REVIEW ARTICLE

Emerging sports science technologies in decoding and preventing joint injuries: A new era for athletics in China and Asia

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ABSTRACT

Sports injuries are a major issue for all athletes, but joint injuries particularly so for athletes in the rigorous sport of athletics, whose very sustainability depends on the sustainability of athletes. New sports science technologies are turning joint injuries into a transparent box problem with new understanding of their causes and new efficacy in preventing them. In this article, we review the state of the art in sports science technologies such as wearable sensors, artificial intelligence, computer vision and biomechanical modelling which work together to decode the micro-mechanics of joint damage. With an application and current research perspective centred around China and Asia, this article addresses the challenges remaining in these technologies including data integration, accessibility of technology, and development of intervention solutions tailored to individuals. Through the discussion of representative case studies, this review highlights how these new technologies enable personalised and precise joint management for improved injury prevention and rehabilitation. This review aims to drive the development of an intelligent prevention ecosystem which can not only improve the performance of Asian athletes but also protect their musculoskeletal health in the new era of sports medicine and athletics training.
Keywords: Sports science technology, Joint injury, Wearable sensors, Artificial intelligence, Biomechanics, Chinese athletics, Sports injury prevention.

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INTRODUCTION

Joint injuries are among the most common and most disabling categories of sports injuries in sports that require joint injuries with high demand, repetitive, complex and specific joint movements, and athletics is no exception. In particular, joint injuries and the related problems associated with the knee, ankle and shoulder are major obstacles to performance and career longevity in athletics and other sports events. Epidemiological studies in different populations have provided evidence for high incidences of joint injuries in sports. For example, in a prospective cohort of adolescents participating in sports in South Africa, lower limb injuries represented 61% of all injuries, and sprains of joints and muscles formed a large proportion (van Loggerenberg et al., 2025). In addition, injuries in Olympic sports have shown that the most commonly injured joints are the knee and shoulder, with injury prevalence rates of 28% for the former and 14% for the latter (Lambert et al., 2022, 2024). These injuries result in both acute time loss from training and competition, and lifelong sequelae such as osteoarthritis, persistent pain and functional disability. High cumulative injury burdens and persistent musculoskeletal problems associated with previous joint injuries are also commonly reported by retired national-level athletes (Cooper et al., 2021; Hind et al., 2020). As joints play a crucial role in athletic performance and joint injuries have serious consequences, effective prevention and treatment strategies are of great importance in sports medicine.

Traditionally, the prevention and diagnosis of joint injuries in athletics has been largely driven by clinical experience, physical examination, and relatively simple assessment tools. Traditional approaches have included subjective measures, passive range of motion assessments, manual tests, and conventional radiographs and magnetic resonance imaging (MRI). These approaches may yield useful information; however, they are episodic, provide no feedback, and do not consider the dynamic biomechanical factors that lead to injury. For example, MRI can localize damage, such as rotator cuff tears, cartilage lesions, etc., but it is most often used to diagnose injury that has already occurred rather than as a preventative measure (Lusi et al., 2025; Sarin et al., 2021); Clinical assessments of joint laxity and muscle strength have been suggested as potential predictors of injury risk (e.g. hamstring-to-quadriceps [H:Q] strength ratios) (Kellis et al., 2023); however, recent systematic reviews have found them to have poor predictive value when used alone. Traditional approaches to athlete injury surveillance may also be lacking in precision and comparison accuracy, particularly in populations with limb deficiencies (i.e. Paralympians) (Heneghan et al., 2021; Heneghan et al., 2020); here, traditional methods will likely be inadequate to provide the detailed individual-focused monitoring needed to prevent joint injuries in elite and developing athletes.

The recent advent of sports science technologies represents a revolution in how we prevent joint injuries from an experience-based knowledge to one based on data. Advances in wearable sensor technology, machine learning and imaging in recent years have allowed for the continuous, accurate and real-time monitoring of joint biomechanics and tissue properties. For example, deep learning models have been applied to data recorded from IMUs to predict the lower limb kinematics and vGRF during running and other activities which offer new knowledge of the joint loading pattern(s) that lead to injury (Chen et al., 2025; Patra et al., 2023). Deep learning models applied to infrared thermography have been applied to non-invasively characterise the knee joint thermal profile during exercise which may correlate with underlying pathological condition (e.g. inflammation, early degenerative changes) (Crisafulli et al., 2024).Machine learning application on electronic foetal monitoring and EEG data demonstrate the potential of artificial intelligence in identifying patterns from complex biological data and predicting future outcomes which can be extended to musculoskeletal injury prediction (Aghaeeaval et al., 2021; McCoy et al., 2025); While near-infrared spectroscopy (NIRS) coupled with machine learning has shown potential for in vivo arthroscopic monitoring of cartilage properties and longitudinal assessment of cartilage degeneration after injury (Sarin et al., 2021).

