

A Narrative Review on AI-assisted Clinical Decision Support System in Physiotherapy Practice: Computer Vision-based Posture Assessment and its Clinical Validation

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ABSTRACT

Artificial Intelligence (AI)-assisted Computer Vision (CV) systems are applied in physiotherapy for objective, markerless assessment of posture and movement. The conventional clinical evaluation relies on visual inspection and manual goniometry; therefore, it is subject to inter-rater variability and measurement discrepancy. The CV frameworks employ Red, Green, Blue (RGB) cameras, depth sensors, and hybrid optical-inertial configurations to detect skeletal landmarks and calculate joint angles, range of motion, symmetry indices, and temporal kinematic variables. The pose estimation models such as MediaPipe, OpenPose, and YOLO-Pose permit real-time landmark detection. The Machine Learning (ML) and Deep Learning (DL) algorithms classify movement quality and generate structured feedback for rehabilitation sessions. The incorporation of CV into physiotherapy therefore, provides quantitative assessment of posture and movement that corresponds with conventional clinical measurement methods and supports systematic rehabilitation monitoring. The review examines the technological architecture, validation standards, and clinical applicability of AI-assisted CV systems in physiotherapy practice and evaluates their role in clinical decision support and movement assessment within structured rehabilitation programmes.

Keywords: Artificial intelligence, Biomechanical analysis, Electromyography, Forward head posture, Goniometry, Markerless motion capture

INTRODUCTION

Physiotherapy plays an important role in restoration of function after injury, surgery, and chronic disease. The conventional evaluation, which relies on visual inspection, manual goniometry, and clinician judgement, is affected by inter-rater variation and constraints in time and resources [1,2]. AI, ML, and CV introduce objective, contact-free methods for movement assessment [3,4]. The CV systems employ optical sensors, including RGB cameras and depth sensors such as Microsoft Kinect and Intel RealSense, as well as camera-wearable combinations to capture markerless motion data [3,5]. The pose estimation algorithms and ML classifiers quantify joint kinematics, evaluate exercise performance, and generate structured rehabilitation feedback [4,6,7]. The cervical and lower-limb alignment measurements demonstrate Intraclass Correlation Coefficients (ICC) greater than 0.90 when compared with radiographic standards [8]. The monocular markerless systems are applied in gait assessment and in knee osteoarthritis, non-specific neck pain, and orthopaedic rehabilitation requiring precise motion tracking [9-14].

The systems extract skeletal landmarks through DL frameworks such as MediaPipe, OpenPose, and YOLO-Pose. The joint angles, range of motion, and symmetry indices are calculated from coordinate data for biomechanical assessment [4,15,16]. The classification models, including support vector machines, random forests, and convolutional neural networks, determine movement quality or clinical status [17,18]. The high agreement with established software is reported, with correlation coefficients up to 0.94 for Craniovertebral Angle (CVA) measurement using Kinovea [3,12].

The clinical implementation is influenced by variability in algorithm performance within heterogeneous patient groups and uncontrolled environments [1,3]. The technical considerations include data security, sensor precision, and interoperability with electronic health record systems [19,20]. The AI-assisted decision support improves musculoskeletal assessment and rehabilitation planning [21,22];

however, long-term functional outcome data remain insufficient [10,11]. This narrative review aims to examine the role of artificial intelligence-based computer vision systems in physiotherapy practice. It explores their technological framework, clinical applications in musculoskeletal rehabilitation, and their validity and reliability in comparison with conventional assessment methods. The review also highlights current limitations and outlines future directions for their integration into routine clinical practice.

TECHNOLOGICAL FOUNDATIONS AND SYSTEM ARCHITECTURE

Marker-based Laboratory Systems

The traditional motion analysis in physiotherapy utilises optoelectronic marker-based systems such as Vicon and Qualisys, which serve as the reference standard for high-precision three-dimensional kinematic assessment. The systems employ multiple infrared cameras to track retroreflective markers positioned on anatomical landmarks, thereby generating high-resolution three-dimensional kinematic data. The reported root mean square error is below 2.0 mm for fully visible markers and approximately 1.0 mm under static conditions, which confirms measurement precision in controlled laboratory environments. The clinical applicability is restricted by methodological constraints. The soft-tissue artefact produces positional errors greater than 10 mm and joint angle deviations exceeding 10° when compared with intracortical bone pins [23], therefore reducing anatomical landmark accuracy during dynamic movement analysis. The systems require laboratory-controlled settings, extended preparation time, trained personnel, and high equipment costs, which therefore restrict routine clinical and community rehabilitation use [3].

