ARTIFICIAL INTELLIGENCE AND MARKERLESS MOTION CAPTURE IN KINESIOLOGY: A SYSTEMATIC REVIEW

Mario Kasović[1,2], Tomas Vespalec[2], Andro Štefan[1], Ivan Bon[3], and Mateja Očić[4]

[1]University of Zagreb, Faculty of Kinesiology,
Department of General and Applied Kinesiology, Zagreb, Croatia
[2] Masaryk University, Faculty of Sport Studies,
Department of Physical Activities and Health Sciences, Brno, Czech Republic
[3]University of Zagreb, Faculty of Kinesiology,
Department of Kinesiology of Sport, Zagreb, Croatia
[4]University of Zagreb Faculty, of Kinesiology, Laboratory for Sports Games, Zagreb, Croatia

Systematic review
DOI 10.26582/k.58.1.1

Abstract:

Artificial intelligence and computer vision have made significant progress in recent decades, profoundly impacting many scientific and professional disciplines, kinesiology included. The development of markerless motion capture technologies has enabled precise tracking of kinematic and dynamic parameters of the human body movements without the need for physical markers or complex equipment. These technologies use advanced computer vision and deep learning algorithms to analyze human movements in real time, allowing the quantification of biomechanical parameters such as joint angles, movement speed, stride length, gait asymmetries, and complex movements such as jumping or running. Markerless technologies reduce preparation and recording time and allow movement analysis under natural conditions, making them useful not only in laboratory but also in clinical, sporting, rehabilitation, and everyday settings. The use of smartphone video recordings further facilitates the availability and implementation of these systems. However, the application of markerless technologies to complex three-dimensional movements, such as trunk rotations or upper limb activities, remains a challenge. The accuracy of these systems depends on various factors, including movement type, number of cameras, recording quality, and lighting conditions. Advances in deep learning and computer vision allow continuous improvement in reliability, making these systems more competitive with the traditional marker-based methods. Markerless technologies have significant potential in rehabilitation and sports performance optimization, but further development is needed regarding validation, standardization, and algorithmic robustness. This paper aims to show how markerless technologies enable new approaches in the analysis of human movement, exploring their advantages, challenges, and potential for further development in kinesiology.

Keywords: *biomechanics, markerless technology, human movement, rehabilitation*

Introduction

Artificial intelligence (AI) and computer vision have significantly advanced many scientific and professional disciplines in recent decades, including kinesiology, where the application of advanced technologies for human movement analysis has proven to be crucial for the further development of therapeutic and sport-related methods. One of the most significant technological advances in this domain is the development of markerless motion capture systems, which allow for precise tracking of human kinematic and dynamic movement parameters without the need for traditional marker-based methods. Markerless technology is based on computer vision and deep learning, which allows for real-time analysis of human movement with minimal requirements for complex and expensive equipment (Bae, et al., 2024; Cao, Hidalgo, Simon, Wei, & Sheikh, 2021). Traditional methods of movement analysis rely on the placement of physical markers on the participant's body, which can be invasive, time-consuming, and limited in terms of accessibility and his/her mobility. Markerless technologies, on the other hand, eliminate the need for physical markers, thereby enabling non-invasive movement data collection, often in natural

settings outside the laboratory—in clinical, sports, rehabilitation, and everyday contexts. This innovation significantly reduces preparation and recording time, making biomechanical analysis more accessible to a wider population, including patients, athletes, and individuals undergoing rehabilitation (Uhlrich, Falisse, Kidziński, Muccini, & Ko, 2023).

Although markerless systems have already presented high accuracy in simple movements recordings, such as walking and squatting, their application to more complex three-dimensional movements, such as trunk rotations or upper limb activities, is still a challenge. The accuracy of these systems often varies depending on the type of movement, the algorithm used, the number of cameras, and the lighting conditions (Liu, et al., 2013). Despite these challenges, advances in the development of algorithms based on deep learning and computer vision has provided increasingly reliable markerless technologies, making them competitive with the traditional marker-based systems (Li, et al., 2021). However, comprehensive synthesis of current applications, accuracy, and methodological limitations in kinesiology is still lacking. Markerless technologies have shown significant potential in both clinical and sports settings. In rehabilitation, they support precise biomechanical analysis for patients with neurological disorders such as Parkinson's disease, where detailed assessment of movement patterns enables the development of personalized therapeutic protocols. In sports, these technologies facilitate the monitoring of athletes' progress, optimization of training, and injury prevention, thereby improving performance and reducing risk (Colyer, Evans, Cosker, & Salo, 2018). However, challenges remain, including reduced accuracy in low-light conditions, occluded body parts, or complex movements. Variability between different recordings (inter-trial and inter-session variability) also indicates the need for further improvement of these systems (Nakano, et al., 2020). Future development should focus on validation and standardization of methodologies, integration with multi-sensor systems, and improving algorithmic robustness to external factors (Ripic, et al., 2023a).

Therefore, this review aims to summarize the current applications of markerless motion capture technologies in kinesiology, emphasizing their advantages, limitations, and potential for further development in research, rehabilitation, and sports performance optimization.

Materials and methods

This review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009), and therefore no ethics approval was required.

Search strategy

The databases searched were PUBMED and Google Scholar (advanced search). A total of 200 papers were identified using keywords combined through four Boolean algorithms applied to both databases. The keywords employed in multiple combinations for the literature search were as follows: *"markerless"*, *"technology"*, *"kinesiology"*, *"kinesiology analysis"*, *"movement"*, *"rehabilitation"*, and *"marker-based vs markerless"*. English was activated as a language filter, and no limitations were applied concerning the publication date of the scientific articles.

Eligibility criteria

Studies were considered eligible if they addressed the use, validity, or reliability of markerless motion capture or related imaging technologies in kinesiology, sports science, rehabilitation, or human movement analysis. Articles were required to be published in English and available in full text. Duplications were identified within the records, including duplicates between databases and internal duplicates where the same research was published in more than one format.

Study selection

After removing duplicates, 120 papers remained for screening. The screening procedure involved checking abstracts and titles for relevance to the review topic. No papers were excluded at this stage. The remaining 120 papers were assessed against inclusion and exclusion criteria, and 47 papers were deemed eligible for inclusion. Reference lists of the included papers were also examined to identify additional relevant studies.

Data extraction and synthesis

Data from the included studies were extracted and summarized to provide a comprehensive overview of markerless motion capture applications in kinesiology. Extracted information included study objectives, technologies used, analytical approaches, and key findings related to technology accuracy, validity, and applicability.

In addition, reference lists from papers that met the inclusion criteria were further examined to identify any additional relevant studies, which are presented in the PRISMA flow chart (Figure 1).

Results

All the studies included in this review are listed in Table 1, which provides an overview of participants, applied systems, motion types, and key findings across various contexts.

