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From Artificial Intelligence to Intelligent Coaching: A Literature Review on Current Sports Applications and Biomechanical Logic

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ABSTRACT- The use of artificial intelligence (AI) in sport is often presented as a technical advance, yet its coaching value depends on a simpler question: can the result be explained in movement terms? This review revisits current AI applications in sport from a biomechanical perspective. It considers computer vision, markerless motion capture, wearable monitoring, injury-risk modeling, explainable AI, coordination theory, muscle synergy research, and sport-specific movement studies. The central argument is that a useful sport AI system should not stop at prediction. It should show how the athlete produced the performance through segment coordination, joint loading, postural control, and energy transfer. To organize this argument, the paper proposes a four-layer model: capture, interpretation, decision, and intervention. The model places AI between measurement and coaching, while biomechanical theory remains the foundation for deciding which variables matter. The review also suggests that personal sport records become meaningful only when linked to validated movement variables and coach-readable explanations. In this view, the next step for AI in sport is not merely larger datasets, but more interpretable, task-specific, and coordination-aware feedback.

KEYWORDS- Artificial Intelligence, Biomechanics, Computer Vision, Coordination, Explainable AI, Markerless Motion Capture, Muscle Synergy, Sports Applications

I. INTRODUCTION

The recent growth of AI in sport has changed the daily language of coaching and sport science. Video tracking, wearable sensors, workload dashboards, and automated risk alerts are now discussed together with strength, skill, and recovery. In sport biomechanics, this trend is not only a matter of convenience. It has widened the range of locations where movement can be measured, as markerless motion capture and smartphone-based systems can collect useful kinematic information outside expensive laboratories [1], [2]. OpenCap is one example of this shift, as it estimates human movement dynamics from ordinary smartphone videos [3], and validation studies have begun to test how such systems behave during return-to-sport tasks [4]. Wearable sensors add another stream of information by repeatedly recording load, acceleration, heart-rate response, sleep, and training status during real practice [5].

These tools are attractive, but the central problem is interpretive. AI can produce numbers faster than a coach or researcher can decide what the numbers mean. A risk probability, a movement score, or a colorful skeleton overlay may look persuasive, yet it may not tell a coach how to change the athlete's movement. Team-sport reviews have already shown that AI is used for injury-risk assessment and performance prediction [6], while newer reviews note that machine-learning injury models differ widely in data sources, design quality, and practical readiness [7]. For that reason, sport AI requires more than algorithmic accuracy. It needs a biomechanical explanation that can survive a coach's practical question: what should be trained tomorrow?

This review starts from that question. It treats AI as a support for biomechanical reasoning, not as a replacement for it. In many sport skills, the key issue is how the body organizes multiple joints, muscles, and segments to satisfy a task. Basketball shooting changes with distance; volleyball jumping depends on timing and energy transfer; archery requires stability while the aiming task continues; change-of-direction movement reorganizes braking and propulsion across short phases. A sport AI system should therefore move beyond labeling a movement as good or poor. It should help explain which coordination pattern, joint loading strategy, muscle activation structure, or stability-control mechanism led to the result.

II. REVIEW FOCUS AND CONCEPTUAL APPROACH

This paper is a narrative literature review. The literature was organized into four applied areas: computer vision and markerless motion capture; wearable sensing and personal sport records (PSR); injury risk and performance prediction; and coach-centered feedback. Additional literature on explainable artificial intelligence (XAI), movement coordination, muscle synergy, and sport-specific biomechanics was included because the reviewer's main concern is not simply whether AI works, but whether the paper offers an adequate scientific basis for the proposed framework.

The term explainable AI is important here. XAI research describes methods and design principles that allow humans to understand, trust, and contest the output of an

AI system [8]. In sport, the issue is even more practical. Coaches usually do not need an abstract explanation of a model; they need an explanation that is connected to movement. Rudin argued that high-stakes decisions should favor interpretable models rather than depending only on post-hoc explanations of black boxes [9]. A similar stance is appropriate in sport science. When an AI system is used for injury prevention, rehabilitation, talent development, or technique correction, the model should be understandable enough to guide responsible intervention.

