ACCELERATION PROFILES OF ADOLESCENT SOCCER PLAYERS ACROSS A SEASON

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Jake Anthony Melaro
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ABSTRACT

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Nomenclature

3D	Three-dimensional
ACL	Anterior cruciate ligament
ACTH	Adrenocorticotropic hormone
AE	Athletic Exposure
ApEn	Approximate entropy
BW	Body weight
CEn	Control entropy
CoM	Center of mass
DHEA	dehydroepiandrosterone
DHT	Dihydrotestosterone
DOF	Degrees of freedom
deg/s	Degrees per second
FEn	Fuzzy entropy
FFM	Fat-free mass
FSH	Follicle stimulating hormone
GRF	Ground reaction force
IMU	Inertial measurement unit
LEFS	Lower Extremity Functional Scale
LH	Luteinizing hormone
ms	Millisecond
MsEn	Multiscale entropy
N	Newton

OSD	Osgood-Schlatter's disease
PHV	Peak height velocity
SEn	Sample entropy
yrs	Years old

Chapter 1: Development of the Problem

Background and Rationale

Almost seven million children and adolescents (6-17 years old) played soccer, or American soccer, in the United States in 2019 (SFIA 2020). Survey data collected by the National Federation of State High School Associations (NFHS) shows that more than 850,000 athletes participated competitively at the high school level that same year (NFHS 2019). Unfortunately, the boon of soccer popularity amongst youth athletes is marred by the injuries that accompany such a dynamic sport. Not including injuries sustained by players on youth and private club rosters, over 400,000 injuries befell high school boys and girls playing or practicing soccer in 2018 (Comstock and Pierpoint 2020). Between youth and high school soccer athletics, the rate per 1,000 athletic exposures is approximately 2.43-17.0 injuries and 2.50-10.60 injuries for boys and girls, respectively (Powell and Barber-Foss 1999; Radelet et al. 2002; Kucera et al. 2005; Comstock and Pierpoint 2020). Identifying and preventing the risk factors inherent to child and adolescent soccer training and competition could prevent time lost to injury in this young population.

Musculoskeletal or connective tissue injuries to athletes commonly occur via one of two scenarios: a) an external load acutely exceeds the maximal material tolerance of the tissue and failure occurs or b) repetitive exposure to submaximal loading causes gradual microtrauma to the tissue that can eventually compromise the integrity of the biological structure (Renström and Johnson 1985; DiFiori 2010; DiFiori et al. 2014). External loads placed on youth soccer athletes over the course of a match stem from covering distances of several kilometers, periods of maximum effort sprints, and rapid changes of direction via accelerations and decelerations.

Further, these external load demands only scale upwards as youth athletes graduate to larger fields and physical maturation drives increases in training load intensity.

Researchers cannot examine the evolution of external loading on developing youth athletes without considering the physical changes due to puberty. While it is understood that the fastest rates of human growth occur *in utero*, this rate declines linearly throughout childhood until puberty and a “growth spurt” occurs (Wood et al. 2019). Periodic release of gonadotrophin hormone from the pituitary gland leads to the production of sex steroid hormones (i.e., androgens and oestrogens) which increase mineral content in bone and muscle mass (Saggese et al. 2002; Wood et al. 2019). Apart from these changes, young athletes undergoing puberty also show increases in muscular strength, power, sprint speed, and endurance (Rowland et al. 1991; Seger and Thorstensson 2000; Van Praagh and Doré 2002; Papaiakovou et al. 2009). Access to these elevated physical attributes, body and segmental mass, and muscle contractility means that dynamic soccer tasks performed as young children now produce greater external and internal loading on these adolescent athletes. Monitoring of these loads could be of utmost importance in preventing these players from being exposed to abnormal and injurious loading patterns, both acutely and chronically.

While motion capture camera systems and force plates are the ‘gold standard’ in biomechanics research when assessing these loads, these systems do not lend themselves to unfettered field-based tasks. Inertial measurement units (IMUs), however, provide estimates of biomechanical loading on body segments via embedded triaxial accelerometers, gyroscopes, and magnetometers. Specifically, when considering the large majority of soccer injuries occur in the lower extremities (Comstock and Pierpoint 2020), metrics derived from IMUs placed on the shank during training (Nedergaard et al. 2017; de Moraes et al. 2018; Willy 2018) seem to be promising potential indicators of leg injury risk in these adolescent athletes. Commonly reported metrics from these sensors include peak resultant accelerations, binned frequencies of accelerations, and other discrete variables (Armitage et al. 2021), though other analyses are available to analyze the collected IMU signals.

The 'complexity' of biological signals (i.e., heart rate variability, electroencephalograms, etc.) has been previously used to delineate healthy and diseased systems (Lake et al. 2002; Costa et al. 2005; Abásolo et al. 2006). The signal complexity is determined via entropy analyses which utilize information theory to calculate the expectation of observing a series of data points in the biological signal based on previous data points (Shannon 1948). It has been postulated that, relative to unhealthy biological systems, healthy systems exhibit greater signal complexity (i.e., higher entropy) as they are capable of greater adaptation and less system constraint (Costa et al. 2002). Previous work has shown that untrained runners exhibit lower center of mass (CoM) acceleration complexity than trained runners (Parshad et al. 2012) and that CoM acceleration complexity decreases before fatigue onset during a long run (McGregor et al. 2009). Further, a prospective proof-of-concept investigation by Gruber et al. (2021) on a small sample of collegiate runner long runs reported that CoM acceleration complexity increased from baseline to immediately pre-injury. Though the complexity differences reported were not statistically significant, the moderate to large group-difference effect sizes between the injured and non-injured runners suggest that entropy analyses could still prove to be a useful tool in identifying injury risk during similar tasks.

Statement of the Problem

Previous investigations have monitored youth soccer athlete training loads in a one-dimensional manner, i.e., by simply reporting global positioning system (GPS) distances covered, binned and absolute CoM acceleration peaks, total accelerations and decelerations, etc. However, a paucity of shank-mounted IMU or accelerometer data exists in these athletes, especially those who have not yet or are in the process of undergoing pubertal development. Further, entropy analyses of these data may show that the movement complexity of these athletes differs between athletes in various pubertal stages or at different time points in their training. If such differences existed and could be characterized, coaches and researchers could potentially use such analyses to monitor these athletes and potentially prevent injury.

Statement of Purpose

The purpose of this study is to collect IMU linear acceleration data from adolescent soccer athletes and determine if derived linear acceleration metrics (discretized peak accelerations, cumulative acceleration loading, etc.) or overall signal complexity differs between athletes based on relation to PHV, sex, or over the course of a season. We propose to accomplish this purpose with two specific aims. Specific aim 1 is to determine if PHV and sex differences exist in shank acceleration signal profiles and if those profiles change over a competitive season. Specific aim 2 is to compare shank acceleration complexity measures across PHV and sex to determine if complexity changes over the course of a season.

Research Hypotheses

This investigation is novel in its methodology and population, therefore directed hypotheses are difficult to form. However, as the literature has made clear that puberty affects a multitude of physical attributes, it is hypothesized that youth soccer athletes at different points of pubertal development and of varying sex will exhibit differing shank-mounted acceleration profiles and complexity metrics. Additionally, to increase the resolution of these time-dependent pubertal changes and consider the effects of training and competition on this data, we hypothesize that the acceleration complexity will differ when measured at the beginning as compared to after a competitive season.

Independent Variables

- Offset in years from peak height velocity (PHV)
- Session – pre-season, post-season
- Sex – female, male

Dependent Variables

- Linear acceleration
    - Resultant linear acceleration peaks
    - Resultant linear acceleration integral
        - "Cumulative acceleration loading"
- Complexity Measures
    - Multiscale Entropy
        - Complexity Index

Limitations of the Study

- Participant relation to pubertal stages will be carried out via cross-sectional anthropometric measurements used to estimate peak height velocity, a surrogate measure, rather than the gold standard of longitudinally collected radiographic measurements.

Delimitations of the Study

- Participants will be between the ages of 9 to 17 years old.

- Any participant who experiences a lower extremity injury in the 6 months prior to the initial testing session will be excluded.
- Any participant who experiences pain on the days of testing will be excluded.

Assumptions of the Study

- Participants will be truthful when answering screening questions regarding lower extremity injury history and weekly soccer participation.
- Participants will be truthful when completing the Lower Extremity Functional Scale and fitness activity questionnaire forms.
- Participants will give maximal effort during the experimental tasks.
- The dual-g IMU sensors (IMeasureU Blue Trident, Vicon Motion Systems Ltd., Oxford, UK) will be accurately calibrated for each data collection throughout the study.

Significance of the Study

This study will utilize a population that is under-represented in the biomechanics literature and analytical methods that have yet to be employed in said population. Complexity analysis of athlete movement during training and drills could provide a robust metric for determining movement complexity evolution in this population over the course of a season and longitudinally over adolescence. Further, by characterizing the profiles of these acceleration data for this population, deviations from these data could serve as indicators of an unhealthy and potentially at-risk system. Therefore, it is vital that the acceleration profiles of these adolescent soccer players be collected and analyzed.

Operational Definition of Terms

Complexity: "… the amount of nonlinear information that a time series conveys over time." Highly complex signals (i.e., biological signals) exhibit patterns of 'structure' and regularity across frequency components and temporal scales. (Omidvarnia et al. 2018)

Entropy: the mean quantity of "surprise" or "uncertainty" produced by a random variable, i.e., the average amount of information expressed by a random trial for a variable.

Information: knowledge that allows for a signal, input, or the entire state of a system to be differentiated from the available potential states, or the "resolution of uncertainty".

Puberty: "… the attainment of reproductive capability and the acquisition of adult body composition and habitus. The pubertal growth spurt and the appearance of secondary sex characteristics are the most visible manifestations of puberty." (Abbassi 1998)

Regularity: the ability of a signal to be locally approximated via a polynomial, i.e., the predictability of a signal.

Chapter 2: Review of the Literature

Introduction

Many sports and the training regimens associated with them dictate that the participating athletes cover a range of distances at moderate to maximal speeds. Ignoring the biomechanical impact of factors like fatigue, coordination, and object manipulation, the vertical ground reaction forces and loading rates experienced during sprinting can surpass 3-5x bodyweight and 100x bodyweight per second, respectively (Udofa et al. 2017; Yu L et al. 2021). Other commonly performed sporting maneuvers (e.g., accelerating, decelerating, and cutting) further increase the internal loading response within the biological structures of the lower extremity. These facts explain why almost 50-70% of sports-related musculoskeletal overuse injuries are predominantly occurring in the lower extremities (Stracciolini A. et al. 2014; Roos et al. 2015). Repeated loading cycles of the musculoskeletal and connective tissues, even sub-maximal relative to their failure point, can lead to injurious damage and potential failure (i.e., tearing and rupture) if adequate recovery and repair does not follow. In the absences of invasive methods, tracking "external loads" such as total distance covered, number of sprints at certain intensities, and accelerometry has become common metrics used to identify athletes potentially at risk of overuse injuries (Gabbett 2016; Bourdon et al. 2017).

Tracking and managing these loading patterns could alleviate substantial financial burdens (Cumps et al. 2008; Ryan JL et al. 2019) and prevent arduous rehabilitation protocols, surgical or otherwise. Small, minimally invasive IMUs have become popular devices for tracking either athlete center of mass or segmental accelerations as a surrogate measure of external loading. The use of accelerometry metrics derived from IMUs have been used to monitor training workloads at the acute and chronic level in efforts to reduce overuse injury in youth and professional athletes (Bowen et al. 2017; Sampson et al. 2018; Izzo et al. 2022; Nobari et al. 2022). As puberty has been shown to drastically alter musculoskeletal strength and power, movement coordination, and fatiguability (Papaiakovou et al. 2009; Perroni et al. 2018; Almeida-Neto et al. 2020), data accounting for the interaction between pubertal status and these IMU metrics during training could be beneficial to the public. Further, the magnitudes, profiles, and rate of change of data collected via IMUs in rapidly developing adolescents is currently not available. Insights from the analysis of such data collected over the course of a season in maturing soccer athletes could, thus, provide insights that could prevent overuse injuries and add to the paucity of IMU external loading literature in this population.

The purpose of this study is to investigate the discrete IMU acceleration metrics and complexity differences between soccer players at different pubertal stages before and after a competitive season. The current literature explored in this chapter includes: the expected aging effects through late childhood and puberty on performance in young athletes; the epidemiology of sports injuries in developing athletes; measurement of external loading via IMUs; and the use of dynamical systems theory to analyze continuous IMU data for injury prevention.

Adolescent Development

Infancy

If humans continued developing at the same *in utero* growth rate once born then we each would achieve our full stature before we were two years old. A variety of factors affect this prenatal rate of growth, notably maternal carbohydrate intake during pregnancy (Scholl et al. 2004), toxic exposure to smoked tobacco or alcohol (Bird et al. 2017), gene expression (Weedon et al. 2005), and hormone regulation (Evain-Brion 1994; Gicquel and Le Bouc 2006; Belkacemi et al. 2010). Peak gestational growth rate is approximately 2.5 cm per week around weeks 20-24

(Kappy et al. 2005) and prenatal androgen profile may not be as influential to birth size as thyroid hormone concentrations (Miles et al. 2010; Shields et al. 2011). The postnatal growth pattern, however, is predictable and split into infancy, childhood, and puberty (ICP) stages (see **Figure 2**) by the Karlberg model of growth (Karlberg 1989). While primarily dependent upon nutritional content and uptake, the average height velocity over infancy is 25 cm per year (Benyi and Sävendahl 2017). Bone diaphyses have ossified by birth but epiphyses are still cartilaginous (Anderson 1996). Bone mineral density rises rapidly over the first 4 years, subsides, and spikes again at puberty (Cech 2011). Over the first 2 years, the brain reaches 80% of adult size during development (Knickmeyer et al. 2008). Myelination of the sensory, then motor and association areas of the brain proceeds rapidly, reaching the frontal lobes within the first year of birth (Barkovich et al. 1988; Barnea-Goraly et al. 2005). Muscle mass, at birth, accounts for roughly 25% total body mass (Cech 2011) and the contractile and relaxation times of certain muscles slow until around age 3 (Gatev et al. 1977). 50% and 95% of infants begin walking by 12 and 15 months, respectively (WHO 2006), yet the literature demonstrates that motor milestones like walking are more due to cerebral maturation instead of via experience (Savelsbergh et al. 2013). This point is supported by a case-study involving a 6-month-old presenting with bilateral hip dysplasia who was placed in a spica cast and immobilized for 12 months, yet she was able to walk within a day of cast removal (Peiper 1963, pp. 233).

Childhood

In the brain, the zona reticularis within the adrenal cortex produces and secretes dehydroepiandrosterone (DHEA), the most abundant circulating steroid hormone, at a very high rate during fetal development (Bech et al. 1969; Belgorosky et al. 2008). DHEA and its sulfate ester metabolite (DHEAS) provide more than 50% and 70% of the androgens and estrogens, respectively, in premenopausal women and men as a precursor to androgen production (Maggio et al. 2015). DHEA production and levels decrease immediately following birth before rising again and marking the beginning of adrenarche, the period of increased adrenal androgen production preceding puberty, peaking in late adolescence (Babalola and Ellis 1985; Havelock et al. 2004; Castellano et al. 2006). Adrenarche typically occurs between ages 6-8 in parallel with skeletal age increase (dePeretti and Forest 1976; Ibáñez et al. 2000), though cases demonstrate it can be observed as early as 3 years of age (Palmert et al. 2001; Remer et al. 2005). Though it is unknown exactly how adrenarche is modulated, nutritional status and paracrine function of adrenocorticotropic (ACTH) hormone production are known contributors to this pubertal phase (Hinson 1990; Ibáñez et al. 2000; Suzuki et al. 2000).

