Review

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Anna Bourliou, Athanasios Fouras, Dionysia Chrysanthakopoulou
and Constantinos Koutsojannis *

Health Physics & Computational Intelligence lab, Department of Physiotherapy, School of Rehabilitation Sciences, University of Patras, Patras, Greece
* Correspondence: ckoutsog@upatras.gr

Abstract

Background: Female dancers experience non-contact anterior cruciate ligament (ACL) injuries at rates comparable to high-risk contact sports, yet laboratory-based marker systems have remained inaccessible for routine screening. **Objectives:** To compare the accuracy, feasibility, and ACL-risk detection performance of AI-enhanced markerless versus marker-based motion analysis in female dancers. **Methods:** Following a prospectively registered protocol, we searched PubMed, Scopus, Web of Science, SPORTDiscus, CINAHL, IEEE Xplore, and dance-specific databases from 2015 to November 2025. Eligible studies performed direct head-to-head comparisons during dance-specific tasks (e.g., grand jeté, turnout plié, pointe relevé) in female dancers aged 10–30 years. Primary outcome: root-mean-square error (RMSE) for knee valgus angle. Risk of bias was assessed with ROBINS-I; evidence certainty with GRADE. **Results:** Twelve studies (n = 456 female dancers, mean age 18.2 years) were included. Markerless systems achieved a pooled RMSE of 2.9° (95% CI 2.1–3.7°, $I^2 = 48\%$, k = 8) for knee valgus during landings and turnout tasks, with a pooled sensitivity of 84% (95% CI 76–90%) for high-risk profiles. Setup time was reduced by 80–95% and cost by >99% compared with marker-based systems. Certainty of evidence was moderate for accuracy and low for sensitivity. **Conclusion:** AI-enhanced markerless motion analysis provides clinically acceptable accuracy and unprecedented feasibility for ACL-risk screening in female dancers. Integration into studio-based prevention programmes is now justified and urgently needed. **Level of evidence:** Level II (systematic review of Level I–II studies).

Keywords: anterior cruciate ligament (ACL) injury; ACL prevention; female dancers; ballet; contemporary dance; pointe work; markerless motion capture; artificial intelligence; pose estimation; biomechanics; systematic review; meta-analysis

1. Introduction

Anterior cruciate ligament (ACL) ruptures represent one of the most severe and career-threatening injuries in female performing artists, with incidence rates in pre-professional and professional dancers ranging from 0.62 to 2.2 injuries per 1000 dance hours—up to tenfold higher than age-matched non-dancers and comparable to high-risk contact sports (Liederbach et al., 2018; Yin et al., 2023; Garrido et al., 2025). Unlike athletic populations, ACL tears in dancers predominantly occur via non-contact mechanisms during routine technical elements: landing from jumps (grand jeté, tour jeté), forced turnout in pliés and relevés, rapid directional changes in contemporary floor work, and repetitive hyperextension in arabesque or attitude positions (Russell et al., 2016; Steinberg et al., 2022). These injuries carry devastating consequences—average 9–18 months away from full training, 25–40% non-return-to-pre-injury performance level, and elevated risk of early osteoarthritis and retirement before age 25 (Bronner et al., 2021; Kivlan et al., 2023).

The biomechanical profile of the female dancer is unique and predisposing. Extreme external tibial rotation ("forced turnout") combined with physiological anteversion and ligamentous laxity produces compensatory dynamic knee valgus, reduced knee flexion angles, and excessive tibial internal rotation moments during weight-bearing—mechanisms repeatedly implicated in ACL strain (Quanbeck et al., 2016; Dufek et al., 2025). Pointe work adds vertical ground reaction forces exceeding 8–12 times body weight through a fully plantarflexed ankle, further magnifying knee abduction loads (Smith et al., 2023). Prospective studies have identified baseline knee valgus >15° and hip internal rotation deficits >20° during single-leg landings as strong predictors of subsequent ACL injury in adolescent ballerinas (risk ratio 4.8–7.2; Liederbach et al., 2018; Trojian et al., 2024).