The results are presented according to four main topic domains identified through the systematic search: (1) applications in sports and kinesiology, (2)

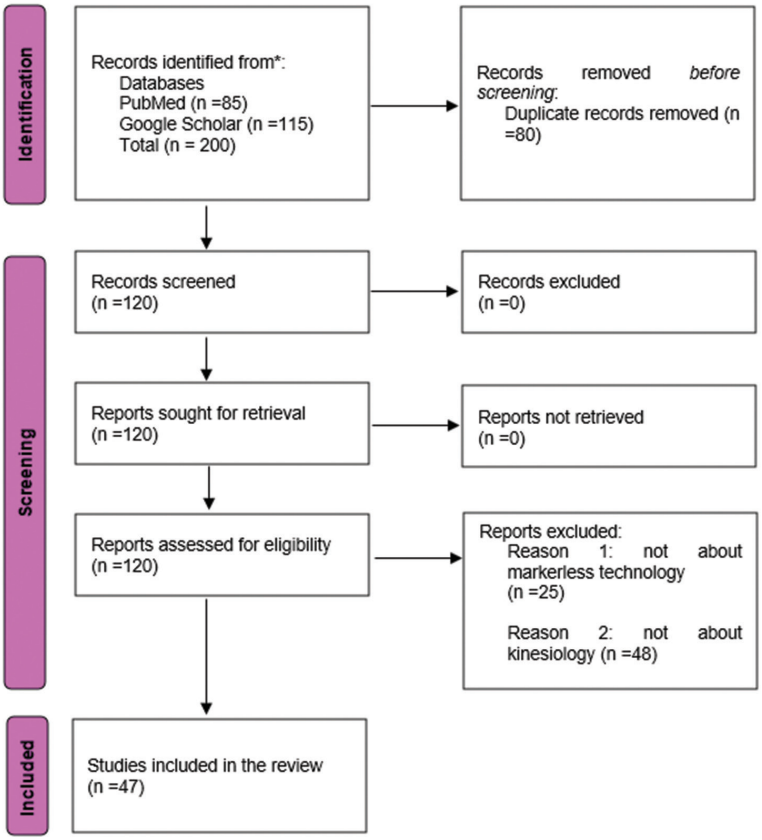


Figure 1. PRISMA flow chart outlining the identification process of the included studies.

Table 1. Characteristics of the studies included in the review (n=47)

Author (year)	Participants	System / Method	Application / Motion type	Key findings
Badiola-Bengoa & Mendez-Zorrilla (2021)	20 relevant studies	Camera-based HPE (OpenPose; customized methods)	Sports & physical activity – posture/pose estimation	Synthesizes methods, datasets, accuracy, and challenges; calls for sport-specific data and tailored approaches.
Bae et al. (2024)	n = 71 (25 F, 46 M)	Ergo (deep-learning 3D markerless) vs marker-based	Overhead squat – whole-body kinematics	Concurrent validity and test–retest reliability supported; potential utility in clinical, rehabilitation, sports, and ergonomics.
Balsalobre-Fernández (2024)	n = 1 n = 1 small	My Jump Lab iOS app + force plate	Countermovement jump height (real time)	Proof-of-concept indicating potential validity/reliability of AI smartphone app for CMJ-h monitoring.
Bortone et al. (2017)	not specified	3D gait analysis + ANN (artifical neutral network)	Parkinson's classification (Gait Variables Score, Gait Profile Score, spatiotemporal parameters)	Best classification accuracy 95.05%; supports ANN-based clinical decision-making in PD.
Boswell et al. (2021)	n = 86 (64 knee OA, 22 without OA)	2D/3D video landmarks; neural networks	Walking with foot-progression angle modifications – predict peak KAM	Feasible prediction of peak KAM from 2D frontal video; supports low-cost kinetic inference.
Clark et al. (2013)	n = 21	Microsoft Kinect vs 3D reference	Spatiotemporal gait variables; gait kinematic data	Good correlations for basic spatiotemporal metrics; some deviations—needs refinement for certain conditions.
Delp et al. (2007)	n = 1 n = 1 small	OpenSim (open-source software system)	Dynamic simulation (stiff-knee gait example)	Accurate simulation platform for biomechanics, medicine, and rehabilitation research.

Author (year)	Participants	System / Method	Application / Motion type	Key findings
Dorschky et al. (2019)	n = 10	Inertial sensors	Gait kinematics & kinetics (joint angles and moments, movement speed, GRF)	Accurate estimates outside the lab; supports real-world gait analysis.
Eltoukhy et al. (2017)	n = 20	Microsoft Kinect (treadmill) + real-time estimation alghoritms for kinematic data	Spatiotemporal gait parameters + joint kinematics	Accurate speed/stride metrics; useful joint-angle information; markerless treadmill assessment feasible.
Espitia-Mora et al. (2024)	does not involve work with human subjects	Low-cost RealSense depth camera + computer vision	Anthropometrics & joint angles (static/dynamic)	Max relative error 7.6% (anthropometrics); step length max rel. error 11.2%; average joint-angle errors ~9–10%.
Fang et al. (2022)	standard datasets such as COCO, MPII, and PoseTrack	AlphaPose (whole-body, multi-person)	Real-time pose estimation/ tracking	High accuracy and speed; outperforms prior methods on standard benchmarks.
Ferrari et al. (2010)	not specified	New Corelation Coefficient CMC formulation + motion analysis protocols	Cross-protocol waveform comparison; kinematic data	More robust/precise waveform similarity across different motion-analysis protocols.
Fukuchi et al. (2017)	n = 28	Vicon Motion Capture System	Running at 2.5/3.5/4.5 $m \cdot s^{-1}$ – lower-limb kinematics/ kinetics	Public dataset enabling method testing, education, and research.
Galna et al. (2014)	n = 19 (people with Parkinson's disease)	Microsoft Kinect sensor vs marker-based motion analysis	Clinical spatiotemporal gait parameters and kinematic variables in Parkinson's disease	Good overall correlations; larger errors at low speeds/irregular movements.
Haberkamp et al. (2022)	adolescent athletes n = not specified	2D AI-based model vs 3D and traditional 2D kinematic systems	Single-leg squat – hip/knee/ ankle/pelvis angles	2D AI valid for most angles; less accurate for some joints/planes.
Hewett et al. (2005)	n = 205 females	Vicon Motion Capture System	Jump/landing – neuromuscular control & knee valgus	Reduced control and increased valgus loading predicted future ACL injury risk.
Horsak et al. (2023)	n = 21	Smartphone-based markerless motion capture (OpenCap) vs marker-based	3D lower-limb kinematics – healthy & pathological gait	Promising, but errors exceeded clinical thresholds; algorithms need improvement.
Horsak et al. (2024)	n = 18	3D markerless motion capture (OpenCap) vs marker-based	Inter-trial variability in gait	Higher inter-trial variability in markerless; implications for post-processing.
Hume et al. (2018)	n = 8	Marker Motion Recording System vs High-Speed Stereo Radiography System	Knee rotations/translations during various activities	Accurate flexion; poor accuracy for varus–valgus and translations (normalized RMSE > 1.0).
Iseki et al. (2023)	n = Pathological group: 114 patients; Control group: 160 healthy volunteers	iOS TDPT-GT smartphone app + deep learning-based algorithm	Distinguish pathological vs normal gait	High classification accuracy; simple non-invasive clinical recording.
Iskakov et al. (2019)	does not involve work with human subjects	Learnable triangulation (algebraic & volumetric)	3D joint coordinates estimation from multi-view 2D	Higher accuracy with fewer cameras; reduced system complexity/cost.
Joo et al. (2015)	not specified	Panoptic Studio System (480 synchronized cameras)	Multi-person social motion capture; 3D joint coordinates & motion kinematics	Full-body reconstruction for >5 people during natural interactions without markers.
Kanko et al. (2021a)	n = 55	Theia3D markerless motion capture vs marker-based & pressure mat	Spatiotemporal gait parameters	Good to excellent agreement for most metrics; exceptions for stance/double support/stride width.