Brain growth slows after age 2 as 90% of adult size is not achieved until year 5 (Dekaban and Sadowsky 1978). This is accompanied by a lifespan peak rate of brain metabolism and white matter development until age 10 (Barnea-Goraly et al. 2005; Snook et al. 2005) thought to be a product of energy demands related to synaptic remodeling and myelination (Tau and Peterson 2010). Bone mass reaches 50% and 60% of adult mass via linear growth rate before puberty in men and women, respectively (Whiting et al. 2004; Ondrak and Morgan 2007). Up to 85% of the fully developed height of an individual can be reached by the end of childhood prior to puberty (Prader 1984; Bogin 1999). Isometric strength increases from ages 3 to 6 proportionally with physiological cross-sectional area (PCSA) and volume increases (Tonson et al. 2008). Before age 10, average cross-sectional area of skeletal muscle is slightly greater in men compared to women (Kanehisa et al. 1994; Deighan et al. 2006). Muscle strength, volume, and PCSA increases up to 19%, 14%, and 11% have been reported, respectively, in 7-8 year old children over just 6 months (Pitcher et al. 2012). As myelination continues and androgen production has not yet peaked, long-term athlete development models have suggested that skill-related training (e.g., speed, agility, coordination, and flexibility training) should take priority over solely resistance training during childhood to maximize future motor performance (Kraemer et al. 1989; Myer et al. 2011). However, the current literature regarding optimal training windows is conflicting (Sañudo et al. 2019).

Only 14% of all children can skip by year 4 (Cech 2011), though by year 4 and 5 approximately 60% of men and women, respectively, have become proficient at running (Seefeldt and Haubenstricker 1982). An adult walking pattern has been established by age 5 (Malina 2004) and no differences in lower extremity landing stiffness strategies has emerged yet by age 10 (Hamstra-Wright et al. 2006).

Puberty

Gonadarche, signalled by the production of follicle-stimulating hormone (FSH) and luteinizing hormone (LH) in the anterior pituitary (Witchel and Topaloglu 2019), marks the beginning of central puberty. FSH and LH promote maturation of the gonads via secretion of testosterone, estrogen and estradiol (Reardon et al. 2009). DHEA and testosterone are converted to dihydrotestosterone (DHT) which stimulates epiphyseal growth in long bones (Nilsson et al. 2005; Zhou and Glowacki 2018). More than 20% of bone density and mineral content is accumulated over puberty (Anderson 1996; Ondrak and Morgan 2007) and differences in testosterone levels contribute to the steady rate of bone mineral content accrual in men compared to the plateauing in women following PHV (Whiting et al. 2004). Men and women reach 90% and 95% of their adult peak bone mass by age 20 following the pubertal growth spurt (Anderson 1996), at which time differences in bony structure geometry appear that will persist across the lifespan (Lauretani et al. 2008).

It has been suggested that DHEA and DHEAS molecules affect neurite growth (Grube et al. 2018; Schverer et al. 2018), catalyzing brain development by fueling neuroplasticity during adrenarche (Greaves et al. 2019). These adrenarchal changes have been posited as a contributor to changes in documented behavior throughout puberty (Del Giudice 2009; Campbell 2011). Further reports suggest that increased intra-adrenal cortisol levels and macro-level growth frequently resets ACTH homeostasis concentrations in the presence of normal cortisol production relative to body size during puberty, leading to PHV (Topor et al. 2011; Majzoub and Topor 2018).

Several reports show that almost all strength increases over puberty can be explained by increases in muscle size when normalized to either muscle volume, PCSA, or fat-free mass (FFM) (Pitcher et al. 2012; Fukunaga et al. 2014). Further, peak power output in age 12 children assessed via Wingate tests is greater in men compared to women (Van Praagh et al. 1990) with a similar divergence in strength also presenting following the pubertal growth spurt (Malina et al. 2004, pp.219). In men, specifically, elevated testosterone levels are directly correlated with improvements in upper limb and squat jump power production (Almeida-Neto et al. 2020). Even when separated by less than one chronological year, strength and muscle volume have been reported to differ by 40-50% between pubertal men and their pre-pubertal counterparts (Tonson et al. 2008; Fukunaga et al. 2014).

Speed has been shown to improve with age across puberty, though when normalized to strength and muscle volume this relationship is no longer significant (Yoshimoto Takaya et al. 2012; Yoshimoto T et al. 2014). As with strength, peak running speed increases at a faster rate following PHV in men compared to women (Papaiakovou et al. 2009). Maximum oxygen uptake increases from infancy to adulthood (Armstrong and Welsman 1994; Viru et al. 1999), though much variation in total aerobic work capacity exists between reports. Adults have been shown to run more economically than children and adolescents (Åstrand 1952; Daniels et al. 1978; Krahenbuhl et al. 1985), yet this relationship does not hold when running at speeds relative to leg length (Maliszewski and Freedson 1996). Aerobic capacity relative to mass remains constant in boys and decreases in girls (Åstrand 1952; Krahenbuhl et al. 1985), dooming children participating in endurance events to operate closer to their maximal oxygen uptake at any speed (Bar-Or 1983; Morgan et al. 1989).

Altered movement strategies also emerge as lower extremity joint stiffness during jump landings increases following puberty (Wang et al. 2004), though neuromuscular components of performance differ based on sport and sex (Quatman et al. 2006; DiCesare et al. 2019). Knee biomechanics during drop vertical jumps are similar between pubertal men and women but only women exhibit an increase in knee abduction angles and moments immediately following puberty (Ford et al. 2010). During a stop-jump task, post-pubertal women soccer players also exhibit greater knee abduction angles compared to pre-pubertal women (Yu B et al. 2005). The next section will cover how the combination of these anthropometric and musculoskeletal changes impart substantial influence on injury risk.

Adolescent Injury Overview

Intrinsic Injury Risk Factors

Across puberty, peak muscle accretion rates and PHV supersede peak bone mineral content accrual (Blimkie et al. 1993; Ruff 2003; Forwood et al. 2004; Rauch et al. 2004). Periosteal modelling and geometric expansion do not take place until bone elongation and muscle hypertrophy, an explanation posed for the greater rate of fractures occurring during puberty (Cooper et al. 2004). A retrospective pediatric clinical study found that adolescents (11-

17 years old) experienced a higher incidence rate of epiphyseal fractures than younger children with the majority occurring at the distal epiphysis of the tibia and fibula (Joeris et al. 2017). Osgood-Schlatter's Disease (OSD), or irregular ossification occurring at the tibial tubercle, is experienced by ~10% of adolescent athletes (Kujala et al. 1985; de Lucena et al. 2011). Sever's disease (calcaneal apophysitis) commonly occurs in athletes between 8 and 15 years as tension in Achilles tendon leads to avulsion of the calcaneal attachment (Ramponi and Baker 2019).

Biological sex is another known risk factor for non-contact injuries during dynamic movements, as women have been reported to be between 2-8x more likely to injure their anterior cruciate ligament (ACL) (Agel et al. 2005; Yu Bing and Garrett 2007). Interestingly, it is unclear if a sex-related difference in ACL injury rates in children or pre-pubertal athletes exists as it does in post-pubertal or adult populations (Andrish 2001; Shea K et al. 2004). In high school sports, women playing soccer, basketball, and softball experience higher ACL injury rates than men (Shea KG et al. 2011). ACL injury rates increase with age for both men and women, but these rates are greater in women immediately following PHV (Tursz and Crost 1986). Sport-related high school injury rates peak during freshman year for women before declining but increase for men until peaking senior year (Comstock and Pierpoint 2020). The rapid increase in stature and weight accompanying PHV may alters center of mass location and may lead to altered movement patterns that predispose women athletes to non-contact lower extremity injuries (Hewett et al. 2005). Men tend to experience OSD most frequently 1-1.5 years preceding PHV and at greater rates than women (Kujala et al. 1985). In fact, men tend to experience apophyseal, cartilaginous, and tendon overuse injuries more frequently than women between ages 5 to 18 (Valasek et al. 2019).

Non-Contact and Overuse Lower Extremity Injury Mechanisms

Across all sports, injury rates are greater in competition compared to practice and more frequently occur in the lower extremities (Sheu et al. 2016; Comstock and Pierpoint 2020). Playing sports exposes athletes to movements during training and competition that stress the structural integrity of the musculoskeletal system to varying degrees. Acute musculoskeletal injuries can occur when internal forces in the tissues exceed failure points due to instantaneous application or propagation of energy (Finch CF 1997). Conversely, the onset of overuse injuries is not typically linked with a specific event but rather repetitive microtrauma being applied to the tissues in the absence of adequate recovery (Finch C 2011). These injuries can culminate in non-contact injuries that are the product of progressively weakened tissue rather than acute application of traumatic force. Repeated bouts of intense training and sport is a risk factor for tendinopathy, particularly if jumping is involved (Ferretti et al. 1984; Warden and Brukner 2003; Gisslèn et al. 2005). One of the most common and debilitating injuries, ACL sprains, have been estimated to be the result of non-contact mechanisms in approximately 70% of reported cases (Gianotti et al. 2009). Overtraining and inadequate recovery between competitions and training increase the risk of musculoskeletal, non-contact injury (Gabbett 2004, 2010, 2016).

During dynamic tasks, athletes can position their joints in ways that forces propagating from the ground through the lower extremity may overload the material strength of soft-tissue. Despite the Achilles tendon being the thickest, strongest tendon in the human body, it is the most frequently injured via acceleration-deceleration events associated with rapid ankle dorsiflexion or a lunging motion (Aicale et al. 2017; Tarantino et al. 2020). Lower extremity muscle strains are also more likely to occur during intense deceleration movements (i.e., late swing of gait cycle) when muscles are eccentrically producing more contractile force (Chumanov et al. 2007;

Kary 2010; Chumanov et al. 2012). 30% of ankle sprains experienced by both men and women high school soccer players during 2019 had non-contact mechanisms (Comstock and Pierpoint 2020). Video evaluation has shown that the deceleration phase of sprinting, landing, or changing direction is when most ACL non-contact injuries occur (McLean et al. 1999; Boden et al. 2000). Cadaveric benchtop testing has shown internal rotation of the hip and extension and adduction of the knee induce the most strain and load on the ACL (Bates NA et al. 2015; Bates NA et al. 2019). Indeed, a prospective study found that knee frontal plane angles and moments during dynamic tasks are considered a risk factor for ACL injury (Hewett et al. 2005). ACL injured athletes demonstrated greater knee abduction angles (>8°) and moments (>150%) at initial contact during a jump landing task than uninjured controls while abduction moments could predict ACL injury with 73% specificity and 78% sensitivity.

Sport-specific Injury Prevalence

Sport demands entailing intense, coordinated movements of the lower extremities (i.e., soccer, football, basketball, etc.) increase non-contact ACL injury risk (Noyes and Barber Westin 2012). Considering injury risk with respect to non-contact ACL injury risk, it is not surprising that ACL injury rates in high school women's sports are higher than those in sex-comparable sports (i.e., basketball and soccer) (Shea KG et al. 2011; Tirabassi et al. 2016). More than 1/3rd of Achilles tendon ruptures reported between 2012-2016 in those less than 18 years old played such sports (i.e., basketball, football, and soccer) and 80% of all AT ruptures over this period were sport-related (Lemme et al. 2018).

Sport specialization may also play a role in overuse injury, particularly for athletes playing year-round with no offseason. Athletes who exhibit a combination of training more than 8 months per year, quitting other sports to focus on a primary sport, or compete more than 60 times per year have 50-80% greater lower extremity injury rates than generalized athletes (McGuine et al. 2017). Adolescent baseball pitchers are 5x more likely to require surgery stemming from overuse injury if they compete more than 8 months out of the year (Olsen et al. 2006). While athletes who participate in sport specialization earlier are more likely to receive collegiate athletic scholarships, they are also more likely to sustain more injuries and miss a greater amount of time due to injuries than those who did not (Ahlquist et al. 2020).

ACL injuries are one of the most serious injuries that occur frequently across all sports, though ACL injury rates are relatively higher in soccer (Shea KG et al. 2011). High school women's soccer injury rates are only eclipsed by those in football (Shea KG et al. 2011; Comstock and Pierpoint 2020). Overall injury rates in high school women soccer players are 50% greater but also 30% and 50% more likely to incur knee and ankle sprains compared to men, respectively, though women are less likely to fracture a bone during competition or practice (Comstock and Pierpoint 2020). An analysis from 2010 demonstrated that women's soccer produced the highest ACL injury rate (13.87 injuries per 100,000 AEs) among the 9 most commonly played high school sports by women and men (Shea KG et al. 2011). The greatest non-football ACL injury rates (4.6 injuries per 100,000 AEs) for men also occurred playing soccer (Shea KG et al. 2011). Men had higher ACL injury rates in practice compared to women (1.04 vs 0.85 injuries per 1000 AEs, respectively), though these rates were below the national average for contact sports (1.51 injuries per 1000 AEs) (Montalvo et al. 2019).

Wearable Sensors

Over the past decade, more than 22 review papers have been published on wearables used to combat musculoskeletal injury in athletes (Preatoni et al. 2022). Almost 75% of these studies used these sensors to measure loading of the lower extremities and pelvis (Preatoni et al. 2022) as these constitute the majority of overuse injuries at all levels of competition (Roos et al. 2015; Schroeder et al. 2015; Stracciolini Andrea et al. 2015). Most of these studies employed IMUs, small housings containing 3 sensors: an accelerometer, gyroscope, and a magnetometer (Ahmad et al. 2013). IMUs were initially designed almost 70 years ago as ground-position indicators in jets before the field exploded with the need for more advanced and accurate guidance systems in missiles and aircraft (Lambert and Kenneth 1952; Robot Navigator Guides Jet Pilots 1954; MacKenzie 1990), but have become popularized in health and sport monitoring in recent decades. The following section will detail the individual components of the IMUs and the principles on which they function; their use cases as they pertain to health monitoring, injury prevention and sport performance; and the use of signals obtained from IMUs in non-linear analyses.

Inertial Measurement Units

The size, processing requirements, and cost of the first IMUs rendered them inappropriate for consumer-application (MacKenzie 1990). 3D optical motion capture systems have been the golden standard for analyzing human kinematics for several decades (Muro-De-La-Herran et al. 2014; Van der Kruk and Reijne 2018), yet the validity and reliability afforded by these systems is overshadowed by their costs, fixed location requirements, and the need for extensive technical training to operate and process captured data. It was not until advancement in micro-fabrication techniques that micro-electromechanical systems (MEMS) made the manufacturing of wearable, research-grade IMU sensors for tracking human motion a possibility (Xu et al. 2019; Bukhari et al. 2020). Following this manufacturing breakthrough, IMUs can now provide athletes, coaches, and researchers the ability to track athlete motion in the field during training and competition in a way that traditional marker motion capture cannot, solidifying a strong basis for their recent popularization. IMUs are small, lightweight, and relatively cheap in comparison to motion capture systems while still measuring linear and angular motion (Boddy et al. 2019).