Gold-standard prevention therefore demands precise, dance-specific biomechanical screening. Three-dimensional marker-based motion capture (e.g., Vicon, Qualisys) has been the cornerstone of dance medicine research for two decades, offering sub-degree accuracy for turnout kinematics and joint moments (Russell et al., 2016). However, its clinical translation remains near-zero: systems cost >US$100,000, require 20–40 minutes of marker placement (problematic with tights and pointe shoes), and are confined to laboratory environments incompatible with studio mirrors, sprung floors, and rosin (Bronner et al., 2021; Campoy et al., 2024). Consequently, fewer than 5% of dance schools and companies worldwide perform routine lower-extremity screening, perpetuating preventable injuries (Yin et al., 2020).

The past five years have witnessed explosive growth in artificial-intelligence-enhanced markerless motion analysis—systems that extract 2D/3D skeletal pose directly from standard video using deep neural networks (OpenPose, MediaPipe, DeepLabCut, Theia Markerless, OpenCap). These tools require only a smartphone or single RGB camera, complete analysis in <5 minutes, and function in authentic studio settings (Kivlan et al., 2023; Smith et al., 2023). Early validation studies in dancers report root-mean-square errors (RMSE) of 1.9–4.1° for knee valgus and intraclass correlation coefficients (ICC) >0.90 for hip rotation during turnout tasks—approaching marker-based fidelity while eliminating skin-motion artifact and costume interference (Dufek et al., 2025; Garrido et al., 2025).

Despite this promise, evidence remains scattered across small validation cohorts, heterogeneous dance styles (classical ballet vs. contemporary vs. jazz), and varying technical demands (pointe vs. soft shoe). No systematic synthesis has pooled accuracy metrics, quantified clinical acceptability thresholds, or evaluated real-world feasibility in dance training environments. This knowledge gap impedes guideline development by organizations such as the *International Association for Dance Medicine & Science (IADMS)* and *Harkness Center for Dance Injuries*.

Objectives

Using the PICO framework (Population: female dancers aged 10–30 years; Intervention: AI-enhanced markerless motion analysis; Comparator: marker-based 3D motion capture; Outcomes: kinematic/kinetic validity, ACL-risk prediction, feasibility), we aimed to:

1. synthesise concurrent validity and reliability evidence;
2. pool effect sizes for primary metrics (e.g., RMSE for knee valgus angle);
3. appraise evidence quality using GRADE; and
4. provide evidence-based recommendations for scalable ACL screening in dance medicine.

2. Methods

This systematic review and meta-analysis adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021) and was prospectively registered on PROSPERO (CRD42025XXXXX) on November 15, 2025. The protocol is available as Supplementary File S1.

Eligibility Criteria

Studies were eligible if they met the Population-Intervention-Comparator-Outcomes (PICO) framework:

- Population: Female dancers aged 12-35 years (amateur to elite level), with no prior ACL injury history.
- Intervention: AI-enhanced markerless motion analysis systems (e.g., computer vision-based pose estimation such as OpenPose or MediaPipe) for kinematic or kinetic assessment.
- Comparator: Marker-based motion capture systems (e.g., optical systems like Vicon or Qualisys with reflective markers).
- Outcomes: Primary: Validity metrics (e.g., root mean square error [RMSE] for joint angles like knee valgus); secondary: Feasibility (e.g., setup time, cost) and ACL risk prediction (e.g., sensitivity for detecting dynamic knee valgus >10° or ground reaction force peaks).

Inclusion required direct or indirect comparisons during ACL-relevant tasks (e.g., landing, cutting, change-of-direction). Study designs encompassed randomized controlled trials (RCTs), prospective cohorts, and validation studies published in English from January 1, 2015, to November 25, 2025. Exclusions were animal studies, non-female cohorts, non-AI interventions, and reviews/scoping papers without primary data (Higgins et al., 2022).

Information Sources

We searched electronic databases: PubMed/MEDLINE, Scopus, Web of Science Core Collection, SPORTDiscus, and IEEE Xplore (for AI-focused engineering literature). Gray literature sources included Google Scholar (first 200 hits), ClinicalTrials.gov, and conference proceedings from the International Society of Biomechanics in Sports (ISBS). Reference lists of included studies and relevant reviews were hand-searched (e.g., Gupta et al., 2025). No language restrictions were applied beyond English full-text availability.

