Longitudinal Monitoring of Biomechanics and Psychological State in Female Basketball Athletes

Longitudinal Monitoring of Biomechanical and Psychological Stress in Collegiate Female Basketball Athletes: Implications to Sports Performance and Injury Susceptibility

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Abstract

The unprecedented growth in participation in collegiate athletics has been accompanied by an increase in injury burden. The complex and multifactorial nature of sports injuries highlights the importance of monitoring athletes prospectively using a novel and holistic biopsychosocial approach, as opposed to contemporary practices that silo these facets of health. Data collected over two competitive, basketball seasons were used in a principal component analysis (PCA) model with the following objectives: i) Determine if on-court, sensor-derived and force-plate-derived countermovement jump (CMJ) biomechanics were correlated, ii) determine the reliability of the biomechanical principal components (PCs) and psychological state metrics (e.g., self-reported pain, etc.) across five preseason weeks, iii) investigate whether biomechanical PCs were correlated with psychological state across a season, and iv) explore whether subject-specific meaningful fluctuations could be detected using minimum detectable change statistics. Weekly CMJ (force plates) and on-court data (inertial measurement units), as well as psychological state (questionnaire) data were collected on the women's basketball team at McMaster University for two seasons. It was found that on-court and CMJ biomechanics were correlated both between and within systems ($r = |0.10, 0.94|$; $p < 0.05$), suggesting that PCA would be an effective method to summarize data. The derived PCs displayed excellent reliability (ICC > 0.9), while psychological state metrics displayed moderate-to-good reliability (ICC = 0.71 – 0.89). While many relationships ($n = 27$) were identified between biomechanical PCs and psychological state metrics, no overarching associations were identified at the group level. However, subject-specific relationships were identified in case-studies, highlighting the potential utility of "red-flagging" meaningful fluctuations from normative biomechanical and psychological patterns. Overall, this work demonstrates the potential of advanced analytical modeling to characterize components of student-athlete performance, health, and well-being, and the need for more tailored and patient-centered athletic monitoring practices.

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List of Abbreviations and Symbols

MSK: Musculoskeletal

IMU: Inertial Measurement Unit

PCA: Principal Component Analysis

MDC: Minimum Detectable Change

PC: Principal Component

CMJ: Countermovement Jump

JH: Jump Height

RSI Mod: The Modified Reactive Strength Index

CMD: Countermovement Depth

ICC: Intraclass Correlation Coefficient

SEM: Standard Error of the Measurement

Declaration of Academic Achievement

I, Joshua A.J. Keogh, hereby declare that I am the sole author of this thesis. The study was conceived by Joshua A.J. Keogh and Dr. Dylan Kobsar. Edits and revisions were conducted by Joshua A.J. Keogh, based on feedback provided by Dr. Dylan Kobsar, Dr. Stuart Phillips, Dr. Jennifer Heisz, and Dr. Matthew Jordan.

Chapter 1: Introduction

Collegiate-level athletics have demonstrated an unprecedented growth in participation over the past two to three decades (1–3). Unfortunately, this increase in participation has been noted to be accompanied by an increase in injury burden (4,5), which ultimately reduces the ability of an individual and a team to perform optimally during competition. Interestingly, female athletes have displayed increased injury susceptibility for severe lower-extremity injuries (6–9), which may be partially attributed to biomechanical differences (i.e., greater dynamic knee valgus as measured by the knee abduction moment, greater knee abduction loading during the impact phase of jump-landing tasks, and at times, greater frontal plane knee kinematic asymmetry) (10–12). Despite the increased risk of sustaining lower-extremity injuries in females relative to their male counterparts, this population has been vastly understudied (13–15). Additionally, basketball has been reported to have one the highest frequency of injuries amongst all college sports (16,17), with lower extremity injuries being the most severe and prevalent (1,9,18).

Many of these sports-induced injuries are non-contact (1,6,7) and may be related to the exceedance of musculoskeletal (MSK) structure load tolerance from repeated bouts of vertical jumping, cutting, and pivoting tasks experienced during training and competition (1,19–21). Additionally, it has been demonstrated that between-limb differences (e.g., biomechanical deficiencies in strength, range of motion, ability to dissipate external load, etc.) are crucial to monitor during rehabilitation and return-to-sport protocols (5,22–28). Moreover, these between-limb differences can continue throughout a seemingly successful rehabilitation and persist well after athletes have returned-to-sport (5,29–32). While the importance of between-limb differences in rehabilitative settings is well-established, more limited evidence suggests that asymmetry may also be related to sports performance (15,33–39) and injury risk (34,40–43) in healthy, competitive athletic populations.

Fortunately, given that these MSK injuries are overuse in nature, some of which may be preventable by prospectively monitoring athletic workload, intensity, and biomechanical deficiencies (e.g., asymmetry) (13,18,44,45). However, biomechanics are often assessed in-laboratory settings using proxies of sports performance, such as vertical jump testing (46–48), which might not necessarily be indicative of the biomechanical patterns that individuals exhibit in their sporting environments due to the principle of specificity (49–52). Additionally, these traditional in-laboratory biomechanical assessments are both costly and cumbersome, which limits the practicality of employing these methodologies in regular, longitudinal athletic monitoring practices. Luckily, biomechanics has seen tremendous growth in the availability of accessible and more cost-effective modalities that can be seamlessly applied in sport-specific settings (53). Specifically, the advent of wearable technology, such as inertial measurement units (IMUs) and portable force plate systems, have enabled researchers and clinicians to monitor individualized biomechanical patterns and fluctuations in real-world settings (53–56). In doing so, this provides a more complete understanding of biomechanical profiles (e.g., on- and off-court), which might lead to a more comprehensive picture of contributory factors for sports performance and for injury susceptibility.

Nevertheless, assessing sports performance and injury susceptibility through a purely biomechanical lens fails to represent the athlete's readiness to perform on a given day (57). Psychological stressors may be modifiable risk factors for injury and reinjury in and of themselves (58–65) or may add to the demands of a task in conjunction with the biomechanical stressors experienced (58,66). Remarkably, there is very limited research to date that has directly examined the link between biomechanical outcomes and psychological state as it relates to sports performance and risk of injury, with even fewer research studies doing so longitudinally throughout several competitive seasons (67).

The complex and multifactorial nature of sports injuries (1,7,68–70) highlights the importance of monitoring basketball athletes prospectively using a novel and holistic biopsychosocial approach. Specifically, defining a more comprehensive biomechanical profile consisting of on- and off-court patterns and contextualizing biomechanical changes with concurrent changes in psychological state might improve our understanding of specific underlying domains or facets that lead to such injuries. However, in taking this approach, an issue that may arise with identifying modifiable risk factors for sports performance and injury is how best to summarize and interpret the multiple and diverse forms of data being collected (57,71,72). Typically, key performance indicators are identified via evidence-based research and utilized in athletic monitoring (13,44,45,48,58), but this technique often involves oversimplifications and omitting potentially important variables (71,73). As such, statistical techniques such as principal component analysis (PCA) that retain discriminatory information from many variables while reducing dimensionality through grouping interrelated metrics (71–76) have been gaining interest to highlight changes or trends in athlete readiness or performance. However, to our knowledge, there have yet to be any PCA investigations using more holistic biomechanical profiles consisting of both on- and off-court patterns and fluctuations. Therefore, there is a need to establish a more complete and comprehensive biomechanical profile, whereby multiple facets of sports performance and injury risk are considered and contextualized with concurrent changes in psychological state. In doing so, sports biomechanists, physicians, and other practitioners within the healthcare system of these athletes may be able to prospectively identify whether there has been true change outside of the measurement error (i.e., greater than the minimum detectable change (MDC)) for these variables (34,59,77), which can help them determine whether an intervention is necessary to prevent injuries and optimize sports performance.

Therefore, the overarching aim of this project was to improve athletic monitoring practices by examining the utility of integrating on- and off-court biomechanical data into more holistic biomechanical metrics (e.g., principal components; PCs), with concurrent longitudinal monitoring of psychological state to contextualize these subject-specific biomechanical fluctuations. Specifically, data collected over two competitive collegiate female basketball seasons were used in a PCA model to support the following research questions:

(i) *Correlations Between On-Court and Vertical Jump Biomechanics:* Are on-court, sensor-derived metrics and force-plate-derived vertical jump metrics significantly correlated throughout the 2021-2022 and 2022-2023 competitive collegiate female basketball seasons?

(ii) *Reliability of Biomechanical Principal Components and Introspective, Psychological State:* What is the reliability of the biomechanical PCs (i.e., on-court and countermovement jump (CMJ) biomechanics) and introspective, psychological state metrics across the 2022-2023 competitive, collegiate female basketball preseason?

(iii) *Longitudinal PCA Application & Association Between Biomechanical and Introspective, Psychological State:*

(A) Are PC scores derived from a biomechanical model (i.e., on-court and vertical jump data) significantly correlated with introspective, psychological state (e.g., self-reported pain, sleep quality, sleep quantity, etc.) across the 2022-2023 regular season?

(B) Can we detect subject-specific meaningful changes in these measures using PCs and associated MDC statistics?

The remainder of this document is comprised of a Literature Review (Chapter 2), followed by further definition of the Thesis Research Questions (Chapter 3), Research Methodology (Chapter 4), Results (Chapter 5), Discussion (Chapter 6), and the Conclusion and Significance of this study (Chapter 7). The Literature Review will first look at the use of biomechanical and psychological data in athletic monitoring as they relate to sports performance and risk of injury, which will be followed by a summary of those studies that have used advanced analytical models (i.e., PCA) to monitor sports performance or injury susceptibility in basketball athletes. The Methods, Results, and Discussion outline the sample, study design, protocol, and key findings from the thesis "Longitudinal Monitoring of Biomechanical and Psychological Stress in Collegiate Female Basketball Athletes: Implications to Sports Performance and Injury Susceptibility."

Chapter 2: Literature Review

Given that the proposed research utilizes a holistic and biopsychosocial model of sports performance and injury risk, this literature review will first provide a *brief overview* of the individual research landscapes that will be integrated in the proposed study. This will begin with a subsection on biomechanical and between-limb difference metrics obtained via traditional CMJ testing and during sport-specific on-court assessments related to sports performance and injury outcomes (Chapter 2.1 and Chapter 2.2, respectively). The relationship between psychological state and sports performance and injury will be discussed, along with a brief review of research that has integrated biomechanical and psychological state assessments in competitive athletic populations (Chapter 2.3). Finally, and most importantly, an *in-depth review and critical appraisal* of investigations utilizing advanced analytical models (i.e., PCA) of sports performance and injury susceptibility will be presented (Chapter 2.4). In doing so, this review will highlight the paucity of research conducted in this area, ultimately demonstrating the necessity and the rationale for the present research project.

2.1: Traditional Lab-based Assessments of CMJ Biomechanical and Between-limb Difference Metrics Obtained from Force-Time Waveforms in Athletic Monitoring

The CMJ and the associated kinetic force-time waveform data captured are the most frequent assessment of lower extremity force and power production in team sport athletes (46–48). This vertical jump assessment and the biomechanical data outputted from force plates become increasingly more pertinent and important to examine in team sport athletes that undergo high volume of jumping and cutting in competition, such as volleyball and basketball athletes, as these absorptive loads may place these athletes at a heightened risk of injury (1,19–21). As depicted in Figure 1, the CMJ consists of several successive key phases of movement, paralleled in the kinetic force plate tracing. The waveform generated from the dual force plate system provides a visual assessment of the external forces generated by participants (78). These forces are often measured simultaneously in the three planes of motion: vertical (Fz), anterior-posterior (Fy), and medial-lateral force (Fx) production (78), with the vertical force production often being the vector of interest during vertical jump assessment. Furthermore, these initial kinetic variables outputted by the force plates can be used to calculate several other kinetic or kinematic variables during the movement and for different phases of movement during the CMJ (78). The stratification of biomechanical data into such phases of movement enables researchers and practitioners to discern whether overarching movement patterns are (dis)advantageous for vertical jump performance (79–82).

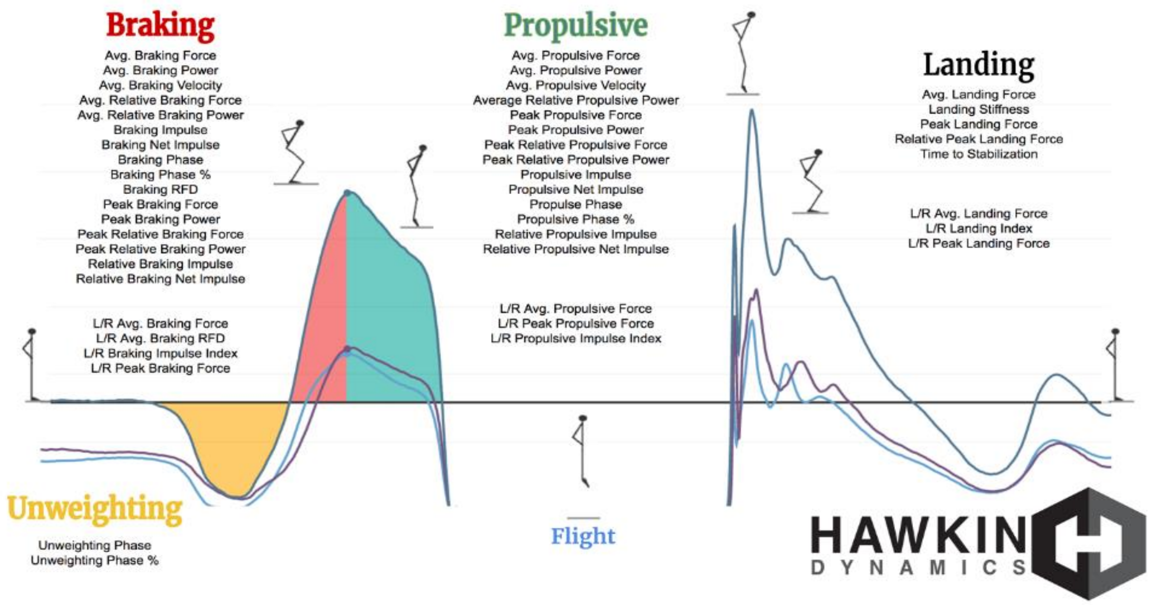

Figure 1. Phases of the CMJ and direct comparison to a kinetic force-time waveform (83).

In a practical sense, these key phases of CMJs can be used to monitor training adaptations using key performance indicators longitudinally. Specifically, jump height (JH), which occurs during the flight phase of movement in Figure 1, appears to be the most standard biomechanical variable utilized to monitor explosive power and athlete responsiveness to a training regimen. Additionally, JH has been deemed highly reliable as an indicator of neuromuscular performance and readiness when baseline values are established (33,46–48,78,84,85). However, it should be noted that in isolation, this variable is not sensitive enough to detect alterations indicative of potential injury and exceedance of tolerable training volume (46,48,78,86).

Fortunately, the eccentric rate of force development and the modified reactive strength index (RSI mod) may indicate the physical capacity to effectively utilize a stretch-shortening cycle, which is essential in vertical jumping performance and for elite basketball players (47,87–91). The RSI mod offers a reliable means of monitoring an athlete's stretch-load tolerance, quickness and reactivity, all essential qualities in an explosive athlete (46–48,85,87,88). Moreover, RSI mod assesses the athlete's ability to rapidly change from an eccentric to concentric muscle action, utilizing a stretch-shortening cycle, which is said to underpin optimal jumping and sprinting performance (88). In elite basketball athletes, incorporating RSI mod may provide a heightened dimension and understanding of the athlete's neuromuscular performance and fatigue when used in conjunction with JH.

Moreover, biomechanical variables captured by the force plate can identify potential injuries compared to individualized baseline values, especially if comparing bilateral values and between-limb differences (i.e., increased inter-limb asymmetry) (33). For those athletes that have sustained injuries and are progressing through rehabilitation toward return-to-play, these biomechanical variables may serve as a benchmark for normative pre-injury performance and a threshold for an effective return-to-play protocol.

Cumulatively, the widespread integration of CMJ and force plate analysis could aid in informing coaching staff, athletes, sports scientists, and sports medicine practitioners of individual and team neuromuscular readiness, performance, and potential indicators of injury, consequently improving athletic success and reducing injury incidence.

However, an inherent limitation of force plate analysis and interpretation is the multitude of biomechanical variables captured (78), as shown in Figure 1. The rationale behind companies like Hawkin Dynamics and other industry leaders is that this comprehensive approach will allow training staff to identify the variables they deem relevant and necessary for monitoring their athletes. However, without diving into the literature or the direct support of sports scientists, it can be difficult to determine relevant, reliable, and valid variables to longitudinally assess individual athletes and teams. Another limitation to the practical use of the CMJ and associated force-time waveform analyses for monitoring sports performance and injury susceptibility is the principal of task specificity (49–51), which dictates that these proxies for sports performance might not be telling of what on-court performance in a truly dynamic and unpredictable in-game or on-court scenario might be. Additionally, asymmetry has been influenced highly by the motor task at play, the associated participating muscular groups, and whether the task is unilateral or bilateral (50,51). Therefore, it might be necessary to concurrently capture and measure the between-limb differences in traditional laboratory settings and expand these assessments to the field.

Fortunately, the advent of innovative technology, such as the IMU, permits biomechanists, researchers, and even practitioners to monitor kinetic and kinematic variables in a truly sport-specific setting, which in theory, would be most telling of sports performance and injury risk for competitive athletic populations.

2.2: Expanding Biomechanical Assessments to the Field and into Sport-Specific Settings Using Wearable Sensors

Recent efforts have been made to better understand whether wearable sensor-derived biomechanical information provides a plausible indication of injury susceptibility and sports performance. Benson and colleagues (53) conducted a comprehensive scoping review, which summarized the use of wearable sensors and the associated metrics used to monitor workload and assess injury risk over the last two decades. This scoping review included 407 studies which used wearable sensors to monitor team-sport athletes, 41 (10%) of which reported injuries across the monitoring period, with 36 (8.8%) studies statistically evaluating the association between workload and injury. Some concerning results pertaining to the lack of diversity and generalizability in this research landscape were highlighted by Benson and colleagues: 1) Male participants were disproportionately selected in research, such that 81% of all studies included males; 2) Approximately ¾ of included studies were conducted using a sample of elite or professional athletes, highlighting that the feasibility of using wearable sensors might be limited and favour organizations who can afford such innovative technology; 3) Most studies (58%) possessed small sample sizes (i.e., <25 participants) and assessed athletes sparingly (<25 testing sessions per participant (51%)) despite trying to assess changes over time; 4) The majority of studies investigating the workload-injury relationship were in soccer, rugby, or Australian football (81% of the 36 studies which analyzed the workload-injury relationship), which were primarily conducted in Europe and the Oceania, demonstrating the lack of diversity in sports and the continents in which these studies were conducted; and 5) While 40 (10%) studies monitored athletes over multiple seasons, only two of these were in collegiate athletes, which is concerning given that this athletic population is exposed to additional stress (i.e., academic workload) than other athletes which may impact sports performance and injury susceptibility.

Focussing specifically on basketball, and as seen in Figure 2, there were only four (<1%) included studies that analyzed the relationship between workload and sports performance, and no included studies analyzed the workload-injury relationship in basketball athletes (53). This paucity of data is extremely concerning, as basketball has been deemed one of the sports with the highest injury incidence of all collegiate sports (16,17). Cumulatively, and unfortunately, there was inconclusive evidence regarding the workload-injury relationship in team sport athletes using wearable sensors as seen in the thorough review conducted by Benson and colleagues (53), which was attributed to the variety of injury definitions and workload metrics reported and the inability to draw definitive comparisons between studies. These researchers have stressed the importance of increasing the representation of different sports, competitive levels, and female athletes in future wearable sensor research.

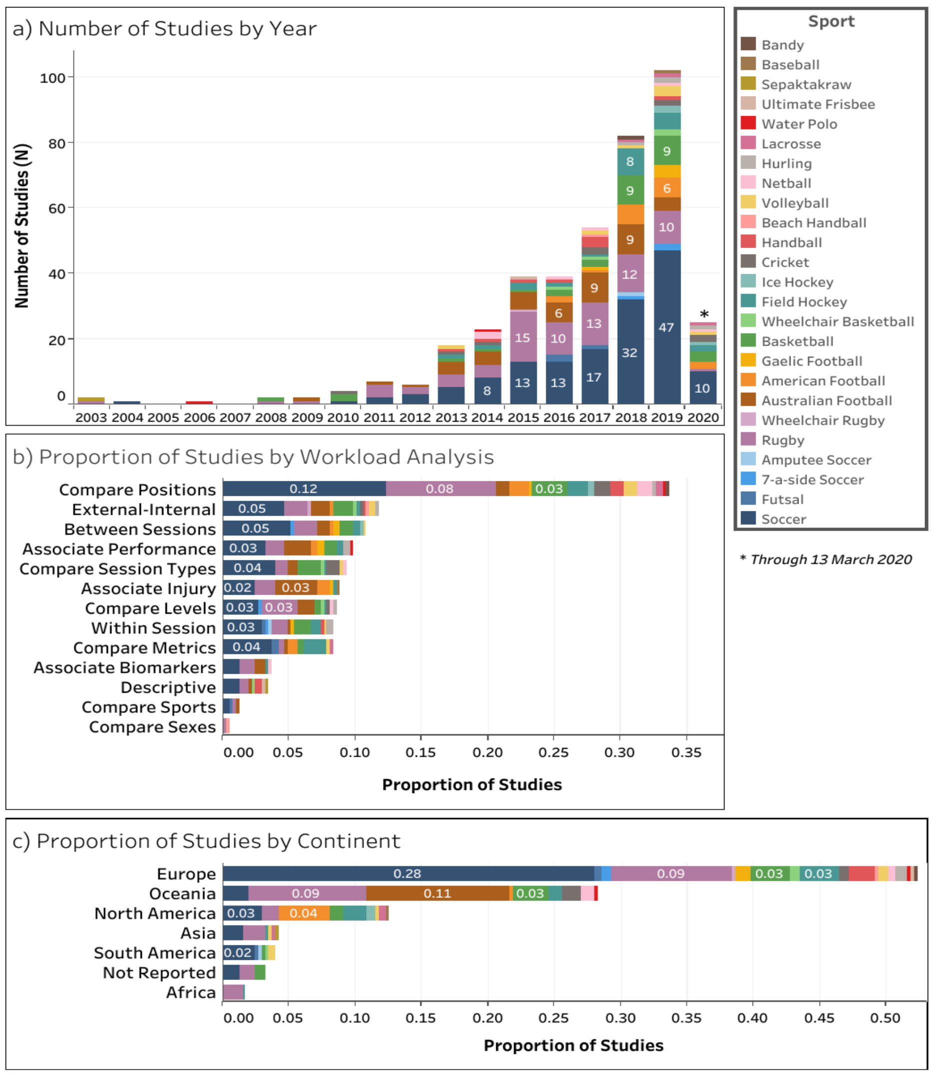

Figure 2. As obtained and described by Benson and colleagues (53), part a) represents the growth in literature that utilizes wearable sensors to monitor athletic workload, part b) indicates the workload analyses conducted by such studies, and part c) indicates the proportion of such studies stratified by continent. These studies are further categorized by sport, as seen by the colour-coded system used by Benson and colleagues (53).

