the skin using double sided tape and adhesive spray. The accelerometer was securely tightened to individual comfort provided to minimize movement artefact using additional self-adhesive bandage (Cipla-Plast, Cipla, South Africa). Tri-axial accelerations signals expressed as g's were processed using customized software in MATLAB version 8.3 (The Mathworks Inc. Natick, MA, USA).

The sensing axis of the accelerometer may not be aligned with the axes of the world-reference orientation while running. Therefore, a trigonometric correction [26] of the dynamic acceleration signal was performed, a procedure consistently applied to CoM

accelerations during walking [19, 26] and running [20, 25]. In this study, calculated deviations of accelerometer axes were between 4.1 degrees to 12.5 degrees (anterior tilt) and 0.1 to 1.6 degrees (laterolateral tilt) prior to transformation. Accelerometry-based measures were then computed from the final twenty consecutive steps of acceleration signals at each runner's individual V_{OBLA} (Figure 3.2). Standardizing acceleration epochs to amount of running steps as opposed to time windows was done to allow cross study comparison [39, 38].

Since filtering of body-worn accelerations is a common [39], yet disputed signal processing approach in terms of potentially eliminating physiologically related signal variance [35], we additionally assessed the effect of filtering by computing a second set of accelerometry-based measures after applying a zero-lag 4th order low-pass Butterworth filter (cut-off frequency 50 Hz).

Moreover, non-linear measures such as sample entropy can be sensitive to input signal length (N) [51] which would undesirably influence the outcome. To determine the optimal amount of continuous running steps required for steady-state sample entropy values, we performed a basic iteration analysis on VT, ML, and AP sample entropy values on N steps ranging from six to 160. Twenty steps were chosen as the optimal (minimal) number of steps required to achieve steady-state sample entropy values, and which appears in the APPENDIX.

Dynamic stability parameters were extracted from each acceleration axis (vertical, ML, AP) and quantified firstly using both absolute and ratio of each linear acceleration axis root mean square (RMS) relative to the resultant vector RMS to capture movement variability [25, 41]; secondly using step regularity (inter-step symmetry) and stride regularity using the unbiased autocorrelation procedure, with perfect regularities equivalent to one [26]; and thirdly using sample entropy to capture the waveform predictability, with values typically in range of 0 to 2 for physiological systems and higher values indicating less periodicity or more unpredictability [35]. Detailed procedures and algorithm inputs for the computation and extraction of these dynamic stability parameters are the same as previously explained [39]. Spatio-temporal parameters including step frequency [26, 38, 39] and contact time [12, 38] were additionally computed from vertical trunk accelerations.

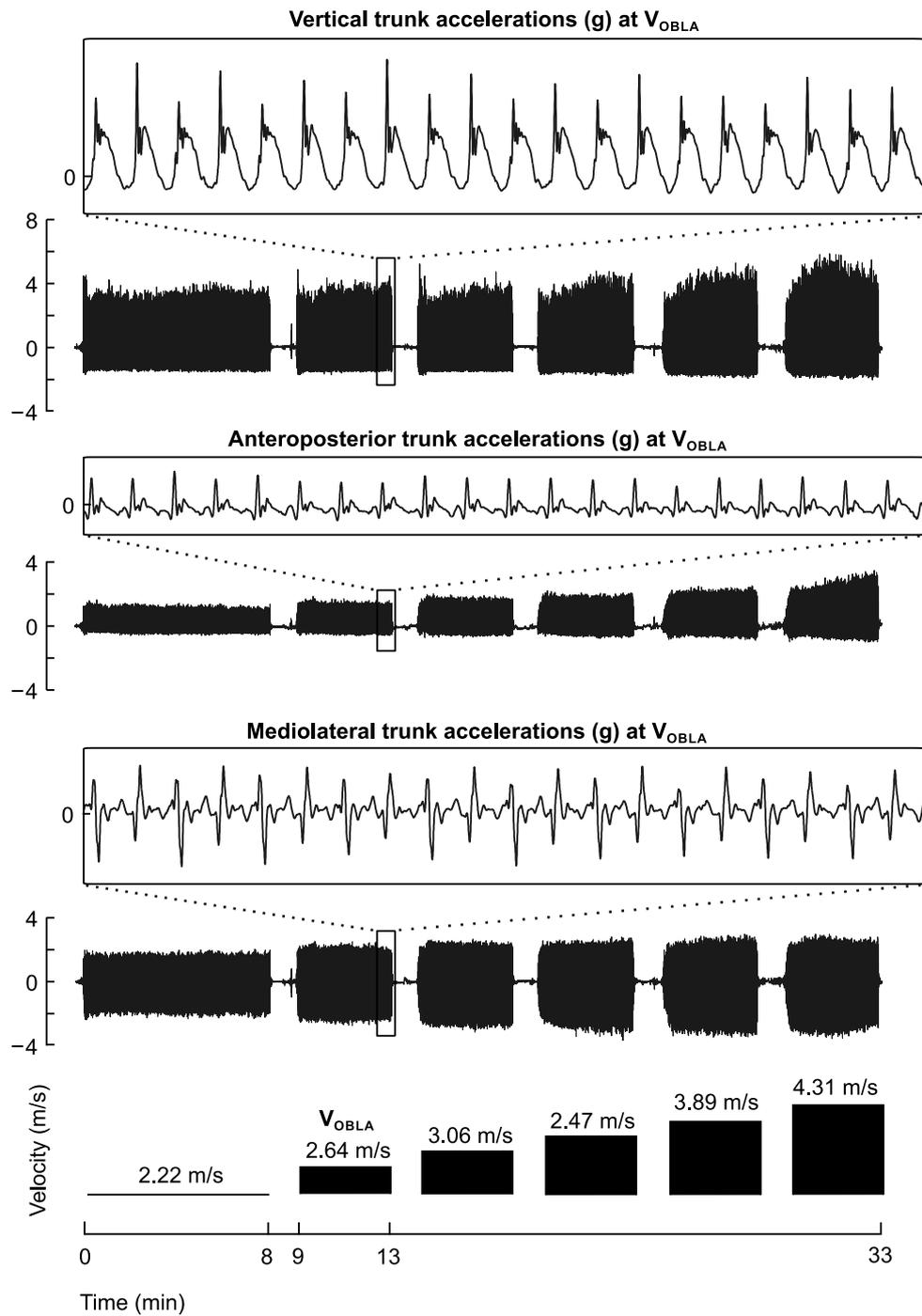


Figure 3.2: Representative example of tri-axial trunk accelerations extracted for computing dynamic stability measures of running. Accelerations used for analysis represented the final 20 running steps at V_{OBLA} for each runner (here 2.64 $m \cdot s^{-1}$ for the same female runner as shown in Figure 3.1).

3.0.4 Statistical analysis

Sex differences were analysed with a 2-tailed independent t-test. Factor analysis was performed to reduce dimensionality and possible multicollinearity of the 17 respective accelerometry outcome measures. A scree-plot determined the number of extracted factors (eigenvalues > 1.0). VariMax rotation was used to optimize loadings of variables onto factors, and the most representative accelerometry measures were chosen as the measures which revealed the highest loading per factor. These representative measures were then entered in an a priori hierarchical multiple regression analysis to explain inter-individual variance in E_c . Specifically, body mass was entered first as block 1 into the model. Thereafter, block 2 was entered containing the most representative accelerometry measures from each factor. After the entry of each block, we evaluated the adjusted R^2 change to determine the proportion of additional variance explained and the significance from 0. This sequential order was based on an a priori hypothesis that the additional variance in E_c could be explained by dynamic stability and spatio-temporal parameters, after accounting for body mass that is well known as a primary determinant of running E_c [6]. For each block the beta weights for the independent variables retained in the regression equations and the multiple correlation coefficients are presented. Beta weights further indicate the relative importance of each variable in explaining the variance in E_c . All statistical analyses were performed using SPSS (version 20.0; SPSS Inc, Chicago, IL), and data are reported as mean \pm SD.

Results

3.0.5 Descriptive

All tests were terminated by volitional exhaustion, and all subjects achieved VO_{2max} by the set criteria. All highest stage steady-state slopes used for E_c analysis had a gradient < $0.2 \text{ ml O}_2 \cdot \text{m}^{-1}$ ($p > 0.05$) thus equating to < 24 ml O_2 increase over the final 2 min of each stage. Descriptive characteristics and results for endurance markers combined and per sex are listed in Table 3.1. Height and mass were significantly greater in men compared to the women (both $p < 0.001$). Men also had significantly higher VO_{2max} , V_{peak} and V_{OBLA} (all $p < 0.001$). However, the relative intensity at which V_{OBLA} occurred was not significantly different between sexes ($p = 0.294$) indicating similar running intensity, and thus all subsequent analyses with respect to the primary hypothesis pooled both sexes

together. Men had significantly higher absolute E_c , but not when expressed relative to body mass ($p = 0.44$).

Table 3.1: Descriptive results for endurance markers and running economy. Values are means \pm SD.

	All runners (n = 30)	Males (n = 16)	Females (n = 14)
<i>Descriptive</i>			
Age	21.75 \pm 1.40	21.86 \pm 1.88	21.64 \pm 0.74
Body mass (kg)	68.18 \pm 11.41	74.72 \pm 11.24*	61.64 \pm 7.19
Height (m)	1.73 \pm 0.08	1.78 \pm 0.08*	1.68 \pm 0.06
BMI	22.56 \pm 2.48	23.4 \pm 2.51*	21.72 \pm 2.23
<i>Endurance markers</i>			
VO_{2max} (ml \cdot kg ⁻¹ \cdot min ⁻¹)	48.43 \pm 6.30	52.17 \pm 5.90*	44.70 \pm 4.19
V_{peak} (m \cdot s ⁻¹)	4.15 \pm 0.54	4.50 \pm 0.43*	3.80 \pm 0.39
V_{OBLA} (m \cdot s ⁻¹)	2.89 \pm 0.43	3.09 \pm 0.39*	2.67 \pm 0.37
V_{OBLA} (% VO_{2max})	80.65 \pm 5.99	79.5 \pm 5.30	81.79 \pm 6.60
<i>Running economy and RER</i>			
RER	0.95 \pm 0.03	0.95 \pm 0.03	0.94 \pm 0.03
E_c (J \cdot m ⁻¹)	314.59 \pm 52.51	341.75 \pm 52.89*	287.44 \pm 36.69
E_c relative to body mass (J \cdot kg \cdot m ⁻¹)	4.64 \pm 0.33	4.56 \pm 0.25	4.68 \pm 0.42

* $p < 0.05$ significantly different between sexes

Descriptive statistics for spatio-temporal and dynamic stability accelerometry measures combined and per sex are listed in Table 3.2. At V_{OBLA} , men had significantly shorter contact times ($p = 0.016$), lower dynamic stability in the ML direction for RMS ($p = 0.014$), RMS ratio ($p = 0.003$), step regularity ($p = 0.04$) and stride regularity ($p = 0.026$) as well as higher dynamic stability in the vertical direction for RMS ratio ($p = 0.001$).

Table 3.2: Descriptive results for accelerometry-based dynamic stability measures at V_{OBLA} . Values are means \pm SD.

	Axis	All runners (n = 30)	Males (n = 16)	Females (n = 14)
<i>Spatio-temporal</i>				
Stance-time (s)	VT	0.21 \pm 0.02	0.20 \pm 0.02*	0.22 \pm 0.02
Step frequency (steps.min ⁻¹)	VT	165.24 \pm 10.81	168.50 \pm 9.44	161.98 \pm 11.43
<i>Dynamic stability</i>				
Acceleration RMS	VT	1.22 \pm 0.22	1.29 \pm 0.29	1.16 \pm 0.10
	ML	0.53 \pm 0.14	0.48 \pm 0.13*	0.58 \pm 0.13
	AP	0.41 \pm 0.09	0.39 \pm 0.07	0.43 \pm 0.10
Ratio of acceleration RMS (unitless)	VT	0.87 \pm 0.05	0.89 \pm 0.04*	0.84 \pm 0.05
	ML	0.38 \pm 0.09	0.34 \pm 0.09*	0.42 \pm 0.08
	AP	0.29 \pm 0.05	0.28 \pm 0.04	0.31 \pm 0.06
Step regularity (unitless)	VT	0.91 \pm 0.04	0.92 \pm 0.06	0.91 \pm 0.02
	ML	0.74 \pm 0.14	0.69 \pm 0.16*	0.79 \pm 0.09
	AP	0.72 \pm 0.12	0.70 \pm 0.13	0.74 \pm 0.11
Stride regularity (unitless)	VT	0.92 \pm 0.06	0.92 \pm 0.08	0.92 \pm 0.02
	ML	0.82 \pm 0.09	0.78 \pm 0.10*	0.85 \pm 0.08
	AP	0.77 \pm 0.11	0.75 \pm 0.13	0.79 \pm 0.08
Sample entropy (unitless)	VT	0.11 \pm 0.03	0.10 \pm 0.03	0.11 \pm 0.03
	ML	0.24 \pm 0.09	0.27 \pm 0.08	0.22 \pm 0.09
	AP	0.27 \pm 0.09	0.30 \pm 0.10	0.25 \pm 0.08

* p < 0.05 significantly different between sexes

3.0.6 Factor analysis

Five components explained 86.3% of total variance in unfiltered accelerometry measures. From the rotated matrix, factor one (eigenvalue (λ) = 5.79, 34.0 % of variance) included variables relating mainly to step symmetry and stride regularity from all axes. Factor two ((λ) = 3.89, 22.9% of variance) comprised mainly of dynamic stability parameters in the ML direction. Factor three ((λ) = 2.34, 13.8% of variance) was associated with variability (RMS) in the AP direction. Factor four ((λ) = 1.68, 9.9% of variance) was associated with waveform complexity (sample entropy in all directions) while factor five ((λ) = 1.01, 5.7% of variance) comprised of spatio-temporal measures. Variables with highest loading per factor are bolded in Table 3.3. These five representative accelerometry measures were therefore assessed for their relationship with Ec. Although not reported here, the total variance explained in filtered accelerometry measures was like unfiltered (86.05% variance explained), with the same five measures having the highest loadings per factor.

Table 3.3: Factor analysis on unfiltered accelerometry-based measures revealed five primary factors (eigenvalues greater than one).

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Stride regularity AP	RMS ML	RMS AP	Sample entropy ML	Stance time
-0.93	-0.94	-0.94	-0.93	-0.85
Step regularity AP	RMS ratio ML	RMS ratio AP	Sample entropy VT	Step frequency
-0.9	-0.93	-0.87	-0.8	-0.84
Stride regularity VT	RMS ratio VT		Sample entropy AP	
-0.84	-0.84		-0.63	
RMS VT	Step regularity ML			
-0.84	-0.55			
Stride regularity ML				
-0.68				
Step regularity VT				
-0.67				

Measures (loadings) are sorted from highest to lowest and measures with most representative (highest loading) per factor are bolded. Cross-loadings as well as loadings smaller than 0.4 are suppressed for brevity.

3.0.7 Hierarchical multiple regression analyses

Three unfiltered accelerometry measures were retained in the multiple regression after accounting for block one (body mass) which, as expected, accounted for most of E_c variance (80.8%). Specifically, stride regularity (AP), RMS (AP) and sample entropy (ML) significantly ($p < 0.05$) and independently accounted for an additional 5.2%, 3.2%, and 2.0% of the variance in E_c respectively. Remaining unfiltered accelerometry measures including RMS (ML) as well contact time were not retained as significant predictors (all $p > 0.05$). The final unfiltered regression model accounted for 91.2% variance in E_c . The spread of the partial regression plots is shown in Figure 3.3 B, C, and D with individual beta coefficients in Table 3.4. Partial regression plots were generated to more accurately reflect the scatter of partial correlations [30]. For example, the partial regression plot in Figure 3.3 B reflects the individual residuals of E_c (dependent variable) on body mass, RMS AP and sample entropy ML (remaining explanatory variables) versus individual residuals of AP stride regularity (target explanatory variable) on body mass, RMS AP and sample entropy ML (the remaining explanatory variables). Thereafter, individual residuals are added to the group mean values e.g. of E_c and Stride regularity AP (from Table 3.1 and Table 3.2) on both axes to aid interpretation of understandable values. When filtered accelerometer measures were entered in the regression for model two, sample entropy (ML) was no longer retained in the model as a significant predictor of E_c . The final filtered regression model accounted for 88.8% of variance in E_c .

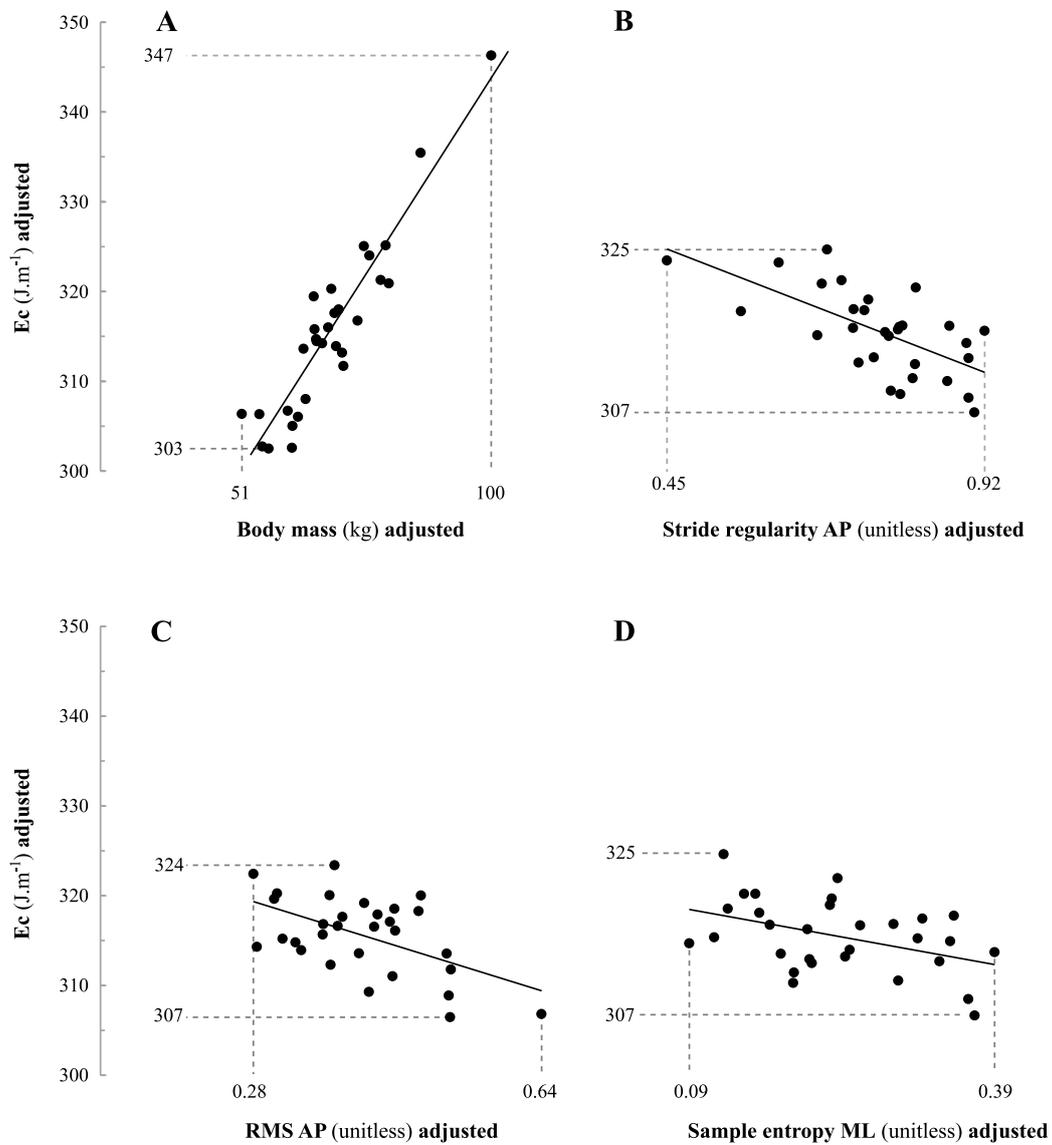


Figure 3.3: Three unfiltered accelerometry-based dynamic stability measures contributed significantly and independently to the inter-individual energetic cost (E_c) of running after controlling for body mass ($n = 30$). Partial regression plots were scaled by adding regression-residuals to group mean values (from Table 3.1 and Table 3.2) on both axes to enhance interpretation [30]. Each plot represents the true correlation coefficient for the specific predictor on E_c , while controlling for the remaining three predictors e.g. in panel B the relationship of stride regularity AP to E_c is shown while controlling for body mass (panel A), root mean square (RMS) AP (panel C), and sample entropy ML (panel D). Minima and maxima highlight the range of the spread on each axis (dashed lines). The final regression equation revealed $E_c = 0.894 \cdot BM - 29.219 \cdot \text{Stride regularity AP} - 27.981 \cdot \text{RMS AP} - 20.382 \cdot \text{Sample entropy ML} + 53.269$.

Table 3.4: Three unfiltered and two filtered accelerometry-based measures were retained in the hierarchical multiple regression analyses for explaining inter-individual Ec after controlling for body mass.

Predictor	Axis	Unique contribution				Overall model	
		B	SE B	β	R ² change	R ²	
Model 1: Unfiltered accelerations							0.912
Body mass	–	0.894	0.071	0.810**	0.808	–	
Stride regularity	AP	-29.219	6.852	-0.279**	0.052	–	
RMS	AP	-27.981	8.65	-0.199**	0.032	–	
Sample entropy	ML	-20.382	8.464	-0.144*	0.02	–	
Model 2: Filtered accelerations							0.888
Body mass	–	0.892	0.078	0.813**	0.8	–	
Stride regularity	AP	-37.069	10.037	-0.266**	0.045	–	
RMS	AP	-30.523	9.673	-0.210**	0.043	–	

β = standardized coefficients; */** p < 0.05 / p < 0.001

; constant for multiple regression equations were 53.269 (unfiltered) and 56.935 (filtered)

Discussion

The current study tested a cost of instability hypothesis that proposes a link between running stability and running Ec using wearable tri-axial trunk accelerometry. Our results lend support to this cost of instability hypothesis, with three accelerometry stability measures explaining an additional 10.4% inter-individual variance in Ec over and above that needed to support body mass (80.8%). Our findings build on limited evidence [3, 24, 8] by suggesting new dynamic instability mechanisms that imposes an Ec to running which could hamper endurance performance.

The first determining accelerometry measure, namely stride regularity AP, explained an additional 5.2% of running economy. The direction of the slope in Figure 3.3 B was as expected, indicating that runners with poor consistency from stride to stride have a more energetically costly gait. Since this measure is directed anteroposteriorly, it could reflect intermittency or alternate decelerations and accelerations corresponding to braking and propulsive forces, analogous to alternately applying “gas-brake-gas” while driving a car. The trunk muscles could be compensating for this instability since they play a critical role by eccentrically contracting to decelerate lumbo-pelvic motion anteroposteriorly during running [34, 37]. Electromyography assessment evaluating relationships between muscle activity, stability and economy would help elucidate on the underlying mechanisms.

