Vol. 11, No. 1, 2026, pp. 983-997
DOI: https://doi.org/10.29210/30036972000

Contents lists available at Journal ELORA

JRTI (Jurnal Riset Tindakan Indonesia)
ISSN: 2502-079X (Print) ISSN: 2503-1619 (Electronic)

Journal homepage: https://jrti.eloracenter.org/jrti

From laboratory to field: accuracy constraints and methodological considerations in markerless pose estimation for sport performance analysis: a systematic review

Ardo Okilanda[*)]**, Rudyanto Rudyanto**
Universitas Negeri Padang, Indonesia

Article Info

Article history:

Received Sep 06th, 2026
Revised Sep 06th, 2026
Accepted Sep 07th, 2026

Keyword:

Computer vision,
Markerless motion capture,
Human pose estimation,
Sport performance analysis,
Deep learning

ABSTRACT

Computer-vision-based markerless pose estimation is increasingly used to quantify sport movement outside laboratory settings, but its validity is not uniform across tasks, joints, anatomical planes, or environmental conditions. This systematic review synthesised peer-reviewed evidence published from 2020 to 2025 using PRISMA 2020 procedures and a PICO-based search across Scopus, PubMed, and ScienceDirect. Eighteen studies met the final eligibility criteria, including 17 empirical studies and one narrative review. A narrative thematic synthesis was combined with methodological appraisal and an operational validity framework linking target variables, reference standards, and intended use. Across validation studies, lower-limb sagittal-plane agreement reached CMC > .90 in the Pose2Sim study, whereas real-competition OpenPose validation reported CMD about .73 for knee-angle waveforms and weaker agreement for hip and ankle measures. A review-level estimate included in the corpus placed markerless sagittal-plane error at approximately 3–15°, with larger errors in the transverse plane. The synthesis therefore supports markerless systems most strongly for spatiotemporal, gross-displacement, and selected sagittal-plane variables when task-specific validation demonstrates small systematic bias. Transverse-plane, rotational, occlusion-prone, and high-speed measures remain conditional and require additional validation. Practitioners should select systems according to the target variable and intended decision, rather than treating markerless capture as a single accuracy class. Future research should standardise validation metrics, report absolute error and bias alongside agreement statistics, and test systems under genuine competition conditions.

Corresponding Author:

Ardo Okilanda,
Universitas Negeri Padang,
Email: ardo.oku@fik.unp.ac.id

Introduction

Quantitative movement analysis is central to contemporary sport science because coaching decisions depend on measurements that are not only precise but also appropriate for the context in which they will be used. Biomechanical outputs such as joint angles, segment displacement, velocity, and temporal events are increasingly generated from video, creating an opportunity to move analysis beyond specialised laboratories (P. Yang et al., 2024; Dorschky et al., 2023). The relevant measurement question, however, is not whether a computer-vision system can detect a pose, but whether the resulting variable is sufficiently valid for the intended sport decision.

Traditional three-dimensional kinematic analysis has relied heavily on marker-based optical motion capture as a laboratory reference. Such systems can provide highly detailed kinematics, but they require specialised hardware, controlled environments, and skin-mounted markers that can introduce soft-tissue artefacts or interfere with natural movement (Nishikawa et al., 2025; Yoma et al., 2025). Wearable sensors increase portability but introduce other issues, including drift, calibration burden, and constraints on placement (Alzahrani & Ullah, 2024). These trade-offs motivate markerless approaches, particularly when measurement must occur during realistic training or competition.

Markerless computer vision estimates anatomical landmarks from video, often using deep-learning pose estimators such as OpenPose, MMPose, DeepLabCut, or related architectures (Xu et al., 2015; Cao et al., 2017; Colyer et al., 2018; Mathis et al., 2018; Bahadori et al., 2019; Nath et al., 2019). Methodological development since the late 2010s has enabled single-camera, multi-view, temporal, and low-cost pipelines (Colyer et al., 2018; Graving et al., 2019; Suo et al., 2024). Sport-specific work has subsequently demonstrated applications in jumping, athletics, swimming, basketball, volleyball, padel, and other settings, showing that markerless analysis is technically feasible across heterogeneous movement tasks (Pagnon et al., 2021, 2022; Javadiha et al., 2021; Cronin et al., 2023; Zheng et al., 2025).

The measurement challenge is therefore one of validity generalisation rather than technology adoption alone. In a measurement argument, evidence that a system produces a visually plausible pose is only one link in the inference chain; validity also depends on whether the derived kinematic variable agrees with a suitable reference, whether systematic error alters the intended interpretation, and whether the measurement remains adequate under the environmental constraints of use. Classical validity theory emphasises the interpretation and use of scores rather than a universal label of “valid” or “invalid” (Messick, 1995; Kane, 2013). For sport applications, this implies that acceptable fidelity should be defined relative to the target variable and decision, not by a single global accuracy value.

No universal numerical threshold can be defended for all sport kinematic variables because joint angles, velocities, event times, and player positions have different scales and decision consequences. Accordingly, this review uses an operational criterion rather than an absolute pass/fail rule. Strong agreement statistics (for example, CMC or ICC values around or above .90 when reported) are treated as supportive evidence, but only when accompanied by small absolute or systematic error and a reference standard that is appropriate to the task. A variable is considered field-ready only when the remaining error is unlikely to change the practical decision and the validation context resembles the intended use. This framework is used to interpret, not to retrofit, the empirical results.

Recent syntheses have established the breadth of motion-capture and artificial-intelligence applications, but important analytical questions remain. Suo et al. (2024) map motion-capture technologies broadly, while Souaifi et al. (2025) review AI applications across wearable technology, motion analysis, and injury prevention. Yoma et al. (2025) focus on reliability and validity of markerless lower-extremity and trunk kinematics, and Adlou et al. (2025) provide a multi-sport technology overview. The present review complements these syntheses by explicitly linking validation evidence to four decision dimensions: target variable, anatomical plane, movement/environmental condition, and intended field use. This permits a more practice-oriented judgement about where markerless measurement is sufficiently mature and where it remains conditional.

The review is therefore designed around an explicit measurement lens. The inference chain is conceptualised as: video acquisition -> pose estimation -> anatomical reconstruction -> derived performance variable -> sport decision. Error can enter at each stage through camera configuration, calibration, occlusion, lighting, model architecture, tracking instability, or the choice of reference standard. Rather than treating methodological categories as ends in themselves, the synthesis asks how those factors influence the credibility of the final sport-performance inference.

Accordingly, this review synthesises peer-reviewed evidence on computer-vision-based markerless pose estimation and motion capture for athletic movement and performance analysis, published between 2020 and 2025. Guided by the PRISMA 2020 framework, it maps the sports and tasks to which these systems have been applied, appraises concurrent validity against established reference standards, and characterises the methodological and ecological conditions under which reported accuracy changes.

RQ1. How have computer-vision-based markerless pose-estimation and motion-capture systems been applied to analyse athletic movement and performance across sport domains?

RQ2. What evidence supports the concurrent validity of markerless systems, and which classes of kinematic or performance variables show sufficient evidence for field use relative to established reference standards?

RQ3. What methodological approaches, enabling technologies, environmental constraints, and validity threats characterise the evidence base, and how can these findings inform a transparent system-selection and validation framework?

Method

Research Design and Framework

This study adopted a systematic literature review (SLR) design and followed the PRISMA 2020 reporting framework (Page et al., 2021). The review was structured as a measurement-validity synthesis: evidence was interpreted along the inference chain from video acquisition to pose estimation, kinematic reconstruction, derived variable, and intended sport decision. Classical validity theory was used as a conceptual lens to distinguish technical feasibility from the validity of an interpretation in a particular use context (Messick, 1995; Kane, 2013).

Search Strategy

The review questions were decomposed using the PICO framework (Population, Intervention/Interest, Comparison, Outcome) to guide a reproducible search. Population (P) comprised athletes or sport participants performing sport-specific movements; Intervention/Interest (I) was a computer-vision-based markerless pose-estimation or motion-capture system; Comparison (C) was marker-based motion capture, force plates, or another instrumented reference standard where reported; Outcome (O) comprised kinematic/kinetic accuracy, movement or performance metrics, and tracking accuracy. Search concepts were expanded with synonyms and combined using Boolean operators.