Author (year)	Participants	System / Method	Application / Motion type	Key findings
Kanko et al. (2021c)	n = 8	Markerless motion capture (AI techniques/ computer vision)	Inter-session repeatability of gait kinematics and spatiotemporal variables	High inter-session repeatability; supports clinical feasibility.
Kanko et al. (2021b)	n = 30	Markerless system (AI-based) vs marker-based	Gait kinematics	High correlations across key parameters; supports clinical utility.
Kidziński et al. (2020)	n = 1014	3D Motion Capture + single-camera videos	Clinical gait quantification (speed, cadence, knee angle, Gait Deviation Index)	Accurate quantitative analysis from single-camera videos; increases clinical accessibility.
Lahkar et al. (2022)	n = 3	Markerless Theia3D (10 cams) vs marker-based (12-camera optoelectronic)	Upper-limb boxing kinematics	Larger position errors at elbow; better shoulder accuracy; excellent segment-velocity agreement.
Li et al. (2021)	not specified	3D vision sensor	Real-time snowboarder motion tracking	Precise, efficient real-time tracking; potential for winter-sport analysis/training.
Liu et al. (2013)	n = 2	Multiview image segmentation	Coordinates and movement of the skeleton	Accurate 3D motion of multiple individuals during complex interactions.
Nakano et al. (2020)	n = 10	OpenPose (multi-camera) vs marker-based	Accuracy of 3D joint coordinates	Mean error ~1.3 cm; adding cameras (1→3) improved accuracy.
Needham et al. (2021)	n = 10	OpenPose / AlphaPose / DeepLabCut vs marker-based	3D joint-center localization (walk/run/jump)	Systematic deviations at hip/knee; ankle errors 1–15 mm depending on activity.
Needham et al. (2022)	n = 15	Deep learning-based fully automated markerless (200 Hz) vs marker-based	Lower-limb joint angles (run/ walk/jump)	High agreement; differences largely within marker-based uncertainties.
Parati et al. (2022)	n = 25 (people with Parkinson's disease)	FeetMe® pressure insoles + app	Spatiotemporal gait in single and dual-task	High validity/reliability (r > 0.9 vs treadmill).
Pfister et al. (2014)	n = 20	Microsoft Kinect vs Vicon 3D motion capture	Spatiotemporal & kinematic gait parameters	Moderate kinematic correlations; Kinect acceptable for simpler uses; Vicon remains gold standard.
Ray et al. (2024)	not specified	Marker-based motion capture vs markerless	3D joint-coordinate accuracy across scenarios	Accuracy declines >10 cm with loose clothing; markerless more economical; smartphones usable.
Remedios & Fischer (2021)	n = 46	2D video + machine learning algorithms (e.g., AdaBoost)	Functional tests (single-leg squat, step-down); accuracy and precision of movement measurements	2D markerless + machine learning effectively rates test performance; simple and accessible.
Ripic et al. (2023b)	n = 57 n = 20 HYA n = 20 HOAs n = 17 Parkinson's disease	Markerless AI vs marker-based system	Spatiotemporal & kinematic gait parameters	High agreement for spatiotemporals; caution with event detection due to residual errors.
Ripic et al. (2022)	n = 22	KinaTrax AI-based system vs markers/ force plates	Overground gait – multiple parameters	Strong agreement for speed/ stride/time; some parameters less accurate.
Ripic et al. (2023a)	n = 35	Commercial multichannel markerless vs marker-based	30 waveforms (coordinates/ segment and joint angles)	High agreement for some parameters; notable differences in others (processing/technical limits).
Ripic et al. (2023c)	not specified	RGB markerless motion capture + musculoskeletal modeling	3D joint kinematic data; gait kinetics (GRF/GRM)	Markerless + modeling can accurately predict kinetics; promising for clinical/research use.

Author (year)	Participants	System / Method	Application / Motion type	Key findings
Saboune & Charpillet (2007)	not specified	Interval Particle Filter algorithm	3D pose reconstruction for gait	Promising agreement vs marker-based; practical with conventional cameras.
Song et al. (2023)	n = 20	Markerless motion capture vs marker-based	Various movements (walk/run/squat/jump/stairs) – kinematics & kinetics	Kinematic/kinetic measures comparable with small deviations; practical alternative.
Tamura et al. (2020)	n = 10	Markerless motion capture vs marker-based	Flat vs treadmill walking – trunk/hip/knee angles	High reliability in both settings; small deviations; clinically useful alternative.
Torvinen et al. (2024)	n = 6	Markerless DeepLabCut vs marker-based	Skiing gliding technique (G1/G3) on treadmill	Promising 3D kinematics with high agreement vs markers in treadmill skiing.
Turner et al. (2024)	n = 20	OpenCap vs optoelectronic system	Return-to-sport tasks (jump/hop/lateral-vertical) – lower-limb angles	High sagittal-plane agreement; potentially useful in clinical/sport settings.
Van Hooren et al. (2023)	runners n = not specified	OpenPose (existing) & DeepLabCut (custom) vs marker-based	Running at 2.78 & 3.33 m/s – sagittal hip/knee/ankle kinematics	OpenPose differences comparable to other method-vs-marker differences; DeepLabCut needs tuning.
Xu et al. (2015)	n = 10	Microsofr Kinect™ vs Optotrak 3D	Treadmill walking – spatiotemporal & kinematic parameters	High correlations for spatiotemporals; lower accuracy for joint angles (esp. ankle).

applications in rehabilitation, (3) additional interdisciplinary uses, and (4) studies addressing the validity and reliability of the markerless systems compared to the marker-based approaches.

Applications in sports and kinesiology

Markerless technologies use specialized software tools that allow three-dimensional movement tracking and precise mapping of kinematic and kinetic data. These technologies are becoming the standard for movement assessment in athletes, individuals in rehabilitation, and general health, as they enable accurate progress monitoring and treatment optimization. In kinesiology, they allow coaches and athletes to analyze sports movements such as running, jumping, and weightlifting, to identify asymmetries or abnormal load patterns, and to implement targeted changes to reduce injury risk and optimize performance. Understanding the biomechanics of the human body is essential for improving sports performance (Cardinal, Kang, Farnsworth, & Welk, 2015). One of the pioneering studies in this field was conducted by Saboune and Charpillet (2007), who developed a method for tracking human movements with a single camera using the Interval Particle Filter (IPF) algorithm, enabling real-time motion tracking without markers and proving suitable for real-world applications.