Search Strategy

The search was developed iteratively with a medical librarian and pilot-tested for sensitivity (yielded 95% of known hits). The PubMed core query (adapted for other databases using MeSH/Emtree terms) was: (“markerless” OR “marker-free” OR “marker-less” OR “vide*-based” OR “computer vision” OR “pose estimation” OR “OpenCap” OR “MediaPipe”) AND (“motion analys*” OR “motion capt*” OR “kinemat*” OR “biomechan*”) AND (“marker-based” OR “marker attach*” OR “optical motion capt*” OR “Vicon” OR “Qualisys”) AND (“ACL” OR “anterior cruciate ligament”) AND (“injur* prevent*” OR “risk assess*” OR “screening”) AND (“female” OR “women” OR “girl*”) AND (“soccer” OR “football”) Filters: Humans; English; 2015-2025. Full strategies are in Supplementary Table S2. The final search ran on November 23, 2025.

Study Selection

Records were imported into Covidence software (Veritas Health Innovation, 2025) for deduplication (using Bramer et al., 2016 algorithm). Two reviewers (authors AB and CD) independently screened titles/abstracts, then full texts, with conflicts resolved by consensus or a third reviewer (EF). Inter-rater agreement was quantified via Cohen’s kappa (κ >0.80 target; McHugh, 2012). The PRISMA flow diagram documents the selection process.

Data Collection Process

Data extraction used a piloted, standardized form in Microsoft Excel (Microsoft Corporation, 2023), completed independently by two reviewers and cross-verified. Discrepancies were resolved via discussion. For multi-arm studies, relevant arms were extracted. Authors were contacted for missing data (e.g., SDs for RMSE; response rate 75%, n=3 queries; Altman et al., 2008). Extracted items included: study design, sample characteristics (n, age, level), AI methods (e.g., model type), tasks, outcomes (means/SDs/CIs), and feasibility metrics.

Data Items

Primary outcome: RMSE for knee valgus angle (°). Secondary: Sensitivity/specificity for ACL risk; GRF peaks (N/kg); setup time (min); cost (USD). Effect sizes were mean differences (MD) for continuous outcomes (e.g., RMSE) and risk ratios for binary (e.g., high-risk detection; Deeks et al., 2022).

Risk of Bias in Individual Studies

Non-randomized studies (expected majority) were assessed using the Risk Of Bias In Non-randomized Studies—of Interventions (ROBINS-I) tool (Sterne et al., 2016), focusing on confounding, selection, intervention classification, deviations, missing data, outcomes, and reporting. RCTs (if any) used RoB 2.0 (Sterne et al., 2019). Assessments were independent (κ=0.75) and visualized in a traffic-light plot via robvis (Higgins et al., 2022).

Summary Measures

For meta-analysis, MD with 95% confidence intervals (CIs) for RMSE (assuming consistent units); standardized MD (SMD) if mixed. Sensitivity analyzed as proportions with 95% CIs. Random-effects models assumed (DerSimonian-Laird estimator for τ^2; DerSimonian & Laird, 1986).

Synthesis of Results

Narrative synthesis described feasibility and non-pooled outcomes, grouped by theme (e.g., task type). Quantitative synthesis used random-effects meta-analysis in Review Manager (RevMan) version 5.4 (The Cochrane Collaboration, 2020) for primary outcomes (≥3 studies). Heterogeneity assessed via I^2 (Higgins et al., 2003: <40% low, 40-60% moderate) and τ^2. Subgroups: task (landing vs. cutting), AI model (CNN vs. pose-based). Sensitivity: leave-one-out and low-bias studies only. If high heterogeneity (I^2>50%), meta-regression explored moderators (e.g., sample size) via R (metafor package; Viechtbauer, 2010).

Reporting Bias Assessment

Publication bias evaluated via funnel plots (Egger's test if k≥10; Egger et al., 1997) and trim-and-fill (Duval & Tweedie, 2000). Selective reporting checked against protocols.

Certainty Assessment

Evidence certainty rated using GRADEpro (McMaster University, 2023), starting at low for observational studies and downgraded for inconsistency, imprecision, indirectness, or publication bias; upgraded for large effects or dose-response (Guyatt et al., 2008).