Boolean search string (Scopus TITLE-ABS-KEY):

("computer vision" OR "pose estimation" OR "markerless" OR "motion capture" OR "video analysis") AND ("sport*" OR "athlet*") AND ("performance" OR "kinematic*" OR "biomechanic*" OR "technique" OR "movement analysis")

The search string was iteratively piloted against known relevant studies, including the Pose2Sim accuracy study (Pagnon et al., 2022), the real-competition OpenPose study (Cronin et al., 2023), and smartphone force-plate validation work (Aleksic et al., 2024). These records served as sentinel examples for checking that the search captured the core methodological and sport-specific evidence. The original search log did not preserve a formal sensitivity percentage; therefore, no unsupported retrieval statistic is reported here. Truncation and wildcard operators were adapted to each database syntax, and the final strings were retained with the screening records.

Database and Information Sources

Three databases were searched: Scopus, PubMed, and ScienceDirect. Scopus served as the principal multidisciplinary source, while PubMed and ScienceDirect broadened coverage of biomedical and applied-technology studies. Searches were limited to English-language peer-reviewed journal articles or reviews published from 2020 to 2025. Because database coverage and indexing practices differ, the possibility of database selection bias was considered explicitly when interpreting generalisability.

Eligibility Criteria

Table 1. Inclusion and exclusion criteria applied during study selection.

Criterion	Inclusion	Exclusion
Language	Published in English	Non-English publications
Document type	Peer-reviewed journal article or review	Conference paper, book chapter, editorial, erratum, retracted item
Publication period	2020–2025	Published before 2020
Population	Athletes / sport participants performing sport movements	Non-sport or purely clinical populations
Intervention	Computer-vision-based markerless pose estimation or motion capture	Marker-based or wearable-only methods without a vision component
Outcome	Reports kinematic/kinetic, performance, or tracking metrics	No movement, performance, or accuracy outcome reported
Accessibility	Full text available	Abstract only / full text not retrievable

Study Selection Process

Study selection proceeded through identification, deduplication, title/abstract screening, full-text retrieval, eligibility assessment, and synthesis. The search yielded 717 records; 17 duplicates were removed, leaving 700 records for screening. Of 58 reports sought for retrieval, six full texts could not be obtained and 52 were assessed

JRTI (Jurnal Riset Tindakan Indonesia)
Vol. 11, No. 1, 2026, pp. 983-997

for eligibility. Thirty-four reports were excluded at full text for being outside scope (n = 18), lacking a genuine computer-vision or markerless method (n = 9), or lacking a performance/kinematic outcome (n = 7). Eighteen studies were retained. The six unretrieved reports represent a potential selection bias and limit certainty about whether relevant evidence was systematically missed. The source manuscript does not document independent dual screening or a reproducible inter-rater coefficient; this is retained as a review-level limitation rather than replaced with an inferred kappa value.

Quality Assessment

Each included study was appraised using the Mixed Methods Appraisal Tool (MMAT), version 2018 (Hong et al., 2018), selected for heterogeneous study designs. For each study, the applicable five-item MMAT checklist was scored as met (1), partially met (0.5), or not met (0). Scores were used descriptively and no study was excluded solely because of appraisal score. The available review records do not document independent duplicate appraisal or inter-rater agreement; this transparency issue is therefore acknowledged in the limitations rather than masked.

Table 2. Summary of methodological quality appraisal (MMAT 2018).

Study	Design	Q1	Q2	Q3	Q4	Q5	Total	Rating
Pagnon et al. (2021)	Quant. descriptive	1	1	1	1	½	4.5/5	High
Pagnon et al. (2022)	Quant. non-randomized	1	1	1	1	1	5/5	High
Javadiha et al. (2021)	Quant. non-randomized	1	1	1	½	1	4.5/5	High
Cronin et al. (2023)	Quant. non-randomized	1	1	1	1	½	4.5/5	High
Giulietti et al. (2023)	Quant. descriptive	1	1	½	1	1	4.5/5	High
L. Liu et al. (2024)	Quant. descriptive	1	1	½	1	½	4/5	Medium
C. Liu & Xie (2024)	Quant. descriptive	1	½	½	1	½	3.5/5	Medium
Xi et al. (2024)	Quant. descriptive	1	1	1	½	1	4.5/5	High
Aleksic et al. (2024)	Quant. non-randomized	1	1	1	1	1	5/5	High
Ren et al. (2025)	Quant. descriptive	1	1	1	½	1	4.5/5	High
Zheng et al. (2025)	Quant. non-randomized	1	1	1	1	1	5/5	High
Apolinário-Souza & Leonardi (2025)	Quant. descriptive	1	½	1	½	1	4/5	Medium
Upadhyay et al. (2025)	Quant. descriptive	1	1	1	1	½	4.5/5	High
Chern et al. (2025)	Quant. descriptive	1	1	1	½	1	4.5/5	High
C. Yang et al. (2025)	Quant. non-randomized	1	1	1	1	1	5/5	High
Nishikawa et al. (2025)	Quant. non-randomized	1	1	1	1	1	5/5	High
Ruiz-Zafra et al. (2025)	Quant. descriptive	1	1	½	1	1	4.5/5	High
Adlou et al. (2025)	Narrative review (JBI[a])	1	1	1	½	1	4.5/5	High

Note. Q1–Q5 = MMAT criteria (1 = met; 0.5 = partial; 0 = not met). The single review was appraised with the equivalent JBI checklist for reviews. Ratings are descriptive (High >= 80%; Medium = 60–79%). No study was excluded solely on appraisal score. The manuscript reports no independent duplicate coding coefficient.

Data Extraction Procedure

A structured extraction form captured author/year, source, sport or movement task, design, computer-vision or pose-estimation approach, enabling technology, reference standard, primary outcomes, and principal findings. For validation studies, extraction additionally recorded agreement statistics (e.g., CMC/ICC/correlation), absolute or root-mean-square error where available, systematic offsets, joint- and plane-specific discrepancies, movement speed, occlusion/lighting conditions, and whether testing occurred in laboratory, training, or competition environments.

Network and Bibliometric Analysis Methodology

Descriptive bibliometric characterisation was performed on the included corpus to contextualise the synthesis. Publication-year distribution, sport application domain, and primary methodological approach were tabulated from the extracted metadata and visualised (Figures 2–4). Formal co-authorship or co-citation network analysis was not undertaken, as the review's focus was evidentiary synthesis rather than science mapping; the descriptive counts nonetheless situate individual studies within the broader trajectory of the field.

Data Analysis and Synthesis

Given the heterogeneity of tasks, systems, and outcome metrics, a narrative thematic synthesis was used following Thomas and Harden (2008). Coding was organised around the three research questions and the validity framework: application context; concurrent validity and error; methodological choices; and ecological constraints. Cross-study comparisons explicitly considered target variable, anatomical plane, movement speed, reference standard, camera configuration, and intended use. A quantitative meta-analysis was not undertaken because the studies used incompatible designs and outcome statistics.

Reporting and Documentation

Reporting followed PRISMA 2020. Figure 1 documents identification, screening, eligibility, and inclusion. The review additionally reports search-pilot sentinel studies and explicitly identifies the absence of a reproducible inter-rater coefficient and the six unretrieved full texts as validity threats to the review process.

PRISMA 2020 Flow Diagram

Figure 1 presents the PRISMA 2020 flow diagram summarising the identification, screening, eligibility, and inclusion of studies. The diagram and its citation follow the PRISMA 2020 statement (Page et al., 2021).