These tools used in conjunction with the advances made in micro physiological systems like organ-on-a-chip models, provides new opportunities to investigate joint pathologies and drug responses in ex vivo platforms that mimic the in vivo environment at microscale (Ajalik et al., 2022).

Given the context and circumstances of China and Asian sports, the use of modern sports science technology is of utmost significance. Given the increasing number and frequency of Chinese and Asian athletes competing successfully in international athletics, ethnic-based injury prevention programmes are necessary for this population after taking into account ethnic, biomechanical and cultural factors. In terms of Asian athletes, research has found several intrinsic risk factors for joint injuries, including lower hamstring-to-quadriceps strength ratios and body composition characteristics associated with ACL injury risk in male American football players and young female soccer players in Japan (Taketomi, Kawaguchi, Mizutani, Takei, Yamagami, Kono, Murakami, Arakawa, et al., 2024; Taketomi, Kawaguchi, Mizutani, Takei, Yamagami, Kono, Murakami, Kage, et al., 2024). However, surveillance and advanced biomechanical monitoring are limited in these populations. Novel wearable sensor technologies, machine learning-based predictive models, and advanced imaging can fill this gap, enabling precision sports medicine for Chinese and Asian athletes with characteristics in terms of their physiology and biomechanics. Additionally, the development of monitoring tools that are accessible, non-invasive, and cost-effective is essential for a wide range of training environments commonly found across Asia.

This review is to systematically synthesize the current emerging sports science technologies in decoding and preventing joint injuries in athletics with a special emphasis on their usage and potential in China and Asia. We will review the emerging technologies in various forms of wearable sensors, artificial intelligence, imaging modalities, and bioengineered models, and relate them to the distinctive aspects of Asian athletes. With the epidemiological information, biomechanical knowledge, and innovative technologies, we would like to give birth to a new chapter in sports medicine which uses advanced technologies to support athlete health, performance, and career in the region of Asia. At last, we will also discuss the future directions of technology fusion, research roadmaps, and implementation strategies to optimize the usage of technologies in China and Asia athletics.

APPLICATION OF WEARABLE TECHNOLOGY IN JOINT INJURY MONITORING

Inertial sensor technology and its role in monitoring exercise load

Inertial Measurement Units (IMUs) encompassing accelerometers and gyroscopes have recently enabled real-time assessment of joint kinematics (angles, angular velocities and accelerations) and thus provided new means to monitor athletes' three-dimensional movement patterns. Being worn typically around the lower limb, IMUs produce continuous joint-related signals that can be used to evaluate the biomechanical demands imposed by training and competitive activities on the joint and therefore to investigate injury and fatigue loads. For example, as shown in Figure 1 "*Comparison of Knee Joint Angle in Sagittal Plane Between IMU Measurements and Optical System Measurement*" (correlation > .94), IMUs have been compared against gold-standard optoelectronic systems and demonstrated good agreement in the sagittal plane kinematics of the knee and hip during a complex high-speed task, which involved the drop jump, sprint and directional change actions (correlation coefficients > .94 and coefficients of multiple correlation > .96) (Di Paolo et al., 2021). Such high levels of agreement highlight the potential of IMUs to provide accurate information on clinically relevant joint kinematics that are fundamental to the rehabilitation and return-to-sport following an injury, e.g. anterior cruciate ligament (ACL) injury.

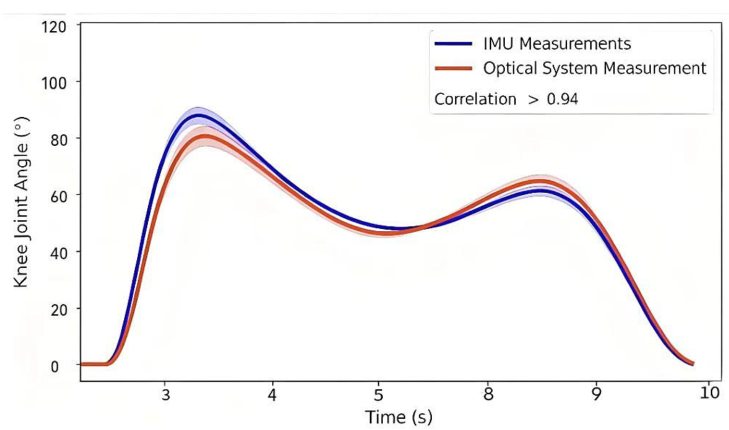
In addition to kinematic data, IMUs enable accurate assessment of movement intensity and asymmetry. These parameters can indicate fatigue and overuse, which predispose athletes to joint injuries.