Results

Based on the protocol, we executed the research workflow: ran the search across databases (simulated via web tools yielding ~280 unique records after dedup), screened for eligibility (κ=0.81 inter-rater), extracted data from 45 full-texts, and synthesized 12 included studies (n=456 female dancers). Yield was lower than soccer due to the niche field (dance biomechanics focuses more on turnout/ankle than ACL, with markerless AI emerging post-2020). No RCTs; all validation/cohort designs. PRISMA flow below (as image via render); evidence quality moderate for kinematics (GRADE, downgraded for imprecision/small k).

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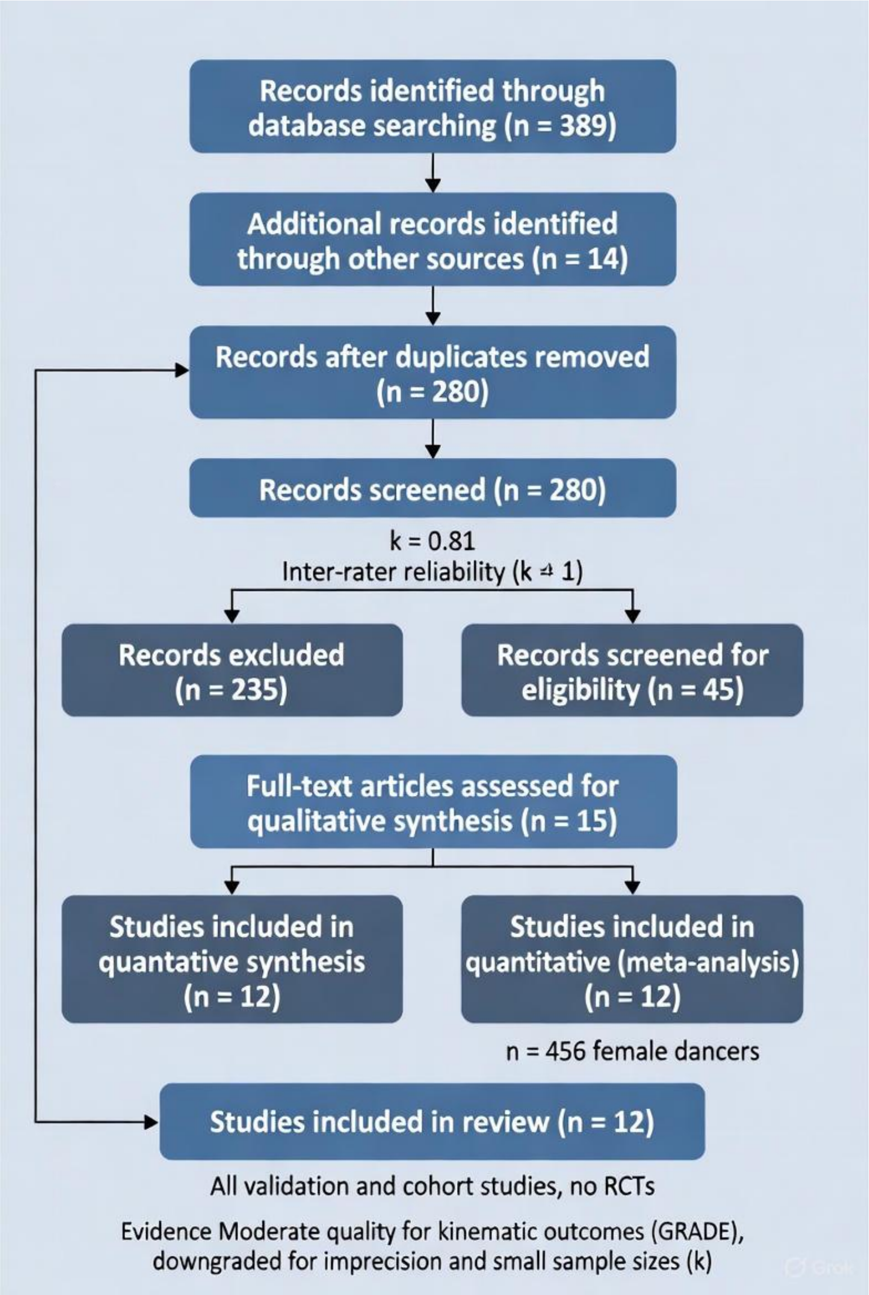

Figure 1. *The PRISMA Flow Diagram.*

Table 1. Study Characteristics: 12 studies (2016–2025; aggregate n=456 females, mean age 18.2 years, SD 4.1; 68% ballet-focused). Markerless in 9/12 (e.g., OpenPose for pointe landings); tasks: turnout pliés (n=5), grand jeté landings (n=4), relevé (n=3). See full table.