Since the review conducted by Benson and colleagues, there have been two other reviews of similar nature in this space which were conducted by Alanen and colleagues (92) and Cheng and Bergmann (93). The former study comprised 49 primary research articles that focused on the reliability and/or the validity of IMUs when analyzing changes of direction movement in sport. The latter review included 252 studies that used wearable sensors and physiological data in sport-specific settings to monitor team-sport athletes to improve health and well-being.

In the review conducted by Cheng and Bergmann (93), 200 of the 252 included studies monitored athlete workload in on-field settings, while the remaining studies monitored the effect of impacts or workload and impacts concurrently on athlete health and wellness. Similar to the reviews conducted by both Benson and colleagues (53) and Alanen and colleagues (92), there was a disproportionate inclusion of male athletes in high-level competition, again highlighting the need for increased diversity and representation in this research landscape. Rate of perceived exertion and heart rate were the most frequent assessments of subjective and objective internal load, respectively. In the included studies in the review, the general trends that emerged where that studies tracked workload to optimize training and prevent overtraining/overuse injury. In contrast, impact monitoring was completed to discern traumatic injuries and potential causal factors for these injuries. The most common external load variables measured using wearable sensors included total distance covered, velocity, and acceleration, with many of the included studies also stratifying such data into distinct zones (e.g., high-speed distance covered, binning acceleration intensity, etc.).

The review conducted by Alanen and colleagues (92) found that while IMU-derived biomechanical data displayed moderate-to-high reliability, there was no standard placement or number of IMUs across studies, making cross comparisons difficult. Furthermore, kinetic, and kinematic data obtained from IMUs were over-estimations of the same data obtained from the traditional in-lab gold standards (i.e., optical motion capture and force plates). It is important to note that while these IMUs may provide over-estimations of kinetic and kinematic biomechanical variables and that current practices are not standard across different research studies, this out-of-lab collection method permits researchers and practitioners to collect large amounts of data in real-world settings and to more easily monitor changes over time, which would not be practical or feasible in traditional lab-based settings due to the time requirements of data collection.

To elaborate on the feasibility and practicality of incorporating IMUs into routine athletic monitoring practices, an overview of the composition and biomechanical data obtained from IMUs will be noted. IMUs are comprised of an accelerometer, a gyroscope, and a magnetometer, which together provide valuable insight and complementary information to one another regarding out-of-lab movement.

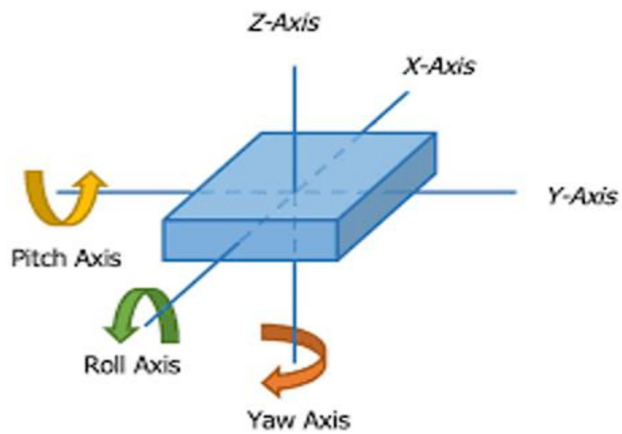

Figure 3. Inertial Measurement Unit which is composed of: i) an accelerometer which measures linear acceleration in the mediolateral (y-axis), anteroposterior (x-axis), and vertical (z-axis) directions; ii) a gyroscope which measures angular rotation termed Roll about the x-axis, Pitch about the y-axis, and Yaw about the z-axis; and iii) a magnetometer which can measure spatial orientation (94). It is important to note that the orientation of the x-, y-, and z-axes can change depending on the convention used by researchers and practitioners. The Inertial Measurement Units used in the present investigation utilized the resultant of these three component parts of the accelerometer (i.e., mediolateral, anteroposterior, and vertical acceleration).

Specifically, these component parts of IMUs unveil and depict acceleration, rotation, and orientation, respectively (Figure 3). Furthermore, given that IMUs can be worn bilaterally, the kinematic, spatiotemporal, and kinetic data obtained or estimated from these wearable sensors can be stratified by limb to yield inter-limb asymmetry metrics in sport-specific settings. Interestingly, and in support of the notion that IMUs may be a useful tool to capture ecologically valid biomechanical data, some studies (54–56) have demonstrated and highlighted a poor association between recognizing specific biomechanical deficiencies, such as kinetic and kinematic information derived from traditional in-lab jump testing, and future injuries. This was believed to be due to the poor relation of in-lab biomechanical data to sport-specific movement, which is highly variant, unanticipated, and spontaneous compared to the highly standardized and controlled environments for athlete testing in-lab. Therefore, it is plausible that the incorporation of IMUs which detail and output kinematic and spatiotemporal metrics (i.e., acceleration, rotation, and orientation), which can also be used to estimate kinetic metrics using inverse dynamics, may aid in sports performance and injury prevention research by bridging the gap between traditional lab-based measurement and sport-specific assessment of human movement.

However, while incorporating sport-specific assessments of human movement using IMUs is crucial in determining ecologically valid biomechanical factors associated with sports performance and injury risk, a purely biomechanical lens does not adequately represent the global state of these competitive athletic populations. In concordance with the holistic athletic assessment model in the present investigation, Cheng and Bergmann (93) concluded that the adoption of analytical models that integrate measures of internal and external load are necessary to better monitor athletic populations, and that the incorporation of extraneous factors related to generalized athlete wellness (e.g., sleep and stress) should also be taken into consideration. However, these authors did not collect or report on extraneous factors, such as markers of psychological state, that might be underpinning determinants of performance and aid in the global representation of the current state of athletes. Therefore, while their conclusions are important and are in-line with the notions of the present investigation, these authors failed to provide evidence of why this relationship between physical/biomechanical and psychological state may be worth investigating and how a biopsychosocial approach to athlete monitoring would enhance the ability to detect injury and optimize sports performance.

2.3: The Importance of Incorporating Psychological State and Well-being into Athletic Monitoring

Several recent review papers and consensus statements have highlighted the need for incorporating a biopsychosocial and more holistic approach to athlete monitoring. For example, Meeusen and colleagues (95) put forth a joint consensus statement on behalf of the European College of Sport Science and the American College of Sports Medicine, which addressed best practices for preventing, diagnosing and treating overtraining syndrome. These authors stated that overtraining syndrome in athletes, which results from an inadequate balance between progressive overload and recovery, presents with symptomatology characteristic of fatigue, mood disturbances, and a resultant decline in sports performance (95). Particularly, these authors highlighted a dose-response relationship in the literature about elevated negative moods and reductions in positive mood states of athletes when training was overtly and abruptly intensified (95). Furthermore, this dose-response relationship to training has also been noted using other psychosocial factors other than mood state, such as sleep, muscle soreness, and perception of effort, which suggests that these negative effects of overtraining may by systemic (95). This consensus statement highlights that non-training and/or non-competition-related stressors may be warranted in athletic monitoring practices to provide a more holistic and global representation of athlete health and well-being.

A similar notion was put forward by Bourdon and colleagues (44), who provided a consensus statement regarding monitoring athletic training loads. Specifically, these authors defined training loads as the cumulative biological, inclusive of both physiological and psychological stress, placed on the athlete during training and competition. Interestingly, and important to note, there are times when the external load (i.e., work performed) remains the same between sessions. At the same time, the internal load (i.e., impact of the work performed on the athlete) may differ substantially, partly attributed to neuromuscular fatigue and emotional/mental state (44). Thus, like the consensus statement provided for overtraining syndrome (95), the consensus statement by Bourdon and colleagues (44) concludes by stressing the importance of considering and integrating non-training and/or non-competition-related factors that may contribute to sports performance and risk of injury, which includes psychological state.

This sentiment regarding the necessity of incorporating subjective internal training load measures, a subsection of psychological state, was reiterated in a recent narrative review (59) and two recent systematic reviews (13,58). The narrative review by Thorpe and colleagues (59) notes that fatigue is multifactorial. Thus, a combination of subjective and objective measures is necessary to adequately monitor the fatigue status of team-sport athletes and the implications of this fatigue status to injury. The systematic review conducted by Saw, Main, and Gastin (58) summarized articles that concurrently utilized objective and subjective measures of athlete well-being to monitor actively training athletes. It was found that subjective measures (specifically, mood disturbances, perceived stress and recovery, and symptoms of stress) were superior in both their sensitivity and consistency to reflect changes in athlete health status due to acute and chronic training loads. The systematic review of longitudinal studies conducted by Jones, Griffiths, and Mellalieu (13) that evaluated the relationship between training load and fatigue to injury and illness concluded by stating that future longitudinal studies should investigate individualized athlete characteristics as they relate to internal training load, due to the significant relationship of internal training load to injury and illness. Moreover, these authors advocated for the continued implementation of subjective markers of training load and fatigue with traditional objective markers so that researchers and practitioners can better understand athletes' health status and changes over time (13). Another recent publication by Montull and colleagues (57) proposes an integrated approach to athletic monitoring, by which healthcare professionals within the immediate care team of competitive athletes should adopt a biopsychosocial approach, as the human body is a complex adaptive system with higher-order perceptual processes that respond distinctively as compared to objective (i.e., physiological and biomechanical) mechanisms, and may contribute to both sports performance and risk of injury.

In light of the notion of monitoring athletes using a biopsychosocial approach, Keogh and colleagues (67) conducted a scoping review and identified 51 primary research articles that concurrently assessed the biomechanical and psychological state of healthy, actively training competitive athletes (96–146). It was found that nearly half of the research published in this field (i.e., 24/51 [47%]) were from the last three years alone. Twenty-two included articles in the review conducted by Keogh and colleagues (67) found a significant relationship between lower-limb biomechanics and introspective psychological state (97,100,105,108,113,114,117,122,124,126,128,129,131–134,137,139–143), while 17 articles found a significant relationship between lower-limb asymmetry and introspective psychological state (96,100,101,108,110,114,122,124,126,128,131–133,137,139,140,146), as seen in Figure 4. However, only 9/22 studies reported a significant relationship between lower-limb biomechanics and psychological state (97,100,113,122,124,134,137,141,142), and 5/17 reported a significant relationship between lower-limb asymmetry and psychological state (100,110,122,124,137) utilized a repeated-measures study design. Therefore, most of the relationships reported thus far in this domain are hypothesis-generating at most, with only a few studies reporting on the interconnectivity of time course changes between biomechanical and psychological states. More importantly, only four of the included studies longitudinally monitored athletes using a biopsychosocial model throughout one or more competitive season(s) (106,120,123,124), and only one of these reported a significant relationship between both lower-limb biomechanics and lower-limb asymmetry vs. psychological state (124). Another noteworthy point of concern is that only one of the four longitudinal studies monitored basketball athletes in particular (124), and none of these longitudinal studies monitored competitive student-athletes.

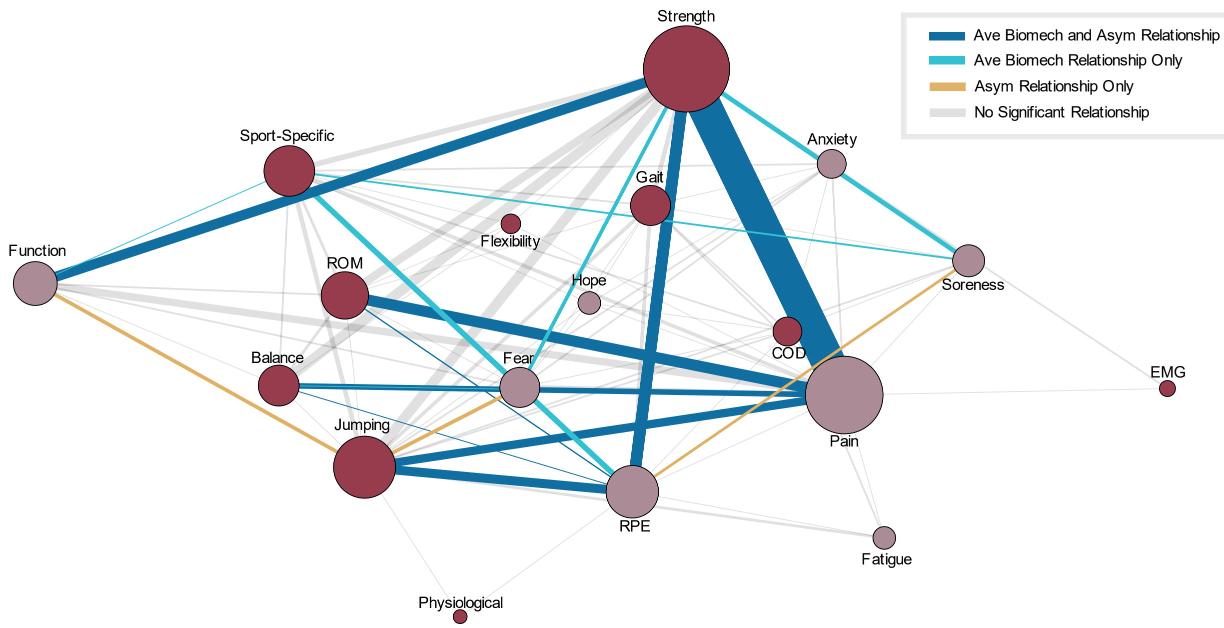

Figure 4. Network graph that depicts studies that have concurrently assessed lower limb biomechanics (including asymmetry) and introspective psychological state in healthy, actively participating competitive athletes. The maroon nodes represent lower limb biomechanical and/or asymmetry assessments conducted in the literature, while the grey nodes represent the introspective, psychological state assessments, with those of increasing size indicating a greater usage rate. The lines that intersect these nodes represent which assessments were conducted concurrently, with the width of such lines representing the proportion of assessments conducted concurrently. The lines are colour coded such that: 1) dark blue represents the relationships that were found for both lower limb biomechanics and asymmetry with an introspective, psychological state measure; 2) teal represents that a relationship was found between lower limb biomechanics and introspective, psychological state; 3) orange represents that a relationship was found between lower limb asymmetry and introspective, psychological state; and 4) grey indicates that there were no statistically significant relationships found between either lower limb biomechanics or asymmetry and introspective, psychological state.

Overall, it is apparent that previous research studies that have taken a purely biomechanical or physiological approach to better understand sports performance and injury susceptibility in athletes are missing key information on athlete health status. Unfortunately, although it seems intuitive and has been suggested that a biopsychosocial model would be the most adept and adequate to capture the global health state of competitive athletes, such research is scarce, especially those that use longitudinal study designs to monitor changes over time attributable to modifiable risk factors for injury and indicators of sports performance. Expanding our understanding of biomechanical patterns and fluctuations by providing context to these changes with respect to concurrent changes in psychological state may provide a more comprehensive and holistic representation of athlete health status.

2.4: Holistic and Multidisciplinary Athletic Monitoring - Integrating Biomechanical and Psychological State Assessments

2.4.1: Using a PCA Model as an Advanced Analytic Tool for Athletic Monitoring – Plausibility of Enhancing Sports Performance and Mitigating Injury Burden

Fortunately, the incorporation of an advanced analytical model, such as PCA, that reduces the dimensionality and in turn, summarizes and enhances the interpretability of large datasets (71) provides the unique opportunity to seamlessly monitor competitive student-athletes over time using a holistic and biopsychosocial model with a multitude of variables related to athlete health status.

Briefly, PCA is a method utilized to convert interrelated variables into orthogonal and statistically linearly independent variables (i.e., PCs) while improving the outcome/variable ratio to ensure we are not overfitting our statistical model (71). This dimensionality reduction process is achieved by either feature elimination or feature extraction (71). Feature elimination involves dropping all variables except those believed to be most predictive of the outcomes of interest, which is advantageous for simplicity and interpretability's sake, but it also means we neglect information from those eliminated features. Feature extraction involves the creation of new and independent variables (PCs), which are a combination of previously correlated independent variables, and the resultant PCs are ordered based on how predictive they are of the outcomes (dependent variables) based on the percentage of the variance explained in the data. When using the feature extraction method for PCA models, there are three ways of determining the cut-off of this dimensionality reduction method: 1) arbitrarily selecting which dimensions to retain, 2) determine the percentage of the variance explained in the data that you hope to be explained by your newly formed PCs and retain only those PCs that explain this threshold of variance in your data, or 3) plotting a cumulative proportion of the variance explained with successive PCs and a cut-off that exists once a large decrease in variance explained with successive PCs is identified visually (71). Together, a PCA model provides insight into the association between variables using a covariance matrix, the directionality of dispersion in the data using Eigenvectors, and the importance of this directionality with the use of Eigenvalues (71). In doing so, this analytical model offers the unique ability to summarize correlated variables into resultant PCs that together describe overarching components of the data.

PCA and other advanced analytical models, such as factor analysis, have been used previously to improve the interpretation of jump (73–75,147–154), change of direction and sprint speed (74,147,153–156), strength (74,147,154), and on-court or other sport-specific assessments of performance in basketball and other team-sports (153,157–161). Additionally, PCA has been used to determine modifiable risk factors for injury in basketball (162). Unfortunately, there have yet to be any longitudinal studies that have utilized these advanced analytical techniques and a holistic biopsychosocial approach in models of sports performance and injury susceptibility, especially in competitive student-athletes. Despite the paucity of longitudinal studies employing a biopsychosocial approach in models of sports performance and injury risk, it should be noted that there has been substantial work as of late using PCA in models of either sports performance or injury risk in basketball athletes.

2.4.2: An Overview of Research that has used Principal Component or Factorial Analysis for Models of Sports Performance and Injury Susceptibility in Basketball Athletes

The preceding sections have provided brief overviews of the utility and pitfalls of the individualized domains of vertical jump testing (CMJ biomechanical analyses), sport-specific monitoring using IMUs, the importance of incorporating psychological state into routine athletic monitoring, and the ability to summarize large and multidisciplinary datasets using PCA. The purpose of this subsection of the literature review is to describe and critique the literature that has used PCA for models of sports performance and injury susceptibility in competitive basketball athletes. In doing so, this section should highlight the current research landscape for studies that have used advanced analytics to assess sports performance and injury risk in basketball athletes, whether any of these studies have employed a multidisciplinary and holistic biopsychosocial approach, and the gaps in the literature that necessitate the present investigation.

A recent systematic review conducted by Pino-Ortega and colleagues (163) highlighted studies that have utilized PCA in either soccer, basketball, or rugby for talent identification, analysis of performance related to the sport, and identifying how training design may be optimized to best serve the sport-specific and positional demands of these athletes. This systematic review found 34 such studies, which cumulatively retained 3.9 ± 2.5 PCs, which explained 80 ± 0.1% of the total variance in the data relating to any of the three aforementioned review study aims. Of these 34 studies, 11 PCA studies possessed a sample of basketball athletes. For simplicity's sake, the authors of this review clustered PCs into one of five overarching domains: technical, tactical, biomechanical, physical/physiological, and anthropometrics. In the subset of basketball studies analyzed, technical and physical or physiological PCs were the most studied (*n* = 5 for both), whilst biomechanical PCs were claimed to be evaluated in one of the 11 included studies. However, this study comprised judoka, handball, and soccer athletes alone. Thus, while kinetic and kinematic measures were incorporated in several studies, there were no PCs pertaining to the biomechanical status of basketball athletes in this systematic review. Furthermore, there was no mention of psychological state as a determinant of performance throughout this review. While a rating of perceived exertion was used in four of the 11 included studies, it was used as a measure of internal load, with no overt mention of the connection to psychological state or other measures of psychological state used in the literature. Another point of concern identified from the included studies in this systematic review is that while a handful of these monitored collegiate or professional male basketball athletes longitudinally throughout one or more competitive season(s), none did so with female basketball athletes, and none used a holistic or biopsychosocial approach.

In addition to the previously highlighted systematic review, several recent articles have employed PCA to analyze the performance of basketball athletes in traditional tasks such as jumping, change of direction and sprint speed, and musculoskeletal strength.

Laffaye and colleagues conducted three studies (150–152) which utilized a PCA model to determine kinetic and kinematic variables that contribute to vertical jumping performance and whether these jump profiles differed depending on the sporting background of athletes. The first of these studies (150) investigated whether jumping expertise impacted leg stiffness, defined as the ratio of the maximal ground reaction force during the active peak to leg shortening (i.e., change in leg length, which is defined as the distance from the body's center of mass to the ball of the foot, or countermovement depth) at the time of maximal leg shortening, and jump profiles as determined through impulse parameters which were obtained from the force-time waveform. The sample comprised 18 male athletes (basketball: *n* = 5; volleyball: *n* = 5; high jump: *n* = 4; and handball: *n* = 4) and 5 male subjects naïve to jumping-based sports. The PCA model resulted in 2 PCs related to vertical force production, stiffness, and contact time (PC1), and leg shortening and jump height (PC2). Interestingly, the jump profiles of athletes from different sporting backgrounds were found to differ when plotting PC scores, such that volleyball athletes demonstrated temporally driven jumping profiles (i.e., long impulse, low vertical ground reaction force, and small leg stiffness value (i.e., low maximal vertical ground reaction force relative to a high level of leg shortening)), while basketball athletes demonstrated heterogenous jumping profiles. The neutrality (i.e., no prevailing dominance of temporal or force-related vertical jump characteristics) of the basketball athletes' jump profile is indicative and suggestive of the necessity for these athletes to be highly adaptable based upon the demands of in game-scenarios. These results were supported by the second study by this group (151), whereby basketball athletes again presented with a heterogenous jumping profile, which this time consisted of a temporal (i.e., impulse time, eccentric time, and vertical displacement of the center of mass/countermovement depth) and force-related (i.e., peak relative force and power production, and rate of force development) PC. In both studies, male subjects naïve to jumping demonstrated either ineffective utilization of the force component or poor jump performance as determined by jump height, which highlights the impact of training experience on these models of jumping performance. The last study conducted by Laffaye and colleagues (152) used a PCA model to determine jump profiles of collegiate and professional team-sport athletes and to ascertain whether these differed based on biological sex. Like the previous work by this group, there was a temporal (i.e., total duration of the jump, time spent in the eccentric phase, and the ratio of the time spent in the eccentric phase relative to the total jump duration) and force-driven (eccentric rate of force development and concentric vertical force production) PC that accounted for most of the variance (i.e., 77%) in jumping performance. It was found that basketball athletes displayed a weak force component with a temporally prevailing jump structure indicated by a large ratio between eccentric to total contact time. Regarding sex-based differences in jumping profiles, it was found that temporal patterns were comparable between male and female athletes. At the same time, the force component was substantially greater in male athletes (specifically, jump height, eccentric rate of force development, and concentric force production).

