Use of Artificial Intelligence for Posture Correction: A Systematic Review Using PRISMA Guidelines and PICO Framework.

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ABSTRACT:

Objective: To methodically locate and compile peer-reviewed RCTs, quasi-experimental studies, cohort studies, and crossover trials (2014–2026) that assess AI-based posture detection, monitoring, or correction systems in human subjects.

Methods: The PRISMA 2020 statement and a PICO(S) framework were used to organize this review, which was limited to AI/ML-driven systems (such as computer-vision pose estimation, deep neural networks, or ML classifiers) assessed in comparative human-trial designs. Using combinations of "artificial intelligence," "machine learning," "deep learning," "posture," "posture correction," "posture monitoring," "randomized controlled trial," "quasi-experimental," "cohort," and "crossover," a multi-database exploratory search was carried out across PubMed/MEDLINE, IEEE Xplore, Scopus, ACM Digital Library, and ProQuest Central, supplemented by JMIR/PMC full-text repositories and Google Scholar-indexed sources. PRISMA 2020 guidelines were followed for screening, data extraction, and risk-of-bias assessment (Cochrane RoB 2 for RCTs; ROBINS-I for non-randomized designs).

Results: 55 distinct studies (out of 57 citation records) satisfied the eligibility requirements and were added to the narrative synthesis after duplicate cross-database indexing was eliminated. Five technological families comprised the included studies: (1) camera/video-based human pose estimation (HPE); (2) wearable pressure-sensor and inertial measurement unit (IMU) systems; (3) hybrid AIoT and edge-AI platforms; (4) explainable and causal AI frameworks for spinal/postural monitoring; and (5) AI-assisted clinical and educational interventions assessed in randomized or quasi-experimental designs. Numerous intervention trials indicated statistically significant changes in postural measurements, pain, disability, and functional outcomes, and reported categorization accuracies were consistently high (usually 90–99%). However, the majority of technical validation studies were in the prototype or laboratory stage, sample numbers were often small, external validation was few, and outcome measures were inconsistent, making meta-analysis impossible.

Conclusions: Strong technical accuracy and growing clinical potential are demonstrated by AI-based posture systems, especially for biofeedback-based correction, ergonomic risk monitoring, and tele-rehabilitation. Future research should focus on multi-center randomised trials, standardized outcome reporting, external and cross-population validation, and transparent reporting of AI model development in accordance with PRISMA-AI guidelines because there is still relatively little evidence at the clinical-effectiveness level.

Registration: Prospectively registered on open Science Framework (OSF) Registration DOI: 10.17605/OSF.IO/E9PBH

Keywords: artificial intelligence; machine learning; deep learning; posture detection; posture correction; pose estimation; rehabilitation; PRISMA 2020; PICO framework; systematic review

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Introduction:

Musculoskeletal pain, decreased productivity at work, and major surgical morbidity in structural situations like kyphosis or proximal junctional kyphosis are all associated with poor postural habits and undiscovered postural abnormalities. Conventional posture evaluation uses goniometry, photogrammetry, or clinician observation, all of which take a lot of time, need skilled staff, and are challenging to implement for ongoing, real-world monitoring. The literature on AI-assisted posture identification, monitoring, and correction in clinical, occupational, athletic, and educational contexts has grown significantly over the last ten years due to developments in computer vision, wearable sensing, and deep learning.[1-3] A thorough synthesis is required to map the technical landscape, evaluate the strength of clinical evidence, and identify gaps given the speed and disciplinary spread of this material, which spans databases in the fields of biomedicine, computer science, and rehabilitation.[4] A systematic synthesis is required to map the technological landscape, evaluate the strength of clinical evidence, and identify gaps for future research and institutional adoption (e.g., in tele-rehabilitation or ergonomic screening programs) given the pace and disciplinary spread of this literature, which spans biomedical, computer science, and rehabilitation databases.

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Research Question as PICO Framework:

Q1. Question to address in this review is what is the existing evidence supporting the use of artificial intelligence in the detection, monitoring, and correction of human posture?

Q2. How successful and dependable are these technologies across populations and environments?