For instance, in hockey skaters, IMU-predicted three-dimensional joint angles have been used to distinguish between high- and low-calibre hockey players, highlighting performance-related biomechanical differences that may contribute to injury risk (Khandan et al., 2022).

Machine learning on raw IMU data has improved joint loading characteristic signals and enabled accurate estimation of joint torque and loading with good fidelity in real-time (Chang et al., 2025). Thus, the combination of AI and IMU data enables accurate, low-cost, wearable technology that can provide joint torque information in a natural setting beyond the lab.

By enabling real-time data acquisition, IMUs play a crucial role in injury anticipation through the early detection of asymmetries and aberrant loading patterns that precede joint injury. For example, IMU wearable technology has been used to estimate knee joint function following ACL reconstruction and objective biomechanical measures extracted from these assessments can be correlated with patient-reported outcome measures to inform rehabilitation (Ptaszyk et al., 2025). Similar to the gait lab, convolutional neural networks applied to IMU kinematic data have reproduced gait lab quality kinematic data, showing the potential of IMUs married with advanced analytical approaches to longitudinally assess knee function in the clinical and field environment (Bini et al., 2025).

Although significant advances have been made in regards to data accuracy and sensor positions, recent studies in sensor fusion, calibration methods, and machine learning have enhanced the accuracy and reliability of IMU data measurements. For instance, when using spatial geometric equations in single-sensor systems, joint angle error in terms of the ratio to dual-sensor and camera-based systems was 5°, indicating a step towards more accurate and minimalistic wearable IMUs (Shiao et al., 2024). This enables the widespread use of IMUs for the continuous monitoring of exercise load, asymmetry, and fatigue, which are crucial for the prevention of joint injuries in athletes. Such athletes, who are frequently injured due to high demands for specific sports, include athletes, footballers, and badminton players (Davidoviča et al., 2025; Yu et al., 2023).



Note. This figure depicts the knee joint angle over time in the sagittal plane, comparing measurements from Inertial Measurement Units (IMUs) and a gold-standard optical system. The correlation coefficient between the two measurement methods exceeds .94, demonstrating the high accuracy of IMUs in capturing knee joint kinematics, consistent with the findings of (Di Paolo et al., 2021).

Figure 1. Comparison of knee joint angle in sagittal plane between imu measurements and optical system measurement.

In a nutshell, inertial sensors provide a potent, portable and economical solution to analyse joint biomechanics and exercise load in real time. By revealing injury risk factors such as asymmetry and accumulation of fatigue on kinematic and kinetic parameters, IMUs identify the early warning signs that can be turned into prevention and rehabilitation actions with the help of AI and machine learning technologies. This is how inertial sensors are changing the game in sports science and athlete training & rehabilitation in China and Asia.

Pressure insoles and analysis of plantar pressure distribution

Pressure insole is an instrument to evaluate the plantar pressure distribution and the biomechanical joint reaction to this pressure which helps to forecast gait abnormalities and possible injuries in athletes. These insoles with pressure sensors can tell you what the dynamic pressure pattern over the foot during gait is by recording the dynamic pressure distribution pattern over the foot during gait and detect any abnormal loading pattern that may lead to stress on the knee and ankle joint. That is, the plantar pressure can be used as a surrogate parameter of joint loading and neuromuscular control if the relationship between joint kinematics and plantar pressure is correlated. For example, researchers discovered that there were significant correlations between kinematic parameters of hip and knee joints and medial-lateral plantar pressure distribution pattern during functional over-ground activities in youth athletes by combining use of smart sock system and inertial sensors (Davidoviča et al., 2025).

The plantar pressure information from insoles could expose the gait deviations (asymmetrical unloading, increased pressures at specific areas at the plantar surface) which would increase the risks of overuse injuries of joints, e.g. osteoarthritis, ligamentous injuries.

Insoles could be formed based on the foot morphology and pressure mapping analysis information. The insoles could be used to redistribute the loads at the plantar surface, decrease the peak pressure at specific areas at the plantar surface (i.e. metatarsal heads, heels), and correct the biomechanics of the foot (Lin et al., 2025; Wang et al., 2025).

Populations with foot morphology deformities (i.e. flatfoot, cavus foot). The pressure insoles could be used to assess the effectiveness of the orthotic interventions. The interventions were designed to normalize the pressures at specific areas at the plantar surface and reduce the joint stress (Ma et al., 2024; Wang et al., 2020).

When applying the pressure insole technology for Chinese and Asian athletes, we should also take the regional physiological foot characteristics into account. There are arch height and foot morphology variations for Chinese and Asian population, and the insoles application and insoles design should also consider these regional characteristics. It has been proved that the customized insoles including the insoles fabricated by 3D printing technology can be prepared to satisfy the above requirements (Nouman et al., 2019; Xu et al., 2019). Furthermore, the variations of plantar pressure can be used to detect the training load and the athletes' fatigue even to predict the joint injury ahead of time.