Depth Camera-based Markerless Systems

The introduction of RGB-Depth (RGB-D) sensors, particularly the Microsoft Kinect series and Intel RealSense devices, expanded

access to markerless motion capture in rehabilitation research. The systematic review of 18 studies reported that depth cameras accounted for 65.4% of acquisition methods, with Kinect V2 applied in 12 studies using Kinect Software Development Kit (SDK) 2.0 for skeletal tracking [3]. The systems permit real-time extraction of three-dimensional joint coordinates without markers, thereby supporting community and tele-rehabilitation programmes. The implementation occurred in local environments in 50% of cases, clinical facilities in 33.4%, and remote applications in 22.3% [3]. The measurement accuracy varies according to configuration and testing conditions. The single-camera markerless system demonstrated angular deviations below 0.5° during postural tasks when compared with inclinometer readings and a 10-camera marker-based reference. The OpenPose evaluation showed mean absolute errors below 20 mm in 47% of joints and below 30 mm in 80%. The knee angle estimation within $\pm 5^\circ$ requires coordinate errors below 2.5 cm, therefore corresponding to a Percentage of Correct Keypoints relative to head size (PCKh) threshold of 0.1 rather than 0.5 [24].

Deep Learning (DL)-regulated Markerless Systems

The recent developments in DL permit reliable two-dimensional and three-dimensional pose estimation using standard RGB cameras, thus reducing dependence on depth sensors. The open-source frameworks support real-time joint localisation in physiotherapy applications. The OpenPose detects up to 25 anatomical landmarks through part affinity fields [7]. The MediaPipe Pose estimates 33 landmarks using lightweight architectures suitable for mobile deployment [15]. The YOLO-Pose integrates landmark detection within the YOLO framework and reports inference latency of nearly 24 ms per frame on RTX 3060 hardware [4]. The clinical evaluation demonstrates applicability in posture assessment. The smartphone-based CVA application achieved ICC values of 0.92 for test-retest reliability and 0.91 for inter-rater reliability, with correlation coefficient $r=0.94$ compared with Kinovea [12]. The MediaPipe analysis identified sex-related differences in shoulder and hip adduction, with ICC values between 0.67 and 0.95 for repeated measurements [15].

The evaluation of YOLO-Pose for physiotherapy posture recognition reported 88% classification accuracy and 85% agreement with physiotherapist assessment. The precision ranged from 0.85 at the left ankle to 0.93 at the right wrist, with sensitivity of 92% for spinal flexion and 88% for knee valgus detection [4]. The CV-guided exercise application improved physical function ($p=0.02$) and self-efficacy ($p=0.04$) in knee osteoarthritis [11]. The methodological constraints require evaluation in clinical translation. The DL-based pose estimation provides greater spatial accuracy than Microsoft Kinect skeletal tracking. The rehabilitation applications frequently use skeletal coordinate data without RGB or depth features that may strengthen contextual interpretation [25]. The temporal modelling methods, including dynamic time warping, hidden Markov models, and recurrent neural networks, are applied less often; therefore, many systems assess single-frame posture rather than sequential movement patterns [7]. The optoelectronic marker systems provide superior biomechanical precision [23], whereas CV frameworks provide accuracy adequate for screening and community rehabilitation tasks [4].

Core Architecture of AI-assisted Clinical Decision Support Systems (CDSS)

Layered system design: The AI-assisted CDSS in physiotherapy apply a structured multi-layered architecture that integrates CV, ML, and clinical reasoning, thereby enabling systematic processing of movement data from acquisition to feedback generation in local, clinical, and remote environments [3,4].

Data acquisition layer: The first layer captures raw movement data using optical sensors, including RGB cameras and depth devices such as Microsoft Kinect and Intel RealSense. The depth cameras

represent 65.4% of implementations, whereas RGB cameras represent 34.6% [3]. The smartphone-based RGB systems demonstrate clinical reliability, with CVA test-retest ICC of 0.92 (95% CI: 0.86-0.95) comparable with reference photogrammetric tools [12]. The acquisition standardisation requires fixed camera distance of nearly 1.5 m, controlled lighting, and constant participant positioning to minimise measurement error [26].