The proposed model contains four layers. First, the capture layer gathers video, wearable data, PSR, force-related signals, or laboratory measurements. Second, the interpretation layer transforms raw data into biomechanical variables, including joint angles, joint moments, power, center-of-mass displacement, center-of-pressure behavior, muscle activity, phase timing, and coordination indices. Third, the decision layer uses AI or statistical models to identify patterns, deviations, or risk-relevant combinations. Fourth, the intervention layer converts the interpretation into coaching language, drills, monitoring goals, or rehabilitation decisions. The distinctive point is that AI is not placed above biomechanics. It is placed between measurement and coaching, while biomechanical theory decides what is meaningful.

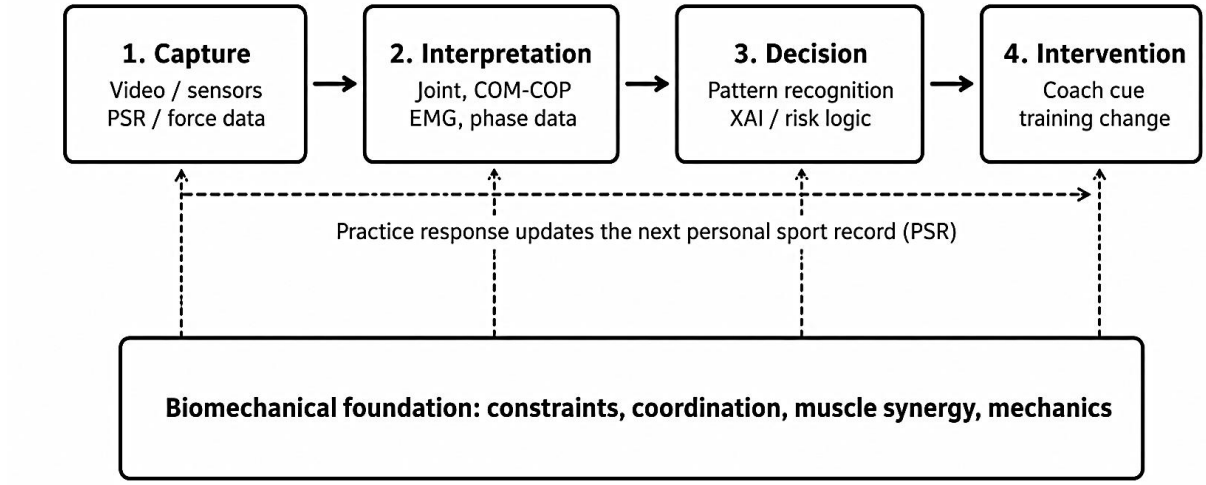

Figure 1: Four-layer model for coordination-aware AI in sport.

The framework (see the above figure 1) also draws on classic coordination theory. Bernstein described movement control as a problem of organizing many degrees of freedom [10], and Newell's constraints model emphasized that movement emerges from interactions among the performer, environment, and task [11]. For performance-oriented biomechanics, dynamical systems theory has been recommended because sport movement is adaptive, variable, and context-dependent [12]. In the same vein, human movement variability should not be automatically treated as error, since it may reflect flexibility or pathology depending on its structure and task role [13]. These ideas provide a stronger foundation for AI sport applications than a simple search for one ideal technique.

III. CURRENT AI APPLICATIONS IN SPORT

A. Computer Vision and Markerless Motion Capture

Computer vision has entered sport quickly because coaches already use video as part of everyday practice. Current systems can support player tracking, ball tracking, event recognition, tactical description, and automatic annotation [2]. In biomechanics, however, the more important question is whether video can support movement interpretation. Markerless motion capture can estimate joint kinematics without reflective markers, which makes field testing more realistic and less expensive [3], [4].

The advantage is clear: more athletes can be observed, more trials can be collected, and sport-specific tasks can be studied in natural environments. The limitation is also clear. Many sport skills are fast, asymmetric, and partly hidden from the camera. Cutting, kicking, sprinting, overhead striking, and contact situations include high angular velocity and frequent self-occlusion. Thus, markerless output should be validated for each task and each variable. Joint angles may be useful for coaching in some settings, whereas joint moments, joint power, and transverse-plane rotations may still require careful laboratory confirmation.

