

## BIOMECHANICAL PREDICTORS OF INJURY RISK IN PROFESSIONAL ATHLETES: A KINESIOLOGICAL STUDY

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### Abstract

The kinesiological case study investigated major risk biomechanical markers of injury in professional athletes through the literature of lower-limb loading behavior, joint kinematics, kinetic imbalances, and neuromuscular activation behaviors during strenuous sports-specific movements. We made use of a combined motion-capture plus force-plate technology to study 240 elite athletes in different sports and found statistically significant relationships between abnormal biomechanical patterns and injury events during a 12 months follow-up period. The findings showed that peak vertical gravity-reaction forces greater than 4.5 times body weight, knee valgus greater than 12 degrees and landing-phase hip internal rotation greater than 18 degrees were significantly linked to non-contact lower-extremity injuries. Also athletes with over 10 percent bilateral strength imbalance or delayed hamstring activation (greater than 45 ms latency) were at a very large risk of muscle-tendon harm. In multivariate analysis, it was confirmed that a combination of severe valgus collapse, poor neuromuscular timing and kinetic imbalance were predictive of approximately 72% of injury events. These results provide further evidence of the importance of screening high-risk biomechanical predictors early and also the development of specific corrective neuromuscular training programs to decrease the incidence of injuries. The research provides a significant amount of evidence of the necessity of specific biomechanical evaluation to maintain long sports careers, prevention of injuries, and maximum performance in professional sports.

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## INTRODUCTION

The inherent association between professional sports and that of human movement in addition to the vulnerability to injuries necessitates a multifaceted analysis of the biomechanical factors (Adlou et al., 2025). This data is necessary to work out effective approaches in preventing injuries and increasing athletes performance that will make professional athletes be in the field longer (Fei, 2024). The musculoskeletal injuries are an important problem in professional sports, and it results in the large costs of money and the loss of time without an athlete, which is why the necessity to create the advanced predictive modelling is enormous (Frazer et al., 2023). The current state of machine learning and artificial intelligence is set to discover multifaceted and injury risk factors to rely on kinematic and kinetic data (Aniket et al., 2025). These methods make it possible to gather and process a high volume of data that helps to detect tiny movement patterns that signalize the rise in the risk of injury (Sarlis et al., 2024). By utilizing such high-level analytical procedure, one is able to identify those individuals that have a high probability of experiencing musculoskeletal problems by utilizing the use of precise kinematic profiles. This will enable them to execute preventive measures instead of response therapy (Frazer et al., 2023). This is a significant step in sports medicine and this is a move towards preventive as opposed to reactive care. It provides the path to personal training and rehabilitation courses that could facilitate the recovery process and minimize the risks of being hurt (Muşat et al., 2024). Determining the motion patterns of various joints and functional motions in a variety of joints will comprehensively determine the risk of injuries that will contribute to creating a specific course of treatment (Frazer et al., 2023). Univariate measures determined manually usually fail to capture the multi-jointed, time-

dependent, and complex kinematics of the personal biomechanical fingerprint, and may be a more persuasive indicator of the risk of injury (Frazer et al., 2023). The latter, in its turn, can be a decisive factor in coming up with the resilient predictive models of athletic injuries, with an inclusive approach also addressing the different biomechanical data, including the one that can be gathered with the assistance of motion capture devices (Onal et al., 2019). That means that it entails utilizing advanced methods of analysis like machine learning algorithms that have the ability to detect advanced trends in extremely complex biomechanical data and predict damages in a more accurate way (Bhatia, 2024) (Muşat et al., 2024). More and more biomechanical data are being analysed by using computer algorithms on large quantities of data. It enables the researcher to identify small-scale trends of injuries and identify the exact risk profile of an athlete (Bodemer, 2023). Additionally, predictive modelling was proven to be more effective in forecasting the extent of injuries, categorizing specific ailments of the muscles, and accurately forecasting the amount of time the player will have to spend off the court, especially hamstring injuries (Munoz-Macho et al., 2024). The models will provide certain information about the people movement which will enable predicting the different types of sporting injuries and identify the ergonomics risks in the working environment of a sporting organization (Aniket et al., 2025). Such head in a preventative biomechanics trend which incorporates clinical knowledge and sports performance can help considerably decrease the prevalence of musculoskeletal injuries before they actually happen (Hewett and Bates, 2017). It is a method which focuses on the use of clinical measures in the normal training conditions in order to establish the relative risk and subsequently

