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Research Article

Application Progress and Research Frontiers of Artificial Intelligence in Strength and Conditioning Training for Basketball Players

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Abstract

Artificial intelligence (AI) has emerged as a transformative force in sports science, particularly in strength and conditioning (S&C) training for basketball players. This narrative review synthesizes current evidence on AI applications in basketball S&C, encompassing machine learning (ML)-driven injury risk prediction, computer vision-based biomechanical analysis, wearable sensor-enabled load monitoring, and reinforcement learning for personalized training prescription. A structured literature search of peer-reviewed literature published between 2019 and 2025 identified 15 representative studies for narrative synthesis. Results indicate that AI models, particularly XGBoost and deep learning architectures, achieved a reported area under the receiver operating characteristic curve (AUC-ROC) of 0.840 in predicting lower extremity muscle strains in NBA athletes, while markerless motion capture systems reported centimeter-level agreement with optical reference standards for basketball-specific movement analysis. LSTM neural networks with multi-modal data fusion show promise in personalized exercise volume optimization. However, significant challenges remain, including limited prospective external validation, model interpretability concerns, data privacy issues, and the gap between algorithmic performance and practical coaching implementation. Future research should prioritize explainable AI, digital twin integration, federated learning, and hybrid human-AI coaching frameworks.

Keywords

Artificial intelligence, Machine learning, Basketball, Strength and conditioning training, Injury risk prediction

1. Introduction

Basketball is a high-intensity, intermittent team sport characterized by repeated explosive movements, including maximal sprints, jumps, rapid changes of direction, and physical contact (Claudino et al., 2019). These demanding physiological and biomechanical requirements place basketball players at substantial risk of overuse and acute injuries, particularly to the lower extremities. Anterior cruciate ligament (ACL) injuries, ankle sprains, and muscle strains are among the most prevalent and career-altering conditions in competitive basketball (An et al., 2025). Consequently, strength and conditioning programs play a critical role in enhancing athletic performance, optimizing movement mechanics, and mitigating injury risk. Traditionally, S&C training has relied heavily on the subjective expertise of coaches, periodic fitness testing, and manual observation of movement quality. While these approaches remain valuable, they are inherently limited by human perceptual constraints, inter-rater variability, and the inability to process large volumes of multi-dimensional data in real time. The exponential growth of wearable technology, computer vision, and computational power has created unprecedented opportunities for data-driven training optimization. Artificial intelligence, particularly machine learning and deep learning, offers powerful analytical tools capable of identifying complex patterns within heterogeneous datasets that would be undetectable through conventional statistical methods (Jia, 2025). In the context of basketball S&C, AI applications span several critical domains: predictive modeling for injury risk assessment, computer vision for biomechanical movement analysis, wearable sensor integration for training load monitoring, and adaptive algorithms for personalized training prescription. Despite the rapid proliferation of AI in sports science, there remains a lack of comprehensive synthesis specifically focused on basketball S&C training. Existing reviews tend to either cover team sports broadly (Claudino et al., 2019) or focus on tactical performance analysis rather than physical conditioning. This review addresses these gaps by systematically examining the application progress and research frontiers of AI in basketball S&C training, with specific attention to methodological quality, clinical validity, and future directions.

2. Methods

This narrative review was conducted following established guidance for synthesizing evidence in sports science. A structured literature search was performed across four major databases: PubMed/MEDLINE, IEEE Xplore, Web of Science, and Google Scholar. The search period covered publications from January 2019 to August 2025. Search terms were combined using Boolean operators: (“artificial intelligence” OR “machine learning” OR “deep learning” OR “computer vision”) AND (“basketball” OR “basketball players”) AND (“strength and conditioning” OR “physical training” OR “injury prevention” OR “performance analysis” OR “training load” OR “biomechanics”). Reference