The second determining accelerometry measure, namely RMS AP, explained a slightly less but additional 3.2% of running economy. However, the direction of the slope as shown in Figure 3.3 C is unexpected, since it was hypothesized that runners with higher RMS AP would have the poorest running economy due to larger changes in momentum. Our data

counterintuitively suggest that higher amplitudes or variability of AP trunk accelerations while running is a kinematic adjustment advantageous to economy. On the one hand this confirms previous paradoxical evidence that greater changes in horizontal velocity of the CoM were related to better economy in elite female runners [49]. On the other hand this contradicts more recent work [11] showing that endurance runners with smaller minimum AP horizontal velocity of the pelvis, i.e. less deceleration/braking velocity were more energetically costly. Additionally, Ijmker et al.[17] showed a decrease in E_c , and variability in horizontal plane trunk accelerations when external balance support was provided during walking. Notably, the RMS measure used in the current study considers all amplitude variability during the running step and perhaps more knowledge could be gained from detecting and separately calculating RMS during braking and propulsive phases of stance. For example, Chang and Kram [9] revealed that increases and decreases in propulsive impulses were primarily linked to costs and savings in E_c when impeding or aiding horizontal forces were externally applied to the individual. However, Heise et al.[13] revealed that neither braking nor propulsive impulses showed sensitivity to inter-individual differences in E_c . Therefore, it remains inconclusive how AP changes in momentum explain economy between runners and further research is needed.

The third determining measure, namely sample entropy of ML trunk accelerations explained an additional 2.0% of running economy when accelerations were left unfiltered. Sample entropy is becoming an increasingly popular complexity measure to capture both performance-related [31, 39] and pathologically-related [46] non-linear dynamics of human gait. Unexpectedly, lower sample entropy ML values, i.e. less complexity, were related with costlier running gait (Figure 3.3 D). Although, this relationship may be supported from a dynamical systems perspective, suggesting that a reduction or “freezing” in the interacting degrees of freedom contributing to ML trunk control of stability is associated with poorer movement economy [7]. Murray et al.[31] similarly found, in one of their six subjects, a decrease in sample entropy of ML trunk accelerations to be retained as a determinant of higher submaximal VO_2 with increasing running speed. However, their pilot sample was too small to conduct inter-individual group statistics, and it is possible that both oxygen consumption and sample entropy correlates were similarly detecting correlations with intra-individual changes in running speed. Here, for the first time, we show a relationship between ML sample entropy of movement and E_c of running in a larger sample of runners, while accounting for running speed effects by expressing running economy per unit distance.

On a technology level, it is often argued that signal waveforms should be left unfiltered when assessing complexity measures such as sample entropy [35], and our current findings support this notion. Specifically, sample entropy ML was no longer retained as a significant predictor of E_c when accelerations were low-pass filtered prior to calculation. This result suggests that filtering either “washed out” or “masked” some inherent physiological variations in the signal needed to explain some variance in E_c . Clearly, the choice to filter is important because in contrast to the other two significant (linear) predictors, this complexity measure is not robust to low-pass filtering and researchers should carefully consider this approach. Additionally, based on incremental iteration tests, we recommend that 20 running steps is optimal for calculating sample entropy measures from both an accuracy and computing stand-point (see APPENDIX).

In terms of generalizability, men displayed some significantly different aspects of dynamic stability compared to women. For instance, women had higher RMS ML as well as higher step- and stride- regularity in the ML direction. This sex difference could be attributed partly to female breast biomechanics since larger ML breast accelerations have translated to larger ML trunk displacements and ground reaction forces while running [40]. Notwithstanding, none of the stability measures retained in the regression models showed significant sex effects. Although not presented here, sex-specific regression models were checked but retained the same determining stability measures. Therefore, it is possible that the relationship between running stability and E_c is generalizable to both sexes. With respect to the calibre of our recreational to moderately trained participants, we suggest future studies assess and extend the generalizability of our findings to more elite distance runners whom are expected to have superior running stability. Furthermore, it is equally possible that the goal of the recreational runner might be to increase energy expenditure, rather than save it. Thus, trunk accelerometry could be proposed as a tool to test paradigms which deliberately attempt to increase the E_c of instability experimentally through training e.g. irregular surfaces, external perturbations, or unstable types of footwear.

Implications and future directions. Arguably, explaining an additional 10.4% inter-individual variance in E_c might be considered relatively low. However, the measures examined in this study were not expected to account for the majority of variance in E_c since the remaining variance could be attributed to numerous other factors. Nonetheless, using the final multiple regression equation of unfiltered accelerations, we estimated the energy cost for the runners using the lowest and highest values of these three accelerometry

measures in our sample while holding body mass constant in the equation (by using a group mean value of 68.18 kg). Hypothetically, the runner with poorest of all three stability measures, i.e. 51% lower stride regularity AP, 56% lower RMS AP, and 76% lower sample entropy ML would correspond to a total additional energy cost of 49% or $125 \text{ J} \cdot \text{m}^{-1}$ ($57.46 \text{ J} \cdot \text{m}^{-1} + 42.15 \text{ J} \cdot \text{m}^{-1} + 25.67 \text{ J} \cdot \text{m}^{-1}$ respectively) compared to the runner with the best of these three stability measures (see dotted lines on the x-axis of Figure 3.3 B, C, D for visual comparison of maximum and minimum). Quantitatively, however, it remains unclear how much this additional energetic cost would translate to impaired outdoor endurance performance as has been shown by adding shoe weight [15], but warrants an interesting question for future research. Notably, other accelerometry measures that loaded together in factor one of the factor analysis correlated strongly with stride regularity AP. Therefore, these other measures could have been substituted as inputs in the multiple regression analysis, and shouldn't necessarily be excluded from future investigations.

Further interpretation is needed with regards to how a runner could collectively target these accelerometry measures and apply them to practice. For instance, an immediate question raised by our findings is why the first two results appear to contradict each other: higher stride regularity AP implies that higher consistency is good, while higher RMS AP implies higher amplitude or variability is good for economy. One plausible explanation for our results is that RMS amplitudes could be influenced by the different individual speeds used, given that speeds were chosen as relative intensity rather than absolute. However, neither RMS AP nor the other two retained accelerometry measures were correlated to running individual speed at V_{OBLA} (a posteriori Pearson's correlation r values between -0.03 and 0.04; all $p > 0.05$), indicating that individual speed was not an influencing factor on the relevant accelerometry parameters. Since these accelerometry measures were uncorrelated and resided on independent factors (see Table 3.3), they seem to represent different constructs of dynamic stability. Nevertheless, a combined recommendation for a recreational runner based on these three measures would be to target larger overall acceleration amplitudes (RMS AP), provided these amplitudes are consistent between strides (stride regularity AP) and are maintained to produce high complexity in ML control of movement (ML entropy) possibly by exploring multiple movement strategies.

The E_c of dynamic instability could be influenced by altering the task from treadmill to over ground running, especially in self-paced situations. Subject to the laboratory limitations of this study, stability measures identified here may be used as a potential

basis for examining stability of an individual in relation to E_c in more ecological, i.e. over-ground outdoor settings. In addition, the relationships with stability observed here could be subject to the specific types of parameters extracted and thus other parameter selections or combinations thereof could yield different insights in the future.

Using trunk accelerometry as a tool to continuously examine the instability of running could reveal more about how and when this instability arises at the individual level and how this instability could be used to predict early decline in uneconomical performance. As previously highlighted [28], it is also plausible that running economy could be improved by training dynamic stability, requiring intervention studies. Indeed, it has been shown that dynamic postural stability training reduces the level of coactivation needed during functional tasks [32], which would improve economy. How stability measures change with various types of endurance training could elucidate further on how runners “self-optimize” their stability patterns to innately reduce E_c and is a focus of ongoing research.

Conclusion

Our results suggest that male and female recreational runners with lower stride regularity AP, lower RMS AP, and lower sample entropy ML have a more energetically costly running gait at similar relative intensities. Stated differently, characteristics of dynamic stability may be an adaptation to improved endurance running performance. Additionally, sample entropy ML was no longer retained as a significant predictor of E_c when accelerations were low-pass filtered prior to calculation, indicating that researchers should carefully consider this signal processing step when analysing acceleration waveform complexity. Overall, targeting these stability characteristics non-invasively and unobtrusively with a simple accelerometer in real competition settings could be useful for coaches and practitioners identifying athletes with favourable economy potential.

Appendix

Non-linear measures such as sample entropy are known to be sensitive to length of input signal used [51]. Therefore, we computed sample entropy values as a function of number (N) running steps over averages ranging from six to 160 consecutive running steps (see Figure 3.4 for visual example of one participant). We observed that sample entropy values stabilized, i.e. less variable or levelled off from around 20 running steps (range of 16 -

20 in all runners). Knowing when this biomechanical “steady-state” occurs is useful in two ways. Firstly, steady-state eliminates the influence of average N steps used on the outcome thus improving accuracy, and secondly minimizes the computational time, better suited to achieve outputs for real-time application.

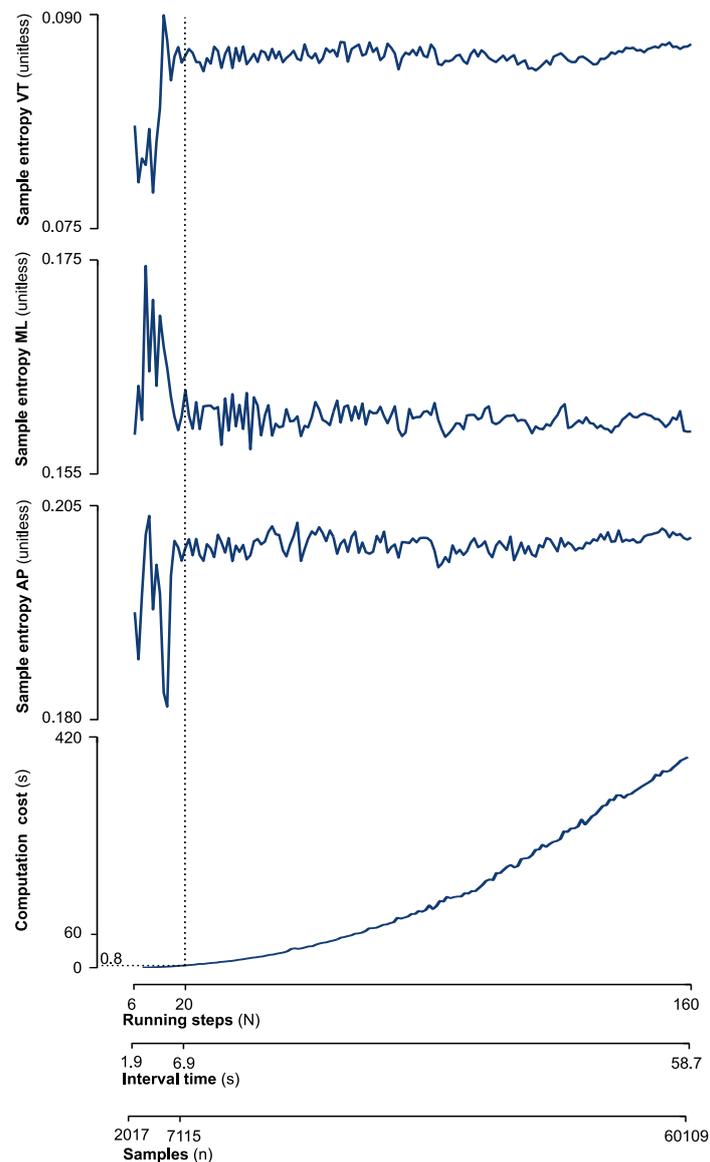


Figure 3.4: Non-linear sample entropy values were highly variable when averaged at a low number of steps but stabilized from around 20 running steps (interval time of 6.9 seconds and 7115 acceleration samples), with a combined computation time of approximately 0.8 sec on an Intel Core i5 CPU.

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Part II

Outdoor over-ground running

Chapter 4

Study III: Surface-related dynamic instability and loading

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Author Contributions

K.H.S, J.A, and B.V conceived and designed research;

K.H.S, and J.A performed experiments;

K.H.S, T.O.D.B, and B.C.V.D.Z analysed data;

K.H.S, J.A, T.O.D.B, B.C.V.D.Z, R.V, and B.V interpreted results of experiments;

K.H.S drafted manuscript;

K.H.S prepared figures;

K.H.S, J.A, T.O.D.B, B.C.V.D.Z, R.V, and B.V revised manuscript.

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Abstract

Despite frequently declared benefits of using wireless accelerometers to assess running gait in real-world settings, available research is limited. The purpose of this study was to investigate outdoor surface effects on dynamic stability and dynamic loading during running using tri-axial trunk accelerometry. Twenty eight runners (11 highly-trained, 17 recreational) performed outdoor running on three outdoor training surfaces (concrete road, synthetic track and woodchip trail) at self-selected comfortable running speeds. Dynamic postural stability (tri-axial acceleration root mean square (RMS) ratio, step and stride regularity, sample entropy), dynamic loading (impact and breaking peak amplitudes and median frequencies), as well as spatio-temporal running gait measures (step frequency, stance time) were derived from trunk accelerations sampled at 1024 Hz. Results from generalized estimating equations (GEE) analysis showed that compared to concrete road, woodchip trail had several significant effects on dynamic stability (higher AP ratio of acceleration RMS, lower ML inter-step and inter-stride regularity), on dynamic loading (downward shift in vertical and AP median frequency) , and reduced step frequency ($p < 0.05$). Surface effects were unaffected when both running level and running speed were added as potential confounders. Results suggest that woodchip trails disrupt aspects of dynamic stability and loading that are detectable using a single trunk accelerometer. These results provide further insight into how runners adapt their locomotor biomechanics on outdoor surfaces in situ.

Keywords: Running gait, running surface; trunk accelerometer; dynamic stability; dynamic loading.

Introduction

Worldwide millions of people participate in recreational and competitive running. It is an easily accessible sport with numerous proven health benefits. However, repetitive collisions with the ground also make running a sport with a high incidence of chronic overload injuries [27]. Dynamic loading related variables such as higher vertical loading rates [32] or peak tibial accelerations [15] have been prospectively associated with lower-limb overuse running injuries such as stress fractures. It is commonly believed that these dynamic loads and subsequently overuse injury risk is exacerbated on harder surfaces such as concrete or asphalt. However, epidemiological research has thus far failed to find any relationship between surface hardness and injury, possibly due to difficulty in accurately quantifying time and intensity on typical running surfaces [23]. **Identifying how dynamic loads are moderated on typical running surfaces could therefore add insights into appropriate preventative strategies for overuse running injury.**

Laboratory studies have shown that **small alterations in running surface can induce changes in human running mechanics**. For example, it is known that softer [4, 8, 9] or uneven [7, 30] running surfaces cause runners' to rapidly increase their leg stiffness, while peak ground reaction forces are mostly moderated with a stable centre of mass (CoM) trajectory [4, 8, 9]. Although, Dixon et al. [3] reported individual specific adaptations in knee kinematics between asphalt and a softer rubber-modified surface, they [3] also observed an overall reduction in vertical loading rates when switching to the softer surface. While these aforementioned studies provide essential insights, the **mechanisms for moderating are perhaps not directly applicable to "real-world" running surfaces that naturally vary in composites of hardness, evenness, and gradient.**

In attempt to secure ecological validity, some researchers have investigated how runners adapt their loading and mechanics to typical outdoor running surfaces. Using cinematography, Creagh et al. [2] found that running in long grass decreased step lengths while increased hip vertical displacement, knee lift and peak upper leg angles compared to running on tarmac. Others who have used portable wearable devices such as in-shoe plantar pressure measurements or tibial accelerometry have found conflicting results. For example, Tessutti et al. [24] reported higher central and lateral peak plantar pressures along with shorter contact times when running on asphalt compared to natural grass. In contrast, no differences in peak plantar pressure [5], impulse [25], tibial shock

[5] or contact times [5, 25] have been found between concrete, grass, or synthetic track. Discrepancies in findings could be attributed to large inter-individual responses [3]. **It appears that there is a need for a better understanding of how runners moderate their loading and gait in response to “real-world” surfaces.**

Measures derived from wireless tri-axial trunk accelerometers have become a popular approach to reliably and unobtrusively capture dynamic loading and CoM stability in various environments. The acceleration root mean square (RMS) as well as the autocorrelation-based coefficients referred to as inter-step and inter-stride regularity have identified a wide variety of impaired or asymmetrical stability patterns related to ageing [10], lower limb prosthesis [26], hemiplegia [21], and gross motor function [19]. When applied to running gait, these measures can detect compensations in dynamic stability due to fatigue [12, 20], predict oxygen consumption [13], and classify athletes based on their training background [11]. **The current paper includes stability and impact frequency components of running gait, which may be more sensitive to changes in surface relative to other measures i.e. spatio-temporal or impact peaks.** However, these accelerometer measures have usually been investigated on a single running surface, thus limiting multi-terrain generalizability.

Woodchip trails are becoming popular running surfaces that are specifically constructed to have “structural dampening” to reduce impact-loading related injuries and enhance participation of recreational running. Indeed, animal studies suggest that woodchip surfaces have injury preventative properties. For example, adult sheep that were exposed to prolonged activities on woodchips were less prone to development of knee osteoarthritis compared to sheep exposed to activities on hard concrete [17]. In addition, hoof impact accelerations were significantly more dampened when horses trotted at $4 \text{ m} \cdot \text{s}^{-1}$ on woodchip surface compared to asphalt [1]. Unfortunately, previous research on human running has primarily focused on other outdoor surfaces such as grass [2, 5, 24, 25], with no apparent evidence on woodchip trails.

The purpose of this study was to investigate outdoor surface effects on dynamic stability and loading during running using tri-axial trunk accelerometry. Based on previous laboratory research indicating smoothness of CoM trajectory under different surface conditions, we hypothesized that trunk accelerometry measures of dynamic stability and loading would be minimally affected by running surface.

Methods

4.0.1 Participants

Two predetermined age-matched groups of endurance runners aged 18 to 33 years of mixed gender (# women 14, 50 %) were recruited for this study; highly-trained runners (mileage $> 50 \text{ km} \cdot \text{week}^{-1}$, $n = 13$) and recreational runners (mileage $< 30 \text{ km} \cdot \text{week}^{-1}$, $n = 17$). All participants were screened to have no history of lower extremity injury within the past three months. Written informed consent was received from all runners prior to participation in accordance with the Declaration of Helsinki. The study was approved by the local ethics committee (Commissie Medische Ethiek KU Leuven).

4.0.2 Experimental protocol

All runners ($n = 17$ recreational; $n = 13$ highly-trained) performed a standardized warm-up. Outdoor running was performed on 90m of straight and flat concrete road, synthetic track, and woodchip trail. Photo electronic timing gates (RaceTime 2 system, Microgate, Bolzano, Italy) were positioned to capture average running speed from the 10m to 70m mark. A practice trial was provided to familiarize participants to each surface. The self-selected running speed on concrete was used as control speed on the other surfaces, and trials on subsequent running surfaces were discarded if the running speed differed by $\pm 1 \text{ m} \cdot \text{s}^{-1}$ of control speed. The order of the other two surfaces was randomized. To avoid any fatigue effect runners were allowed to rest during five minutes between each surface.

4.0.3 Accelerometry measurements

Tri-axial accelerometry (X50-2 wireless accelerometer, range $\pm 50\text{g}$, sampling at 1024 Hz, 0.016g/count resolution, 33g weight, Gulf Coast Data Concepts, MS, USA) was acquired during each running trial. The accelerometer was securely positioned over L3 spinous process of the trunk [16], and directly mounted to the skin using double sided tape and adhesive spray. Accelerometer position was unaltered between all running trials and was routinely checked between running trials for security. Trials were discarded in the case the investigators deemed the accelerometer to be not securely fastened upon its removal (after data collection).

All signal processing of acceleration curves was performed using customized software in MATLAB version 8.3 (The Mathworks Inc., Natick, MA, USA). Accelerometry-derived parameters were computed from the middle ten consecutive strides of the 10-70m measurement zone, that were first trigonometrically tilt-corrected and filtered using a zero-lag 4th order low-pass Butterworth filter (cut-off frequency 50 Hz) [16, 20]. Accelerometry-derived parameters were averaged over two running trials per surface per participant.

4.0.4 Outcome measures

Spatio-temporal parameters were quantified by step frequency and stance time. The former was acquired using the time lag of the first dominant peak of the vertical acceleration's unbiased autocorrelation [16, 20]. The latter was acquired based on the heuristic that as long as the body is accelerating upwards, the foot should still be in contact with the ground [6]. Therefore, zero crossings of vertical accelerations identified periods where the vertical acceleration was positive and accelerating upwards (initial contact to final contact) [6].

Dynamic postural stability parameters were quantified from tri-axial (vertical, ML, AP) accelerations firstly using the ratio of each linear acceleration axis root mean square (RMS) relative to the resultant vector RMS to capture variability (McGregor et al.2009); secondly using step and stride regularity (unbiased autocorrelations procedure) to capture symmetry and consistency of running steps and strides respectively, with perfect regularity equivalent to one [16]; and thirdly using sample entropy from raw accelerations to capture the waveform predictability, with higher values indicating less periodicity or more unpredictability [18]. Detailed procedures and algorithm inputs for the computation and extraction of these dynamic postural stability parameters are explained previously [20].

Dynamic loading parameters during stance were computed from extracted stance phases firstly in the time domain and secondly in the frequency domain. The former was acquired by extracting the peak positive vertical (impact) and peak negative anteroposterior (breaking) accelerations identified between 1% and 20% stance. The latter was acquired from the median frequency of vertical and AP accelerations of the entire stance phase calculated as the centroid of the power spectral density (PSD) curves within the 1 – 100 Hz range [29]. PSD was calculated from the Fast Fourier Transform (FFT) of unfiltered vertical stance phase accelerations from 0 to the Nyquist (F_N) frequency, that were first processed in line with previous methods (Shorten & Winslow, 1992): detrended, padded

with zeros to equal 2048 data points (ensuring $2n$ periodicity), and interpolated to 1 Hz bins.

4.0.5 Statistical analysis

Group descriptive characteristics were compared using independent t-tests. Each accelerometry-derived parameter was individually evaluated for normality; skewness between > -1 and < 1 was accepted. Subsequently, normally distributed data was analyzed by means of linear regression using generalized estimating equations (GEE). GEE analysis is more sophisticated than linear regression because it takes into account that measures within one subject are correlated with repeated observations. An exchangeable correlation structure was used for the GEE analysis in this study since it fit the data well (high within-subject correlations) and for simplicity to minimize the number of parameters needed. The effect of surface type on accelerometry-derived parameters was evaluated in three models: Firstly an unadjusted model, the effect of surface type (woodchips and synthetic) compared to concrete (control reference category) on each accelerometry outcome measure. Secondly, we assessed if training status (highly-trained vs. recreational) was a confounding variable to the model, since trunk accelerometry parameters have been found to significantly differ between trained and untrained runners [13]. From this step, training status was only included in the model if it significantly changed any of the regression coefficients for surface type ($>10\%$). Thirdly, we assessed the potential role of running speed as a confounder to surface type by adding it as a time-dependent continuous covariate, since some trunk accelerometry parameters show strong relationships with gait speed during running [13].

Results

Two subjects from the group of competitive runners were excluded from analysis since the investigator deemed the attachment of their accelerometer to not be securely fasted upon removal, and body sweat interfered with attempts at reattachment. Characteristics of the remaining participants are shown in Table 4.1.

Table 4.1: Descriptive results of participant characteristics

	Mean (SD)
n	28
Male (female)	14 (14)
Age (years) (SD)	22.62 (3.07)
Height (m) (SD)	1.76 (6.24)
Weight (kg) (SD)	63.05 (5.57)
Training volume ($\text{km} \cdot \text{week}^{-1}$) (SD)	41.22 (9.91)
Recreational (n = 17)	9.56 (11.88)*
Highly-trained (n = 11)	72.88 (7.94)
Concrete road running speed ($\text{m} \cdot \text{s}^{-1}$) (SD)†	3.79 (0.51)
Recreational (n = 17)	3.56 (0.44)*
Highly-trained (n = 11)	4.02 (0.58)
Synthetic track running speed ($\text{m} \cdot \text{s}^{-1}$) (SD)†	3.73 (0.45)
Recreational (n = 17)	3.54 (0.42)*
Highly-trained (n = 11)	3.92 (0.48)
Woodchip trail running speed ($\text{m} \cdot \text{s}^{-1}$) (SD)†	3.73 (0.45)
Recreational (n = 17)	3.47 (0.23)*
Highly-trained (n = 11)	3.99 (0.51)

†: based on self-selected speeds acquired from timing gates

*: t-test detected significantly different from highly-trained group ($p < 0.05$).