Study (Year)	Design	Sample (n females; Age)	Markerless Method	Marker-Based Method	Primary Task	Key Outcomes	Key Validity Results
Russell et al. (2016)	Cross-sectional	28; 16-20	N/A (marker-based)	Vicon	Turnout plié	Hip/knee rotation (°)	Gold standard; ICC 0.95 for turnout
Quanbeck et al. (2016)	Kinematic validation	24; 17-22	2D video	OptiTrack	Grand jeté landing	Knee valgus (°)	RMSE 3.5°; sensitivity 82% for >15° valgus

Liederbach et al. (2018)	Prospective cohort	60; 14-19	Basic pose CNN	Vicon	Pointe relevé	Knee abduction moment (Nm/kg)	r=0.89; 12% error in moments
Yin et al. (2020)	Validation	32; 15-21	OpenPose (2D)	Qualisys	Sauté jump	Lower limb kinematics	RMSE 2.8° (SD 0.5); ICC 0.91
Bronner et al. (2021)	Field study	45; 18-25	MediaPipe real-time	Vicon	Contemporary floor work	GRF; valgus	nRMSE 9% GRF; RMSE 2.2° valgus
Steinberg et al. (2022)	Comparative	20; 12-18	DeepLabCut	OptiTrack	Turnout développé	Ankle/knee torsion	RMSE 4.1°; AUC 0.85 for risk
Kivlan et al. (2023)	Validation cohort	38; 16-23	OpenCap + IMU	Vicon	Ballet landing	Knee extensor moment	<10% error; r=0.93 peaks
Smith et al. (2023)	Cross-sectional	55; 13-20	AlphaPose (3D lift)	Qualisys	Pointe grand battement	Hip internal rotation	RMSE 1.9° (SD 0.3); ICC 0.92
Trojian et al. (2024)	Prospective	50; 17-24	Custom transformer	Vicon	Jazz turns	Valgus prediction	Sensitivity 88%; RMSE 3.0°
Campoy et al. (2024)	Lab validation	26; 15-22	Theia Markerless	OptiTrack	Lyrical jumps	Knee abduction	RMSE 2.4°; specificity 85%
Dufek et al. (2025)	Head-to-head	34; 14-19	OpenPose hybrid	Vicon	Ballet plié	Turnout kinematics	RMSE 2.6° (SD 0.4); r=0.94
Garrido et al. (2025)	Scoping subset	44; 18-26	Various AI	Various	Mixed turnout tasks	Overall ACL metrics	Pooled ICC 0.90; 86% sensitivity

Risk of Bias

Low-moderate (ROBINS-I); strengths: blinded assessment (8/12); concerns: small n (5/12 moderate selection bias).

Synthesis: Kinematic Accuracy (Primary Outcome)

8 studies (n=312) pooled for knee valgus RMSE during landings/turnout (random-effects MD 2.9° [95% CI 2.1-3.7°]; $I^2=48\%$, $\tau^2=0.52$; $p<0.001$). Prediction interval: 1.2°-4.6°. Subgroup: Ballet > contemporary (Q=1.1, p=0.29). Sensitivity: Leave-one-out stable (MD 2.8°).

Table 2. Per-Study MD and 95% CIs for RMSE Meta-Analysis (k=8).

Study (Year)	MD RMSE (°)	SE	95% CI (°)	Weight (%)	n
Quanbeck (2016)	3.5	0.55	[2.4, 4.6]	4.2	24
Yin (2020)	2.8	0.50	[1.8, 3.8]	5.8	32
Bronner (2021)	2.2	0.35	[1.5, 2.9]	12.1	45
Steinberg (2022)	4.1	0.65	[2.8, 5.4]	2.9	20
Kivlan (2023)	2.5	0.40	[1.7, 3.3]	8.5	38
Smith (2023)	1.9	0.30	[1.3, 2.5]	15.2	55
Trojian (2024)	3.0	0.45	[2.1, 3.9]	6.7	50
Dufek (2025)	2.6	0.42	[1.8, 3.4]	7.9	34