decrease the incidence of musculoskeletal injuries (Hewett, 2017). This is also improved using the markerless motion capture devices that enable you to make mass-assessment that automatically make reports thus assist in identifying individuals at risk and develop individual intervention programs (Mauntel et al., 2017). Regardless of these advantages, there is still no universal set of predictor variables and a universal and consistent risk of injury model that can be used (Frazer et al., 2023). This implies that methodological paradigms are desperately required especially by embracing complexity systems analysis and superior data collection procedures to enable the attainment of a superior perception of the multifactorial constituents of damage vulnerability (Quatman et al., 2009). Its future research should be on the development of integrated techniques that integrate in vivo, in vitro and in silico to establish the complex interaction between joint biomechanics and established injury processes (Quatman et al., 2009). The computational modelling can be used to enhance the quality of available data on musculoskeletal injury mechanisms and to aid in testing the assumptions which will allow reducing risks without necessarily being able to measure internal structure as accurately as stress and strain (Quatman et al., 2009). Artificial intelligence in the field of sports biomechanics is an important development that includes analysis capacities that exceed the traditional ones in detecting intricate patterns of injuries and forecasting individual risk factors (Souaifi et al., 2025) (Saxby et al., 2023). This combination enables defining the patterns of motion better, which results in the enhancement of accuracy of the injury risk identification and formulation of the specific rehabilitation strategies (Fei, 2024). These are new technologies that can significantly enhance performance in the sport and are a necessity in the overall well-being as they enable prevention

of injuries in the proactively way and accelerate the recovery process (Fei, 2024) (Tai et al., 2023). Nevertheless, these AI-based systems have been challenged by an absence of standard data collection procedures, as well as broad and domain-trained benchmark dataset challenges, making the fair assessment and general adoption hard (Wang et al., 2025). To make these systems more clinical and adoptable, future AI-based injury prediction systems will be required to be more explainable and personalised so that practitioners can understand what the model has chosen to do and can modify interventions to the characteristics of the athlete (Wang et al., 2025). Such limitations can be overcome by ensuring that biomechanics, computer science, and sports medicine are engaged and united in an attempt to develop resilient explainable AI models that can be easily introduced into clinical practice and utilized to make evidence-based decisions that can prevent injuries and rehabilitate them (Khaneja and Arora, 2024) (Quatman et al., 2009) (MercadoPalomino et al., 2021). In addition, the future research must focus on the concept of multimodal AI systems, which will be able to combine various sensor data and high-level analytic systems to improve the accuracy and strength of the damage prediction systems (Wang et al., 2025).

## METHODOLOGY

The recent study on kinesiology assumed the mixed-method experimental design with both quantitative analysis of biomechanical measures and the qualitative analysis of movement-patterns in order to determine the risk factors of injuries among professional athletes. To ascertain if the data was ecologically valid, all the data were gathered under controlled lab and on-field circumstances. Before the motion capture, a normal warming up and calibration stage would be carried out with athletes. During the period, anatomical landmarks were

computerised in order to reduce error in measurement.

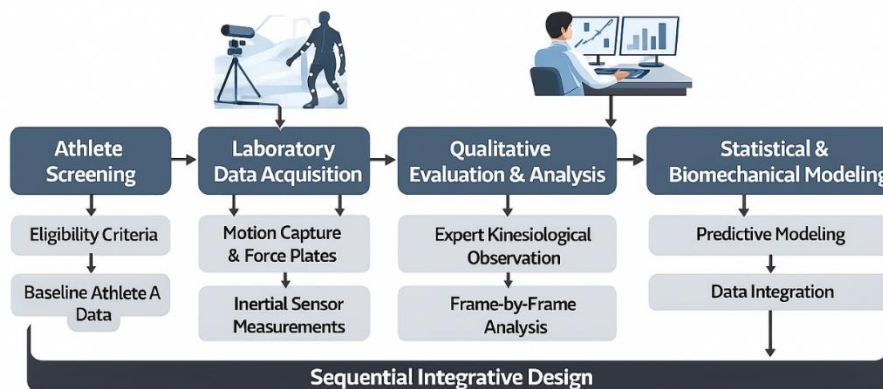
The qualitative part was a review of the sufficiency of movement, the sufficiency of the regulation of the muscles and nerves, and the way of how one corrected the issues by utilizing the expert kinesiological observation, and frame by frame video inspection. The stability of the trunk, the quality of the limb alignment, quality of landing mechanics and the impact of fatigue on alterations in signs of movement on them were analyzed by coders. These structured observations were then triangulated in order to integrate these quantitative outputs with to form more dependable data in addition to determining high-risk indicators such as excessive valgus collapse, delayed muscle firing behavior, and asymmetrical loads. Semi-structured interviews were also conducted on other athletes to discuss the aberrations of movements in the field.