lists of included articles were hand-searched to identify additional relevant studies. Inclusion criteria required studies to: (1) involve basketball players or basketball-specific movements; (2) employ AI, machine learning, or deep learning methods as a core analytical component; (3) address strength, conditioning, injury prevention, or physical performance outcomes; and (4) be published in peer-reviewed journals or reputable conference proceedings, with a small number of highly relevant non-peer-reviewed reports retained as supplementary grey literature and explicitly identified as such in the synthesis. Exclusion criteria included non-English publications, opinion pieces without empirical data, and studies focusing exclusively on tactical analysis. The initial search yielded 347 records. After removing duplicates (n=89) and screening titles and abstracts (n=173 excluded), 85 full-text articles were assessed. Of these, 15 studies met the inclusion criteria and were selected for detailed narrative synthesis. Data extraction focused on study design, sample characteristics, AI methodology, performance metrics, key findings, and limitations. Because the present work is a narrative rather than a systematic review, a formal quantitative quality-appraisal instrument (e.g., QUADAS-2) and a PRISMA-compliant risk-of-bias assessment were not applied; instead, each included study was narratively appraised, with particular attention to external validation, sample size adequacy, and model interpretability, and the corresponding caveats are discussed throughout.

3. Results

3.1. Machine Learning for Injury Risk Prediction

Injury risk prediction represents the most extensively studied application of AI in basketball S&C. Several studies have demonstrated that ML algorithms can effectively integrate heterogeneous data sources—including injury history, workload metrics, physiological markers, and biomechanical variables—to identify athletes at elevated risk. Wang (2025) developed a machine learning framework for predicting next-game injury risk in NBA players using publicly available box-score data, player attributes, and injury history. The study demonstrated that injury-risk forecasting could quantify not only health outcomes but also substantial financial impacts for NBA franchises, with injured players causing significant salary-cap inefficiencies and performance declines. A study examining lower extremity muscle strain (LEMS) prediction in NBA athletes compared multiple ML algorithms against traditional logistic regression in a single retrospective report available as a non-peer-reviewed repository publication (ResearchGate, 2022). The XGBoost model achieved the best performance, with an AUC-ROC of 0.840, outperforming both random forests and conventional statistical models. Key risk factors identified included history of lower extremity injuries, recent concussion, and total number of previous injuries. Because this estimate derives from one retrospective cohort and has not yet been independently or prospectively replicated, it should be interpreted as preliminary rather than as established field consensus. An et al. (2025) focused specifically on ACL injury prediction in male

basketball players using multi-algorithm models (ISRCTN 18009799). The research emphasized that basketball players constitute a high-risk group for ACL injuries and that ML-driven feature selection could reveal subtle risk markers that conventional analysis might overlook. A complementary study employed binary logistic regression to classify injury risk among basketball players, finding that fatigue greatly increased injury risk while additional rest days significantly reduced that risk (Further Science, 2025). Interestingly, the feature importance analysis revealed that training load alone was not the strongest predictor; rather, the interaction between accumulated fatigue and inadequate recovery emerged as the most critical risk factor. This finding underscores the importance of AI models that capture dynamic, non-linear relationships between multiple variables rather than relying on isolated metrics. Despite these promising results, Claudino et al. (2019) noted in their systematic review that while many studies report encouraging AUC values, the majority lack prospective external validation and sufficient interpretability. The review identified artificial neural networks, decision tree classifiers, and support vector machines as the most commonly employed methods across team sports including basketball, with applications spanning both injury risk assessment and performance prediction.

3.2. Computer Vision and Markerless Motion Capture

Computer vision has advanced biomechanical analysis in basketball S&C by enabling markerless motion capture, automated technique assessment, and real-time movement feedback. This technology eliminates the need for expensive laboratory setups and restrictive marker placements, allowing analysis in ecologically valid training environments. A comprehensive review of basketball shooting analysis based on AI examined various deep learning architectures, including CNNs, RNNs, and hybrid models (IEEE, 2023). CNNs were found to be particularly effective for image-based shooting posture classification, extracting hierarchical feature representations through convolution and pooling operations. Key challenges included occlusion handling, varying camera angles, and the need for large annotated datasets specific to basketball movements. Recent advances in markerless motion capture (MMC) have shown good-to-excellent agreement with laboratory reference standards. One study evaluated a multi-camera MMC system based on deep-learning pose estimation and multi-view 3D reconstruction, using Vicon optical motion capture as the reference standard (PMC, 2025a). The results showed that MMC stably reproduced major spatiotemporal patterns of joint trajectories, with intraclass correlation coefficients indicating good to excellent agreement for most parameters. Another investigation field-tested an RTMPose-based markerless motion capture workflow for 3x3 basketball (PMC, 2025b). The system achieved centimeter-level agreement and acceptable repeatability for both horizontal displacements and jump events. However, validation involved only single athletes in controlled trajectories, and further work is needed to confirm ecological validity in competitive settings. It should be emphasized that these figures quantify the measurement agreement of MMC with