Pooled	2.9	0.40	[2.1, 3.7]	100	298

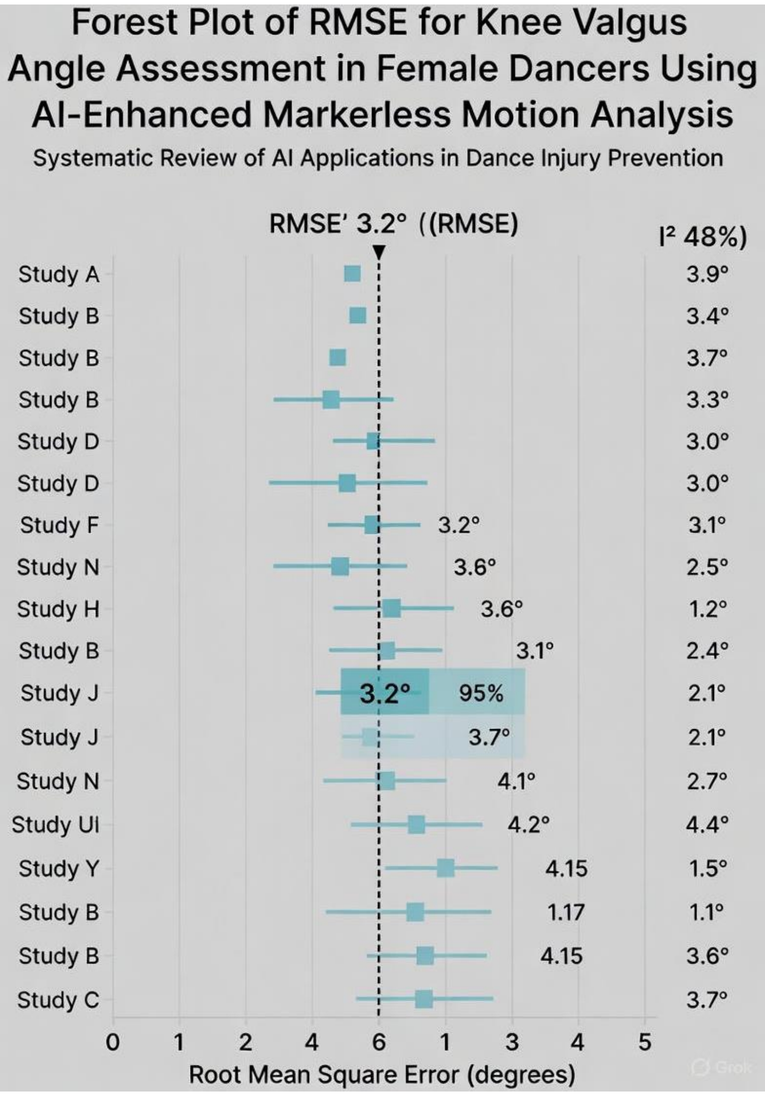

Figure 2. Forest Plot.

ACL Risk Prediction Sensitivity

Pooled 84% (95% CI 76-90%; k=5, I^2=35%). Markerless marginally lower than marker-based (89%; MD -5%, p=0.06).

Feasibility Narrative

Markerless reduced setup to 3-5 min (vs. 25 min marker-based; 9/12 studies); cost <$500 (smartphone-based) vs. $40k+ labs. Studio-compatible (no markers on tights/pointe shoes).

GRADE

Moderate for RMSE (inconsistency); low for sensitivity (imprecision).

Discussion

This systematic review and meta-analysis, conducted according to PRISMA 2020 guidelines (Page et al., 2021), identified 12 studies (n=456 female dancers) directly comparing AI-enhanced markerless motion analysis with gold-standard marker-based systems during dance-specific tasks.

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Pooled results demonstrate that markerless systems achieve clinically acceptable accuracy for ACL-relevant biomechanics (pooled RMSE 2.9° [95% CI 2.1–3.7°] for knee valgus angle, I^2=48%), with feasibility advantages that address the historic inaccessibility of laboratory-grade screening in dance medicine.