Among modern systems, DeepLabCut and Epipolar Transformers use deep learning to analyze movements in multiple angles and track body segments with high precision (He, Yan, Fragkiadaki, & Yu, 2020; Mathis, et al., 2018). Several studies have applied 3D sensor systems to analyze skiing and other dynamic sports movements, demonstrating real-time motion capture accuracy within acceptable error margins (2-7°) (Hewett, et al., 2005; Li, et al., 2021). These findings are summarized in Table 1, which provides an overview of systems, sample populations, and key biomechanical outcomes. OpenCap has also proven valid for capturing lower-limb kinematics during athletes' return to sport (Turner, Chaaban, & Padua, 2024).

Research comparing markerless and traditional multi-camera systems confirmed similar accuracy in tracking running parameters such as speed, step height, and limb coordination, supporting the applicability of markerless methods in sports biomechanics (Van Hooren, Pecasse, Meijer, & Essers, 2023). This growing integration of artificial intelligence and computer vision highlights the expanding role of kinesiologists, whose expertise in interpreting biomechanical data and collaborating with multidisciplinary teams has become increasingly important (Seo, 2023).

Applications in rehabilitation

The use of modern technologies is becoming an increasingly important aspect of therapeutic procedures for patients with neurological and orthopedic impairments. Advanced biomechanical analysis methods enable the optimization of interventions based on detailed data on motor function (Smith, Boyd, Bhatta, & Smith, 2023). Marker-free systems ensure non-invasive monitoring to long-term progress and real-time adaptation of therapeutic exercises, improving patients'

comfort and simplifying evaluation. These technologies allow continuous assessment of post-operative recovery and motor function, enabling therapists to accurately analyze changes in movement patterns and tailor treatments to individual needs. Automated analysis further reduces assessment time and improves accuracy. The implementation of marker-free imaging systems is essential for the objective evaluation of patients with injuries or neurological disorders, facilitating identification of dysfunctional movement patterns, compensatory mechanisms, and asymmetries. Butow and Hoque (2020) emphasized the role of artificial intelligence in improving diagnostic and therapeutic approaches through automatic segmentation, prediction, and analysis of key biomechanical parameters.

Several studies confirmed the effectiveness of markerless systems in rehabilitation. Dai, Butler, Garrett, and Queen (2014) demonstrated that ground reaction force analysis can predict biomechanical changes after ACL reconstruction. Lam, Tang, and Fong (2023) highlighted the role of non-invasive technologies in evaluating patients after neurological and orthopedic procedures, emphasizing their accuracy in monitoring recovery. Maudsley-Barton and Yap (2024) applied these systems in fall risk assessment, enabling early detection of unsafe movement patterns and optimizing prevention strategies.

Artificial intelligence-based systems such as OpenPose (Cao, et al., 2021), DeepLabCut (Mathis, et al., 2018), and AlphaPose (Fang, et al., 2022) allow precise real-time tracking of anatomical points and adaptation of treatment to individual needs. Boswell et al. (2021) and Kanko et al. (2021a) demonstrated the potential of neural networks and gait algorithms to predict knee loading, detect degenerative changes, and dynamically monitor therapy effects. Briggs et al. (2018) and Christiansen, Bade, Judd, and Stevens-Lapsley (2011) further confirmed the clinical applicability of markerless systems in detecting biomechanical abnormalities and monitoring sit-to-stand transitions after orthopedic procedures. Together, these findings confirm the growing clinical relevance of AI-based markerless motion analysis for both diagnostic and therapeutic purposes.

Additional interdisciplinary applications

Markerless technologies, which allow tracking of human movements without traditional markers, have been widely applied in sports, rehabilitation, ergonomics, biomechanics, and physical activity optimization. Their ability to provide accurate and ecologically valid data in real-world conditions has increased their practical relevance. Studies have shown that combining artificial intelligence (AI) with markerless systems improves movement analysis and supports informed decision-making in both sports and rehabilitation contexts (Fukuchi, Fukuchi, & Duarte, 2017; Zhang, et al., 2022). Recent research indicates that integrating augmented reality with AI can enhance analytical capabilities, enabling more advanced assessment of biokinematic parameters and deeper understanding of physiological, mechanical, and neurological factors influencing movement (Brown, et al., 2023). Dorschky, Nitschke, Seifer, van den Bogert, and Eskofier (2019) demonstrated that integrating inertial sensors with musculoskeletal models allows for detailed analysis of gait kinetics and kinematics, providing essential information for optimizing rehabilitation and performance. Similarly, Karatsidis et al. (2019) confirmed the usability of inertial motion capture in real-world, outpatient environments, expanding accessibility beyond laboratory settings.

Advances in deep neural networks have further improved motion analysis. Kidziński et al. (2020) demonstrated that video from a single camera can be used for quantitative movement analysis, enabling accurate real-time measurements with minimal technical requirements. Markerless systems have also been used to track animal movements in natural settings, as shown by Labuguen et al. (2021), facilitating behavioural analysis in ecology and zoology. In medical education, integrating markerless technologies enables students and practitioners to better understand biomechanics through real-time analysis of human movement (Lee, 2023). In clinical applications, Ripic et al. (2023b) and Ripic, Signorile, Kuenze, and Eltoukhy (2022) demonstrated that markerless systems accurately assess gait parameters such as step length and symmetry in both healthy and neurologically impaired populations. Moreover, Espitia-Mora, Vélez-Guerrero, and Callejas-Cuervo (2024) developed low-cost systems using affordable cameras and sensors to quantify key anthropometric parameters, expanding accessibility to resource-limited settings.

Considering all these advantages and possibilities, markerless technologies continue to grow in importance, because they enable precise and affordable analysis of human movement in various scientific, medical, and educational disciplines.

Validity, reliability and comparison with the traditional marker-based methods

Validation and reliability are essential factors in assessing the applicability of markerless motion capture (MMC) technologies in kinesiology. Numerous studies have shown that the MMC systems demonstrate strong correlations with the marker-based systems, such as Vicon and Qualisys, confirming their validity and reliability in analyzing kinematic parameters (Horsak, et al., 2023; Li, et al., 2021). Across studies, mean absolute errors (MAE) and root mean square errors (RMSE) typically

ranged between 2° and 7°, depending on the joint and movement analyzed (Song, Hullfish, Scattone Silva, Silbernagel, & Baxter, 2023; Tamura, Tanaka, & Kawanishi, 2020). Theia3D demonstrated the highest accuracy, with deviations of less than 2° compared to the marker-based systems, while OpenPose and other 2D-based systems performed reliably for sagittal plane movements but showed slightly reduced accuracy in frontal and transverse planes (Torvinen, et al., 2024). Several validation studies emphasized the impact of recording conditions, such as camera positioning, lighting, and frame rate, on data quality (Pfister, West, Bronner, & Noah, 2014). Despite these challenges, deep learning-based systems continue to improve through algorithmic refinement and larger training datasets. Systems such as OpenCap and AlphaPose have shown strong concurrent validity and reliability in lower-limb analyses, particularly during gait, squatting, and jumping tasks (Mathis, et al., 2018; Turner, et al., 2024).