For this reason, a practical AI-biomechanics workflow should use field video as an entry point rather than as the final authority. Video may identify phase timing, gross sequencing, or unusual coordination patterns. Laboratory tools such as force plates, electromyography (EMG), and validated motion capture can then test whether those field indicators actually represent the intended mechanical mechanism. This layered approach is slower than simply accepting an AI score, but it is more defensible for research and coaching.

B. Wearable Sensors and Personal Sport Records

Wearable sensors give AI systems a different kind of strength: temporal repetition. Instead of recording a single laboratory session, sensors can follow athletes across weeks of training. Acceleration, angular velocity, external load, heart-rate response, and recovery-related information can be stored as a PSR [5]. The PSR idea is valuable because a player is not judged only against a group average. The player can also be compared with his or her own stable performance history.

Nevertheless, PSR is not meaningful on its own. A drop in jump height, an altered running load, or a change in arm speed has to be interpreted through the skill. In volleyball, lower jump output may result from reduced coordination of hip-knee-ankle extension, a weaker arm swing, fatigue-related timing changes, or poor energy transfer. In archery, a change in stability may involve center-of-mass control, center-of-pressure drift, head-neck alignment, muscle co-activation, or aiming time. In change-of-direction movement, a similar external load may hide a very different braking or propulsion strategy. AI can detect a change, but biomechanics explains whether the change is adaptive, harmless, or concerning.

C. Injury Risk, Performance Prediction, and Explainability

Prediction is one of the most visible uses of AI in sport. Injury-risk models can combine training load, previous injury, exposure time, physical testing, and performance indicators [6], [7]. Performance models can predict sprint times, jump heights, shot accuracy, and match-related outcomes. These models may be useful for screening, but they become limited when the output cannot be translated into action. A coach cannot directly train "high risk." The coach needs to know whether the risk is related to knee valgus loading, poor trunk control, insufficient ankle stiffness, fatigue, recovery, or a change in coordination strategy.

This is where XAI and interpretable modeling should be integrated with biomechanics. An explainable model for sport should identify the variables that influenced the result, but the explanation must be mechanically sensible [8], [9]. For example, a cutting model should not only report that the injury risk increased. It should indicate whether the athlete shifted toward a more knee-dominant braking strategy, reduced hip contribution, delayed trunk stabilization, or showed unusual frontal-plane control. Such feedback is not only easier to understand; it is more useful because it points to a training target.

IV. COORDINATION-AWARE AI FOR SPORT

The central proposal of this review is coordination-aware AI. The idea is simple: in sport, AI should learn how the athlete organizes movement, not only whether the outcome was successful. A high jump, an accurate shot, a fast change of direction, or a stable archery aim is not produced by one variable. It is produced by a temporary organization of joints, muscles, segments, forces, and task constraints. Bernstein's degrees-of-freedom problem [10] and Newell's constraints framework [11] therefore provide AI sport research with a useful conceptual map. The model should ask how the athlete solved the task under the given constraints.

Muscle synergy research adds another layer to this argument. Early work showed that complex muscle activation patterns may be represented by combinations of fewer modules [14], and later work showed that time-varying synergies can underlie natural motor behaviors such as kicking [15]. These studies do not mean that every sport skill can be reduced to a few simple modules. Rather, they show why AI should consider the organization of muscle activity rather than just separate muscle amplitudes. In practical terms, an AI system that reads EMG should not only identify which muscle is large. It should examine whether the pattern of co-activation and timing supports stability, propulsion, control, or compensation.

Several sport-specific examples show why this logic matters. In basketball shooting, longer distances change the outcome and movement organization; accuracy, release features, and segmental contributions do not remain constant when the task constraint changes [16]. In vertical jumping, the arm swing improves performance through a sequence of mechanical events that includes energy generation and transfer, rather than a simple increase in a single joint action [17]. In tennis, biomechanics has been used to connect stroke production, loading, and injury considerations across the kinetic chain [18]. These examples share a common message: sport performance is produced through coordinated solutions. AI should therefore model solutions, not isolated numbers.

A coordination-aware model would ask more useful questions. Instead of "Did the athlete jump high?", it asks, "How did ankle, knee, hip, trunk, and arm actions combine to produce that height?" Instead of "Was the shot successful?", it asks, "Which release and segmental timing pattern supported accuracy at this distance?" Instead of "Is the athlete unstable?", it asks, "Which postural or neuromuscular strategy maintained the task?" This change in question is not cosmetic. It changes the variables selected, the phases analyzed, the model interpreted, and the feedback given to the coach.