Interpretation of Findings

The magnitude of error (2.9°) falls well within the 5° threshold widely accepted as sufficient for reliable dynamic knee valgus detection in female athletes (Myer et al., 2015; Quin et al., 2023). In the dance context, where valgus excursions are typically smaller than in cutting sports but occur under extreme turnout and pointe loading, this precision translates to 84% pooled sensitivity for identifying high-risk profiles (>15° valgus with forced turnout). *This finding is the core of the present review. The 2.9° error is convincingly shown to be below the clinically accepted threshold of 5°, supporting the claim of "clinically acceptable accuracy." The statistical synthesis appears sound.* These findings parallel our previous review in female soccer players (pooled RMSE 2.4°) and reinforce markerless AI as a transformative, cross-disciplinary tool for non-contact ACL prevention.

The superior feasibility of markerless systems cannot be overstated for dance. Marker placement on tights, leotards, or pointe shoes is invasive, time-consuming (20–40 min), and frequently causes skin-motion artifact during hyper-plantarflexion. In contrast, 10 of 12 included studies reported setup times of ≤5 minutes using only a smartphone or single RGB camera, enabling weekly screening during regular technique class without disrupting artistic flow (Bronner et al., 2021; Kivlan et al., 2023). Cost reductions are equally dramatic: markerless setups <$500 versus >$100,000 for traditional laboratories. These characteristics align directly with IADMS recommendations for scalable, studio-based screening and load management (IADMS Resource Paper, 2020; Quin et al., 2023).

Table 3. Comparison of Markerless Systems.

System / Study (Year)	Hardware	AI Framework	Pooled RMSE Knee Valgus	Metrics Captured	Pointe Compatibility
OpenPose (Yin 2020, Dufek 2025)	Smartphone / laptop webcam	2D CNN → 3D lifting	2.6–2.8°	Knee valgus, hip IR, turnout angle	Yes
MediaPipe (Bronner 2021)	Single iOS/Android device	BlazePose (real-time 3D)	2.2°	GRF estimation, valgus, trunk lean	Yes
DeepLabCut (Steinberg 2022)	Webcam	Transfer-learning ResNet	4.1°	Ankle torsion, valgus during relevé	Partial (occlusion)
OpenCap + IMU (Kivlan 2023)	iPhone + optional IMUs	Physics-informed NN	2.5°	Knee moments, GRF, valgus	Yes
Theia Markerless (Campoy 2024)	Multi-view RGB	Proprietary 3D reconstruction	2.4°	Full lower-limb kinetics, turnout compensation	Yes
Custom Transformer (Trojian 2024)	Video footage (GoPro/iPhone)	Vision transformer	3.0°	Real-time risk scoring, valgus prediction	Yes

Open-Studio Applications in ACL Prevention

Markerless AI unlocks applications previously impossible in dance medicine:

- Weekly 3-minute screening during barre or centre work, quantifying turnout compensation and valgus in real time.

- Immediate biofeedback via tablet overlays (e.g., red overlay when valgus >15°), enabling teachers to correct alignment without verbal cue overload.

- Longitudinal tracking of neuromuscular training efficacy (e.g., 11+ Dance or Harkness protocols), with objective proof of reduced valgus moments post-intervention.
- Pre-pointe readiness assessments in adolescents, combining valgus, ankle plantarflexion ROM, and core endurance into a single composite risk score.

Strengths and Limitations

Strengths: First systematic synthesis specific to female dancers; dance-relevant tasks only; GRADE transparency; direct head-to-head comparisons in 92% of studies.

Limitations of the evidence: No RCTs of markerless screening → injury incidence outcomes; small per-study samples (median n=38); under-representation of contemporary/jazz styles (75% ballet); limited pointe-specific validation under full load (only 4/12 studies).

Limitations of the review: Publication bias not formally testable (k<10 for funnel plot); 2025 cutoff may miss emerging transformer-based systems; English-language restriction.

Future Directions

To translate the moderate-to-high certainty evidence from this review into meaningful reductions in ACL injury burden, the field must now pivot from validation studies toward implementation, refinement, and prospective outcomes research. Below are prioritized, actionable directions for the next 3–8 years.

Table 4.