A review of biomechanical studies over the past decade employing IMUS for examining musculoskeletal health found that over 60% only used 1D or 3D accelerometers in their experiments (Preatoni et al. 2022). The first accelerometer was devised in the late 1700s by George Atwood before the more modern spring mass system or piezoelectric accelerometers were commercialized in the 1900s (Greenslade Jr 1985; Walter 1997). Atwood's machine consisted of two unequal masses m_1 and m_2 connected by string or rope over a pulley, whereby both masses would experience uniform acceleration due to Earth's gravity (assuming massless, inextensible string and pulley):

$$a = g\frac{m_1 - m_2}{m_1 + m_2} \qquad \text{Eq. (1)}$$

In the 1920s, the first resistance-bridge accelerometers were commercially developed by McCollum and Peters in a Wheatstone half-bridge configuration for use in bridges, dynamometers, and aircraft (McCullom and Peters 1924; Stein 1996). This iteration weighed over a pound and was more than 8 inches long. It was not until the invention of the strain gauge that the form factor could be reduced (to less than 2 grams) and the strain gauge accelerometer was created more than 15 years later by J. Hans Meier while working for Douglas Aircraft (Starr et al. 1988). Piezoelectric accelerometers developed en masse at the midpoint of the 1900s improved on resonant frequency response, dynamic signal ranges, and apparatus size, which shortly thereafter led to the introduction of modern integrated circuits to combat cable noise due to static electricity interference (Walter 1997). The first silicon, micromachined MEMS accelerometer was proposed by Lynn Roylance in his dissertation at Stanford University prior to its funding and development through a NASA grant in 1979 (Lee et al. 2005; Bimm 2018).

These devices use inertia and a combination of free-moving and stationary electrodes or piezoelectric strain gauges that create differential capacitance via their displacement proportional to linear accelerations experienced by the system (Aydemir et al. 2016). The mechanism is similar to vestibular function in the human inner ear used for balance and orientation within the world coordinate frame (Day and Fitzpatrick 2005; Fortenberry et al. 2012). Skin-mounted accelerometers have been used to quantify human segment kinematics and energy transfer during walking, running, and other dynamic tasks (Lafortune et al. 1995; Whittle 1999; Mercer et al. 2002; Coventry et al. 2006; Simons and Bradshaw 2016; Brennan et al. 2017) and provide a less invasive alternative to bone-pin accelerometers. However, skin-mounted accelerometers move relative to the bone motion we are trying to measure due to subcutaneous tissue deformation during movement (Cappozzo et al. 1996). The mechanical properties of soft-tissue exhibit high inter-subject variability regarding movement artefact of skin-mounted accelerometers (Ziegert and Lewis 1979; Fuller et al. 1997; Holden et al. 1997), though this issue can be addressed by modelling the soft-tissue attachment as a second-order mass-spring-damper system (Kim et al. 1993; Luo et al. 2002). Researchers and coaches should be cognizant of the effects of sensor placement at the proximal or distal portion of the segment of interest as segment angular velocity will affect results (Mathie et al. 2004; Schwartz et al. 2004; Clark et al. 2010). Accelerometers have been used to quantify stride length, running velocity, tibial acceleration, vertical stiffness, and other biomechanical variables (Eggers et al. 2018; Mitschke et al. 2018), though the accuracy of these measures can be improved by combining accelerometer and gyroscope results (Boonstra et al. 2006).

Gyroscopes have also become more prominent in wearables to measure angular motion due to advances in MEMS technology (Yazdi et al. 1998) yet they are typically used in conjunction with at least accelerometers when measuring biomechanical variables (Norris et al. 2014; Preatoni et al. 2022). Like accelerometers, MEMS gyroscopes contain a moving mass whose displacements produce measurable voltage differences that are proportional to the rate of angular velocity experienced by the system (Passaro et al. 2017). However, this mass is constantly oscillating or vibrating so applying principles of gyroscopic procession and the Coriolis effect in conjunction with Newton's 2nd Law of motion allow us to determine angular velocity (Maenaka et al. 1996; Xie and Fedder 2003). The first MEMS gyroscopes were designed by Draper Laboratory in the 1980s for military and space inertial navigation applications (Greiff et al. 1991) as they can measure inclination and heading with less interference than magnetometers alone (Fan et al. 2017). Gyroscope scale factor and bias stability (i.e., resolution of measurement and drift, respectively) are susceptible to error, however, in the presence of extreme temperatures or internal friction and vibration (Yoon et al. 2012; Jiang et al. 2014; Chong et al. 2016). More sophisticated ring laser and fiber optic gyroscopes can achieve bias stability of less than .0001°/hour drift while most commercially available MEMS equivalents are 4-7x less precise (Passaro et al. 2017). Bias stability can be improved via sensor fusion algorithms including correction inputs from magnetometers (Chang et al. 2008; Fan et al. 2017).

The magnetometer was first invented by Gauss in 1832 to measure the absolute value of Earth's magnetic field strength from a given location (Gauss 1832, 1877). MEMS magnetometers are designed with magnetoresistive conductive plates to measure heading and inclination using principles of the Hall effect and Lorentz force to measure voltage differentials based on deflection of electrons due to strength and direction of an external magnetic field (Smith et al. 1991; Tumanski 2001; Ramsden 2011). Magnetometers have been used in applications ranging from early compass navigation to geospace and military projectile applications (Rogers et al. 2011; Brown et al. 2012). Exclusive use of magnetometers in biomechanical investigations is unusual, though for less-dynamic tasks requiring fewer DOFs removing accelerometer input may improve accuracy by removing inertial error (Bonnet and Heliot 2007). Magnetometers vulnerability to ferromagnetic disturbances is well-documented, especially when deployed indoors (Bachmann et al. 2004; De Vries et al. 2009). In recent years, though, the accuracy obtained from IMUs using magnetometers for orientation drift-correction in gyroscope and accelerometer measurements has improved beyond magnetometer use alone (Han and Wang 2011; Wittmann et al. 2019; Preatoni et al. 2022).

Sport-Specific Implementation for IMUs

Early uses of IMUS were predominantly for navigation and industrial applications. MEMS IMUs have been used in recent years by coaches and researchers across sports to quantify and monitor impact loads athletes experience performing dynamic movements during training and competition in athletes (Wilkerson et al. 2016; Jaspers et al. 2018; Mehta 2019; de Leeuw et al. 2022; Miltko et al. 2022). Some previous reviews have covered best practices for sensor placement, fixation techniques, and data capture and processing based on the task being analyzed (Camomilla et al. 2018; Sheerin et al. 2019). Special consideration should be given to sensor mass and the need for all 3 internal sensors as the derived metrics from some dynamic tasks may sacrifice accuracy with more massive IMUs instead of a single sensor (i.e., an accelerometer) (Forner-Cordero et al. 2008).

As most sports-related injuries involve the lower extremity, the most common site of IMU fixation is the tibia (Preatoni et al. 2022). Tibial shock is the most common reported variable when study participants play sports involving considerable distance running for its link to tibial stress fractures (Mathie et al. 2004; Zifchock et al. 2006; Crowell et al. 2010). Researchers should be wary of comparing study results in which different tibial sites of attachment (proximal or distal) were used as results will vary (Lucas-Cuevas et al. 2017). Further, the greater intensity of dynamic movements in the field relative to lab protocols show that IMU data collected in the field produces higher peak tibial accelerations compared to lab-based testing (Milner et al. 2020; Slaughter and Adamczyk 2020). The effects of fatigue, surface-interaction, and potentially other factors dictate that athletic loading measures collected on IMUs should be measured *in situ* during training or competition sessions (Boey et al. 2017; Johnson et al. 2020). Entropy analyses (see *IMUs and Non-linear Entropy Analysis* section) derived from accelerometer data have been used to quantify movement complexity and regularity in runners (Moe-Nilssen and Helbostad 2004; McGregor et al. 2009; Parshad et al. 2012; Schütte Kurt H et al. 2018; Rojas-Valverde et al. 2019). Nonlinear measures of movement regularity and complexity have been linked with pathophysiological conditions (Lamoth et al. 2010; Tochigi et al. 2012; Quirino et al. 2021; Gates et al. 2022) and may be suitable for injury forecasting in other athletic populations.

IMUs and similar global positioning system (GPS) units have been used to monitor athlete workloads in adults (i.e., (Arrones et al. 2014; Kempton et al. 2015; Gallo et al. 2016; Fox et al. 2018; Allard et al. 2022; Mamon et al. 2022) and youth athletes (Langendam et al. 2017; Ryan MR et al. 2021; Pino-Ortega et al. 2022) across soccer, football, rugby, basketball, and others. Commonly tracked variables include segment and whole-body accelerometry, speed, total distance covered, frequency and intensity of change-in-directions, proprietary workload metrics, etc.). Training loads can be categorized into 2 groups: external loads that are measures of the work done by the athlete (i.e., those listed in the previous paragraph) and internal loads which are biological stress responses to the external loads (Bourdon et al. 2017). The overarching purpose of these load monitoring investigations is to reduce overuse injury due to overtraining by optimizing athlete intra- and inter-session recovery.

Recently, these load monitoring paradigms are being applied to youth and adolescent soccer athletes (Barron et al. 2014; Castillo et al. 2020a, 2020b; Marynowicz et al. 2020; Nobari et al. 2021; Nobari et al. 2022; Salter et al. 2022). Adolescent athletes experiencing the effects of puberty are prone to inadequate recovery bouts between training and competition due to increases in training volume in conjunction with typical age-related academic and recreational activities (Phibbs et al. 2018). Additionally, adolescents are commonly subjected to training modalities that influence movement strategies and coordination (Venturelli et al. 2008; Rumpf et al. 2013; Deprez DN et al. 2015; Trecroci et al. 2015). Changes in the movement coordination of youth soccer players have been examined (Deprez D et al. 2014; Rommers et al. 2019) using a movement battery scoring system to measure gross motor coordination (Vandorpe et al. 2011; Iivonen et al. 2016). However, entropy-related measures of movement complexity have yet to be deployed on a population of developing (i.e., pubertal) soccer athletes.

Dynamical Systems Theory

Variability is inherent to human movement and motor performance across repetitions of dynamic tasks (Stergiou et al. 2006). In the field of motor control, the generalized motor program theory (Schmidt 1975) and uncontrolled manifold hypotheses (Schoner 1995) offer frameworks for explaining the systemic variability in our movement patterns. While these theories suggest that movement variability can be considered error in the face of a discrete movement outcome, dynamical systems theory (DST) focuses on the motor system behavior rather than the outcome (Kamm et al. 1990; Thelen et al. 1991; Thelen 1995). Specifically, DST states that, once a threshold of variability and system instability is created, a more stable movement pattern ("attractor state") is adopted to achieve a movement outcome (Stergiou and Decker 2011). This postulate suggests that trained, healthy individuals can execute a simple movement with any number of movement patterns and that naïve, unhealthy individuals will be forced to adopt more stable patterns out of necessity (Stergiou and Decker 2011).

While the blueprint outlining the cause for many overuse sports injuries has not yet been elucidated, many researchers have sought to characterize the different parameters that precede them so that future injuries can be forecast and potentially circumvented. Modelling the complex systems and elements producing these injuries is a difficult task. More sensitive and specific injury forecast models requiring the identification of "… factors that would prevent the state of the system from desired to undesired state shifts as a result of perturbations" (Tu et al. 2021, p.1). Many non-linear systems analyses aiming to prevent injury operate via holistic interpretation of the system's resilience and behavior both in the long-term and within attractor states. These goals require metrics that accurately reflect the behavior of the physiological signals measured in the system, a purpose served well by information theory and entropy.

Entropy

In the context of information theory, entropy is the loss of information in a time series and quantifies the probability of the next state of a system given a current state (Yentes 2018). A completely random, white noise signal would exhibit maximum entropy (in arbitrary units) compared to its reciprocal, a predictable sine wave or similar function. In his seminal paper, Shannon (1948) was trying to optimally design the framework for telephone communications, introducing the "bit" as the most basic unit of information and how it could be quantified in a signal. His work led to the invention of Huffman encoding and lossless data compression

(Huffman 1952) through the paradigm that source information contained redundancy and could be recreated by a signal containing fewer bits. In essence, Shannon viewed any chaotic process as a source of information and developed his entropy statistic as a metric to measure the amount of uncertainty in that process (Shannon 1948).

Almost 40 years later, Approximate entropy (ApEn) (Pincus 1991) was created to quantify the rate of regularity in a time data series:

$$\mathrm{ApEn}\ (m, r, N) = \lim_{N\to\infty} [\phi^m(r) - \phi^{m+1}(r)] \qquad \text{Eq. (2)}$$

and

$$\Phi^{\mathrm{m}}(\mathrm{r}) = (\mathrm{N} - \mathrm{m} + 1)^{-1} \sum_{i=1}^{N-m+1} ln\ \mathrm{C}_m^i(r) \qquad \text{Eq. (3)}$$

whereby *m* is the embedding template dimension, *r* is the resolution threshold, and *N* is the length of the time-series vector. The ApEn algorithm divides the series into vector templates of length *m* for comparison. Blocks are considered possible matches if the difference between all the corresponding block elements is ≤ *r*. Once that condition is met, if the subsequent point difference is also ≤ *r* then the blocks are a match and conditional probabilities calculated (template matches divided by possible matches). In layman's terms, ApEn is the "…(logarithmic) likelihood that runs of patterns that are close for *m* observations remain close on next incremental comparisons" and ApEn values approach zero for patterns in which successive points remain close with regularity (Pincus and Goldberger 1994, pp.H1644). A thorough explanation and interpretation is provided by Pincus & Goldberger (1994).

Sample entropy (SampEn) (Richman and Moorman 2000) was developed to address the regularity bias present from self-counting template matches in ApEn and sensitivity to smaller time series:

$$\text{SampEn}\ (m, r, N) = -ln\left(\frac{A}{B}\right) \qquad \text{Eq. (4)}$$

whereby *B* and *A* are defined as the total number of template matches of length *m* and total number of forward matches of length *m+1*, respectively:

$$A = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} A^m(r),\ \ B = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} B^m(r) \qquad \text{Eq. (5)}$$

Multiscale entropy (MScE) (Costa et al. 2002) was introduced to address the inconsistencies that the traditional ApEn and SampEn algorithms exhibited between random noise and physiologically complex signals. Some pathologies (i.e., cardiac arrythmias) have statistical properties associated with uncorrelated noise because of the erratic fluctuations in the original signal (Zeng and Glass 1996; Hayano et al. 1997; Di Rienzo 1998). MScE accounts for these complex temporal fluctuations by working across temporal scales via coarse-graining the original time series:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \qquad 1 \leqslant j \leqslant N/\tau \qquad \text{Eq. (6)}$$

before employing another entropy algorithm (typically SampEn) on the coarse-grained time series. Unlike ApEn and SampEn, MScE employs a 3rd parameter, τ, which signifies the number of time scales computed during the coarse-graining procedure prior to the execution of whichever base entropy analysis is preferred, ApEn or the more common SampEn. The area under the curve of the ApEn or SampEn values plotted across time scales, known as the complexity index (C_I), is defined as:

$$C_I = \sum_{i=1}^{\tau} \text{SampEn}(i) \qquad \text{Eq. (7)}$$

whereby we need only sum the entropy values (in this case, SampEn values) across the time scales of interest.

Previous studies have claimed that constant parameters *m* and *r* are suitable for analyzing physiological time series (Pincus 1991; Pincus and Huang 1992). Chon et al. (2009) developed equations to estimate maximum values for *r* by fitting multiple nonlinear least squares to Monte-Carlo simulations and normalizing *r* to the short-term (sd_1) and long-term (sd_2) variability of the signal based on the embedding dimension *m*:

$$\begin{aligned}
m = 2&: \hat{r}_{max} = \left(-0.036 + 0.26\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000} \\
m = 3&: \hat{r}_{max} = \left(-0.08 + 0.46\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000} \\
m = 4&: \hat{r}_{max} = \left(-0.12 + 0.62\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000} \\
m = 5&: \hat{r}_{max} = \left(-0.16 + 0.78\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000} \\
\mathrm{m} = 6&: \hat{r}_{max} = \left(-0.19 + 0.91\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000} \\
m = 7&: \hat{r}_{max} = \left(-0.2 + 1.0\sqrt{\mathrm{sd}_1/\mathrm{sd}_2}\right)/\sqrt[4]{N/1{,}000}
\end{aligned} \qquad \text{Eq. (8)}$$

Where for a sequence $x(n) = \{x(1), x(2), \ldots, x(N)\}$:

$$sd_1 = \{x(2) - x(1), x(3) - x(4), \ldots, x(N) - x(N-1)\} \qquad \text{Eq. (9)}$$

and sd_2 is simply the standard deviation of *x(n)*. This method results in *r* values that increase with sample size, however, and may be inappropriate for nonlinear signals (Castiglioni and Di Rienzo 2008; Liu et al. 2010). For most entropy analyses and datasets, *r* can be set between 10-30% of the standard deviation of the signal (Yentes et al. 2013).