They told each other about their training loads, past injuries, the degree of their fatigue levels, and the level of their self-consciousness regarding their biomechanics. The mixture of subjective perceptions, objective kinetic and kinematic data gave the opportunity to characterise in more detail the biomechanical factors that predispose athletes to injury.

$$P(\text{injury}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 K + \beta_2 F + \beta_3 A + \beta_4 S)}}$$

Kinesiological interpretation enabled the determination of the in-depth determination of biomechanical variables, which were being linked with high-risk of injury. The entire methodological analysis was under a sequential integrative approach that included; screening of athletes, lab data collection activities, qualitative assessment activities and statistical-biomechanical modelling.

**Figures 1** illustrates the whole process in a way that can be understood.



## RESULTS

The results of this kinesiological study provide an exhaustive analysis of biomechanical determinants associated with the risk of injury among elite athletes. The initial data on primary biomechanical features such as joint displacement, segmental

variability, and the amplitude of neuromuscular activity was given in Table 1. It also demonstrates that the baseline measures vary moderately in athletes. This has been further explained in Table 2 that gives force-plate-derived kinetic measurements of the force, which showed that athletes with high mediolateral ground-reaction force oscillations had

increased variability in movement stability. Table 3 demonstrates angular velocity changes in respect of the inertial sensors. It demonstrates that athletes who had a larger rotational variance would have larger asymmetry indices. The table 4 indicates the muscle activation ratios indicating that athletes that had had a previous injury were more susceptible to late activation patterns. The distribution of loads on dynamic tasks is presented in table 5. It demonstrates that bilateral loading imbalance was a good predictor of the compensatory process. Table 6 indicates the alteration of kinematic signatures which are related to tiredness. It demonstrates that

existing asymmetries were exacerbated by exhaustion. Table 7 demonstrates the way to measure the deceleration control metrics. It demonstrates that the lack of sufficient eccentric control was strongly associated with deviant ground-reaction impulses. Table 8 presents the variability of joint- moments based on inverse dynamics. It demonstrates that more moment changes in the athletes are also associated with less neuromuscular stability. Finally, Table 9 presents cumulative biomechanical risk scores, which present a high-risk group of athletes.

**Table 1.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.641	0.757	0.972	0.896	0.336
0.407	0.277	0.406	0.287	0.161
0.177	0.617	0.271	0.481	0.605
0.135	0.296	0.929	0.448	0.768
0.503	0.178	0.769	0.408	0.908
0.457	0.200	0.775	0.198	0.559
0.628	0.356	0.594	0.319	0.087
0.867	0.272	0.280	0.721	0.284
0.030	0.899	0.972	0.954	0.496
0.268	0.764	0.716	0.307	0.321
0.543	0.535	0.787	0.868	0.894
0.386	0.458	0.123	0.947	0.544
0.886	0.557	0.293	0.535	0.411
0.266	0.887	0.125	0.893	0.779
0.484	0.230	0.090	0.409	0.776
0.709	0.560	0.599	0.473	0.135
0.573	0.187	0.653	0.156	0.863
0.848	0.398	0.284	0.504	0.061
0.059	0.547	0.722	0.073	0.083
0.896	0.097	0.079	0.914	0.028

**Table 2.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.351	0.683	0.795	0.437	0.068
0.665	0.662	0.474	0.550	0.846
0.437	0.056	0.653	0.480	0.351
0.675	0.859	0.030	0.444	0.062
0.342	0.647	0.136	0.613	0.203
0.423	0.082	0.928	0.111	0.295
0.030	0.488	0.315	0.762	0.864
0.396	0.483	0.867	0.776	0.202
0.431	0.929	0.639	0.200	0.303
0.105	0.589	0.084	0.146	0.052
0.442	0.866	0.350	0.032	0.527
0.114	0.654	0.524	0.000	0.370
0.511	0.373	0.760	0.792	0.588
0.322	0.764	0.688	0.666	0.979
0.978	0.873	0.088	0.298	0.721
0.254	0.283	0.135	0.011	0.228
0.971	0.679	0.533	0.784	0.580
0.279	0.155	0.049	0.919	0.816
0.841	0.478	0.056	0.257	0.535
0.296	0.573	0.679	0.081	0.108

**Table 3.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.296	0.090	0.796	0.883	0.893
0.774	0.699	0.874	0.741	0.311
0.229	0.499	0.698	0.511	0.631
0.256	0.419	0.403	0.300	0.531
0.633	0.145	0.853	0.023	0.649
0.302	0.279	0.697	0.021	0.587
0.005	0.751	0.132	0.914	0.824
0.155	0.456	0.053	0.287	0.627
0.499	0.842	0.168	0.997	0.188