The authors postulated that these sex-based differences might be attributed to differences in muscle architecture and dimensions between male and female athletes, particularly differences in muscle thickness, size, and even pennation angle, which may be the underpinning factors which allow male athletes to produce greater levels of force and attain higher jump heights. However, without the concurrent physiological assessment of these cohorts of athletes, these underpinning factors are speculative based on previously defined differences identified in work outside the scope of this review. Additionally, while this group presents interesting findings on variance in jump strategy between team-sport athletes, all three of these studies were cross-sectional, and athletes' vertical jump performance was assessed during one stand-alone testing session. Therefore, these results may not necessarily be indicative of between sport variations from a normative basis, as various extraneous factors may have negatively affected their ability to carry out these tests at a maximal level (e.g., pain, inadequate sleep, acute and chronic training loads, etc.). Furthermore, the variations in jump strategy may not represent what would be observed during different stages of competition across a competitive season and provide no information regarding the time course changes of these jump profiles and how these sport-related differences pertain to sports performance in game situations and injury risk.

Various other groups have conducted similar work pertaining to analyzing jump performance in basketball athletes. Floría and colleagues (73) followed a cohort of women's basketball athletes through a randomized control trial to improve vertical jumping performance. The PCA demonstrated that the intervention group displayed positive and significant adaptations compared to the control group, which were characterized by a faster and deeper counter movement with greater propulsive force production, increasing impulse and jump height. Floría and colleagues computed their PCA models separately for the respective waveforms' force, displacement, and velocity data. This was done to identify how the intervention and control groups differed regarding their force production, displacement, and velocity characteristics throughout the vertical jump. While these researchers contributed some valuable results regarding the effect of a training intervention on jump performance as measured by force, displacement, and velocity-based biomechanical metrics using PCA, the application to sports performance during competition and injury risk were not explored, nor was a biopsychosocial model employed.

Rodríguez-Rosell and colleagues (149) assessed the correlation of various traditional and more sport-specific jumping tasks in basketball athletes using PCA. One PC relating to explosive power explained a minimum of 90% of the variance in jumping performance across all jumping tasks for basketball athletes, which all had high interrelationships to the PC (*r* = 0.79-0.99) and redundancy to one another. While these authors assessed a variety of jumping tasks, with some of which having enhanced specificty to basketball movements that would be seen in-game (i.e., one- or two-legged takeoff for a vertical jump with a running leadup), the assessment was cross-sectional and conducted during one testing session. Additionally, the testing methodology used to quantify jump-related data was the Optojump system. This system quantifies interruptions in communication between the units and, thus, uses these intervals to derive contact time and flight time, with the latter of these metrics used to extrapolate jump height. In doing so, these researchers limited their results and the cross-comparisons between jumping tests and sprint speed and leg strength to jump height while neglecting any kinematic or kinetic data that provides pertinent information about jump strategy (164).

The results of Rodríguez-Rosell and colleagues were paralleled in a study conducted by Markovic and colleagues (148), who also found one significant PC relating to explosive power, which was highly correlated to seven different jumping tests (r = 0.76-0.87). However, this study was completed using a sample of college students enrolled in exercise science who were not competitive athletes that were well-versed in jumping. Furthermore, this study was cross-sectional, and all subjects performed each of the different jumping tests during only one of the four testing sessions conducted. As such, not only were these subjects naïve to maximal vertical jumping protocols, but they were also not provided with a familiarization period in an attempt to mitigate the effects of such naivety. Given the work conducted by Laffaye and colleagues (150,151), which highlighted the importance of training expereince when using these PCA models for jumping performance, it is not possible to compare and extrapolate these vertical jump PCA makeup results to other PCA studies that assessed vertical jump performance in basketball athletes, as there was no comparator group with training experience in jumping sports in this investigation.

Lachlan and colleagues (75) presented interesting results that indicate that jump performance may be able to be characterized by principal components that relate to output (i.e., velocities and displacements), causal (i.e., forces and impulses), and timing metrics (i.e., proxies for underlying jump strategy). Unfortunately, this study did not incorporate basketball athletes, and given that previous work has identified that these jump profiles vary substantially based upon sporting background, it cannot be inferred that these results hold for basketball athletes. Moreover, this study assessed biomechanics explicitly using jump testing, and there was no incorporation of biomechanical assessment in a sport-specific context to bridge the gap between lab-based and in-field assessments.

Another study which was conducted by Gómez-Carmona and colleagues (153) used a PCA model to characterize physical fitness profiles of semiprofessional basketball athletes (n = 13 females and n = 13 males) and distinguish whether these were influenced by both biological sex and positional roles. Various field-based tests (e.g., jumping, sprinting, agility tasks) and simulated on-court performance were assessed to develop profiles for these athletes. There were four PCs identified for both male and female basketball athletes, with two divergent and two common PCs between the sexes. The two PCs that were similar between the sexes related to aerobic capacity and in-game physical conditioning (PC1 for both) and unilateral jumping performance (PC4 for male and PC3 for female athletes). The two divergent PCs were as follows: bilateral jumping capacity and acceleration and curvilinear displacement for male athletes (PC2 and PC3, respectively), and bilateral jumping capacity and curvilinear displacement, and deceleration for female basketball athletes (PC2 and PC4, respectively). Similar to the work conducted by Laffaye and colleagues (152), it appears that physical fitness and jumping profiles differ between male and female basketball athletes, which suggests that models built out for one should not be universally used for the other.

In the context of psychological state inclusion in basketball PCA literature, it is important to note that only 4/11 included studies in the previously mentioned systematic review conducted by Pino-Ortega and colleagues (163) utilized the rating of perceived exertion, a measure commonly employed for assessing psychological state in the context of neuromuscular fatigue. However, this was categorized as physical or physiological; thus, no connection was drawn to the psychological aspect inherent in the readiness to perform for athletes. Two other studies (161,162) not included in this systematic review used rate of perceived exertion while monitoring basketball athletes longitudinally over a competitive season (n = 4 months of in-season training for both studies).

The first of these studies, conducted by Svilar and colleagues (161), used a PCA model to define interrelationships between external and internal training load and to distinguish how this differed between positional roles. It was found that rate of perceived exertion was highly correlated to the total amount of acceleration and deceleration (anteroposterior vector component) and change of direction (mediolateral vector component) experienced on-court across the season, irrespective of position. When stratifying the PCA model by position, two (centers) to three (forwards and guards) PCs arose which explained the original external training load variables; however, the relative importance of these original variables differed by playing position. Despite this group incorporating the rating of perceived exertion across the season, they failed to incorporate this measure into their PCA models and defined this model with on-court biomechanical data explicitly.

The second study, which used rating of perceived exertion while monitoring basketball athletes longitudinally was conducted by Benson and colleagues (162). Surprisingly, this study conducted by Benson and colleagues was the only study of all PCA studies in basketball athletes which used this advanced analytical model to determine differences in injured and uninjured athletes. Specifically, differences in injured and uninjured youth basketball athletes (*n* = 4 teams, with an even distribution of female and male teams) were identified and characterized at either one-, two-, three-, or four-weeks preceding the injury. This study found that the first PC was related to overall workload magnitude, and the other PCs were representative of differences between specific workload variables and the number of weeks with which these workloads were accumulated. Injured youth basketball athletes demonstrated a low previous three- and four-week workload (i.e., chronic workload period) which was identified using PC2, coupled with a high previous one-week workload (i.e., the acute workload period) which was identified using PC1, suggesting an exceedance of the acute to chronic workload ratio (although this ratio was not directly calculated in the investigation by Benson and colleagues). Rating of perceived exertion (i.e., internal workload) demonstrated similar results to the external workload measures, such that it was lower in injured athletes in two-, three-, and four-weeks preceding overuse injury; however, some injured athletes displayed contradictory results (i.e., one standard deviation above the mean of uninjured participants across the same timeframe).

Cumulatively, this study by Benson and colleagues provides some very important results for the workload-injury relationship and models of injury susceptibility in basketball athletes, as it is the first and only study to utilize PCA to summarize and identify differences between injured and uninjured male and female basketball athletes across a competitive season. However, this study only incorporated one measure of psychological state and did so in a sample of youth athletes. Given that previous work has identified differences in sports performance between naïve and highly trained athletes (150,151), there is the potential that the importance of training experience could transverse to models of injury risk, which would perturb the ability to use such findings in a collegiate or professional athletic population. Moreover, without an adequate representation of both the biomechanical and psychological state of the athlete, there might be underpinning and contributting factors to acute and/or oversue injury that Benson and colleagues do not realize.

Unfortunately, there are some overarching trends in all the aforementioned studies which utilized a PCA model to assess and characterize jumping or other measures of sports performance – only six of these studies (161,162,165–168) monitored or attempted to characterize psychological stressors/state as a determinant of performance, with only three of these studies in basketball athletes (161,162,165). Furthermore, only five studies (153,157–160) monitored biomechanics in a sport-specific context using wearable technology. This purely physical lens, whether physiological and/or biomechanical requirements and profiles in sports performance models, fails to adequately represent the global state of the athlete. Furthermore, the lack of assessment in sport-specific contexts during practice and/or in-game perturbs the ability of these researchers to draw definitive conclusions of how these traditional lab-based biomechanical assessments relate to sports performance and injury susceptibility in the environment that matters most. Studies in this space have done an abysmal job at adequately representing the global state of these athletic populations, which, unfortunately, persists in other studies which utilized PCA to model performance during change of direction and sprint speed (74,147,153–156), strength (74,147,154), and on-court performance (153,157–160). Ultimately, there is a dire need for the integration of psychological state and in-field or sport-specific monitoring using wearable sensors, such as IMUs, in conjunction with traditional performance assessments (i.e., CMJ and other proxies for sport-related performance) if we are to enhance our ability to detect a change and improve our overall understanding of contributory factors to sports performance and injury susceptibility in competitive basketball athletes, and athletic populations at large.

2.5: Synopsis of Literature Review

Cumulatively, while there has been substantial research conducted in the individualized domains of lower limb biomechanics, both in a traditional lab-based setting (i.e., CMJ testing using force plates) and in sport-specific contexts (i.e., on-court or on-field assessments using IMUs and other wearable sensors), there has yet to be a push towards the integration of these assessments to define a more comprehensive biomechanical profile for athletic populations. Additionally, while sport psychology is well-studied, researchers and practitioners often treat biomechanics and psychology as separate entities rather than contextualizing changes in one domain with the other in a longitudinal fashion. While each of these domains provides important information about biomechanical and psychological factors that may be associated with sports performance and/or injury risk, they can each be missing the global state of the athlete. Such isolated monitoring practices are analogous to the parable of "*The Blind Men and The Elephant*", whereby each assessment of the elephant, or in this case, the athlete, is not incorrect in its own right but is nevertheless widely misinterpreting the overall state of the elephant or athlete when not taken together.

Additionally, those studies that have integrated these domains for contextual purposes have rarely used a longitudinal study design to monitor changes over time relative to normative, individualized baseline values. Furthermore, there has been a disproportionate selection bias in favour of male competitive athletes with an underrepresentation of female athletes, who have been reported to sustain more severe lower extremity injuries than their male counterparts. It is worthy noting that a recent scoping review conducted by Keogh and colleagues (67) highlighted and delineated significant relationships between lower limb biomechanics and asymmetry to introspective psychological state (which primarily pertained to the rating of perceived exertion and pain) that have been reported in the literature (Figure 4); however, these authors were unable to draw definitive conclusions about how these holistic assessments relate to sports performance and injury risk given the scoping nature of their review, rather than a meta-analytic approach.

Therefore, it is evident that there is a dire need for longitudinal studies that employ a holistic, biopsychosocial approach in models of sports performance and injury susceptibility in competitive athletes, especially female athletes. A holistic, biopsychosocial approach can be accomplished using advanced statistical models such as PCA which summarizes correlated variables into resultant PCs that together describe overarching components of the multivariate biomechanical data, which are concurrently monitored with fluctuations in psychological state. In doing so, a better understanding of contributory factors to sports performance and injury risk might be realized in competitive student-athletes and may improve patient-centred preventive and prognostic medical practices.

Chapter 3: Thesis Research Questions and Hypotheses

Research Questions

The overarching aim of this project was to improve athletic monitoring practices by examining the utility of integrating on- and off-court biomechanical data into more holistic metrics (i.e., PCs that define overarching biomechanical concepts – jump power, asymmetry, etc.), with concurrent longitudinal monitoring of psychological state to contextualize these subject-specific biomechanical fluctuations. Specifically, data collected over two competitive collegiate female basketball seasons were used in a PCA model to support the following research questions:

(i) *Correlations Between On-Court and Vertical Jump Biomechanics:* Are on-court, sensor-derived, and force-plate-derived vertical jump metrics significantly correlated throughout the 2021-2022 and 2022-2023 competitive collegiate female basketball seasons?

(ii) *Reliability of Biomechanical Principal Components and Introspective, Psychological State:* What is the reliability of the biomechanical PCs (i.e., on-court and countermovement jump (CMJ) biomechanics) and introspective, psychological state metrics across the 2022-2023 competitive, collegiate female basketball preseason?

(iii) *Longitudinal PCA Application & Association Between Biomechanical and Introspective, Psychological State:*

(A) Are PC scores derived from a biomechanical model (i.e., on-court and vertical jump data) significantly correlated with introspective, psychological state (e.g., self-reported pain, sleep quality, sleep quantity, etc.) across the 2022-2023 regular season?

(B) Could we detect subject-specific meaningful changes in these measures using PCs and associated MDC statistics?

Hypotheses

For the initial research question, following previous research by Lachlan and colleagues and Keogh and colleagues, which found biomechanical metrics to be significantly correlated (75,169), we hypothesized that on-court and vertical jump biomechanics would be significantly correlated, justifying the computation and utility of a PCA model for research questions (ii) and

(iii) (i.e., the reliability of the biomechanical PCA model and introspective, psychological state, and longitudinal PCA application and detection of minimally important, and subject-specific changes, respectively).

Regarding the second research question, we hypothesized that the biomechanical PCA model and introspective, psychological state metrics would display good-to-excellent reliability across the 2022-2023 preseason, which is in line with previous work by Keogh and colleagues who conducted a similar use-case and longitudinal PCA investigation (169). If the biomechanical PCs and introspective, psychological state metrics are highly reliable metrics, as hypothesized, this will allow us to look at in-season and subject-specific changes in these constructs. We will also highlight the use of this approach for the purposes of "red-flagging" individualized fluctuations from normative patterns, which could potentially aid in the clinical decision-making process.

As for the third and final research question, while self-reported pain and rate of perceived exertion can be associated with some biomechanical measures (e.g., jump testing, lower-limb strength, range of motion, and lower-limb asymmetry – (67)), the associations between other introspective and biomechanical metrics are relatively unknown. Nevertheless, we hypothesized that changes in biomechanical variables collected during vertical jump testing and on-court practices would significantly correlate with changes in the introspective, psychological state measures collected in the 2022-2023 basketball regular season. Additionally, and in more of an exploratory lens, we hypothesized that subject-specific MDC statistics would provide a feasible and practical means of "red-flagging" alterations in these outcome measures, highlighting the ability to provide patient-centred prognostic and preventive medical practices using this approach.

Chapter 4: Research Methodology

4.1: Study Design

This study was a longitudinal cohort design that collected repeated data on athletes across multiple seasons. Specifically, biomechanical, and psychological data were collected in two consecutive seven-month collegiate female basketball seasons (i.e., the 2021-2022 and 2022-2023 competitive seasons) at McMaster University. These data were collected during three consecutive training phases, namely, one-month of offseason training, two-months of preseason training, and during the four-month regular season. Data were collected weekly, such that CMJ testing and psychological state questionnaires were completed on Monday mornings, while on-court biomechanical assessments with IMUs were completed during three weekly basketball practices. All data (i.e., CMJ, on-court IMU, and psychological state) were then summarized as weekly averages. Research question (i) examined associations between biomechanical variables across the 2021-2022 and 2022-2023 seasons. Additionally, the biomechanical PCA model for research questions (ii) and (iii) was developed from 2021-2022 data and applied to 2022-2023 season data to assess the relationship between biomechanical PCs and introspective, psychological state data and to highlight the ability to "red-flag" subject-specific alterations in these outcome measures.

4.2: Sample

Sixteen female collegiate basketball athletes (eight guards, five forwards, and three centers) from McMaster University volunteered to participate in the study: age 20 (2) years, height 178 (9) cm, body mass 73 (11) kg, and training experience 3 (1) years. All athletes were free from musculoskeletal injury or disorder at initial screening that would perturb their performance at the initiation of the 2021-2022 competitive season. Typical sample size calculations were challenging for this project as the pool of potential participants was limited to the number of players on the McMaster Women's Basketball team. However, to counter this limitation, given the study involves a within-subject design, many samples were collected within each individual participant (e.g., 28 weeks x 2 seasons = up to 56 potential weeks of data for each participant), which resulted in sufficient data for running PCA models and within-subject analyses (170).

4.3: Protocol

Data Collected: First, *on-court impact asymmetry (overall impact asymmetry* as well as *impact acceleration asymmetry stratified into low-, medium-, and high-intensity bins;* i.e., overall/averaged, 1-5g, 6-20g, and 21-200+g, respectively*), impact load, step count, and average intensity* (i.e., *n* = 7 metrics) were assessed as weekly average values using peak resultant linear accelerations from IMUs (iMeasureU, Vicon) placed bilaterally anterosuperior to the medial malleoli in on-court practices. Second, *between-limb differences in force production during braking-*, *propulsive-*, and *landing-phases of movement, peak power production during the braking- and propulsive-phases of movement, jump strategy metrics (i.e., countermovement depth (CMD), time to takeoff*, and *RSI mod),* and *JH* (i.e., *n* = 10 metrics, cumulatively) were assessed weekly with vertical jump tests (i.e., the countermovement jump without an arm-swing) using bilateral force plates (Hawkin Dynamics). The reliability of these CMJ metrics was assessed in work parallel to this thesis by Keogh and colleagues (169), in which 17/18 CMJ metrics displayed excellent reliability (ICC ≥ 0.90) when assessed longitudinally. Additionally, I also compared the ecological validity of these force-plate derived inter-limb asymmetry metrics relative to the aforementioned on-court asymmetry metrics (52), which highlighted the need to measure lower-limb asymmetry in sport-specific contexts, as this metric was deemed to be highly task-specific in concordance with work completed by other researchers in this field (50,51). Finally, weekly questionnaires were completed via Google Forms, on the athletes' own volition, on Monday mornings using a questionnaire that was conceived with the McMaster University Strength and Conditioning team, Biomechanics Laboratory, and NeuroFit Laboratory. Specifically, this weekly questionnaire was comprised of the following self-report measures: *self-reported pain, sleep quality* and *sleep quantity*, a *general feeling scale*, and *academic workload* (i.e., *n* = 5 metrics), which were assessed using the Visual Analogue Pain Scale (171), a subsection of the Pittsburgh Sleep Quality Index (172), and a 0-10 Likert scale, respectively. Thus, seven on-court metrics, ten metrics during CMJ testing, and five metrics on introspective, psychological state and well-being via the previously noted questionnaire were collected across the two, seven-month study periods.

Testing Procedures: CMJ testing was conducted on Monday mornings in which participants first completed a low- to moderate-intensity dynamic warm-up to prepare the neuromuscular system. This dynamic warm-up was led by the strength and conditioning staff and was the same for all athletes. Two portable force platforms (Hawkin Dynamics, Westbrook, ME, USA) were utilized to collect the ten CMJ biomechanical variables of interest at a sampling frequency of 1000 Hz; this method of biomechanical assessment during vertical jump testing has been deemed valid when compared to the in-laboratory gold standard (173,174). Subjects were instructed to stand still with feet shoulder-width apart on the dual force plates, allowing for proper establishment of body weight calculation. Additionally, subjects were told to self-select CMD, as this has been said to allow for fluid movement, as would regularly be seen when jumping in competition, without tampering with the reliability of the metrics obtained (47,175). No instructions were provided for the landing phase of the CMJ aside from ensuring that both feet made contact with the force platform prior to concluding the downward motion of this phase of movement and, subsequently, returning to an upright standing position (80), which was accomplished by providing synchronous visual feedback of bilateral weight distribution on either a monitor or portable device in front of the athletes (47). Additionally, jumps were visually monitored by the research team such that those attempts in which an athlete was unable to land with both feet on the force platform or failed to return to an upright standing position to conclude the trial were identified as mistrials, discarded, and the attempt was then repeated after the provision of sufficient rest (80,81). Athletes were then verbally cued to jump as high as possible while also completing the movement as quickly as possible to effectively utilize a stretch-shortening cycle and mimic the explosive performance in a game (18,29). All jumps were completed with hands placed on hips and without an arm-swing (47,176). Athletes completed three jumps per day, with a minimum of 30-seconds rest between each trial. Subsequently, the average of these three jumps was used to determine CMJ metrics for each weekly session, as this is preferable to using the best jump approach (177). However, if an individual jump had a JH that deviated by ≥20% within a session, then this specific jump attempt was removed from the computation of the weekly average and, as such, was excluded from statistical analyses. The impulse-momentum theorem and take-off velocity were used to derive JH, rather than flight time, as this has been previously noted as the gold standard (47,82).

During on-court sessions, participants were fitted with two IMUs (Vicon IMeasureU Step, Denver, CO), which were positioned bilaterally anterosuperior to the medial malleoli. These wearable sensors collected sessional impact load, step count, average intensity, and impact asymmetry data, as well as impact asymmetry stratified into low, medium, and high-intensity bins (1-5g, 6-20g, and 21-200+g, respectively) throughout 90- to 120-minute on-court basketball training sessions (178). CMJ testing was completed once per week, while on-court sessions were completed three times per week across the 2021-2022 and 2022-2023 competitive collegiate basketball seasons (i.e., seven-months each).

All previously outlined biomechanical data were computed from either ground reaction force data or using resultant accelerometer data from IMU's, all obtained from the respective manufacturer-provided software.