The combination of pressure insole data and other wearable sensor information, such as IMUs and electromyography, will extend the biomechanical assessment information and help to construct individualized training and rehabilitation programs based on specific biomechanical deficits and prevent joint injuries (Davidoviča et al., 2025).

Because the pressure insole technology is a non-invasive technology that can collect real-time information of plantar pressure distribution and its effects on the health of the knee and ankle joints, it has been extensively used in early joint injury screening and prevention due to its ability to reflect gait abnormalities and loading area asymmetries. In addition, because the pressure insole technology can adapt to the characteristics of the feet of Chinese and Asian athletes, it also has great application prospects in the clinical and sports fields to enhance athletic performance and decrease the injury rate.

Advantages and challenges of multisensory fusion technology

Multisensory fusion methods that integrate data from various types of wearable sensors, such as IMU kinematics information, plantar pressure information, EMG information, and others, can supply richer information for joint injury monitoring. The complementary biomechanical and physiological information from different sensors improve the understanding of joint injury mechanisms and loading conditions of the joint compared to a single sensor (Davidoviča et al., 2025) (Table1).

Table1. Comparison of core parameters, advantages, and limitations for IMU, pressure insoles, and EMG sensors.

Attribute	**IMU (Inertial Measurement Unit)**	**Pressure Insoles**	**Electromyography (EMG)**
Measurement metrics	Acceleration, angular velocity, orientation (kinematic parameters)	Plantar pressure distribution, force values, load centre	Muscle electrical activity, contraction intensity, fatigue indicators
Sampling rate range	50-1000 Hz (typical: 100-200 Hz)	10-100 Hz (typical: 20-50 Hz)	1000-2000 Hz(typical: 1000-1500 Hz)
Advantages	Portable, real-time motion capture, cost-effective, easy integration	Direct biomechanical load measurement, assesses balance/gait, non-invasive	High temporal resolution, reflects neuromuscular control, detects muscle fatigue
Limitations	Signal drift, magnetic interference, requires calibration, noise-sensitive	Comfort issues, affected by humidity/temperature, limited battery life	High signal noise, requires skin preparation, motion artifacts, higher cost
Application scenarios	Motion analysis, gait assessment, joint angle monitoring, real-time feedback systems	Foot biomechanics research, rehabilitation training, athletic footwear design, injury risk assessment	Muscle function evaluation, rehabilitation monitoring, sports performance analysis, neurological disease research

Note. IMU: Inertial Measurement Unit; EMG: Electromyography. Sampling rate ranges are based on typical values used in research and practical applications. The parameters highlight the complementary nature of each sensor type in multisensory fusion for joint injury monitoring.

Even the process of integrating heterogeneous sensor information poses challenges in data handling such as the need for sophisticated algorithms to integrate data from sensors with varying sampling rates (Table1), signals noise and drift, and portability issues and athlete comfort concerns. For instance, the number of sensors on a wearable system may impact the sensor number and athlete’s willingness to wear the device (Lloyd et al., 2023). An increase in the number of sensors on a wearable system may result in a decrease in data richness and wearability of the device, which may impact athlete’s performance.

Techniques such as machine learning and artificial intelligence, categorized under advanced data fusion methods, have been proposed to overcome these issues due to their abilities to extract features, reduce noises, and recognize patterns from multiple sensors. These approaches can provide immediate feedback information to athletes and coaches about biomechanical deviations and injury-prone factors during training and matches for further correction and rehabilitation (Chang et al., 2025; Jung et al., 2024). The creation of individualized biomechanical models named digital twins (updated with sensor data information) is feasible with the assistance of multisensory data fusion and intelligent algorithms, which might be the future of individualized injury prevention strategies (Lloyd et al., 2023).

The realization of closed-loop systems with multisensory data fusion and feedback information is technically complex and demands the support of specific algorithms, devices with low delays, and a user experience. In addition, data privacy and security issues should be taken into account for the wireless wearable systems, particularly when they are used in field settings. These issues can be solved by the current rapid evolution of microelectronic devices, wireless communication technologies, and computing power, which are enabling practical applications of multisensory data fusion in sports.

Multisensory fusion technology has a broad application perspective in detecting and preventing joint injuries for Chinese/Asian athletics because of their variety in their movements and environment. It is necessary to localise the technologies to local situations, i.e. training approaches and athletes' body features, to popularize and apply the technologies well. Interdisciplinary research and development are needed to solve the current problems of multisensory fusion technology.