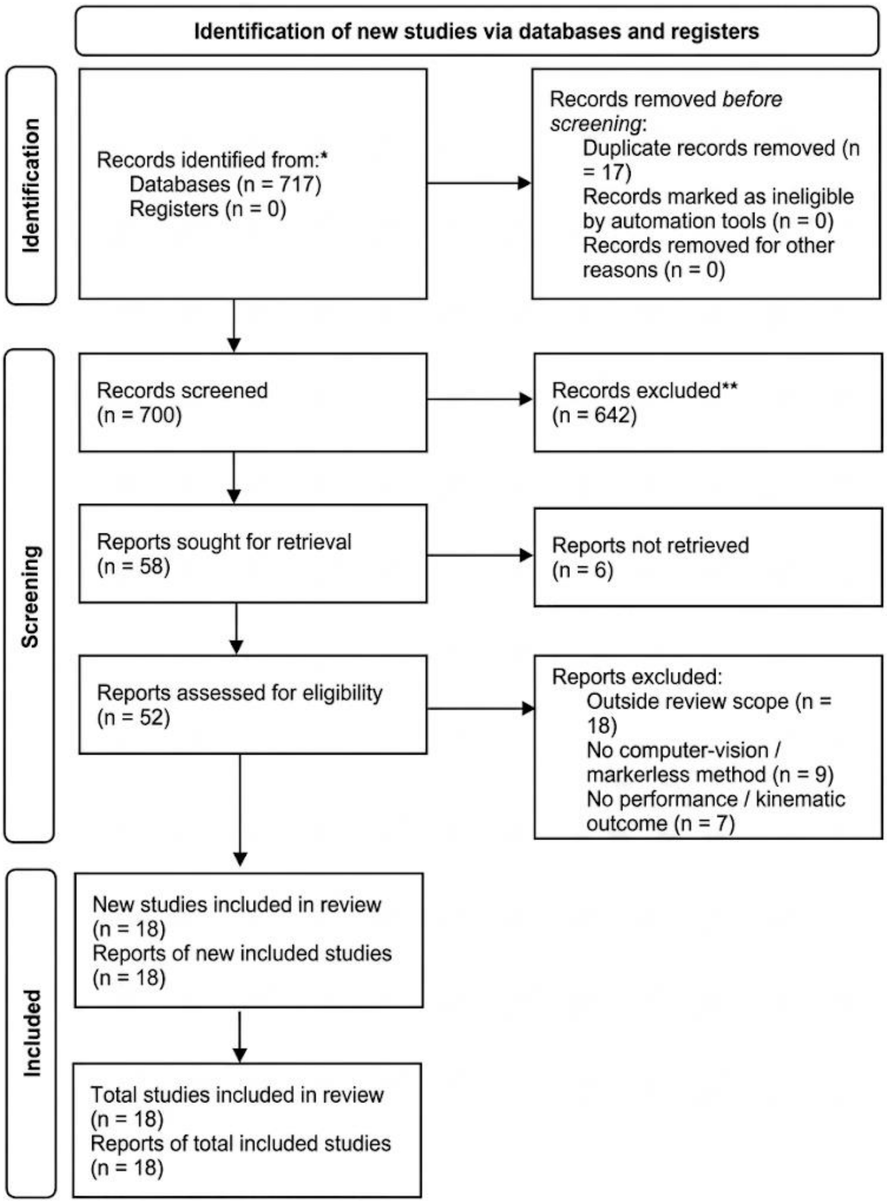

Figure 1. PRISMA 2020 flow diagram of the study selection process (adapted from Page et al., 2021).

Results and Discussions

Study Selection Results

Database searches identified 717 records (Scopus, n = 487; PubMed, n = 130; ScienceDirect, n = 100). After 17 duplicates were removed, 700 records were screened and 642 were excluded. Fifty-eight reports were sought for retrieval; six could not be obtained, leaving 52 full texts. At full text, 34 reports were excluded: 18 outside the review scope, nine without a genuine computer-vision/markerless method, and seven without a performance or kinematic outcome. Eighteen studies were included. The six unretrieved reports should be treated as a possible source of selection bias, and the use of three databases may also limit generalisability beyond the indexed literature.

Descriptive Characteristics

The 18 included studies span 2021–2025, with 13 published in 2024–2025. Eight addressed multi-sport or general methodological questions, three team sports, two athletics, two aquatic sports, two jump/strength testing, and one racket sport. Methodologically, eight used three-dimensional multi-view markerless pipelines, seven used two-dimensional pose-estimation systems, two used hybrid deep models, and one was a narrative review. The concentration in 2024–2025 is an observed publication pattern rather than evidence that technological "maturation" was caused by any single factor. It is compatible with accelerating computational capacity, open-source model availability, and increasing translational interest, but causal attribution is beyond this dataset. The concentration of studies in Sensors should likewise be interpreted as a publication and disciplinary-coverage pattern, not direct evidence of field-wide legitimacy.

Table 3. Characteristics of the 18 included studies.

Author(s), Year	Title	Source (Year)	Method / system	Key findings
Pagnon et al. (2021)	Pose2sim: An end-to-end workflow for 3D markerless sports kinematics-Part 1: Robustness	Sensors (2021)	Markerless 3D kinematics workflow (Pose2Sim) from calibrated multi-camera OpenPose input feeding an OpenSim model.	The workflow produced biomechanically consistent 3D joint angles that remained robust to degraded image quality, fewer cameras (4 vs. 8), and calibration error, supporting field deployment.
Pagnon et al. (2022)	Pose2Sim: An End-to-End Workflow for 3D Markerless Sports Kinematics-Part 2: Accuracy	Sensors (2022)	Concurrent-validity study of the Pose2Sim workflow against a reference marker-based system.	Lower-limb sagittal-plane joint angles showed strong agreement (CMC > 0.9) with marker-based capture, except a systematic hip offset in running and partial ankle occlusion in cycling.
Javadiha et al. (2021)	Estimating player positions from padel high-angle videos: Accuracy comparison of recent computer vision methods	Sensors (2021)	Comparison of state-of-the-art vision methods for single high-angle-camera player-position estimation in padel.	Deep-learning detection, segmentation, and pose methods were benchmarked for player-position estimation, quantifying accuracy trade-offs and establishing feasibility of image-based tracking from one camera.
Cronin et al. (2023)	Feasibility of OpenPose markerless motion analysis in a real athletics competition	Frontiers in Sports and Active Living (2023)	Field validation of OpenPose against manually digitised data at a World Championships long-jump final.	OpenPose reconstructed take-off kinematics in real competition; knee-angle waveforms agreed well (CMD ≈ 0.73), whereas hip and ankle angles agreed less, indicating joint-specific reliability.
Giulietti et al. (2023)	SwimmerNET: Underwater 2D Swimmer Pose Estimation Exploiting Fully Convolutional Neural Networks	Sensors (2023)	Underwater swimmer pose-estimation network designed to resist visual disturbances.	A fully convolutional network estimated underwater swimmer pose robustly against bubbles, splashes, and reflections, overcoming style-specific limitations of earlier vision methods.
L. Liu et al. (2024)	Real-time pose estimation and motion tracking for motion performance using deep learning models	Journal of Intelligent Systems (2024)	Real-time pose-estimation and multi-object tracking pipeline applied to aerial volleyball footage.	The OpenPose–DeepSORT pipeline achieved accurate, identity-consistent real-time tracking on UAV volleyball video, improving accuracy and latency over baseline models.
C. Liu & Xie (2024)	Innovative Application of Computer Vision and Motion Tracking Technology in Sports Training	EAI Endorsed Transactions on Pervasive Health and Technology (2024)	Computer-vision monitoring of athlete posture, muscle activation, and joint angles during training.	Real-time vision monitoring provided coaches with biomechanical-efficiency feedback and automated alerts for hazardous deviations in movement form.