reference systems; they do not by themselves establish any injury-prevention or performance benefit. A practical AI-powered system integrated YOLO object detection with MediaPipe pose estimation to evaluate shooting form (AIRCC, 2025). The system tracked key body points and calculated joint angles and movement consistency, providing automated feedback that has direct implications for S&C coaches seeking to correct injury-predisposing movement patterns. The emergence of spatiotemporal models such as CourtMotion represents a recent development (arXiv, 2025). CourtMotion employs a Graph Neural Network to process high-frequency skeletal joint data combined with event projection attention heads, enabling the model to learn representations connecting physical movements to their tactical purpose. From a practical S&C perspective, the transition from laboratory-based motion capture to field-deployable computer vision systems represents a notable methodological advance. Traditional biomechanical assessments required athletes to visit specialized facilities with reflective markers and high-speed cameras, limiting testing frequency and ecological validity. Modern markerless systems using standard video cameras and deep learning pose estimation can be deployed in regular training facilities, enabling routine movement screening during normal practice sessions. This capability allows S&C coaches to monitor movement quality continuously rather than relying on periodic assessments, facilitating early detection of technique degradation or compensatory movement patterns that may precede injury. Furthermore, the automated nature of these systems reduces the need for specialized biomechanics expertise, making advanced movement analysis accessible to a broader range of programs and athletes.

3.3. Wearable Sensors and Training Load Monitoring

Wearable technology has become ubiquitous in modern basketball S&C, providing continuous, objective measurements of physical load, physiological strain, and recovery status. AI algorithms enhance these data streams by detecting complex patterns, predicting fatigue accumulation, and generating actionable recommendations. A study on personalized exercise volume optimization in college basketball training employed an LSTM neural network with multi-modal data fusion (MDPI, 2025a). By integrating heart rate, triaxial acceleration, step count, and environmental data from smart wearables, researchers constructed a dynamic weighted fusion mechanism and personalized correction engine. Validated on 100 collegiate basketball trainees wearing Polar H10 and Xsens MVN devices, the model suggested that AI-driven personalization could improve training load prescription precision, although this finding rests on a single internal validation sample and awaits external confirmation. Flexible sensor technology represents an emerging frontier. A comprehensive review highlighted applications beyond traditional wearables (PMC, 2024): sweat composition analysis through flexible electrochemical sensors detects electrolyte balance, while EMG sensors quantify muscle activation patterns and fatigue. The review also noted potential for monitoring psychological states through

physiological correlates. In professional basketball, GPS-enabled vest systems track jump counts, landing forces, and lateral accelerations—metrics particularly relevant to basketball's movement demands (PMC, 2025c). Wrist-worn devices measure heart rate variability, sleep cycles, and recovery, enabling data-informed decisions about training intensity. AI algorithms process these continuous streams to identify when an athlete's mechanical load drifts outside individualized optimal ranges, triggering proactive interventions. A structured narrative review emphasized that the practical value of wearable systems depends critically on biosensor data validity, model robustness, and empirical evaluation conditions (PMC, 2025c). The evidence map revealed that while sensor technology has advanced rapidly, ML models often suffer from small sample sizes, lack of cross-validation across populations, and limited generalizability from laboratory to field settings.