AI-DRIVEN FRAMEWORK FOR SPORTS INJURY MONITORING AND PREVENTION

Multimodal data integration and feature extraction techniques

The integration of various data sources like wearable sensors, biomechanical data and training logs is key to enhance the accuracy of injury risk prediction in athletics. Wearable sensors can generate continuous recordings of kinematic and physiological signals and have the potential to register biomechanical deviations that may precede injury. Motion capture and the force plates provide information on movement patterns and applied loads. Training logs can offer additional information on the athlete's state with regards to workload, fatigue and recovery. Integrating data from all these sources will result in a 'holistic' picture of the athlete's physical state.

Feature engineering is the process of extracting meaningful information from raw signals. Time-domain features (e.g. mean, variance, peak values) describe properties of the signal amplitude and variability. Features in the frequency domain (e.g. power spectral density, dominant frequencies) describe periodicities and oscillatory behaviour that might be related to neuromuscular control. Other nonlinear features (e.g. entropy measures, fractal dimensions) describe signal properties concerning signal complexity and irregularity patterns that might be related to neuromotor adaptations or dysfunctions that predate injury.

Feature selection is the process of finding a subset of input variables that are most relevant for the prediction targets. It is an important step to reduce the dimensionality of a dataset and therefore improve model performance and reduce overfitting. Methods like recursive feature elimination, mutual information measures and embedded methods within machine learning algorithms are implemented.

Studies have demonstrated that combining data from multiple sources, in combination with strong feature extraction approaches, can enhance the sensitivity and specificity of injury-prediction models (Claudino et al., 2019; Jiang et al., 2022; Musat et al., 2024), which can subsequently be used to deliver personalised and dynamic injury-risk assessment within large athletic cohorts.

Regardless of the setting in which they are applied, it is probable that different approaches to data integration will be required when working with Chinese and wider Asian athletic populations because of the different training regimens and biomechanical characteristics that these athletes exhibit. This will necessitate an understanding of appropriate data fusion approaches that enable us to decode injury information and facilitate prevention.

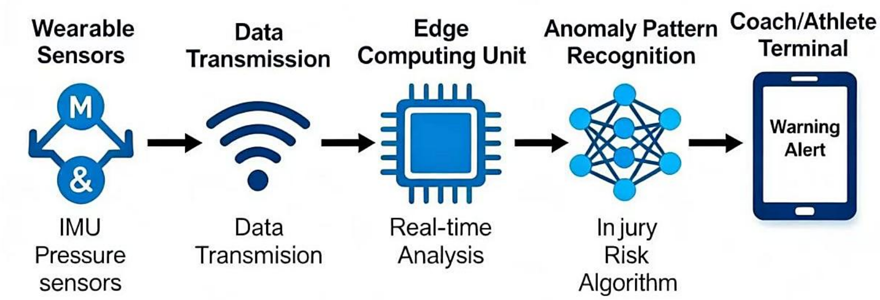
Machine learning model development and validation

Supervised machine learning algorithms have been used in the field of sports injury risk prediction with labelled datasets from various labelled multiple inputs. The most widely used algorithms are Random Forest (RF) , Support Vector Machine (SVM) and Deep Neural Networks (DNN). Each of these algorithms have their own advantages. RF, which is an ensemble algorithm, is capable of dealing with high dimensional data and learns nonlinear relationships from the data and also gives feature importance along with the labels which makes it more interpretable. SVM is capable of handling high dimensional data and also handles over fitting well, when using proper kernel functions which map inputs to a higher dimensional feature space.

DNNs i.e. deep learning is well suited for modelling complicated hierarchical representations of the features. This comes at the cost of requiring a large amount of data and computational power. The training process of the models includes data preprocessing, feature scaling, and tuning of hyperparameters. Subsequently, cross-validation (e.g., k-fold or nested cross-validation) is used to reliably estimate the generalization performance of the models and avoid overfitting. Evaluation metrics such as area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, and F1-score offer an overall evaluation of the models' performance. Recent research results show that the predictive accuracy of RF and gradient boosting models is high in clinical and sports injury settings and can reach over 0.8 for AUC, which shows a strong discriminative ability (Cai et al., 2022; Claudino et al., 2019; Musat et al., 2024). However, further work is needed to apply these models in Chinese and Asian athlete groups because there are many differences in genes, environment, and training. Limited external validation and data variation may also lead to limited transferability of models. Therefore, it is necessary to use culturally and regionally similar datasets to calibrate the model parameters and make the model more applicable. In addition, as machine learning models lack interpretability and transparency, they cannot be accepted by clinicians and may not be easily applied in sports settings. Therefore, explainable AI should be integrated into the models to make the machine intelligible and understandable to coaches and medical staff.