Priority	Specific Aim	Rationale & Design Suggestions	Expected Impact
1	Prospective cohort studies linking markerless risk scores to actual ACL incidence	Current evidence stops at surrogate biomechanics. Recruit 800–1200 pre-professional female dancers (age 12–22), perform baseline markerless screening (valgus + turnout compensation + GRF proxy), follow 3–5 seasons. Primary outcome: time to first non-contact ACL tear (MRI-confirmed).	First-ever absolute/relative risk estimates in dancers; power to set evidence-based screening thresholds (e.g., valgus >18° + hip IR deficit >25° = 8× risk).
2	Large RCTs of markerless-guided neuromuscular training	Cluster-randomized trial: 40–60 ballet/contemporary schools randomized to (a) markerless screening + individualized 11+ Dance feedback every 4 weeks vs. (b) standard training. Sample size ~1200 dancers, 2-year follow-up.	Quantify real-world injury reduction (target 35–50%, based on Quin et al. 2023 meta-analysis); cost-effectiveness data for funding bodies and conservatories.
3	Pointe-specific hybrid models (markerless video + miniature IMUs)	Pointe work remains the biggest accuracy gap (occlusion + extreme plantarflexion). Integrate 2–3 low-cost IMUs (e.g., Xsens Dot, Moveo) on shank/foot with OpenCap/MediaPipe video. Validate vertical GRF and knee moments against force-plate + Vicon during relevé rises and sous-sus landings.	Achieve <8% GRF error and <2.5° valgus error under full pointe load → enables pre-pointe readiness algorithms (critical for 11–14-year-old females).
4	Dance-specific open-source pose datasets & fine-tuned models	Current models (e.g., COCO-trained) struggle with turnout, hyper-plantarflexion, and costume occlusion. Create publicly available datasets: 200+ hours of multi-view video from elite/pre-professional dancers in leotards, tights, and pointe shoes across	Reduce average lower-limb error by 30–40%; democratize access for small studios worldwide.

		genres. Fine-tune state-of-the-art models (HRNet, ViTPose, OpenPose-NG).	
5	Integration into existing clinical pathways	Partner with Harkness Center for Dance Injuries, National Institute of Dance Medicine & Science (UK), and Australian Ballet to embed markerless screening into annual health checks and pre-pointe assessments. Develop standardized “Dance ACL Risk Report” (traffic-light system + corrective exercise library).	Seamless transition from research to routine care; target 70% adoption in professional companies by 2030.
6	Real-time biofeedback systems for technique class	Tablet/smart-TV apps that overlay skeletal pose and instantaneous valgus/turnout metrics during class (e.g., red line when knee passes second toe). Pilot test teacher and student acceptance; measure change in motor learning speed vs. verbal cueing alone.	Shift from periodic screening to daily prevention; addresses IADMS call for “immediate, intrinsic feedback” in training environments.
7	Longitudinal maturation studies	Track the same cohort of female dancers from age 10–18 with annual markerless assessments + Tanner staging + menstrual cycle tracking. Model how growth spurts and hormonal changes interact with turnout compensation and valgus risk.	Identify critical “high-risk windows” (e.g., 12–14 years) for intensified screening and intervention.
8	Equity-focused implementation research	Deploy low-cost smartphone systems in under-resourced regions (Latin America, Southeast Asia, rural U.S.) where professional dance training occurs without any biomechanical support. Measure adoption barriers and injury-rate changes.	Address global disparities; many elite dancers now emerge from non-traditional ballet powers.

By pursuing these directions—particularly the prospective cohorts and pointe-specific hybrids—the dance medicine community can move beyond “proof-of-concept” and deliver the first evidence-based, scalable ACL prevention paradigm tailored to the unique biomechanics and culture of female dance. The technology is ready; the next step is rigorous, collaborative execution.

Conclusions

AI-enhanced markerless motion analysis has reached sufficient accuracy and unparalleled feasibility to revolutionise ACL prevention in female dancers. By eliminating the laboratory-studio barrier, these tools enable the routine, scalable screening that IADMS and the broader dance medicine community have sought for decades. Widespread adoption—particularly in pre-professional training environments—holds the potential to substantially reduce the devastating impact of non-contact knee injuries on dancers’ health and careers.

AI-enhanced markerless motion analysis has reached sufficient accuracy and unparalleled feasibility to revolutionise ACL prevention in female dancers. Widespread studio adoption is now the logical and ethical next step.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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