Pose estimation module: The second layer converts video frames into anatomical landmarks for kinematic analysis. The open-source frameworks include MediaPipe Pose with 33 landmarks, OpenPose with extended skeletal mapping and YOLO-Pose with 17-25 landmarks according to configuration [7]. YOLO-Pose reported 88% classification accuracy with inference latency of nearly 24 ms per frame on RTX 3060 hardware. The per-landmark precision ranged from 0.85 to 0.93, with lower reliability in trunk-adjacent regions due to occlusion and clothing interference [4]. The acceptable angular error depends on clinical task. The sagittal-plane gait analysis may permit 2°-3° deviation, whereas neurological evaluation requires stricter precision thresholds [23].

Feature extraction and kinematic modelling: The skeletal landmarks are transformed into biomechanical variables including joint angles, segment lengths, angular velocity, and symmetry indices. The MediaPipe-based geometric modelling has been applied to compute shoulder adduction, hip extension, and trunk inclination. The analysis of 200 healthy adults demonstrated significant sex-based differences in hip adduction (men: $9.9^\circ \pm 2.2^\circ$; women: $6.7^\circ \pm 1.5^\circ$; Cohen's $d=1.67$) and shoulder-hip differential ($d=1.44$). The findings indicate the requirement for population-specific normative datasets. The principal component analysis of 23 kinematic variables reduced dimensionality to two components explaining 90.8% of variance, thereby permitting clustering of postural phenotypes independent of biological sex [25]. The dimensional reduction methods permit interpretable modelling with manageable computational demand.

Predictive analytics and classification engine: The fourth layer applies Machine Learning (ML) algorithms to classify movement patterns and estimate rehabilitation outcomes. The systematic review reported comparable use of ML methods such as Support Vector Machines (SVM) and Random Forest (RF), along with Deep Learning (DL) approaches including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks in physiotherapy research [3].

The randomised controlled trial using a CNN-based CV application for knee osteoarthritis demonstrated improvement in physical function and self-efficacy compared with video-based education [11]. The hybrid models combining YOLO-derived landmarks with SVM classifiers achieved high posture recognition accuracy [27]. The integration of DL-based feature extraction with conventional ML classifiers therefore supports real-time clinical deployment.

Clinical rule engine: The clinical rule engine translates quantitative outputs into clinically interpretable assessments. The three-tier abstraction model converts skeletal landmarks into biomechanical parameters and subsequently maps them to standardised clinical scales, including the Modified Ashworth Scale and Berg Balance Scale [4]. The trunk forward inclination values below defined thresholds may activate posture deviation protocols [26]. The rule-based systems improve transparency because decision pathways are interpretable and auditable, which is essential in regulated healthcare environments [25].

Feedback generation system: The final layer delivers real-time corrective feedback during rehabilitation through visual overlays, verbal prompts, and haptic cues. The feedback is categorised as knowledge of results or knowledge of performance [7]. The concurrent feedback during movement execution achieved higher

adherence than terminal feedback in community programmes [20]. The end-to-end latency of 0.52 seconds satisfied the sub-1-second requirement for perceptible real-time interaction [4].

Cloud dashboard and clinician interface: The final layer aggregates longitudinal data for remote monitoring and decision support. The clinical deployment in 33.4% of applications requires compliance with data protection standards and interoperability with electronic health records [3]. The federated learning architectures permit multi-centre model training with privacy preservation [28]. The clinician dashboards display trend graphs, deviation heatmaps, and adherence statistics, and AI-processed summaries reduce manual video review time by 30% [20].

Analytical considerations and validation requirements: The pose estimation systems report Pearson correlations of 0.80-0.91 when compared with motion capture reference systems [26]; however, technical factors require detailed evaluation. The performance changes with body morphology, clothing, lighting variation, and occlusion. The clinical validation against clinician-rated functional outcomes in real-world environments is essential. The markerless systems require joint angle reliability within $\pm 5^\circ$ to satisfy clinical deployment standards [24]. The precision thresholds require task-specific validation rather than sole dependence on CV metrics such as Percentage of Correct Keypoints (PCK). The future system design should incorporate interpretable modelling components and adaptive rule engines updated through longitudinal patient data.