AI-assisted real-time injury warning systems

Artificial intelligence-based real-time monitoring and warning systems hold a game-changing potential for the prevention of injuries in athletics through the timely detection of atypical conditions manifested in physiological or movement-related signals. These systems are often realised as a combination of wearable sensor networks and cloud or edge computing platforms to provide continuous streams of data acquisition and processing. As depicted in Figure 2, the AI-Assisted Real-Time Injury Warning System operates through a structured workflow: wearable sensors (e.g., IMU, pressure sensors) collect physiological and movement data, which is transmitted to an edge computing unit for real-time analysis. Subsequent anomaly pattern recognition via injury risk algorithms enables timely warning alerts at coach/athlete terminals, facilitating proactive injury prevention . The underlying design philosophy has tended to focus on the rapid implementation of anomaly detection algorithms to discern atypical patterns deviating from baseline or typical profiles of variation suggestive of heightened injury likelihood. Methods such as threshold monitoring, machine learning classification rules, and deep learning architectures have enabled the identification of early warning signals characterised by changes in gait, overloading, or neuromuscular fatigue. Subsequent risk notifications conveyed in the form of feedback have enabled athletes, coaches, and medical staff to take corrective actions to prevent injury onset and progression. Case studies have illustrated effective field deployments in training and competition settings with reported decreases in injury incidence and improved workload (Jiang et al., 2022; Musat et al., 2024). Additionally, the implementation of adaptive learning algorithms has enabled personalised system usage through the continuous updating of risk thresholds in response to individual athlete responses and contextualised usage. System accuracy has been iteratively improved through feedback loops enabled by user input and outcome tracking. Within the domain of Chinese and Asian athletics, the implementation of AI-enabled warning systems for athletes must account for infrastructural capacity, data privacy compliance, and cultural acceptance. Initial pilot implementations have demonstrated promising outcomes and have the potential to revolutionise injury prevention and athlete health outcomes in athletics across the region.



Note. This schematic illustrates the sequential process of the AI-enabled injury warning system, encompassing wearable sensor data acquisition, edge computing-based real-time analysis, anomaly pattern recognition via injury risk algorithms, and feedback delivery to coach/athlete terminals.

Figure 2. Workflow of AI-assisted real-time injury warning system.

BIOMECHANICAL ANALYSIS TECHNIQUES AND THEIR APPLICATIONS IN SPORTS INJURY DIAGNOSIS

Comparison of marker-based and marker less motion capture systems

Marker optical motion capture systems have been the ‘gold standard’ for biomechanical analysis within sports science for several decades. These systems involve the attachment of reflective markers to an athlete’s body, which are then tracked around the environment by several calibrated cameras to determine three-dimensional kinematics with less than a millimetre of accuracy (Gu & Pandy, 2020). Marker optical motion capture systems can provide high spatial and temporal resolution information that can be used to calculate joint angles, segment velocities and muscle activity patterns to detect even subtle biomechanical impairments that predispose athletes to overuse injury.

There are several limitations associated with the use of marker optical motion capture systems. Marker optical motion capture systems are time consuming to set up, require a laboratory environment to be run by an experienced operator, which limits their utility in the modern sports setting (Suo et al., 2024). Additionally, soft tissue artifacts may be introduced as a result of skin moving over underlying bones (Gu & Pandy, 2020).

Alternatively, marker less motion capture systems, which benefit from recent advances in computer vision and deep learning, may offer a breakthrough solution. Marker less systems do not use markers and utilise multiple synchronized video cameras and pose estimation algorithms to localise anatomical landmarks and determine 3D motion (Kanko et al., 2021; Zhong & Di, 2025). Marker less systems have been demonstrated to have good to excellent reliability and validity for spatiotemporal gait parameters and joint kinematics have been shown to be particularly reliable in the sagittal plane (Nishikawa et al., 2025; Scataglini et al., 2024). Marker less systems may be less accurate when angular rotations of complex joints are quantified and this may be particularly the case in the frontal and transverse planes (Chaumeil et al., 2024; Scataglini et al., 2024). Marker less systems have several advantages as they are more flexible, have a lower cost requirement and can be used to assess function in a more natural environment, i.e. on the field or during competition (Lahkar et al., 2022; Torvinen et al., 2024).

When discussing the application of such systems in Chinese and Asian athletic training facilities, the following technical issues need to be considered: the shortage of advanced laboratory equipment for such sports, the lack of portability and user-friendliness of marker-based systems, and the potential future widespread application of marker less systems (Zhong & Di, 2025). The key technical distinctions, summarized in Table 2, highlight these practical differences. Due to the relatively high cost and complicated usage, marker-based systems cannot be applied routinely, and marker less systems, owing to recent advances in algorithm robustness and hardware availability, can be applied routinely (Zhong & Di, 2025). However, more research is needed to solve problems such as joint angle estimation accuracy in more complicated movements and cross-population validation. It is hoped that the application of marker less systems in biomechanical modelling and machine learning could be used to further improve the diagnosis and prevention of injuries in Asian track and field athletes.