Author(s), Year	Title	Source (Year)	Method / system	Key findings
Xi et al. (2024)	Enhancing human pose estimation in sports training: Integrating spatiotemporal transformer for improved accuracy and real-time performance	Alexandria Engineering Journal (2024)	Dual-channel pose-estimation architecture fusing global spatiotemporal and local temporal features in an IoT system.	Combining a Spatiotemporal Transformer with a Temporal Convolutional Network improved pose-estimation accuracy and real-time performance for high-speed movements.
Aleksic et al. (2024)	Advancing Field-Based Vertical Jump Analysis: Markerless Pose Estimation vs. Force Plates	Life (2024)	Validation of a smartphone markerless framework for countermovement-jump analysis against force plates.	Smartphone MMPose estimates of vertical-velocity profiles and temporal jump variables agreed closely with force-plate references, supporting affordable field-based jump testing.
Ren et al. (2025)	IoT-based 3D pose estimation and motion optimization for athletes: Application of C3D and OpenPose	Alexandria Engineering Journal (2025)	IoT-enhanced network (IE-PONet) for high-precision 3D pose estimation and motion optimisation of athletes.	IE-PONet delivered high-precision 3D pose estimation (APp50 up to 91.0), with ablation confirming the contribution of each module for performance analysis and injury prevention.
Zheng et al. (2025)	Feasibility and Accuracy of an RTMPose-Based Markerless Motion Capture System for Single-Player Tasks in 3x3 Basketball	Sensors (2025)	Feasibility and accuracy study of a multi-camera RTMPose system for single-player 3x3 basketball tasks.	The system reconstructed hip/ankle displacement and average speed with acceptable precision, validating markerless external-load monitoring where wearables are restricted.
Apolinário-Souza & Leonardi (2025)	Markerless tracking in sports using DeepLabCut: A methodological tutorial	Brazilian Journal of Motor Behavior (2025)	Practical tutorial implementing and evaluating DeepLabCut for tracking athletes and the ball during gameplay.	DeepLabCut enabled precise markerless tracking of players and the ball in dynamic gameplay, demonstrating feasibility for motor-behaviour and performance analysis in team sport.
Upadhyay et al. (2025)	Simple yet robust markerless motion capture system using deep learning	Engineering Applications of Artificial Intelligence (2025)	Unified low-cost multi-view markerless system fusing 2D poses via learned triangulation into absolute 3D pose.	A Raspberry-Pi multi-camera system with learned triangulation produced accurate, temporally consistent absolute 3D poses suitable for real-time deployment at low cost.
Chern et al. (2025)	A butterfly stroke swimming recording and performance analysis system based on computer vision and machine learning	Measurement: Journal of the International Measurement Confederation (2025)	Intelligent camera-and-accelerometer system for automated butterfly-stroke performance recording.	Using transfer-learned YOLOv4, the system automatically derived split times, stroke counts, and underwater knee angles, reducing labour-intensive manual video analysis.
C. Yang et al. (2025)	Comparison of lower limb kinematic and kinetic estimation during athlete jumping between markerless and marker-based motion capture systems	Scientific Reports (2025)	Comparison of lower-limb kinematic and kinetic estimates between markerless and marker-based systems during jumps.	Markerless estimates of lower-limb kinematics/kinetics showed variable agreement with marker-based/force-plate references, with joint- and plane-specific discrepancies revealed by statistical parametric mapping.
Nishikawa et al. (2025)	Comparison of kinematics between markerless and marker-based motion	Journal of Biomechanics (2025)	Comparison of markerless and marker-based kinematics during	Markerless (Theia3D) kinematics broadly tracked marker-based data with minimal inter-session

Author(s), Year	Title	Source (Year)	Method / system	Key findings
	capture systems for change of direction maneuvers		90° change-of-direction manoeuvres.	variation, though joint-angle discrepancies (RMSD) limited applicability for some variables.
Ruiz-Zafra et al. (2025)	PyBodyTrack: A python library for multi-algorithm motion quantification and tracking in videos	SoftwareX (2025)	Open-source Python library for standardised motion quantification from video across pose estimators.	PyBodyTrack standardised objective motion-quantification metrics from video across multiple estimators, facilitating reproducible movement assessment for sport and rehabilitation.
Adlou et al. (2025)	Motion Capture Technologies for Athletic Performance Enhancement and Injury Risk Assessment: A Review for Multi-Sport Organizations	Sensors (2025)	Narrative review of motion-capture technologies for athletic monitoring across environments.	Synthesised accuracy across optical, IMU, and markerless systems (markerless sagittal error ≈3–15°, larger in the transverse plane) and proposed an implementation framework for multi-sport organisations.

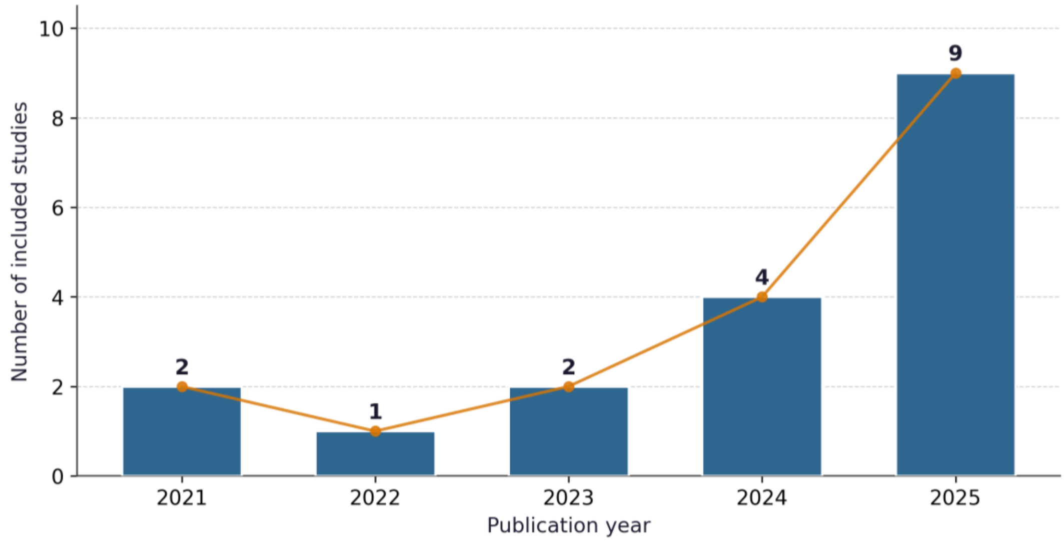

Figure 2. Annual distribution of the 18 included studies (2021–2025).

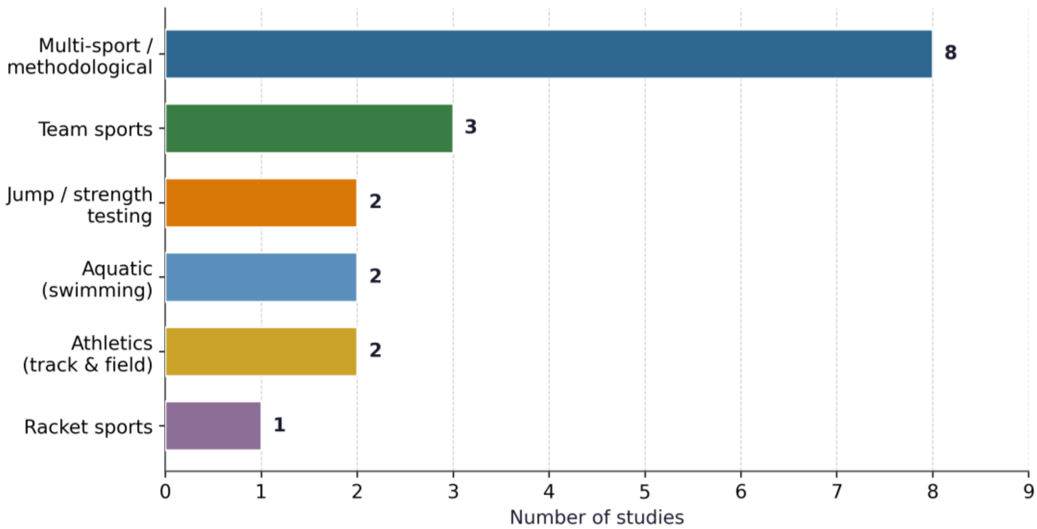

Figure 3. Distribution of included studies by sport application domain.