GEE results of the crude analysis for surface effects on accelerometry-derived parameters are shown in Figure 4.1. Synthetic track did not significantly change from concrete besides one dynamic stability parameter (higher vertical stride regularity). Woodchip trail changed significantly from concrete for several parameters, including spatio-temporal (lower step frequency), dynamic stability (lower vertical but higher AP ratio of acceleration RMS, and lower step regularity and stride regularity in the ML direction only) and dynamic loading (lower vertical and AP median frequencies). The downward shift in vertical and AP median frequencies during stance from concrete to woodchips can be observed in Figure 4.2, overlaid with plots of trunk acceleration signals during stance in the frequency domain. When either training status (model two) or running speed (model three) were added as potential confounders, statistical outcomes related to surface effects were unchanged. Therefore all results pooled trained and untrained runners together ($n = 28$) and results from the crude analysis on surface effects were reported (Table 4.2).

Table 4.2: Descriptive results (mean; SD) of accelerometry-derived parameters for repeated measures (n = 28).

Running gait parameter	Axis	Concrete road	Synthetic track	Woodchip trail
Spatio-temporal				
Step frequency (steps.min ⁻¹)	VT	169.75 (7.73)	169.03 (8.75)	167.4 (7.31)
Stance time (s)	VT	0.22 (0.02)	0.22 (0.02)	0.22 (0.02)
Dynamic stability				
Ratio of acceleration RMS (a.u)	VT	1.10 (0.08)	1.09 (0.07)	1.07 (0.07)
	ML	0.47 (0.11)	0.48 (0.11)	0.49 (0.11)
	AP	0.42 (0.10)	0.43 (0.10)	0.45 (0.09)
Step regularity (a.u)	VT	0.8 (0.09)	0.82 (0.08)	0.81 (0.08)
	ML	0.55 (0.13)	0.57 (0.12)	0.51 (0.12)
	AP	0.58 (0.12)	0.59 (0.13)	0.55 (0.11)
Stride regularity (a.u)	VT	0.81 (0.09)	0.84 (0.06)	0.82 (0.08)
	ML	0.69 (0.12)	0.70 (0.09)	0.64 (0.10)
	AP	0.65 (0.12)	0.67 (0.13)	0.63 (0.12)
Sample entropy (a.u)	VT	0.12 (0.02)	0.12 (0.02)	0.12 (0.02)
	ML	0.32 (0.07)	0.32 (0.07)	0.32 (0.07)
	AP	0.37 (0.10)	0.38 (0.11)	0.38 (0.11)
Dynamic loading				
Impact peak (g)	VT	4.02 (1.54)	3.91 (1.39)	3.67 (1.40)
Breaking peak (g)	AP	1.77 (0.60)	1.85 (0.70)	1.84 (0.66)
Median frequency during stance (Hz)	VT	16.19 (5.90)	14.82 (5.29)	13.90 (4.14)
	AP	15.55 (5.34)	14.99 (5.17)	13.72 (5.04)

VT: vertical; ML: mediolateral; AP: anteroposterior; a.u: arbitrary units

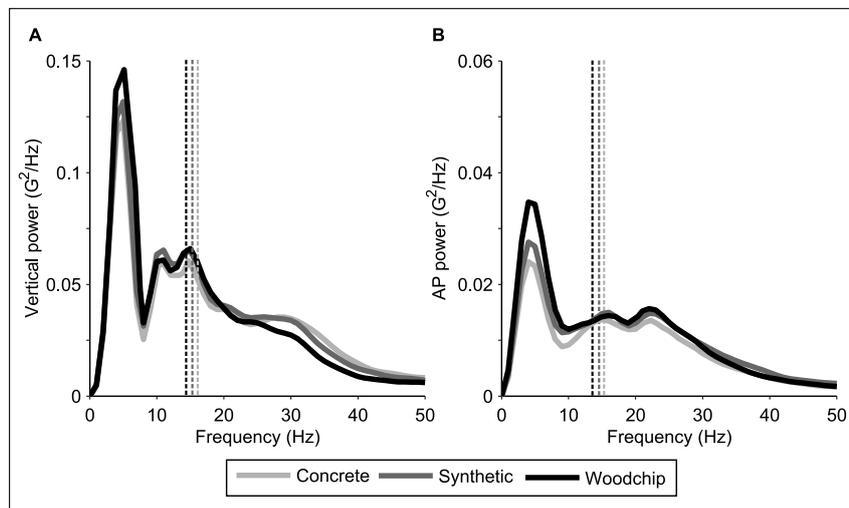


Figure 4.2: Group mean (n = 28) power spectra of A) vertical and B) AP trunk acceleration signals compared between concrete (light grey), synthetic track (dark grey), and woodchips (black). Vertical dashed lines indicate the median frequency for each surface respectively.

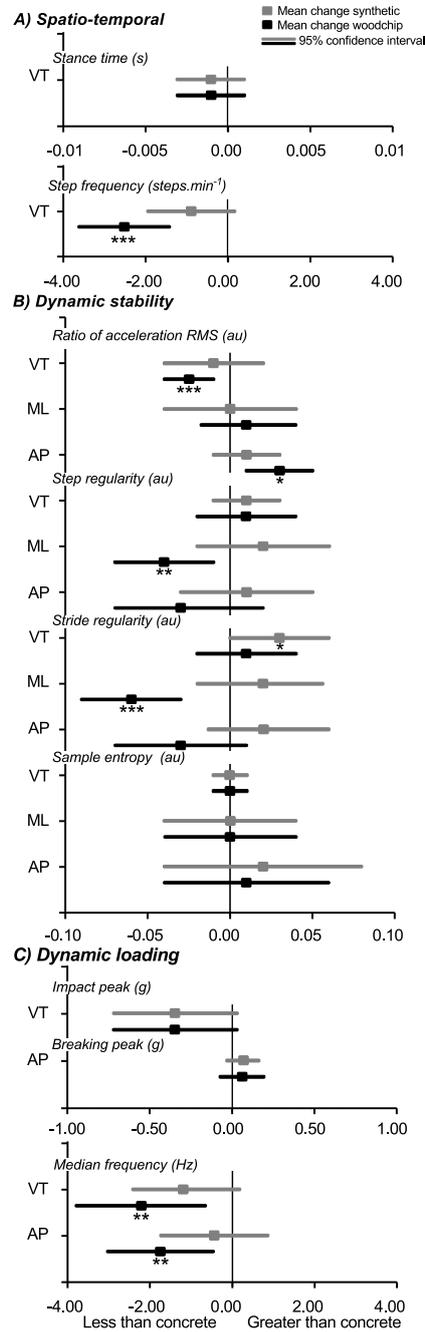


Figure 4.1: Regression coefficients (95% confidence intervals) regarding GEE results for surface effects on accelerometry-derived parameters for repeated measures (n = 28). VT: vertical; ML: mediolateral; AP: anteroposterior; a.u: arbitrary units. */**/** Regression coefficient significantly different from reference category concrete road surface (p < 0.05)/ (p < 0.01)/ (p < 0.001).

Discussion

Despite the frequently cited benefits of using wireless accelerometers to assess running gait in ecological (i.e. real-world) rather than traditional (i.e. laboratory) settings, few studies have actually done so. Therefore, this study sought to investigate outdoor surface effects on dynamic stability and loading during running using tri-axial trunk accelerometry. Importantly, there were no significant ($p > 0.05$) differences in all parameters with exception to vertical stride regularity between concrete and synthetic track. In contrast, **woodchip trail altered measures of dynamic stability compared to concrete**; revealing significantly higher AP ratio of acceleration RMS as well as lower ML inter-step and -stride regularity. Woodchip trail additionally decreased median frequencies of both vertical (impact) and AP (breaking) accelerations compared to concrete. In light of these results, it is reasonable to hypothesize that differences may exist in injury risk and performance between concrete and woodchip running surfaces.

In agreement with previous research [4, 5, 25], we found that contact time was unaffected by running surface. On the other hand, we did find significantly reduced step frequencies on woodchips. Thus, **our hypothesis based on the principle of smoothness of CoM trajectory under different surface conditions [4], active “self-stabilization” [7, 30] or maintenance of global support kinematics over different terrain [4, 9] was not completely supported**. From a biomechanical perspective, woodchip trails differ fundamentally from concrete road and synthetic track due to the presence of variously sized detached or scattered particles. Both compression and displacement of the woodchips under the foot may then occur with each consecutive running stride, causing dynamic instability and forcing lower-limb musculature to provide additional work to the point of reaction force on the surface [6]. Therefore, the irregular nature of woodchips could have interfered with the step length-step frequency relationship, as has previously been observed when running on irregular [31] or rough [2] terrain.

The directional-shift in variation (ratio of acceleration RMS) from vertical to AP as well as the decrease in inter-step and inter-stride regularity mediolaterally could indeed also be directly related to the woodchip properties. This is consistent with past research, which has shown similar destabilizations and directional shift from vertical to horizontal accelerations when walking on uneven ground [14]. Thus, the runner's dynamic stability may be compromised as a result of the irregularity of the uneven woodchips. Based on previous research in our laboratory [20], running-related fatigue on an indoor treadmill

results in a 13% increase in the AP ratio of acceleration RMS. The runners in this study showed a 7% increase in the AP ratio of acceleration RMS from concrete to woodchip surface. **Thus, although both internal (fatigue) and external (surface) factors contribute to destabilizing the stability of running, the magnitude of changes due to running surface appear to be relatively smaller.** It would be interesting to examine the destabilizing running-related fatigue effects on a range of running surfaces, including woodchips, since energy expenditure is increased when running on uneven terrain [30]. This could provide insight into whether uneven surfaces such as woodchips are more detrimental to a runner's stability when in a fatigued state.

Dynamic loading parameters were analyzed to provide information on magnitude and proportion of propagated shock waves reaching the spine. We found no significant surface effects for the amplitudes of vertical impact shock or AP breaking peak in the time domain. It is possible that the amplitude of impact shock accelerations reaching the spine were unaffected due to initial impact attenuations by the lower extremity, acting as a low-pass filter [28]. However, we also analyzed the frequency content of impact shock waves to gain better insights in the distribution of the power content of impact, and observed a significant downward shift in the median frequencies of vertical impact and AP breaking accelerations on woodchips. Visual inspection of the frequency curves in Figure 4.2 indicates that on woodchips a larger proportion of both vertical and AP accelerations during stance were contained in the low frequency component (4-8 Hz), while the proportion in the high frequency "impact" component (10-20 Hz) appeared relatively unaltered. **These results suggest that during stance a greater proportion of accelerations may be needed for voluntary movements [22] and stability of the CoM on woodchips, rather than any additional "structural dampening" provided as has anecdotally been suggested.**

Although we observed no confounding influence of training status, it is reasonable to argue that maintaining dynamic stability could be more difficult for recreational compared to highly trained runners [13]. Unfortunately, effect modification i.e. surface type x group interaction was not directly investigated here due to low sample size and is a limitation of the current study. Secondly, given that competitive runners were more familiar with synthetic track while recreational runners were more familiar with wood chip trail, another limitation worth mentioning is that surface habituation was unaccounted for. However, all participants had at least some experience with running on all three surfaces and familiarization trials were provided for each running surface to help minimize any

immediate psychological adjustments.

We found that all surface effects were unaffected when running speed was added to the GEE model as a covariate. The need to control for running speed was warranted given that previous research has indicated that adjustments in running mechanics can often be explained by variable running speed [13], presenting a major analytical problem. Additionally, running speed in itself may be an adjustment to outdoor surfaces, even when pacing methods are enforced [2]. In contrast, **our in-field and statistical approach to deal with running speed as a potential confounder enabled our runners to self-select speeds that were comfortable to them, with arguably more real-world applicability.**

Conclusion

The current results suggest that woodchip trails alter running mechanics by disrupting aspects of dynamic stability and loading. The analysis presented here provides further insights into running gait adaptations in typical, real-world settings.

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Chapter 5

Study IV: Fatigue- and injury-related dynamic instability and loading

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Author Contributions

K.H.S, and B.V conceived and designed research;

K.H.S, and S.S performed experiments;

K.H.S, and S.S, analysed data;

K.H.S, S.S, R.V, and B.V interpreted results of experiments;

K.H.S drafted manuscript;

K.H.S prepared figures;

K.H.S, S.S, R.V, and B.V revised manuscript;

K.H.S, S.S, R.V, and B.V approved final manuscript.

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Abstract

Medial tibial stress syndrome (MTSS) is a common overuse running injury with pathomechanics likely to be exaggerated by fatigue. Wearable accelerometry provides a novel alternative to assess biomechanical parameters continuously while running in more ecologically valid settings. The purpose of this study was to determine the influence of outdoor running fatigue and MTSS on both dynamic loading and dynamic stability derived from trunk and tibial accelerometry. Runners with ($n=14$) and without ($n=16$) history of MTSS performed an outdoor fatigue run of 3200m. Accelerometer-based measures averaged per lap included dynamic loading of the trunk and tibia (i.e. axial peak positive acceleration, signal power magnitude, and shock attenuation) as well as dynamic trunk stability (i.e. tri-axial root mean square ratio, step and stride regularity, and sample entropy). Regression coefficients from generalised estimating equations were used to evaluate group by fatigue interactions. No evidence could be found for dynamic loading being higher with fatigue in runners with MTSS history (all measures $p>0.05$). One significant group by running fatigue interaction effect was detected for dynamic stability. Specifically, in MTSS only, decreases mediolateral sample entropy i.e. loss of complexity was associated with running fatigue ($p<0.01$). The current results indicate that entire acceleration waveform signals reflecting mediolateral trunk control is related to MTSS history, a compensation that went undetected in the non-fatigued running state. We suggest that a practical outdoor running fatigue protocol that concurrently captures trunk accelerometry-based movement complexity warrants further prospective investigation as an in-situ screening tool for MTSS individuals.

Keywords: Accelerometer; Running; Overuse Injury; Fatigue; Body-worn sensor; Complexity

Introduction

Medial tibial stress syndrome (MTSS) is a debilitating overuse injury of the tibia prevalent in runners and military recruits. MTSS is a primary running-related musculoskeletal injury with a prospective incidence rate up to 20% [13], and a multi-factorial aetiology involving numerous extrinsic and intrinsic factors. The former includes training shoes, surface, interval training and intrinsic factors while the latter includes higher body mass index, fatigability, female gender, running experience, previous MTSS, and faulty biomechanics [21, 22]. Identifying modifiable risk factors could therefore reduce MTSS reoccurrence rates by allowing for earlier intervention.

Biomechanical compensatory mechanisms related to MTSS have mainly been recognized distal to the site of tibial injury. For example, it has been demonstrated that excessive or prolonged pronation contributes to MTSS whether it be statically i.e. standing [1, 21, 31] or dynamically i.e. running [6, 30]. However, the torso constitutes 40% of body mass and plays an important role in distributing loads while also maintaining balance and stability. It has also been postulated that compensatory mechanisms proximal to the site of injury can inappropriately distribute loads to distal structures via unsolicited accessory movements throughout the kinetic chain [3, 14, 28]. Dynamic proximal movement dysfunctions that have been identified with MTSS include excess trunk and hip motions in the transverse plane [28] and greater frontal plane pelvic tilt [14].

Ideally, MTSS pathomechanics should be detectable as soon as compensatory movements and accumulated loads become intolerable and potentially injurious.

Literature has indicated that inclusion of a fatigue protocol could enhance the possibility of detecting proximal movement compensations related to MTSS [29]. Wireless accelerometry is a popular approach to continuously assess both proximal (i.e. trunk) and distal (i.e. tibial) mechanics in human locomotion unobtrusively. From a fatigue-ability standpoint, trunk accelerometry has shown potential to capture proximal dynamic instabilities due to lower-limb fatigue [17] as well as running fatigue [11, 24] using various linear i.e. root mean square (RMS) or regularity, and non-linear measures i.e. sample entropy. From a clinical standpoint, it has been reported that accelerometry can detect variabilities and movement complexity related to walking pathomechanics [10, 27]. Distally, peak positive accelerations along the axis of the tibia have been associated with tibial stress fractures [19]. Various types of dynamic loading and dynamic stability measures have since been reported in the literature, and thus these terms need to be more specifically

defined. Here, dynamic loading is operationally defined as the magnitude and attenuation of time domain and frequency domain accelerations along the longitudinal axis of the trunk and tibia during ground contact while running. Additionally, dynamic stability is defined operationally as the ability to maintain optimal variability, symmetry, regularity, or complexity of tri-axial trunk acceleration patterns while running. Unfortunately, **it remains unknown if either dynamic loading or dynamic stability measures derived from wearable accelerometry are different in runners with a history of MTSS, and whether running fatigue in an outdoor situation would exacerbate these differences.**

In this study, **we hypothesized that runners with history of MTSS injury would reveal higher dynamic loading and reduced dynamic stability with outdoor running fatigue compared to uninjured healthy controls.** Specifically, we expected greater acceleration impacts, less shock attenuation, greater trunk variability, less step and stride consistency, and reduced complexity in MTSS runners when fatigued. To evaluate these hypotheses we used accelerometer-based linear and non-linear measures of dynamic stability as well as time- and frequency- domain measures of dynamic loading.

Methods

5.0.1 Participants

This study employed a cross-sectional repeated measures design between runners with and without MTSS history. MTSS was evaluated retrospectively due to high reoccurrence rates among MTSS patients [13, 22]. Thirty young adult recreational runners (age range 19 to 22 years) including 14 with history of MTSS injury and 16 controls without any history of overuse injury participated in this study. Based on a priori sample size estimates ($\alpha = 0.05$, Power=0.90) and using biomechanical walking gait data from Griebert et al. [7] (effect size=1.26), at least 12 participants per group were needed to provide sufficient power to detect group differences, calculated using G*Power. MTSS criteria were defined as previously confirmed diagnosis of exercise induced pain in the posteromedial aspect of the tibia and pain on palpation in the area of ≥ 5 cm in the posteromedial tibial region, excluding pain from ischaemic origin or signs of stress fracture [31]. All participants were asymptomatic at the time of testing. Written informed consent was received from all runners prior to participation in accordance with the Declaration of Helsinki. The local

ethics committee approved the study.

5.0.2 Experimental protocol

Participants performed a continuous maximal effort fatiguing run of 3200m (~2 mile), chosen for its relative ease of use and popularity among coaches. The run was performed on typical 400m synthetic track surface in dry and non-windy outdoor conditions. A standardized comfortable warm-up lap was provided prior to start. Split times per lap ($n_{laps} = 8$) were recorded and used to calculate average lap running speeds. Participants verbally communicated their rating of perceived exertion (RPE) using BORG [2] scale of 6 – 20 prior to starting as well as after each lap completion. Participants could run in their own relatively new (within three months of use) conventional shod running shoes. Two wireless tri-axial accelerometers (X50-2 wireless accelerometer, range $\pm 50g$, sampling at 1024 Hz, 0.016g/count resolution, 33g weight, Gulf Coast Data Concepts, MS) were mounted to the body. One accelerometer was located distally on the anteromedial aspect of the right tibia, specifically 0.08m proximal to the medial malleolus, placed directly to the skin with double-sided tape, and tightly fixed with extra self-adhesive tape to improve mechanical coupling with the tibia [19]. A second accelerometer was located over the L3-L5 spinous process of the lower back in a custom-designed neoprene pocket, tightly secured within a waist belt to participant comfort [20]. Prior to data collection the two accelerometers were synchronized with the clock of the same laptop, and this procedure was repeated at the end of the experiment to ensure units had not drifted relative to each other.

5.0.3 Accelerometry processing

All signal processing of acceleration curves was performed using customized software in MATLAB version 8.3 (The Mathworks Inc., Natick, MA, USA). Tri-axial trunk accelerations were trigonometrically tilt-corrected [20]. Both trunk and tibial accelerations were filtered prior to extraction of time-domain measures using a zero-lag 4th order low-pass Butterworth filter (cut-off frequency 50 Hz; with 99% signal power below this cut-off). All accelerometry-based measures were computed in windows consisting of ten consecutive strides. The number of windows was normalized from 0% to 100% test duration [18], and finally segmented into eight equal laps to ensure temporal alignment with lap speeds and RPE.

5.0.4 Accelerometry-based measures

Firstly, we quantified spatio-temporal measures by step frequency and contact time. The former was acquired using the time lag of the first dominant peak of the vertical trunk acceleration's unbiased autocorrelation [20], while the latter was quantified using zero crossings of vertical trunk accelerations specifically identifying periods where the vertical acceleration was positive and accelerating upwards [5].

Secondly, we extracted dynamic stability measures from tri-axial trunk accelerations (vertical, mediolateral, anteroposterior) (see Figure 5.1), and were quantified by 1) the ratio of each linear acceleration axis root mean square (RMS) relative to the resultant vector RMS to capture variability in accelerations [17]; 2) the regularity of steps and strides using the unbiased autocorrelation procedure to indicate consistency between steps and strides, with perfect regularities equivalent to one [20]; and 3) sample entropy as a non-linear measure to capture complexity of raw acceleration waveforms, with values typically in range of 0 to 2 for physiological systems, and higher values indicating less periodicity or more unpredictability [23]. Detailed procedures and algorithm inputs for the computation and extraction of these dynamic stability parameters are the same as previously explained [24].

Thirdly, we computed dynamic loading measures from identified stance phases of vertical trunk and axial tibial accelerations (see Figure 5.2). In the time domain, peak positive vertical impact accelerations (g) were identified between 1% and 30% stance time. A Fast Fourier Transform (FFT) of accelerations from 0 to the Nyquist (FN) frequency was performed. Recommended preprocessing techniques were followed, which included detrending, padding with zeros to equal 2048 data points (ensuring 2n periodicity), and interpolating to 1 Hz bins [8, 25]. Thereafter, from the frequency domain, the signal power magnitude in both the active and impact phases of stance were quantified by the integral of the power in the active (5-8 Hz) and impact (12-20 Hz) ranges respectively [25]. The attenuation of shock i.e. the transmission of acceleration through the kinetic chain from tibia to trunk was examined using a transfer function, applied to each frequency bin (i) from 0 to FN frequency by:

$$Transfer\ function_i = 10\log_{10}\left(\frac{PSD_{trunk,i}}{PSD_{tibia,i}}\right) \quad (5.1)$$

with $(Transfer\ function_i)$, representing the attenuation (in dB) between the PSD of

the trunk $PSD_{trunk,i}$ and tibia $PSD_{tibia,i}$ respectively. Positive values indicate gain or increase in signal strength while negative values indicate attenuation or decrease in signal strength.

5.0.5 Statistical analysis

After normal distribution was confirmed ($-1 < \text{accepted skewness} < 1$), differences between MTSS and control groups for descriptive and accelerometry-based measures at baseline (lap one) were assessed using independent t-tests. Repeated measure lap fatigue effects on accelerometry-based measures were further analysed by means of linear regression using generalized estimating equations (GEE). GEE analysis is more sophisticated than traditional linear regression because it considers that measures within one subject are correlated with repeated observations (exchangeable correlation structure) and allows discrete and continuous inputs. A group factor was added to the model with participants dichotomously categorized as MTSS or control. Fatigue by group interaction effects were additionally assessed, and fatigue effects were reported separately for each group where a significant interaction effect was present. We also adjusted for changes in running speed (per lap) as a time-dependent covariate for fatigue effects in a follow-up model, given that time-trials for middle distance running typically exhibit faster first and final laps compared to slower middle laps. Alpha level was set to 0.05 for all analysis and all statistical analyses were performed using SPSS (version 20.0; SPSS Inc, Chicago, IL).