Complexity

A complex system is one composed of many interwoven subunits whose constant interactions provide feedback to many of the individual subunits and drive the behavior of the system (Rickles et al. 2007). In the context of an athlete performing a movement task, the complex system entails the cellular and biochemical processes interacting to liberate energy for muscular fiber contraction to the central nervous system integrating sensory information to formulate further responses to environmental constraints. Patterns of complex behavior are dynamic and self-organizing, meaning that the state of the system at a given time point depends on the previous states and determines future states (Adami 2002). The human body is a complex system in that it operates within certain physiological constraints yet still exhibits variability in how it accomplishes most homeostatic processes.

Dynamical Systems in Injury Prevention and Sport Performance

The resilience of a complex system is operationally defined as its ability to maintain its operational status in the presence of perturbations, whereby the duration of the system response to the perturbation is inversely proportional to the resiliency of the system (Arnoldi et al. 2016; May 2019). Attractor states are defined as a system's convergence towards or divergence from a set of states, and in this biomechanical context an example could be the coordination patterns between joints used to navigate the demands imposed by the system (Hill et al. 2018). Injuries are the undesirable attractor to which the system is moved towards by specific biomechanical perturbations (excessive tissue loading during dynamic movements, initial joint contact angles, lack of tissue recovery, joint coordination, etc.). Previous biomechanics investigations have quantified complexity differences within human movement and trends delineating variation between groups (e.g., pathological and non-pathological) in measured biological signals via entropy analyses (Costa et al. 2002; Costa et al. 2003; McGregor et al. 2009; Bisi and Stagni 2016; Gruber et al. 2021; Gates et al. 2022).

ApEn has been used to quantify the regularity of postural sway in concussed athletes (Cavanaugh et al. 2006), minimal toe clearance in elderly adults during treadmill walking (Karmakar et al. 2007), and knee kinematics during walking between legs in ACLR patients (Georgoulis et al. 2006). Currently (for reasons outlined in the next paragraph), there is a paucity of ApEn analyses deployed on IMU-derived data. However, some investigations have used this approach to validate IMU and force plate postural sway comparisons (Soangra and Lockhart

2013); to examine the influence of fatigue on trunk acceleration variability during walking (Soangra et al. 2017); and as a correlate with other external load indicators of musculoskeletal injury in trail running (Rojas-Valverde et al. 2019). SampEn used in conjunction with IMU-based signals have been correlated with VO_2, blood lactate, energy cost, and medial tibial stress syndrome during running (Murray AM et al. 2017; Schütte K. H. et al. 2018; Schütte Kurt H et al. 2018). With IMUs, MScE has been used to highlight differences between fallers and non-fallers in elderly walkers (Howcroft et al. 2016; Bizovska et al. 2017), as well as comparisons of stride variability between treadmill and overground running (Lindsay et al. 2014).

Conclusion

Prevention of overuse and non-contact injuries is paramount in youth sports as injured individuals are at risk of re-injury and complications when returning to play or later in life (Taylor et al. 1993; Barber-Westin and Noyes 2011; Friel and Chu 2013; Herzog et al. 2019). While training load monitoring is becoming more common in youth soccer, movement complexity has not yet been considered for quantifying movement complexity during puberty nor for assessing injury risk. This population of athletes experiences physiological changes at rates which predispose them to certain sports-related injuries and monitoring movement complexity via IMUs in the field may provide insight into how these injuries may be prevented.

Chapter 3. Methods

The purpose of this study is to collect IMU linear acceleration data from adolescent soccer athletes and determine if derived linear acceleration metrics (discretized peak accelerations, binned acceleration frequencies, etc.) or overall signal complexity differs between groups stratified by pubertal status or over the course of a season.

Participants

Participants were recruited via word of mouth, fliers, social media, and emails. If participants are recruited via word of mouth, flyer (***Appendix D***), or social media, an email containing a pre-approved email script (***Appendix C***) will be sent to the participant's guardian to ensure they are still interested and qualified to participate in the study. Healthy adolescent soccer players between 9 and 17 years will be asked to participate in the study. Due to the paucity of literature regarding mixed-model statistical entropy comparisons, we planned for medium effect sizes between groups. An *a priori* power analysis for a mixed model repeated measures ANOVA with an *alpha* of 0.05, a *beta* of 0.80, and effect size (*f*) of 0.20 indicated that a minimum of 66 participants (22 per group) are needed.

Each participant and their guardian will provide written informed assent and consent, respectively, as well as complete the Lower Extremity Functional Scale (LEFS)(Binkley et al. 1999) and a musculoskeletal health history questionnaire. Participants will be excluded from testing if they have not been participating in club soccer training or play at least twice per week. Inclusion criteria includes the following: no history of lower extremity surgical repair, no lower extremity injuries within the past six months, and no lower extremity pain on the day of testing.

Experimental Procedures

Data collections were preceded by the informed consent and assent process prior to any testing. Participants and their guardian(s) met with the primary investigator to give consent and assent before filling out the LEFS and musculoskeletal questionnaire. Height and seated height were measured via stadiometer and mass via digital scale. Sex-specific equations (Mirwald et al. 2002) utilizing standing height, seated height, leg length, and age were used to estimate the time offset (in years) of each participant from their PHV:

$$\begin{aligned} &\text{Male Maturity Offset (years)} \\ &\quad = -9.236 + 0.0002708 \times (\text{Leg Length} \times \text{Sitting Height}) \\ &\quad - 0.001663 \times (\text{Age} \times \text{Leg Length}) + 0.007216 \times (\text{Age} \times \text{Sitting Height}) \\ &\quad + 0.02292 \times ((\text{Weight/Height}) \times 100) \end{aligned} \qquad \text{Eq. (10)}$$

$$\begin{aligned} &\text{Female Maturity Offset (years)} \\ &\quad = -0.376 + 0.0001882 \times (\text{Leg Length} \times \text{Sitting Height}) \\ &\quad + 0.0022 \times (\text{Age} \times \text{Leg Length}) + 0.005841 \times (\text{Age} \times \text{Sitting Height}) \\ &\quad - 0.002658 \times (\text{Age} \times \text{Weight}) + 0.07693 \times (\text{Weight/Height} \times 100) \end{aligned} \qquad \text{Eq. (11)}$$

All experimental testing (see **Figure 1**) took place following a brief dynamic warm-up and each drill was completed one (1) time successfully (i.e., no slipping, maximal effort, etc). Participants were then fitted with small inertial measurement units (IMUs) on their distal-medial tibia just superior to the medial malleolus and data collection began with an “easy pace” jog lengthwise down the field and back. Following the jog, each subsequent drill was completed by each participant, beginning with a 40-yard (36.6 meters) dash. Then, participants completed an M-cone drill in which they sprinted and changed direction rapidly around a series of cones in both directions. Then participants completed a 5-10-5 shuffle drill where they began by straddling a central cone and then laterally shuffling between cones placed 5 meters from the middle cone. Finally, participants performed a broad jump for maximum horizontal displacement. Following the triple hop task, each participant had completed testing. The participants were then asked to complete the same experimental protocol following the end of their season (~3 months later, e.g., February through May).

Instrumentation

A fixed stadiometer was be used to measure participant standing height and then seated height and leg length, respectively, to the nearest millimeter. An IMU with high-g accelerometer (1600 Hz; Vicon Blue Trident, Vicon Motion Systems Ltd, Oxford, UK) was used to measure 3D linear accelerations at the tibia during testing. These data was then imported into Python v3.10.4 (Python Software Foundation, Beaverton, OR, USA) computing software for subsequent data processing and analysis and R 4.2.1 (R Foundation for Statistical Computing, Vienna, AUST) for visualization.

Data Reduction & Analysis

Raw data was imported from the IMU sensors for entropy analysis. The EntropyHub toolkit (Flood and Grimm 2021) has functions native to both Python and was used to analyze the acceleration time series for each experimental task (jog, 40-yard dash, M-cone drill, 5-10-5 shuffle drill, and broad jump). For each resultant acceleration-time series, we calculated the Multiscale Entropy (MScE) of the signal (Costa et al. 2002; McGregor et al. 2009; Parshad et al. 2012). MScE values are unitless and used to examine signal regularity on different temporal scales by coarse-graining the original time series via:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \qquad 1 \leqslant j \leqslant N/\tau \qquad \text{Eq. (12)}$$

Once the time series has been “coarse-grained,” Sample Entropy (SampEn) is then calculated for each new time scale:

$$\text{SampEn } (m, r, N) = -ln\left(\frac{A}{B}\right) \qquad \text{Eq. (13)}$$

whereby *B* and *A* are defined as the total number of template matches of length *m* and total number of forward matches of length *m+1*, respectively:

$$A = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} A^m(r),\ \ B = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} B^m(r) \qquad \text{Eq. (14)}$$

This allows for SampEn values to be plotted at each time scale and, by calculating the area under this curve, complexity index (CI) may be reported. The data cleaning and analysis process can be visualized in **Figures 4 & 5**.

Further, discrete peak resultant acceleration magnitudes and cumulative acceleration were reported. Peak resultant accelerations were the greatest magnitude resultant acceleration in each trial. Integrated acceleration was calculated as the area under the resultant acceleration curve. Both can be respectively thought of as the peak and cumulative loading experienced during each task.

Statistical Analysis

Linear mixed effects regression (LMER) was chosen for this study over traditional repeated measures ANOVA due to its ability to account for variability originating from both participants and the independent variables and preservation of statistical power {Brown, 2021 #373}. The 'lme4' package (Bates D et al. 2014) in R was used to conduct all LMER tests and all assumption tests (i.e., linearity, homoscedasticity (equal variances), and normality of residuals) carried out with the R 'performance' package (Lüdecke et al. 2021). Diagnostic plots were used to visually inspect residuals against predicted values (linearity), across levels of the independent variables (homoscedasticity), and against a normal distribution (Q-Q plot for normality).

An iterative method was used to develop the LMER models, initiated with a null model and successively incorporating fixed effects until a complete model was achieved. The process began with the formation of a null model only including random effects, providing a benchmark for subsequent model performance. Subsequent to the formation of the null model, fixed effects were methodically added one at a time (PHV offset followed by sex and then testing session) to determine their effect on modelling the relationship with CI. With the addition of each new fixed effect, the current model was compared to its predecessor. The comparison aimed to assess the model using Akaike (AIC) and Bayesian (BIC) Information Criterion, marginal and conditional R^2, intraclass correlation coefficients (ICC), and root-mean-square error (RMSE) values as guides. The iterative process continued until all fixed effects had been integrated, thus arriving at the full model. An essential consideration throughout this process was to maintain a balance between model complexity and model fit, ensuring the final model was neither underfitted nor overfitted. This systematic, iterative approach enabled a robust and quantitative evaluation of the contribution of each fixed effect and facilitated the construction of a model that optimally represented the data.

Chapter 4: *Relationship between multiscale entropy measures, accelerometry, and peak height velocity in adolescent soccer players*

Introduction

Puberty is a critical period of development characterized by rapid changes in body composition, physical attributes, and hormonal levels. These changes can significantly influence competitive performance and injury risk in adolescent athletes. In sports such as soccer, puberty-related changes can affect the biomechanics of movement, potentially leading to an increased risk of injuries (Ford et al. 2010; Bergeron et al. 2015). Overuse injuries are particularly common in children and adolescents who participate in sports. These injuries occur because of repetitive submaximal loading of the musculoskeletal system, which can lead to microtrauma and eventual tissue damage (Myer et al. 2011; Valovich McLeod et al. 2011). The risk of overuse injuries is further increased during puberty, due to the rapid growth and changes in body composition that occur during this period (Ford et al. 2010; Myer et al. 2013). This risk may also differ between sexes as girls typically begin exhibiting puberty-related changes before boys (Hewett et al. 2006; Ford et al. 2010). Current methods for tracking injury risk factors in adolescent athletes include the use of global positioning system (GPS) distances covered, center of mass (CoM) acceleration peaks, total accelerations and decelerations, etc. (Hartwig et al. 2011; Malone et al. 2015; Haddad et al. 2017; Jones et al. 2017; McLaren et al. 2018). However, these methods provide a one-dimensional view of the biomechanical loads experienced by the athletes. Multiscale entropy (MSE) analysis is a powerful tool that allows for the examination of the complexity of biological signals over multiple temporal scales. This method has been used to analyze various biological signals, including heart rate variability and gait dynamics, providing insights into the health and function of the system under study (Bosl et al. 2011; Bravi et al. 2011; Riva et al. 2013). The use of MSE analysis in the context of adolescent athletes is justified by the potential insights it can provide into how puberty-related changes affect movement patterns and injury risk. Specifically, changes in movement complexity, as measured by MSE, could be indicative of altered biomechanics and increased injury risk. Therefore, the purpose of this study is to investigate the impact of puberty, sex, and time on the biomechanics of movement in adolescent soccer players using MSE analysis. Our primary hypothesis is that puberty-related changes will result in altered movement complexity and our secondary hypothesis is that sex and testing session will also alter movement complexity.

Methods

Participants

Table 1. Participant characteristics

	Male (n = 55)	Female (n = 52)
Age (years)	12.29 (1.23)	12.77 (1.18)
Height (cm)	154.18 (10.83)	157.92 (8.1)
Mass (kg)	44.62 (10.65)	48.04 (9.63)
PHV offset (years)	-1.82 (1.2)	0.63 (1.04)

Participants were recruited via word of mouth, fliers, social media, and emails. If participants were recruited via word of mouth, flyer (Appendix D), or social media, an email containing a pre-approved email script (Appendix C) was sent to the participant's guardian to ensure they were still interested and qualified to participate in the study. Healthy adolescent soccer players between 9 and 17 years were asked to participate in the current study. Due to the paucity of literature regarding mixed-model statistical entropy comparisons, we planned for medium effect sizes between groups. An a priori power analysis for a mixed model repeated measures ANOVA with an *alpha* of 0.05, a *beta* of 0.80, and effect size (*f*) of 0.20 indicated that a minimum of 66 participants (22 per group) were needed.

Once guardian consent had been obtained, each participant provided written informed assent and completed the Lower Extremity Functional Scale (LEFS) (Binkley et al. 1999) and a musculoskeletal health history questionnaire. Participants were excluded from testing if they had not been participating in club soccer training or play at least twice per week. Inclusion criteria included the following: no history of lower extremity surgical repair, no lower extremity injuries within the past six months, and no lower extremity pain on the day of testing.