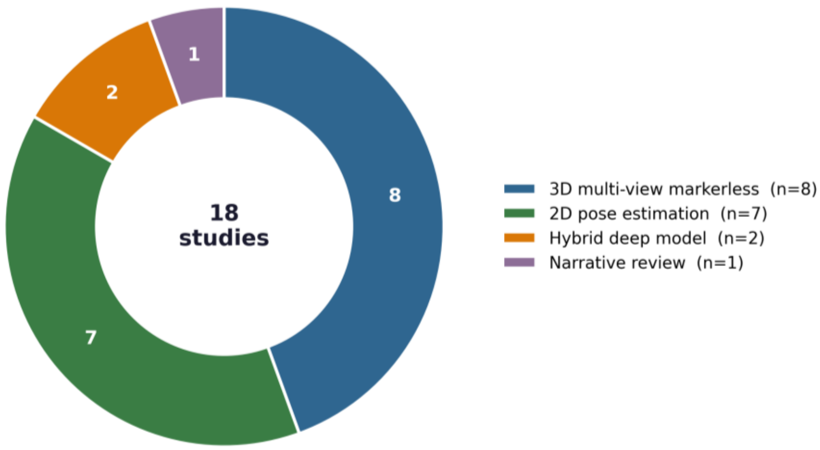

Figure 4. Distribution of included studies by primary methodological approach.

Thematic Synthesis

Findings for RQ1 - Applications across sport domains

The 17 empirical studies show three linked application functions: technique and joint-kinematic quantification, external-load/displacement monitoring, and player/implement tracking. Applications range from long-jump take-off and lower-limb jump mechanics to underwater swimming, volleyball, basketball, and padel. The important analytical distinction is that the same technical family is used for different inferential purposes: estimating a joint angle demands different evidence from estimating a player position or event time. Consequently, "markerless analysis" should not be treated as a homogeneous outcome class.

Findings for RQ2 - Concurrent validity and accuracy

Concurrent validity was conditional rather than universal. Pagnon et al. (2022) reported strong sagittal-plane lower-limb agreement with a marker-based reference (CMC > .90), although systematic hip offset in running and partial ankle occlusion in cycling remained. Cronin et al. (2023) reported good knee-angle waveform agreement in a genuine competition setting (CMD approximately .73), with weaker hip and ankle performance. Aleksic et al. (2024) found close agreement with force plates for vertical-velocity profiles and temporal jump variables. Zheng et al. (2025) reported acceptable precision for hip/ankle displacement and average speed in 3x3 basketball. In contrast, C. Yang et al. (2025) identified joint- and plane-specific discrepancies in jumping, while Nishikawa et al. (2025) found that Theia3D broadly tracked marker-based kinematics but retained RMSD discrepancies that constrained some joint-angle applications. Adlou et al. (2025) summarised markerless sagittal errors of roughly 3–15 degrees, with larger errors in the transverse plane. Earlier validation also shows that agreement depends on the variable: Drazan et al. (2021) reported very strong agreement for sagittal-plane vertical-jump kinematics (overall CMC > .991; RMSE < 3.22 degrees), whereas Bahadori et al. (2019) found larger joint-angle differences with a low-cost Kinect system. Taken together, the evidence supports a context-dependent interpretation in which agreement statistics are necessary but not sufficient without error magnitude, bias, and use-context evidence.

Findings for RQ3 - Methods, technologies, and constraints

Methodologically, the corpus separates into accessible two-dimensional pipelines and richer three-dimensional multi-view reconstruction. Two-dimensional approaches favour portability and real-time use, whereas multi-view systems add calibration and triangulation requirements to recover out-of-plane information. The newer studies also show a shift toward temporal modelling, IoT/edge deployment, low-cost multi-camera hardware, and sensor fusion. The recurring validity threats are technically coherent: occlusion and lighting degrade pose localisation; camera count and calibration influence 3D reconstruction; high-speed and transverse-plane movement expose weaknesses not visible in sagittal-plane testing; and competition introduces unconstrained trajectories. These constraints explain why a system may be technically accurate in a controlled task yet insufficient for a particular field decision.

Comparative and Critical Analysis

The comparison across the 17 empirical studies shows a consistent division of labour rather than a single "best" markerless method. Two-dimensional systems are efficient for timing, gross displacement, and player-position tasks when camera geometry is stable. Multi-view three-dimensional pipelines are better suited to richer joint kinematics but introduce calibration and hardware dependencies. Validation against reference standards is strongest when the target variable is low-dimensional and relatively observable, and weakest when the movement is fast, rotational, or partially occluded. This pattern is not a new theory of measurement; it is an empirical consolidation interpreted through established validity principles.

Interpretation of findings. Markerless vision has moved beyond proof-of-concept in several sport contexts, but maturity is variable by measurement purpose. The strongest evidence concerns spatiotemporal and selected sagittal-plane variables for which the reference relationship is direct and the visual signal remains stable. The evidence is weaker for transverse-plane rotation, joint-specific estimates affected by occlusion, and high-speed actions. Earlier foundational and validation work established the technical basis of pose estimation and markerless biomechanics (Xu et al., 2015; Cao et al., 2017; Colyer et al., 2018; Mathis et al., 2018; Bahadori et al., 2019; Graving et al., 2019; Nath et al., 2019; Chakraborty et al., 2020; Nakano et al., 2020; Tamura et al., 2020; Drazan et al., 2021), while the recent sport literature demonstrates broader application but not universal validity.

Theoretical implications. The review does not claim a new validity theory. Instead, it applies classical measurement theory to markerless sport analysis by treating validity as a question of score interpretation and use rather than a property of the device alone (Messick, 1995; Kane, 2013). The inference chain used here links video acquisition, pose estimation, anatomical reconstruction, kinematic variable, and decision. This framing clarifies why two studies can report different conclusions about the same broad technology without contradiction: their target variables, reference standards, movement constraints, and intended decisions differ. The value of the present synthesis is therefore conceptual clarification and empirical consolidation, not theoretical replacement of established validity frameworks.

Practical implications. System selection should proceed backward from the decision. For event timing, gross displacement, or player position, a validated two-dimensional configuration may be sufficient when the camera view is stable. For three-dimensional joint-angle analysis, multi-view reconstruction is preferable when calibration can be controlled. Transverse-plane, rotational, high-speed, and occlusion-prone outputs should be treated as conditional unless task-specific validation demonstrates acceptably small error. Agreement statistics such as CMC or ICC around .90 are useful supporting evidence but should not be used as the sole threshold; absolute error, systematic bias, and similarity between validation and intended field conditions must also be considered.

Comparison with prior syntheses. The present review complements Colyer et al. (2018), which charted the evolution of vision-based motion analysis; Suo et al. (2024), which surveyed motion-capture technologies; Souaifi et al. (2025), which synthesised AI in sports biomechanics; Jia et al. (2025), which reviewed deep-learning applications in sport-performance analysis; Yoma et al. (2025), which systematically examined lower-extremity and trunk markerless validity; and Adlou et al. (2025), which considered motion-capture technologies across multi-sport organisations. These reviews establish technological breadth, whereas the present synthesis explicitly organises empirical sport evidence around variable, plane, context, reference, and intended use. The 17 empirical studies in the present corpus provide the primary comparison base; the review does not inflate the evidence with weakly related literature merely to reach an arbitrary reference count.

Contradictions and boundary conditions. Apparent contradictions - strong agreement in some validation studies and notable discrepancies in others - are best understood as differences in measurement conditions. Nakano et al. (2020), Pagnon et al. (2022), Cronin et al. (2023), Aleksic et al. (2024), C. Yang et al. (2025), and Nishikawa et al. (2025) collectively show that agreement varies by variable and task. The main unresolved boundary is ecological validity: the six full texts that could not be retrieved may contain relevant counter-evidence, while database restriction to Scopus, PubMed, and ScienceDirect may underrepresent conference, engineering, or local-indexed research.