Model Development: A total of seven-months of data were collected during the 2021-2022 season, resulting in a total of 448 possible weekly observations (28 weeks x 16 athletes) of the abovementioned 22 variables. Coefficients for the PC analysis were derived from the resulting data matrix, which was completed using the "pca" function in MATLAB R2021a (MathWorks, Inc., Natick, MA, USA) following the standardization of variables (i.e., mean of zero and standard deviation of one). Standardization of input variables was required given the varying scales of our biomechanical variables (71,179). This function utilizes the singular value decomposition approach to consolidate commonalities between the original biomechanical variables by uniquely loading (i.e., rotating) them onto new variables (i.e., PCs). Therefore, the newly developed PCs utilize commonalities between all original biomechanical variables (i.e., on-court and vertical jump biomechanics), but they are orthogonal (i.e., uncorrelated). Further, these newly developed PCs are derived in order of maximum variance explained in the data and presented in descending order from PC1 to n-PC. This reduces the dimensionality of the data whereby a limited number of new independent variables (PCs) were selected based upon a threshold in which those PCs that explain ≥90% of the variance in the data (71,179) were retained in the final PCA model. While the number of retained PCs can also be determined visually through a scree plot analysis (71,179) by finding the 'elbow' in the plot of variance or taking only those with an eigenvalue >1, as per the Kaiser rule (179), these retention approaches were initially conceived for factor analysis, not for PCA, and often retain an insufficient number of PCs (179). Jolliffe (180) suggested that a lower eigenvalue cutoff of 0.7 should be used based on simulation studies and following this recommendation, we cross-validated our ≥90% variance threshold retention approach with a scree plot retention approach using this 0.7 eigenvalue cutoff. In other words, we used the ≥90% approach as the primary method for retaining PCs but confirmed this aligned well with the two previously proposed methods. As such, the final PCA model describes the overarching components of the biomechanical state of participants by providing insight regarding the association between original variables in a covariance matrix, the directionality of dispersion in the data via outputted Eigenvectors, and the importance of the directionality of this data via computed Eigenvalues. Therefore, these model coefficients allowed for PC scores, defining a more holistic measure of the biomechanical state of the athlete, to be computed weekly for each athlete during the 2022-2023 season, and ultimately, were utilized to address research questions (ii) and (iii).

4.4: Statistical Analysis

i) Correlation between on-court and vertical jump biomechanics: The correlation between on-court and vertical jump biomechanical metrics was assessed using a series of Pearson's correlation coefficients (α = 0.05, β = 0.20). Given the repeated measures of these data, it is important to note that the independence of observations assumption was violated for this correlation analysis. While this limits the potential interpretation of these correlations, it remains consistent with the rationale and use of a PCA as a data reduction tool (71,179). The presence of correlations in these metrics would give credence to the use of a PCA as it suggests these metrics have some redundancy and share commonalities to similar, underlying components of biomechanical movement patterns. *ii) Reliability of biomechanical PCA model and introspective, psychological state:* The reliability of the biomechanical PCs and introspective, psychological state metrics were assessed across five consecutive and unperturbed (i.e., no scheduled periods of intensified competition or extended rest that would implicate the consistency of these measures) weeks in the 2022-2023 preseason using an intraclass correlation coefficient ($ICC_{3,k}$) with 95% confidence intervals, standardized error of the measurement (SEM), and minimum detectable change (MDC_{95}) statistics (77,181). We interpreted ICCs as poor (<0.5), moderate (0.5-0.75), good (0.75-0.89), and excellent (>0.9) (182). *iii) Longitudinal PCA application & association between biomechanical and introspective, psychological state:* The relationship of subject-specific weekly biomechanical PC scores to introspective, psychological state metrics were assessed using Pearson's correlation coefficients (α = 0.05, β = 0.20). Additionally, these relationships were examined using a repeated measures correlation statistical approach to determine the common within-individual associations between these continuous variables (i.e., biomechanical PCs and psychological state), while ensuring that the assumption of independence of observations was not violated by controlling for the effect of between-individual variance (183). Additionally, and as previously outlined for research question (ii), standardized error of the measurement (SEM) and MDC statistics (77) were computed for "red-flagging" and identifying subject-specific statistically important levels of change in our biomechanical PCs and introspective, psychological state metrics across the 2022-2023 season. These MDC statistics were defined using preseason data as normative baseline values and were carried forth across the season to discern when subjects had exhibited fluctuations outside of their normative patterns demonstrated in the preseason. This methodological approach has been proven reliable and was applied in a similar use-case example by Keogh and colleagues (169) in a longitudinal (i.e., across one competitive season) jump-testing PCA model. All statistical analyses aside from the repeated measures correlation (i.e., completed using RStudio (RStudio Team, 2021) and the "rmcorr" R package) were performed using MATLAB R2021a (MathWorks, Inc., Natick, MA, USA).

Chapter 5: Results

5.1: Summary of Data Collected

The sixteen female basketball athletes were prospectively monitored across two competitive, collegiate basketball seasons, which consisted of i) two-to-three on-court sessions per week in which IMU-derived metrics were obtained, ii) three CMJ attempts per week completed on Monday mornings in which force-plate-derived metrics were obtained, and iii) a weekly questionnaire which was completed once per week on Monday mornings to obtain introspective, psychological state data. Across the two competitive collegiate basketball seasons, a total of 1,226 on-court sessions were collected (mean per athlete = 77; SD per athlete = 26), 1,936 CMJ trials were performed (mean per athlete = 121; SD per athlete = 42), and 910 weekly self-reported questionnaires were completed (mean per athlete = 57; SD per athlete = 28).

5.2: Research Question I – Correlations Between On-Court and Countermovement Jump Biomechanics

It was found that on-court and CMJ biomechanical metrics obtained from IMUs, and dual force plates were correlated between and within systems (Table 1). In terms of the inter-connectivity of these biomechanical data (i.e., relationships between systems), it was found that 58 of 70 total relationships reached statistical significance (r = |0.10, 0.58|; $p < 0.05$). Meanwhile, when looking at the intra-connectivity of biomechanical data within systems, 13 of 21 and 41 of 45 total relationships reached statistical significance for on-court (r = |0.11, 0.87|; $p < 0.05$) and CMJ biomechanical metrics (r = |0.12, 0.94|; $p < 0.05$), respectively. For example, on-court total impact load was closely related to total step count and average intensity (r = 0.75, and 0.83, respectively; $p < 0.001$), as were the four on-court asymmetry metrics (r = |0.13, 0.87|; $p < 0.01$). For the within-system relationships identified for CMJ biomechanics, strong correlations were observed between "explosive-based metrics" such as JH, peak relative propulsive power, and RSI mod (r = 0.85, 0.94; $p < 0.001$), as well as "CMJ asymmetry metrics" such as peak braking force, peak propulsive force, average braking rate of force development, and peak landing force asymmetry (r = |0.29, 0.87|; $p < 0.001$). These biomechanical associations also happened to cross systems, but most related to loading/intensity and explosive capabilities (i.e., on-court total impact load and average intensity with JH, peak relative propulsive power, and RSI mod; r = 0.46, 0.58; $p < 0.001$). Interestingly, on-court and CMJ asymmetry displayed very weak associations (r = |0.11, 0.27|; $p < 0.05$), suggesting that these biomechanical asymmetries might be distinct. Cumulatively and per our hypothesis, the correlated nature of these biomechanical metrics supported the implementation of a biomechanical PCA model to reduce the dimensionality of the biomechanical data before conducting research questions (ii) and (iii) (71,179).

Table 1. Correlations between on-court inertial measurement unit-derived and force plate-derived countermovement jump biomechanical metrics in a cohort of collegiate female basketball athletes from data across two competitive seasons.

	TIL	TSC	Ave Int	Impact Asym	Low-G Asym	Medium-G Asym	High-G Asym	JH	CMD	TTTo	PRBP	PRPP	PBF Asym	PPF Asym	Ave BRFD Asym	PLF Asym	RSI Mod
TIL	1.00 (1.00, 1.00)	0.75 (0.70, 0.79) ***	0.83 (0.80, 0.86) ***	0.14 (0.04, 0.23) **	0.08 (-0.02, 0.18)	0.08 (-0.02, 0.18)	-0.11 (-0.21, -0.01) *	0.46 (0.38, 0.54) ***	-0.04 (-0.14, 0.06)	-0.11 (-0.21, -0.01) *	-0.12 (-0.22, -0.02) *	0.50 (0.42, 0.57) ***	-0.33 (-0.42, -0.24) ***	-0.36 (-0.45, -0.27) ***	-0.36 (-0.44, -0.26) ***	-0.18 (-0.27, -0.08) ***	0.47 (0.39, 0.55) ***
TSC	0.75 (0.70, 0.79) ***	1.00 (1.00, 1.00)	0.28 (0.19, 0.37) ***	0.08 (-0.03, 0.17)	0.07 (-0.03, 0.17)	0.05 (-0.05, 0.15)	-0.05 (-0.15, 0.05)	0.16 (0.06, 0.25) **	0.10 (0.00, 0.20)	-0.15 (-0.24, -0.05) **	-0.10 (-0.20, 0.00) *	0.19 (0.09, 0.28) ***	-0.11 (-0.21, -0.01) *	-0.17 (-0.27, -0.07) ***	-0.08 (-0.18, 0.02)	-0.05 (-0.15, 0.05)	0.22 (0.12, 0.31) ***
Ave Int	0.83 (0.80, 0.86) ***	0.28 (0.19, 0.37) ***	1.00 (1.00, 1.00)	0.13 (0.03, 0.23) *	0.07 (-0.03, 0.17)	0.04 (-0.06, 0.14)	-0.12 (-0.22, -0.02) *	0.56 (0.49, 0.63) ***	-0.17 (-0.26, -0.07) **	-0.02 (-0.12, 0.08)	-0.09 (-0.19, 0.01)	0.58 (0.50, 0.64) ***	-0.39 (-0.48, -0.31) ***	-0.38 (-0.46, -0.29) ***	-0.46 (-0.53, -0.37) ***	-0.24 (-0.33, -0.14) ***	0.50 (0.42, 0.57) ***
Impact Asym	0.14 (0.04, 0.23) **	0.08 (-0.03, 0.17)	0.13 (0.03, 0.23) *	1.00 (1.00, 1.00)	0.65 (0.59, 0.71) ***	0.62 (0.55, 0.68) ***	-0.87 (-0.89, -0.85) ***	0.16 (0.06, 0.26) **	-0.06 (-0.16, 0.04)	-0.13 (-0.23, -0.03) **	-0.25 (-0.34, -0.15) ***	0.20 (0.10, 0.29) ***	-0.15 (-0.25, -0.06) **	-0.23 (-0.32, -0.13) ***	-0.13 (-0.23, -0.03) **	-0.26 (-0.35, -0.16) ***	0.22 (0.12, 0.31) ***
Low-G Asym	0.08 (-0.02, 0.18)	0.07 (-0.03, 0.17)	0.07 (-0.03, 0.17)	0.65 (0.59, 0.71) ***	1.00 (1.00, 1.00)	0.13 (0.03, 0.23) **	-0.55 (-0.62, -0.48) ***	0.08 (-0.03, 0.17)	0.07 (-0.03, 0.17)	-0.22 (-0.32, -0.13) ***	-0.20 (-0.29, -0.10) ***	0.10 (0.00, 0.20)	-0.16 (-0.25, -0.06) **	-0.18 (-0.28, -0.08) ***	-0.14 (-0.24, -0.04) **	-0.15 (-0.25, -0.05) **	0.18 (0.08, 0.27) ***
Medium-G Asym	0.08 (-0.02, 0.18)	0.05 (-0.05, 0.15)	0.04 (-0.06, 0.14)	0.62 (0.55, 0.68) ***	0.13 (0.03, 0.23) **	1.00 (1.00, 1.00)	-0.56 (-0.63, -0.49) ***	0.08 (-0.02, 0.18)	-0.11 (-0.21, -0.01) *	-0.19 (-0.28, -0.09) ***	-0.29 (-0.38, -0.19) ***	0.16 (0.06, 0.25) **	-0.11 (-0.21, 0.01) *	-0.22 (-0.31, -0.12) ***	-0.11 (-0.21, 0.01) *	-0.27 (-0.36, -0.18) ***	0.19 (0.09, 0.28) ***
High-G Asym	-0.11 (-0.21, -0.01) *	-0.05 (-0.15, 0.05)	-0.12 (-0.22, -0.02) *	-0.87 (-0.89, -0.85) ***	-0.55 (-0.62, -0.48) ***	-0.56 (-0.63, -0.49) ***	1.00 (1.00, 1.00)	-0.18 (-0.27, -0.08) ***	0.05 (-0.05, 0.15)	0.12 (0.01, 0.21) *	0.21 (0.11, 0.30) ***	-0.24 (-0.33, -0.14) ***	0.14 (0.04, 0.24) **	0.23 (0.13, 0.32) ***	0.14 (0.04, 0.23) **	0.26 (0.16, 0.35) ***	-0.22 (-0.31, -0.12) ***
JH	0.46 (0.38, 0.54) ***	0.16 (0.06, 0.25) **	0.56 (0.49, 0.63) ***	0.16 (0.06, 0.26) **	0.08 (-0.03, 0.17)	0.08 (-0.02, 0.18)	-0.18 (-0.27, -0.08) ***	1.00 (1.00, 1.00)	-0.43 (-0.51, -0.34) ***	-0.01 (-0.11, 0.09)	-0.32 (-0.41, -0.23) ***	0.94 (0.93, 0.95) ***	-0.51 (-0.58, -0.44) ***	-0.50 (-0.57, -0.42) ***	-0.46 (-0.54, -0.38) ***	-0.43 (-0.51, -0.35) ***	0.85 (0.82, 0.87) ***
CMD	-0.04 (-0.14, 0.06)	0.10 (-0.00, 0.20)	-0.17 (-0.26, -0.07) **	-0.06 (-0.16, 0.04)	0.07 (-0.03, 0.17)	-0.11 (-0.21, -0.01) *	0.05 (-0.05, 0.15)	-0.43 (-0.51, -0.34) ***	1.00 (1.00, 1.00)	-0.50 (-0.57, -0.42) ***	0.21 (0.11, 0.31) ***	-0.21 (-0.30, -0.11) ***	0.27 (0.18, 0.36) ***	0.21 (0.11, 0.30) ***	0.25 (0.16, 0.35) ***	0.32 (0.23, 0.41) ***	-0.08 (-0.18, -0.02)

TTTo	-0.11 (-0.21, -0.01) *	-0.15 (-0.24, -0.05) **	0.02 (-0.12, 0.08)	-0.13 (-0.23, -0.03) **	-0.22 (-0.32, -0.13) ***	-0.19 (-0.28, -0.09) ***	0.12 (0.01, 0.21) *	0.01 (-0.11, 0.09)	-0.50 (-0.57, -0.42) ***	1.00 (1.00, 1.00)	0.53 (0.45, 0.60) ***	-0.13 (-0.23, -0.03) *	0.06 (-0.04, 0.16)	0.13 (0.03, 0.23) *	0.12 (0.02, 0.21) *	-0.03 (-0.13, 0.07)	-0.51 (-0.58, -0.43) ***
PRBP	-0.12 (-0.22, -0.02) *	-0.10 (-0.20, 0.00) *	0.09 (-0.19, 0.01)	-0.25 (-0.34, -0.15) ***	-0.20 (-0.29, -0.10) ***	-0.29 (-0.38, -0.19) ***	0.21 (0.11, 0.30) ***	-0.32 (-0.41, -0.23) ***	0.21 (0.11, 0.31) ***	0.53 (0.45, 0.60) ***	1.00 (1.00, 1.00)	-0.24 (-0.33, -0.14) ***	0.17 (0.07, 0.27) ***	0.28 (0.18, 0.37) ***	0.22 (0.12, 0.32) ***	0.16 (0.06, 0.26) **	-0.55 (-0.61, -0.47) ***
PRPP	0.50 (0.42, 0.57) ***	0.19 (0.09, 0.28) ***	0.58 (0.50, 0.64) ***	0.20 (0.10, 0.29) ***	0.10 (0.00, 0.20)	0.16 (0.06, 0.25) **	-0.24 (-0.33, -0.14) ***	0.94 (0.93, 0.95) ***	-0.21 (-0.30, -0.11) ***	-0.13 (-0.23, -0.03) *	-0.24 (-0.33, -0.14) ***	1.00 (1.00, 1.00)	-0.48 (-0.55, -0.40) ***	-0.49 (-0.56, -0.41) ***	-0.40 (-0.48, -0.31) ***	-0.43 (-0.51, -0.34) ***	0.87 (0.84, 0.89) ***
PBF Asym	-0.33 (-0.42, -0.24) ***	-0.11 (-0.21, -0.01) *	-0.39 (-0.48, -0.31) ***	-0.15 (-0.25, -0.06) **	-0.16 (-0.25, -0.06) **	-0.11 (-0.21, 0.01) *	0.14 (0.04, 0.24) **	-0.51 (-0.58, -0.44) ***	0.27 (0.18, 0.36) ***	0.06 (-0.04, 0.16)	0.17 (0.07, 0.27) ***	-0.48 (-0.55, -0.40) ***	1.00 (1.00, 1.00)	0.87 (0.84, 0.89) ***	0.73 (0.68, 0.78) ***	0.43 (0.34, 0.51) ***	-0.46 (-0.53, -0.37) ***
PPF Asym	-0.36 (-0.45, -0.27) ***	-0.17 (-0.27, -0.07) ***	-0.38 (-0.46, -0.29) ***	-0.23 (-0.32, -0.13) ***	-0.18 (-0.28, -0.08) ***	-0.22 (-0.31, -0.12) ***	0.23 (0.13, 0.32) ***	-0.50 (-0.57, -0.42) ***	0.21 (0.11, 0.30) ***	0.13 (0.03, 0.23) *	0.28 (0.18, 0.37) ***	-0.49 (-0.56, -0.41) ***	0.87 (0.84, 0.89) ***	1.00 (1.00, 1.00)	0.65 (0.58, 0.70) ***	0.41 (0.32, 0.49) ***	-0.49 (-0.56, -0.41) ***
Ave BRFD Asym	-0.36 (-0.44, -0.26) ***	-0.08 (-0.18, 0.02)	-0.46 (-0.53, -0.37) ***	-0.13 (-0.23, -0.03) **	-0.14 (-0.24, -0.04) **	-0.11 (-0.21, 0.01) *	0.14 (0.04, 0.23) **	-0.46 (-0.54, -0.38) ***	0.25 (0.16, 0.35) ***	0.12 (0.02, 0.21) *	0.22 (0.12, 0.32) ***	-0.40 (-0.48, -0.31) ***	0.73 (0.68, 0.78) ***	0.65 (0.58, 0.70) ***	1.00 (1.00, 1.00)	0.29 (0.20, 0.38) ***	-0.44 (-0.52, -0.36) ***
PLF Asym	-0.18 (-0.27, -0.08) ***	-0.05 (-0.15, 0.05)	-0.24 (-0.33, -0.14) ***	-0.26 (-0.35, -0.16) ***	-0.15 (-0.25, -0.05) **	-0.27 (-0.36, -0.18) ***	0.26 (0.16, 0.35) ***	-0.43 (-0.51, -0.35) ***	0.32 (0.23, 0.41) ***	-0.03 (-0.13, 0.07)	0.16 (0.06, 0.26) **	-0.43 (-0.51, -0.34) ***	0.43 (0.34, 0.51) ***	0.41 (0.32, 0.49) ***	0.29 (0.20, 0.38) ***	1.00 (1.00, 1.00)	-0.36 (-0.44, -0.27) ***
RSI Mod	0.47 (0.39, 0.55) ***	0.22 (0.12, 0.31) ***	0.50 (0.42, 0.57) ***	0.22 (0.12, 0.31) ***	0.18 (0.08, 0.27) ***	0.19 (0.09, 0.28) ***	-0.22 (-0.31, -0.12) ***	0.85 (0.82, 0.87) ***	-0.08 (-0.18, -0.02)	-0.51 (-0.58, -0.43) ***	-0.55 (-0.61, -0.47) ***	0.87 (0.84, 0.89) ***	-0.46 (-0.53, -0.37) ***	-0.49 (-0.56, -0.41) ***	-0.44 (-0.52, -0.36) ***	-0.36 (-0.44, -0.27) ***	1.00 (1.00, 1.00)

Abbreviations: TIL = on-court total impact load; TSC = on-court total step count; Ave Int = on-court average intensity; Impact Asym = on-court impact asymmetry; Low-G Asym = on-court low-intensity impact asymmetry; Medium-G Asym = on-court medium-intensity impact asymmetry; High-G Asym = on-court high-intensity impact asymmetry; JH = jump height; CMD = countermovement depth; TTTo = time to takeoff; PRBP = peak relative braking power; PRPP = peak relative propulsive power; PBF Asym = peak braking force asymmetry; PPF Asym = peak propulsive force asymmetry; Ave BRFD Asym = average braking rate of force development asymmetry; PLF Asym = peak landing force asymmetry; RSI mod = the modified reactive strength index; * = p<0.05; ** = p<0.01; *** = p<0.001.

5.3: Biomechanical PCA Model Development

Given the highly correlated nature and redundancy of the included biomechanical metrics (Table 1), a biomechanically-focused PCA was trained using on-court and CMJ testing data obtained across two competitive seasons (i.e., 14-months of training). Initially, there were 865 weekly observations (i.e., on-court, CMJ, or self-reported introspective, psychological state data) amongst the cohort of 16 female basketball athletes. However, after filtering for weeks in which there were no missing biomechanical data, our model consisted of 394 synonymous weekly observations (i.e., on-court and CMJ data collected during the same week of training; mean number of weeks that biomechanical data were collected per athlete = 25 (9)).

Following suggestions made by Bartholomew, and Jolliffe and Cadima (71,179), we retained n-PCs that explained ≥90% of the variance in our biomechanical data, which resulted in a total of eight PCs that were extracted in our trained biomechanical PCA model (Table 2 and Figure 5). Additionally, the correlation between the original biomechanical metrics and the newly derived PCs are presented in the Appendix in Table 4.