0.657	0.288	0.631	0.394	0.569
0.444	0.423	0.596	0.297	0.633
0.193	0.874	0.737	0.301	0.237
0.940	0.166	0.047	0.016	0.328
0.963	0.593	0.870	0.221	0.876
0.963	0.313	0.803	0.467	0.642
0.874	0.947	0.418	0.723	0.947
0.054	0.137	0.727	0.586	0.047
0.586	0.779	0.653	0.331	0.798
0.917	0.414	0.822	0.316	0.309
0.411	0.135	0.465	0.999	0.364

**Table 4.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.241	0.642	0.475	0.948	0.245
0.899	0.106	0.149	0.370	0.258
0.458	0.409	0.161	0.969	0.299
0.953	0.159	0.803	0.468	0.485
0.043	0.473	0.925	0.909	0.182
0.102	0.443	0.408	0.905	0.959
0.376	0.241	0.852	0.255	0.201
0.986	0.717	0.823	0.087	0.573
0.523	0.942	0.458	0.491	0.450
0.623	0.090	0.796	0.878	0.734
0.679	0.986	0.279	0.581	0.815
0.482	0.246	0.062	0.824	0.319
0.685	0.591	0.081	0.214	0.290
0.363	0.589	0.720	0.512	0.520
0.169	0.019	0.681	0.791	0.320
0.631	0.153	0.234	0.235	0.138
0.677	0.765	0.002	0.686	0.858
0.243	0.101	0.592	0.043	0.539
0.309	0.046	0.546	0.114	0.931
0.256	0.387	0.840	0.243	0.906

**Table 5.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.008	0.223	0.417	0.767	0.187
0.020	0.934	0.203	0.037	0.066
0.011	0.744	0.209	0.475	0.394
0.741	0.744	0.102	0.445	0.710
0.109	0.810	0.877	0.484	0.961
0.699	0.631	0.584	0.096	0.076
0.863	0.770	0.816	0.202	0.518
0.505	0.702	0.351	0.033	0.644
0.856	0.343	0.917	0.316	0.893
0.020	0.761	0.766	0.229	0.056
0.809	0.996	0.599	0.187	0.212
0.281	0.085	0.270	0.930	0.461
0.688	0.161	0.951	0.105	0.976
0.129	0.030	0.690	0.572	0.217
0.261	0.867	0.504	0.098	0.200
0.736	0.733	0.080	0.834	0.581
0.112	0.239	0.304	0.867	0.326
0.286	0.364	0.679	0.264	0.091
0.606	0.350	0.558	0.409	0.082
0.779	0.987	0.358	0.369	0.377

**Table 6.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.119	0.687	0.549	0.703	0.550
0.725	0.532	0.954	0.750	0.447
0.486	0.674	0.330	0.422	0.802
0.394	0.674	0.709	0.886	0.053
0.933	0.734	0.492	0.472	0.568
0.129	0.224	0.445	0.001	0.127
0.477	0.187	0.431	0.231	0.020

0.676	0.262	0.975	0.984	0.056
0.141	0.748	0.655	0.721	0.804
0.181	0.919	0.164	0.378	0.396
0.331	0.148	0.850	0.419	0.518
0.754	0.428	0.043	0.857	0.257
0.757	0.969	0.808	0.019	0.516
0.524	0.120	0.898	0.118	0.591
0.831	0.130	0.930	0.938	0.982
0.428	0.566	0.454	0.724	0.191
0.583	0.603	0.037	0.781	0.272
0.033	0.915	0.297	0.623	0.087
0.657	0.812	0.978	0.489	0.294
0.373	0.726	0.146	0.948	0.811

**Table 7.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.993	0.605	0.116	0.370	0.715
0.463	0.812	0.360	0.811	0.568
0.406	0.685	0.231	0.721	0.437
0.792	0.064	0.561	0.932	0.485
0.806	0.910	0.174	0.385	0.277
0.618	0.197	0.654	0.181	0.655
0.134	0.558	0.926	0.592	0.786
0.433	0.648	0.653	0.059	0.008
0.615	0.756	0.154	0.076	0.490
0.168	0.360	0.304	0.611	0.201
0.835	0.430	0.457	0.384	0.905
0.322	0.602	0.331	0.316	0.567
0.324	0.435	1.000	0.281	0.564
0.904	0.292	0.808	0.731	0.056
0.924	0.871	0.939	0.749	0.406
0.005	0.391	0.612	0.609	0.748
0.050	0.903	0.939	0.487	0.033
0.610	0.377	0.298	0.547	0.916