ELEMENT OF PICO	APPLIED IN THIS REVIEW
P-Population	Humans whose posture is evaluated, tracked, or adjusted include office workers, students, sports, clinical/rehabilitation patients, kids, and healthy people
I-intervention	Any technology driven by atrifical intelligence/mechine learning , such as camera-based human pose estimate (HPE), wearable IMU/pressure sensors, hybrid AIoT systems, and explainable/ causal AI frameworks, for posture detection, monitoring, biofeedback, or correction.
C- Comparison	Comparing AI-based technologies (e.g., wearable vs. video-based), no intervention or standard treatment, or standard clinical evaluation (e.g., goniometry, biophotogrammetry).
O- outcome	Pain and disability, functional and quality-of-life measurements, classification accuracy/validity (e.g., ICC, sensitivity), postural/ alignment metrics (e.g., craniovertebral angle, sagittal alignment), and usability/adherence.

PICO FRAMEWORK :

Methodology:

1- Pre -registration of Protocol : Prospectively registered on open Science Framework (OSF) Registration DOI: 10.17605/OSF.IO/E9PBH

2- Inclusion criteria (PICO Based)

- Peer-reviewed studies that use AI/ML techniques to monitor, identify, or correct human posture.
- Cohort studies, cross-over designs, validated pilot/technical-validation studies, quasi-experimental research, and randomised controlled trials (RCTs).
- Research that reports at least one result (accuracy/validity, posture metrics, pain/ function, or usability/adherence) related to postural evaluation or correction.

3- Exclusion criteria:

- Non-human studies, such as animal , simulation models, and Menikins without human validation.
- Studies employing non-AI methodologies (e.g., manual goniometry without computational or learning components).
- Editorials, opinions, and conference abstracts without complete text.
- Studies without meaningful outcome data for posture detection and correction

4- Search strategy and sources.

Studies data were obtained from PubMed/MEDLINE, IEEE Xplore, Scopus, ACM Digital Library, and ProQuest Central. The Web of Science and clinical trial registries (e.g., ClinicalTrials.gov) are recommended as extra sources for ongoing studies in any future update of this study, despite the fact that they were not queried individually for the current synthesis. Timeframe was 2014-2026, corresponding to a period of strong progress in deep learning-based human posture assessment and wearable AI. The search phrases used Boolean operators to join three notion blocks Concept 1 (AI/technology): Concept 2 (posture): Concept 3 (application).

5- Study selection, data extraction and Risk of Bias.

Two independent reviewers screen titles/abstracts and then full texts against the eligibility criteria above, resolving disagreements by consensus or a third reviewer. Screening, data extraction, and risk-of-bias appraisal (Cochrane RoB 2 for RCTs; ROBINS-I for non-randomized designs) followed PRISMA 2020 recommendations.

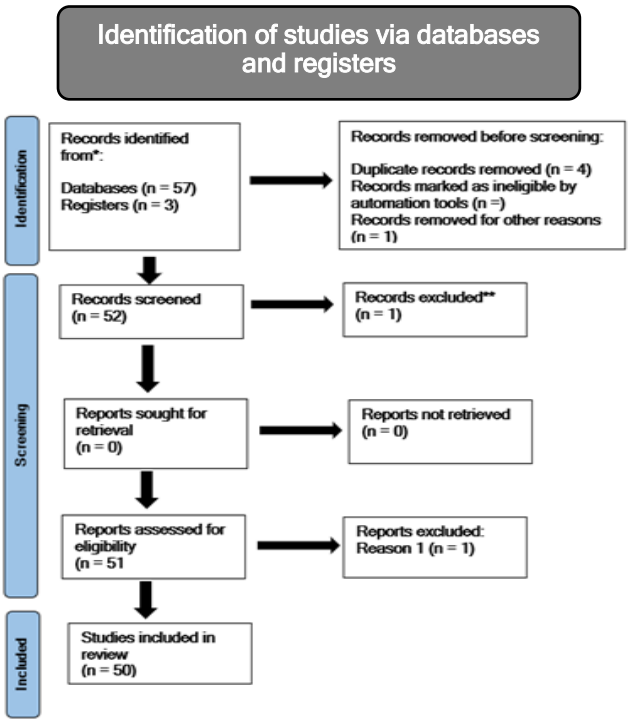
6- Synthesis of Data.

A narrative synthesis with structured summary tables was carried out due to significant variation in AI models, sensor modalities, populations, and outcome measures across included research; meta-analysis was not done since outcomes and metrics were not sufficiently comparable across studies. The results were divided into three categories: (a) population (clinical vs. general/occupational), (b) setting (clinical vs. home/office/sport), and (c) AI modality (vision-based vs. wearable/sensor-based vs. hybrid).