While the loading coefficients for the biomechanical PCs represent complex relationships between the on-court and CMJ metrics used in the PCA, some general interpretations can be made of each biomechanical PC. Specifically, PC1 was loaded towards various biomechanical metrics and thus signifies an "Overall Magnitude Component", as is often the case for the first PC in a model (184,185). Next, PC2 signified an "On-Court Asymmetry Component", reiterating the task-specific nature of biomechanical asymmetry previously highlighted in research question (i). Interestingly, PC1 (i.e., overall biomechanical magnitude) and PC2 (i.e., on-court asymmetry) accounted for ~50% of the variance in the data, suggesting the importance of both biomechanical constructs in our cohort. While PC3 was loaded with some on-court loading metrics, it was most heavily loaded with CMJ strategy metrics, signifying a "Jump Movement Strategy Component". PC4 was loaded with vertical jump braking power production and time-to-takeoff and with on-court impact loading metrics, signifying an "On-Court Impact Loading Component" that has interplay with the braking phase of vertical jump completion. PC5 was heavily loaded toward between-limb difference metrics from vertical jump testing and signified a "Jump Asymmetry Component". While the relative importance of jump asymmetry was less than that of on-court asymmetry in our model (explained 7%, and 15% of the variance in the data, respectively), the composition of this PC further demonstrates the task specificity of biomechanical asymmetry. PCs six and seven presented similar, albeit inverse, loadings of initial biomechanical metrics, suggesting that on-court asymmetry in low- to medium-intensity bins may be associated with vertical jump power production. Lastly, PC8 was almost entirely related to the asymmetry that exists during the landing-phase of movement during vertical jump testing, and thus, signifies a "Jump Landing-Phase Asymmetry Component".

Table 2. Summary of principal component analysis loading coefficients.

Biomechanical Metrics Included	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Total Impact Load	0.26	-0.17	-0.29	0.45	0.04	0.13	-0.03	0.07
Total Step Count	0.13	-0.07	-0.36	0.46	-0.02	0.37	-0.16	-0.37
Ave. Intensity	0.28	-0.20	-0.11	0.28	0.09	-0.13	0.05	0.38
Impact Asym.	0.19	0.50	0.11	0.20	0.04	-0.08	-0.02	0.10
Low-G Asym.	0.13	0.39	-0.02	0.12	-0.20	-0.41	-0.48	-0.20
Medium-G Asym.	0.15	0.37	0.11	0.03	0.12	0.46	0.48	0.21
High-G Asym.	-0.18	-0.47	-0.12	-0.18	-0.07	0.11	-0.04	-0.12
Jump Height	0.34	-0.18	0.07	-0.12	0.32	-0.19	-0.06	-0.01
CMD	-0.12	0.13	-0.51	-0.01	-0.25	-0.32	0.44	-0.08
Time to Takeoff	-0.11	-0.20	0.51	0.38	0.16	-0.06	-0.09	0.03
Pk Rel. Brk Power	-0.19	-0.16	0.16	0.41	-0.12	-0.42	0.44	-0.05
Pk Rel. Prop Power	0.34	-0.13	-0.04	-0.09	0.31	-0.28	0.16	-0.04
Pk Brk Force Asym.	-0.30	0.14	-0.19	0.06	0.47	-0.01	-0.05	0.06
Pk Prop Force Asym.	-0.31	0.07	-0.13	0.06	0.42	-0.10	-0.08	0.07
Ave. Brk RFD Asym.	-0.27	0.13	-0.12	0.06	0.43	-0.04	0.05	-0.30
Pk Lnd Force Asym.	-0.23	-0.02	-0.27	0.03	-0.09	-0.05	-0.27	0.70
RSI Mod.	0.35	-0.04	-0.22	-0.28	0.20	-0.13	0.03	-0.01
Individual % Var. Exp.	*34*	*15*	*11*	*9*	*7*	*5*	*5*	*4*
Cumulative % Var. Exp.	*34*	*49*	*60*	*70*	*77*	*83*	*87*	*91*

Abbreviations: PC = principal component; Ave. = average; Asym. = asymmetry; CMD = countermovement depth; Pk = peak; Rel. = relative; Brk = braking; Prop = propulsive; RFD = rate of force development; Lnd = landing; RSI Mod. = the modified reactive strength index; % Var. Exp. = percent variance explained.

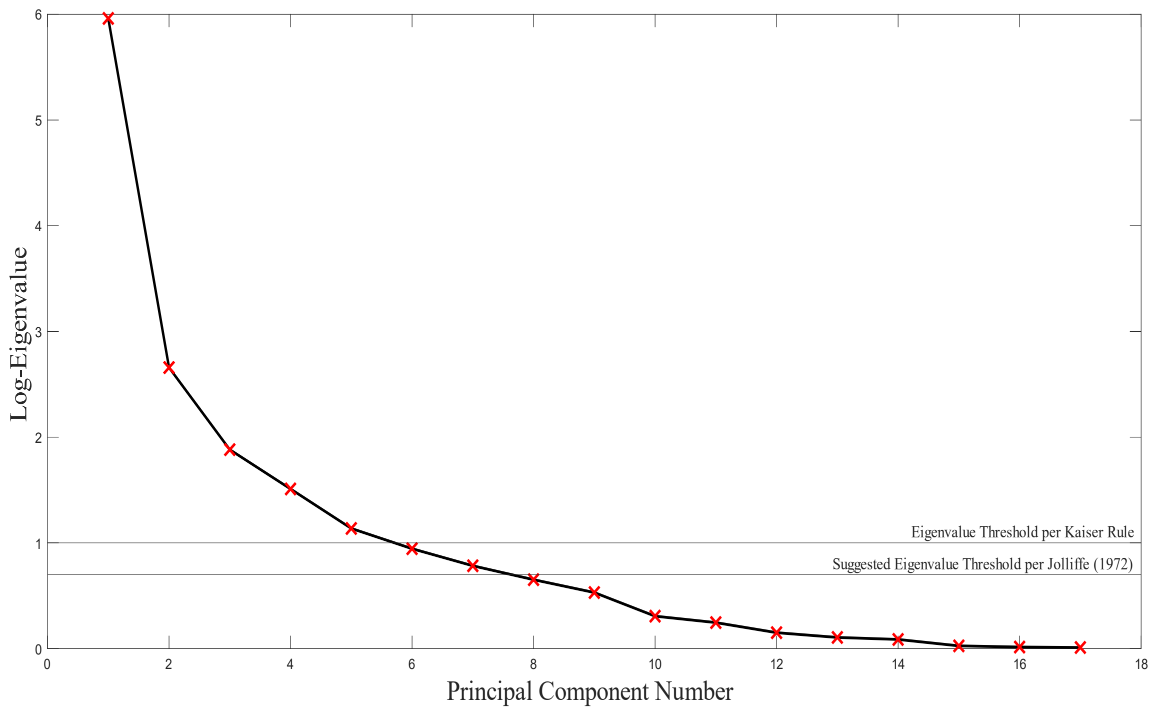

Figure 5. Scree plot of log-eigenvalues of each principal component in the biomechanical PCA model vs. the number of principal components in the model.

5.4: Research Question II – Preseason Reliability of Biomechanical Principal Components and Introspective, Psychological State

The cohort examined in the 2022-2023 collegiate basketball season consisted of 15 athletes, which was less than the data used for the research question (i). This dropout was due to discontinuing participation on the team from the first to second season. There were 182 weekly observations obtained in the 2022-2023 competitive collegiate basketball season in which all three forms of data were concurrently collected in a week (i.e., on-court biomechanics, CMJ biomechanics, and introspective, psychological state; mean number of weeks that all data were collected per athlete = 12 (4)). Meanwhile, the reliability was examined across five preseason weeks between mid-September 2022 to mid-October 2022. The group mean and standard deviations, preseason reliability analyses, SEM, and MDC statistics for all preseason biomechanical PCs and introspective, psychological state metrics, are presented in Table 3. It was found that all eight biomechanical PCs displayed excellent reliability (ICC>0.9), while the introspective, psychological state metrics displayed moderate-to-good reliability (ICC = 0.71 – 0.89).

Table 3. The reliability of biomechanical principal component scores and psychological state metrics collected across five-weeks of the 2022-2023 competitive, collegiate female basketball preseason, along with the corresponding standard error of the measurement and minimum detectable change statistics.

PCs and Psychological State Metrics	Mean (SD)	ICC	95% CI	SEM	MDC
PC1	0.41 (2.22)	1.00	0.99 - 1.00	0.15	0.42
PC2	-0.29 (1.46)	0.95	0.90 - 0.98	0.32	0.88
PC3	-0.75 (1.18)	0.93	0.85 - 0.97	0.32	0.89
PC4	0.59 (0.97)	0.91	0.81 - 0.97	0.29	0.81
PC5	0.07 (1.07)	0.95	0.89 - 0.98	0.23	0.64
PC6	0.28 (0.92)	0.92	0.83 - 0.97	0.27	0.74
PC7	-0.25 (0.84)	0.93	0.83 - 0.98	0.22	0.60
PC8	-0.38 (0.83)	0.91	0.81 - 0.97	0.25	0.69
Academic Workload	5.25 (1.90)	0.71	0.41 - 0.89	1.02	2.83
Feeling	6.15 (1.63)	0.77	0.52 - 0.91	0.78	2.16
Sleep Quantity	0.66 (0.86)	0.72	0.42 - 0.89	0.46	1.26
Sleep Quality	1.01 (0.74)	0.89	0.77 - 0.96	0.24	0.68
Pain	1 (1.29)	0.89	0.76 - 0.96	0.44	1.21

Abbreviations: PC = principal component; SD = standard deviation; ICC = intraclass correlation coefficient; CI = confidence interval; SEM = standard error of the measurement; MDC = minimum detectable change.

5.5: Research Question III - Association Between Biomechanics and Introspective, Psychological State Across a Competitive, Collegiate Basketball Season

Associations between biomechanical PCs and psychological state metrics were examined within each subject across the 2022-2023 season and summarized in this section, and in the Appendix in Figures 8-12. It is important to note that the Supplementary Figures are vastly under-representative of the amount of data that was collected per participant over the two-year study period, as i) only data from the 2022-2023 season are presented, as the first season (2021-2022) was only used to train the PCA model, and ii) only weeks in which all three forms of data (i.e., on-court biomechanics, CMJ biomechanics, and psychological state) were concurrently collected are visually represented for simplicity sake and interpretability. Additionally, even though data has been vastly reduced using the PCA, many variables remain examined within each individual that are summarized below. Further, it is important to acknowledge that identifying or interpreting relationships at a group level can be difficult given the subject-specific nature of potential longitudinal relationships in these variables. Therefore, the following summary of significant relationships between variables should be viewed as exploratory and useful in highlighting which variables more often exhibited associations at the individual level. For a more appropriate and robust interpretation of the associations found between the biomechanical PCs and psychological state metrics, see Figures 13-17 in the Appendix. These figures display the results from the repeated measures correlation analyses that determined the common within-individual associations between these continuous variables (i.e., biomechanical PCs and psychological state), while ensuring that the assumption of independence of observations was not violated by controlling for the effect of between-individual variance (183).

Academic Workload: Only two of the 15 athletes (13%) included in this analysis demonstrated significant relationships between biomechanical PCs and self-reported academic workload. Specifically, there were two significant relationships ($r = |0.49 – 0.63|$; $p < 0.05$) identified between academic workload and biomechanical PCs (PC2 – on-court asymmetry and PC4 – on-court impact loading, respectively), with both athletes demonstrating different relationships from the other.

Feeling: Seven of the 15 athletes (47%) included in this analysis demonstrated significant relationships between biomechanical PCs and self-reported feeling. Specifically, four athletes demonstrated significant associations between jump asymmetry (i.e., PC5) and self-reported feeling ($r = |0.55 – 0.62|$; $p < 0.05$). It is important to note that the directionality of this association is challenging to summarize, given the influence of whether an athlete displays left (positive value) or right (negative value) limb dominance. Secondly, two athletes displayed significant associations between self-reported feeling and PC3 – jump movement strategy. However, one athlete displayed a positive association ($r = 0.61$; $p < 0.05$), while the other displayed a negative association between these outcome measures ($r = -0.59$; $p < 0.05$). Finally, feeling had a significant association with on-court impact loading (i.e., PC4) in one athlete ($r = -0.54$; $p < 0.05$), PC7 (i.e., low- to moderate-intensity on-court asymmetry and jump power production) in one athlete ($r = 0.64$; $p < 0.05$), and jump-landing asymmetry (i.e., PC8) in another athlete ($r = 0.56$; $p < 0.05$).

Sleep Quantity: Two athletes (13%) displayed a significant association between self-reported sleep quantity and biomechanical PCs. Namely, jump asymmetry (i.e., PC5), and PC7 (i.e., low- to moderate-intensity on-court asymmetry and jump power production). Jump asymmetry was found to be associated with sleep quantity in one athlete ($r = -0.62$; $p < 0.05$), while PC7 was associated with sleep quantity in another ($r = 0.77$; $p < 0.05$).

Sleep Quality: Four athletes (27%) displayed a significant association between self-reported sleep quality and biomechanical PCs, each being subject-specific and different. Specifically, one subject displayed a significant positive association with PC1 (i.e., overall magnitude; $r = 0.77$; $p < 0.01$), one subject displayed a significant positive association with jump movement strategy (i.e., PC3; $r = 0.53$; $p < 0.05$), one subject displayed a significant association with jump asymmetry (i.e., PC5; $r = 0.56$; $p < 0.05$), and one subject displayed a significant positive association with PC7 (i.e., low- to moderate-intensity on-court impact asymmetry and jump power production; $r = 0.71$; $p < 0.05$).

Pain: Four subjects (27%) displayed a significant association between self-reported pain and biomechanical PCs. Specifically, jump movement strategy (i.e., PC3) was significantly positively associated with pain in three athletes ($r = 0.58 – 0.66$; $p < 0.05$). Secondly, PC6 and PC7 (i.e., low- to moderate-intensity on-court asymmetry and jump power production) were significantly associated with pain in two athletes. However, one athlete displayed a significant negative association with PC6 ($r = -0.61$; $p < 0.05$), and a positive association with PC7 ($r = 0.84$; $p < 0.01$), while the other athlete presented discordant and inverse relationships (i.e., PC6: $r = 0.51$; $p < 0.05$; PC7: $r = -0.69$; $p < 0.01$). Additionally, one subject displayed a significant negative association with overall biomechanical magnitude (i.e., PC1: $r = -0.56$; $p < 0.05$), one subject displayed a significant negative association with on-court impact loading (i.e., PC4: $r = -0.54$; $p < 0.05$), and one subject displayed a significant association with jump-landing asymmetry (i.e., PC8: $r = 0.68$; $p < 0.05$).

Take Home Message and Necessity for Patient-Centered, and Individualized Monitoring Practices: While many relationships ($n = 27$) were identified between biomechanical PCs and introspective, psychological state metrics, no clear overarching associations were identified at the cohort or group level. The predominant psychological state metrics associated with biomechanics were self-reported feeling ($n = 9$) and pain ($n = 10$), with fewer relationships identified in academic workload ($n = 2$), sleep quantity ($n = 2$), and sleep quality ($n = 4$). While these results are exploratory, they can begin to highlight the complexity of these relationships and the difficulty in defining group-based relationships across these biopsychosocial domains. Therefore, if we are to utilize such models for preventive, prognostic, or rehabilitate purposes in future research and clinical application, it appears necessary to assess on a subject-specific basis whether biomechanics or psychological state changes exceed normatively defined minimum detectable change thresholds.

The following section of the results will provide two use-case examples in our cohort of how this might be applied for subject-specific purposes in future work.

5.6: Research Question III – Longitudinal PCA Use-Case and Application of Patient-Centered Monitoring Using Minimum Detectable Change Statistics

To demonstrate the potential utility and challenges of incorporating PCs into athletic monitoring practices, Figures 6 and 7 highlight two unique and interesting case studies. Specifically, the first example (Figure 6) demonstrates an apparent connection between on-court asymmetry and impact loading related to pain. The athlete in the second example (Figure 7) was found to exhibit significant fluctuations in jump asymmetry, as well as pain across the season, but highlights the difficulty in establishing normative biomechanical patterns as our “unperturbed” baseline period was confounded with elevated levels of self-reported pain. In both examples, the interpretation of meaningful changes can be defined based on subject-specific normative preseason baseline values in combination with the MDC statistics reported in Table 3. In doing so, this provides a viable means of prospectively identifying and red-flagging deviations from their typical biomechanical and/or psychological patterns on a subject-specific basis relative to individualized patterns previously exhibited across a longitudinal period. However, the second case study highlights a consideration that needs to be made when establishing normative patterns and demonstrates why a biopsychosocial model is likely necessary for monitoring athlete health and well-being; in contrast, traditional models have placed these constructs into silos. This methodological framework for athletic monitoring can lead to a deeper dive into the specific metrics attributed to the PC that might be driving such fluctuations from normative patterns, which I will demonstrate in the discussion by walking through both use-case examples to aid in the interpretation and utility of this work.

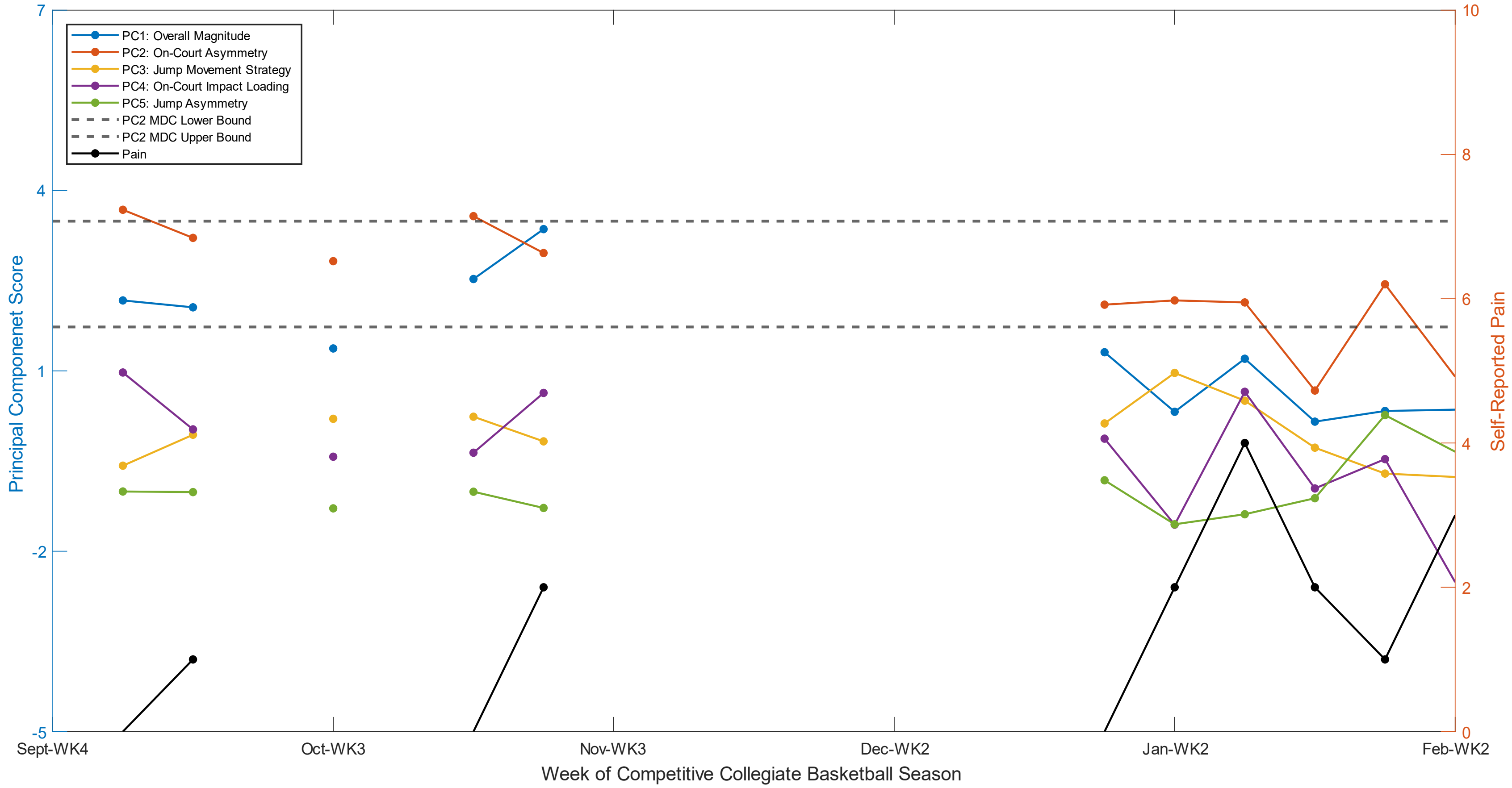

Figure 6. Use-case example of weekly changes in biomechanical principal component scores and self-reported pain in a collegiate female basketball athlete across the 2022-2023 competitive season. Specifically, on-court impact load and self-reported pain levels peaked before the detection of statistically significant alterations in on-court asymmetry. To highlight the on-court asymmetry-specific minimum detectable change (MDC), upper and lower bounds are depicted for "red-flagging" biomechanical fluctuations above and beyond the measurement error of the system. The MDC statistics are derived based on five-weeks of preseason training and normative biomechanical patterns exhibited at the cohort level, with this MDC value applied (±) to the average value that this subject displayed across the same timeframe to calculate individualized bounds by which their on-court asymmetry fluctuated from their normative patterns.