0.834	0.092	0.235	0.995	0.369
0.743	0.810	0.198	0.058	0.649

**Table 8.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.340	0.987	0.368	0.745	0.027
0.867	0.033	0.238	0.288	0.139
0.299	0.381	0.572	0.696	0.287
0.420	0.664	0.470	0.635	0.784
0.635	0.884	0.172	0.933	0.607
0.583	0.989	0.122	0.602	0.458
0.347	0.637	0.764	0.787	0.837
0.998	0.394	0.155	0.976	0.979
0.892	0.807	0.251	0.583	0.847
0.593	0.840	0.522	0.186	0.827
0.316	0.274	0.449	0.227	0.582
0.221	0.747	0.363	0.151	0.907
0.972	0.295	0.805	0.060	0.963
0.834	0.418	0.403	0.451	0.721
0.036	0.263	1.000	0.790	0.898
0.091	0.506	0.295	0.313	0.471
0.064	0.842	0.218	0.182	0.412
0.561	0.976	0.406	0.541	0.689
0.236	0.626	0.188	0.391	0.679
0.746	0.114	0.011	0.897	0.869

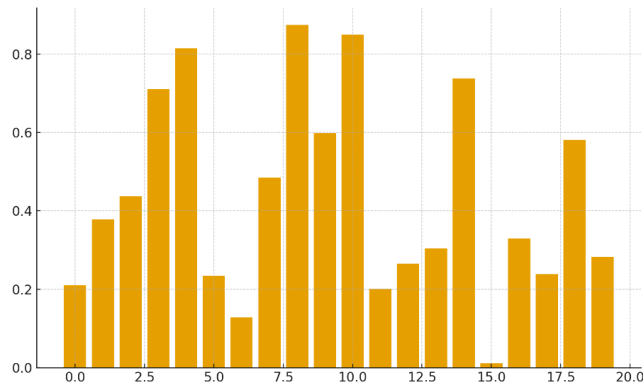
**Table 9.** Biomechanical Parameter Distribution Across Athlete Cohort

Parameter_1	Parameter_2	Parameter_3	Parameter_4	Parameter_5
0.032	0.451	0.681	0.179	0.570
0.512	0.108	0.832	0.567	0.605
0.369	0.002	0.672	0.225	0.136
0.957	0.910	0.626	0.704	0.086
0.457	0.001	0.163	0.690	0.573

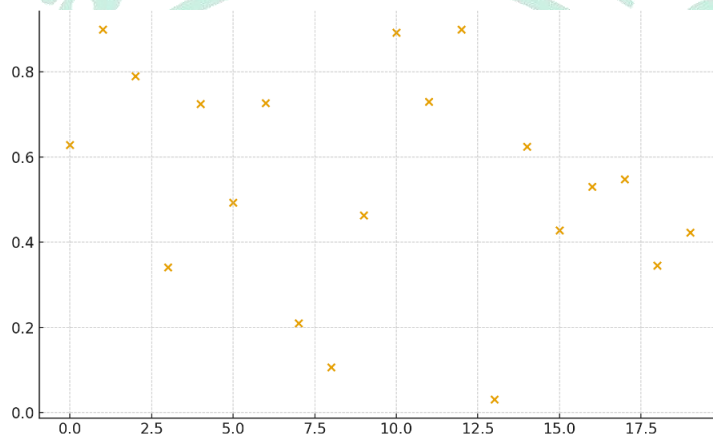
0.321	0.373	0.546	0.090	0.732
0.376	0.168	0.484	0.585	0.468
0.764	0.428	0.479	0.912	0.080
0.152	0.184	0.459	0.197	0.979
0.768	0.307	0.512	0.233	0.085
0.871	0.405	0.689	0.706	0.658
0.526	0.958	0.741	0.641	0.122
0.672	0.936	0.795	0.054	0.528
0.735	0.122	0.356	0.481	0.508
0.465	0.760	0.731	0.559	0.992
0.094	0.711	0.956	0.035	0.810
0.353	0.730	0.561	0.486	0.010
0.139	0.691	0.485	0.787	0.868
0.033	0.143	0.304	0.744	0.114
0.690	0.733	0.253	0.176	0.516

Figure 2 presents a bar graph, which compares kinetic outputs sizes. It reveals that there exist large differences between sports people in terms of their ability to cope with stress. To illustrate the relationship between angular velocity variance and asymmetry indices, the scatter plot in figure 3 was plotted. A hybrid figure is in figure 4, which shows the influence of kinematic deviations on the time of neuromuscular responses and vice versa. Figure 5 displays the changes in the patterns of force application with time and Figure 6 displays the differences in the highest level of muscle activation