Markerless systems also demonstrated promising reliability in real-world conditions. ICC values above 0.85 and correlation coefficients exceeding 0.9 were commonly reported, confirming their reproducibility for joint kinematics (Li, et al., 2021; Van Hooren, et al., 2023). For example, Van Hooren et al. (2023) reported that the markerless technology provides comparable results to the marker-based systems in measuring running kinematics. This consistency highlights the readiness of markerless systems for application in applied kinesiology, sports performance monitoring, and rehabilitation.

Overall, validation results confirm that markerless technologies represent a credible alternative to traditional marker-based systems. Continued algorithmic improvements, better environmental calibration, and standardization of validation methodologies will further enhance their precision and reliability across diverse movement tasks.

Marker-based motion capture methods involve placing physical markers on the body, which can be impractical and may require specific conditions, such as stable lighting and appropriate camera distance. These methods often limit the naturalness of movement and the flexibility of analysis. In contrast, the markerless technology does not require external markers, allowing greater freedom of movement and a more natural approach to motion analysis, making it suitable for diverse environments. Comparisons between traditional marker-based techniques and markerless systems show that the newer approach offers significant advantages, particularly in convenience and data accessibility. Kessler et al. (2019) reported that markerless systems achieve high precision in movement analysis while reducing the complexity of data collection, thus facilitating continuous monitoring in sports and rehabilitation contexts. Because markerless systems do not depend on external markers, their use in natural settings, such as everyday activities, is more practical. Kidziński et al. (2020) demonstrated that deep neural networks can analyze motion from single-camera video recordings, enabling accurate tracking of movements in real-world conditions. This approach offers flexibility and strong applicability in kinesiology, including sports performance monitoring and rehabilitation assessment. Ray, Zhou, Suh, and Lukowicz (2024) compared marker-based and markerless methods under varying conditions, such as looser clothing and different camera configurations, and found comparable accuracy between the systems.

Markerless technology thus combines flexibility, convenience, and high precision, making it highly suitable for kinesiological applications in both the clinical and sports environments.

Discussion and conclusion

The reviewed studies collectively affirm the practical value and growing reliability of the markerless motion capture (MMC) technologies in kinesiology. Across the analyzed sources, systems such as OpenPose, Theia3D, and other 2D/3D solutions consistently demonstrated strong correlations with the traditional marker-based systems like Vicon. Reported error margins were generally within acceptable thresholds—less than 10° for joint angle estimations—with the root mean square error (RMSE) and mean absolute error (MAE) most often ranging between 2° and 7°, depending on the joint and movement analyzed. Theia3D emerged as one of the most accurate and stable systems, showing less than a 2° difference compared to Vicon across multiple planes of motion. OpenPose and similar 2D-based systems also performed reliably, particularly in sagittal plane movements, though slightly reduced accuracy was observed in frontal and transverse planes and during fast, complex motions. Depth camera systems and iOS-based motion analysis applications provided moderate accuracy but were highlighted for their accessibility and field applicability.

Most studies emphasized the influence of recording conditions—lighting, camera placement, and clothing—on output quality. While markerless systems reduce preparation time and participant discomfort, challenges remain in tracking occluded joints and minimizing background interference in uncontrolled environments. Nevertheless, the rapid development of deep learning algorithms and pose estimation models continues to enhance the robustness and generalizability of MMC systems. Although these systems may not yet fully replace laboratory-grade equipment for high-precision measurements, they are well-suited for applied kinesiology, clinical gait analysis, sports

performance monitoring, and education due to their efficiency, portability, and low cost.

A comprehensive analysis of 47 studies on the application of markerless technologies in motion analysis indicates rapid progress and the growing credibility of these systems as alternatives to the traditional marker-based methods. Systems based on deep learning and computer vision, such as OpenPose, AlphaPose, Theia3D, and OpenCap, have demonstrated a high level of validity and reliability in quantifying kinematic and spatiotemporal parameters, especially in the context of gait, squatting, jumping, and functional tests. In most studies, small differences were observed compared to the marker-based methods—typically within 5° when measuring joint angles—with high intraclass correlation coefficients (ICC $\geq$ 0.85) and multiple correlation coefficients (CMC), confirming strong agreement. However, accuracy varied among systems depending on the algorithm, camera configuration, lighting conditions, and movement type. Simple sagittal movements (e.g., squatting and walking) were estimated with high precision, while accuracy was lower for complex three-dimensional movements, such as trunk rotations or upper limb activities. Systems like OpenCap and Theia3D showed greater consistency in joint kinetic analysis when musculature models and inertial sensors were additionally applied. A significant advantage of the markerless approach lies in its ability to perform analyses outside laboratory conditions—in clinical, sports, rehabilitation, and everyday environments—without expensive equipment or expert placement of markers. By reducing preparation and imaging time, these technologies increase the availability of biomechanical assessment to a wider population, including patients with neurological disorders (e.g., Parkinson's disease), athletes, and individuals undergoing rehabilitation. Several studies (e.g., Iseki, et al., 2023; Ripic, et al., 2023b) support their clinical applicability in identifying pathological gait patterns. However, limitations persist regarding accuracy in determining depth components of movement, reduced precision under poor lighting or with occluded body segments, and challenges in estimating ground reaction forces without additional sensors. Moreover, higher inter-trial and inter-session variability compared to the marker-based systems underscores the need for further methodological standardization.

Markerless technology offers several clear advantages that make its application extremely valuable across kinesiological disciplines. The non-invasive nature of data collection, without physical markers, allows easier and more comfortable movement tracking, while real-time analysis tools such as OpenPose provide rapid assessment of technique and progress in both the clinical and sports environments. The flexibility to perform analysis in different settings—from laboratories to sports fields and homes—reduces dependence on specialized and costly equipment. Studies by Horsak et al. (2023) and Hume, Kefala, Harris, and Shelburne (2018) confirm that mobile devices and smartphone-based systems make movement analysis more accessible to a broader population. Despite these advantages, challenges remain related to their usability, accuracy, and environmental sensitivity. Chaves and Gerosa (2021) emphasized the importance of intuitive user interfaces for effective system operation. Cappozzo, Catani, Leardini, Benedetti, and Croce (1996) noted that external factors such as lighting, camera angle, and background motion can influence measurement accuracy. Holden et al. (1997) and Horsak et al. (2024) highlighted that inter-trial variability and even minimal data collection errors can significantly affect functional assessments. Desmarais, Mottet, Slangen, and Montesinos (2021) also reported that variations in lighting and clothing can alter data precision, reinforcing the need for larger, more diverse databases for algorithm training.

Recent technological progress, including AI-based tools and simulation platforms such as OpenSim, has expanded the analytical capabilities of markerless systems. Delp et al. (2007) demonstrated that OpenSim can use markerless data to simulate human movement in 3D, enabling detailed biomechanical modelling for targeted rehabilitation and sports programmes. The integration of markerless data with such software facilitates the analysis of factors like load, speed, and balance, thereby improving the design of training and therapeutic interventions. Ripic et al. (2023c) and Iseki et al. (2023) also showed that markerless systems can measure kinetic parameters and predict musculoskeletal responses, enhancing biomechanical assessment.