Experimental Procedures

Data collections were preceded by the informed consent and assent process prior to any testing. Participants and their guardian(s) met with the primary investigator to give consent and assent before filling out the LEFS and musculoskeletal questionnaire. Height was measured via stadiometer and all other measurements were performed by the same investigator three times with the median measurement being reported. Once the investigator had obtained all IRB documents and anthropometric measurements, the participant was stratified into their experimental group. Sex-specific equations (Mirwald et al. 2002) utilizing standing height, seated height, leg length, and age were used to estimate the time offset (in years) of each participant from their PHV:

$$\begin{aligned}\text{Male Maturity Offset (years)} &\\ &= -9.236 + 0.0002708 \times (\text{Leg Length} \times \text{Sitting Height})\\ &- 0.001663 \times (\text{Age} \times \text{Leg Length}) + 0.007216 \times (\text{Age} \times \text{Sitting Height})\\ &+ 0.02292 \times ((\text{Weight}/\text{Height}) \times 100)\end{aligned} \qquad \text{Eq. (10)}$$

$$
\begin{aligned}
&\text{Female Maturity Offset (years)} \\
&\quad = -0.376 + 0.0001882 \times (\text{Leg Length} \times \text{Sitting Height}) \\
&\quad + 0.0022 \times (\text{Age} \times \text{Leg Length}) + 0.005841 \times (\text{Age} \times \text{Sitting Height}) \\
&\quad - 0.002658 \times (\text{Age} \times \text{Weight}) + 0.07693 \times (\text{Weight/Height} \times 100)
\end{aligned}
\qquad \text{Eq. (11)}
$$

All experimental testing (see **Figure 1**) took place following a brief dynamic warm-up and each drill was completed one time. Participants were then fitted with inertial measurement units (IMUs) on their distal-medial tibia just superior to the medial malleolus and data collection began with an “easy pace” jog lengthwise down the field and back. Following the jog, each subsequent drill was completed once by each participant, beginning with a 40-yard (36.6 meters) dash. Then, participants completed an M-cone drill in which they sprinted and changed direction rapidly around a series of cones in both directions. Then participants completed a 5-10-5 shuffle drill where they began by straddling a central cone and then laterally shuffled between cones placed 5 meters from the middle cone. Finally, participants performed a broad jump for maximum horizontal displacement. Following the broad jump, each participant had completed testing. The participants were then asked to complete the same experimental protocol following the end of their season (~3 months later, e.g., February through May).

Instrumentation

A fixed stadiometer was used to measure participant standing height and then seated height to calculate leg length to the nearest millimeter. An IMU (1600 Hz; Vicon Blue Trident, Vicon Motion Systems Ltd, Oxford, UK) was used to measure 3D linear accelerations at the tibia during testing. These data were then imported into Python v3.10.4 (Python Software Foundation, Beaverton, OR, USA) computing software for subsequent data processing and analysis and R 4.2.1 (R Foundation for Statistical Computing, Vienna, AUST) for visualization.

Data Reduction & Analysis

Raw data were imported from the IMU sensors for entropy analysis. The EntropyHub toolkit (Flood and Grimm 2021) has native Python functions and was used to analyze the acceleration time series for each experimental task (jog, 40-yard dash, M-cone drill, 5-10-5 shuffle drill, and broad jump). For each resultant acceleration-time series, we calculated the Multiscale Entropy (MScE) of the signal (Costa et al. 2002; McGregor et al. 2009; Parshad et al. 2012). MScE values are unitless and used to examine signal regularity on different temporal scales by coarse-graining the original time series:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \qquad 1 \leqslant j \leqslant N/\tau \qquad \text{Eq. (12)}$$

Once the time series has been coarse-grained, Sample Entropy (SampEn) is then calculated for each new time scale:

$$\text{SampEn}\ (m, r, N) = \ -ln\left(\frac{A}{B}\right) \qquad \text{Eq. (13)}$$

whereby *B* and *A* are defined as the total number of template matches of length *m* and total number of forward matches of length *m+1*, respectively:

$$A = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} A^m(r),\ \ B = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} B^m(r) \qquad \text{Eq. (14)}$$

This allows for SampEn (m = 2, r = 0.2*SD, τ = 16) values (determined a priori via pilot testing and parameterization) to be plotted at each time scale and, by calculating the area under this curve, complexity index (CI) may be reported. The data cleaning and analysis process can be visualized in **Figures 4 & 5**.

Commented [J1]: Need more information. What was the m and r? How many time scales?

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Statistical Analysis

Linear mixed effects regression (LMER) was chosen for this study due to its ability to handle repeated measures and non-independence in the data. The ‘lme4’ package (Bates D et al.

2014) in R was used to conduct all LMER tests. Before conducting the analysis, the assumptions of the linear mixed model were checked (i.e., linearity, homoscedasticity (equal variances), and normality of residuals) using the R ‘performance’ package (Lüdecke et al. 2021). Diagnostic plots were used to visually inspect these assumptions. Linearity was checked by plotting the residuals against the predicted values. Homoscedasticity was assessed by looking at the spread of residuals across levels of the independent variables. Normality of residuals was checked using a Q-Q plot, where the residuals are plotted against a normal distribution.

An iterative method was used to develop the LMER models, initiated with a null model and successively incorporating fixed effects until a complete model was achieved. The process began with the formation of a null model only including random effects, providing a benchmark for subsequent model performance. Subsequent to the formation of the null model, fixed effects were methodically added one at a time (PHV offset followed by sex and then testing session) to determine their effect on modelling the relationship with CI. With the addition of each new fixed effect, the current model was compared to its predecessor. The comparison aimed to assess the model using Akaike (AIC) and Bayesian (BIC) Information Criterion, marginal and conditional R^2, intraclass correlation coefficients (ICC), and root-mean-square error (RMSE) values as guides. The iterative process continued until all fixed effects had been integrated, thus arriving at the full model. An essential consideration throughout this process was to maintain a balance between model complexity and model fit, ensuring the final model was neither underfitted nor overfitted. This systematic, iterative approach enabled a robust and quantitative evaluation of the contribution of each fixed effect and facilitated the construction of a model that optimally represented the data.

Results

CI results parsed by drill, session, and sex can be found in **Table 2**. Model comparisons for CI by drill are detailed in **Tables 3-8**. Interestingly, the null LMER models, which only incorporated random effects, consistently matched the fit of the more complex models which also considered PHV, sex, and testing session. This suggests that the added fixed effects in subsequent models are not capturing the relationship with CI in this context.

Table 2. CI results

	Female		**Male**	
Drill	**Pre**	**Post**	**Pre**	**Post**
40yd	6.98 (0.91)	7.11 (1.03)	6.95 (1.03)	7.08 (0.96)
5-10-5	4.94 (0.82)	5.08 (0.97)	5.32 (0.9)	5.25 (0.87)
Broad	3.16 (1.28)	3.37 (1.27)	3.15 (1.28)	3.37 (1.3)
DNB	6.39 (1.31)	6.25 (1.4)	6.15 (1.43)	6.45 (1.35)
M-L	5.63 (0.94)	5.78 (0.95)	5.68 (0.84)	5.78 (1.02)
M-R	5.49 (0.93)	5.79 (0.94)	5.61 (0.92)	5.66 (0.92)

Table 3. Model comparisons for 40yd dash drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	6.971***	6.989***	6.952***	6.917***
	(0.079)	(0.085)	(0.123)	(0.131)
PHV		0.030	0.052	0.052
		(0.048)	(0.071)	(0.071)
SEX (Male)			0.099	0.099
			(0.237)	(0.237)
SESSION (Post-season)				0.071
				(0.088)
SD (Intercept SUBJECT)	0.684	0.686	0.690	0.690
SD (Observations)	0.641	0.641	0.641	0.642
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.003	0.004	0.005
R2 Cond.	0.532	0.535	0.539	0.538
AIC	552.2	558.1	561.0	565.3
BIC	562.3	571.6	577.8	585.5
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.51

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Model comparisons for 5-10-5 drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	4.946***	4.907***	4.797***	4.805***
	(0.075)	(0.080)	(0.114)	(0.122)
PHV		-0.063	0.004	0.004
		(0.045)	(0.066)	(0.066)
SEX (Male)			0.299	0.299
			(0.222)	(0.222)
SESSION (Post-season)				-0.016
				(0.089)
SD (Intercept SUBJECT)	0.625	0.621	0.617	0.616
SD (Observations)	0.640	0.640	0.640	0.643
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.014	0.026	0.026
R2 Cond.	0.489	0.492	0.496	0.492
AIC	528.9	533.3	534.7	539.7
BIC	538.9	546.7	551.4	559.8
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.52

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Model results for Broad Jump drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	3.162***	3.179***	3.139***	2.993***
	(0.093)	(0.099)	(0.144)	(0.160)
PHV		0.028	0.052	0.052
		(0.056)	(0.084)	(0.084)
SEX (Male)			0.109	0.109
			(0.277)	(0.277)
SESSION (Post-season)				0.291*
				(0.141)
SD (Intercept SUBJECT)	0.607	0.612	0.618	0.631
SD (Observations)	1.048	1.048	1.048	1.033
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.002	0.017
R2 Cond.	0.251	0.255	0.260	0.284
AIC	690.2	695.9	698.5	698.4
BIC	700.3	709.4	715.3	718.5
ICC	0.3	0.3	0.3	0.3
RMSE	0.94	0.93	0.93	0.91

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Model results for M-drill (Left)

	NULL	Model 1	Model 2	Model 3
(Intercept)	5.782***	5.771***	5.714***	5.710***
	(0.072)	(0.077)	(0.111)	(0.121)
PHV		-0.016	0.018	0.018
		(0.043)	(0.065)	(0.065)
SEX (Male)			0.154	0.154
			(0.214)	(0.214)
SESSION (Post-season)				0.008
				(0.097)
SD (Intercept SUBJECT)	0.546	0.550	0.552	0.550
SD (Observations)	0.709	0.709	0.709	0.712
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.004	0.004
R2 Cond.	0.372	0.376	0.380	0.377
AIC	552.2	558.5	561.2	566.0
BIC	562.3	571.9	578.0	586.2
ICC	0.4	0.4	0.4	0.4
RMSE	0.60	0.60	0.60	0.60

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Model results for M-drill (Right)

	NULL	Model 1	Model 2	Model 3
(Intercept)	5.494***	5.503***	5.481***	5.387***
	(0.071)	(0.076)	(0.110)	(0.118)
PHV		0.014	0.028	0.028
		(0.043)	(0.064)	(0.064)
SEX (Male)			0.059	0.059
			(0.212)	(0.212)
SESSION (Post-season)				0.187*
				(0.084)
SD (Intercept SUBJECT)	0.582	0.586	0.590	0.596
SD (Observations)	0.627	0.627	0.627	0.616
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.001	0.013
R2 Cond.	0.463	0.467	0.470	0.490
AIC	523.1	529.4	532.6	532.9
BIC	533.2	542.9	549.4	553.1
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.50

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Model results for DNB drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	6.144***	6.100***	6.255***	6.170***
	(0.110)	(0.117)	(0.172)	(0.186)
PHV		-0.069	-0.160	-0.160
		(0.066)	(0.099)	(0.099)
SEX (Male)			-0.406	-0.406
			(0.330)	(0.330)
SESSION (Post-season)				0.171
				(0.138)
SD (Intercept SUBJECT)	0.874	0.873	0.870	0.871
SD (Observations)	1.005	1.005	1.005	1.003
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.008	0.018	0.022
R2 Cond.	0.430	0.434	0.438	0.442
AIC	702.5	707.0	707.9	710.5
BIC	712.6	720.4	724.6	730.6
ICC	0.4	0.4	0.4	0.4
RMSE	0.84	0.84	0.84	0.83

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion

In the realm of sports science, the biomechanics of movement in adolescent athletes has been a topic of growing interest. The onset of puberty introduces a myriad of physiological changes that can significantly impact an athlete's performance and injury risk. In this study, we hypothesized that puberty- and sex-related changes would result in altered movement complexity. However, our results did not support our primary or secondary hypotheses. Despite an adequately powered study design and careful measurement of key variables such as PHV, sex, and testing session, we found no significant effects of these variables on the complexity index (CI) calculated from 3D resultant tibial accelerometer signals.

Our study was adequately powered as stated in the methods section. However, it's important to note that statistical power is not a guarantee of significant results. It merely increases the likelihood of detecting a true effect if one exists. The lack of significant findings could potentially be attributed to the true absence of an effect rather than a lack of power. This could suggest that the variables we studied may not have a significant impact on the calculated complexity index (CI) in the context of adolescent soccer players performing these discrete drills. PHV was estimated from chronological age, height, weight, and leg length based on sex-specific equations. This is a common, non-invasive method used to estimate the timing of PHV (Van Der Sluis Alien et al. 2013; Van der Sluis A et al. 2015), especially in field settings where more invasive measures are not feasible. However, it's worth noting that this method provides an estimate and not an exact measure of PHV, which itself is only a highly correlated surrogate measure of pubertal development (Kelly et al. 2014){Granados, 2015 #372}. Furthermore, the impact of puberty on biomechanics is complex and may not be fully captured by PHV alone.

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Our study included children aged 9-17, a range that encompasses the typical age of pubertal onset and progression. This means that our sample likely included children at various stages of pubertal development, from pre-pubertal to post-pubertal. Puberty is a time of significant physiological changes, including changes in body composition, muscle development, and motor control, all of which could potentially impact biomechanics. However, these changes are not linear and can vary greatly between individuals. This variability could have introduced noise into our data, making it harder to detect significant effects. Further, only one trial of each drill was analyzed from both testing sessions. This was necessary due to logistical constraints but not ideal as collecting several trials could have allowed for more stable metric calculations following averaging of trials. The CI, a novel and complex measure in this context, was calculated from 3D resultant tibial accelerometer signals. However, it's possible that the CI may not be sensitive to the variables we studied. In other words, factors such as age, sex, and PHV may not have a significant impact on movement complexity as captured by the CI. Another plausible explanation is that other sources of noise were present and exacerbating the variability of the accelerometer signals used in our calculations. Whether these noise sources would be biological in nature or the product of some measurement error or both is unclear, but their presence would unduly influence our statistical results.

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Fix in Chapter 3 as well if necessary.

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Commented [J7]: Could it also be due to high variability in the accelerometer signal? Creating "noise" that we cannot discern if it is error in the measurement or true biological variability from MScSE?

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LMER was the appropriate statistical approach for our study design, which included repeated measures and random effects. However, like any statistical test, LMER has certain assumptions and limitations. One key assumption is that the relationship between the predictors and the outcome variable is linear. If this assumption is violated, the results of the LMER may not be valid. In our case, it's possible that the relationship between our predictors and the CI is not linear, which could explain our lack of significant findings. Stature, weight, and timing of pubertal-related changes in these PHV-predictors has been posited to hold a non-linear relationship{Marceau, 2011 #374}, as well as the possibility that alterations to brain function {Gracia-Tabuenca, 2021 #375} could potentially affect movement complexity in a non-linear fashion.

Commented [J9]: Briefly expand on this and provide an explanation. What makes you think the relationship between any predictor and CI may not be linear.

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In conclusion, our hypothesis that PHV and other associated factors were predictive of movement complexity in adolescent soccer players was not supported by our findings. However, future directions could focus on other variables (i.e., tibial acceleration metrics associated with lower extremity loading), explore alternate accelerometer placements, and investigate whether rate of change in PHV contributes to changes in movement complexity.