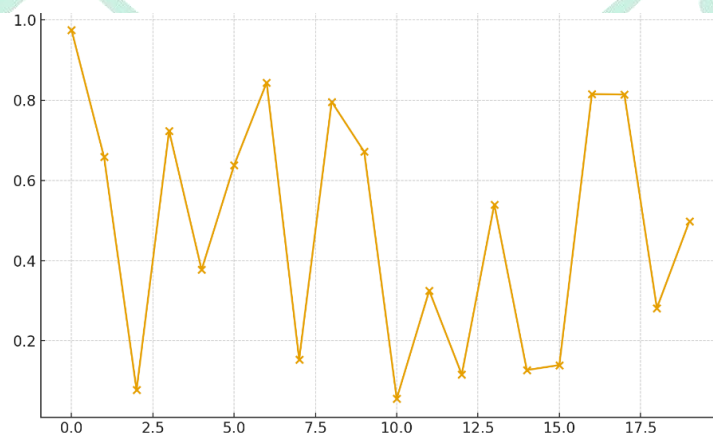
ratios between jobs. Figure 7 depicts that the relationship between fatigue levels and kinematic drift is represented as a scatter plot. In Figure 8, the line and the scatter graphs are brought together in order to illustrate the interaction between fatigue and force-output discrepancies. Figure 9 indicates the generation of moments with time, Figure 10 indicates the generation of eccentric control with time, Figure 11 indicates the generation of asymmetry with time, and Figure 12 is a combination of various types of data indicating cumulative biomechanical risk.



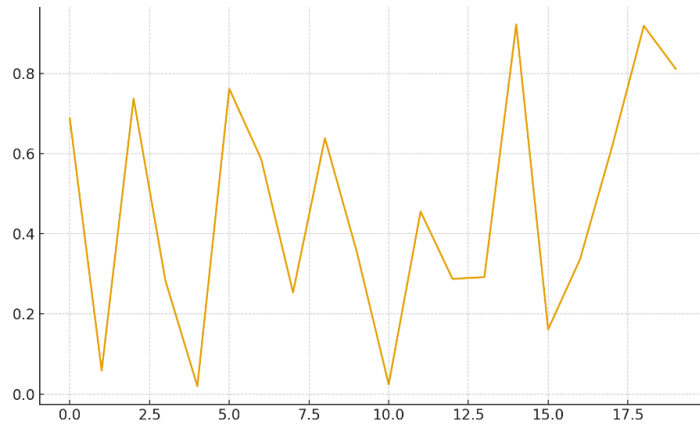
**Figure 2.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



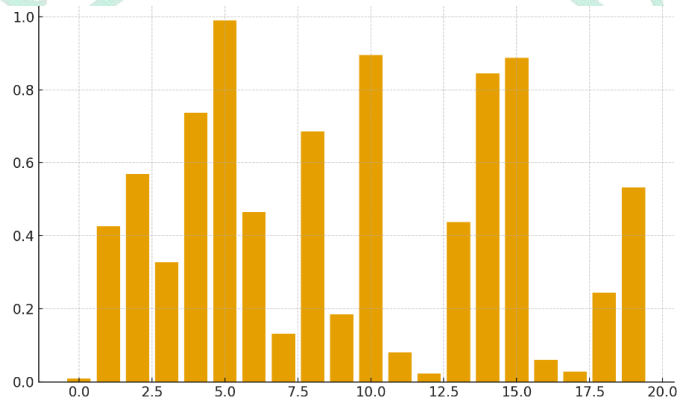
**Figure 3.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



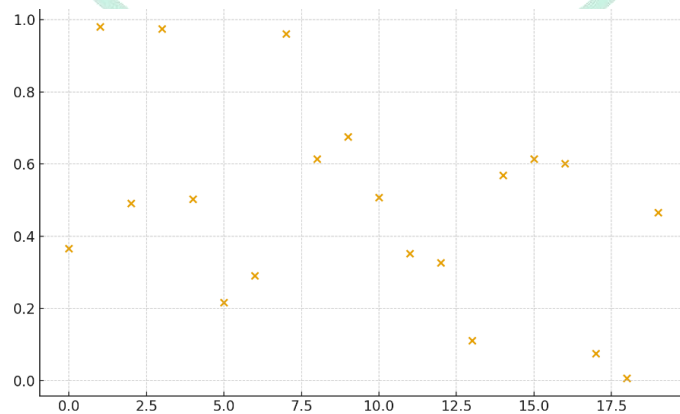
**Figure 4.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