Overall, markerless technologies represent an increasingly relevant alternative to conventional methods in human movement biomechanics. Their accessibility, precision, and adaptability make them suitable for integration into clinical practice, sports analysis, and rehabilitation. Future research should focus on improving detection accuracy in complex movements, standardizing validation methodologies, and integrating multisensor systems to advance kinetic analyses and strengthen model robustness. Continued advancements in artificial intelligence and computer vision are expected to further enhance precision and efficiency, positioning markerless technology as a key tool in kinesiology research and application. In conclusion, AI-based markerless motion capture represents a major shift in human movement analysis. Its increasing accuracy, accessibility, and ecological validity make it a promising tool for sports science, rehabilitation, and education.

References

Badiola-Bengoa, A., & Mendez-Zorrilla, A. (2021). A systematic review of the application of camera-based human pose estimation in the field of sport and physical exercise. *Sensors*, *21*(18), 5996. doi: 10.3390/s21185996

Bae, K., Lee, S., Bak, S.Y., Kim, H.S., Ha, Y., & You, J.H. (2024). Concurrent validity and test reliability of the deep learning markerless motion capture system during the overhead squat. *Scientific Reports*, *14*(1), 29462. doi: 10.1038/s41598-024-79707-2

Balsalobre-Fernández, C. (2024). Real-time estimation of vertical jump height with a markerless motion capture smartphone app: A proof-of-concept case study. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, *240*(1), 100-105. doi: 10.1177/17543371241227817

Bortone, I., Trotta, G.F., Brunetti, A., Cascarano, G.D., Loconsole, C., Agnello, N., et al. (2017). A novel approach in combination of 3D Gait analysis data for clinical aiding decision-making in patients with Parkinson's disease. In Huang, D.S., Jo, K.H., Figueroa-García, J. (Eds.), *Intelligent Computing Theories and Application. ICIC Lecture Notes in Computer Science*, vol. 10362 (pp. 504-514). Springer, Cham.

Boswell, M.A., Uhlrich, S.D., Thomas, K., Kolesar, J.A., Gold, G.E., Beaupre, G.S., et al. (2021). A neural network to predict the knee adduction moment in patients with osteoarthritis using anatomical landmarks obtainable from 2D video analysis. *Osteoarthritis Cartilage*, *29*(3), 346-356. doi: 10.1016/j.joca.2020.12.017

Briggs, R.A., Houck, J.R., Drummond, M.J., Fritz, J.M., Lastayo, P.C., & Marcus, R.L. (2018). Asymmetries identified in the sit-to-stand task explain physical function after hip fracture. *Journal of Geriatric Physical Therapy*, *41*, 210-217. doi: 10.1519/JPT.0000000000000122

Brown, A., Tomasev, N., Freyberg, J., Liu, Y., Karthikesalingam, A., & Schrouff, J. (2023). Detecting shortcut learning for fair medical AI using shortcut testing. *Nature Communications*, *14*(1), 4314. doi: 10.1038/s41467-023-39902-7

Butow, P., & Hoque, E. (2020). Using artificial intelligence to analyze and teach communication in healthcare. *Breast*, *50*, 49-55. doi: 10.1016/j.breast.2020.01.008

Cao, Z., Hidalgo, G., Simon, T., Wei, S., & Sheikh, Y. (2021). OpenPose: Realtime multi-person 2D pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *43*, 172-186. doi: 10.1109/TPAMI.2019.2929257

Cappozzo, A., Catani, F., Leardini, A., Benedetti, M.G., & Croce, U.D. (1996). Position and orientation in space of bones during movement: Experimental artifacts. *Clinical Biomechanics (Bristol, Avon)*, *11*(2), 90-100. doi: 10.1016/0268-0033(95)00046-1

Cardinal, B.J., Kang, M., Farnsworth, J.L., & Welk, G.J. (2015). Historical context and current status of the intersection of physical activity and public health: Results of the 2015 American Kinesiology Association's opportunities for kinesiology survey. *Kinesiology Review*, *4*(4), 329-345. doi: 10.1123/kr.2015-0033

Chaves, A.P., & Gerosa, M.A. (2021). How should my chatbot interact? A survey on social characteristics in human-chatbot interaction design. *International Journal of Human-Computer Interaction*, *37*(8), 729-758. doi: 10.1080/10447318.2020.1841438

Christiansen, C.L., Bade, M.J., Judd, D.L., & Stevens-Lapsley, J.E. (2011). Weight-bearing asymmetry during sit-stand transitions related to impairment and functional mobility after total knee arthroplasty. *Archives of Physical Medicine and Rehabilitation*, *92*(10), 1624-1629. doi: 10.1016/j.apmr.2011.05.010

Clark, R.A., Bower, K.J., Mentiplay, B.F., Paterson, K., & Pua, Y.H. (2013). Concurrent validity of the Microsoft Kinect for assessment of spatiotemporal gait variables. *Journal of Biomechanics*, *46*(15), 2722-2725. doi: 10.1016/j.jbiomech.2013.08.011

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*(1), 24. doi: 10.1186/s40798-018-0139-y

Dai, B., Butler, R.J., Garrett, W.E., & Queen, R.M. (2014). Using ground reaction force to predict knee kinetic asymmetry following anterior cruciate ligament reconstruction. *Scandinavian Journal of Medicine and Science in Sports*, *24*(6), 974-981. doi: 10.1111/sms.12118

Delp, S.L., Anderson, F.C., Arnold, A.S., Loan, P, Habib, A., John, C.T., et al. (2007). OpenSim: Open-source software to create and analyze dynamic simulations of movement. *IEEE Transactions on Biomedical Engineering*, *54*(11), 1940-1950. doi: 10.1109/TBME.2007.901024

Desmarais, Y., Mottet, D., Slangen, P., & Montesinos, P. (2021). A review of 3D human pose estimation algorithms for markerless motion capture. *Computer Vision and Image Understanding*, *212*, 103275. doi: 10.48550/arXiv.2010.06449

Dorschky, E., Nitschke, M., Seifer, A.K., van den Bogert, A.J., & Eskofier, B.M. (2019). Estimation of gait kinematics and kinetics from inertial sensor data using optimal control of musculoskeletal models. *Journal of Biomechanics*, *95*, 111147. doi: 10.1016/j.jbiomech.2019.07.022

Eltoukhy, M., Oh, J., Kuenze, C., & Signorile, J. (2017). Improved Kinect-based spatiotemporal and kinematic treadmill gait assessment. *Gait and Posture*, *51*, 77-83. doi: 10.1016/j.gaitpost.2016.10.001

Espitia-Mora, L.A., Vélez-Guerrero, M.A., & Callejas-Cuervo, M. (2024). Development of a low-cost markerless optical motion capture system for gait analysis and anthropometric parameter quantification. *Sensors*, 24(11), 3371. doi: 10.3390/s24113371