Research gaps and future review recommendations. First, future studies should pre-specify sport- and variable-specific error tolerances rather than relying on global “accuracy” claims. Second, validation papers should report absolute error and systematic bias alongside correlation or agreement coefficients. Third, genuine competition validation should become a routine stage rather than an exception. Fourth, systematic reviews should maintain a searchable sensitivity log, report independent screening and appraisal procedures with inter-rater agreement, document reasons for all unavailable full texts, and consider database combinations that better capture engineering and computer-vision outlets. Finally, prospective validation should test whether measurement error actually changes the coaching decision, which is the practical endpoint of validity. Cross-study validity synthesis

Table 4. Cross-study validity evidence and interpretation across the 17 empirical studies.

Study	Task / reference	Reported evidence	Framework interpretation
Pagnon et al. (2021)	3D sports kinematics; robustness	Robust joint-angle workflow under degraded image quality, fewer cameras (4 vs. 8), and calibration error	Supports field robustness, but not a universal validity claim
Pagnon et al. (2022)	3D lower-limb kinematics vs. markers	CMC > .90 in sagittal-plane joint angles; hip offset and ankle occlusion noted	Strong selected sagittal-plane evidence; context-dependent
Javadiha et al. (2021)	Padel player position; single high-angle camera	Compared deep-learning detection/segmentation/pose methods for position estimation	Supportive for player-position tracking when camera geometry is controlled
Cronin et al. (2023)	Long jump competition vs. manual digitisation	CMD about .73 for knee-angle waveform; hip/ankle agreement weaker	Field feasibility demonstrated; joint-specific accuracy differs
Giulietti et al. (2023)	Underwater swimmer pose	Network remained robust to bubbles, splashes, and reflections	Environmental robustness is possible but task-specific
Liu et al. (2024)	Aerial volleyball tracking	OpenPose–DeepSORT improved identity consistency, accuracy, and latency	Supportive for tracking; absolute kinematic validity not established
Liu & Xie (2024)	Training posture and joint monitoring	Real-time monitoring with biomechanical-efficiency feedback and movement alerts	Application feasibility; validity thresholds not fully quantified
Xi et al. (2024)	High-speed sports pose estimation	Spatiotemporal Transformer + temporal convolution improved accuracy and real-time performance	Temporal modelling may reduce high-speed error; external validation still needed
Aleksic et al. (2024)	Countermovement jump vs. force plates	Vertical-velocity profiles and temporal variables agreed closely with force-plate references	Supportive for validated jump variables
Ren et al. (2025)	3D athlete pose; C3D/OpenPose	APp50 reported up to 91.0 with module ablation	Strong model-performance evidence; practical validity depends on target use
Zheng et al. (2025)	3x3 basketball vs. reference	Hip/ankle displacement and average speed reconstructed with acceptable precision	Supportive for selected external-load/displacement variables
Apolinário-Souza & Leonardi (2025)	DeepLabCut player/ball tracking	Precise markerless tracking demonstrated in dynamic gameplay	Useful for tracking; tutorial design limits validity inference
Upadhyay et al. (2025)	Low-cost multi-view absolute 3D pose	Learned triangulation produced accurate, temporally consistent 3D poses	Promising low-cost 3D implementation; task-specific validation remains important
Chern et al. (2025)	Butterfly swimming; video + accelerometer	Automated split times, stroke counts, and knee angles	Supports automated performance metrics; sensor fusion may improve robustness
C. Yang et al. (2025)	Jumping vs. marker/force-plate references	Variable lower-limb kinematic/kinetic agreement with joint- and plane-specific discrepancies	Confirms that validity is variable-, joint-, and plane-specific
Nishikawa et al. (2025)	90-degree change of direction vs. markers	Broad kinematic tracking with RMSD discrepancies for some joint angles	Useful for some outputs; joint-angle errors can limit application
Ruiz-Zafra et al. (2025)	Open-source video motion quantification	Standardised objective metrics across multiple pose estimators	Improves reproducibility; not itself a concurrent-validity study

Table 5. Operational decision matrix for interpreting markerless sport-performance measurements.

Measurement target	Typical evidence needed	Preferred configuration	Current evidence judgement
Timing / event variables	Agreement with instrumented timing reference; small absolute bias	2D video or smartphone when view is stable	Generally supportive for validated tasks
Gross displacement / player position	Position error and task-level agreement	2D single-camera or low-cost multi-view	Supportive when geometry is controlled

Measurement target	Typical evidence needed	Preferred configuration	Current evidence judgement
Sagittal-plane joint kinematics	CMC/ICC plus absolute/systematic error against marker-based reference	Validated multi-view 3D or well-controlled 2D	Relatively strong for selected lower-limb variables
Transverse-plane / rotational kinematics	Plane-specific absolute error, bias and repeatability	Multi-view 3D with careful calibration; sensor fusion may help	Conditional; evidence remains inconsistent
High-speed / occlusion-prone movement	Frame-level tracking stability and competition-like validation	Multi-view, temporal models, and/or complementary sensors	Conditional; field robustness requires additional testing

Conclusions

This systematic review of 18 peer-reviewed studies establishes that computer-vision-based markerless pose estimation has become a viable instrument for athletic movement and performance analysis across individual, team, and aquatic sports, supporting technique assessment, load monitoring, and player tracking. Its concurrent validity is strong for sagittal-plane and spatiotemporal variables but conditional and weaker for transverse-plane angles and fast, occlusion-prone actions, with two-dimensional and multi-view three-dimensional pipelines - increasingly integrated with IoT, low-cost hardware, and complementary sensors - defining the methodological landscape. The core contribution of this review is to reframe accuracy as variable-, task-, and plane-specific, offering practitioners a basis for matching systems to purpose while interpreting out-of-plane outputs cautiously. Its principal limitations are reliance on English-language sources and a narrative synthesis. Future work should prioritise standardised validation, improved transverse-plane accuracy, and rigorous testing under genuine competition conditions.

Acknowledgments

The Authors would like to thank Faculty of Sport Sciences, Universitas Negeri Padang for providing excellent facilities, as well as for being very supportive of this research from the beginning. Authors also thank the team members who had generously shared their brilliant ideas, engaging discussion, and academic supports during the study.

References

Abdelmohsen, A. M. (2025). Artificial Intelligence in Biomechanics: A Narrative Review of Current Applications in Diagnostic and Physical Rehabilitation. Physiotherapy Research International: the Journal for Researchers and Clinicians in Physical Therapy, 30(4), e70120. https://doi.org/10.1002/pri.70120

Ackland, D. C., Fang, Z., & Senanayake, D. (2025). A machine learning approach to real-time calculation of joint angles during walking and running using self-placed inertial measurement units. Gait & Posture, 118, 85-91. https://doi.org/10.1016/j.gaitpost.2025.01.028

Adlou, B., Wilburn, C., & Weimar, W. (2025). Motion Capture Technologies for Athletic Performance Enhancement and Injury Risk Assessment: A Review for Multi-Sport Organizations. Sensors, 25. https://doi.org/10.3390/s25144384

Aleksic, J., Mesaroš, D., Kanevsky, D., Knežević, O. M., Cabarkapa, D., Faj, L., & Mirkov, D. M. (2024). Advancing Field-Based Vertical Jump Analysis: Markerless Pose Estimation vs. Force Plates. Life, 14. https://doi.org/10.3390/life14121641

Alshardan, A., Mahgoub, H., Alahmari, S., Alonazi, M., Marzouk, R., & Mohamed, A. (2025). Cloud-to-Thing continuum-based sports monitoring system using machine learning and deep learning model. PeerJ Computer Science, 11, e2539. https://doi.org/10.7717/peerj-cs.2539

Alzahrani, A., & Ullah, A. (2024). Advanced biomechanical analytics: Wearable technologies for precision health monitoring in sports performance. Digital Health, 10, 20552076241256745. https://doi.org/10.1177/20552076241256745

Apolinário-Souza, T., & Leonardi, T. J. (2025). Markerless tracking in sports using DeepLabCut: A methodological tutorial. Brazilian Journal of Motor Behavior, 19. https://doi.org/10.20338/bjmb.v19i1.484

Bahadori, S., Davenport, P., Immins, T., & Wainwright, T. W. (2019). Validation of joint angle measurements: Comparison of a novel low-cost marker-less system with an industry standard marker-based system.