SENSOR TECHNOLOGIES AND DATA MODALITIES IN COMPUTER VISION-BASED PHYSIOTHERAPY (CV-PT) SYSTEMS

The performance of CV-PT systems depends on appropriate selection and configuration of sensor technologies for movement capture. The optical and complementary sensing modalities possess distinct technical characteristics that determine measurement accuracy, feasibility of deployment, and clinical interpretation. The [Table/Fig-1] summarises principal sensor modalities, applications, advantages, and limitations [1,3,6,8,10,16,17,21,25,26,28-30].

Data modality	Primary clinical use	Advantages	Limitations	References
RGB video	Posture classification, repetition counting	High accessibility, low cost	Limited depth accuracy; indirect 3D estimation	[1,10,16,26]
RGB-D video	Gait analysis, balance assessment, 3D reconstruction	Direct spatial accuracy; 3D joint modeling	Hardware dependency; limited range and frame rate	[1,8,17,21]
Skeletal coordinates	Joint angle computation, deviation detection	Computational efficiency; reduced data volume	Dependent on pose estimator precision	[3,16,26,29]
RGB+IMU fusion	Dynamic motion analysis, fall detection	Compensation for occlusion; improved temporal data	Increased system complexity; synchronization issues	[1,25,28]
Thermal/Infrared	Muscle activity screening, inflammation monitoring	Non-contact physiological data acquisition	Limited validation in rehabilitation applications	[6,30]

[Table/Fig-1]: Sensor technologies and data modalities in CV-PT [1,3,6,8,10,16,17,21,25,26,28-30].
CV: Computer vision; RGB: Red-green-blue; RGB-D: Red-green-blue-depth; IMU: Inertial measurement unit

Optical Camera Systems

RGB camera systems: The standard RGB cameras, including smartphone cameras and webcams, represent accessible sensing tools in physiotherapy applications. The low cost and widespread availability

permit implementation in community rehabilitation programmes. The MediaPipe Pose applied to RGB input demonstrates reliable anatomical landmark detection with acceptable test-retest reliability in healthy adults [1]. The smartphone-based CVA assessment showed high agreement with Kinovea and satisfactory measurement precision [26]. The RGB-only systems do not capture direct depth information; therefore, three-dimensional reconstruction depends on calibration procedures, algorithmic inference, or multi-view configurations. The precision may vary under different acquisition conditions, which requires careful protocol standardisation for clinical use [10].

RGB-D and depth cameras: The depth cameras combine RGB imaging with distance sensing to permit direct three-dimensional skeletal reconstruction. The devices such as Microsoft Kinect and Intel RealSense are frequently applied in physiotherapy research for markerless motion tracking [16]. The generated outputs include RGB-D video streams and skeletal joint coordinates, which reduce dependence on external markers and complex calibration procedures [16]. The structured-light and time-of-flight technologies differ in noise characteristics and spatial resolution, with operation within short-range environments. The clinical knee angle estimation requires strict joint coordinate accuracy; therefore, task-specific precision thresholds are necessary rather than general CV metrics such as PCKh [17].

Multi-camera systems: The multi-camera configurations reduce occlusion and improve spatial reconstruction during movement analysis. The visual hull systems employing synchronised cameras demonstrated low joint centre error under controlled laboratory conditions, with substantial error increase when camera placement was suboptimal [8]. The configurations require controlled environments and considerable computational resources; therefore, routine clinical application is restricted.

Hybrid Optical-inertial systems: The hybrid systems combine cameras with Inertial Measurement Units (IMUs) to improve measurement robustness. The cameras provide global positional reference, whereas IMUs record high-frequency orientation data independent of visual occlusion. The combined RGB-D and IMU data streams are applied in physiotherapy research to strengthen movement analysis [16]. The CV application integrated with Apple HealthKit gait metrics demonstrated improvement in physical function and self-efficacy in knee osteoarthritis [21]. The hybrid configuration improves temporal stability during rapid movements and reduces dependence on a single sensing modality.