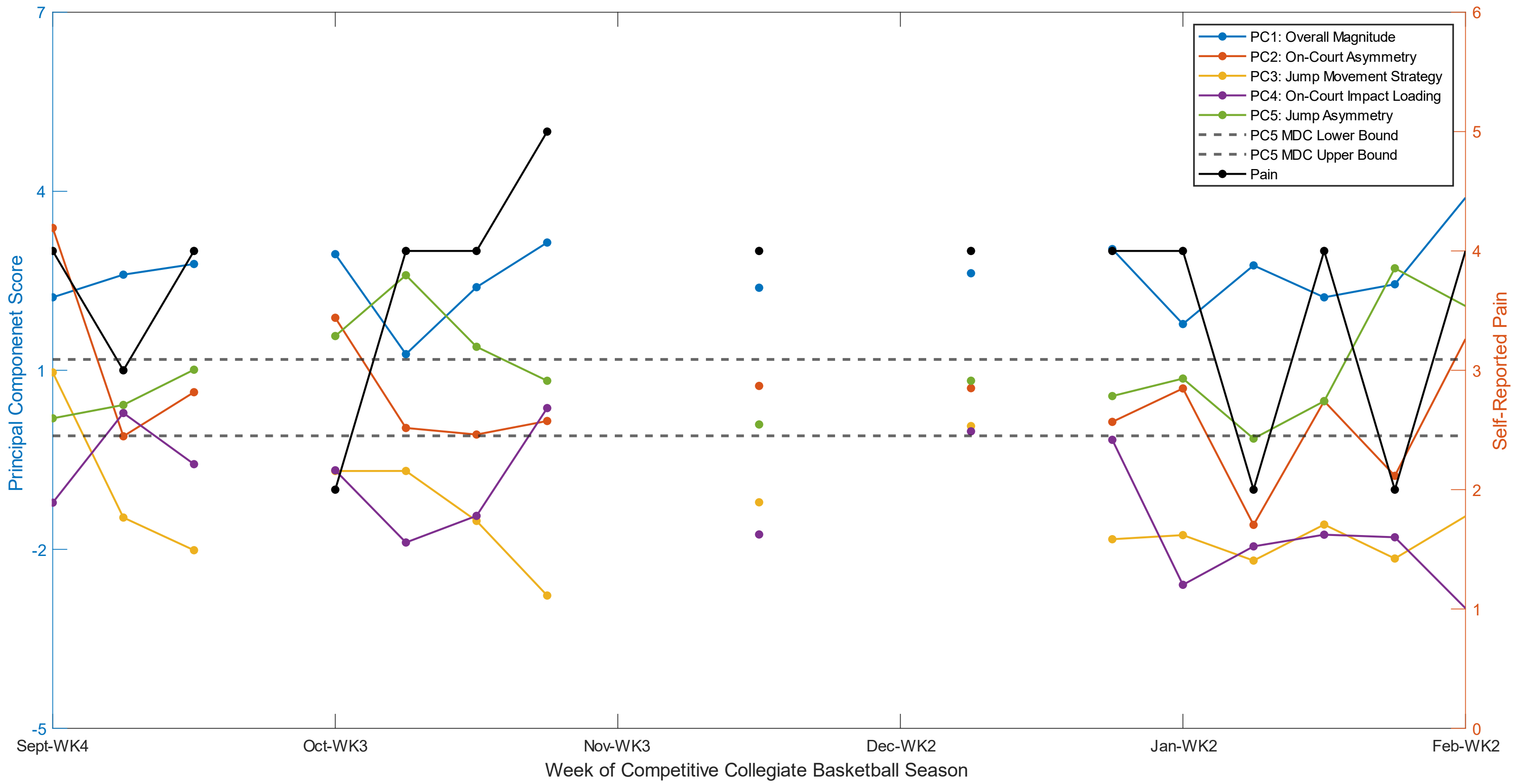

Figure 7. Use-case example of weekly changes in biomechanical principal component scores and self-reported pain in a collegiate female basketball athlete across the 2022-2023 competitive season. Specifically, jump asymmetry-specific minimum detectable change (MDC) upper and lower bounds are depicted for "red-flagging" biomechanical fluctuations above and beyond the measurement error of the system, which were paralleled, to some extent, by seasonal changes in self-reported levels of pain. The MDC statistics are derived based on five-weeks of preseason training and normative biomechanical patterns exhibited at the cohort level, with this MDC value applied (±) to the average value that this subject displayed across the same timeframe to calculate individualized bounds by which their jump asymmetry fluctuated from their normative patterns. However, this "unperturbed" baseline period was confounded by high levels of self-reported pain in this athlete, suggesting that our normative biomechanical patterns might not necessarily indicate what we would expect in this athlete.

Chapter 6: Discussion

This investigation aimed to determine the utility, reliability, and longitudinal application of biopsychosocial athletic monitoring practices using a PCA model in female basketball athletes. This is the first study to integrate these health domains using a holistic, biopsychosocial approach for future application in sports performance and injury risk. Additionally, this is the only study to date that has used advanced analytical modelling to characterize components of student-athlete performance, health, and well-being, and the first to delineate subject-specific associations between biomechanics and introspective, psychological states, especially throughout multiple competitive seasons. In doing so, this investigation demonstrates the potential utility of prospectively and longitudinally monitoring student-athletes using a subject-specific approach. It highlights the potential for integrating such models in future research and clinical work for preventive, prognostic, and rehabilitative purposes.

6.1: Correlation of On-Court and Countermovement Jump Biomechanics

The first objective of this study was to determine the inter- and intra-connectivity or correlation between on-court and CMJ biomechanical metrics and, in doing so, the utility of incorporating such data into a biomechanical PCA model that reduces the dimensionality of biomechanical factors. While there were many statistically significant relationships identified both between (i.e., on-court vs. CMJ – 58/70) and within (i.e., on-court vs. on-court – 13/21, and CMJ vs. CMJ – 41/45) systems, there were only 4/70, 7/21, and 12/45 of these that displayed correlations ≥ |0.5| (i.e., a moderate effect size; (186)), respectively.

First, the observed associations across CMJ metrics align with previous work (73,75,80,81,169). The current findings demonstrate that the largest associations exist between explosive-based CMJ metrics such as JH, peak relative propulsive power, and RSI mod (73,75,80,81,169), while CMJ asymmetry metrics also displayed significant correlations with one another (169). Together, this suggests that the outcome of vertical jump testing (i.e., JH) is significantly associated with both the force and power-producing capabilities of the athlete, and might also be influenced by the underlying jump strategy (i.e., RSI mod is implicitly impacted by the amount of time the athlete spends on the ground due to the denominator of time to take-off, and thus, is inherently related to the jump strategy; (79–81,164). Furthermore, the association between CMJ asymmetry metrics suggests that between-limb differences present in one phase of the CMJ may traverse and be related to between-limb differences in other phases of the CMJ (169).

Following previous work by Keogh and colleagues (169), this association between CMJ asymmetry metrics is most pronounced in the phases prior to take-off (i.e., braking and propulsive phases) but to a lesser extent thereafter during the landing phase.

Alternative to comparisons within the CMJ metrics, examining wearable-sensor or on-court data is novel and exploratory, with the associations observed being some of the first ever reported. Specifically, it was found that metrics relating to load and intensity (i.e., overall impact load, step count, and average intensity) were significantly associated with one another. In contrast, on-court asymmetry metrics (i.e., low-, medium-, high-, and overall impact acceleration asymmetry) were also significantly associated with each other. However, these two aspects of on-court data remained somewhat independent. Interestingly, in comparing between systems, on-court impact load and intensity were shown to be moderately associated with CMJ power and explosive capabilities. This finding suggests that the more explosive athletes during vertical jump testing practice and play in a manner conducive to utilizing their physical strengths. Meanwhile, and in concordance with previous literature that has suggested that lower limb asymmetry is a highly task-specific measure (50–52), on-court and CMJ asymmetry displayed weak correlations in the present investigation and were relatively independent of one another.

Overall, the correlations exhibited within and across these biomechanical collections provided rationale for developing and applying a biomechanical PCA model to reduce the dimensionality of the redundant data. In doing so, this biomechanical PCA enabled the characterization of overarching components of athletes' biomechanical profiles. While PCAs have been applied in many isolated tests of sports performance, such as the interpretation of jump (73–75,147–154), change of direction and sprint speed (74,147,153–156), strength (74,147,154), and on-court or other sport-specific assessments of performance in basketball and other team-sports (153,157–161), this is to our knowledge the first investigation to integrate traditional performance testing and on-court, sport-specific training biomechanics into one overarching biomechanical PCA model. However, to confidently apply the PCA model for red-flagging fluctuations from normative biomechanical patterns, the reliability of these biomechanical PCs and the included introspective, psychological state metrics must be established.

6.2: Reliability of Biomechanical Principal Components and Introspective, Psychological State

Previous work by our research laboratory has demonstrated the longitudinal, preseason reliability of PCs when compared to traditional key performance indicators in a vertical jump model alone (169). However, given that the present investigation is the first to integrate sport-specific biomechanics into such a model, this study is also the first to demonstrate the reliability of biomechanical PCs in this fashion. The former study by our laboratory found that three of six, and five of six jump PCs displayed excellent reliability (ICC>0.9) when assessed week-to-week (i.e., comparing successive weeks temporally) and over the entire preseason (i.e., comparing each successive week to the preseason average as a normative baseline value), respectively (169). As such, we hypothesized that the biomechanical PCs and introspective, psychological state metrics in the present investigation would display good-to-excellent reliability across the 2022-2023 preseason. The results supported our hypothesis for the most part, as eight biomechanical PCs in the present investigation displayed excellent reliability (ICC>0.9), while the psychological state metrics ranged from moderate-to-good reliability (ICC = 0.71 – 0.89).

Previous research has demonstrated that the biomechanical PCs that appear to be most prominent in this cohort of athletes and/or performance assessments are output (e.g.., velocities and displacements) (73,75,153,161,162,165), causal (e.g.., forces, power, and impulses) (73,75,148–153), and timing-based PCs (i.e., proxies for underlying jump or movement strategy) (75,150–152). In concordance with previous findings, the present investigation displayed an output-based PC (i.e., PC4 – on-court impact acceleration and loading), a timing-based PC (i.e., PC3 – jump movement strategy), and two causal-based PCs (i.e., PCs six and seven which together described jump power production and low to medium intensity on-court asymmetry). Additionally, most biomechanical PCA models result in the first PC being loaded towards various metrics and signifying overall magnitude (162,184,185), which was also the case in our PCA. To our knowledge, recent work by Keogh and colleagues (169) is the only study that has defined a unique asymmetry component derived from a vertical jump PCA model. Interestingly, on-court and jump asymmetry assembled into their own unique PCs (i.e., PC2 and PC5, respectively) in the present investigation, both of which were found to be highly reliable (r = 0.95; p < 0.001). Lower limb asymmetry is typically a noisy metric subject to large between and within-athlete variability (34,36,40,187,188) that can make this biomechanical metric challenging to interpret with any level of consistency and at the group level. Additionally, lower limb asymmetry has been demonstrated to be a highly task-specific metric (50–52), which is further supported by the results of the present investigation, whereby a separate PC was developed for on-court and vertical jump asymmetry. Therefore, the present PCA model gives rise to an alternative method of prospectively monitoring lower limb asymmetry – a well-documented measure for rehabilitation and return-to-sport (25,189–191), with some implications for sports performance (15,33–39) and injury susceptibility (34,40–43) – that is highly reliable and accounts for the task specificity of this measure. In doing so, this approach might enhance preventive medical practices by allowing researchers and clinicians to "red-flag" athletes who might be at a heightened level of injury risk and to subsequently refer these athletes for diagnostic imaging and referrals to the necessary healthcare staff.

Regarding the reliability of the psychological state metrics in the present investigation, academic workload, feeling, and sleep quantity displayed moderate reliability (ICC = 0.71 – 0.77), while sleep quality and pain demonstrated good reliability (ICC = 0.89). This is, to our knowledge, the first longitudinal investigation of the reliability of these metrics conducted alongside biomechanical analyses of data in this manner. Previous PCA work has concurrently monitored the sessional rate of perceived exertion with on-court biomechanical metrics for load monitoring (161,165), to identify positional differences in biomechanical loading patterns (161), and to determine whether workload differed between injured and uninjured basketball athletes (162). Unfortunately, none of the previous studies incorporated psychological state/stress into their PCA models. For instance, while this previous work found positional differences in on-court biomechanical demands (i.e., forwards – the predominance of high-intensity and cumulative deceleration and change-of-direction; guards – the predominance of deceleration and high-intensity jumping; and centers – the predominance of acceleration and change-of-direction; (161), and differences between injured and uninjured basketball athletes (i.e., injured athletes demonstrated significantly lower acute workload coupled with a significantly greater chronic workload on-court; (162), none incorporated psychological state into their PCA model. Furthermore, the previous investigations utilized a sessional rate of perceived exertion as a measure of internal workload. They included this more for load monitoring purposes rather than attempting to encapsulate a more holistic picture of athletic health and well-being by incorporating psychological state and biopsychosocial monitoring practices. Also, previous research has demonstrated that sleep (192,193) and mental health (64,194) can impact sports performance, and as such, the present investigation aimed to determine how reliable these metrics are when assessed longitudinally. Interestingly, the reliability of these metrics was less than that of the included objective, biomechanical metrics. These results suggest that these subjective markers of athlete health status may either be more sensitive to change, or alternatively, they may simply include more week-to-week fluctuations or measurement error. These results are discordant with a systematic review conducted by Saw, Main, and Gastin (58), who found subjective measures (e.g., mood disturbances, perceived stress and recovery, and symptoms of stress) to be superior in both their sensitivity and consistency to reflect changes in athlete health status. Alternatively, these reliability results might be a testament to the difficulty of incorporating subjective measures of psychological state in athletic monitoring practices. A study conducted by Neupert and colleagues (195) highlighted that athletes and coaches sometimes feel that the bridge between healthcare and research staff to end-users and the feedback processes put in place are insufficient and ineffective. As such, and in concordance with previous work by our laboratory (67), we urge researchers and clinicians to work with end-users in developing projects and questionnaires that are both meaningful and practical for the athletes and coaching staff. In doing so, this might enhance the compliance rates and validity of this psychological data and improve the ability to contextualize this data with biomechanical data in a longitudinal and subject-specific fashion for the purposes of patient-centred preventive, prognostic, and rehabilitative practices.

6.3: Association Between Biomechanics and Introspective, Psychological State

My third research question was to determine whether there were any overarching associations between biomechanics and psychology throughout a competitive collegiate basketball season on a subject-specific basis. A recent scoping review conducted in our research laboratory by Keogh and colleagues (67) found that pain and rate of perceived exertion were related to lower limb biomechanics and asymmetry. However, only four included studies that monitored athletes longitudinally throughout one or more competitive season(s), and most of the relationships identified were established cross-sectionally. Furthermore, while relationships were identified between biomechanics, including asymmetry, and psychology, these were limited in their scope, as many factors known to affect sports performance and injury susceptibility were neglected in the included studies in this scoping review (67). As such, we hypothesized that pain would demonstrate significant relationships with biomechanics, including asymmetry, and that other previously unexplored psychological states would similarly display significant relationships with biomechanics in some fashion. Following our hypotheses, there were several subject-specific relationships identified between our biomechanical PCs and introspective, psychological state (n = 27). The psychological state metrics most predominantly associated with biomechanics were self-reported feeling and pain (n = 9 and 10, respectively), with only a select few associations identified in academic workload, sleep quantity, and sleep quality (n = 8, cumulatively). However, as previously stated in *Chapter 5.5*, no clear or overarching associations were identified at the cohort level, and it is important to not "miss the forest for the trees" by delving too deep into each association and the nuances that exist to this respect. Instead, these results emphasize the individualistic and subject-specific nature of the overlap between these domains, highlighting the necessity to undertake a subject-specific approach in such work, rather than trying to establish contributory factors to sports performance and risk of [re]injury at the group level. Similar subject-specific machine-learning model suggestions have been made in runners (196,197) and patients diagnosed with knee osteoarthritis (198) to identify biomechanical patterns and alterations in individual biomechanical patterns. If such an approach were to be incorporated into sports medicine and athletic monitoring practices, it might enable practitioners to reduce the overall injury burden present, which, unfortunately, has been noted to be quite substantial (4,5). As such, it is theorized that developing subject-specific models and associated MDC thresholds in athletic populations might lead to a "red-flag" or stoplight-based system and an improvement in preventive medical practices. Specifically, these individualized biomechanical patterns can signify: i) a "green-light" with no sign of concern when individuals display normative or unchanging biomechanical patterns, ii) changes outside or nearing outside of this MDC threshold might signify a "yellow-light" where some concern is present and follow-up may be required, and iii) significant biomechanical alterations from normal patterns signifying a "red-light" which might be indicative of larger concern and an immediate and further investigation of the athlete's current condition. The following section will provide practical use-case examples of how PCs and associated MDCs can be used for prospectively "red-flagging" meaningful changes in biomechanics and psychology to detect potentially deleterious alterations from normative patterns that might be indicative of impeding injury or decrements in sports performance.

6.4: Longitudinal PCA Use-Case and Application of Patient-Centered Monitoring Using Minimum Detectable Change Statistics for "Red-Flagging" Athletes

Previously, two use-case examples were highlighted in *Chapter 5.6* that demonstrate the utility of incorporating longitudinal monitoring using PCs and associated MDCs to identify alterations from normative biomechanical patterns on a subject-specific basis. The first use-case example focuses on identifying fluctuations in on-court asymmetry patterns and concurrent or prior changes in perceived pain and on-court impact load (Figure 6). In contrast, the second use-case example focuses on identifying alterations in jump asymmetry patterns while highlighting the potential difficulty in establishing normative biomechanical patterns without contextualizing them with other facets of health, such as self-reported levels of pain (Figure 7).

In the first use-case example in Figure 6, it is apparent that this female athlete showed fluctuations from their typical on-court asymmetry patterns near the end of the 2022-2023 competitive basketball season. During the preseason (i.e., September and October), this individual displayed consistent PC2 scores near 3, which can be contextualized further in the metrics for this example as being left limb dominant (-18.1% between limb difference in favour of left limb) during high-intensity aspects of practices. However, when this athlete returned from the scheduled holiday break after final examinations, the on-court impact loading PC was near the boundary of the MDC with a score of 2.1, relating to a -10.5% between limb difference favouring the left limb in high-intensity aspects of practice. Most importantly, this PC2 deviation was also met with a gradual increase in pain towards an eventual peak in the third week of January. Consequently, while the athlete was nearing "red-flagging" before this elevated pain, they reached a clear breach from their normal pattern of on-court asymmetry in the week following peak pain onset (e.g., PC2 score of 0.7 and a -0.5% between limb difference in favour of left limb during high-intensity aspects of these sessions). Therefore, not only did this week represent an exceedance of statistically relevant thresholds (i.e., MDC) relative to this individual's normative asymmetry patterns, but it also represented an exceedance of the 10-15% clinically relevant threshold from normative asymmetry patterns that are often used to deem when an athlete is at risk of suboptimal sports performance (15,33–39) and a possible heightened level of injury risk (34,40–43). Interestingly, this fluctuation from normative asymmetry patterns appeared to be most pronounced during high-intensity efforts (i.e., ~17% change from baseline patterns), which provided additional concern given the fact that most serious lower limb MSK injuries (e.g., anterior cruciate ligament rupture) are sustained during high-intensity landings from bouts of jumping, during change-of-direction, or cutting tasks in basketball (1,19–21). Afterwards, in the weeks following this "red-flag", the athlete had various additional biomechanical changes. Most notably, the continued reduction of on-court loading (PC4) highlights the likely attempt to manage this pain and potential underlying injury. Generally, the exceedance of MSK structure load tolerance during training and competition leads to injury (1,19–21), which may be exacerbated if there are large between-limb differences that exist and one limb is unduly stressed (34,40–43) or in this case, stressed more (right limb) than it typically was. As such, athletes will often attempt to restore and maintain homeostasis and mitigate the underlying cause of pain by reducing the load and frequency of the activities leading to the underlying pathology (199). It appears this was the case for this athlete, as evident in not only on-court loading (PC4) but also jump movement strategy (PC3).

The second use-case example in Figure 7 highlights seasonal fluctuations that exceeded the MDC threshold in normative jump asymmetry patterns in one of the female basketball athletes in the present investigation. An important distinction that should be made prior to delving into this case study for interpretability and clarity purposes is that a decrease in the jump asymmetry PC does not necessarily mean that there is a decrease in the asymmetry present, nor does an increase mean that the athlete is inherently becoming more asymmetrical. The data in our biomechanical PCA model uses *both the magnitude and direction of asymmetry* (177,188,200), as reporting the magnitude of asymmetry in isolation as an absolute value blinds researchers and clinicians from detecting fluctuations in limb dominance (e.g., using magnitude alone would mask a 20% change occurring from 10% left- to 10% right-dominance). Subsequently, and to this respect, we were able to "red-flag" specific periods for further examination of jump asymmetry and comparison to subject-specific normative patterns. Specifically, there were two periods in which this athlete's jump asymmetry exceeded the MDC threshold, indicating a statistically meaningful alteration from normative biomechanical patterns: i) during the end of the preseason (i.e., October 2022) and ii) after the regular season just before collegiate-level playoffs (i.e., February 2023). Identifying periods in which this athlete fluctuated from typical jump asymmetry patterns allowed us to "red-flag" these weeks and examine the force-time waveforms to determine whether these fluctuations were of clinical importance. For example, in reviewing the force-time waveforms and associated jump asymmetry metrics that were heavily loaded in PC5 during the final week in October, it was found that peak braking force asymmetry (seasonal mean = -2.6% in favour of right limb; week four of October = 5% in favour of left limb; Δ from mean = 7.6%), peak propulsive force asymmetry (seasonal mean = -3.6% in favour of right limb; week four of October = 5.3% in favour of left limb; Δ from mean = 8.9%), and average braking rate of force development asymmetry (seasonal mean = 3.0% in favour of left limb; week four of October = 14.8% in favour of left limb; Δ from mean = 11.8%) had all fluctuated from normative patterns. While the fluctuations this athlete exhibited in jump asymmetry exceeded the MDC thresholds for statistical relevance, none of which exceeded the 10-15% threshold for clinical relevance (34,201), and thus did not pose any serious or urgent concern, but rather an indication to keep an eye on this athlete. Interestingly, the level of on-court asymmetry exhibited and perceived pain that this athlete self-reported across the last six weeks of the season, as seen in orange and black, respectively, in Figure 7, displayed similar and somewhat paralleled fluctuations to jump asymmetry. However, it is noteworthy that this athlete was experiencing moderate levels of perceived pain during the preseason period, which was used to define normative biomechanical patterns for this individual and for building out the associated MDC values. As such, these fluctuations identified as "red-flags" might not necessarily indicate meaningful fluctuations from this individual's pain-free normative biomechanical patterns, since this predefined baseline period might be a misleading representation of what normal is for this individual. This highlights a potential limitation of this PCA model since the MDC values used for "red-flagging" purposes are thought to be established during a stable period, but this stability cannot be universally said for all athletes in this cohort, nor can the potential parallels between jump asymmetry and perceived pain. However, this case provides a practical example of how PCA and this biopsychosocial model can be applied in longitudinal contexts for potential preventive, prognostic, and rehabilitative purposes, while also highlighting considerations that need to be made when employing such models for these purposes.