Journal of Medical Engineering & Technology, 43(1), 19–24. https://doi.org/10.1080/03091902.2019.1599072

Balci, I. C., Sayin, I., Salturk, S., Gursoy, R., Ozsoy, U., Dogru, H. C., Akca, G., Eraslan, A., Sahin, O., Demircali, A. A., & Uvet, H. (2025). Reliability assessment of markerless technologies in biomechanical motion analysis: a performance comparison. Frontiers in Sports and Active Living, 7, 1712332. https://doi.org/10.3389/fspor.2025.1712332

Biró, A., Cuesta-Vargas, A. I., & Szilágyi, L. (2023). AI-Assisted Fatigue and Stamina Control for Performance Sports on IMU-Generated Multivariate Times Series Datasets. Sensors, 24(1). https://doi.org/10.3390/s24010132

Boey, D., Girard, O., Lee, M., Elliott, B., & Reid, M. (2026). Unlocking the potential of video-based markerless motion analysis to study world-class sporting performance. Journal of Sports Sciences, 44(10), 1261-1274. https://doi.org/10.1080/02640414.2025.2576412

Cao, Z., Simon, T., Wei, S.-E., & Sheikh, Y. (2017). Realtime multi-person 2D pose estimation using part affinity fields. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 7291–7299). https://doi.org/10.1109/CVPR.2017.143

Chakraborty, S., Nandy, A., Yamaguchi, T., Bonnet, V., & Venture, G. (2020). Accuracy of image data stream of a markerless motion capture system in determining the local dynamic stability and joint kinematics of human gait. Journal of Biomechanics, 104, 109718. https://doi.org/10.1016/j.jbiomech.2020.109718

Chern, Y. R., Chen, Y. H., Lin, F. S., Lin, H. C., Chen, G. T., Chu, C. P., Machtsiras, G., Huang, T. H., Lien, J. J. J., & Huang, C. H. (2025). A butterfly stroke swimming recording and performance analysis system based on computer vision and machine learning. Measurement: Journal of the International Measurement Confederation, 251. https://doi.org/10.1016/j.measurement.2025.117171

Colyer, S. L., Evans, M., Cosker, D. P., & Salo, A. I. T. (2018). A review of the evolution of vision-based motion analysis and the integration of advanced computer vision methods towards developing a markerless system. Sports Medicine - Open, 4, 24. https://doi.org/10.1186/s40798-018-0139-y

Cronin, N. J. (2021). Using deep neural networks for kinematic analysis: Challenges and opportunities. Journal of Biomechanics, 123, 110460. https://doi.org/10.1016/j.jbiomech.2021.110460

Cronin, N. J., Rantalainen, T., Ahtiainen, J. P., Hynynen, E., & Waller, B. (2019). Markerless 2D kinematic analysis of underwater running: A deep learning approach. Journal of Biomechanics, 87, 75–82. https://doi.org/10.1016/j.jbiomech.2019.02.021

Cronin, N. J., Walker, J., Tucker, C. B., Nicholson, G., Cooke, M., Merlino, S., & Bissas, A. (2023). Feasibility of OpenPose markerless motion analysis in a real athletics competition. Frontiers in Sports and Active Living, 5. https://doi.org/10.3389/fspor.2023.1298003

Dorschky, E., Camomilla, V., Davis, J., Federolf, P., Reenalda, J., & Koelewijn, A. D. (2023). Perspective on "in the wild" movement analysis using machine learning. Human Movement Science, 87, 103042. https://doi.org/10.1016/j.humov.2022.103042

Drazan, J. F., Phillips, W. T., Seethapathi, N., Hullfish, T. J., & Baxter, J. R. (2021). Moving outside the lab: Markerless motion capture accurately quantifies sagittal plane kinematics during the vertical jump. Journal of Biomechanics, 125, 110547. https://doi.org/10.1016/j.jbiomech.2021.110547

Edriss, S., Romagnoli, C., Caprioli, L., Bonaiuto, V., Padua, E., & Annino, G. (2025). Commercial vision sensors and AI-based pose estimation frameworks for markerless motion analysis in sports and exercises: a mini review. Frontiers in Physiology, 16, 1649330. https://doi.org/10.3389/fphys.2025.1649330

Faj, L., Aleksić, J., Knežević, O. M., Božović, B., Brkić, H., Sekulić, D., & Mirkov, D. M. (2025). From Laboratory to Field: Concurrent Validity of Kinovea's Linear Kinematics Tracking Tool for Semi-Automated Countermovement Jump Analysis. Sensors, 26(1). https://doi.org/10.3390/s26010024

Giulietti, N., Caputo, A., Chiariotti, P., & Castellini, P. (2023). SwimmerNET: Underwater 2D Swimmer Pose Estimation Exploiting Fully Convolutional Neural Networks. Sensors, 23. https://doi.org/10.3390/s23042364

Gorges, T., Davidson, P., Boeschen, M., Hotho, A., & Merz, C. (2024). IMU Airtime Detection in Snowboard Halfpipe: U-Net Deep Learning Approach Outperforms Traditional Threshold Algorithms. Sensors, 24(21). https://doi.org/10.3390/s24216773

Graving, J. M., Chae, D., Naik, H., Li, L., Koger, B., Costelloe, B. R., & Couzin, I. D. (2019). DeepPoseKit, a software toolkit for fast and robust animal pose estimation using deep learning. eLife, 8, e47994. https://doi.org/10.7554/eLife.47994

Grivas, G. V., & Safari, K. (2025). Artificial Intelligence in Endurance Sports: Metabolic, Recovery, and Nutritional Perspectives. Nutrients, 17(20). https://doi.org/10.3390/nu17203209

Haberkamp, L. D., Garcia, M. C., & Bazett-Jones, D. M. (2022). Validity of an artificial intelligence, human pose estimation model for measuring single-leg squat kinematics. Journal of Biomechanics, 144, 111333. https://doi.org/10.1016/j.jbiomech.2022.111333

Hong, Q. N., Pluye, P., Bujold, M., & Vedel, I. (2018). Mixed Methods Appraisal Tool (MMAT), version 2018. Canadian Intellectual Property Office, Industry Canada.

Hu, Y., Li, Y., Cui, B., Su, H., & Zhu, P. (2025). Internet of things enabled deep learning monitoring system for realtime performance metrics and athlete feedback in college sports. Scientific Reports, 15(1), 28405. https://doi.org/10.1038/s41598-025-13949-6

Huang, S. C., Pierce, T., Lin, Y. A., & Loh, K. J. (2025). Boxing Punch Detection and Classification Using Motion Tape and Machine Learning. Sensors, 25(16). https://doi.org/10.3390/s25165027

Javadiha, M., Andujar, C., Lacasa, E., Ric, A., & Susin, A. (2021). Estimating player positions from padel high-angle videos: Accuracy comparison of recent computer vision methods. Sensors, 21. https://doi.org/10.3390/s21103368

Jia, Y., Anida Abdullah, N., Eliza, H., Lu, Q., Si, D., Guo, H., & Wang, W. (2025). A narrative review of deep learning applications in sports performance analysis: current practices, challenges, and future directions. BMC Sports Science, Medicine & Rehabilitation, 17(1), 249. https://doi.org/10.1186/s13102-025-01294-0

Kane, M. T. (2013). Validating the interpretations and uses of test scores. Journal of Educational Measurement, 50(1), 1–73. https://doi.org/10.1111/jedm.12000

Kim, M., & Park, S. (2020). Golf Swing Segmentation from a Single IMU Using Machine Learning. Sensors, 20(16). https://doi.org/10.3390/s20164466

Kranzinger, S., Kranzinger, C., Kremser, W., & Duemler, B. (2025). Performance tracking in female youth soccer through wearables and subjective assessments. Frontiers in Sports and Active Living, 7, 1627820. https://doi.org/10.3389/fspor.2025.1627820

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. PLoS Medicine, 6(7), e1000100. https://doi.org/10.1371/journal.pmed.1000100

Liu, C., & Xie, Y. (2024). Innovative Application of Computer Vision and Motion Tracking Technology in Sports Training. EAI Endorsed Transactions on Pervasive Health and Technology, 10. https://doi.org/10.4108/eetpht.10.5763