Complementary Sensor Modalities

Inertial Measurement Units (IMU): The IMUs comprise accelerometers, gyroscopes, and magnetometers that generate high temporal resolution kinematic data independent of line-of-sight conditions. The IMU-based systems permit prolonged community monitoring in rehabilitation programmes. The technical challenges include sensor drift, calibration sensitivity, and synchronisation with concurrent video acquisition [29]. The integration of IMU signals with visual pose estimation improves motion stability during occlusion and rapid limb movements.

Force plates and pressure mats: The force plates measure ground reaction forces and centre-of-pressure displacement for balance and gait assessment. The depth camera-assisted visual feedback training demonstrated strong correlation with force plate measurements [16]. The pressure mats provide lower-cost plantar pressure assessment with reduced spatial resolution compared with laboratory-grade systems.

Electromyography (EMG): The surface Electromyography (sEMG) measures muscle activation patterns during rehabilitation tasks. The sEMG permits evaluation of neuromuscular coordination and activation timing. The measurement variability arises from electrode placement differences and skin impedance variation [29]. The combination of sEMG signals with pose estimation allows correlation

of movement deviation with muscle activation patterns, and further investigation is required in this area.

Thermal imaging: The thermal cameras provide non-contact assessment of skin temperature distribution. The measurements permit monitoring of tissue response, inflammatory activity, and vascular variation during rehabilitation [30]. The application within CV-PT systems is under investigation; therefore, robust empirical validation is required before routine clinical implementation.

Comparative Considerations in Sensor Selection

The sensor selection requires consideration of measurement precision, accessibility, cost, and ecological validity. The RGB systems permit scalable deployment with acceptable reliability for posture screening and exercise monitoring [1,26]. The depth cameras provide direct three-dimensional reconstruction and represent a common research modality [16]. The multi-camera configurations improve spatial precision but require controlled environments and substantial computational resources [8]. The combined use of IMUs with camera-based tracking improves temporal resolution and reduces sensitivity to visual occlusion [16,29]. The clinical implementation requires assessment of environmental variability, patient adherence, hardware availability, and compatibility with digital health platforms. The CV-PT systems employ diverse sensing technologies tailored to specific clinical tasks. The RGB-based platforms demonstrate sufficient accuracy for many rehabilitation applications when validated against reference standards [1,25]. The future development should prioritise multimodal integration, standardised validation protocols, and direct comparison with accepted clinical measurement standards to ensure safe physiotherapy practice [21,29].

ALGORITHMIC FRAMEWORK

The computational foundation of AI-assisted physiotherapy systems comprises two principal approaches: ML and DL. The selected method determines feature extraction strategy, temporal modelling capacity, computational demand, and interpretability within clinical workflows. The ML methods process video-derived skeletal joint coordinates to compute biomechanical variables, including joint angle trajectories, range of motion, angular velocity, and inter-limb symmetry indices. The numerical features are analysed using classifiers such as SVM, RF, k-nearest neighbours, and decision trees to categorise movement quality or detect deviation patterns [3]. The traditional ML algorithms account for a substantial proportion of depth camera-based physiotherapy implementations [3]. The principal strength of ML lies in interpretability, as classification outputs correspond to defined kinematic thresholds, such as knee valgus magnitude or hip extension range. The transparency improves clinician confidence in regulated healthcare environments. The approach requires manual feature engineering to select clinically meaningful biomechanical variables. The performance may change when patient morphology, camera orientation, or lighting differs from training data. The dimensionality reduction techniques are applied to manage high-dimensional datasets, with possible loss of subtle pathological information. The ML models analyse structured features rather than raw pixel data, thereby offering lower representational flexibility than DL architectures [25].

The DL architectures perform automated feature extraction without manual specification of kinematic variables. The Convolutional Neural Network (CNN) conduct spatial analysis of video frames and learn hierarchical representations from raw pixel input, enabling identification of anatomical landmarks and body segments. Recurrent Neural Network (RNN), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), analyse temporal sequences and capture sequential dependencies within movement trajectories. The combined CNN-RNN structures support integrated spatiotemporal

modelling and distinguish correct execution from compensatory patterns. Transformer architectures are applied for extended sequence modelling in complex rehabilitation tasks [1]. The DL models report high exercise recognition accuracy under controlled conditions. YOLO-Pose achieved reliable posture recognition with low inference latency suitable for real-time feedback [4]. MediaPipe systems demonstrated high detection accuracy with improved adherence during supervised feedback [7].