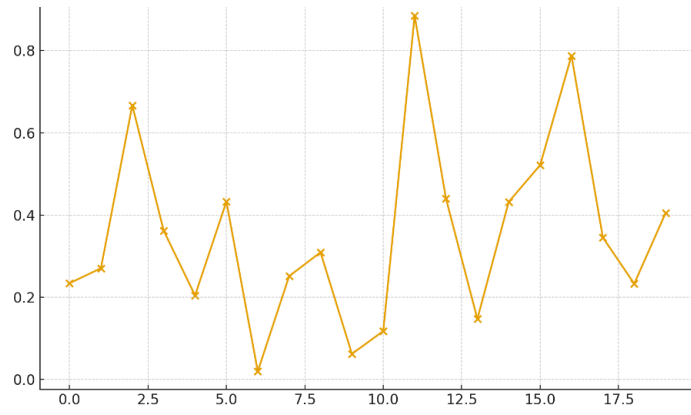
**Figure 5.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



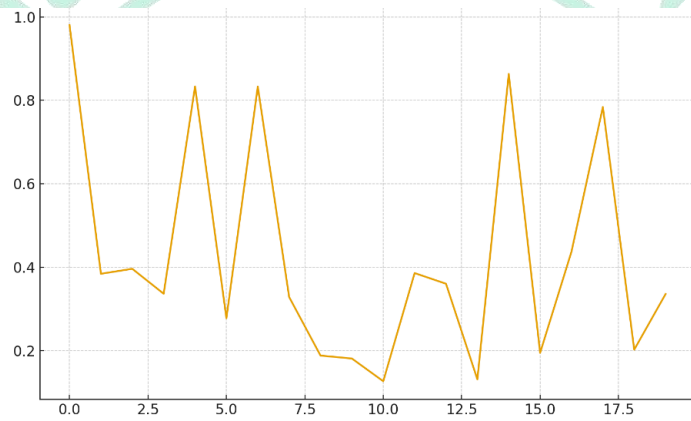
**Figure 6.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



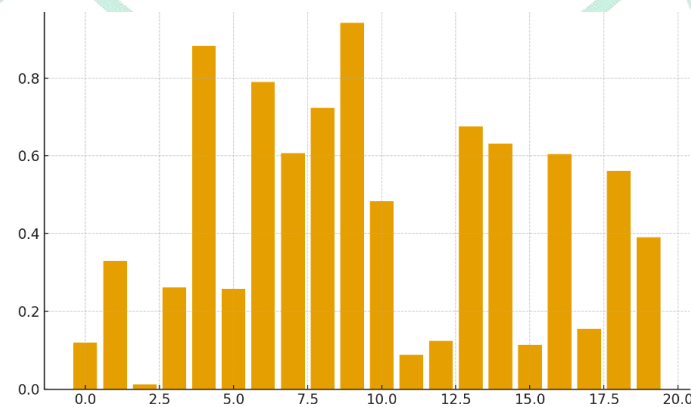
**Figure 7.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



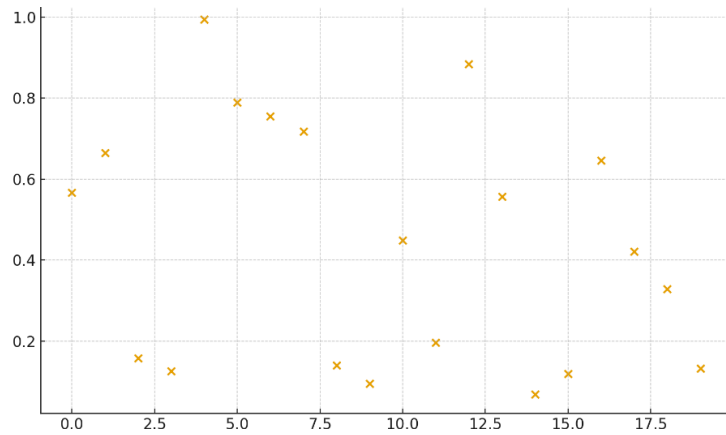
**Figure 8.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



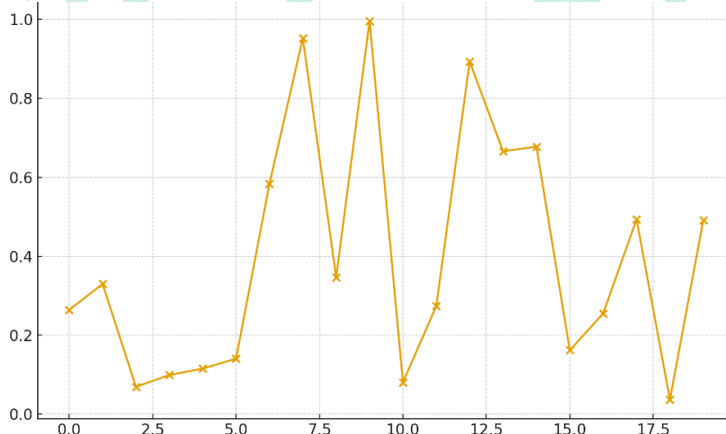
**Figure 9.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