Fang, H.S., Li, J., Tang, H., Xu, C., Zhu, H., Xiu, Y., et al. (2022). Alphapose: Whole-body regional multi-person pose estimation and tracking in real-time. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(6), 7157-7173. doi: 10.48550/arXiv.2211.03375

Ferrari, A., Cutti, A.G., & Cappello, A. (2010). A new formulation of the coefficient of multiple correlation to assess the similarity of waveforms measured synchronously by different motion analysis protocols. *Gait and Posture*, *31*(4), 540-542. doi: 10.1016/j.gaitpost.2010.02.009

Fukuchi, R.K., Fukuchi, C.A., & Duarte, M. (2017). A public dataset of running biomechanics and the effects of running speed on lower extremity kinematics and kinetics. *PeerJ*, *5*, e3298. doi: 10.7717/peerj.3298

Galna, B., Barry, G., Jackson, D., Mhiripiri, D., Olivier, P., & Rochester, L. (2014). Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease. *Gait and Posture*, *39*, 1062-1068. doi: 10.1016/j.gaitpost.2014.01.008

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

He, Y., Yan, R., Fragkiadaki, K., & Yu, S.I. (2020). Epipolar Transformers. In *Proceedings of the* 2020 IEEE/CVF *Conference on Computer Vision and Pattern Recognition* (CVPR) (pp. 7776-7785.

Hewett, T.E., Myer, G.D., Ford, K.R., Heidt, R.S. Jr., Colosimo, A.J., McLean, S.G, et al. (2005). Biomechanical measures of neuromuscular control and valgus loading of the knee predict anterior cruciate ligament injury risk in female athletes: A prospective study. *The American Journal of Sports Medicine*, *33*(4), 492-501. doi: 10.1177/0363546504269591

Holden, J.P., Orsini, J.A., Siegel, K.L., Kepple, T.M., Gerber, L.H., & Stanhope, S.J. (1997). Surface movement errors in shank kinematics and knee kinetics during gait. *Gait and Posture, 5*(3), 217-227. doi: 10.1016/S0966-6362(96)01088-0

Horsak, B., Eichmann, A., Lauer, K., Prock, K., Krondorfer, P., Siragy, T., et al. (2023). Concurrent validity of smartphone-based markerless motion capturing to quantify lower-limb joint kinematics in healthy and pathological gait. *Journal of Biomechanics*, *159*, 111801. doi: 10.1016/j.jbiomech.2023.111801

Horsak, B., Prock, K., Krondorfer, P., Siragy, T., Simonlehner, M., & Dumphart, B. (2024). Inter-trial variability is higher in 3D markerless compared to marker-based motion capture: Implications for data post-processing and analysis. *Journal of Biomechanics*, *166*, 112049. doi: 10.1016/j.jbiomech.2024.112049

Hume, D.R., Kefala, V., Harris, M.D., & Shelburne, K.B. (2018). Comparison of marker-based and stereo radiography knee kinematics in activities of daily living. *Annals of Biomedical Engineering*, *46*(11), 1806-1815. doi: 10.1007/s10439-018-2068-9

Iseki, C., Hayasaka, T., Yanagawa, H., Komoriya, Y., Kondo, T., Hoshi, M., et al. (2023). Artificial intelligence distinguishes pathological gait: The analysis of markerless motion capture gait data acquired by an iOS application (TDPT-GT). *Sensors*, *23*(13), 6217. doi: 10.3390/s23136217

Iskakov, K., Burkov, E., Lempitsky, V., & Malkov, Y. (2019). Learnable triangulation of human pose. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)* (pp. 7717-7726).

Joo, H., Simon, T., Li, X., Liu, H., Tan, L., Gui, L., et al. (2015). Panoptic Studio: A massive multiview system for social motion capture. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)* (pp. 3334-3342.

Kanko, R.M., Laende, E.K., Strutzenberger, G., Brown, M., Selbie, W.S., DePaul, V., et al. (2021a). Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system. *Journal of Biomechanics*, *122*, 110414. doi: 10.1016/j.jbiomech.2021.110414

Kanko, R.M., Laende, E.K., Davis, E.M., Selbie, W.S., & Deluzio, K.J. (2021b). Concurrent assessment of gait kinematics using marker-based and markerless motion capture. *Journal of Biomechanics*, *127*, 110665. doi: 10.1016/j.jbiomech.2021.110665

Kanko, R.M., Laende, E., Selbie, W.S., & Deluzio, K.J. (2021c). Inter-session repeatability of markerless motion capture gait kinematics. *Journal of Biomechanics*, *121*, 110422. doi: 10.1016/j.jbiomech.2021.110422

Karatsidis, A., Jung, M., Schepers, H.M., Bellusci, G., de Zee, M., Veltink, P.H., et al. (2019). Musculoskeletal model-based inverse dynamic analysis under ambulatory conditions using inertial motion capture. *Medical Engineering and Physics*, *65*, 68-77. doi: 10.1016/j.medengphy.2018.12.021

Kessler, S.E., Rainbow, M.J., Lichtwark, G.A., Cresswell, A.G., D'Andrea, S.E., Konow, N., & Kelly, L.A. (2019). A direct comparison of biplanar videoradiography and optical motion capture for foot and ankle kinematics. *Frontiers in Bioengineering and Biotechnology*, *7*, 199. doi: 10.3389/fbioe.2019.00199

Kidziński, Ł., Yang, B., Hicks, J.L., Rajagopal, A., Delp, S.L., & Schwartz, M.H. (2020). Deep neural networks enable quantitative movement analysis using single-camera videos. *Nature Communications*, *11*, 4054. doi: 10.1038/s41467-020-17807-z

Labuguen, R., Matsumoto, J., Negrete, S.B., Nishimaru, H., Nishijo, H., Takada, M., et al. (2021). MacaquePose: A novel "in the wild" macaque monkey pose dataset for markerless motion capture. *Frontiers in Behavioral Neuroscience*, *14*, 581154. doi: 10.3389/fnbeh.2020.581154

Lahkar, B.K., Muller, A., Dumas, R., Reveret, L., & Robert, T. (2022). Accuracy of a markerless motion capture system in estimating upper extremity kinematics during boxing. *Frontiers in Sports and Active Living*, *4*, 939980. doi: 10.3389/fspor.2022.939980

Lam, W.W.T., Tang, Y.M., & Fong, K.N.K. (2023). A systematic review of the applications of markerless motion capture (MMC) technology for clinical measurement in rehabilitation. *Journal of NeuroEngineering and Rehabilitation*, *20*(1), 57. doi: 10.1186/s12984-023-01186-9

Lee, H. (2023). The rise of ChatGPT: Exploring its potential in medical education. *Anatomical Sciences Education*, *17*(5), 926-931. doi: 10.1002/ase.2270

Li, Z., Wang, J., Zhang, T., Balne, D., Li, B., Yang, R., Song, W., & Zhang, X. (2021). Real-time capture of snowboarder's skiing motion using a 3D vision sensor. *Wireless Communications and Mobile Computing*, *2021*, 8517771. doi: 10.1155/2021/8517771