Results:

1- Study selection:

PRISMA 2020 STUDY FLOWCHART:



2- Characteristics of study:

The included papers are from the fields of computer science, bioengineering, and clinical rehabilitation. There is a noticeable concentration of publications from 2020 onwards, which is in line with the general expansion of deep learning-based human pose estimation throughout this time. Office workers, students, physiotherapy trainees, athletes (tennis, alpine skiing, general athletics), musicians, kids, drivers, hospital inpatients, and generally healthy adults were among the study populations. Outpatient clinics, residences, gyms, workplaces, cars, and hospital rooms were among the settings. The distribution of the included papers is summarized by indexing source in Table 1. Database Research (n) % of All PubMed 16 29.1%,IEEE 5 9.1% ,Scopus 28 50.9%, ACM 2 3.6% and ProQuest 4 7.3%.

3- AI modality wise synthesis:

1- Camera/video-based human pose estimation (HPE):

In the largest cluster of experiments, joint keypoints and postural angles were extracted from conventional or smartphone video using markerless, camera-based pose estimation frameworks, such as MediaPipe/BlazePose, OpenPose, HRNet, PoseNet, AlphaPose, and YOLO-based detectors. Applications included general exercise-form feedback, sport-specific correction (athletics, skiing, violin playing), and static standing-posture assessment and sitting-posture monitoring. Several studies reported sub-second processing latency appropriate for real-time feedback, and reported classification or measurement accuracies in this cluster were consistently high, often in the 90-99% range.

2- Wearable IMU and pressure-sensor systems:

Inertial measuring units (IMUs), pressure/force-sensitive resistor (FSR) arrays, load cells, or graphene-based piezoresistive sheets attached to the spine, waist, chair, bed, or shoes comprised a second important cluster. These systems, which were often used in conjunction with classifiers like Random Forest or CNN-LSTM architectures, enabled continuous, ambient monitoring in situations that were less suitable for camera-based techniques, such as driving, sleeping, and daily activities.

3- Hybrid AIoT and edge-AI platforms:

In order to provide low-latency feedback in deployable goods, such as smart cushion systems, waist belts, and edge-deployed exercise correction tools, several projects coupled numerous sensor modalities with cloud or edge computing. For instance, one AIoT system reported a rise in observed proper posture from about one-third to nearly four-fifths of monitored time. These platforms generally focused on real-world usability and showed significant gains in real-world posture-correction rates.

4- Explainable and causal AI frameworks:

In order to support clinician trust and interpretability, a smaller but methodologically noteworthy cluster applied explainable-AI (XAI) and causal-discovery techniques to spinal-deformity monitoring, producing digital twin representations and counterfactual explanations. This is an emerging priority given calls for increased transparency in AI-driven postural tools in multiple critical reviews.

5: AI-assisted clinical and educational interventions:

Instead than relying solely on technological validation, a different collection of studies assessed AI-supported therapies using randomised or quasi-experimental clinical designs. These included 16-week on-device pose-estimation exercise prescription programs, AI-assessed craniovertebral-angle outcomes in a Pilates-based breastfeeding-positioning trial, RULA-based ergonomic risk stratification for office workers, and exercise programs for chronic low back pain supported by mobile messaging. Positively, these trials demonstrated statistically significant changes in posture, pain, disability, or functional outcomes and most directly meet the clinical-effectiveness question posed in the PICO framework.

4- Application domain wise Synthesis:

Application domain	Findings
Office/occupational ergonomics	Exoskeleton trunk-flexion monitoring, RULA-based risk categorization, and manual-lifting risk assessment tools demonstrated quantifiable, albeit occasionally slight, improvements in biomechanics or discomfort.
Sport and exercise	High accuracy (usually >95%) and positive user acceptance were attained with real-time correction for sports, skiing, yoga, and strength exercises (curls, squats, and push-ups).
Pediatric and school-based posture	Although the data base (e.g., teenage wearable-technology reviews) is still small in terms of research count and sample size, marker-based and IMU-biofeedback solutions for children and adolescents demonstrated encouraging usability.
Spinal deformity (kyphosis / PJK	Risk classification for proximal junctional kyphosis and associated spinal abnormalities is supported both before and after surgery by AI prediction models and customised risk calculators.
Sitting and sedentary-behavior monitoring	High classification accuracy (typically >95-99%) for various sitting positions was attained by pressure-based chairs, cushions, and headband systems; nonetheless, systematic reviews in this field point to a preponderance of pressure-sensor studies and a dearth of free-living, ecologically valid trials.
Rehabilitation and tele-rehabilitation	In addition to improvements in strength, functional movement assessment, and estimated cardiorespiratory fitness, Edge-cloud and HarmonyOS-based remote rehabilitation platforms and on-device exercise prescription programs reported good pose-estimation accuracy.