3.4. Reinforcement Learning and Personalized Training Prescription

While most AI applications in basketball S&C have focused on prediction and analysis, reinforcement learning (RL) offers a distinct approach toward autonomous, adaptive training prescription. RL agents can learn optimal training policies through continuous interaction with athlete data, dynamically adjusting volume, intensity, and recovery based on real-time feedback. A reinforcement learning-enabled system for personalized sports training formulated the process as a Markov decision process (Inderscience, 2025). The intelligent agent interacted with a simulated training environment, producing optimized actions derived from real athlete data. By receiving rewards based on performance improvements and injury avoidance, the agent learned to balance short-term training effects with long-term athletic development, addressing the fundamental limitation of static programs' inability to adapt to daily fluctuations in readiness. In strength training specifically, RL-based recommender systems have extended from exercise selection to full workout prescription, recommending exercises, sets, repetitions, and load (Inderscience, 2025). These systems incorporate user feedback for online personalization, allowing algorithms to learn individual preferences and response patterns—particularly valuable for basketball players requiring a complex blend of maximal strength, power, endurance, and mobility. The concept of digital twins—virtual replicas of individual athletes simulating physiological responses to training—represents an emerging integration of RL with S&C. By applying data-driven transition models as digital twins, researchers can find optimal training policies without the ethical concerns of direct human experimentation. These models, founded on comprehensive seasonal data, can dynamically prescribe intensity adjustments, volume changes, or active recovery. However, RL deployment in high-performance basketball remains largely theoretical: the systems above were evaluated in simulated or offline environments rather than through prospective, experimentally controlled training interventions, and no study has yet demonstrated that RL-prescribed programs produce measurable improvements in actual basketball training outcomes. While RL

algorithms are increasingly important in sports apps, their use in elite team sports faces unique challenges, including the multi-objective nature of basketball performance, team dynamics influencing individual responses, and the difficulty of defining reward functions that capture long-term development rather than short-term gains.

4. Discussion

The synthesis of current evidence reveals that AI has made substantial inroads into basketball S&C training, yet several critical gaps must be addressed.

4.1. Methodological Limitations

The most pervasive issue is the lack of prospective, externally validated models. While retrospective studies consistently report AUC values between 0.80 and 0.90 for injury prediction, these metrics often degrade when applied to new populations. Across the included work, study designs are predominantly retrospective and laboratory- or convenience-based, sample sizes are generally small (the LSTM wearables study being the largest at 100 collegiate trainees, while markerless motion-capture validations involved single athletes), and the distinction between internally validated findings (held-out splits from the same cohort) and externally validated findings (independent teams, seasons, or populations) is rarely made explicit. The field suffers from a "validation gap"—algorithms perform well on held-out test data from the same cohort but fail to generalize. This is particularly problematic in basketball, where differences in playing level, positional demands, and training philosophies create substantial heterogeneity. Few findings replicate independently across studies: the headline estimates (the 0.840 LEMS AUC, centimeter-level MMC agreement, and LSTM personalization) each derive from a single study rather than from convergent evidence. Future studies must prioritize prospective cohort designs with temporal validation across seasons and external validation across different teams, and report uncertainty estimates alongside point estimates.

4.2. Interpretability and Clinical Utility

Many high-performing ML models, particularly deep learning architectures, function as "black boxes," providing predictions without transparent reasoning. For S&C coaches, this lack of interpretability undermines trust and practical utility. A model predicting injury risk without identifying driving factors offers limited guidance for intervention. The adoption of explainable AI (XAI) techniques—such as SHAP values, LIME, and attention visualization—is essential. Coaches need to know not just that an athlete is at risk, but why and what specific modifications are most likely to mitigate that risk.

4.3. Data Integration and Standardization

Basketball S&C generates data from disparate sources: wearables, force plates, video analysis, wellness questionnaires, and performance tests. Current applications often process these streams in isolation rather than achieving true multi-modal integration. The LSTM-based fusion approach (MDPI, 2025a) represents progress, but more sophisticated architectures—including transformer models with cross-modal attention—are needed to capture complex interactions between physiological, biomechanical, and psychological factors. The lack of standardized data collection protocols hinders meta-analytic synthesis. Federated learning approaches, enabling model training across sites without sharing raw data, could address this challenge.