Results

No significant differences between MTSS and control groups were observed for any descriptive characteristics (Table 5.1) (all $p > 0.05$). Figure 5.6 A (supplementary) shows self-selected running speeds per lap per group as means (SD), used in this study as a time-dependent covariate. Figure 5.6 B (supplementary) shows self-reported ratings of perceived exertion changes per lap per group as means (SD), used in this study as a subjective measure of running fatigue. All runners in this study reached a rating of perceived exertion level $\geq 18/20$ at test completion.

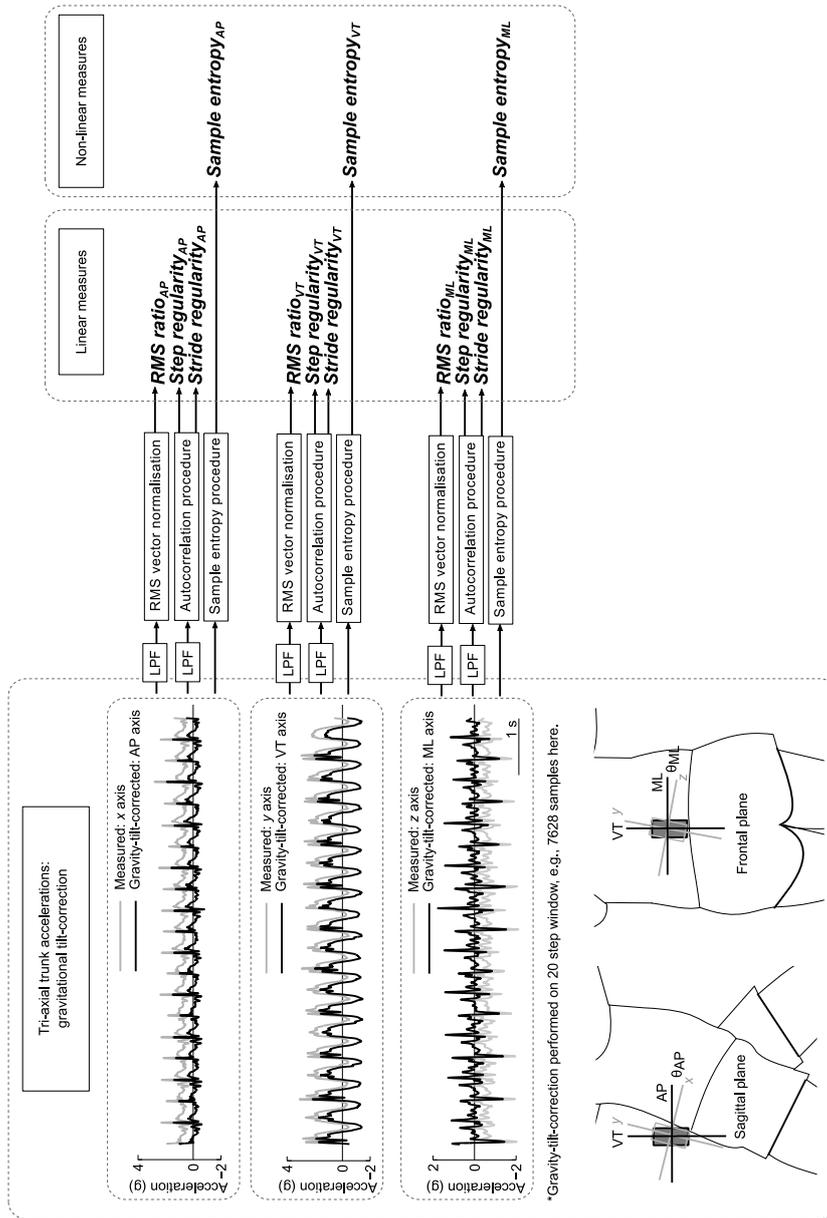


Figure 5.1: Deriving dynamic stability measures in this study. Measured tri-axial (x, y, z) trunk accelerations per 20-running-step window were first gravitationally-tilt-corrected to anteroposterior (AP), vertical (VT), and mediolateral (ML) accelerations respectively (corrected angles shown as θ_{AP} and θ_{ML} in bottom panel). After low-pass filtering (LPF), linear measures such as the acceleration root mean square (RMS) ratio and the step and stride regularity were computed per axis. Additionally, non-linear measures including sample entropy per axis were computed from unfiltered accelerations.

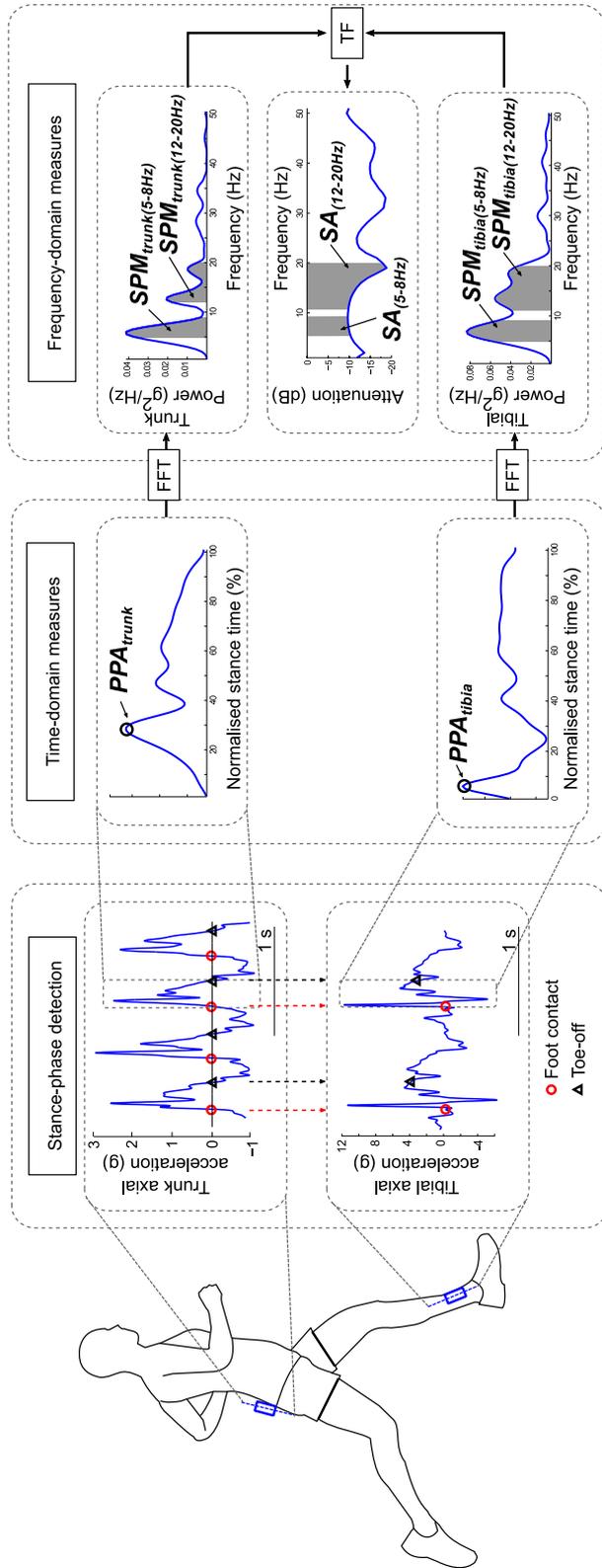


Figure 5.2: Deriving dynamic loading measures in this study. After stance phases were detected using zero crossings, trunk and tibial acceleration waveforms along the longitudinal axis were used to extract peak positive accelerations (PPA) in the time domain. After converting to the frequency domain using Fast Fourier transformation (FFT), the signal power magnitudes (SPM) in the low and high frequency ranges were extracted (see grey areas under the curve). After applying a transfer function (TF) between trunk and tibial power spectral density, shock attenuation (SA) was extracted from low and high frequency ranges respectively.

Table 5.1: Descriptive characteristics of participants with and without previous medial tibial stress syndrome (MTSS). Data are reported as mean (SD), with p-value for two-sampled t-test.

Variables	Control	MTSS	p-value
Sex (n = male ; n = female)	10; 6	8; 6	–
Age (years)	20.13 (0.72)	20.36 (0.84)	0.43
Height (m)	174.75 (7.34)	176.93 (10.03)	0.51
Weight (kg)	63.06 (9.45)	68.29 (9.02)	0.13
Body mass index (kg ■ m ²)	20.61 (2.25)	21.72 (1.22)	0.36
Weekly training mileage (km)	26.44 (6.26)	24.14 (5.64)	0.52
Experience running (years)	3.22 (1.57)	3.15 (1.33)	0.78
Time since MTSS (months)	–	13.9 (7.7)	–
MTSS location (n = bilateral; n = unilateral*)	–	12; 2	–
Fatigue run			
Time to completion (min)	13.63 (1.86)	14.14 (1.79)	0.45
Rating of perceived exertion at completion	19.44 (0.63)	19.29 (0.83)	0.58
Running steps analysed (n)	2229 (260)	2324 (297)	0.36

* In both unilateral cases injury occurred in the right leg

No significant main effects between groups were detected for any accelerometry-based outcome measure, either at baseline (independent t-tests all $p > 0.05$, Table 5.2) or over the entire fatiguing protocol (GEE results all $p > 0.05$).

Spatio-temporal measures showed significant main effects for fatigue, independent of group ($n=30$). Compared to baseline, step frequency decreased by 3 steps.min⁻¹ (95% CI 1–5, $p < 0.01$) and contact time increased by 6 ms (95% CI 4–8, $p < 0.01$) in laps two to seven (all $p < 0.05$). However, these fatigue effects were confounded by running speed and no longer persisted with inclusion of running speed in the model (all $p > 0.05$).

One dynamic stability measure, mediolateral sample entropy, revealed a significant running fatigue by group interaction effect, which persisted when adjusting for running speed ($p < 0.01$). Subsequent group specific analysis for mediolateral sample entropy are shown in Figure 5.3 A (MTSS; $n = 14$) and Figure 5.3 B (controls; $n = 16$). Mediolateral sample entropy in the MTSS group significantly declined from 2 km onwards (lap six, seven and eight; all $p < 0.01$), with slightly augmented declines with running speed inclusion. The control group showed no significant lap changes in mediolateral sample entropy relative to baseline (all lap changes $p > 0.05$) - with speed adjustment the coefficients remained non-significant, although the 95% confidence intervals were narrowed.

Table 5.2: Trunk accelerometry-based measures in participants with and without previous medial tibial stress syndrome (MTSS) at baseline i.e. during the first 400m lap of fatigue run. Data are shown as mean (SD).

Measures	Axis	Control	MTSS	P value
Spatio-temporal				
Step frequency (steps \cdot min ⁻¹)	VT	175.60 (11.15)	171.66 (7.53)	0.29
Contact time (ms)	VT	217 (20)	218 (13)	0.96
Dynamic stability				
RMS ratio (unitless)	VT	1.03 (0.09)	1.05 (0.11)	0.57
	ML	0.70 (0.11)	0.65 (0.13)	0.46
	AP	0.58 (0.10)	0.55 (0.11)	0.73
Step regularity (unitless)	VT	0.85 (0.04)	0.86 (0.02)	0.19
	ML	0.53 (0.10)	0.57 (0.07)	0.18
	AP	0.56 (0.10)	0.60 (0.08)	0.45
Stride regularity (unitless)	VT	0.86 (0.04)	0.87 (0.02)	0.56
	ML	0.64 (0.06)	0.66 (0.1)	0.68
	AP	0.66 (0.05)	0.66 (0.08)	0.5
Sample entropy (unitless)	VT	0.14 (0.02)	0.13 (0.02)	0.5
	ML	0.27 (0.05)	0.29 (0.07)	0.62
	AP	0.31 (0.04)	0.34 (0.07)	0.13
Dynamic loading				
Impact acceleration peak (g)				
Trunk	#	1.96 (1.14)	2.21 (0.98)	0.54
Tibia	#	6.43 (1.51)	6.62 (1.20)	0.71
Signal power magnitude (5-8Hz) (g ² /Hz)				
Trunk	#	0.008 (0.006)	0.007 (0.003)	0.68
Tibia	#	0.038 (0.023)	0.052 (0.078)	0.92
Signal power magnitude (12-20Hz) (g ² /Hz)				
Trunk	#	0.047 (0.021)	0.047 (0.021)	0.92
Tibia	#	0.357 (0.117)	0.424 (0.292)	0.3
Shock attenuation				
Active phase magnitude (5-8Hz) (dB)	#	-34.22 (26.89)	-26.66 (20.21)	0.41
Impact phase magnitude (12-20Hz) (dB)	#	-99.11 (23.93)	-101.35 (19.68)	0.79

VT: vertical; ML: mediolateral; AP: anteroposterior;

* Two-sampled t-test of differences between MTSS and controls

derived from the accelerometer sensing axis in line with the longitudinal axial direction of the trunk or tibia respectively

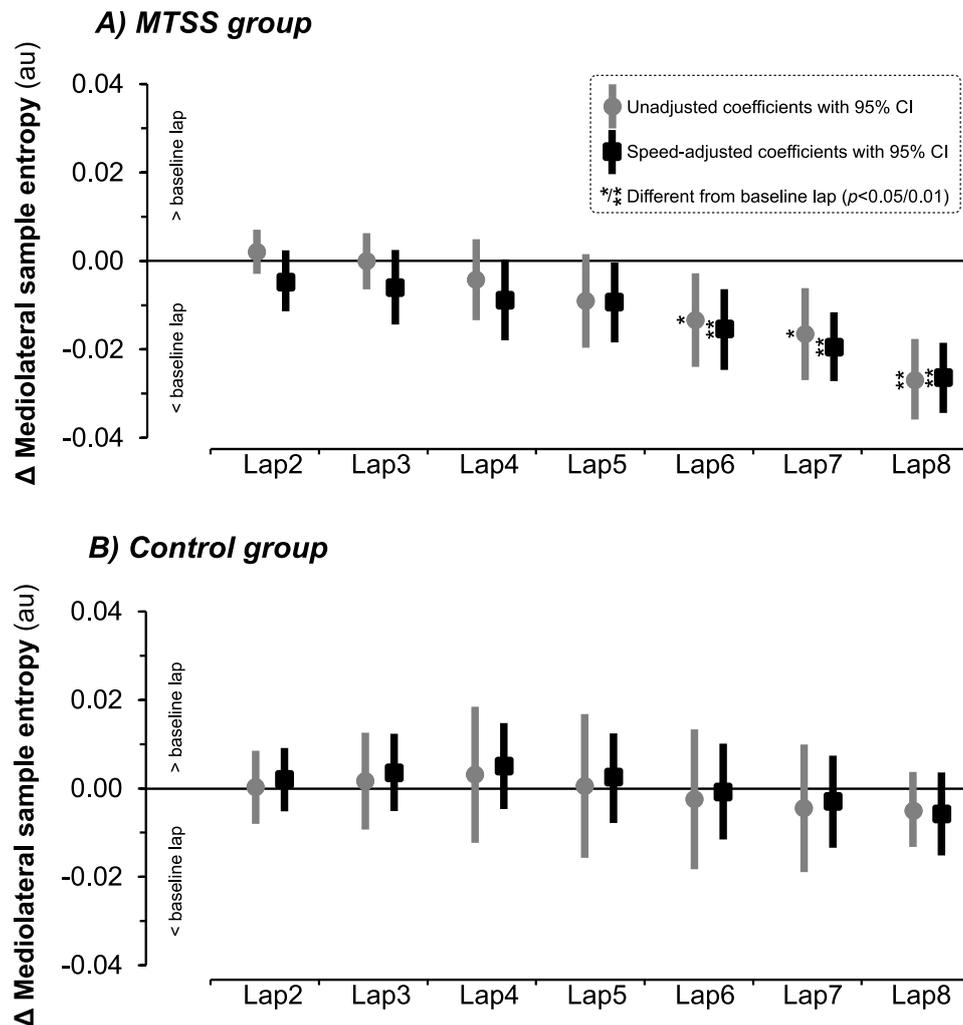


Figure 5.3: Sample entropy of mediolateral trunk accelerations as a function of outdoor lap fatigue, presented separately for medial tibial stress syndrome (MTSS) (A) and uninjured control (B) groups due to a significant fatigue by group interaction ($p < 0.01$). Both unadjusted (circles) and running-speed-adjusted (squares) regression coefficients with 95% confidence intervals are presented, with differences with respect to reference baseline lap. In MTSS, values significantly decreased in the final three laps, while in uninjured controls no significant changes were observed with fatigue.

Two dynamic stability measures, namely vertical step symmetry and mediolateral RMS ratio, revealed significant main effects for running fatigue, independent of group ($n = 30$). Figure 5.4 shows the loci of these fatigue effects with both unadjusted and running-speed-adjusted regression coefficients with 95% confidence intervals shown as differences to the reference baseline lap. Firstly, vertical step regularity decreased with fatigue in the final lap ($p < 0.01$), which was not confounded with inclusion of running speed (Figure 5.4 A). Secondly, mediolateral RMS ratio increased with fatigue in the final two laps ($p < 0.01$),

with augmented increases with running speed inclusion. Specifically, when running speed was adjusted for, increases in mediolateral RMS ratio became significant in lap three ($p < 0.05$), four ($p < 0.05$), and five ($p < 0.01$) (Figure 5.4 B).

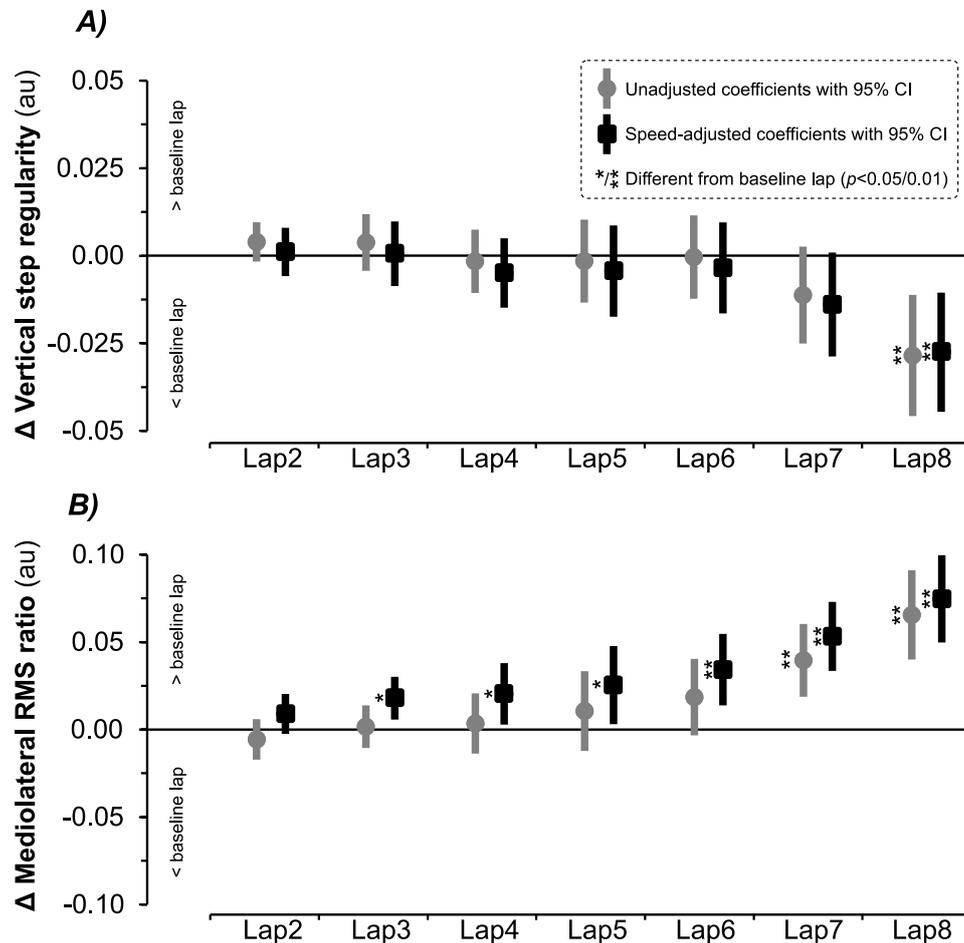


Figure 5.4: Dynamic stability measures as a function of outdoor lap fatigue for all subjects combined ($n = 30$). Both unadjusted (circles) and running-speed-adjusted (squares) regression coefficients with 95% confidence intervals are presented, with differences with respect to reference baseline lap. Vertical step regularity (A) significantly decreased with fatigue in the final lap. Mediolateral RMS ratio (B) increased significantly in lap seven, and from lap three when adjusted for running speed.

One dynamic loading measure showed a significant main effect for fatigue ($n = 30$). Specifically, shock attenuation of impact phase magnitude (9 20Hz) demonstrated a decrease (more shock attenuation) of 10.71 dB (95% CI 4.09–17.33, $p < 0.01$) in the final lap (Figure 5.5), which was not confounded by running speed.

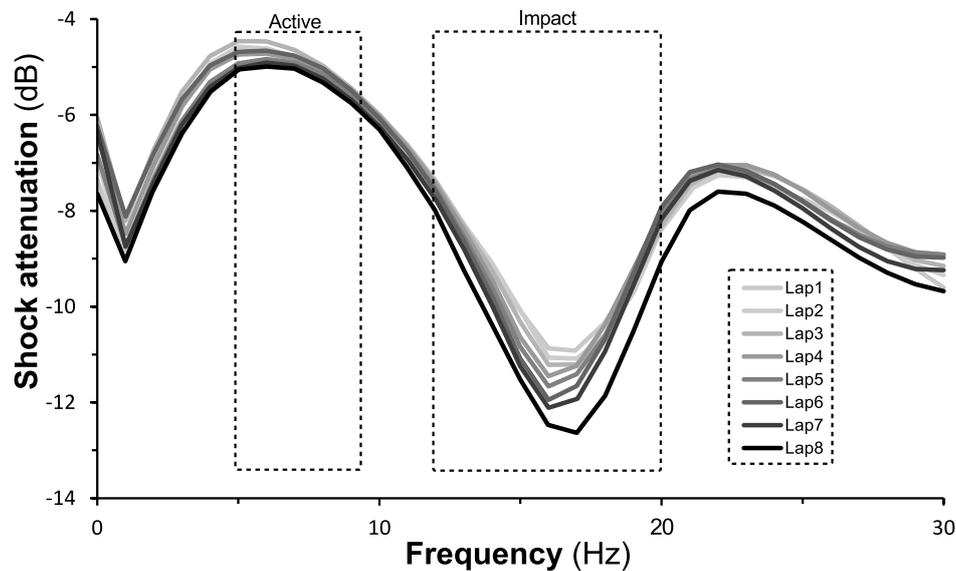


Figure 5.5: Mean transfer of shock between the tibia and the trunk as a function of lap fatigue for all subjects combined ($n = 30$). Here, a significant shift to greater attenuation is observed in the impact (12-20 Hz) range with lap eight (black).