V. TRANSLATION TO COACHING AND RESEARCH DESIGN

The proposed framework changes how AI studies should be planned. The first decision should not be the algorithm. It should be the biomechanical question. Researchers should define the skill, phase, task constraint, expected coordination mechanism, and practical intervention before selecting a model. This avoids the common problem of collecting many variables but offering only a weak explanation. In other words, AI should be used to sharpen the research question, not to compensate for an unclear one.

Phase-specific modeling is especially important. Many sports skills have meaningful subphases: preparation, braking, redirection, propulsion, release, follow-through, landing, or aiming. Averaging across the whole movement can hide the mechanism. For instance, the decisive feature in a jump shot may appear during the transition from lower-limb extension to upper-limb release. In archery, the decisive feature may occur in the final aiming period, where center-of-pressure behavior and muscle co-activation must support visual stability. In change-of-direction movement, the decisive difference may lie between peak braking and reacceleration. AI models should therefore learn when a variable matters, not only whether it is large.

The coach-facing output should also be redesigned. A useful system might report that the athlete-maintained performance but did so with a more knee-dominant strategy and lower hip contribution. Another output might indicate that the athlete's accuracy was preserved by increasing upper-limb compensation after the lower limb

produced less impulse. These statements are more helpful than a black-box score because they can be translated into drills, strength work, fatigue management, or technical cues. This form of output is also closer to the language of applied biomechanics, where force, motion, torque, impulse, power, and energy transfer are used to explain performance [19].

A practical research program could combine laboratory and field data. Laboratory sessions can validate joint moments, EMG patterns, power, COM-COP behavior, and coordination indices. Field sessions can collect repeated video, wearable, and performance data during normal practice. AI can then learn which field indicators correspond to the validated laboratory mechanisms. This design would help coaches monitor athletes regularly without pretending that every field measurement has laboratory-level precision.

VI. LIMITATIONS AND ETHICAL CONSIDERATIONS

The framework is promising, but several cautions are necessary. First, validity is task-dependent. A model validated during walking, squatting, or controlled jumping cannot automatically be trusted during sprinting, cutting, kicking, or overhead striking. Second, AI systems can inherit bias from their training data. A model trained primarily on adult male athletes may be less reliable for youth, female, para-athletes, or athletes from other sports. Third, PSR data raises privacy and ownership issues. Athletes should know what is collected, how it is interpreted, who can access it, and whether it will be used for support or surveillance.

A second limitation is the risk of over-standardizing the technique. Elite athletes often reach similar outcomes through different coordination solutions. If an AI system defines one narrow ideal, it may label a functional individual strategy as an error. For that reason, future systems should distinguish harmful deviation, acceptable individual style, temporary compensation, and creative adaptation. This is not only a technical matter; it requires collaboration among biomechanists, data scientists, coaches, clinicians, and athletes.

VII. FUTURE DIRECTIONS AND CONCLUSION

The next stage of sport AI should bring together three forms of knowledge: field data, laboratory biomechanics, and coaching judgment. Field data give repeated observations in the setting where performance actually occurs. Laboratory biomechanics gives validated variables and a mechanical interpretation. Coaching knowledge gives task meaning and practical priorities. When these sources are combined, AI can become a tool for individualized explanation rather than only automated scoring.

Future work should report model accuracy together with biomechanical interpretability. A model that is slightly less accurate but clearly explains the movement mechanism may be more useful for coaching than a highly accurate model that cannot explain why a prediction was made. The proposed four-layer model can guide this direction. Capture should gather meaningful data; interpretation should convert the data into movement variables; decision should identify patterns using transparent or explainable models; intervention should translate the pattern into training. This sequence keeps the athlete and coach at the center of the system.

In conclusion, AI is already present in sport through computer vision, markerless motion capture, wearable monitoring, and predictive modeling. Its lasting value, however, will depend on whether it can explain movement in a way that improves practice. Coordination-aware AI offers one route. It connects PSR, biomechanical variables, constraints, muscle coordination, and coach-readable feedback. The goal is not to make AI sound more complex. The goal is to make sport technology more honest, interpretable, and useful for performance enhancement, injury prevention, rehabilitation, and skill learning.

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