6.5: Limitations and Future Directions

There are several limitations to the present investigation, many of which have been previously outlined in a similar longitudinal vertical jump PCA application study by Keogh and colleagues (169). First, this sample consisted of a homogenous group of collegiate female basketball athletes and, thus, may limit the generalizability to the male counterpart or other competitive athletic populations. While the PCs and associated MDCs from the current work are specific to this cohort and dataset, the reliability of this method and the practical use-case examples should provide confidence in using such methods in future research and clinical applications. Second, the sample size was relatively small (n = 16 athletes), and thus limited the ability to run between-subject analyses as they would have been underpowered. However, the immense breadth of data collected (i.e., 1,226 on-court sessions (mean per athlete = 77; SD per athlete = 26), 1,936 CMJ trials (mean per athlete = 121; SD per athlete = 42), and 910 weekly self-reported questionnaires (mean per athlete = 57; SD per athlete = 28)) across two competitive seasons makes this the most comprehensive study in this space, and should provide confidence in the within-subject analyses and applications. Third, the associations identified between biomechanical and psychological states were established across all data rather than assessing the association between weekly changes in these constructs. Therefore, it is suggested that future research examines the temporal association between biomechanics and psychological state using cross-correlation to discern whether changes in one entity precede the other. Fourth, while this PCA model includes both on-court and traditional CMJ biomechanics, it was unable to include our psychological state metrics in this model due to the low compliance rates exhibited in the first year of our investigation (compliance rates in season one: academic workload = 67 ± 16%; feeling = 80 ± 11%; sleep = 55 ± 29%; pain = 49 ± 29%). Therefore, it is suggested that future research integrates psychological stress into their PCA models to define multivariate and holistic PCs that encapsulate a greater degree of the current health status of the athlete. Fifth, given that our sample consisted exclusively of female athletes, the effects of the menstrual cycle may have affected jump performance and neuromuscular function (202). However, recent systematic reviews have suggested that the effect of the menstrual cycle on exercise performance is inconclusive and trivial (203,204). Sixth, the PCA model in the present investigation was built on variation in data between athletes rather than developing numerous potentially more sensitive subject-specific models on the variations and relationships across variables within each athlete. Unfortunately, training a multivariate, subject-specific PCA model may require a large number of jumps and on-court sessions (e.g., 50+) from each athlete and result in similar but unique PC profiles across athletes that would require separate interpretations. Since the overarching purpose and proposed utility of the PCA model and the associated MDCs in the present investigation is for "red-flagging" athletes, this might not be necessary, and doing so may cause more difficulty and time constraints in this process. However, future work can aim to ascertain whether subject-specific models are more adept at detecting more subtle individual changes in biomechanical and psychological patterns than the present between-subject model.

Chapter 7: Conclusion and Significance

Our study is the only study to use advanced analytical modelling to characterize components of student-athlete performance, health, and well-being, and the only study to integrate these domains of health in a longitudinal and biopsychosocial fashion over multiple competitive seasons. This study highlighted the associations and overlap between biomechanical and psychological patterns in athletic populations but also emphasized the highly subject-specific nature of these associations. This study highlights the necessity of more tailored and subject-specific athletic monitoring practices, particularly those that include integrated, as opposed to traditionally isolated, biomechanical, physiological, and psychological athletic monitoring. This investigation highlighted the reliability, utility, and application of biopsychosocial athletic monitoring practices using a PCA model. Specifically, this study demonstrated the ability to incorporate this methodological approach for prospectively "red-flagging" athletes who demonstrate statistically and clinically relevant fluctuations in normative biomechanical and psychological patterns that might indicate a heightened risk of injury or decrements in sports performance capabilities. Future research should employ similar biopsychosocial PCA models to prospectively monitor athletic populations to determine the potential preventive, prognostic, and rehabilitative capabilities of athletic monitoring practices.

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Appendix

Supplementary Figures

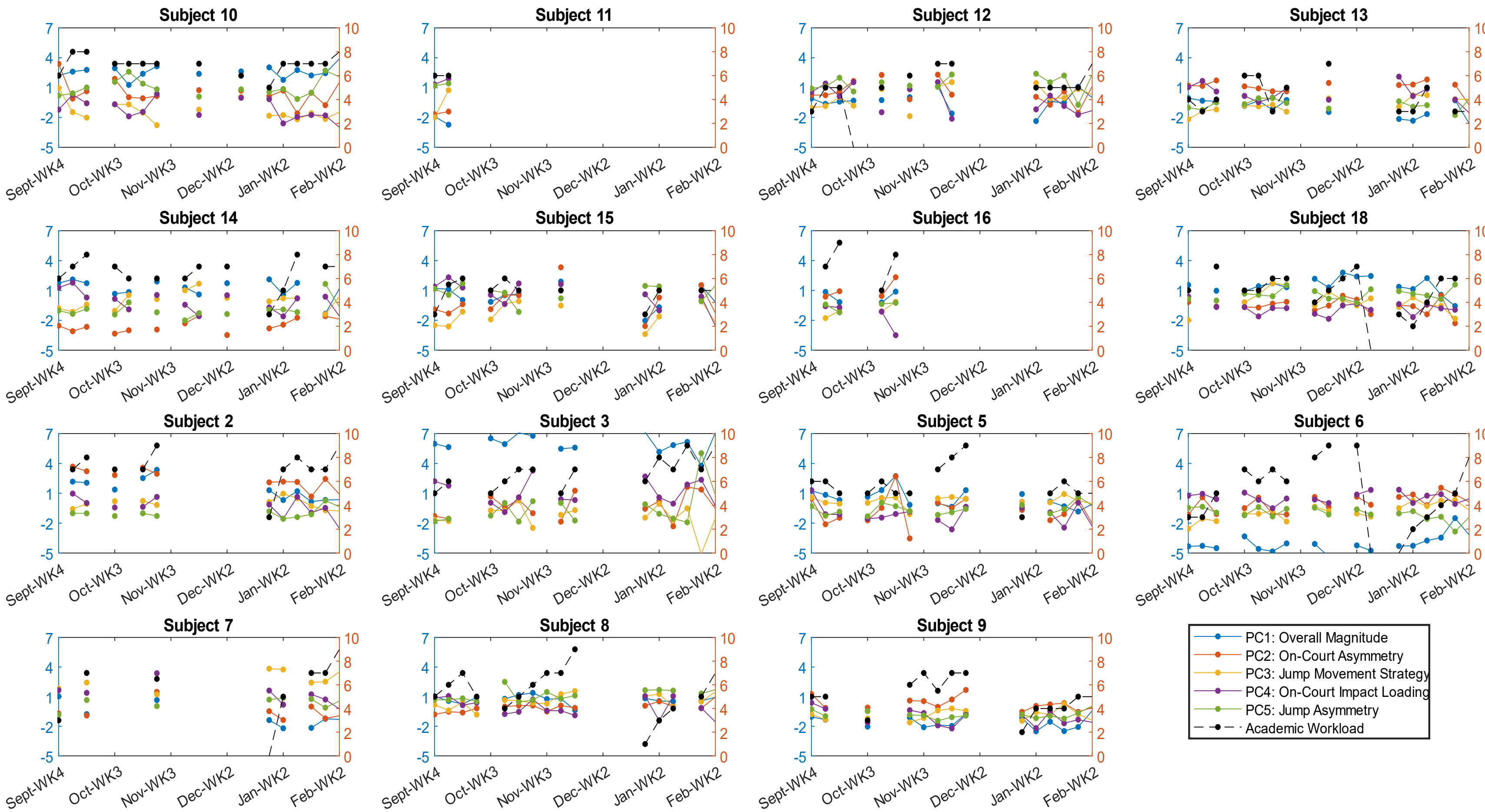

Figure 8 (Appendix): Weekly changes in biomechanical principal component scores and self-reported academic workload in a cohort of collegiate female basketball athletes across the 2022-2023 competitive season.

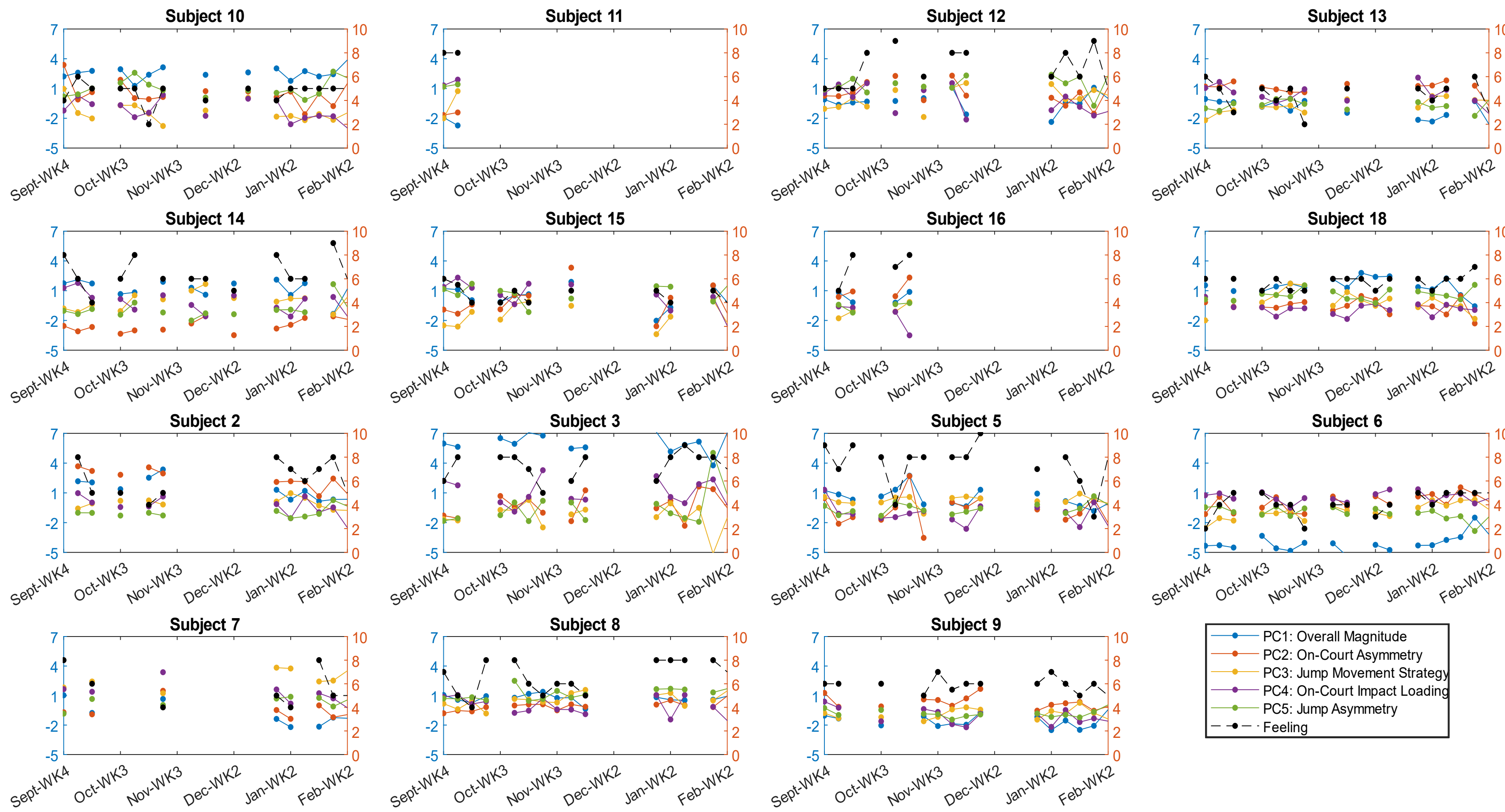

Figure 9 (Appendix): Weekly changes in biomechanical principal component scores and self-reported feeling in a cohort of collegiate female basketball athletes across the 2022-2023 competitive season.

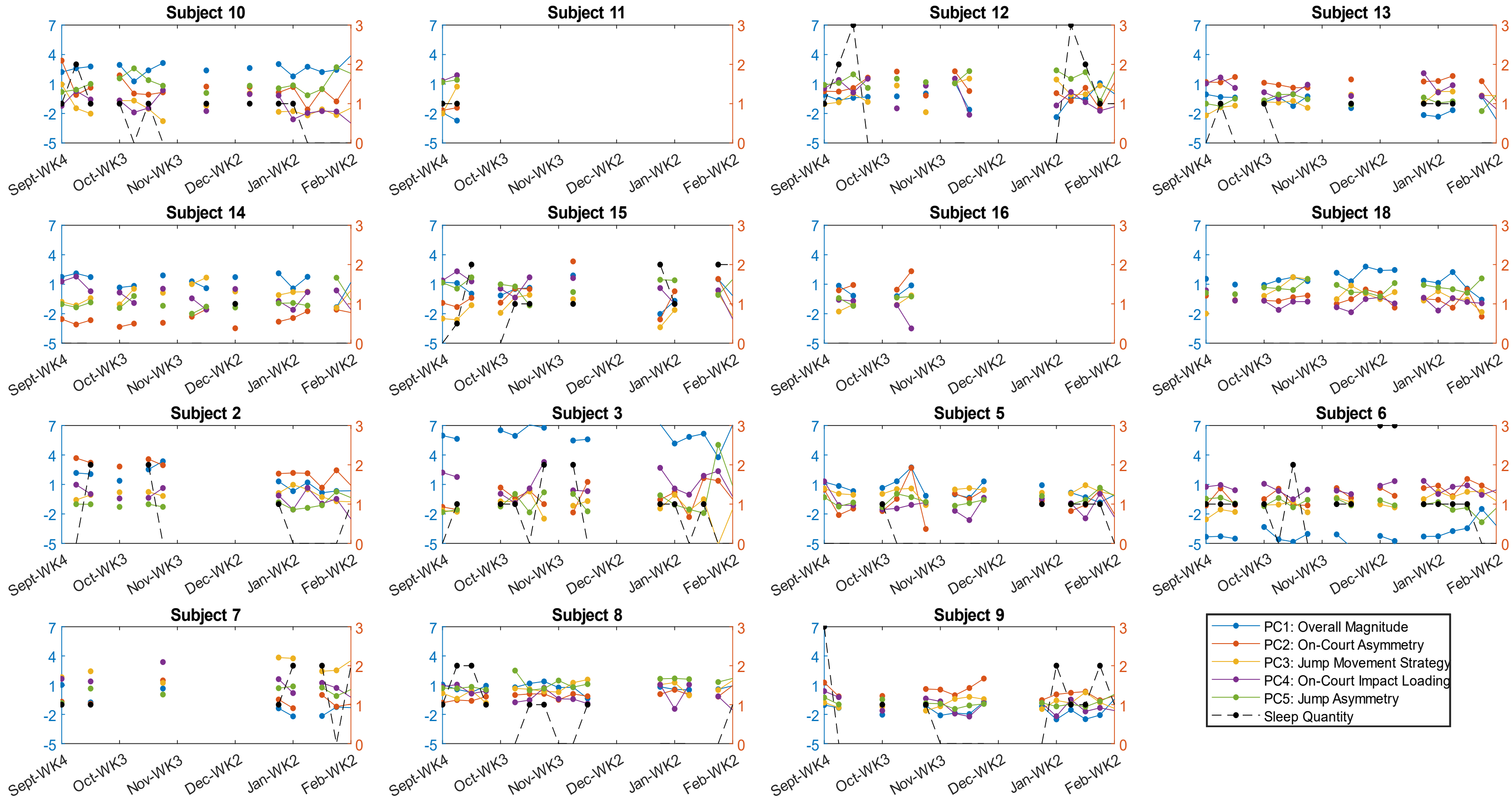

Figure 10 (Appendix): Weekly changes in biomechanical principal component scores and self-reported sleep quantity in a cohort of collegiate female basketball athletes across the 2022-2023 competitive season.

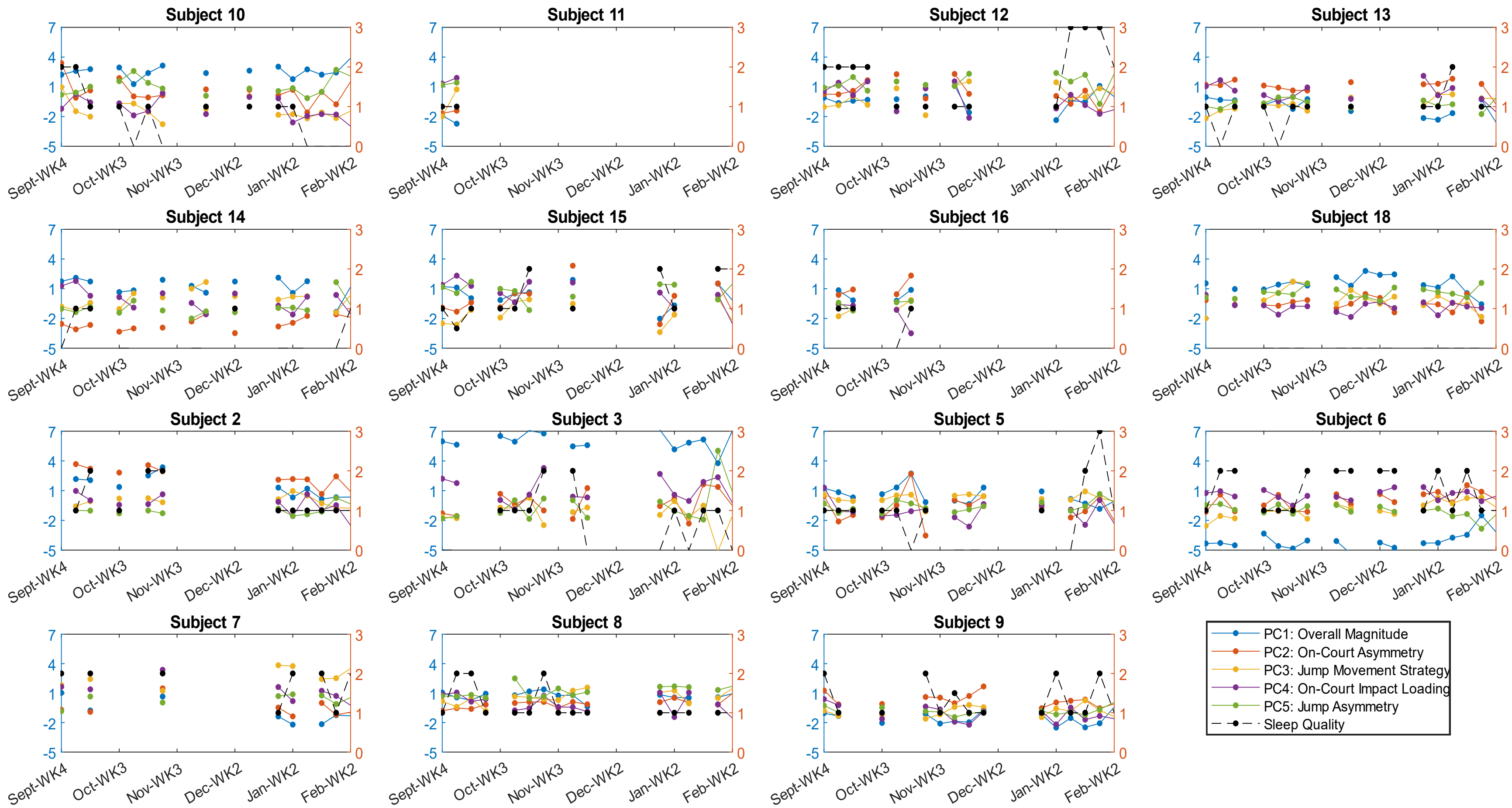

Figure 11 (Appendix): Weekly changes in biomechanical principal component scores and self-reported sleep quality in a cohort of collegiate female basketball athletes across the 2022-2023 competitive season.

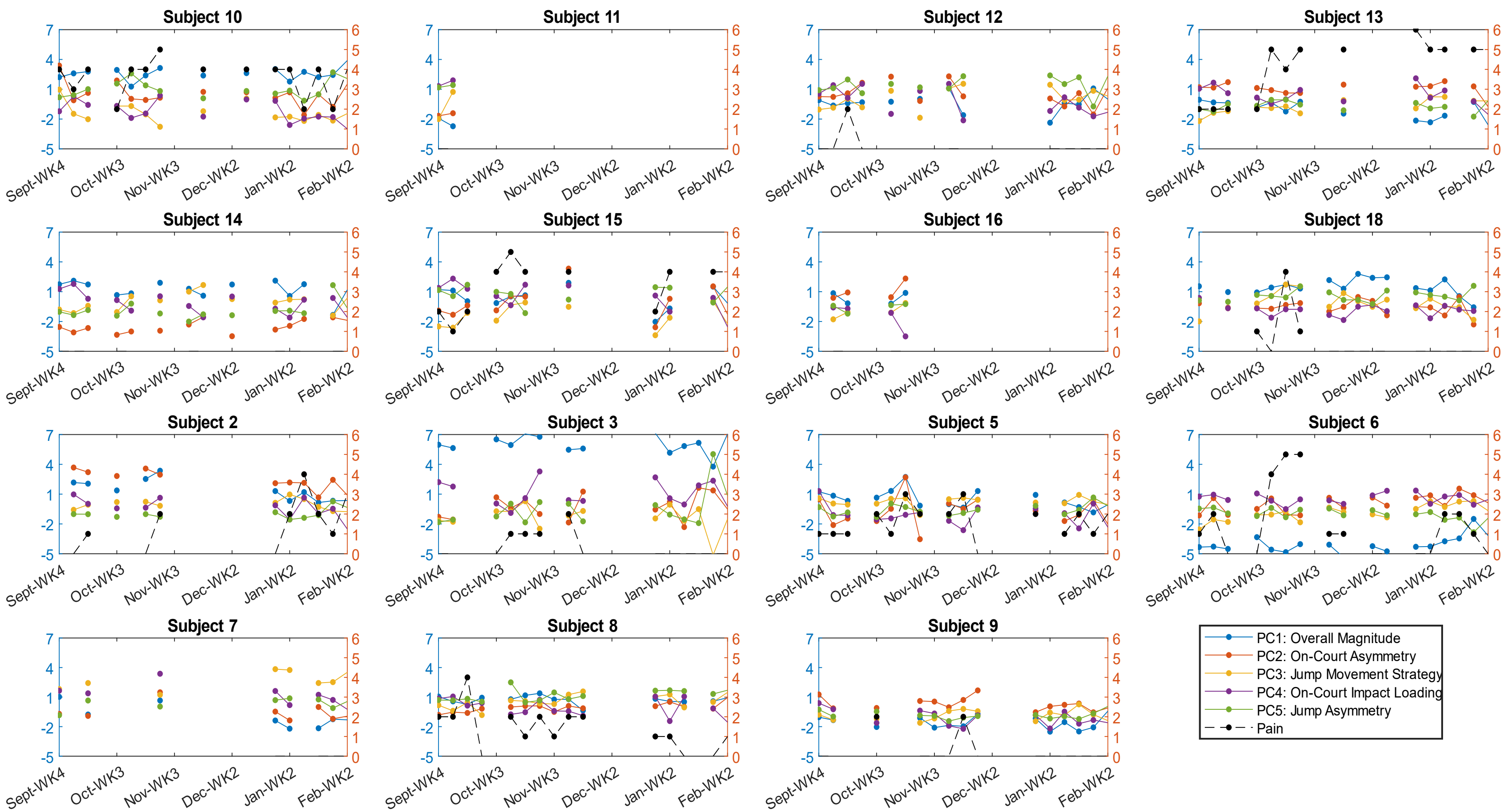

Figure 12 (Appendix): Weekly changes in biomechanical principal component scores and self-reported pain in a cohort of collegiate female basketball athletes across the 2022-2023 competitive season.