Chapter 5: *Relationship between peak height velocity and tibial acceleration metrics in adolescent soccer players*

Introduction

Athlete load monitoring has become a popular topic with regards to managing external loading on biological tissues to reduce injury rates (West et al. 2021). Of note, accelerometers have been garnering favor over gold-standards biomechanical motion capture systems for the fact that they can be used to collect impact and loading data during practice and games (Cummins et al. 2013; Dalen et al. 2016). Though many of the loads and impacts placed on tissues during dynamic movements (i.e., landing, cutting, accelerating and decelerating, etc.) are submaximal, the magnitude of the loading in relation to the failure point of the tissues and the cumulative effects of exposure to cycles of these loads can lead to overuse injuries in these athletes, particularly in adolescent athletes (Myer et al. 2011; Valovich McLeod et al. 2011). The confounding rapid physiological changes accompanying puberty in these athletes affects tissue morphology and distribution, which further impacts movement coordination and biomechanics that increases injury risk (Ford et al. 2010; Myer et al. 2013). Overuse injury risk in pubertal athletes is also modified by sex due to the differential timing in puberty onset between girls and boys (Ford et al., 2010; Hewett, Myer, Ford, & Slauterbeck, 2006. Further, while normal puberty-related tissue changes (e.g., epiphyseal bone remodeling) will predispose these athletes to certain overuse injuries, fatigue-related damage through excessive training intensities and volumes over the course of a competitive season should also be taken into account (Drew and Finch 2016; Murray A 2017).

While the predominant method for accelerometry-based load monitoring has been either global positioning system (GPS) based (Rago et al. 2020; de Dios-Álvarez et al. 2023) or utilized

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an accelerometer fixed near the center-of-mass (CoM) (Aristizábal Pla et al. 2021) in these athletes, little to no data has been collected at the site of most sport-related injuries: the lower-extremity. Tibial-mounted accelerometry has used measured accelerations as a surrogate measure for impact loading during running and other dynamic tasks (Butler et al. 2007; García-Pérez et al. 2014; McGinnis et al. 2016; Sandrey et al. 2019). Some have also integrated metrics over the duration of tasks and movements for the purpose of quantifying 'cumulative loading effects' on tissues (Miller et al. 2015; Kiernan et al. 2018), though none have examined anything resembling cumulative tibial loading in this population in a longitudinal context.

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Therefore, the purpose of this study was to investigate the impact of puberty, sex, and time on the peak and cumulative tibial accelerations in adolescent soccer players. We primarily hypothesize that puberty-related changes will result in altered peaks and cumulative acceleration metrics. Our secondary hypothesis is that differences in peaks and cumulative accelerations will also present as a function of sex and testing session.

Methods

Participants

Participants were recruited via word of mouth, fliers, social media, and emails. If participants were recruited via word of mouth, flyer (Appendix D), or social media, an email containing a pre-approved email script (Appendix C) was sent to the participant's guardian to ensure they were still interested and qualified to participate in the study. 90 healthy adolescent soccer players either pre-, mid-, or post-peak height velocity (PHV) (30 per group), between 9 and 17 years were asked to participate in the current study. Due to the paucity of literature regarding mixed-model statistical entropy comparisons, we planned for small effect sizes between groups. An a priori power analysis for a mixed model repeated measures ANOVA with an *alpha* of 0.05, a *beta* of 0.80, and effect size (*f*) of 0.20 indicated that a minimum of 66 participants (22 per group) are needed.

Table 8. Participant characteristics

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	Male (n = 55)	Female (n = 52)
Age (years)	12.29 (1.23)	12.77 (1.18)
Height (cm)	154.18 (10.83)	157.92 (8.1)
Mass (kg)	44.62 (10.65)	48.04 (9.63)
PHV offset (years)	-1.82 (1.2)	0.63 (1.04)

Each participant provided assent following guardian consent, as well as a completed Lower Extremity Functional Scale (LEFS) (Binkley et al. 1999) and musculoskeletal health history questionnaire. Participants were excluded from testing if they had not been participating in club soccer training or play at least twice per week. Inclusion criteria included the following: no history of lower extremity surgical repair, no lower extremity injuries within the past six months, and no lower extremity pain on the day of testing.

Experimental Procedures

Data collections were preceded by the informed consent and assent process prior to any testing. Participants and their guardian(s) met with the primary investigator to give consent and assent before filling out the LEFS and musculoskeletal questionnaire. Height was measured via stadiometer and all other measurements were performed by the same investigator three times with the median measurement being reported. Once the investigator had obtained all IRB documents and anthropometric measurements, the participant was stratified into their experimental group. Sex-specific equations (Mirwald et al. 2002) utilizing standing height, seated height, leg length, and age were used to estimate the time offset (in years) of each participant from their PHV:

$$\begin{aligned}\text{Male Maturity Offset (years)} &\\ = -9.236 + 0.0002708 \times (\text{Leg Length} \times \text{Sitting Height}) &\\ - 0.001663 \times (\text{Age} \times \text{Leg Length}) + 0.007216 \times (\text{Age} \times \text{Sitting Height}) &\\ + 0.02292 \times ((\text{Weight/Height}) \times 100)\end{aligned} \quad \text{Eq. (10)}$$

$$\begin{aligned}\text{Female Maturity Offset (years)} &\\ = -0.376 + 0.0001882 \times (\text{Leg Length} \times \text{Sitting Height}) &\\ + 0.0022 \times (\text{Age} \times \text{Leg Length}) + 0.005841 \times (\text{Age} \times \text{Sitting Height}) &\\ - 0.002658 \times (\text{Age} \times \text{Weight}) + 0.07693 \times (\text{Weight/Height} \times 100)\end{aligned} \quad \text{Eq. (11)}$$

All experimental testing (see **Figure 1**) took place on an indoor, synthetic turf soccer field following a brief dynamic warm-up and each drill was completed 3 times. Participants were then fitted with small inertial measurement units (IMUs) on their distal-medial tibia just superior to the medial malleolus and data collection began with an "easy pace" jog lengthwise down the field and back. Following the jog, each subsequent drill was completed 3 times by each participant, beginning with a 40-yard (36.6 meters) dash. Then, participants completed an M-cone drill in which they sprinted and changed direction rapidly around a series of cones in both directions. Then participants completed a 5-10-5 shuffle drill where they began by straddling a central cone and then laterally shuffled between cones placed 5 meters from the middle cone. Finally, participants performed a broad jump for maximum horizontal displacement. Following the triple hop task, each participant had completed testing. The participants were then asked to

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complete the same experimental protocol following the end of their season (~3 months later, e.g., February through May).

Instrumentation

A fixed stadiometer was used to measure participant standing height and then seated height and leg length to the nearest millimeter. An IMU with high-g accelerometer (1600 Hz; Vicon Blue Trident, Vicon Motion Systems Ltd, Oxford, UK) was used to measure 3D linear accelerations at the tibia during testing. These data were then imported into Python v3.10.4 (Python Software Foundation, Beaverton, OR, USA) computing software for subsequent data processing and analysis and R 4.2.1 (R Foundation for Statistical Computing, Vienna, AUST) for visualization.

Data Reduction & Analysis

Raw data were imported from the IMU sensors and cleaned (**Figure 4**) before 3D resultant accelerations and acceleration integrals were calculated for each experimental task (jog, 40-yard dash, M-cone drill, 5-10-5 shuffle drill, and broad jump). Each axial component (**Figure 3**) of the accelerometer signal at each time point within a trial was used to calculate the 3D resultant acceleration:

$$A_R = \sqrt{{A_x}^2 + {A_y}^2 + {A_z}^2} \qquad \text{Eq. (15)}$$

Acceleration integrals was calculated as the area under the resultant acceleration curve (though not for the broad jump drill). Both can be respectively thought of as the peak and cumulative loading experienced during each task.

Statistical Analysis

Due to the longitudinal component of testing, linear mixed effects regression (LMER) was chosen for this study and carried out in R using the 'lme4' package (Bates D et al. 2014). The R 'performance' package (Lüdecke et al. 2021) was used to check model assumptions (i.e., normality, homoscedasticity, and linearity). Normality of residuals was checked plotting residuals against a normal distribution. Plotting the spread of residuals across levels of the independent variables assessed homoscedasticity. Finally, linearity was checked by plotting residuals against predicted values.

Beginning with a null model, an iterative method was used to develop the full LMER models whereby the fixed effect terms were successively incorporated until a complete model was produced. The null model only included random effects, providing a baseline for measuring the ensuing models. Fixed effects were methodically added one at a time (PHV offset followed by sex and then testing session) to determine their effect on modelling the relationship with resultant acceleration and the acceleration integral. Metrics used to determine model fit were Akaike (AIC) and Bayesian (BIC) Information Criterion, marginal and conditional R^2, intraclass correlation coefficients (ICC), and root-mean-square error (RMSE). Optimization of both model complexity and fit was considered when comparing model iterations to prevent over- or under-fitting the final model to the data.

Results

Acceleration peak and integral results parsed by drill, session, and sex can be found in **Table 8**. Model comparisons for acceleration peaks by drill are detailed in **Tables 9-15** while acceleration integral model comparisons can be found in **Tables 16-20**. The null model results were consistently indistinguishable from the complex models for both peaks and integrals.

Table 9. Acceleration peak and integrals

	Peaks				Integrals			
	Female		Male		Female		Male	
Drill	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
40yd	41.45 (9.12)	40 (7.9)	42.36 (7.7)	41.56 (7.26)	61775 (9766)	59540 (7623)	61886 (7679)	60840 (8012)
5-10-5	25.17 (5.78)	24.41 (6.18)	24.77 (6.77)	23.91 (5.36)	39479 (5605)	38514 (5474)	42604 (7426)	38889 (5961)
Broad	45.69 (15.35)	46.78 (15.26)	46.67 (14.64)	46.93 (19.15)	N/A	N/A	N/A	N/A
DNB	17.82 (5.91)	17.83 (6.11)	15.72 (6.14)	16.86 (6.37)	25328 (4500)	23987 (5069)	22140 (6284)	23665 (4770)
M-L	26.61 (5.82)	25.43 (5.29)	28.81 (5.27)	29.76 (6.16)	39046 (5368)	37895 (5424)	41547 (5957)	40571 (5927)
M-R	27 (6.04)	26.22 (5.71)	29.56 (5.19)	29.3 (5.5)	38995 (5491)	37184 (4062)	41140 (5333)	40322 (5761)

Table 10. Acceleration peaks model comparisons for 40yd dash drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	6.971***	6.989***	6.952***	6.917***
	(0.079)	(0.085)	(0.123)	(0.131)
PHV		0.030	0.052	0.052
		(0.048)	(0.071)	(0.071)
SEX (Male)			0.099	0.099
			(0.237)	(0.237)
SESSION (Post-season)				0.071
				(0.088)
SD (Intercept SUBJECT)	0.684	0.686	0.690	0.690
SD (Observations)	0.641	0.641	0.641	0.642
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.003	0.004	0.005
R2 Cond.	0.532	0.535	0.539	0.538
AIC	552.2	558.1	561.0	565.3
BIC	562.3	571.6	577.8	585.5
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.51

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11. Acceleration peaks model comparisons for 5-10-5 drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	24.913***	25.245***	24.518***	25.017***
	(0.588)	(0.624)	(0.891)	(0.933)
PHV		0.535	0.973+	0.973+
		(0.350)	(0.519)	(0.519)
SEX (Male)			1.979	1.979
			(1.735)	(1.735)
SESSION (Post-season)				-0.998+
				(0.550)
SD (Intercept SUBJECT)	5.313	5.270	5.260	5.276
SD (Observations)	4.027	4.027	4.027	3.983
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.018	0.028	0.033
R2 Cond.	0.635	0.638	0.641	0.649
AIC	1342.7	1342.7	1340.4	1338.5
BIC	1352.8	1356.1	1357.2	1358.6
ICC	0.6	0.6	0.6	0.6
RMSE	3.15	3.15	3.15	3.09

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12. Acceleration peaks model comparisons for Broad Jump drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	47.134***	47.063***	45.909***	46.008***
	(1.363)	(1.466)	(2.114)	(2.302)
PHV		-0.112	0.576	0.576
		(0.826)	(1.228)	(1.228)
SEX (Male)			3.091	3.091
			(4.074)	(4.074)
SESSION (Post-season)				-0.197
				(1.822)
SD (Intercept SUBJECT)	10.528	10.616	10.654	10.615
SD (Observations)	13.268	13.268	13.268	13.330
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.000	0.004	0.004
R2 Cond.	0.386	0.390	0.394	0.390
AIC	1803.6	1804.1	1800.9	1799.9
BIC	1813.7	1817.6	1817.7	1820.1
ICC	0.4	0.4	0.4	0.4
RMSE	11.25	11.22	11.20	11.23

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 13. Acceleration peaks model comparisons for M-drill (Left)

	NULL	**Model 1**	**Model 2**	**Model 3**
(Intercept)	27.174***	26.891***	25.498***	25.451***
	(0.461)	(0.489)	(0.682)	(0.748)
PHV		-0.447	0.384	0.384
		(0.276)	(0.396)	(0.396)
SEX (Male)			3.733**	3.733**
			(1.314)	(1.314)
SESSION (Post-season)				0.093
				(0.617)
SD (Intercept SUBJECT)	3.550	3.502	3.294	3.280
SD (Observations)	4.495	4.495	4.495	4.516
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.017	0.064	0.064
R2 Cond.	0.384	0.388	0.391	0.387
AIC	1342.0	1342.1	1333.9	1335.0
BIC	1352.1	1355.6	1350.7	1355.2
ICC	0.4	0.4	0.3	0.3
RMSE	3.82	3.82	3.85	3.86

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14. Acceleration peaks model comparisons for M-drill (Right)

	NULL	Model 1	Model 2	Model 3
(Intercept)	28.368***	28.026***	26.839***	27.500***
	(0.487)	(0.515)	(0.727)	(0.782)
PHV		-0.541+	0.168	0.168
		(0.290)	(0.422)	(0.422)
SEX (Male)			3.182*	3.182*
			(1.400)	(1.400)
SESSION (Post-season)				-1.322*
				(0.576)
SD (Intercept SUBJECT)	4.011	3.939	3.817	3.863
SD (Observations)	4.298	4.298	4.298	4.214
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.023	0.056	0.068
R2 Cond.	0.466	0.469	0.472	0.494
AIC	1343.9	1343.1	1337.5	1333.6
BIC	1354.0	1356.6	1354.3	1353.8
ICC	0.5	0.5	0.4	0.5
RMSE	3.55	3.55	3.57	3.47

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 15. Acceleration peaks model comparisons for DNB drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	17.446***	17.247***	19.301***	19.218***
	(0.506)	(0.540)	(0.749)	(0.806)
PHV		-0.316	-1.511***	-1.511***
		(0.302)	(0.428)	(0.428)
SEX (Male)			-5.361***	-5.361***
			(1.435)	(1.435)
SESSION (Post-season)				0.166
				(0.594)
SD (Intercept SUBJECT)	4.206	4.203	3.830	3.819
SD (Observations)	4.282	4.282	4.282	4.301
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.008	0.095	0.095
R2 Cond.	0.491	0.495	0.497	0.494
AIC	1324.2	1325.7	1311.9	1313.0
BIC	1334.2	1339.1	1328.6	1333.1
ICC	0.5	0.5	0.4	0.4
RMSE	3.50	3.50	3.55	3.56

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16. Acceleration integral model comparisons for 40yd dash drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	61504.631***	61483.088***	61040.309***	62050.013***
	(641.984)	(690.303)	(996.581)	(1086.649)
PHV		-34.084	230.161	230.161
		(389.089)	(579.043)	(579.043)
SEX (Male)			1186.332	1186.332
			(1920.570)	(1920.570)
SESSION (Post-season)				-2019.407*
				(866.332)
SD (Intercept SUBJECT)	4815.681	4858.758	4885.825	4970.226
SD (Observations)	6466.618	6466.618	6466.618	6336.672
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.000	0.002	0.018
R2 Cond.	0.357	0.361	0.365	0.392
AIC	4432.8	4421.1	4405.7	4387.0
BIC	4442.9	4434.5	4422.6	4407.2
ICC	0.4	0.4	0.4	0.4
RMSE	5543.39	5526.80	5513.39	5351.44