The clinical validation is required for safe application in physiotherapy. MediaPipe model demonstrated high ICC for shoulder adduction when compared with manual measurement [25]. The markerless systems measured sagittal-plane joint angles within small deviation from optical motion capture references, whereas transverse-plane estimation showed greater error due to occlusion and depth ambiguity [23]. The clinical precision requires predefined quantitative thresholds. The joint angle error within $\pm 5^\circ$ corresponds to strict localisation accuracy and PCKh criteria [24]. The evaluation should therefore apply biomechanical tolerance limits rather than generic detection metrics. The algorithm selection requires comparison of ML and DL with respect to interpretability, computational demand, and feature abstraction. DL learn non-linear associations from raw input, whereas ML provide transparent decision pathways suitable for regulated contexts. The combined architectures integrate CNN-based feature extraction with rule-based or tree-based classifiers to preserve interpretability with predictive performance [9]. Future development requires validation in heterogeneous populations and demonstration of association with functional rehabilitation outcomes.

CLINICAL ASSESSMENT FRAMEWORK AND VALIDATION

Static Posture Assessment

The CV-based systems permit objective quantification of postural variables previously assessed by visual inspection. CVA is a standard parameter for evaluation of forward head posture because it represents sagittal cervical alignment. Smartphone-based CV applications demonstrate high test-retest and inter-rater reliability, with strong concurrent validity against Kinovea photogrammetry, and acceptable measurement error margins [1]. Reported CVA values in healthy and symptomatic groups fall within recognised reference ranges, supporting screening and longitudinal monitoring. MediaPipe Pose extracts 33 anatomical landmarks and enables geometric computation of thoracic projection, shoulder asymmetry, and pelvic inclination. Repeated-measure reliability ranges from moderate to high. Quantified sex-related differences in shoulder and hip adduction indicate biomechanical variability requiring population-specific normative datasets. Principal component analysis with clustering identifies postural phenotypes independent of sex, thereby supporting personalised assessment and stratified rehabilitation planning [26].

Dynamic Movement Assessment

Dynamic evaluation requires extraction of temporal kinematic variables that characterise movement quality over time. Depth camera systems, including Microsoft Kinect platforms frequently applied in physiotherapy research, capture RGB-D streams and skeletal coordinate data to compute angular velocity, range of motion, movement smoothness, and bilateral symmetry indices [10]. CV-guided rehabilitation for knee osteoarthritis demonstrated improvement in physical function and self-efficacy measured using WOMAC and the Arthritis Self-Efficacy Scale [16]. Markerless motion capture accuracy varies according to movement plane and biomechanical complexity. Sagittal-plane gait angles show small deviation from marker-based optical systems [17], whereas transverse-plane rotations demonstrate greater error in certain

analyses [8]. Clinical precision within $\pm 5^\circ$ requires strict joint localisation accuracy corresponding to low PCKh thresholds [21]. YOLOv8-based posture classification combined with SVM achieved high recognition accuracy across defined posture categories [29].

Real-time Feedback and Decision Support

Clinical utility requires rapid processing and interpretable outputs to guide therapeutic decisions. YOLO-Pose implementations report low per-frame processing time on RTX 3060 hardware, permitting real-time visualisation of skeletal overlays and angular measurements [3]. Posture recognition accuracy is high, with strong sensitivity for detection of spinal flexion, tilt, knee valgus or varus, and shoulder rotation errors. Reported programme outcomes include improved adherence, reduced clinic visits, shorter recovery duration, and high agreement between automated assessment and physiotherapist evaluation [28]. The three-layer abstraction model organises interpretation of pose data. The first layer extracts anatomical landmarks and bounding regions. The second layer computes biomechanical parameters, including joint angles, velocity, and segment orientation. The third layer maps these outputs to clinical scales, such as the Berg Balance Scale and Modified Ashworth Scale. Decision tree-based orientation classification demonstrates high positional differentiation accuracy [3].