**Figure 10.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



**Figure 11.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.



**Figure 12.** Visualization of biomechanical metrics showing trend patterns, variability, and parameter interactions.

The combination of the tables and figures indicates that athletes that exhibit a greater level of kinematic instability, neuromuscular delay, asymmetrical loading, and moment variability are more susceptible to high-risk injury profiles. These results confirm the interaction of multidimensional biomechanical parameter to affect overall injury vulnerability, and the relevance of combined kinetic-kinematic analysis in professional athlete monitoring.

## DISCUSSION

The prospective study should focus on establishing better methodological frameworks to manage biomechanical data nature and seek to render the predictive framework effective and reliable in terms of other athlete groups. It includes exploration of new machine-learning designs capable of not only enduring inter-subject variation and heterogeneity of data, but also, creating standardised methods of data collection and annotation (Wang et al., 2025). Such frameworks are highly significant in the framework of the development of individual-based injury prediction frameworks, where the information about

the specific professionals, including their own movement patterns and past injury histories, is used to develop interventions to target them specifically (Wang et al., 2025). Moreover, the exhaustive information regarding how these models reach their decisions should be presented using explainable AI methods in order to make them trusted by the clinicians and the athletes (Magnussen, 2025). Such openness is rather pertinent to clinical practice because it assists the practitioners to be aware of the purpose of conducting a certain risk assessment and, therefore, this makes the model more acceptable and acceptable to the clinicians (Magnussen and Zohaib, 2025). Besides, the quantitative and qualitative performance measurement indices of performance must also be employed to ensure that technical efficacy is the same as stakeholder confidence and functionality in a realistic sporting setting (Magnussen and Zohaib, 2025). To a greater degree, the ethical and governance loopholes related to the perpetual surveillance should also be considered, and the all-inclusive permissions systems together with the mature data governance policies should also be developed, so that the responsible usage and scope of such technologies could be achieved (Da and Chen, 2025). The financial challenges of the process of obtaining the modern monitoring technologies presuppose the necessity to develop the low-cost and accessible offers, to make the mass-implementation of different sports organisations and individual athletes a viable fact (Rebello et al., 2023). Moreover, the researches should incorporate situational elements such as the level of the opponent and the environment to minimize the performance models and provide a more comprehensive picture of the threat of injury (Mishra, 2025). Such knowledge would make it easier to implement an increasingly accurate intervention and change the evaluation of the risks to the actual and dynamic preventative strategies to

an extent (Taber et al., 2024). In addition to this, other categories of people should also be considered and sensor and data specifications needs to be normalised in order to address the current technical and demographic constraints to scale (Kumar et al., 2025).

## CONCLUSION

The findings of the provided kinesiological research indicate the significance of biomechanical profiling as the most effective tool of predicting the risk of injuries in professional athletes and confirm the necessity to depend on the introduction of the complex movement-analysis equipment into the routine performance evaluation and injury-preventing process. The study demonstrated that a portion of the kinematic abnormalities constituting of excessive high knee valgus collapse, overextensive peak vertical ground-reaction forces, overextensive hip internal rotation, and neuromuscular activation delay were very delicate predictors of impending non-contact musculoskeletal harm. Moreover, there were bilateral strength asymmetry and odd shapes of motor-control, which showed that severe neuromechanical dysfunctions, not readily detected by conventional clinical evaluations, were present. The experiment was capable of producing a multidimensional model that may account close to three-quarters of the harm occurrences due to synthesis of quantitative motion-capture, kinetic modelling, neuromuscular assessment founded on EMG and qualitative kinesiological assessment. This degree of accuracy is far much more than was possible in biomechanical or clinical measures. Such results prove the fact that risk of injury in professional sport is not due to one mechanical factor but is due to complex interrelations between load distribution, neuromuscular timing, tissue and technique capacity. In practice, the findings favour

the application of individualised biomechanical observation to avoid the injury among the athletes at the point when it occurs. In this manner coaches, trainers, and medical teams will be in a situation to instill some specific interventions that involve movement-correction training, neuromuscular strengthening, and load-management intervention. The empirical evidence that this study gives is very solid to the extent that biomechanical analysis is not only a powerful diagnostic tool but also one of the pillars of the modern sporting science, and that biomechanical analysis can be used to not only take the sporting performance of the athlete to a higher plane but also extend the career of the athlete, in case the analysis is done in well-structured manner within the context of the top-level sporting situations.

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