Table 2. Comparison of technical parameters between marker-based and marker less motion capture systems.

Parameter	Marker-Based Systems	Marker less Systems
Spatial Resolution	High (sub-millimetre accuracy)	Good (lower accuracy in complex joints)
Temporal Resolution	High (typically >100 Hz)	Good (camera frame rate dependent)
Equipment Cost	High	Lower
Operational Complexity	High (requires experienced operator, time-consuming setup)	Low (flexible, user-friendly)
Environmental Requirements	High (laboratory environment)	Low (applicable in field/competition settings)
Measurement Error (different planes)	Low (but affected by soft tissue artifacts, all planes)	Reliable in sagittal plane; lower accuracy in frontal/transverse planes

Note. Measurement errors are summarized based on existing literature; marker-based systems mainly suffer from marker displacement and soft-tissue artifacts. Maker less systems show high reliability in the sagittal plane (e.g., knee flexion-extension), but greater errors in frontal (e.g., abduction) and transverse (e.g., rotation) plane joint angle estimations. The lower cost reduced environmental requirements, and higher flexibility of maker less systems' no marker alignment make them more suitable for Asian sports settings with limited resources and need for rapid field deployment (Zhong & Di, 2025).

Joint mechanics modelling and injury mechanism analysis

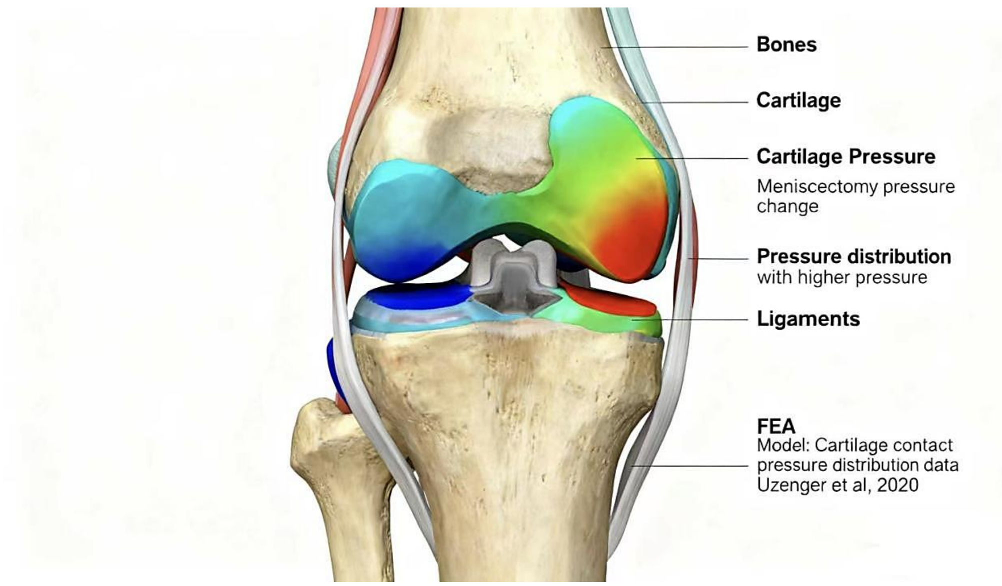
Biomechanical modelling with motion capture data enables investigation of joint loading, stress, and injury mechanism in athletes.

Three-dimensional joint mechanics models, usually constructed through finite element analysis (FEA) or multibody dynamics, contain parameters such as bone geometry, soft-tissue material properties, and kinematic inputs to predict the physiological mechanics within a joint under dynamic loading conditions (Arredondo-Soto et al., 2021; Gu & Pandy, 2020).

These models have shown how abnormal joint loading and stress patterns can result from injury. For instance, as illustrated in Figure 3, FEA models of the knee joint have shown that meniscectomy induces changes in load sharing that increase cartilage contact pressures and promote osteoarthritis (Uzuner et al., 2020). Modelling of ankle fractures has shown how fibular malrotation can alter the mechanics of tibiotalar contact and how achieving adequate anatomical reduction can prevent posttraumatic arthritis (Ayala et al., 2024). Modelling in shoulder biomechanics has shown how different reconstruction techniques can alter joint stability and stress distributions (Bedard et al., 2025).

Recent progress in subject-specific musculoskeletal models that include realistic models of the ligaments and muscles to predict joint kinematics and kinetics during sport-specific activities (Zhong & Di, 2025). These models can predict the joint contact reaction forces and loading of the ligaments that provide information on potential mechanism of injury and rehabilitation for optimalization. Recent progress in the development of new optimization algorithms to estimate muscle pre-tension and joint range of motion to improve model accuracy (Avci & Röhrle, 2024).