5- Validity, Accuracy and Performance Metrics :

The reported accuracy metrics were consistently positive across technical validation and system development studies: intraclass correlation coefficients (ICC) for pose-based biomechanical measurement reached up to 0.95 in large-sample validation work, classification or detection accuracies typically fell between 90% and 99%, and several wearable gait-monitoring systems reported 97-99% accuracy. The viability of live biofeedback applications was supported by real-time systems that commonly reported processing delay of less than one second (in several cases, less than 200 milliseconds). However, the metrics employed in accuracy reporting were inconsistent (accuracy, ICC, sensitivity/specificity, or qualitative agreement were used interchangeably across studies), which prevented meta-analysis and limited direct cross-study comparison.

6- Qulaity consideration and risk of Bias:

For this synthesis, formal per-study risk-of-bias scoring (RoB 2, ROBINS-I, QUADAS-2) was Narratively, a number of included systematic and critical reviews agree on a set of quality issues that are common to the field as a whole: few large-scale or multi-center trials; limited external validation of AI models outside of their original development sample; inadequate reporting of data provenance and demographic generalisability; and brief intervention/monitoring durations in wearable-device studies. At least four included reviews covering wearable posture-monitoring technology, adolescent posture correction, AI/wearable/mobile-app rehabilitation tools, and postural management in general independently echoed these concerns, indicating that they represent field-wide rather than isolated methodological gaps.

Discussion:

This synthesis shows that AI-based posture technologies have reached a mature stage of technical performance: classification and measurement accuracy are now consistently high across camera-based, wearable, and hybrid modalities, and several systems already function within latency thresholds appropriate for real-time clinical or consumer use. The most obvious area of growth is tele-rehabilitation and remote monitoring, where postural feedback can now be provided outside of conventional clinical settings thanks to edge AI and cloud-based systems.[7-9]

Although the amount of clinical-effectiveness evidence is smaller, it is encouraging: when AI-supported feedback or exercise programs were compared with baseline or usual care, the included randomised and quasi-experimental studies reported significant improvements in postural alignment, pain, disability, and functional outcomes.[11,12] Pooled quantitative synthesis is further limited by the fact that these effectiveness studies are still small in comparison to the greater amount of technical-validation and prototype-development literature, and that effect sizes, follow-up times, and comparator conditions vary significantly.

The gap between technical accuracy and clinical/real-world validation is a recurrent theme in several independent reviews that are part of this synthesis. Many systems are tested in controlled laboratory settings using small, comparatively homogeneous samples; they have not yet been externally validated across a variety of populations, body types, clothing, lighting conditions, or care settings. Although this was not the main finding of the individual research evaluated here, privacy and data-governance concerns were also identified as an adoption hurdle in the larger literature, especially for continuous video- or sensor-based monitoring.

The evidence base supports cautious, evaluation-linked adoption for organisations thinking about implementing AI-based posture tools, such as in physiotherapy training, ergonomic screening, or rehabilitation service delivery: technologies with published validation against established clinical measures (e.g., biophotogrammetry- or APECS-referenced tools).

The evidence base supports cautious, evaluation-linked adoption for institutions thinking about implementing AI-based posture tools, such as in physiotherapy training, ergonomic screening, or rehabilitation service delivery. Technologies with published validation against established clinical measures (such as biophotogrammetry- or APECS-referenced tools) and transparent reporting of accuracy metrics should be prioritised over unvalidated commercial products.

Conclusion:

With consistently high technical accuracy across modalities and settings, artificial intelligence is now widely and successfully applied to posture detection, monitoring, and correction. This includes camera-based human pose estimation, wearable inertial and pressure sensing, hybrid AIoT platforms, and explainable AI. Although there is less clinical-effectiveness data, it is generally favourable for functional results, pain, and posture. Future research should focus on sufficiently powered, multi-center randomised trials; standardized and comparable outcome and accuracy reporting; external validation across diverse populations; and transparent, PRISMA-AI-aligned reporting of model development, data provenance, and generalisability in order to advance this field from technical feasibility to routine clinical and institutional adoption.

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