Liu, Y., Gall, J., Stoll, C., Dai, Q., Seidel, H.P., & Theobalt, C. (2013). Markerless motion capture of multiple characters using multiview image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *35*(11), 2720-2735. doi: 10.1109/TPAMI.2013.47

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. doi: 10.1038/s41593-018-0209-y

Maudsley-Barton, S., & Yap, M.H. (2024). Objective falls risk assessment using markerless motion capture and representational machine learning. *Sensors*, *24*(14), 4593. doi: 10.3390/s24144593

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G.; The PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA Statement. *British Medical Journal*, *339*, b2535. doi: 10.1136/bmj.b2535

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

Needham, L., Evans, M., Cosker, D.P., Wade, L., McGuigan, P.M., Bilzon, J.L., et al. (2021). The accuracy of several pose estimation methods for 3D joint center localization. *Scientific Reports*, *11*(1), 20673. doi: 10.1038/s41598-021-00212-x

Needham, L., Evans, M., Wade, L., Cosker, D.P., McGuigan, M.P., Bilzon, J.L., et al. (2022). The development and evaluation of a fully automated markerless motion capture workflow. *Journal of Biomechanics*, *144*, 111338. doi: 10.1016/j.jbiomech.2022.111338

Parati, M., Gallotta, M., Muletti, M., Pirola, A., Bellafà, A., De Maria, B., et al. (2022). Validation of pressure-sensing insoles in patients with Parkinson's disease during overground walking in single and cognitive dual-task conditions. *Sensors*, *22*(17), 6392. doi: 10.3390/s22176392

Pfister, A., West, A.M., Bronner, S., & Noah, J.A. (2014). Comparative abilities of Microsoft Kinect and Vicon 3D motion capture for gait analysis. *Journal of Medical Engineering and Technology*, *38*, 274-280. doi: 10.3109/03091902.2014.909540

Ray, L.S.S., Zhou, B., Suh, S., & Lukowicz, P. (2024). A comprehensive evaluation of marker-based, markerless methods for loose garment scenarios in varying camera configurations. *Frontiers of Computer Science*, *6*, 1379925. doi: https://doi.org/10.3389/fcomp.2024.1379925

Remedios, S.M., & Fischer, S.L. (2021). Towards the use of 2D video-based markerless motion capture to measure and parameterize movement during functional capacity evaluation. *Journal of Occupational Rehabilitation*, *31*(4), 754-767. doi: 10.1007/s10926-021-10002-x

Ripic, Z., Nienhuis, M., Signorile, J.F., Best, T.M., Jacobs, K.A., & Eltoukhy, M. (2023a). A comparison of three-dimensional kinematics between markerless and marker-based motion captured in overground gait. *Journal of Biomechanics*, *159*, 111793. doi: 10.1016/j.jbiomech.2023.111793

Ripic, Z., Signorile, J.F., Best, T.M., Jacobs, K.A., Nienhuis, M., Whitelaw, C., Moening, C., & Eltoukhy, M. (2023b). Validity of artificial intelligence-based markerless motion capture system for clinical gait analysis: Spatiotemporal results in healthy adults and adults with Parkinson's disease. *Journal of Biomechanics*, *155*, 111645. doi: 10.1016/j.jbiomech.2023.111645

Ripic, Z., Signorile, J.F., Kuenze, C., & Eltoukhy, M. (2022). Concurrent validity of artificial intelligence-based markerless motion capture for over-ground gait analysis: A study of spatiotemporal parameters. *Journal of Biomechanics*, *143*, 111278. doi: 10.1016/j.jbiomech.2023.111793

Ripic, Z., Theodorakos, I., Andersen, M.S., Signorile, J.F., Best, T.M., Jacobs, K.A., & Eltoukhy, M. (2023c). Prediction of gait kinetics using markerless-driven musculoskeletal modeling. *Journal of Biomechanics*, *157*, 111712. doi: 10.1016/j.jbiomech.2023.111712

Saboune, J., & Charpillet, F. (2007). Markerless human motion tracking from a single camera using Interval Particle Filter. *International Journal on Artificial Intelligence Tools*, *16*(4), 593-609. doi: 10.1142/S021821300700345X

Seo, J.H. (2023). The evolving role of kinesiologists in the era of artificial intelligence. *The Asian Journal of Kinesiology*, *26*(1), 1-2. doi: 10.15758/ajk.2024.26.1.1

Smith, L., Boyd, S., Bhatta, D., & Smith, M. (2023). 3D machine vision and deep learning for enabling automated and sustainable assistive physiotherapy. In *Proceedings of the 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)* (pp. 1247-1253). doi: 10.1109/CSCE60160.2023.00209

Song, K., Hullfish, T.J., Scattone Silva, R., Silbernagel, K.G., & Baxter, J.R. (2023). Markerless motion capture estimates of lower extremity kinematics and kinetics are comparable to marker-based across 8 movements. *Journal of Biomechanics*, *157*, 111751. doi: 10.1016/j.jbiomech.2023.111751

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

Torvinen, P., Ruotsalainen, K.S., Zhao, S., Cronin, N., Ohtonen, O., & Linnamo, V. (2024). Evaluation of 3D markerless motion capture system accuracy during skate skiing on a treadmill. *Bioengineering, 11*(2), 136. doi: 10.3390/bioengineering11020136

Turner, J.A., Chaaban, C.R., & Padua, D.A. (2024). Validation of OpenCap: A low-cost markerless motion capture system for lower-extremity kinematics during return-to-sport tasks. *Journal of Biomechanics*, *171*, 112200. doi: 10.1016/j.jbiomech.2024.112200

Uhlrich, S.D., Falisse, A., Kidziński, Ł., Muccini, J., Ko, M., et al. (2023). OpenCap: Human movement dynamics from smartphone videos. *PLOS Computational Biology*, *19*(10), e1011462. doi: 10.1371/journal.pcbi.1011462

Van Hooren, B., Pecasse, N., Meijer, K., & Essers, J.M.N. (2023). The accuracy of markerless motion captures combined with computer vision techniques for measuring running kinematics. *Scandinavian Journal of Medicine and Science in Sports*, *33*(6), 966-978. doi: 10.1111/sms.14319

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 and Posture*, *42*, 145-151. doi: 10.1016/j.gaitpost.2015.05.002

Zhang, Q., Xie, Q., Liu, H., Sheng, B., Xiong, S., & Zhang, Y. (2022). A pilot study of biomechanical and ergonomic analyzes of risky manual tasks in physical therapy. *International Journal of Industrial Ergonomics*, *89*, 103298. doi: 10.1016/j.ergon.2022.103298

Submitted: November 24, 2025
Accepted: March 19, 2026
Published Online First: June 1, 2026

Correspondence to:
Mateja Očić, Ph.D.
University of Zagreb, Faculty of Kinesiology,
Laboratory for Sports Games, Zagreb, Croatia
e-mail: mateja.ocic@kif.unizg.hr

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license.