Discussion

This study quantified accelerometry-based dynamic loading and dynamic stability in relation to outdoor over-ground running fatigue in runners with and without MTSS history. It was hypothesised that runners with a history of MTSS would reveal greater dynamic loading and reduced dynamic stability when fatigued compared to uninjured healthy controls. The results of this study partially supported the second part of this hypothesis by showing that in **only the runners with MTSS history, sample entropy of mediolateral trunk accelerations, a non-linear dynamic stability measure relating to movement complexity, decreased with outdoor running related fatigue.**

Movement complexity has been studied in numerous human populations using various techniques such as sample entropy [24, 27] and control entropy [16]. It has previously been shown that both musculoskeletal pathology (e.g. knee osteoarthritis[27] or chronic ankle instability citeTerada2014 can decrease movement complexity. Collectively, these studies support the “loss of complexity hypothesis” [12], and suggest that movement entropy derived from either lower-limb trajectories or body-worn accelerometry can capture pathology-related declines in physiological signals - a mechanism suggested to

be brought about by a reduction or freezing of the interacting degrees of freedom [27, 26]. Other studies have focused on using entropy from body-worn accelerometry to detect deficits in movement complexity due to muscle fatigue, but have revealed opposite effects. For example, McGregor et al., [15] found that lower extremity fatigue increased complexity of trunk accelerations in all axes, and suggested that fatiguing exercise affects the non-linear control of postural control by requiring more degrees of freedom in a fatigued state. Schütte et al., [24] showed that treadmill running-induced fatigue resulted in increased complexity of anteroposterior trunk accelerations. Although, the question remains whether complexity increases due to running fatigue would similarly occur in a population of runners with a history of overuse injury. To the best of our knowledge, no previous research has attempted to *use wearable trunk accelerometry as an in-situ tool to identify running gait pathomechanics*.

In this study, an entropy interaction was observed between running fatigue and MTSS injury. Specifically, the complexity of mediolateral trunk acceleration waveforms decreased with running fatigue, but in the MTSS group only and not in uninjured healthy controls. **This finding is interesting as it contributes to three primary kinematic concepts linking movement patterns to running-related injury.** Firstly, it confirms that reduced dynamic stability (proximally) is a promising approach to detect lower-limb injury, even if the site of injury is more distal to the site of movement detection [3, 28, 29]. Secondly, this finding supports the inclusion of a fatigue protocol to enhance detection of proximal compensations related to MTSS that would otherwise go unnoticed in a non-fatigued state [29]. Thus, fatigue probably serves as an internal constraint that alters the proximal mechanics or stability of running, whether it be via increased discomfort, compromised neuromuscular function, or impaired movement control [1]. Hence, we recommend that fatigue-related decline in mediolateral sample entropy be included in future screening protocols for runners with MTSS. Thirdly, this finding builds on limited available evidence to support the 'loss of complexity hypothesis' applied either generally to gait-related pathology [27, 26] or to specifically to running-related injury [9]. Ongoing research investigations are considering whether changes in mediolateral sample entropy primarily occur prior, during, or after onset of MTSS. As a practical implication, monitoring these changes both within- and between-training sessions would elucidate on whether the decline in complexity can be detected prior to injury, and therefore **be implemented in a way that serves as an early warning tool for external feedback**.

We also tested the hypothesis that runners with a history of MTSS would reveal higher dynamic loading with outdoor running fatigue compared to uninjured controls. This hypothesis was refuted. Dynamic loading measures acquired from both trunk and tibial accelerometry in the time-domain and frequency domain showed non-significant interaction or main group effects. Our hypothesis was based on previous literature linking higher tibial axial acceleration impact peaks while running with history of tibial stress fracture [19]. MTSS microtrauma (i.e. periostitis) has been considered a prologue to end state stress fractures as a consequence of repetitive overloading and eccentric muscle fatigue which impairs shock absorption function and exacerbates structural bone stress (i.e. tibial bending or bowing) [4]. Milner et al., [19] set a 'clinically significant defined threshold' of 15 % between runners with and without history of tibial stress fracture using a measure of dynamic loading (i.e. tibial axial acceleration peaks) as the discriminatory measure. In this study, for the same dynamic loading measure, there was only a 3 % difference (higher) between runners with and without history of MTSS. A post hoc power analysis from baseline comparisons of dynamic loading (highest effect size (d) of 0.32 from all eight measures) suggests that the sample size would have to be expanded to a minimum 157 per group to be able to detect a significant difference ($p < 0.05$) with adequate power ($1 - \beta$ of 0.80). Thus, low statistical power alone cannot explain our lack of significant findings, and suggests that runners with a history of MTSS do not have different dynamic loading to that of uninjured runners. It remains unclear why after MTSS dynamic loading is attenuated similarly to uninjured runners (as seen in Figure 5.5), possibly as a protective strategy to avoid pain or symptom reoccurrence. Alternatively, the dynamic loading measures employed as used in this study could have been sensitive to additional factors, both intrinsically (e.g. foot strike pattern, or leg tissue mass composition) and extrinsically (e.g. running shoe selection, or training surface). These factors may mask changes in dynamic loading in MTSS and could be accounted for as covariates in future investigations.

This study's methodological approach prioritised ecological validity and changes in pacing strategy were accounted for a posteriori using generalised estimating equations. This enabled us to distinguish between accelerometry parameters that were robust running speed. For example, the overall decline in symmetry of vertical accelerations relating to body support observed overall in the final lap were robust to running speed. In contrast, increases in mediolateral RMS ratio (variability) were augmented after adjusting for speed. This latter finding suggests that changes in running speed could mask early

onset of excessive mediolateral trunk movement induced by running fatigue. Therefore, we recommend simultaneous recording self-selected running speed (e.g. via GPS sensors, provided accuracy is sufficiently high) to improve earlier identification of fatigue related compensatory movements.

Regarding the generalisability of the results, our MTSS group were all asymptomatic at the time of testing with variable duration from previously noted symptoms. Notwithstanding, the relapse rate among MTSS runners is prevalent [13, 22], and the fatigue decline in mediolateral trunk complexity we observed suggests that compensatory residuals were still harboured in our MTSS cohort at the time of testing.

Conclusion

No evidence could be found for dynamic loading being higher with outdoor running fatigue in runners with previous MTSS compared to uninjured controls. However, in MTSS only, running fatigue was associated with decreased mediolateral sample entropy. The current results infer that entire acceleration waveform complexity reflecting mediolateral trunk control with running fatigue is related to MTSS history.

Supplementary data

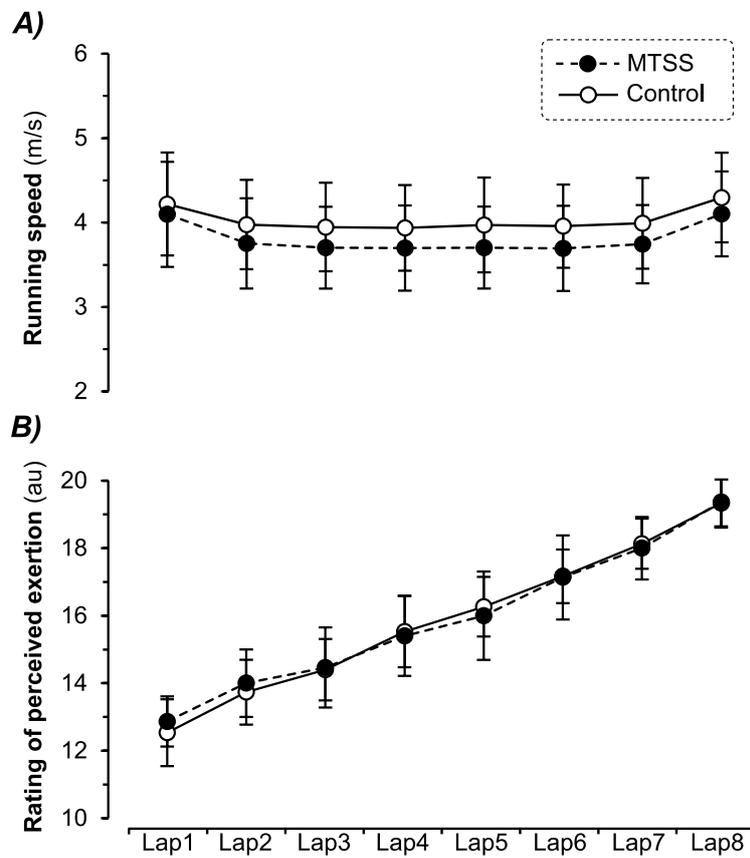


Figure 5.6: A) Self-selected running speed as a function of lap fatigue used as time-dependent covariate in this study, with relatively faster first and final laps for groups both with and without medial tibial stress syndrome (MTSS) history. B) Self-reported ratings of perceived exertion (RPE) as a function of lap fatigue, used in this study as a subjective measure of running fatigue and physiological demand. Runners with and without MTSS history similarly increased RPE levels.

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Chapter 6

General discussion

6.1 Overview

The overall objective of this thesis is to expand the understanding with regards to detecting fatigue-, energy-, and injury-related dynamic instability and dynamic loading in runners using wearable trunk accelerometry with transferability to 'real-world' ecologically-valid settings. In this chapter, a specific discussion will firstly provide a concise summary of the primary studies performed in chapter two through five. This will be followed by general conclusions in line with the four primary research gaps identified in the general introduction. Thereafter, methodological considerations related to the limitations of this research are provided along with suggestions for future work to build upon. Table 6.1 provides an overview of the hypotheses covered in chapters two through five and their outcomes.

Table 6.1: Chapter overview revisited

Chapter	Hypothesis	Results
Part I: Indoor laboratory treadmill running		
2	A fatigue-ability hypothesis, that WTA would be able to detect fatigue changes primarily occurring in the horizontal plane (CONFIRMED)	WTA dynamic stability: increase in AP and ML RMS ratio, decrease in AP step regularity, and increase in AP sample entropy with fatigue. Sacral marker trajectory: increase in ML and AP displacement, increase in ML and AP range with fatigue.
3	A cost of instability hypothesis that proposes a link between a runner's stability and running economy, and that this link can be assessed using measures derived from WTA (CONFIRMED).	WTA dynamic stability: Three measures explained an additional 10.4% of inter-individual variance in energy cost of running after controlling for body mass: attributed to anteroposterior stride regularity (5.2%), anteroposterior RMS ratio (3.2%), and mediolateral sample entropy (2.0%)
Part II: Outdoor over-ground running		
4	WTA measures of a) dynamic stability, and b) loading would be minimally affected by outdoor running surface (both a) and b) partially CONFIRMED);	WTA dynamic stability: decrease in VT RMS ratio, increase in AP RMS ratio, decrease in ML step regularity; decrease in ML stride regularity on wood-chip surface. Increase in VT stride regularity on synthetic track surface. WTA dynamic loading: decrease in VT and AP median frequency on wood-chip.
5	Runners with history of MTSS injury would reveal higher a) dynamic instability and b) loading with outdoor running fatigue compared to uninjured healthy controls (a) partially CONFIRMED and b) REJECTED)	WTA dynamic stability: Increase in ML RMS ratio and decrease in vertical step regularity with fatigue in both MTSS and uninjured control runners. Decrease in ML sample entropy with fatigue in MTSS group but not in uninjured control group. WTA dynamic loading: No group differences or group by fatigue interactions. Increase in shock attenuation with fatigue in both MTSS and uninjured controls.

AP: anteroposterior; ML: mediolateral; VT: vertical; RMS: root mean square;
WTA: wearable trunk accelerometry; MTSS: medial tibial stress syndrome

6.2 Specific discussion

6.2.1 Part I: Laboratory treadmill running

Chapter 2: Fatigue-related running instability. Study I was performed indoors on a laboratory treadmill at standardised speeds equivalent to outdoor performance in the 3200 m. Dynamic stability measures were assessed before and after a fatiguing protocol from 20 running steps captured per time interval. We hypothesised that a single trunk-mounted accelerometer would be able to detect fatigue changes primarily occurring in the horizontal plane. **This hypothesis was mostly confirmed** as running-induced fatigue resulted in a higher contribution of variability in horizontal plane trunk accelerations, as evidenced by higher mediolateral and anteroposterior ratios of acceleration root mean square (RMS). Additionally, AP acceleration patterns became less regular and less predictable once running fatigue was induced, as supported by lower step regularity and larger sample entropy values.

Chapter 3: Energy cost of running instability. Study II was also performed indoors on a laboratory treadmill but at speeds ranging from slow running until each individual's maximum (V_{peak}). WTA and indirect calorimetry data were collected concurrently from runners at their highest steady-state running speed ($80.65 \pm 5.99\% \text{ VO}_{2\text{max}}$). We hypothesised that a link exists between a runner's stability and economy, and that this link can be assessed using measures derived from WTA. **Our results lend support to this hypothesis.** An energy cost was associated with the instability of running, with three WTA stability measures that explained an additional 10.4% inter-individual variance in energy cost over and above that needed to support body mass (80.8%). Our findings build on limited evidence by suggesting new dynamic instability mechanisms that impose an energy cost to running which could hamper endurance performance.

6.2.2 Part II: Outdoor over-ground running

Chapter 4: Running instability and loading on real-world surfaces. Study III was performed outdoors on three typical training surfaces known to runners: concrete, synthetic track, and wood-chip trail. WTA was collected during steady-state running on the flat and straight (i.e. non-curved) section on each surface. Based on the mechanical principle of smoothness of CoM trajectory under different surface conditions [15], active 'self-stabilisation' [17, 48], and maintenance of global support kinematics over different

terrain [15, 23], we hypothesised that WTA measures of dynamic stability would be minimally affected by outdoor running surfaces. **This hypothesis was only partially confirmed.** Rather, we found that outdoor wood-chip trails disrupted aspects of dynamic stability during running in both recreational and well-trained runners.

In study III we additionally tested the hypothesis that WTA measures of *dynamic loading* would be minimally affected by outdoor running surfaces. Dynamic loading parameters were derived from the time-domain and frequency-domain, and specifically from vertical (VT) and anteroposterior (AP) stance-phase identified accelerations. We assumed that dynamic loading parameters would be mostly unaltered at the level of the trunk due to adaptations of the lower extremity to attenuate higher impacts while running on the harder concrete surface. Our dynamic loading results were domain dependent, with impact (median frequency) being significantly reduced in the frequency domain but with a trend to decrease in the time domain (impact peaks). Based on these results, **our hypothesis was only partially confirmed.** Interestingly, these findings were not specific to the training status of the runners, with recreational runners showing similar responses in both stability and loading to outdoor surfaces compared to those that were highly trained. These results overall add to the current body of knowledge with respect to biomechanical adaptations on surfaces runners typically encounter while training.

Chapter 5: Fatigue- and injury-related running instability and loading. Study IV was performed on a circular outdoor athletics track. In addition to healthy uninjured controls, runners with history of MTSS were recruited to complete a fatigue protocol consisting of eight laps (3200 m) at maximal effort. WTA, as well as wearable tibial accelerometry was collected to investigate changes in dynamic stability, dynamic loading, and shock attenuation throughout the run. Repeated measures on accelerometry outcome measures were analysed per lap, with running speed (derived from lap splits) and perceived effort (RPE) being collected concurrently. Although the MTSS cohort were asymptomatic at the time of testing, we expected that running fatigue would bring about different movement strategies and loading characteristics compared to the uninjured cohort. This led us to hypothesise that runners with a history of MTSS injury would reveal higher dynamic instability with outdoor running fatigue compared to uninjured controls. **The hypothesis was mostly rejected,** in that only one of the 12 dynamic stability measures revealed a significant fatigue by group interaction. Specifically, sample entropy of ML trunk accelerations declined significantly in the final laps in the MTSS group, but remained constant in the uninjured group throughout the fatigue protocol. This finding is interesting

as it contributes to two primary kinematic concepts linking movement patterns to RRI. Firstly, it confirms that proximal dynamic instability is a promising approach to evaluate lower-limb injury, even if the site of injury is more distal to the site of movement detection. Secondly, it builds on limited available evidence to support the 'loss of complexity hypothesis' applied either generally to gait-related pathology [43, 44] or to specifically to RRI [19, 20].

In study IV, we also empirically tested the hypothesis that runners with a history of MTSS injury would reveal higher *dynamic loading* with outdoor running fatigue compared to uninjured healthy controls. **Our hypothesis was refuted** with all eight dynamic loading measures acquired from the trunk and tibial accelerometry showing non significant interaction or main group effects. These results suggest that runners with history of MTSS do not exhibit higher external loading at the trunk or tibia. These results should also be viewed in light of the heterogeneity of our study sample which is discussed further on in methodological considerations.

6.3 General conclusions and practical implications

In this doctoral thesis WTA was used and experimentally evaluated for the application of fatigue-, energy-, and injury-related aspects of stability and loading in runners. The following sections elaborate on how this research closes some of the research gaps highlighted in the general introduction. Additionally, where possible, findings are translated into practical implications, considerations and take home messages for the broader community, including runners, coaches, practitioners, and researchers.

The first conclusion of this work is that fatigue-related instability can be detected in runners using WTA. Study I added to the current body of knowledge with respect to using more advanced non-linear measures such as sample entropy to detect fatigue. Previously, only linear measures were experimentally evaluated with respect to running fatigue and only on small sample sizes [25]. Here, changes in sample-entropy with fatigue sheds light into coordinative variability and the 'loss of complexity' hypothesis (kinematic concept potentially related to RRI discussed in chapter one). Specifically, a gain in complexity was observed in AP accelerations with running fatigue. Since the study population we recruited were previously uninjured runners, it probably indicates that higher complexity arises with fatigue as a healthy protective compensation to fatigue to avoid

inappropriate distribution of loads in a fatigued state. Based on these results, a practical implication is that:

WTA can be used to detect running instability caused by treadmill running fatigue.

However, study I only addressed changes in instability before and after a fatigue protocol. As pointed out nearly 70 years ago by Bartlett [3]: '*criteria are needed to indicate the beginning of fatigue, not merely a late stage when it is already too late*'. Indeed, findings from study IV revealed temporally different onsets or 'deflection points' in stability and loading characteristics during outdoor over-ground running. For example, we found that vertical shock attenuation (dynamic loading) increased in the final (eighth) lap, yet asymmetry increased in the second-to-last-lap and ML variability increased from midway (fourth lap). These findings suggest that movement compensations occur before runners adapt or shift their loading patterns, probably to prevent injury. Thus, a practical implication for runners and coaches could be that:

WTA can be used to detect the onset of instability and loading due to running fatigue outdoors, and changes in these onsets could potentially be used as monitoring measures of fatigue resistance in relation to endurance performance.

The second conclusion of this work is that energy-related instability can be detected in runners. Researchers have shown that WTA can be used to estimate energy expenditure while running. That is, within the same individual, WTA measures increase proportionally with increases in energy use during an incremental running protocol [28, 49]. However, these studies have not attempted to explain why some runners spend less energy, i.e., are more economical than other runners at the same relative intensity, a primary determinant of endurance running performance. The results of study II addressed this research gap by showing that three WTA measures of dynamic stability can explain an additional percentage to inter-individual variance in energy cost between recreational runners. Thus, a practical implication for practitioners and researchers specifically interested in integrating the fields of biomechanics, physiology, and motor control could be that:

Certain aspects of dynamic stability, including higher consistency between strides, higher variability, and higher complexity of movement are energetically advantageous to running performance.

It should be noted that cardiorespiratory costs (minute ventilation) could mediate the relationship between running economy and dynamic stability [2, 16]. Moreover, there could be an interesting link in locomotor-respiratory coordination, that is, more trained runners could have better coupling between their locomotory and breathing rhythms [27]. To test this hypothesis, the analysis performed in study II was expanded to include minute ventilation and breathing frequency as potential determinants to running economy (entered after body weight, but before dynamic stability measures were entered in the hierarchical regression analysis). The results showed that neither minute ventilation nor breathing rate could replace dynamic stability measures in the model, suggesting no mediating effect. Nevertheless, future work that investigates interventions for running economy and dynamic stability should not ignore the potential mediating relationship with cardiorespiratory parameters [2, 16].

The third conclusion of this work is that one specific aspect of RRI-related instability can be detected in runners using WTA. Study IV revealed that runners with an injury history exhibit similar loading at the trunk and tibia to that of healthy uninjured runners, even when fatigued. However, a novel finding was that in the previously injured group, outdoor running fatigue was associated with decreased mediolateral sample entropy. Therefore, a take home message for clinical practitioners could be that:

WTA can be used to detect a loss of mediolateral movement complexity that arises with fatigue in runners with a history of MTSS. Future work could prospectively investigate whether this loss of complexity could be used as a monitoring tool to predict future relapses or episodes of MTSS related symptoms.

Notwithstanding, the biomechanics literature often addresses RRI risk indirectly by investigating healthy runners in response to the various effects of other internal or external factors known to influence injury risk. For instance, the multifactorial model of athletic injury aetiology proposed by Meeuwisse's [29] and detailed in the general introduction (Figure 1.3) provides numerous intrinsic and extrinsic factors that could influence RRI risk. For example, it is commonly believed that running on softer surfaces will decrease dynamic loading and reduce RRI risk. In light of the surface effects (lower VT and AP median frequencies) detected in chapter four, as well as concurrent research within our biomechanics research group (showing decreased vertical tibial acceleration impact on wood-chip surface [7]), one could indeed speculate that running on softer wood-chip

surface could decrease a runner's susceptibility to impact-related injury. However, an equally important observation was that mediolateral stability was disrupted on wood-chip. Although there is no apparent literature, it could be inferred that runners with a history of chronic lumbar instability [4] could be at higher risk of instability-related-injury when running on wood-chip surface. Thus, from an RRI perspective, it should be noted that:

Wood-chip running surface has the potential to both reduce and enhance RRI risk, with future studies warranted to prospectively link a runner's training surface to injury outcomes.

The fourth conclusion of this work is that more ecologically-valid aspects of running stability and loading can be addressed using WTA. These aspects included the transferability of findings from one experimental setting to another, e.g., the treadmill laboratory to outdoor over-ground running as well as the approach to deal with running speed as a potential confounder to biomechanical adaptations.

With respect to *experimental setting*, study III and IV were performed over-ground, outdoors, and *in situ* (on training surfaces typically encountered by runners in the real-world). Study III specifically investigated running on multiple terrain and found that aspects of stability and loading can change acutely on uneven surfaces such as wood-chip. Furthermore, these adaptations were similar in recreational and highly-trained runner. This has important implications for future research of monitoring in typical environments:

For prospective monitoring of both recreational and high-level runners outdoors, researchers should account for acute biomechanical adaptations that may arise due to the underlying running surface.

With regards to the potential confounding influence of *running speed*, studies III and IV allowed participants to freely choose their running speed. The nature of continuous repeated measures of dependant variables (dynamic stability and loading measures) as well as confounding factors (e.g. speed) required more advanced statistical analysis (e.g. generalized estimating equations used in study III and IV). This type of analysis allowed us to statistically control where need be (i.e. in dynamic stability measures that showed significant changes when running speed was added to statistical models as a continuous covariate). This is in contrast to the traditional research approach which experimentally forces an imposed or fixed speed for all runners. In study II, we showed that running speed

did not confound the primary research hypothesis regarding running surface effects. In study IV, we demonstrated that some dynamic stability measures were in fact influenced by changes in running speed, which confounded the primary fatigue-ability hypothesis of these measures. Therefore, we recommend that conclusions drawn regarding running fatigue in over-ground self-paced conditions be checked while considering changes in running speed, and that:

Researchers should allow their participants to run at self-selected, rather than imposed or fixed speeds, and control for running speed a posteriori using advanced statistics by including it as a continuous covariate.

6.4 Methodological considerations

All results presented in this dissertation should be interpreted in light of certain methodological constraints, assumptions, and limitations. There are several steps along the experimental pipeline for WTA that need addressing and which could confound the internal validity of our results, including the sensor attachment approach, sensor specifications, pre-processing techniques, and statistical analysis.