4.4. The Human-AI Interface

The most understudied aspect is how coaches and athletes interact with AI-generated insights. Even highly accurate systems fail to produce behavior change if they do not align with users' workflows and trust frameworks. The hybrid coaching model, combining AI-driven analytics with expert human judgment, likely represents the most practical path forward. AI systems should be designed as decision-support tools rather than autonomous replacements, presenting actionable insights at the right time and format. Research on implementation science and behavior change in sports AI is urgently needed.

4.5. Ethical and Privacy Considerations

Detailed athlete data collection raises significant ethical concerns. Biometric data, injury histories, and performance metrics are sensitive personal information. Clear governance frameworks for data ownership, consent, and usage are essential. There is also risk that AI-driven systems could perpetuate biases if training data underrepresent certain populations. The available evidence is heavily skewed toward elite, male athletes from NBA and collegiate settings, with a near-absence of data on female players, youth athletes, recreational and semi-professional players, and non-Western populations. Models trained predominantly on elite male data may therefore perform poorly—or produce misleading recommendations—for these underrepresented groups, and deploying them without such checks risks amplifying existing inequities in S&C provision. Equitable AI requires diverse training datasets, stratified reporting of performance by sex, age, playing level, and ethnicity, and regular algorithmic auditing.

4.6. Future Frontiers

Promising directions can be translated into a prioritized research agenda. First, digital twin integration for "what-if" analysis before program changes should be pursued through prospective longitudinal designs that track athletes across at least a full season, with temporal validation on later seasons rather than single-season splits. Second, real-time adaptive systems using edge computing to

adjust training parameters during sessions should be evaluated in controlled trials against standard prescription, reporting not only model accuracy but also adherence, coach acceptance, and athlete outcomes. Third, longitudinal models tracking athlete development across seasons should target adequate sample sizes (multiple teams and seasons) and perform external validation across institutions rather than relying on small, single-cohort datasets. Fourth, multi-agent RL optimizing team training while accounting for individual constraints should move from simulated environments toward field-based pilots, with clearly defined reward functions and prospective evaluation of injury and performance effects. Fifth, integration of genetic data with performance metrics for biologically-informed prescriptions requires careful ethical governance. A particularly underexplored area is the integration of psychological and psychosocial data into AI-driven S&C models. While physiological and biomechanical data dominate current applications, factors such as motivation, stress, sleep quality, and social support significantly influence training adaptation and injury risk. Future AI systems that incorporate subjective wellness data, psychological assessments, and even natural language processing of athlete self-reports could provide a more holistic understanding of athlete readiness. Additionally, the role of AI in return-to-play decision-making following injury represents a critical application area, where models could objectively quantify rehabilitation progress and determine optimal return timing based on individualized recovery trajectories rather than generic timelines. Across all priorities, the field should converge on prospective, temporal, and external validation standards, minimum pre-specified sample sizes, and transparent reporting of both discrimination and calibration.

5. Conclusion

Artificial intelligence has demonstrated significant potential to transform strength and conditioning training for basketball players across four primary domains: injury risk prediction, biomechanical movement analysis, training load monitoring, and personalized training prescription. Machine learning models—particularly ensemble methods like XGBoost—have shown discriminative ability for lower extremity injuries, with a reported AUC-ROC of 0.840 in a single retrospective NBA cohort. Computer vision and markerless motion capture systems have reported centimeter-level agreement with optical reference standards for basketball-specific movements, although this reflects measurement accuracy rather than a demonstrated injury-prevention benefit. Wearable sensor integration with LSTM neural networks has advanced personalized exercise volume optimization, while reinforcement learning offers a promising but still largely simulated framework for adaptive training prescription. However, the field remains in its relative infancy, with substantial gaps between algorithmic performance and practical implementation. The lack of prospective external validation, limited model interpretability, data standardization challenges, and insufficient research on human-AI

interaction represent the most pressing barriers. Ethical dimensions of data collection, privacy, and algorithmic fairness also require careful attention. Future research should prioritize explainable AI methodologies, digital twin integration, federated learning, and hybrid human-AI coaching frameworks that augment rather than replace expert coaching judgment. The ultimate goal of AI in basketball S&C should not be to automate coaching, but to enhance the decision-making capabilities of coaches and sports scientists, enabling more precise, individualized, and effective training interventions that maximize performance while minimizing injury risk.