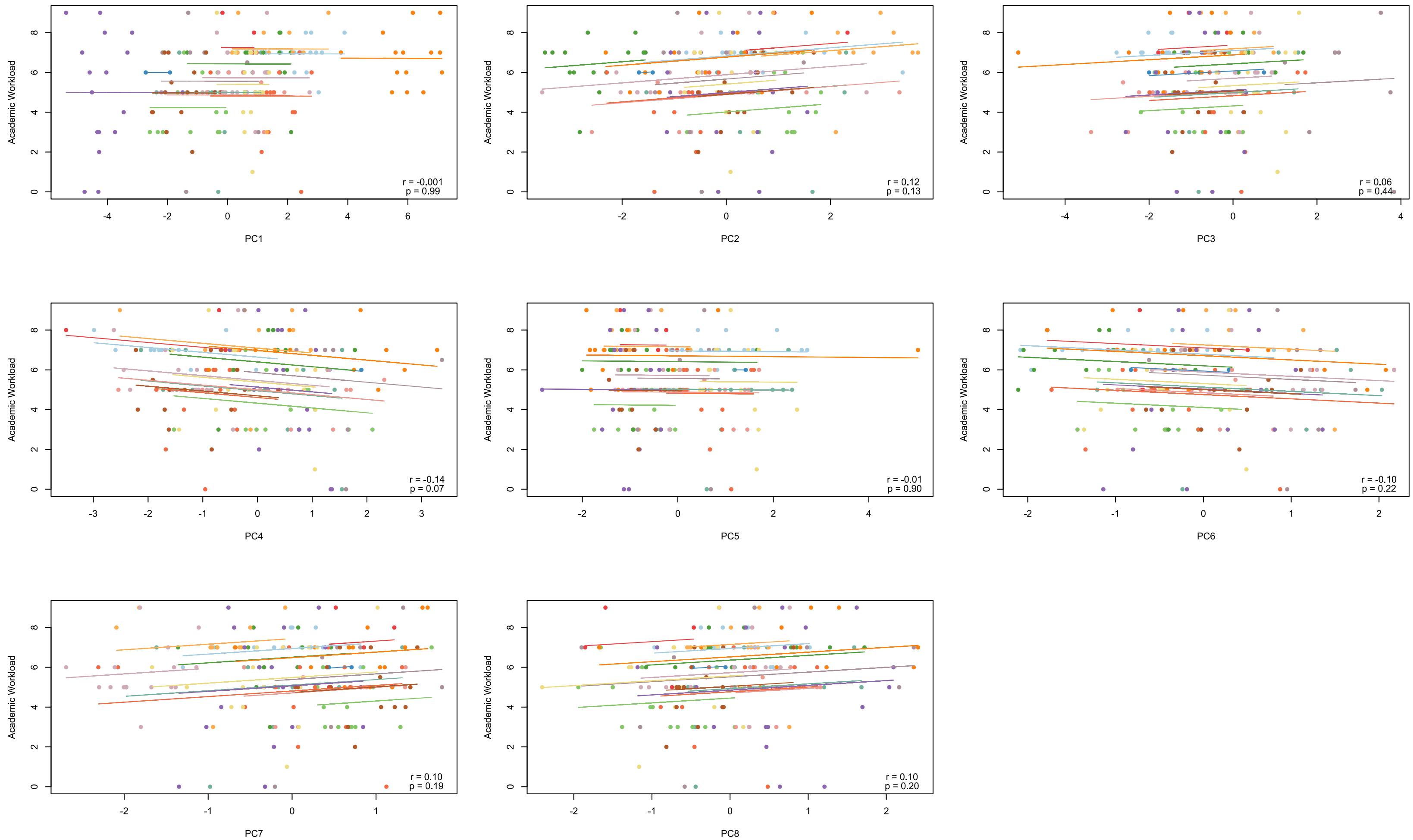

Figure 13 (Appendix). Repeated measures correlation-based associations identified between biomechanical principal component scores and self-reported academic workload across the 2022-2023 season, with subject-specific data distinguished using different colours, and the commonality in within-individual associations after controlling for between-individual variance identified in the bottom right corner of each subplot.

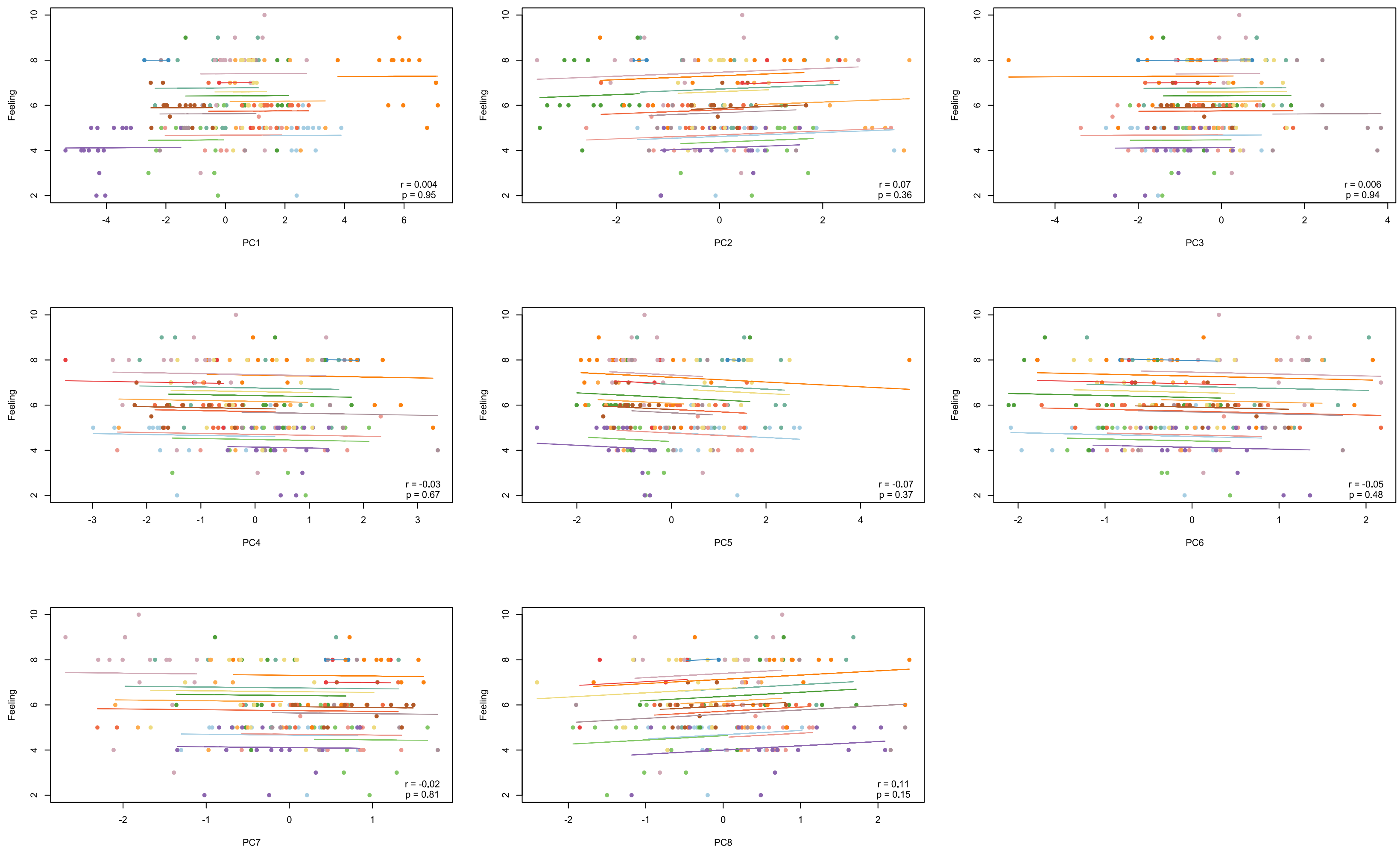

Figure 14 (Appendix). Repeated measures correlation-based associations identified between biomechanical principal component scores and self-reported feeling across the 2022-2023 season, with subject-specific data distinguished using different colours, and the commonality in within-individual associations after controlling for between-individual variance identified in the bottom right corner of each subplot.

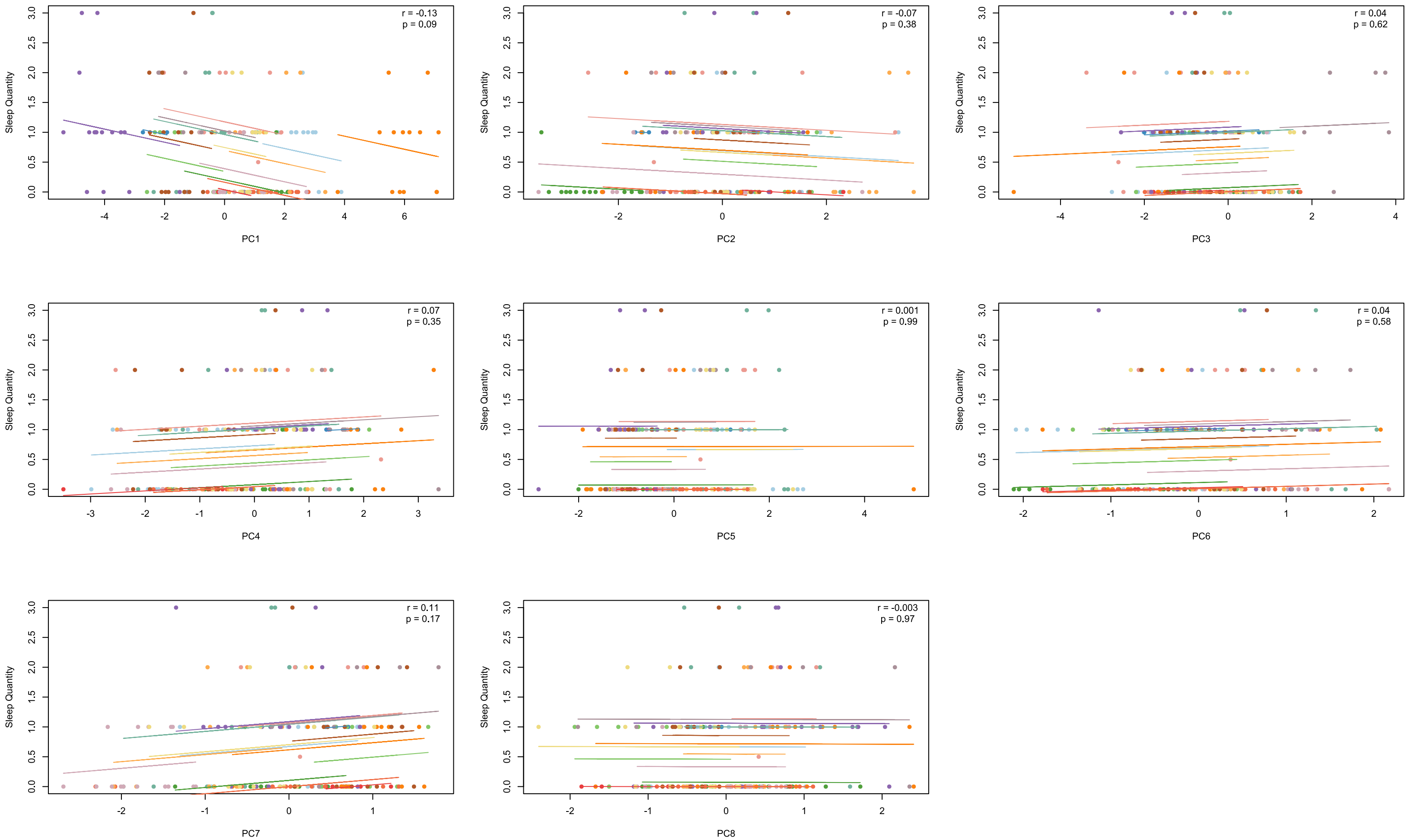

Figure 15 (Appendix). Repeated measures correlation-based associations identified between biomechanical principal component scores and self-reported sleep quantity across the 2022-2023 season, with subject-specific data distinguished using different colours, and the commonality in within-individual associations after controlling for between-individual variance identified in the bottom right corner of each subplot.

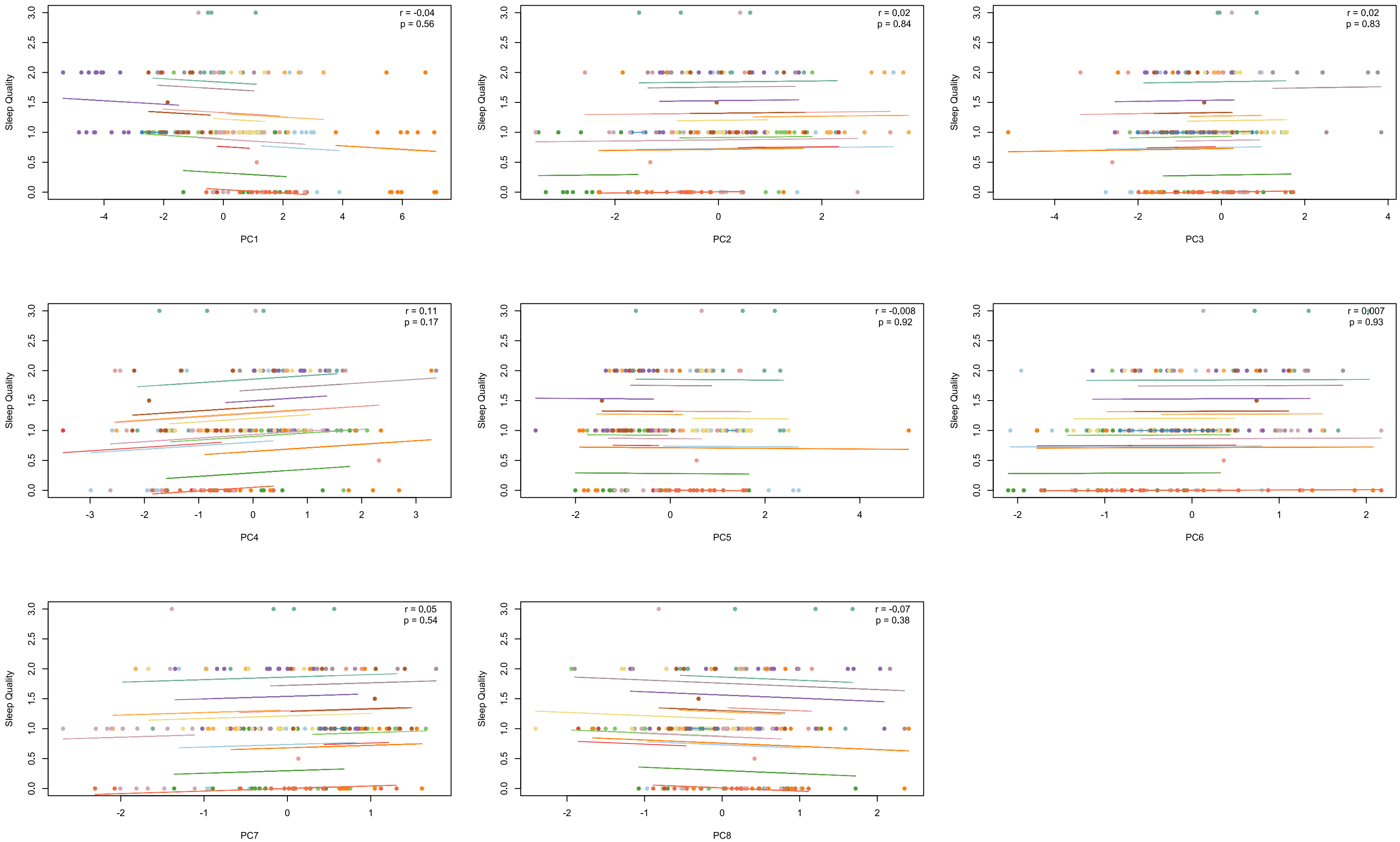

Figure 16 (Appendix). Repeated measures correlation-based associations identified between biomechanical principal component scores and self-reported sleep quality across the 2022-2023 season, with subject-specific data distinguished using different colours, and the commonality in within-individual associations after controlling for between-individual variance identified in the bottom right corner of each subplot.

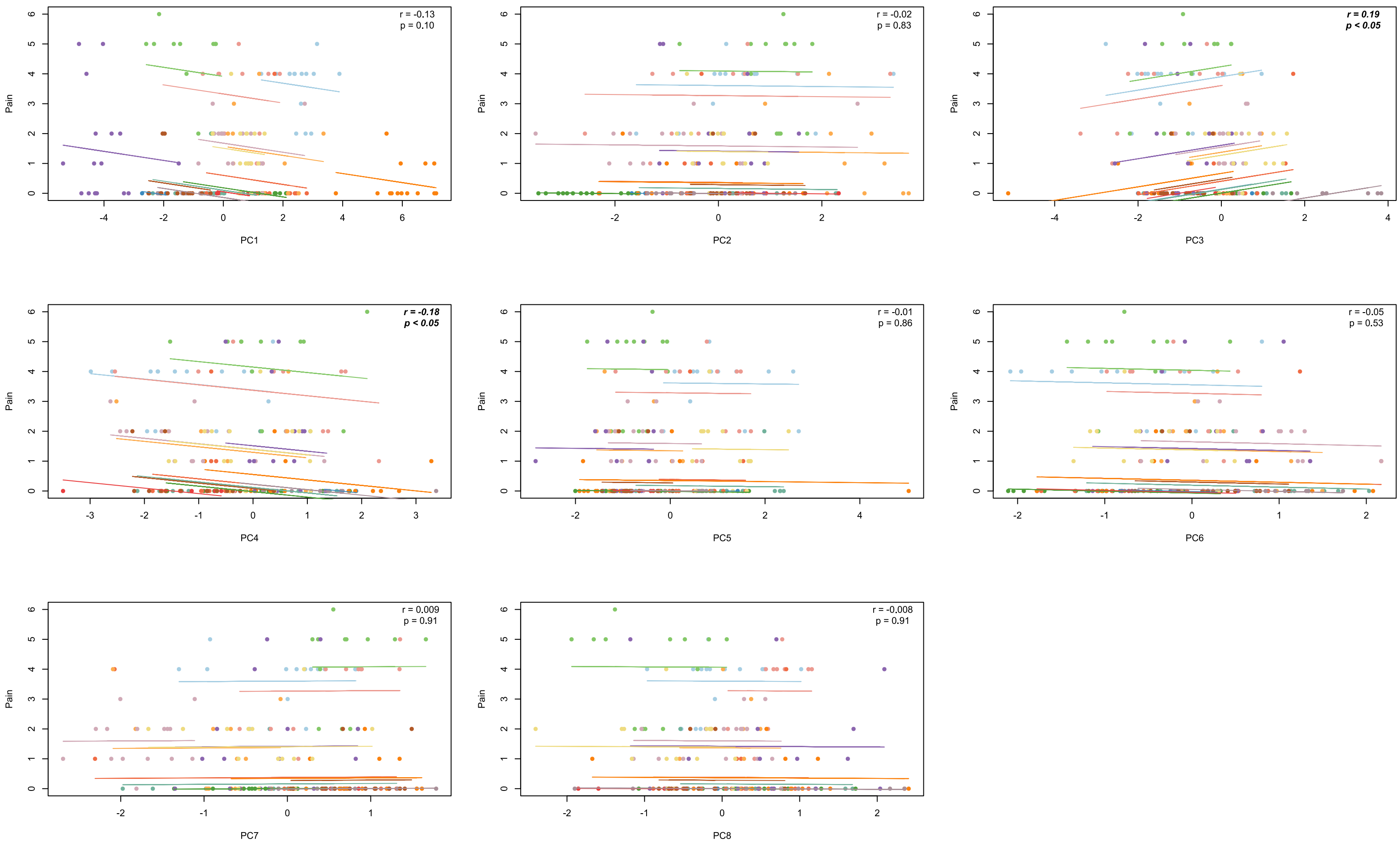

Figure 17 (Appendix). Repeated measures correlation-based associations identified between biomechanical principal component scores and self-reported levels of pain across the 2022-2023 season, with subject-specific data distinguished using different colours, and the commonality in within-individual associations after controlling for between-individual variance identified in the bottom right corner of each subplot.

Supplementary Tables

Table 4 (Appendix). Correlation between original biomechanical variables and newly derived principal component scores.

Biomechanical Metrics Included	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Total Impact Load	0.64	-0.27	-0.40	0.56	0.05	0.13	-0.03	0.06
Total Step Count	0.31	-0.11	-0.50	0.57	-0.03	0.36	-0.15	-0.31
Ave. Intensity	0.68	-0.32	-0.16	0.35	0.11	-0.13	0.04	0.31
Impact Asym.	0.46	0.79	0.15	0.24	0.04	-0.07	-0.02	0.08
Low-G Asym.	0.32	0.62	-0.02	0.15	-0.22	-0.40	-0.43	-0.16
Medium-G Asym.	0.36	0.59	0.15	0.03	0.13	0.44	0.43	0.17
High-G Asym.	-0.45	-0.75	-0.16	-0.22	-0.08	0.11	-0.04	-0.10
Jump Height	0.82	-0.28	0.09	-0.15	0.36	-0.18	-0.06	-0.01
CMD	-0.28	0.21	-0.70	-0.01	-0.29	-0.31	0.39	-0.06
Time to Takeoff	-0.26	-0.32	0.71	0.47	0.17	-0.06	-0.08	0.02
Pk Rel. Brk Power	-0.46	-0.25	0.22	0.51	-0.13	-0.41	0.40	-0.04
Pk Rel. Prop Power	0.82	-0.20	-0.05	-0.11	0.34	-0.27	0.14	-0.03
Pk Brk Force Asym.	-0.72	0.23	-0.26	0.07	0.52	-0.01	-0.05	0.05
Pk Prop Force Asym.	-0.75	0.11	-0.18	0.07	0.48	-0.10	-0.07	0.06
Ave. Brk RFD Asym.	-0.66	0.21	-0.16	0.08	0.48	-0.03	0.04	-0.25
Pk Lnd Force Asym.	-0.55	-0.04	-0.37	0.04	-0.10	-0.05	-0.24	0.58
RSI Mod.	0.83	-0.07	-0.30	-0.35	0.23	-0.13	0.02	-0.01
Individual % Var. Exp.	*34*	*15*	*11*	*9*	*7*	*5*	*5*	*4*
Cumulative % Var. Exp.	*34*	*49*	*60*	*70*	*77*	*83*	*87*	*91*

Abbreviations: PC = principal component; Ave. = average; Asym. = asymmetry; CMD = countermovement depth; Pk = peak; Rel. = relative; Brk = braking; Prop = propulsive; RFD = rate of force development; Lnd = landing; RSI Mod. = the modified reactive strength index; % Var. Exp. = percent variance explained.