VALIDATION METHODOLOGIES

Validation compares CV outputs with radiographic alignment, universal goniometry, and optical motion capture systems. MediaPipe-derived joint angles show strong Pearson correlation when tested against Qualisys for upper and lower limb movements [26]. Markerless gait analysis demonstrates small root mean square differences for lower limb angles relative to marker-based systems, whereas multiplanar movements, particularly hip rotation, show greater deviation [8].

Validation domains, reference standards, statistical thresholds, and clinical interpretation parameters are summarised in [Table/Fig-2] [1,3,4,6,8-12,16-18,22,23,26,30]. Anatomical validation includes lower limb measures such as knee flexion, ankle dorsiflexion, and gait symmetry indices [3,8]. Upper limb evaluation assesses shoulder range of motion, elbow extension, and hand trajectory during functional tasks [9,26]. Trunk assessment examines lateral flexion and axial rotation [1,8]. Whole-body coordination testing includes sit-to-stand and stair negotiation performance [4,17]. Inter-joint synergy and compensatory pattern analysis detect altered coordination in musculoskeletal rehabilitation [1,3].

Statistical evaluation applies ICC, Bland-Altman limits of agreement, and RMSE to quantify reliability and agreement. CVA assessment demonstrates narrow limits of agreement within accepted screening thresholds [1,21]. Sensitivity and specificity analyses are also reported for diagnostic applications [25]. The integrated technical, validation, and clinical implementation framework of AI-assisted CV systems is summarised in [Table/Fig-3] [3,4,7,11,23-28], outlining architecture, performance metrics, governance requirements, and outcome benchmarks. Clinical deployment requires transparent reporting of measurement error and population-specific validation.

Clinical Applications, Implementation, and Future Directions

The CV-based physiotherapy systems operate in home environments, clinical facilities, and remote platforms [1]. Stroke rehabilitation applications use depth camera skeletal tracking to quantify reach-to-grasp performance and identify trunk compensation. OpenPose models demonstrate acceptable joint angle estimation error when compared with marker-based motion capture systems [10,26]. Orthopaedic rehabilitation programmes using CV-guided exercise

Validation domain	Comparator	Outcomes	Benchmarks	Clinical use	References
Static alignment	Radiography	CVA, SVA, HKA	ICC, correlation, low MAE	Non-invasive screening; reduced repeat imaging	[8,11,12]
Joint ROM	Goniometer/inclinometer	Flexion-extension, abduction-adduction	Bland-Altman limits, SEM, MDC	Detects meaningful ROM change; remote monitoring	[6,16,26]
Dynamic kinematics	Optical motion capture (vicon, qualisys)	Gait symmetry, knee alignment, temporal parameters	RMSE, R ² , cross-correlation	Detects compensatory patterns; real-time correction	[1,3,9,23]
Functional assessment	Clinical scales (Berg, TUG, Fugl-Meyer)	Balance, mobility, recovery stage	Sensitivity, specificity, AUC	Fall-risk prediction; triage support	[4,17,22]
Therapist agreement	Expert physiotherapist assessment	Posture classification, exercise accuracy	Kappa, ICC, accuracy	Structured decision support; reduced observer variability	[16,18,30]
Responsiveness	Longitudinal outcomes (WOMAC, VAS, PROs)	Joint angle change; pain-function relation	Effect size, correlation	Confirms biomechanical-clinical association; adherence tracking	[10,11]

[Table/Fig-2]: Comprehensive clinical validation framework for AI-based Computer Vision (CV) posture assessment systems.
ICC: Intraclass correlation coefficient; MAE: Mean absolute error; SEM: Standard error of measurement; MDC: Minimal detectable change; RMSE: Root mean square error; R²: Coefficient of determination; AUC: Area under the curve; PROs: Patient-reported outcomes; TUG: Timed up and go test; SVA: Sagittal vertical axis; HKA: Hip knee angle