WTA specifications. Although we aimed to keep the high-spec WTA sensor methodology consistent between studies, there were some inconsistencies between studies which make direct comparisons difficult (see Table 1.5 in the introduction). Sampling rate, for example, could have affected outcome measures of study I (which used 400 Hz) compared to studies II, II, and IV (which used 1024 Hz). Sufficient sampling rate is a crucial sensor specification when considering the high-impacts generated while running. While studies report sensor specifications, their authors generally do not justify the sampling rate used. Additionally, lower sampling rates could negatively affect non-linear stability measures such as the sample entropy measure which is confounded by shorter data sets [39, 55]. Unfortunately, the specific sampling rate required for either dynamic stability or loading measures has not been scientifically justified in the context of running, warranting methodological papers. Outside this context, research [52] on helmeted versus unhelmeted sports suggests that current accelerometer devices on the market may be insufficient to capture most injury criteria. Their [52] head impact experiments on drop landings showed that impacts can have a frequency response bandwidth of up to 500 Hz, which would require sample rates of even beyond those typically used (1000 Hz) to achieve adequate signal-to-noise ratios.

Therefore, a quick experiment was performed to check the influence of using 400 Hz (study I) rather than 1024 Hz (studies II to IV). A custom MATLAB script was written to down-sample WTA data of 20 consecutive running steps from 1024 Hz to 400 Hz. The results of which are shown in Table 6.2.

Table 6.2: Lowering linear acceleration sampling rate influences non-linear stability measures as well as vertical dynamic loading in the frequency domain.

Running gait parameter	Axis	1024 Hz	400 Hz	Difference (%)
Spatio-temporal				
Step frequency (steps.min-1)	VT	174.05	172.66	-1
Stance time (s)	VT	0.21	0.21	1
Dynamic stability				
Ratio of acceleration RMS (a.u)	VT	0.91	0.91	0
	ML	0.28	0.28	0
	AP	0.32	0.32	0
Step regularity (a.u)	VT	0.92	0.92	0
	ML	0.80	0.79	-1
	AP	0.79	0.79	0
Stride regularity (a.u)	VT	0.90	0.90	0
	ML	0.78	0.78	0
	AP	0.72	0.72	0
Sample entropy (a.u)	VT	0.09	0.18	108
	ML	0.12	0.28	133
	AP	0.14	0.27	92
Dynamic loading				
Impact peak (g)	VT	3.94	3.78	-4
Breaking peak (g)	AP	1.67	1.63	-2
Median frequency during stance (Hz)	VT	43	52	21
	AP	45	45	0

VT: vertical; ML: mediolateral; AP: anteroposterior; a.u: arbitrary units

Additionally, from a processing perspective, study II revealed that it is important to leave the acceleration waveform signals unfiltered prior to the calculation of the sample entropy statistic. This is in agreement with previous research advising to leave waveforms unfiltered so as not to wash out our mask any physiological meaningful 'noise' [39].

There seems to be an **important technology trade-off** when calculating non-linear measures of dynamic stability. On the one hand using signals of too short length can influence and thus confound the output value, while on the other hand using signals of too long length significantly increases the computational cost. Study II additionally revealed that using 20 consecutive running steps equivalent to ~ 7000 consecutive acceleration

data points were an ideal trade-off as values had appeared to stabilise and computational time was within a range more applicable to 'real-time' application (~ 0.8 seconds). As such, from a methodological perspective, we advise that:

Researchers should carefully consider and evaluate whether a) sampling rate; b) low-pass filtering, and c) the amount of running steps analysed from WTA signals are influencing their outcome measures.

WTA body attachment. Another common source of error in wearable technology relates to how the wearable is attached to the body. Attaching WTA in a belt (study IV), for example, may attenuate accelerations compared to direct attachments to the skin (study I, II, and III). Indeed, previous research has shown that additional error can come from skin attachments due to motion artefacts caused by additional adipose tissue [22]. Although, in study II we also measured skin-fold thickness at various closely-situated standardised body sites (including the supra-iliac, supra-spinal, sub-scapular, and abdominal skinfolds according to ISAK standards with Harpenden calliper [26]) the inter-individual correlations with any dynamic stability or dynamic loading measures were non-significant and trivial. Given that the study sample was quite heterogeneous in fat percentage (8% to 24%), and that these correlations with WTA measures were trivial, we could infer that WTA skin attachment is robust to artefacts possibly arising from inter-individual differences in body fat composition. However, motion artefacts could also originate when WTA attachment is in a belt. For example, other researchers have previously commented that:

'The inability of the mounting technique (harness) to hold the accelerometer to the body as the velocity of movement increases, may cause the wearable tracking device (and accelerometer) to be whipped, vibrated or hit against the body during movement.' [54]

For this reason we were meticulous in how our WTA belt attachments were secured. However, we have also observed that other factors can further disturb wearable attachment such as body sweat and high-velocity running (or a combination thereof) that can further cause the belt to shift sideways or upwards around the waist. Indeed, despite best attempts to completely secure WTA attachment, some data from the studies presented here had to be discarded due to belts shifting during the measurement. In our research 'supervised' setting we could identify these measurements and discard them successfully. However, such a procedure is likely not feasible in an 'unsupervised' setting. Certainly, **more**

collaborative work with industry and design engineers may be needed to improve WTA attachment methods and thus data quality. The continued miniaturisation of wearable technology and IMU sensors with lower mass will also help reduce potential motion artefacts. Furthermore, as has been the case for other research apparatus (e.g. electromyography, skinfold measurement etc.), it may be worthwhile from a research perspective to set international standards for methodological aspects concerning IMU design, specifics, wearability, and attachment. The author acknowledges that this may be a considerable challenge, given a) the rapid advancement of sensor technology and the continued proliferation of wearable equipment available on the market, and b) the world-wide commercial drive to have wearable sensors on the market that lack experimental validation and below par accuracy standards.

Focus on one component of wearable technology. Although the scope of this doctoral thesis was to evaluate accelerometry signals, current state-of-the-art inertial measurement units of course contain not only an accelerometer, but also a gyroscope and magnetometer signals. Data from these combined sources could reveal more information about running biomechanics. For instance, Buckley et al. [8] recently demonstrated that combined accelerometer, gyroscope, and magnetometer waveforms from an IMU could classify a runner's binary fatigue status i.e. fatigue or not fatigue with a 75% and 100% accuracy using lumbar and tibial accelerometry respectfully. Unfortunately, their [8] study did not differentiate or elaborate on the additional benefits of incorporating gyroscope features, nor discussed the biomechanical rationale behind the classification of fatigue. Thus, future work should elaborate on how signals from other inertial aspects can advance current knowledge with regards to biomechanically relevant features.

Data analysis and statistical approach. Group statistics were employed in all four studies of this dissertation. However, larger inter-individual variation was often observed. Milner et al. [31] set a 'clinically significant defined threshold' of $\geq 15\%$ between injured and uninjured groups using peak vertical impact accelerations at the tibia as the discriminatory measure. In study IV, peak accelerations at the tibia and trunk were 12% and 3% higher in the MTSS group respectively compared to the uninjured controls. Although dynamic loading measures (i.e. peak vertical trunk acceleration) were on average close to a previously defined clinically significant threshold, our group standard deviations were large, thus reducing effect size. A post hoc power analysis using these effect sizes ($d = 0.24$ and 0.14 for trunk and tibial accelerations respectively) would reveal that additional 270 participants would have to be recruited per group to achieve statistical significance

with acceptable power ($\alpha = 0.05$; $\beta = 0.80$). This amount could increase further if inter-individual differences in MTSS pathology or symptoms are considered. This implies that different research approaches or stricter cohort selection should be exercised when the research aim is to detect higher external loading in runners with MTSS history.

Nevertheless, WTA paves the way for future studies to use more advanced intra-individual statistics by capturing and analysing every stride that a runner makes. Additionally, longitudinal data sets that include monitoring over time, e.g. session or season may provide more tailored insights and better implications to each individual runner. For example, critical turn-points or breakpoints in dynamic instability deteriorates due to fatigue or injury could vary from one runner to the next over an entire training season. Regardless of how they are termed (e.g. turn-points, breakpoints, onsets, events, episodes etc.), it is plausible that their detection could be possible with WTA. Although, their interpretation may be limited to the type of analysis conducted. Advancements in artificial intelligence with larger data sets to base analysis on could improve on fatigue or injury detection methods in the future. A recently published review by Phinyomark et al. [36] revealed the need and potential for advanced machine learning techniques to '*expand the knowledge for testing new hypothesis about biomechanics risk factors with running gait-related musculoskeletal injury*'.

Study design. The studies performed in this thesis employed cross-sectional designs which have limited generalisability to findings that occur over time. Direct links of findings between studies I through IV may be difficult due to differences in study populations, sensor specifics, and experimental settings. Nevertheless, some WTA measures appear to show consistent effects. For example, the acceleration RMS ratio in the ML direction was increased by indoor fatigue (study I) and outdoor fatigue (study IV). Another theoretical consideration to ask is why some WTA measures that were related to fatigue (study I and IV) were not related to running economy (study II). It is plausible that, at least from a biomechanical perspective, that fatigue and economy are not the same constructs and are influenced by different aspects of dynamic stability. An interesting study design would be one that combined the two constructs, that is, determining how WTA measures contribute to running economy when in a fatigued state.

Longitudinally designed studies, by contrast, would increase our understanding with regards to the robustness of WTA measures to day-to-day variability within the same runners and with respect to biomechanical and physiological adaptation with fitness. In terms of RRI, prospective follow-up studies could help identify whether changes in WTA

measures such as dynamic loading are determinants of injury and whether dynamic stability is symptoms to injury. Subject to its inherent specifications e.g. location, attachment, sensitivity, and algorithms, WTA may only be able to be used in a portion of RRI types that have clear changes in motor patterns, movement patterns, or loading patterns. Furthermore, sensitivity to RRI detection may entirely depend on injury type, pathology, location and severity.

Day-to-day variability of WTA measures. WTA dynamic stability measures have previously demonstrated high test-retest reliability (all intraclass correlation coefficients >0.97) during indoor treadmill running [28]. However, in the real-world outdoors, retests can naturally introduce numerous additional sources of variability, including environmental factors (e.g. changes in weather such as temperature, humidity, wind) and intrinsic factors (e.g. changes in self-selected running speed, hydration status, footwear selection, and diet). Therefore, it is important to present some data relating to the between-day variability of WTA measures outdoors.

Figure 6.1 shows test-retest variability of three relevant dynamic stability measures from five healthy runners who were tested on four separate occasions (at least one week apart for repeated tests within subjects). The protocol selected was the same as study IV in this thesis, and consisted of eight laps around a 400m outdoor athletics track at maximal effort. A visual inspection of Figure 6.1 reveals that the absolute values are more reproducible within subjects than between subjects.

For fatigue detection, the magnitudes of changes detected (i.e. change in pre-post fatigue) should ideally be smaller than the typical error (measurement error related to within-subject variability) for the changes detected. For example, study I and IV showed that fatigue-related increases in ML RMS ratio were 0.05 units (indoor fatigue) and 0.07 (outdoor fatigue) units on average. Based on the reproducibility data here ($n = 5$ healthy runners; tests = 4), the cumulative typical error over all tests for ML RMS ratio is 0.02 [90% confidence intervals between 0.01 to 0.05]. These values suggest that the minimum values for detecting running fatigue are robust to various possible sources of measurement error (in the outdoors), and we can be more confident in the magnitudes of our fatigue detection.

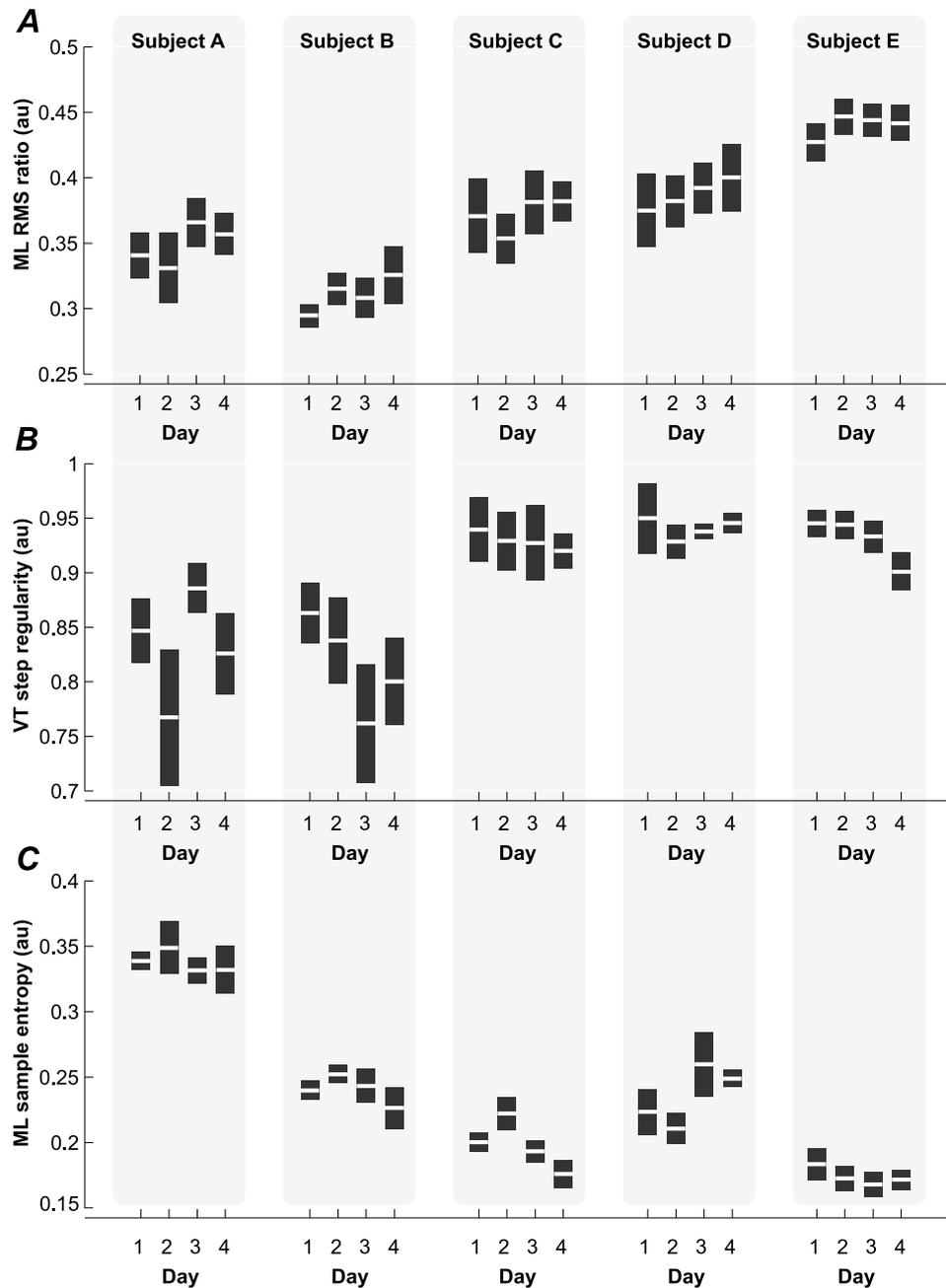


Figure 6.1: **Test-retest variability for relevant dynamic stability measures.** Five runners (subjects A through E) performed four 3200m outdoor fatigue protocols (same as study IV of this thesis) separated by at least one week while WTA measures were continuously recorded. Descriptive data shown are mean (white stripe) \pm standard deviation (dark grey bars) per subject per day, calculated over the entire fatigue protocol.

6.5 Future directions and perspectives

These insights about dynamic instability and dynamic loading in relation to fatigue, energy, and injury immediately generate a multitude of questions. Is there empirical evidence for the long-term monitoring of these kinematic and kinetic measures? Can we use these measures to evaluate global mechanisms for biomechanical adaptation (tissue remodelling) or mal-adaptation (tissue breakdown)? How do these aspects fluctuate within or between training sessions that would resemble everyday running? Could novel insights be generated by integrating empirically based physiological and training principles? If so, is it possible to monitor all aspects simultaneously with a wearable system which combines physiological (e.g. HR monitors), training (e.g. GPS) and biomechanics (e.g. WTA)? **The magnitude and scope of these questions open up a large opportunity for future research.** Therefore, this thesis ends off by presenting first a pilot study, and secondly a case study to understand better why some of these questions could yield valuable insights to runners and researchers if answered, and that may help direct future research.

6.5.1 WTA as a potential tool for evaluating running self-optimisation: An intervention pilot study

As pointed out in chapter 3, it would be particularly interesting to test whether WTA can be used to evaluate the self-optimisation hypothesis. The primary notion behind self-optimisation is that movement patterns will change innately and sub-consciously with training, and that these kinematic adaptations could coincide with physiological adaptations such as improvements in movement economy and higher resistance to fatigue [1, 5, 33]. Anecdotally, it has been suggested that running technique deteriorates with the transition from aerobic (lower) to anaerobic (higher) running intensities. For example, Tucker et al. [45] have speculated how a typical runner who runs a comfortable 5 min/km pace might respond as they enter a faster 4 min/km pace:

'You may feel that you are floundering and losing control of your own movements. It's simply that your neuromuscular system is unused to that speed of movement, and you lack the coordination required'. [45]

Assuming this premise is correct, could 'loss of coordination' be prevented by training at higher (i.e. anaerobic) intensities? To test this self-optimisation hypothesis requires a longitudinally designed study, where runners are evaluated pre and post intervention

(e.g. running training program with respect to dynamic stability and energy cost). In their paper on '*Energetic cost and stability during walking*', Holt et al. [21] specifically point out three criteria for self-optimisation of human locomotion that might serve as a conceptual framework for running:

1. *Minimal energy cost;*
2. *Potential injury to the system i.e. reduce high impacts; and*
3. *Maintaining stability or resistance to perturbations*

To examine these criteria (as well as results from chapter 3) we performed a **pilot study** and formulated two primary hypotheses. Firstly, we **hypothesised that WTA measures can be used to demonstrate that runners have an optimal stability**. Secondly, we **hypothesised that WTA would show potential as a monitoring tool for self-optimisation of stability and fatigue-ability**. This would imply that WTA could be used to track progression of dynamic stability in relation to physiological performance.

Methods: Eight-week running training program. As part of a larger ongoing study, nine runners were recruited to participate in a running training intervention. Ethical clearance was obtained from the local Ethics committee of Stellenbosch University (part of study II). Pre- and post intervention VO_2 max protocols were performed in an identical manner to that of study II.

The training intervention was designed firstly for recreational runners to improve their running fitness from baseline, and secondly to provide an opportunity to monitor WTA from session-to-session concurrently with traditional HR and running speed monitoring. To achieve this, subjects were asked to complete three training sessions per week over eight weeks, with each session set according to individual intensity zones of running speed and HR. Training sessions were devised, adapted, and customized according to those typically used in evidence-based endurance running programs for novice [32], untrained [24], recreational [16], and well-trained [6] runners. Runners performed three types of running sessions based on intensity and duration, namely long slow distance (LSD); lactate threshold (LT); and tempo (aerobic endurance) training. Further details of the training intervention are summarised in Table 6.3.

Table 6.3: Runners performed three specific running training sessions per week over an eight-week intervention. Sessions were designed differently according to individual training intensity thresholds.

Session	Type	Set speed type	Duration (min)	Intensity (% PTS)	Mileage (km) **	Surface
1	Supervised	LSD	60	60 - 70	~ 10.2	concrete road
2	Supervised	LT	2 x 15 *	85	~10.5	synthetic track
3	Unsupervised	Tempo	45	70 - 80	~ 9	concrete road

LSD: long slow distance; LT: lactate threshold; PTS: peak treadmill speed; with 5 minute rest or easy run at 60% PTS in between; * example runner with PTS of 17 km/h

Firstly, **LSD training** sessions were designed to build basic endurance and develop running economy with high volume but low intensity. The rationale behind this training is to improve oxidation and utilisation of fats as an energy source while sparing muscle glycogen stores [12]. Secondly, **LT training** sessions were designed to closely relate to race pace intensity and exercise tolerance, with the aim of adapting (raising) the runners anaerobic threshold, improve lactate clearance, and familiarisation to race speed type intervals [6, 30]. Lastly, **tempo training** sessions were designed to be longer-fast sessions with the aim of building aerobic capacity and speed endurance with moderate volume [6, 30].

LSD and LT sessions were supervised in the presence of the primary investigator, while tempo sessions were completed as homework. Prior to the start of training, participants were familiarised to their individualised training intensity (speed) zones using feedback from their personal mobile smart-phone applications worn on their upper-arm.

Methods: Outcome measures. The methodology employed in this pilot study with regards to experimental protocol, determination of energy cost, blood lactate, WTA (i.e. sensor specifics, attachment, processing, outcome measures etc.), are identical to that of chapter three (study II). For this pilot study, one dynamic stability (acceleration AP RMS ratio measure) was computed per VO_2max stage from continuous WTA waveforms using non-overlapping moving averages of 20 running steps. This measure was chosen since we previously showed that it increases with fatigue (study I) and also explains inter-individual variance in the energy cost of running (study II), giving it functional meaning to both fatigue-ability and energy cost. Since the protocol was discontinuous, originally segmented stages per running speed were merged into one single time-series to create a complete profile per subject per test (pre- versus post-intervention) over the whole running protocol.

Methods: Statistical analysis. To evaluate the first (i.e. optimal stability) hypothesis,

we compared linear and quadratic fits for each subject's dynamic stability profiles of runners per pre and post test respectively. R^2 s and p -values were calculated for each subject under a linear and a curvilinear model respectively. Comparisons between the models at baseline (pre-test) were done using paired t-tests. To evaluate the second hypothesis regarding self-optimisation from training, we visually inspected AP RMS ratio curves as well as blood lactate curves for three representative runners pre- and post-training intervention.

Results and discussion. Fitting a curvilinear (quadratic) model to AP RMS ratio consistently produced higher R^2 values than compared to fitting a linear model (Figure 6.2), with mean R^2 values being 0.64 and 0.92 for linear and quadratic fits respectively. The difference between the two models were also significantly different (paired t-test $p = 0.001$).

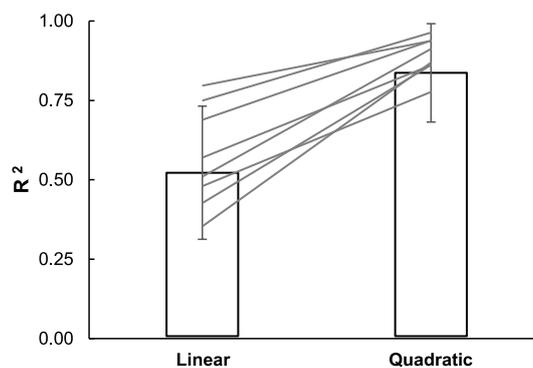


Figure 6.2: Quadratic curves outperformed linear fits for all nine subject's AP RMS RATIO measure.

This result **supports our first self-optimisation hypothesis** in that WTA stability measures can demonstrate that runners have an optimum stability. This result is interesting, given that previous research has shown AP RMS ratio increases linearly during a continuous VO_2 max protocol [28], which contradicts our findings. Rather, our data suggest that WTA could be used to detect an optimum stability in runners.

Figure 6.3 shows individual results for three participants with respect to AP RMS ratio and blood lactate profiles before and after training. These examples show that each individual runner reaches a time-point during his or her protocol where AP RMS RATIO is at a minimum or 'stability optimum' (here denoted as S_{opt}) as well as a time-point (LT) where blood lactate rises above what is known as onset of blood lactate accumulation (OBLA). It further can be observed in these three runners that both time-points shifted to the

right at post-test, indicating a delayed S_{opt} or time to 'loss of instability'. These examples **would support our second hypothesis** that WTA shows potential to be used as a tool to track self-optimisation of running stability and its fatigue-ability.