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17. Acceleration integral model comparisons for 5-10-5 drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	40886.200***	40573.136***	40166.604***	41373.255***
	(518.771)	(548.924)	(787.525)	(855.511)
PHV		-504.942	-259.968	-259.968
		(308.092)	(458.959)	(458.959)
SEX (Male)			1106.296	1106.296
			(1533.300)	(1533.300)
SESSION (Post-season)				-2413.302***
				(668.440)
SD (Intercept SUBJECT)	3896.776	3838.494	3855.396	4025.963
SD (Observations)	5113.339	5113.339	5113.339	4843.308
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.017	0.020	0.055
R2 Cond.	0.367	0.371	0.375	0.441
AIC	4254.2	4240.2	4225.2	4199.9
BIC	4264.2	4253.6	4241.9	4220.0
ICC	0.4	0.4	0.4	0.4
RMSE	4366.19	4370.60	4360.72	4049.75

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18. Acceleration integral model comparisons for M-drill (Left)

	NULL	Model 1	Model 2	Model 3
(Intercept)	38993.755***	38569.977***	38012.538***	38419.491***
	(429.377)	(446.879)	(641.852)	(738.371)
PHV		-670.475**	-337.803	-337.803
		(251.883)	(372.935)	(372.935)
SEX (Male)			1493.539	1493.539
			(1236.951)	(1236.951)
SESSION (Post-season)				-813.908
				(729.979)
SD (Intercept SUBJECT)	2332.452	2090.285	2070.818	2078.625
SD (Observations)	5345.400	5345.400	5345.400	5339.336
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.036	0.044	0.048
R2 Cond.	0.160	0.164	0.168	0.173
AIC	4306.8	4289.0	4273.5	4259.2
BIC	4316.9	4302.5	4290.3	4279.4
ICC	0.2	0.1	0.1	0.1
RMSE	4953.44	5002.28	4996.69	4975.23

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19. Acceleration integral model comparisons for M-drill (Right)

	NULL	Model 1	Model 2	Model 3
(Intercept)	39746.233***	39150.267***	38818.482***	39622.081***
	(395.241)	(392.399)	(565.734)	(661.078)
PHV		-942.901***	-744.896*	-744.896*
		(221.175)	(328.708)	(328.708)
SEX (Male)			888.946	888.946
			(1090.259)	(1090.259)
SESSION (Post-season)				-1607.198*
				(684.014)
SD (Intercept SUBJECT)	1915.880	1157.581	1177.311	1383.786
SD (Observations)	5107.730	5107.730	5107.730	5003.129
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.082	0.085	0.106
R2 Cond.	0.123	0.127	0.131	0.169
AIC	4279.5	4252.0	4237.5	4219.2
BIC	4289.6	4265.4	4254.3	4239.4
ICC	0.1	0.0	0.1	0.1
RMSE	4809.29	4965.14	4950.29	4790.53

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20. Acceleration integral model comparisons for DNB drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	23833.434***	23473.741***	26095.674***	26050.219***
	(448.629)	(471.214)	(600.215)	(666.941)
PHV		-569.907*	-2095.469***	-2095.469***
		(263.467)	(343.002)	(343.002)
SEX (Male)			-6843.672***	-6843.672***
			(1149.294)	(1149.294)
SESSION (Post-season)				90.910
				(581.560)
SD (Intercept SUBJECT)	3512.487	3408.155	2549.284	2533.054
SD (Observations)	4194.179	4194.179	4194.179	4213.800
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.030	0.202	0.202
R2 Cond.	0.412	0.416	0.417	0.414
AIC	4182.4	4166.8	4122.1	4109.5
BIC	4192.4	4180.1	4138.8	4129.6
ICC	0.4	0.4	0.3	0.3
RMSE	3524.40	3537.45	3702.60	3714.80

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Discussion

Chapter 6: Conclusion

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

Appendices

Appendix A. IRB Approval Letter

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

Appendix B. Informed Consent

CONSENT FOR RESEARCH PARTICIPATION

Research Study Title: Acceleration profiles and sex differences among adolescent soccer players

Researcher(s): Joshua T. Weinhandl, PhD, University of Tennessee, Knoxville
Jake A. Melaro, MS, University of Tennessee, Knoxville
Joshua Lardie, MS, University of Tennessee, Knoxville

Why am I being asked to be in this research study?

We are asking your child to be in this research study because he/she is between the ages of 9 to 17 years old and is recreationally active. We are also asking your child to be in this research study because he/she is currently playing on a competitive soccer team that practices at least twice a week. Individuals who are not between the ages of 9 to 17 or have sustained a musculoskeletal injury of the lower extremity during the past 6 months will not be asked to be in this research study.

How long will I be in the research study?

If you agree for your child to be in the study, his/her participation will involve 2 study sessions lasting approximately 20 minutes each.

What will happen if I say "Yes, I want to be in this research study"?

If you agree for your child to be in this study, we will visit him/her at the Crushplex training facility on two separate occasions during scheduled practices, once at the beginning of the season and again at the end of the season.

You will fill out the informed consent and your child will be given an assent form (which will be thoroughly explained to them), as well as a fitness activity questionnaire and lower extremity functional scale form prior to the first testing session.

After these forms are completed and on the day of the first testing session, we will then place two small sensors on your child's leg directly above your ankle at the beginning of practice. He/she will then jog from one end of the turf field to the other and back at an easy pace. Following the jog and a slight break, he/she will then sprint around cones in the shape of an 'M' twice, once in both directions. Following another short break, he/she will then do a side-shuffling drill between two cones as fast as he/she can. Then, following a final short break, he/she will hop three times (3x) as far as they can on their right leg before again hopping three times (3x) on the other leg as far as they can. The testing session will then be completed. The testing session will be repeated again at the conclusion of the season at another scheduled practice.

What happens if I say "No, I do not want to be in this research study"?

Being in this study is up to you and your child. You can say no now or leave the study later. Either way, your decision(s) won't affect your standing with the club, your relationship with your coaches, or standing with the University of Tennessee, Knoxville.

What happens if I say "Yes" but change my mind later?

Even if you decide to be in the study now, you can change your mind and stop at any time. If you decide to stop before the study is completed, you can tell the PI and/or co-PI that you wantto withdraw from the study at any time. If you decide to withdraw from the study, your information will be kept de-identified and kept in a locked drawer in our Biomechanics lab on the university campus. Only study personnel will have access to any forms and data that have already been collected.

Are there any possible risks to me?

It is possible that someone could find out you were in this study or see your study information,but we believe this risk is small because of the procedures we use to protect your information. These procedures are described later in this form.

Possible risks include lower extremity injury during the study movements. These risks will be minimized. Your child will complete a required to warm up before data collection, so his/her muscles are ready to move, and provided ample opportunity to familiarize themselves with the movements to reduce risk of injury. Further, breaks will be provided in the unlikely case that they experience discomfort or pain. The movements included are movements they should be familiar with, due to their practicing at least twice a week. In the *very* unlikely case that they hurt themselves during the study visit, Knox Crush FC staff will provide appropriate first-aid and contact medical services. If you realize afterwards that they have become injured, you should seek medical assistance.

Are there any benefits to being in this research study?

We do not expect you or your child to directly benefit from being in this study. Your participation may help us to learn more about the relationship between youth athletes' physical development and the differences in complexity of their movements. We hope the knowledge gained from this study will benefit others in the future.

Who can see or use the information collected for this research study?

We will protect the confidentiality of your information by keeping all forms in a locker drawer or on a password-encrypted computer drive in the Biomechanics lab, which is locked every day. Only the investigators conducting this study will have access to your personal information. If information from this study is published or presented at scientific meetings, your name and other personal information will not be used. We will make every effort to prevent anyone who is not on the research team from knowing that you gave us information or what information came from you. Although it is unlikely, there are times when others may need to see the information we collect about you. These include people at the University of Tennessee, Knoxville who oversee research to make sure it is conducted properly.

We will keep your information to use for future research. Your name and other information thatcan directly identify you will be kept secure and stored separately from your research data collected as

What will happen to my information after this study is over?

part of the study. We will not share your research data with other researchers.

Will I be paid for being in this research study?

You and your child will not be paid for being in this study.

Will it cost me anything to be in this research study?

It will not cost you anything to be in this study

What else do I need to know?

We may need to stop your and your child's participation in the study without your consent if he/she does not follow the study instructions, no longer meet the study's eligibility requirements, if his/her safety comes into question, or if the study is stopped for any reason.

The University of Tennessee does not automatically pay for medical claims or give other compensation for injuries or other problems should you realize your child is injured outside of the study visit.

Who can answer my questions about this research study?

If you have questions or concerns about this study, or have experienced a research related problem or injury, contact the researchers, Dr. Joshua Weinhandl (**jweinhan@utk.edu**, 865-974-9556), Jake Melaro (**jmelaro@vols.utk.edu**, 865-974-2091) or Joshua Lardie (**jlardie@vols.utk.edu**, 865-974-2091).

For questions or concerns about your rights or to speak with someone other than the researchteam about the study, please contact:

Institutional Review Board
The University of Tennessee, Knoxville
1534 White Avenue
Blount Hall, Room 408
Knoxville, TN 37996-1529
Phone: 865-974-7697
Email: **utkirb@utk.edu**

IRB NUMBER: UTK IRB-XX-XXXX-XX
IRB APPROVAL DATE: XX/XX/XXXX
IRB EXPIRATION ATE: XX/XX/XXXX

STATEMENT OF CONSENT

I have read this form and the research study has been explained to me. I have been given the chance to ask questions and my questions have been answered. If I have more questions, I havebeen told who to contact. By signing this document, I am agreeing to be in this study. I will receive a copy of this document after I sign it.

Name of Adult Participant	Signature of Adult Participant	Date

Researcher Signature (to be completed at time of informed consent)

I have explained the study to the participant and answered all his/her questions. I believe that he/she understands the information described in this consent form and freely consents to be inthe study.

Name of Research Team Member	Signature of Research Team Member	Date

Appendix C. Recruitment Announcement

Hello,

Your child is invited to participate in a biomechanical research study investigating how movement complexity differs among males and female soccer players at different stages of development and over the course of a season. This information will hopefully aid in preventing injury and improving performance in adolescent athletes.

We are particularly interested in recruiting males and female soccer players that practice at least twice (2x) per week. We ask that the player be between the ages of 9 and 17. We also ask that the player not have any lower back or leg injuries within the past six months prior to testing.

This study will involve placing two small sensors on your child right above their ankles before they perform several movement tasks. For task 1, the player will jog the length of a turf field and back at an easy pace; for task 2, the player will sprint twice around cones in the shape of an 'M', once in both directions and with a small break in between sprints; for task 3, following a short break the player will perform a shuffle drill between two cones as fast as they can; and finally for task 4, following a short break the player will hop three (3x) times as far as they can on both their right and left legs.

The current study will require you to come the Crushplex training facility (1501 Kirby Road, Knoxville, TN) for two sessions (once at the beginning of the season and again at the end of the season), which will last approximately 15 minutes each. If you feel your child fits the criteria for this study and are willing to let them participate, please contact the research investigators Dr. Joshua Weinhandl (jweinhan@utk.edu), Jake Melaro (jmelaro@vols.utk.edu), or Joshua Lardie (jlardie@vols.utk.edu) via email or telephone (865) 974-2091 (office number).

Thank you for your time,
Jake Melaro, MS
Graduate Assistant/PhD Candidate, Biomechanics
The University of Tennessee, Knoxville
Department of Kinesiology, Recreation, and Sports Studies

Appendix D. Study Recruitment Flyer

Male and Female Soccer Players Needed for a Biomechanics Study

Your child may be able to participate if he/she:

- Practices at least twice (2_x) per week
- Are between the age of 9 to 17 years
- No previous lower back or lower extremity injury that required surgery

The University of Tennessee Biomechanics/Sports Medicine Lab is conducting a research study to examine if there are differences in movement complexity over the course of a season.

Participants will be required to perform **two (2)** 15-minute testing sessions at the Crushplex facility (**1501 Kirby Rd, Knoxville, TN**)

- **One (1)** session at the beginning of the season
- **One (1)** session at the end of the end of the season.

Contact: Jake Melaro
jmelaro@vols.utk.edu

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BIOMECHANICS

Appendix E. Lower Extremity Functional Scale Form

Lower Extremity Functional Scale

We are interested in knowing whether or not you are having any difficulty at all with the activities listed below. Please provide an honest answer for each activity.

KEY
0 - Extreme difficulty or unable to perform activity
1 - Quite a bit of difficulty
2 - Moderate difficulty
3 - A little bit of difficulty
4 - No difficulty

Today, ***do you*** or ***would you*** have any difficulty at all with:	Extreme 0	Quite a bit 1	Moderate 2	Minimal 3	None 4
1. Any of your usual work, housework or school activities	☐	☐	☐	☐	☐
2. Your usual hobbies, recreational or sporting activities	☐	☐	☐	☐	☐
3. Getting into or out of the bath	☐	☐	☐	☐	☐
4. Walking between rooms	☐	☐	☐	☐	☐
5. Putting on your shoes or socks	☐	☐	☐	☐	☐
6. Squatting	☐	☐	☐	☐	☐
7. Lifting an object, like a bag of groceries from the floor	☐	☐	☐	☐	☐
8. Performing light activities around your home	☐	☐	☐	☐	☐
9. Performing heavy activities around your home	☐	☐	☐	☐	☐
10. Getting into or out of a car	☐	☐	☐	☐	☐
11. Walking 2 blocks	☐	☐	☐	☐	☐
12. Walking a mile	☐	☐	☐	☐	☐
13. Going up or down 10 stairs (about 1 flight)	☐	☐	☐	☐	☐
14. Standing for 1 hour	☐	☐	☐	☐	☐
15. Sitting for 1 hour	☐	☐	☐	☐	☐
16. Running on even ground	☐	☐	☐	☐	☐
17. Running on uneven ground	☐	☐	☐	☐	☐
18. Making sharp turns while running fast	☐	☐	☐	☐	☐
19. Hopping	☐	☐	☐	☐	☐
20. Rolling over in bed	☐	☐	☐	☐	☐

Appendix F. Fitness Activity Questionnaire

FITNESS ACTIVITY QUESTIONNAIRE

Please describe your current participation in the following types of exercise:

1. *Aerobic (aerobic classes, walking, jogging, stair climbing, hiking, cycling, etc.)*

Frequency (# of days per week): ___________________
Duration (time spent per session): ___________________minutes
Intensity (difficulty level): light somewhat hard hard very hard
How long have you been participating in aerobic activity as described above?
___________________Years

2. *Anaerobic (weight training, sprinting, etc.)*

Frequency (# of days per week): ___________________
Duration (time spent per session): ___________________minutes
Intensity (difficulty level): light somewhat hard hard very hard
How long have you been participating in anaerobic activity as described above?
___________________Years

3. *Organized or Recreational sports*

Type of sport(s):____
Frequency (# of days per week): ___________________
Duration (time spent per session): ___________________minutes
Intensity (difficulty level): light somewhat hard hard very hard
How long have you been participating in sports activity as described above?
___________________Years