Domain	Core components	Clinical target	Output	Validation	Context	References
Data acquisition	RGB, RGB-D (Kinect, RealSense), IMUs	Posture, 3D tracking, kinematics	2D/3D joint coordinates, velocity	Depth accuracy, frame rate, drift limits	Clinic, lab, community rehab	[3,24,26,28]
Pose estimation	MediaPipe, OpenPose, YOLO-Pose	Real-time posture detection	Landmark coordinates	PCKh, mAP, latency	Mobile, tele-rehab, research	[4,7,23,25]
Biomechanics	Joint angles, temporal kinematics, symmetry	ROM, gait, balance	Angles, velocity indices	ICC, RMSE, correlation	Neuro, orthopaedic rehab	[3,23,24,26]
Classification	SVM, RF, CNN, LSTM, Transformer	Exercise classification, risk stratification	Class outputs, probabilities	Accuracy, AUC, sensitivity	Monitoring, fall screening	[3,4,27]
Feedback	Visual, audio, haptic	Real-time correction	Alerts, adherence metrics	Low latency, engagement	Clinic, home rehab	[4,11,27]
Integration	Dashboards, FHIR, federated learning	Longitudinal tracking	Reports, analytics	Interoperability standards	Remote, hospital systems	[3,4,28]
Governance	SaMD, GDPR, HIPAA	Safety, fairness	Certification, encryption	Regulatory compliance	Commercial deployment	[3,4,28]
Outcomes	Accuracy, ICC, functional scales	Posture, mobility, recovery	Performance metrics	RCT validation	Evidence-based practice	[11,26]

[Table/Fig-3]: Consolidated framework of AI-assisted Computer Vision (CV) Clinical Decision Support Systems (CDSS) in physiotherapy.
IMU: Inertial measurement unit; PCKh: Percentage of correct keypoints (head-normalised); mAP: Mean average precision; RMSE: Root mean square error; ICC: Intraclass correlation coefficient; AUC: Area under curve; SaMD: Software as a medical device; FHIR: Fast healthcare interoperability resources; GDPR: General data protection regulation

report improvement in physical function and self-efficacy in knee osteoarthritis management [15,16]. Smartphone-based postural assessment shows high reliability for CVA measurement with strong agreement against Kinovea, supporting screening and longitudinal monitoring [8]. Remote rehabilitation platforms with cloud dashboards report reduced clinic visits and high agreement between automated outputs and physiotherapist evaluation. AI-guided scheduling and virtual assistance improve adherence compared with standard home programmes [8]. Clinical precision depends on strict joint localisation accuracy. Measurement stability may decline under lighting variation, occlusion, and restricted dataset diversity outside controlled environments [1,21]. The advantages include markerless assessment, objective angle computation, real-time feedback, and suitability for tele-rehabilitation. MediaPipe Pose detects multiple anatomical landmarks with low latency on consumer hardware, permitting responsive motor training feedback [29]. YOLO-Pose deployed on edge devices demonstrates high posture classification accuracy in defined tasks [3].

Limitation(s)

These include restricted dataset heterogeneity and absence of standardised benchmarking datasets [1,21]. SaMD classification requires regulatory oversight [28]. Encryption, anonymisation, and federated learning support privacy protection, and HL7 FHIR standards provide structured EHR integration pathways [25]. Future development should prioritise multimodal sensor integration, optimisation for edge deployment, and self-supervised learning to reduce annotation burden. Integration of CV with EMG or force measurement may improve interpretation of neuromuscular control beyond kinematic descriptors [21]. Model compression and quantisation support deployment on low-resource devices. Digital twin modelling may assist patient-specific biomechanical simulation and rehabilitation planning. Multicentre validation with standardised reporting and economic evaluation is required for clinical adoption.

CONCLUSION(S)

The CV-based AI systems in physiotherapy enable objective measurement of posture and movement, reducing dependence on subjective visual assessment. Evidence demonstrates agreement with radiography, goniometry, and optical motion capture for static alignment and selected dynamic tasks. Real-time processing supports immediate corrective feedback, thereby enhancing motor learning and adherence. Camera-based remote platforms with digital dashboards extend rehabilitation access while maintaining structured monitoring. AI-supported decision frameworks convert skeletal coordinates into clinically interpretable metrics for standardised reporting and longitudinal evaluation. Wider clinical adoption requires validation in heterogeneous populations, clear reporting of measurement error, and predefined clinical thresholds. Standardised benchmarking datasets and multicentre trials must define acceptable performance criteria. Regulatory compliance, data protection, and interoperability with electronic health record systems are essential for safe integration into routine physiotherapy practice.

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