However, even though these findings appear promising, a deeper look into additional participants and their response to the training intervention could reveal inconsistent and variable results. Thus, intervention effects essentially remain untested until all participants have been analysed. Nevertheless, with a greater sample size we could statistically evaluate whether or not individual improvements in S_{opt} actually coincide with improvements in endurance performance characteristics, whether it be blood lactate, HR, or running economy profiles. Furthermore, biomechanically it is not clear which dynamic stability measure or which feature from the stability curve is most representative as an endurance marker. This might require a considerable amount of research, as has been over the past several decades for physiological markers, resulting in a multitude of ways in which researcher have calculate turn-points, breakpoints, or thresholds (e.g. see Newell et al. [34] for a comprehensive list of blood lactate endurance markers). Although speculation, we would expect that runners who self optimise from training would do so by shifting their S_{opt} to the right (i.e. longer time and higher running speed before the runner starts to lose control over his or her movements and coordination due to physiological performance limits).

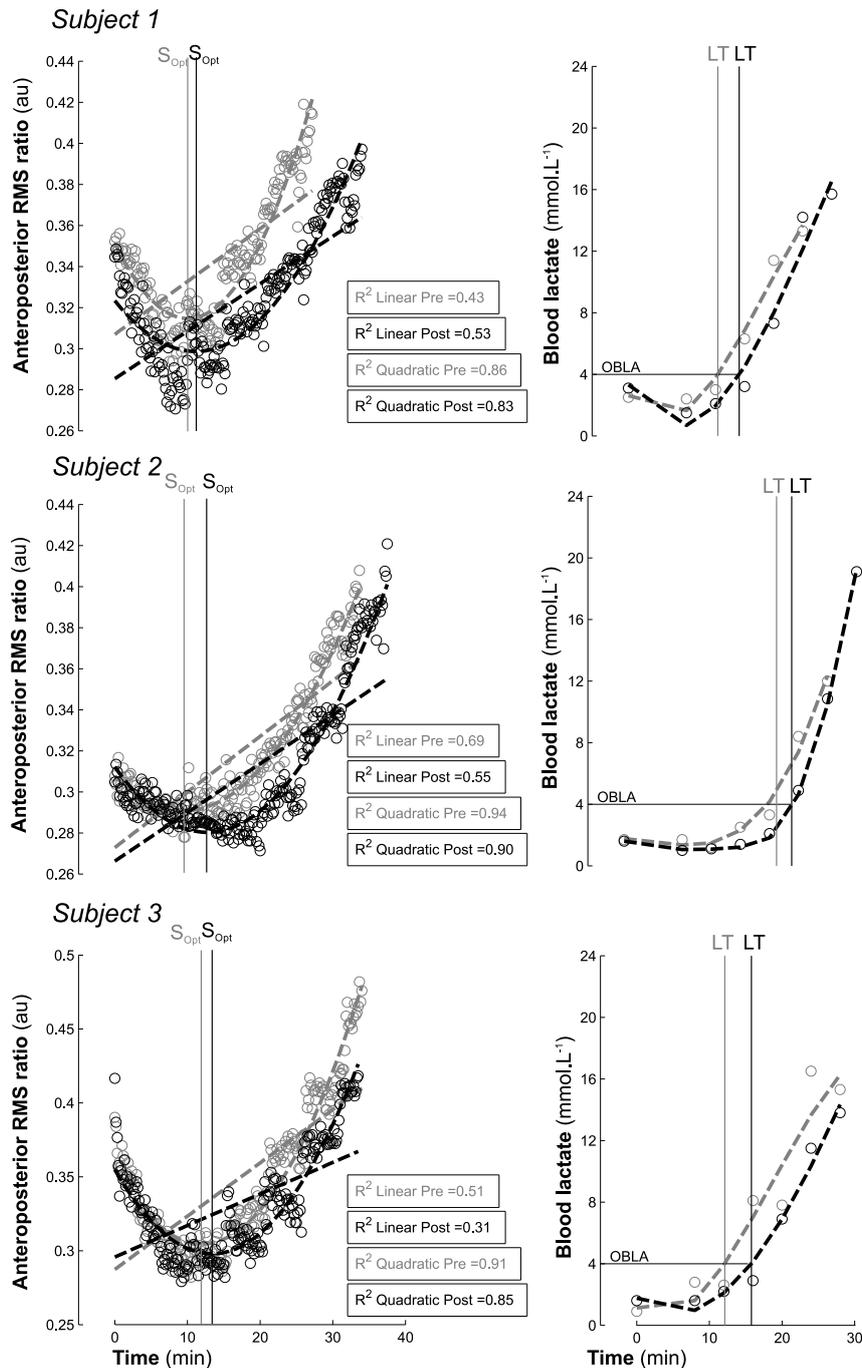


Figure 6.3: Individual profiles of acceleration AP RMS ratio (left panels) as well as blood lactate (right panels) for three subjects during an incremental speed $VO_2\max$ protocol before (grey) and after (black) eight weeks of endurance running training. For AP RMS profiles, both linear and quadratic curves were fitted to raw data (circles representing non-overlapping moving averages over 10-seconds of running), and running stability optima (S_{OPT} ; vertical lines) were calculated as the time required to achieve the minimal value on the quadratic curve. For post-stage blood lactate, cubic curves were fit to the data and lactate thresholds (LT; vertical lines) were determined at the time required to achieve onset of blood lactate (OBLA).

6.5.2 Towards real-world injury-detection using WTA: A case study

This case study describes a female runner who sustained MTSS twice during an individualised running training program (session details outlined in Table 6.3). In both cases she suffered from MTSS in both legs, with no previous history leading up to that point. In the first case she prematurely ended her third LSD session on concrete road (completed ~ 2.5 km from session goal of ~ 10 km), resulting in a time loss of 8 days to training. In the second case she was unable to start her fourth LT (lactate threshold) session due to severe pain during her warm up, and resulted in a time loss due to training of 14 days. From a research perspective, her MTSS injury met various RRI criteria previously set in the literature, as it: caused significant pain from running [42], required medical attention from a physiotherapist [46], and caused restriction of running i.e. time-loss to training for at least one week [9]. Additionally, her symptoms included running induced pain in the posteromedial aspect of both tibias, as well as pain on palpation in the area of ≥ 5 cm in the posteromedial tibial region. Her physiotherapist ruled out pain from either neurological, ischaemic or stress fracture origin.

Training, physiological, and biomechanical aspects were monitored during each running session. A GPS sensor embedded in a smart phone combined with a popular running app (Strava) was used to quantify her training metrics (e.g. pace, distance, duration). Her training pace and training intensity zones were predetermined based on her performance and physiological response (HR, blood lactate, oxygen consumption) during a maximal graded $VO_{2\max}$ protocol. A Polar HR monitor was used to calculate average and maximum HR per session. A WTA (Shimmer device; sampling frequency 1024Hz) was used to quantify dynamic stability and loading characteristics. The WTA was attached by the same researcher prior to the start of each training session. The attachment was directly to the skin with double-sided tape, secured in a clip-on waist belt tightened to comfort, and tucked underneath the participant's running shorts.

Integrating WTA into the 'Multifactorial Athletic Injury Causation Model'. Here, in combination with various other data sources (Table 6.4), examples will be shown for how WTA could be practically integrated into current models and theoretical frameworks for RRI. Drawing from the most recent systematic review and meta-analysis on risk factors related to MTSS [35], we can build an individualised injury risk profile for this injury case study.

Table 6.4: Additional data relating to the injured runner case study

Variable	
Demographic	
Age	22
Sex	Female
Anthropometrical	
Height (cm)	1.64
Weight (kg)	55.5
BMI	20.64
Waist circumference (cm)	69
Calf circumference (cm)	left 31.8; right 31.5
Leg length discrepancy*	0.2 cm
Foot posture index	left 10; right 11
Physiological and performance	
VO ₂ max (mlO ₂ .kg ⁻¹ .min ⁻¹)	46
Peak treadmill speed (m.s ⁻¹)	4.16
Lactate threshold speed (m.s ⁻¹)	3.2
Age-predicted HR maximum	217
Best 10 km race time (min)	51
Training history	
Running shoes	Nike Free 5.0
Wears insoles or orthotics	No
Shoe wear pattern	left none; right:none
running -related injury history	None
Training session (n per week)	3 to 4
Average training mileage (km per week)	20
Years running experience	one
Perceived training status	moderately trained
Perceived running level	recreational
Typical running surface	concrete road
Cross-training activities	plyometrics

Intrinsic risk factors. Certain risk factors could have predisposed her to MTSS. *Demographically*, her female sex increases her risk [35], although it is not known whether her age would have altered her injury risk. *Historically*, her lack of running related injury history decreases [35], but her fewer years of running experience increases her injury risk [35]. Anecdotally, her cross-training activities included plyometric training which could have increased her injury risk due to the high eccentric muscle activity and impact forces known to be generated during landing [13].

Anthropometrically, her pronated foot type (determined using the foot posture index [38]) increases her injury risk [35]. Although higher BMI, lower calf circumference, and greater leg length discrepancy have been implicated with injury, these are based on group differences in study cohorts, with 95% confidence intervals that overlap between studies

[35]. Thus, with her absolute values (that could fall injured or uninjured category group depending on study used), we cannot ascertain whether her BMI category, maximal calf circumferences, or leg length discrepancy would alter her injury risk [35]. *Physiologically*, although better aerobic fitness is said to positively affect injury risk [50], there is no available literature to ascertain whether her aerobic capacity i.e. VO_2max or aerobic fitness were associated to her injury.

Extrinsic risk factors. Exposure to certain risk factors could have altered her susceptibility to MTSS. Her lack of prior insoles or orthotics use would decrease her injury risk [35]. In terms of *footwear*, she ran in the same relatively new pair running shoes prior to the start of the intervention. Indeed, one prospective study has shown that the specific shoes she ran in (Nike Free v5.0; defined as partially minimalist) increases RRI risk in runners training of a 10 km event [40], which suggests a possible link. However, it is not clear how any causal relationship could be evaluated in this case study. The same may apply for running *surface*, although she had no previous history of training on synthetic track, the surface which was used specifically for LT training sessions. In Clement and Taunton's [10] 1981 'Guide to the Prevention of Running Injuries' they recommend decreasing training load when running on a new surface. Based on surveys, running on a particular surface has not been prospectively associated with either higher or lower RRI risk [42]. However, a limitation acknowledged by the authors of that study was:

'The apparent lack of effect of training surface may stem from the difficulty of adequately quantifying the time and intensity of running spent on each of the running surfaces.' [42]

Nowadays, various technology solutions could be employed to more objectively quantify the time and intensity on each training surface. The former could be quantified either automatically (e.g. using GPS terrain maps) or semi-automatically (e.g. using user-based context on their smart-phone, smart-watch, or fitness tracker uploaded to a database). The latter could be quantified automatically either by GPS speed or from WTA dynamic loading measures. Thus far we have answered this question acutely at the trunk (study III [41]) and tibia (Boey et al. [7]), but prospective monitoring studies (similar to this case study, but with a larger sample size) are needed to determine whether these dynamic loading measures could be used to identify chronic dynamic loads potentially related to the RRI 'inciting' event.

Inciting event. *Biomechanically*, based on findings derived from WTA, it can be hypothesised that at least three WTA measures detected compensations possibly related to the progression, mechanism, and onset of her MTSS. Step frequency and vertical impact accelerations at the trunk increased during the sessions where she sustained injury (Figure 6.4, top and bottom panel respectively), despite reductions in GPS recorded running speed (Figure 6.5). Additionally, ML sample entropy showed gradual decline overall in the sessions leading up to her MTSS injury (Figure 6.4, middle panel). This fatigue-related decline in ML sample entropy (both within session and between session) lends some additional support to the findings of study IV.

Expanded concepts on a causation model for RRI. It should be noted that recent studies have made interesting expansions to the original athletic injury causation model proposed by Meeuwisse in 1994 [29]. The first expansion is that of *workload* [50], since monitoring of a runner's training status should also take into consideration the external load applied (i.e. the work completed) in relationship to how the individual responds to the load (i.e. internal load response). A comprehensive list of existing external and internal load parameters can be found in more detail by Halson [18]. The second expansion is that of *separating the physiological and biomechanical load-adaptation pathways* [47] to better rationalise measures of training load for prevention of RRI. In other words, measures that are used to monitor runners should distinguish not only between external and internal loads, but also between physiological and biomechanical loads.

The biomechanical measures derived from WTA in this doctoral project could serve as novel candidate variables for monitoring different aspects of biomechanical workload. For example, in contrast to using external load measures such as total GPS distance run, *dynamic loading* measures could elaborate more accurately the magnitude and frequency of external loads caused by each cumulative running step. Additionally, in contrast to using invasive internal load measures (e.g. blood lactate analysis), post exercise measures (e.g. heart rate variability), or subjective measures (e.g. RPE scale), WTA measures of dynamic stability could non-invasively, continuously, and objectively explore how the individual responds to the applied workload throughout the run. This idea would align with what Halson et al., [18] describes as 'movement deviations'. Future work is encouraged to use WTA measures as surrogate inputs to athlete monitoring systems, or apply them to concepts such as the acute:chronic ratio [50]. Accordingly, it will be important to help runners decide which measures are most effective for monitoring adaptation to training and best for optimising performance and promoting health [14].

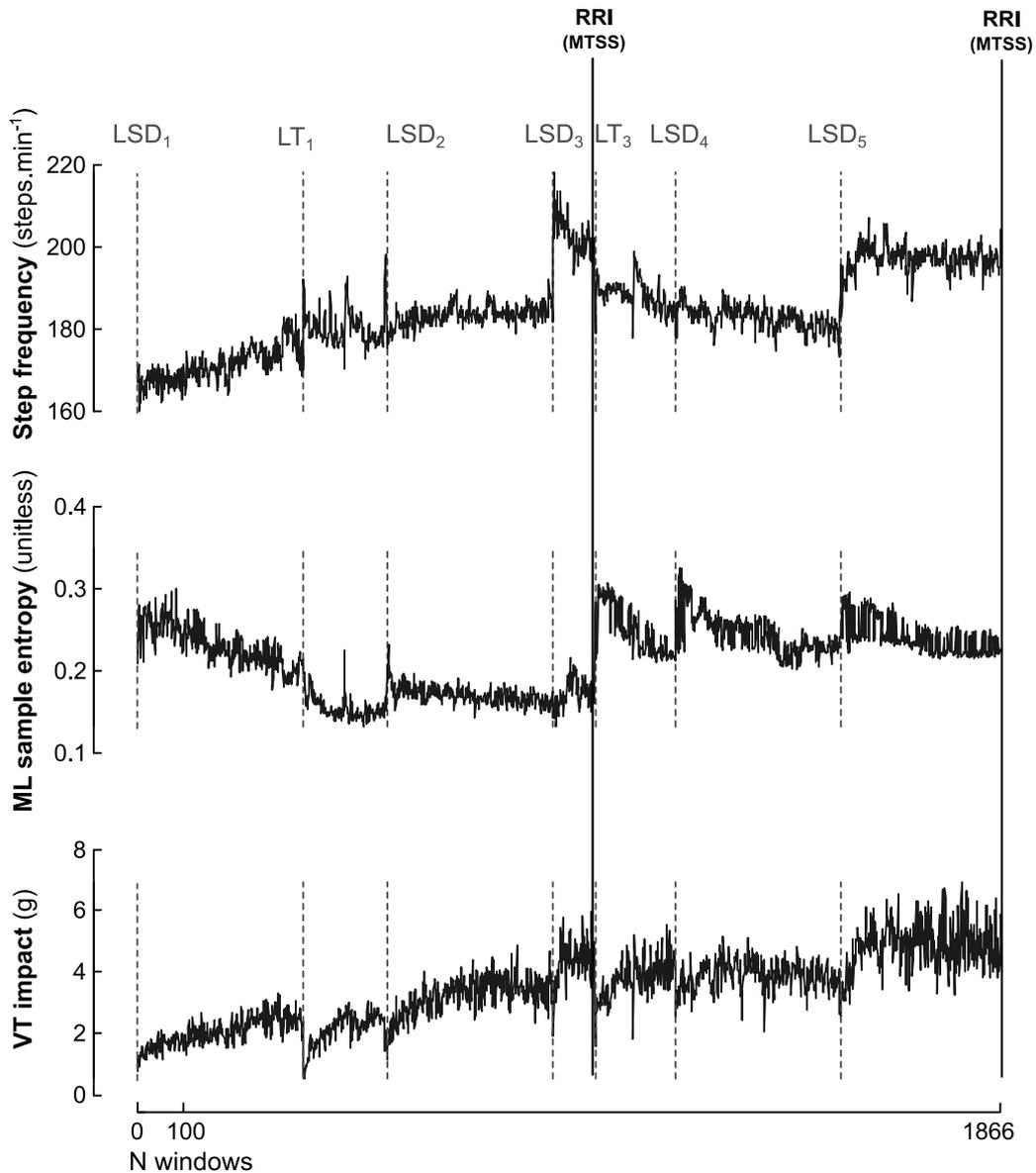


Figure 6.4: **Real-world injury detection case study: wearable trunk accelerometry measures.** One female recreational runner sustained a running related injury (RRI) twice over the first intended four-weeks of individualised running training program. Her RRI was characterised and defined by bilateral MTSS, which caused her to prematurely stop running during her third and after her fifth long slow duration (LSD) training sessions. Her RRI was preceded by increases in step frequency (top), decreases in mediolateral sample entropy (middle), and increases in vertical impact (bottom). All of these biomechanical parameters were extracted from a single wearable trunk accelerometer (WTA). A total of 37320 running steps were captured and each data point over time represents a non-overlapping window average of 20 consecutive running steps

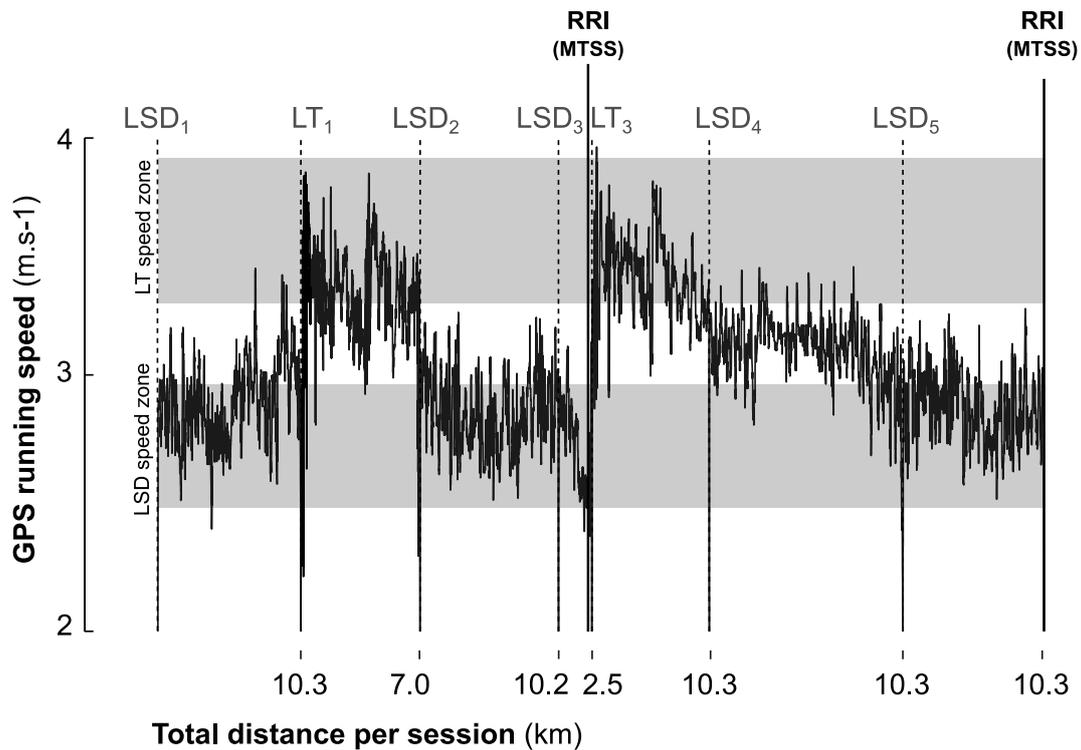


Figure 6.5: **Real-world injury detection case study: running speed.** Here, actual GPS-based running speed is compared to pre-determined running speed zones (grey bands). Her running speed declined rapidly in the third LSD session until she stopped due to MTSS related pain. Running speed was computed from GPS coordinates (raw latitude and longitude values sampled at 1Hz) that were downloaded with permission from the runner's Strava account. GPS coordinates were imported and processed in MATLAB using a customised script. A one-dimensional median filter was applied to the raw speed signals to remove outliers caused due to dropped or poor GPS signal.

6.5.3 Towards real-world and real-time gait re-training using WTA

Notwithstanding the complexity of fatigue and injury, the case study presents some interesting insights and could set the stage for future research to quantify real-world running biomechanics. Systems that are capable of detecting ongoing instability or loading compensations in relation to fatigue, energy, or injury could be extremely useful for the monitoring and management of the endurance runner. Moreover, if these detections occur in real-time both runners and practitioners could make immediate training decisions and adapt appropriately (e.g intensity, duration, running technique, recovery etc.). In other fields it has been demonstrated, for example, that seizures can be detected with wearable accelerometry in people with epilepsy [37], and closed-loop systems can be built around these detections to provide rapid response, biofeedback and recommendations

automatically. Feedback refers to the '*provision of externally generated information which supplements internal pathways to guide motor performance and learning*' [53].

For running, some promising ground work has been laid down with regards to giving external feedback, either visually [11] or audibly [51], as a means to reduce dynamic loading (i.e. peak acceleration impacts at the tibia) while running. It was shown that runners can modify (reduce) their impacts immediately after being instructed to 'run softer' [11]. **The question remains how WTA measures could also be implemented in a real-time setting as a biofeedback system to improve a runner's performance while also reducing RRI risk.** Training advice could be provided immediately when changes in the biomechanical measures are detected while running. This type of prediction would require pre-existing knowledge of the biomechanical measures and accurate labels to when a previous RRI was recorded in the same runner.

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Appendix I

Computation of WTA dynamic stability measures

Acceleration root mean square (RMS). The acceleration RMS constitutes a statistical measure of the magnitude or variability of acceleration [3] and is computed as follows:

$$RMS = \sqrt{\frac{a_1^2 + a_2^2 + a_3^2 + \dots + a_n^2}{N}} \quad (I.1)$$

with a representing each acceleration value in the time series for a given N data points. Thereafter, the ratio of acceleration RMS (RMSR) in each direction can be calculated using the following equations:

$$RMS_T = \sqrt{RMS_{VT}^2 + RMS_{ML}^2 + RMS_{AP}^2} \quad (I.2)$$

$$RMSR_x = \sqrt{\frac{RMS_x}{RMS_T}} \quad (I.3)$$

where RMS_T represents the RMS vector magnitude and x represents the respective acceleration axes (i.e. vertical (VT), mediolateral (ML), and anteroposterior (AP)).

Step and stride regularity. A raw autocorrelation coefficient A is the sum of the products of the acceleration time series $a_i(a_1, a_2, \dots, a_N)$ with a time-lagged replication of the time series (a_{i+m}) , where the lag parameter m is the phase shift in number of samples:

$$A_{raw} = \sum_{i=1}^{N-|m|} a_i a_{i+m}. \quad (I.4)$$

This produces a sequence of autocorrelation coefficients over increasing time lags. Time series with cyclic components such as running will produce dominant periods i.e. peak values for lags equivalent to the periodicity of the signal (usually per step and strides for human running).

$$A_{unbiased} = \frac{1}{N - |m|} \sum_{i=1}^{N-|m|} a_i a_{i+m}. \quad (I.5)$$

where N represents the number of samples in the time series. Unbiased refers to the robustness of the algorithm to tapering or attenuating values towards the tails (see Moenilssen and Helbostad [1] for detailed explanation and exemplary figures).