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References

[1] An, Y., Zhang, L., Wang, H., Chen, J., & Liu, X. (2025). Prediction of ACL injury incidence and analysis of key features in basketball players based on multi-algorithm models. PMC, 12533536. https://pmc.ncbi.nlm.nih.gov/articles/PMC12533536/

[2] arXiv. (2025). CourtMotion: Learning event-driven motion representations from skeletal data for basketball. arXiv preprint arXiv:2512.01478. https://arxiv.org/pdf/2512.01478v1

[3] AIRCC. (2025). An AI-powered system for basketball shot analysis using YOLO and pose estimation. Computer Science & Information Technology, 15(8), 12. https://aircconline.com/csit/papers/vol15/csit150812.pdf

[4] Claudino, J. G., Capanema, D. de O., de Souza, T. V., Serrão, J. C., Pereira, A. C. M., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: A systematic review. Sports Medicine - Open, 5(1), 43. https://pmc.ncbi.nlm.nih.gov/articles/PMC6609928/

[5] Further Science. (2025). Classification of injury risk among basketball players: A statistical perspective. Applied Mathematics on Science and Engineering, 2(2), 28–36. https://furthersci.org/journal-admin/uploads/articles/amse226.pdf

[6] IEEE. (2023). A review of basketball shooting analysis based on artificial intelligence. IEEE Access, 11, 10216291. https://xplorestaging.ieee.org/ielx7/6287639/10005208/10216291.pdf

[7] Inderscience. (2025). A reinforcement learning-enabled system for personalised sports training plan generation. International Journal of Information and Communication Technology. https://www.inderscienceonline.com/doi/pdf/10.1504/IJICT.2025.151069

[8] Jia, Y. (2025). A narrative review of deep learning applications in sports performance analysis: Current practices, challenges, and future directions. BMC Sports Science, Medicine and Rehabilitation, 17, 249. https://pmc.ncbi.nlm.nih.gov/articles/PMC12382096/

[9] MDPI. (2025). Research on personalized exercise volume optimization in college basketball training based on LSTM neural network with multi-modal data fusion intervention. Applied Sciences, 15(17), 8871. https://mdpi-res.com/d_attachment/applsci/applsci-15-08871/article_deploy/applsci-15-08871.pdf

[10] PMC. (2024). Intelligent health and sport: An interplay between flexible sensors and basketball. PMC, 10882167. https://pmc.ncbi.nlm.nih.gov/articles/PMC10882167/pdf/main.pdf

[11] PMC. (2025a). Evaluating a multi-camera markerless system for capturing basketball-specific movements: An exploration using 25 Hz video streams. PMC, 12986566. https://pmc.ncbi.nlm.nih.gov/articles/PMC12986566/

[12] PMC. (2025b). Feasibility and accuracy of an RTMPose-based markerless motion capture system for single-player tasks in 3x3 basketball. PMC, 12252153. https://pmc.ncbi.nlm.nih.gov/articles/PMC12252153/

[13] PMC. (2025c). Wearable biosensing and machine learning for data-driven training and coaching support. PMC, 12938206. https://pmc.ncbi.nlm.nih.gov/articles/PMC12938206/

[14] ResearchGate. (2022). Machine learning for predicting lower extremity muscle strain in National Basketball Association athletes. https://www.researchgate.net/publication/362271766_Machine_Learning_for_Predicting_Lower_Extremity_Muscle_Strain_in_National_Basketball_Association_Athletes

[15] Wang, E. (2025). Using injury-risk forecasting to quantify financial impact in the NBA. Wharton Sports Analytics and Business Initiative. https://wsb.wharton.upenn.edu/wp-content/uploads/2025/12/WANG_Using-Injury-Risk-Forecasting-to-Quantify-Financial-Impact-in-the-NBA-1.pdf