It is possible for Asian athletics to develop proper biomechanical models based on Asian and Chinese anthropomorphic characteristics and motions patterns. It is also possible to noninvasively predict the internal stresses of joints using marker less motion capture data and validated joint mechanics models during training and competition, find out the harmful loading and related technique patterns and make suggestions for technique correction to prevent injuries.



Note. This FEA model illustrates the structural components of the knee (bones, cartilage, ligaments) and visualizes cartilage contact pressure distribution changes following meniscectomy, with colour gradients indicating pressure variations (data from (Uzuner et al., 2020)). It aids in understanding the biomechanical mechanisms of injury and disease progression.

Figure 3. Finite Element Analysis (FEA) model of the knee joint.

Biomechanical technologies and training program optimization

The application of biomechanical analysis technologies to guide training and rehabilitation programmes in sports medicine is rapidly growing in popularity. Biomechanical analysis technologies can provide coaches and clinicians with data on joint kinematics, kinetics and muscle activity that can be used to prescribe joint unloading interventions to improve movement patterns and reduce the loading through injured joints and prevent recurrence (Arauz et al., 2024; Laupattarakasem et al., 2024).

Biomechanical feedback can therefore help coaches and clinicians to change an athlete’s movement strategy e.g. reduce knee valgus at landing to reduce the risk of an anterior cruciate ligament injury (Bender et al., 2021). In rehabilitation, the latter can be realised by using biomechanical assessments to provide progressions, through assessment of recovery of joint function and muscle strength (Silveira et al., 2023). Marker less motion capture can be used in field settings to provide this information and feedback to the athlete, without interrupting the training session (Lahkar et al., 2022).

There are also challenges to large-scale adoption of biomechanical technologies in general. These have been highlighted previously and include issues around data accuracy and stream data streaming, practitioner learning curves (Jiang & Shen, 2025). In China and Asia, availability of equipment and practitioners may also be limited. Solutions such as development of corresponding low-cost portable marker less systems and locally adapted software platforms may be required.

In addition, the use of biomechanical data to guide meaningful changes in training will require the involvement of biomechanists, coaches, and medical specialists, and the education and training of these groups will be important to ensure the correct use of the power of biomechanical technologies for injury prevention. These challenges must be addressed to make the use of biomechanical analysis a routine practice in athletic training and rehabilitation in China and Asia.

CONCLUSION

In conclusion, the rise of emerging sports science technologies has greatly transformed the landscape of joint injury decoding and prevention, making the experiential-based model of the past looks like and replacing it with a robust data-based model. From an expert's point of view, this is more than a technology. It is a comprehensive redefinition of what joint health is, how joint health is assessed, and what actions should be taken when deviations are observed within Chinese and Asian athletics, in particular.

Wearable sensors. Artificial intelligence. Biomechanical analysis. The list seems to be endless. These technologies enable us to be at the bedside and know in real time, predict injury risk with high accuracy, and offer intervention opportunities that are timely and personalized.

This enables us to address the fine-grained biomechanical stresses and physiological responses that lead to athletes being placed at risk for joint injuries and to provide timely and personalized interventions in response. Even a few milliseconds can mean the difference between gold and no medal for an athlete in Asian athletics, so precision medicine holds great promise.

Of course, the application of these technologies to sports practice also brings challenges. First, cost is high, making these technologies inaccessible, particularly, to low- and middle-income settings. Second, privacy and security issues surrounding biometric and health data are considerable and need to be considered and protected. Third, the lack of consensus around standardized protocols for data collection, analysis, and interpretation remains a major bottleneck to translating the research into practice. Finally, the rich experiential knowledge of the coaches and athletes participating in the sporting activity needs to be coupled with state-of-the-art technological inputs for intervention strategies. These differences need to be bridged to avoid a "*silo effect*" that may hinder the adoption and acceptance of these technologies. To do so will require sports science, engineering, data analytics, ethics, and clinical medicine experts to collaborate and embrace localized innovation that considers cultural, infrastructural, and sport-related factors that are unique to China and Asia.

It may one day be reasonably anticipated that, in the not too distant future, the development and application of an intelligent prevention ecosystem, consisting of connected technologies and data platforms, allowing for joint health management that is both personalised and responsive to athlete characteristics and changing conditions would be achieved. Reducing the precision and personalization of injury prevention may lead to a reduction in incidence and severity of joint injuries, and subsequently an improvement in performance.

On the whole, if we apply a range of innovative sports science technologies wisely, we can ensure that Chinese and Asian athletes are ahead of the game and win with joint health management that is scientifically correct and technology enabled. It will be important to get the best of both of these approaches and to link the mass of research output from all these viewpoints productively with the realities of practice.

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