Next, the primary and secondary dominant autocorrelation coefficients representing the time lag of one running step and one stride needs to be located (see chapter two, Figure 2.1 for example of the location process). The locations of the dominant autocorrelation coefficients can be identified automatically from the generated signal of autocorrelation coefficients. This automation is accomplished in custom MATLAB software that uses a step frequency search window, which assumes step frequency for endurance running will be between 2.33 and 5 Hz (i.e. 140 and 300 steps.min⁻¹). The maximum value within the search window is identified as the dominant autocorrelation coefficient.

Sample entropy. Sample entropy is defined as the negative natural logarithm of the conditional probability that a given short sequence of epoch of data m , or template, will be repeated during the accelerometry time series $a_i(a_1, a_2, \dots, a_N)$, and where self-matches are not included [2]. A low probability of repeated sequences in the data results in high values for sample entropy, and implies that there is lower regularity and more complexity in the data.

Once the length of the template m is selected (typically recommended as $m = 2$), other templates from the time series that match within a predetermined tolerance r (typically recommended as $r = 0.2 * SD$, where SD is the standard deviation of acceleration time series) are identified and counted. In other words, each m -length vector are considered a

match if both the tail and head of the vector falls within the set tolerance r level. The process is repeated for template lengths of $m + 1$ and the final output is obtained from the expression below:

$$SampEn(m, r, N) = -\ln\left(\frac{\sum A_i}{\sum B_i}\right) = -\ln\frac{A}{B} \quad (I.6)$$

where A_i is the count of matches of length $m + 1$ and B_i is the count of the matches of length m with the i th template respectively. The output value is a non-negative number and is unitless.

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Appendix II

WTA-based ground contact time: A validation study

Background. Contact time, that is, the time which a runner's foot is in contact with the ground, is an important temporal parameter of human locomotion and performance. Determining contact time enables extraction of important kinetics and kinematic aspects of running as well as further computation of parameters such as impulse and total stiffness [2]. Gaudino et al., [2] proposed a method to derive contact time from an accelerometer attached close to the centre of mass (CoM) of the body. Their method makes use of the vertical (VT) accelerations signals and the time-points where the acceleration makes zero crossing. Specifically, their reasoning was that "as long as the acceleration is greater than zero, the body is accelerating upward, and to do that the foot should still be in contact with the ground" [2]. Thereafter, this approach been validated with respect to a force platform in one participant [1], but used a different attachment site (i.e. between scapulars at height of T2 vertebrae). Therefore, the validity of WTA for calculating ground contact time at the lumbar area (L3 to L5) still needs to be assessed. **The aim of this study was to determine the concurrent validity of WTA for calculating ground contact times based on the vertical-acceleration zero-crossing method.**

Methods. Three recreational runners performed five one-minute running bouts at incremental running speeds (9.0, 10.5, 12.0, 13.5, and 15 km/h for two male runners) and (8.0, 9.5, 11.0, 12.5, and 14 km/h for a female runner).

Ground reaction force data were collected from an instrumented force treadmill (ForceLink, Culemborg, the Netherlands) sampling at 1000 Hz. The vertical component was used to calculate the start and end of each foot contact using a threshold of 50 Hz after being

low-pass filtered (4th order Butterworth filter).

Tri-axial accelerometry was acquired during the entire running test using a Shimmer3 wireless device (± 16 g range, sampling at 1024 Hz, 16-bit resolution, 0.023 kg weight, Shimmer Sensing, Dublin, Ireland). The accelerometer was securely positioned over L3 spinous process of the trunk and directly mounted to the skin using double sided tape and adhesive spray. The accelerometer was securely tightened to individual comfort. Contact time was derived from vertical trunk accelerations according to the procedures of [1] and [2].

The agreement between force treadmill (criterion measure) and accelerometer-derived stance times were examined using a specifically-designed spreadsheet [3], which calculated the mean bias (90% confidence limits, CL) and the typical error of the estimate (TEE, 90% CL) both in percentage and standardized units, and Pearson correlation coefficients (r , 90% CL). Threshold values for biases, TEE and standardized differences, were >0.2 (small), >0.6 (moderate), >1.2 (large) and very large (>2) [3]. The following criteria were adopted to interpret the magnitude of the correlation: ≤ 0.1 , trivial; $>0.1-0.3$, small; $>0.3-0.5$, moderate; $>0.5-0.7$, large; $>0.7-0.9$, very large; and $>0.9-1.0$, almost perfect [3]. This agreement was tested on every steady-state running step per running speed interval (i.e. excluding first and last 10 steps due to the treadmill belt accelerating and decelerating).

Results and conclusion. A total of 2094 steps were analysed from three subjects respectively. Figures II.1, II.2, and II.3 visually show the relationship between accelerometry-based contact time with force-based contact time for three subjects, as well as representative mean vertical and force curves from which they were calculated. Table II.1 shows validity results for mean bias (%), TEE (%), and Pearson's r for each subject and combined respectively. Based on standardised units, biases were small (-0.27) and TEE was small (0.57). Additionally, correlations were very large (0.87). **Overall, these results support the use of WTA for deriving contact times while running at speeds ranging from 8km/h to 15km/h.**

Table II.1: Validity results of contact times for subject means (all speeds combined) and combined presented as mean \pm 90% confidence interval]

Subject	N steps	Mean Bias (%)	TEE (%)	Pearson's r
1	699	-2.81 [-3.25 to -2.38]	6.09 [5.83 to 6.38]	0.83 [0.81 to 0.85]
2	703	-5.75 [-6.05 to -5.45]	4.27 [4.08 to 4.47]	0.87 [0.86 to 0.89]
3	692	-1.74 [-2.26 to -1.23]	6.99 [6.69 to 7.33]	0.83 [0.81 to 0.85]
All	2094	-3.47 [-3.72 to -3.22]	6.80 [6.63 to 6.99]	0.87 [0.86 to 0.88]

Subject A:

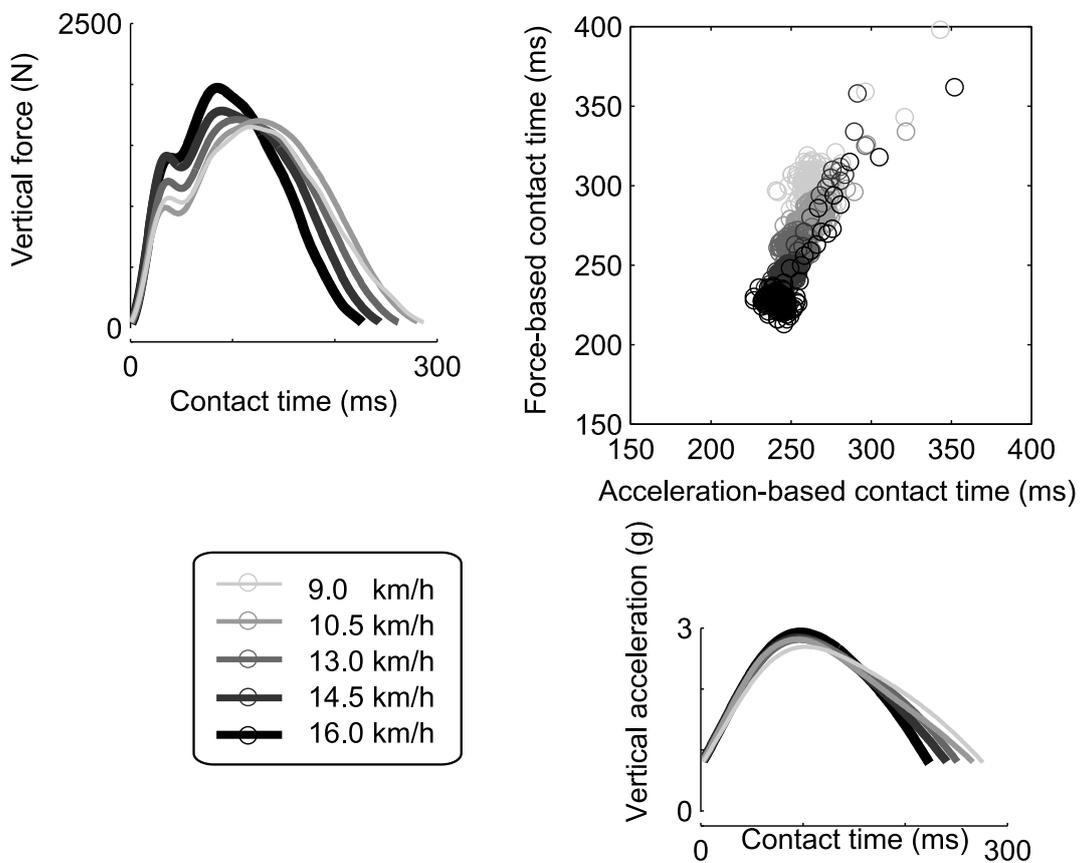


Figure II.1: Scatter plots for **subject A** of each calculated contact time (per step) with trial-averaged composites of force and acceleration curves (median per running speed).

Subject B:

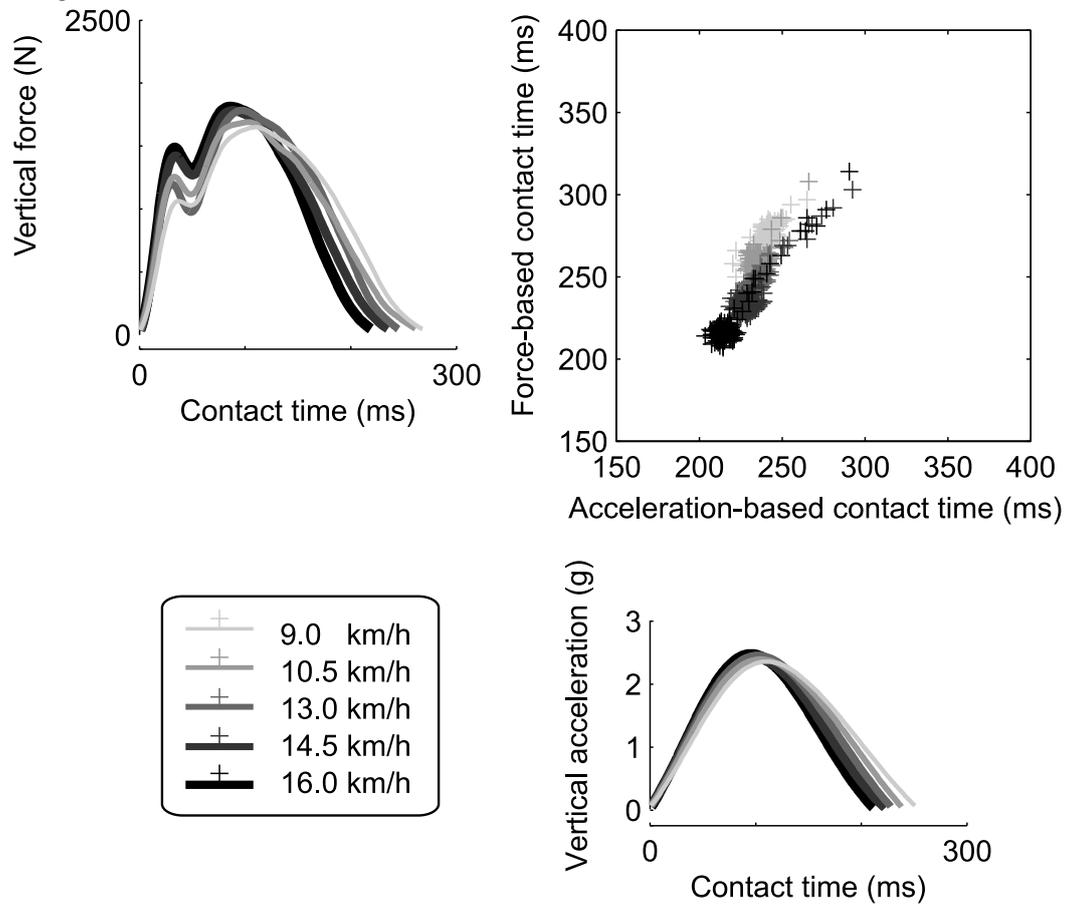


Figure II.2: Scatter plots for **subject B** of each calculated contact time (per step) with trial-averaged composites of force and acceleration curves (median per running speed).

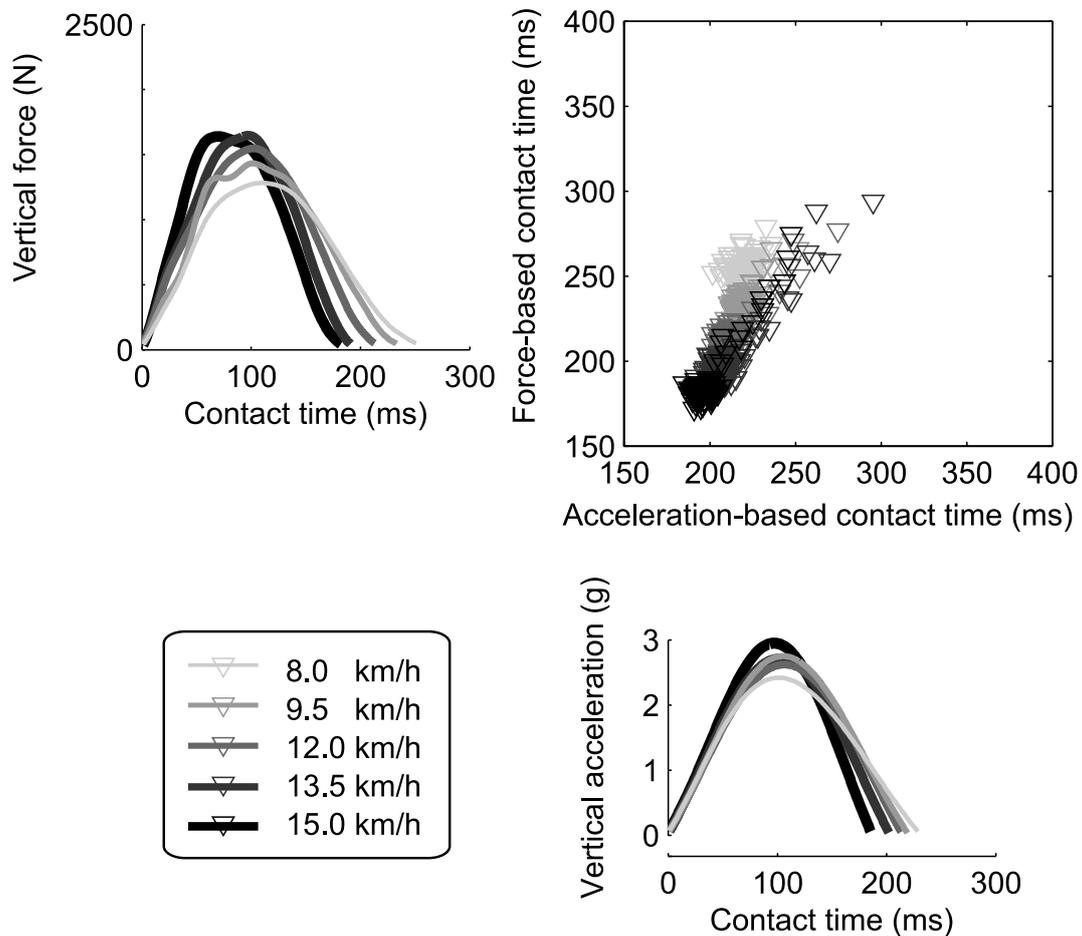
Subject C:

Figure II.3: Scatter plots for **subject C** of each calculated contact time (per step) with trial-averaged composites of force and acceleration curves (median per running speed).

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Appendix III

Appositions

1. Theoretical and practical reasoning is not mutually exclusive in sport science. For example, in the 2048 Olympics, can the fastest human on the planet really be running like a quadruped? [1]
2. The morphology of foot muscles plays an important role in balance performance and control mechanisms [3].
3. Of the many cognitive biases inherent to human thinking, researchers, coaches, and practitioners should specifically acknowledge the *regression to the mean phenomenon* and accept that poor performances are more likely to be followed by good ones (and vice versa) [2].

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Appendix IV

Professional career Kurt Schütte

Biography

Kurt Heinrich Schütte was born on April 25th 1988, in Johannesburg, South Africa. He grew up surfing, trail running, playing rugby in and around the town of Stellenbosch, the heart of the winelands region of the country. In 2010, Kurt received a young investigator award for his co-shared research project on '*the influence of minimalist footwear on running mechanics*' during his Honours degree at Stellenbosch university. A departmental bursary was offered to him to further pursue his postgraduate research interests, while also undergoing an intensive internship in the clinical practice (as a Biokineticist). In 2012, he graduated from his Master's with cum laude.

Kurt developed a keen curiosity for research in running biomechanics. With assistance from Prof. Dr. Ranel Venter and Prof. Dr. Elmarie Terblanche (both Stellenbosch University) he was able to present some of his research findings at his first international academic conference. In the pursuit of gaining more knowledge, he was awarded a doctoral scholarship offered by the Erasmus Mundus Call to South Africa (EMA2SA) programme.

Three factors led Kurt to doing a joint PhD programme in Belgium at KU Leuven. Firstly, KU Leuven was one of two possible universities on the EMA2SA list which offered a PhD in his line of interests. Secondly, Kurt received a recommendation letter in support of his PhD application from Prof. Dr. Daniel Berckmans (KU Leuven), whom he had met a year previously during an guest lecture on '*real-time monitoring in sports*' in Stellenbosch. Thirdly, while presenting at the International Society of Biomechanics conference in Natal, Brazil, Kurt met Prof. Dr. Benedicte Vanwanseele (KU Leuven). With common research interests, she was willing to take on Kurt as her PhD student.

This thesis is the product of a unique collaboration between countries, universities, faculties, and departments. During his PhD Kurt received additional financial support in the form of doctoral scholarships from the National Research Foundation of South Africa, as well as from internal (BOF) funding of KU Leuven. This enabled him to carry out additional studies at both universities. Kurt also gained insights into using advanced machine learning approaches under co-supervision from Prof. Dr. Jesse Davis. During his Phd, Kurt has presented his research findings at four international academic conferences, including France, Scotland, Germany and Japan. In his final year of his PhD, Kurt was awarded a post doctoral mandate at KU Leuven which enabled him to take the next step in his research career.

List of Publications

Peer-reviewed academic journal articles

1. Dixon, PC., **Schütte, KH.**, Vanwanseele, B., Jacobs, JV., Dennerlein, JT., and Schiffman, JM. (2017). Gait adaptations of older adults on an uneven brick surface can be predicted by age-related physiological changes in strength. *Gait and Posture (in review)*.
2. De Brabandere, A., Op De Beéck, T., **Schütte, KH.**, Venter, R., Meert, W., Vanwanseele, B, and Davis, J. (2017). Data fusion of body-worn accelerometers and heart rate to predict VO_{2max} during submaximal running. *PloS One (to be submitted)*.
3. **Schütte, KH.**, Seerden, S., Venter, R., and Vanwanseele, B. (2017). Influence of outdoor running fatigue and medial tibial stress syndrome on accelerometer-based loading and stability. *Gait and Posture (in press)*.
4. **Schütte, KH.**, Sackey, S., Venter, R., and Vanwanseele, B. (2017). Energetic cost of running stability evaluated with wireless trunk accelerometry. *Journal of Applied Physiology (in press)*.
5. Boey, H., Aeles, J., **Schütte, KH.**, and Vanwanseele, B. (2017). The effect of three surface conditions, speed and running experience on vertical acceleration of the tibia during running. *Sports Biomechanics*, 16 (2), 166-76.
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Peer-reviewed international scientific conferences

1. Sackey S., **Schütte KH.**, and Venter, R. (2017). Runners self-optimize their kinematics in response to running-induced fatigue after eight weeks of endurance training. To be presented at the 17th *South African Sports Medicine Association*. Cape Town, South Africa.
2. **Schütte, KH.**, Sackey, S., Venter R., and Vanwanseele B. (2017). Energetic cost of running stability evaluated with wireless trunk accelerometry. 35th International Conference of Biomechanics in Sport. *International Society of Sports Biomechanics Congress*. Cologne, Germany, 14-18 June.
3. **Schütte, KH.**, Aeles J., Venter R., Berckmans D., and Vanwanseele B. (2015). Acute effects of outdoor running surfaces on running gait symmetry and regularity assessed by trunk accelerometry. 33rd *International Society of Sports Biomechanics Congress*. Poitiers, France, 29 June - 03 July 2015.
4. **Schütte KH.**, and Venter R. (2013). Effect of minimalist shoe training on lower limb joint moments. Proceedings of the Eleventh Footwear Biomechanics Symposium: Vol. 5 (1). Footwear Science Symposium, 9 July 2013 (pp. S52-S53).
5. Zhang X., **Schütte KH.**, and Vanwanseele B. (2017). The morphology of abductor hallucis is related to balance control mechanics during single-leg standing. 26th *International Society of Biomechanics Congress*. Brisbane, Australia, 23-27 July 2017.
6. **Schütte KH.**, Seerden S., Venter R., and Vanwanseele B. (2016). Fatigue-related asymmetry and instability during a 3200-m time-trial performance in healthy runners. *International Society of Sports Biomechanics Congress*. Tskuba, Japan, 18-22 July 2016.

7. **Schütte KH.**, Maas E., Venter R., Berckmans D., and Vanwanseele B. (2015). Identifying treadmill running fatigue using trunk accelerometry based measures. *International Society of Biomechanics Congress*. Glasgow, Scotland, 12-16 July 2015.
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Invited presentations

1. **Schütte, KH.** (2013). Natural running: implications for athletes and clinicians. *Leukotape Sport Physio congress*. Gauteng, South Africa, 30 August - 1 September 2013.
2. **Schütte KH.**, Du Plessis E., Venter R., and Zech A. (2013). Barefoot training, biomechanics and performance. *South African Sports Medicine Association Conference*. Kwazulu Natal, South Africa, 24-27 October 2013.
3. **Schütte, KH.**, and Verstockt S. (2016). Data science and algorithms for body worn sensors in sport. *Hack4Sports*.
4. **Schütte, KH.** (2017). Wearables for the prevention of running injuries, fact or fiction? To be presented at the 36th *Limburg's Sport Congress*.

Appendix V

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Appendix VI

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The author, Kurt Schütte, has contributed to every part of this project and was involved in the design of the studies, data collection, data processing and analyses, and writing of all papers. He wrote this manuscript and created the figures (does not include figures copied with permission).

Neither the author, nor any of the co-authors have any conflict of interest.

Appendix VII

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Kurt

Appendix VIII

List of abbreviations

AP	anteroposterior
BLa	blood lactate
BMI	body mass index
CoM	centre of mass
CPU	central processing unit
Ec	energetic cost
FFT	fast Fourier transformation
GEE	generalised estimating equations
g	acceleration due to gravity
GPS	global positioning system
HR	heart rate
IMU	inertial measurement unit
MEMS	microelectricalmechanical systems
ML	mediolateral
MTSS	medial tibial stress syndrome
OBLA	onset of blood lactate accumulation
PPA	peak positive acceleration
PSD	power spectral density
RER	respiratory exchange ratio
RMS	root mean square
RRI	running-related injury
SA	shock attenuation
SPM	signal power magnitude
V_{OBLA}	treadmill velocity at blood lactate accumulation
VO_2	oxygen consumption
VO_{2max}	maximal aerobic power
V_{peak}	peak treadmill velocity
VT	vertical
WTA	wearable trunk accelerometry