Liu, L., Dai, Y., & Liu, Z. (2024). Real-time pose estimation and motion tracking for motion performance using deep learning models. Journal of Intelligent Systems, 33. https://doi.org/10.1515/jisys-2023-0288

Mathis, A., Mamidanna, P., Cury, K. M., Abe, T., Murthy, V. N., Mathis, M. W., & Bethge, M. (2018). DeepLabCut: Markerless pose estimation of user-defined body parts with deep learning. Nature Neuroscience, 21, 1281–1289. https://doi.org/10.1038/s41593-018-0209-y

Mekruksavanich, S., Phaphan, W., Hnoohom, N., & Jitpattanakul, A. (2024). Recognition of sports and daily activities through deep learning and convolutional block attention. PeerJ Computer Science, 10, e2100. https://doi.org/10.7717/peerj-cs.2100

Messick, S. (1995). Validity of psychological assessment: Validation of inferences from persons' responses and performances as scientific inquiry into score meaning. American Psychologist, 50(9), 741–749. https://doi.org/10.1037/0003-066X.50.9.741

Morouço, P. (2024). Wearable Technology and Its Influence on Motor Development and Biomechanical Analysis. International Journal of Environmental Research and Public Health, 21(9). https://doi.org/10.3390/ijerph21091126

Nakano, N., Sakura, T., Ueda, K., Omura, L., Kimura, A., Iino, Y., Fukashiro, S., & Yoshioka, S. (2020). Evaluation of 3D markerless motion capture accuracy using OpenPose with multiple video cameras. Frontiers in Sports and Active Living, 2, 50. https://doi.org/10.3389/fspor.2020.00050

Nath, T., Mathis, A., Chen, A. C., Patel, A., Bethge, M., & Mathis, M. W. (2019). Using DeepLabCut for 3D markerless pose estimation across species and behaviors. Nature Protocols, 14, 2152–2176. https://doi.org/10.1038/s41596-019-0176-0

Nishikawa, N., Watanabe, S., & Yamamoto, K. (2025). Comparison of kinematics between markerless and marker-based motion capture systems for change of direction maneuvers. Journal of Biomechanics, 192. https://doi.org/10.1016/j.jbiomech.2025.112965

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Pagnon, D., Domalain, M., & Reveret, L. (2021). Pose2sim: An end-to-end workflow for 3D markerless sports kinematics-Part 1: Robustness. Sensors, 21. https://doi.org/10.3390/s21196530

Pagnon, D., Domalain, M., & Reveret, L. (2022). Pose2Sim: An End-to-End Workflow for 3D Markerless Sports Kinematics-Part 2: Accuracy. Sensors, 22. https://doi.org/10.3390/s22072712

Ren, F., Ren, C., & Lyu, T. (2025). IoT-based 3D pose estimation and motion optimization for athletes: Application of C3D and OpenPose. Alexandria Engineering Journal, 115. https://doi.org/10.1016/j.aej.2024.10.079

Ruiz-Zafra, A., Pigueiras-del-Real, J., Heredia-Jimenez, J., Shah, S. T. H., Shah, S. A. H., & Gontard, L. C. (2025). PyBodyTrack: A python library for multi-algorithm motion quantification and tracking in videos. SoftwareX, 31. https://doi.org/10.1016/j.softx.2025.102272

Schortgen, A., Goyallon, T., Saulière, G., Muller, A., & Revéret, L. (2026). Monocular markerless position tracking of elite amateur boxing fighters in real combat situation. Journal of Sports Sciences, 44(10), 1319-1333. https://doi.org/10.1080/02640414.2025.2510774

Sharifi-Renani, M., Mahoor, M. H., & Clary, C. W. (2023). BioMAT: An Open-Source Biomechanics Multi-Activity Transformer for Joint Kinematic Predictions Using Wearable Sensors. Sensors, 23(13). https://doi.org/10.3390/s23135778

Souaifi, M., Dhahbi, W., Jebabli, N., Ceylan, H. İ., Boujabli, M., Muntean, R. I., & Dergaa, I. (2025). Artificial Intelligence in Sports Biomechanics: A Scoping Review on Wearable Technology, Motion Analysis, and Injury Prevention. Bioengineering, 12(8). https://doi.org/10.3390/bioengineering12080887

Stadnyk, A. M., Impellizzeri, F. M., Stanley, J., Menaspà, P., & Slattery, K. M. (2024). Performance determinants and evidence-based practice in track cycling: A survey of coaches, practitioners, and athletes. Journal of Science and Medicine in Sport, 27, 726–733. https://doi.org/10.1016/j.jsams.2024.06.001

Suo, X., Tang, W., & Li, Z. (2024). Motion Capture Technology in Sports Scenarios: A Survey. Sensors, 24(9). https://doi.org/10.3390/s24092947

Tamura, H., Tanaka, R., & Kawanishi, H. (2020). Reliability of a markerless motion capture system to measure the trunk, hip and knee angle during walking on a flatland and a treadmill. Journal of Biomechanics, 109, 109929. https://doi.org/10.1016/j.jbiomech.2020.109929

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8, 45. https://doi.org/10.1186/1471-2288-8-45

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Upadhyay, A., Shukla, A., Sharma, M., & Abraham, A. (2025). Simple yet robust markerless motion capture system using deep learning. Engineering Applications of Artificial Intelligence, 160. https://doi.org/10.1016/j.engappai.2025.111905

Xi, X., Zhang, C., Jia, W., & Jiang, R. (2024). Enhancing human pose estimation in sports training: Integrating spatiotemporal transformer for improved accuracy and real-time performance. Alexandria Engineering Journal, 109. https://doi.org/10.1016/j.aej.2024.08.072

Xu, X., McGorry, R. W., Chou, L.-S., Lin, J.-H., & Chang, C.-C. (2015). Accuracy of the Microsoft Kinect for measuring gait parameters during treadmill walking. Gait & Posture, 42(2), 145–151. https://doi.org/10.1016/j.gaitpost.2015.05.002

Xue, H., Han, C., & Zhu, D. (2025). Limb biomechanics in combat sports: insights from wearable sensor technology. Frontiers in Bioengineering and Biotechnology, 13, 1663592. https://doi.org/10.3389/fbioe.2025.1663592

Yang, C., Wei, L., Huang, X., Tu, L., Xu, Y., Li, X., & Hu, Z. (2025). Comparison of lower limb kinematic and kinetic estimation during athlete jumping between markerless and marker-based motion capture systems. Scientific Reports, 15. https://doi.org/10.1038/s41598-025-02739-9

Yang, P., Xu, R., & Le, Y. (2024). Factors influencing sports performance: A multi-dimensional analysis of coaching quality, athlete well-being, training intensity, and nutrition with self-efficacy mediation and cultural values moderation. Heliyon, 10, e36646. https://doi.org/10.1016/j.heliyon.2024.e36646

Yoma, M., Llurda-Almuzara, L., Herrington, L., & Jones, R. (2025). Reliability and validity of lower extremity and trunk kinematics measured with markerless motion capture during sports-related and functional tasks: A systematic review. Journal of Sports Sciences, 43(17), 1703-1730. https://doi.org/10.1080/02640414.2025.2518359

Zhang, K., Guo, B., Yang, M., Jia, Y., Zhang, K., & Wang, L. (2024). The assessment of sports performance by grip pressure using flexible piezoresistive pressure sensors in seven sports events. Scientific Reports, 14(1), 31750. https://doi.org/10.1038/s41598-024-82274-1

Zheng, W., Zhang, M., Dong, R., Qiu, M., & Wang, W. (2025). Feasibility and Accuracy of an RTMPose-Based Markerless Motion Capture System for Single-Player Tasks in 3x3 Basketball. Sensors, 25. https://doi.org/10.3390/s25134003

Zhu, Z. (2025). Design and implementation of an intelligent sports management system (ISMS) using wireless sensor networks. PeerJ Computer Science, 11, e2637. https://doi.org/10.7717/peerj-cs.2637