Appendix G. Figures

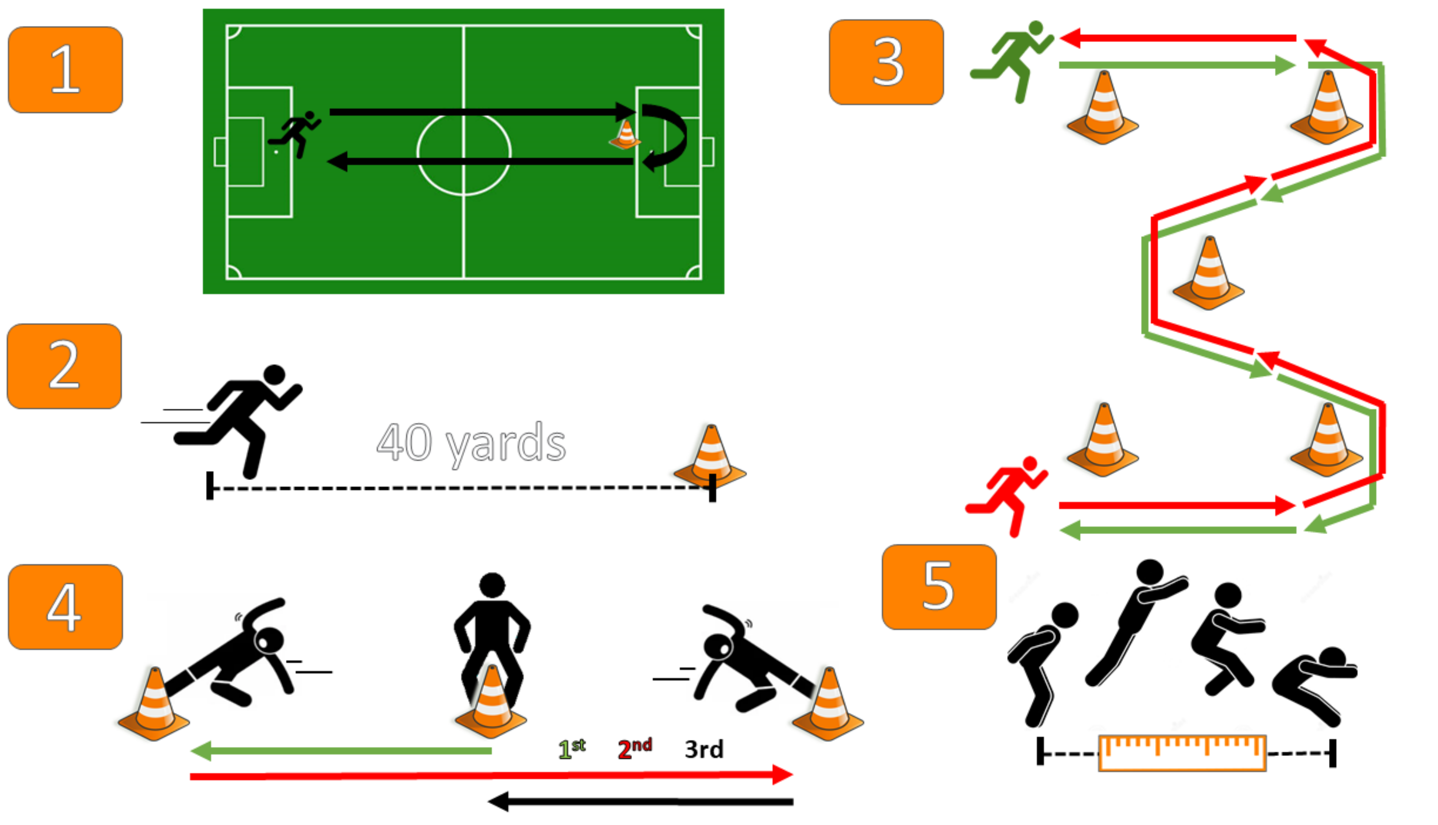

Figure 1 Experimental protocol including (1) down and back jog, (2) 40-yd dash , (3) M-cone drill, (4) 5-10-5 drill, and (5) standing broad jump.

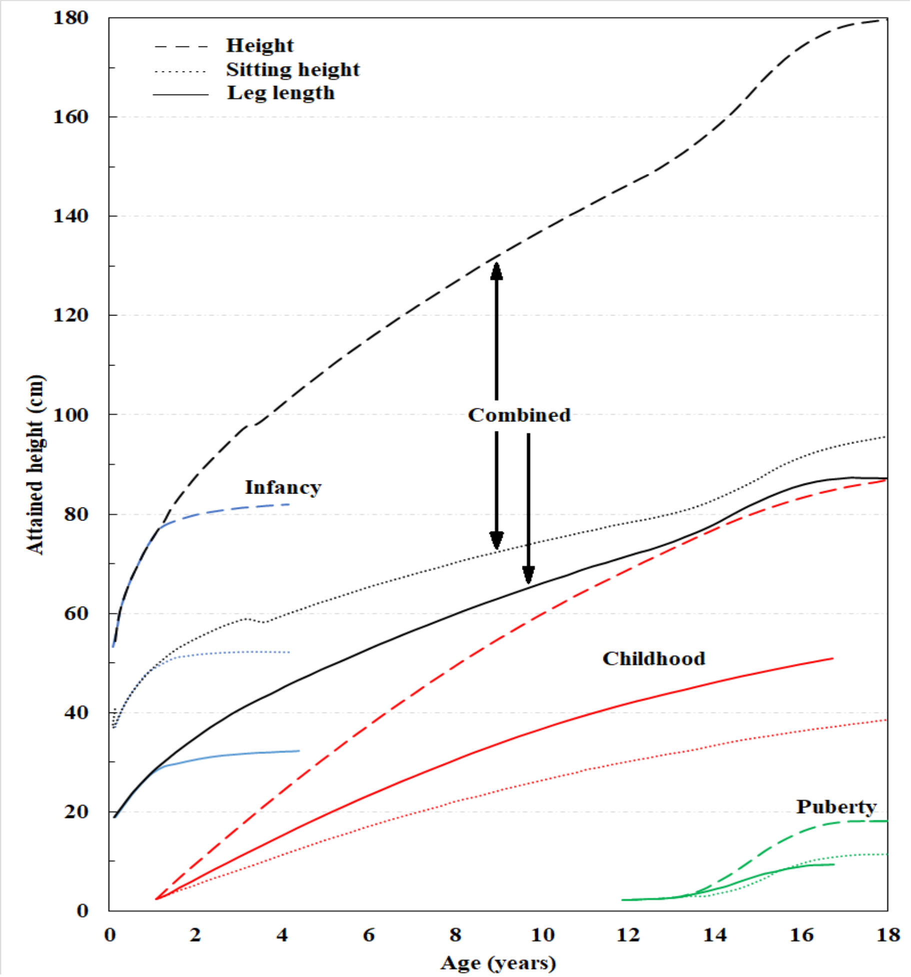

Figure 2 Karlberg ICP model illustrating growth rates for height (dashed), sitting height (dotted), leg length (solid), and their combined lengths through adolescence. Recreated from Karlberg (1989).

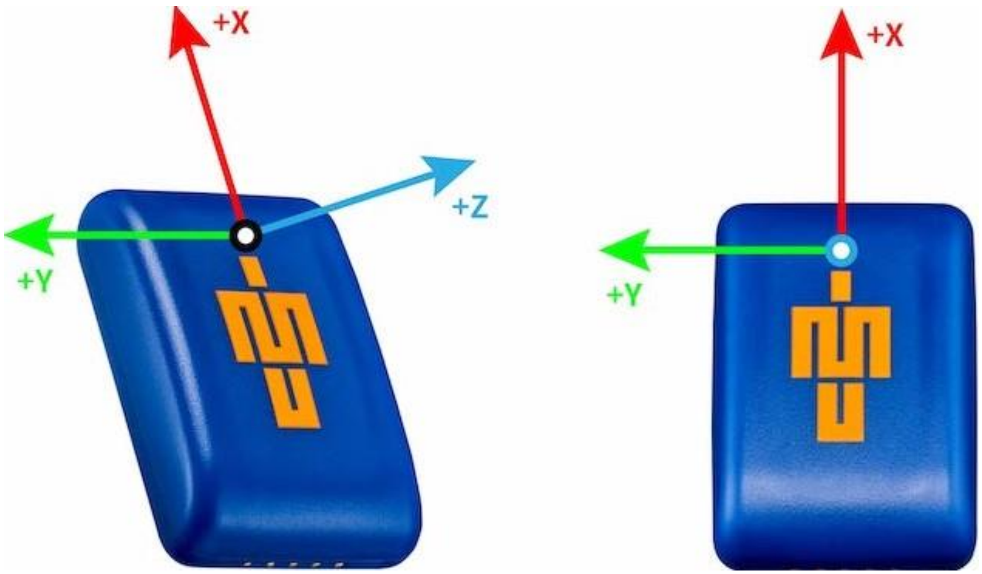

Figure 3 Vicon© Blue Trident dual-g inertial measurement unit coordinate system conventions

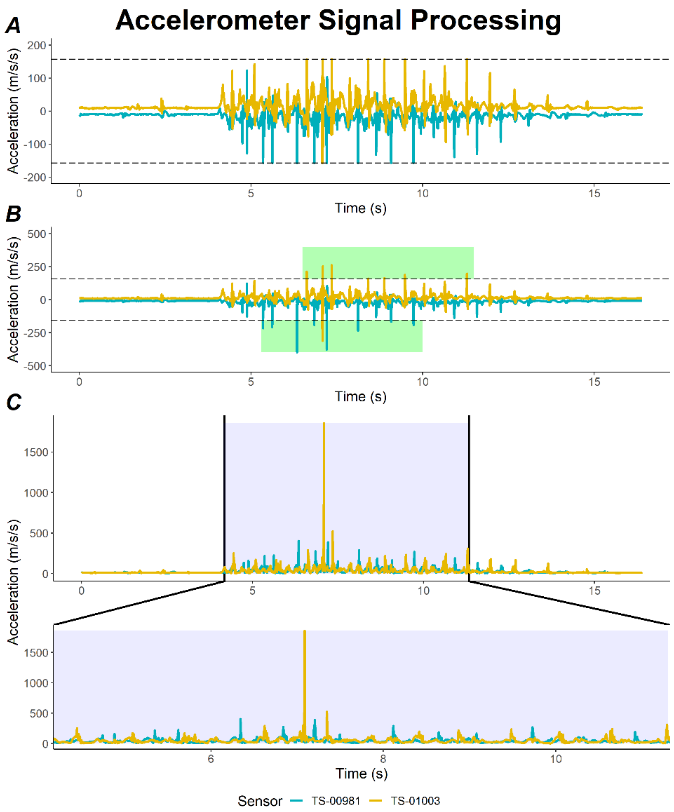

Figure 4 (A) Raw 3D acceleration components saturate low-g sensor at 16 G's. (B) Saturated data points replaced at same time points with high-g sensor data. (C) Resultant acceleration calculated from XYZ components and signal clipped following visual examination to remove data collected before and after drill

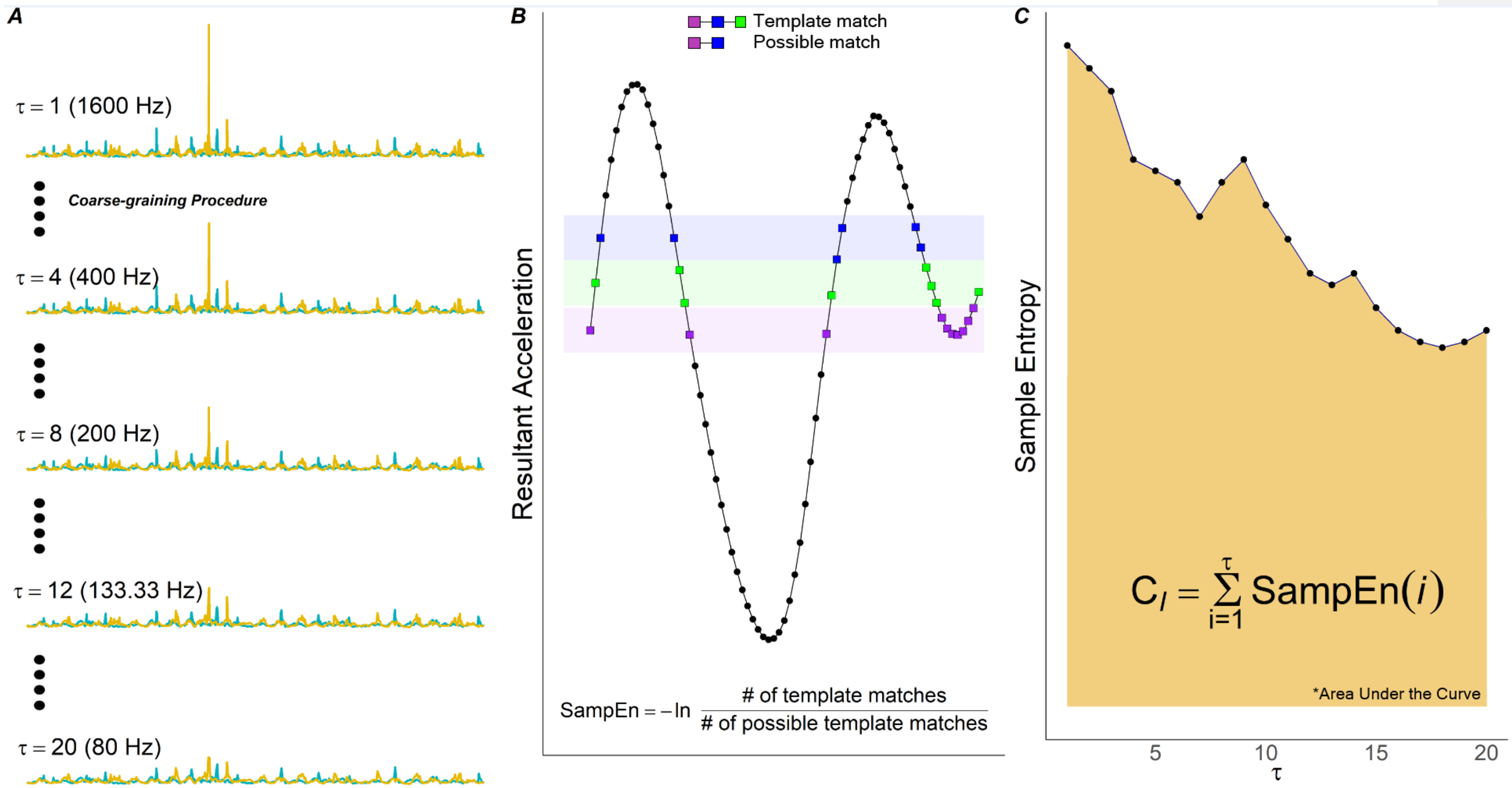

Figure 5 (A) A coarse-graining procedure will be used on the original resultant acceleration time series from τ=[1 20]. (B) Each coarse-grained time series will then be fed into a base SampEn algorithm. (C) SampEn values will be plotted across τ and the area under the curve will be calculated to determine CI.

Vita

Jake Melaro was born in Henderson, TN in 1993 and is the son of Joseph and Laura Melaro. He is the oldest of three children, with younger, less attractive siblings, Noah and Cami Melaro. Jake graduated from Chester County High School in Henderson, Tennessee in 2012 (shoutout to Bush Jr and the No Child Left Behind Act). After high school, Jake attended the University of Tennessee-Martin where he was conscripted into the Pi Kappa Alpha fraternity, got entangled in some shenanigans, and finally graduated with a Bachelors in Exercise Science and Wellness in 2017. Jake next fell ass-backwards into the University of Memphis where he earned his Masters of Science degree in Health and Human Performance with a concentration in Exercise and Sports Science in 2019. Jake also “earned” a second Masters degree in Statistics during his time at the University of Tennessee, Knoxville in 2023. He completed his education at the University of Tennessee, Knoxville, earning a Doctor of Philosophy in Kinesiology and Sports Studies with a concentration in Biomechanics in 2023. Jake is a degenerate gambler who plans on using these degrees to get rich and retire to the beach with his girlfriend, Jenna, and their dog, Nala, well before he’s earned the right to do so. He’s still waiting for someone to thoroughly explain what entropy really is…

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