Cureus
Part of SPRINGER NATURE

Open Access Review Article

Wearable Sensors and Candidate Digital Gait Biomarkers in Early Knee Osteoarthritis: A Narrative Review

Review began 10/11/2026
Review ended 10/29/2026
Published 11/01/2026

© Copyright 2026
Kumandan et al. This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

DOI: 10.7759/cureus.118932

Kothakota Bhanutej Kumandan [1], Navaneetha Krishnan Sekar [1], Suresh Krishna Lokayah [1], Rohith Kumaar [1], Shanmuga Boopathy Gangadharan [1], Sumesh Subramanian [1], Siddarth Rangabashyam [1], Nishanthan Vengappa [1], Sankalp Yadav [2], Naveen Jeyaraman [3, 4], Madhan Jeyaraman [4, 3]

1. Orthopedics, Faculty of Medicine, Sri Lalithambigai Medical College and Hospital, Dr MGR Educational and Research Institute, Chennai, IND 2. Medicine, Shri Madan Lal Khurana Chest Clinic, New Delhi, IND 3. Orthopedics, ACS Medical College and Hospital, Dr MGR Educational and Research Institute, Chennai, IND 4. Regenerative Medicine, Agathisha Institute of Stemcell and Regenerative Medicine (AISRM), Chennai, IND

Corresponding author: Sankalp Yadav, drsankalpyadav@gmail.com

Abstract

Knee osteoarthritis (KOA) is a whole-joint disease involving articular cartilage, subchondral bone, synovium (with low-grade inflammation), menisci, ligaments, periarticular muscles, and nerves. Diagnosis still relies on clinical examination and radiography; however, radiographic changes are frequently absent when symptoms begin, and early KOA has only recently been assigned consensus classification criteria. This discordance between joint structure and joint function has motivated the search for objective functional measures. Wearable sensors, including inertial measurement units, wearable surface electromyography, pressure-sensing insoles, flexible goniometers, smart textiles, and multimodal systems, can measure gait, joint motion, postural stability, muscle activation, and plantar loading outside the laboratory. A growing number of studies propose candidate digital gait biomarkers, such as walking speed, stride length, cadence, double-support time, knee range of motion, inter-limb asymmetry, stride-to-stride variability, and trunk or pelvic compensation, that are associated with pain, functional limitation, and disease progression. Machine learning (ML) offers a means of combining these multidimensional signals into classifiers and prognostic models. However, most evidence comes from small studies comparing established or end-stage KOA with healthy controls. Early KOA is defined inconsistently, sensor placement and signal processing are not standardized, external validation is rare, and the specificity of gait markers against hip, spinal, and neurological causes of altered gait is largely untested. No sensor-derived marker has yet been validated for the diagnosis of early KOA. This narrative review summarizes current wearable technologies, candidate movement markers of early KOA, ML methods, and clinical applications; tabulates the key primary studies; and outlines the evidence needed before wearable gait measures can be used as diagnostic or prognostic tools alongside conventional imaging and clinical assessment.

Categories: Pain Management, Orthopedics, Healthcare Technology
Keywords: digital biomarkers, gait analysis, kinematic signature, knee osteoarthritis, machine learning, wearable sensor

Introduction And Background

Knee osteoarthritis (KOA) is a major cause of chronic pain and disability globally, and its burden is rising with population aging and increasing obesity [1,2]. Once viewed primarily as a cartilage-only ("wear and tear") disease, KOA is now recognized as a whole-joint disease involving cartilage degradation, subchondral bone remodeling, low-grade synovial inflammation, meniscal degeneration, capsuloligamentous changes, and loss of periarticular muscle strength and sensorimotor function [3]. Age, obesity, previous joint injury, and occupational loading interact, which partly explains the marked heterogeneity between patients.

Plain radiography remains the first-line imaging investigation. The Kellgren-Lawrence (KL) system, which is still the standard grading scheme nearly 70 years after its publication, grades osteophytes, joint space narrowing, subchondral sclerosis, and bony deformity [4]. However, radiographs describe structure, not function. Pain, stiffness, instability, and reduced activity can occur with only trivial radiographic changes, while marked joint space narrowing sometimes causes comparatively little pain [5]. MRI provides some of this missing information by visualizing cartilage defects, meniscal tears, synovitis, and bone marrow lesions before they appear on a plain film [6]; however, its cost and duration make it impractical for routine screening. Patient-reported measures such as the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC) and the Knee Injury and Osteoarthritis Outcome Score (KOOS) reflect patients' lived experiences and functioning [7,8]; however, they are influenced by mood, expectations, and sociocultural factors.

A further obstacle is that "early KOA" has no single universally accepted definition. In this review, we adopt the consensus classification criteria proposed by Luyten et al., which require (1) knee pain, symptoms, or

reduced function (KOOS ⩽85 in at least two of four subscales); (2) at least one of the following findings on examination: joint-line tenderness or crepitus; and (3) a KL grade of 0 or 1 on radiographs [9]. These criteria have since been shown to enrich for both clinical and structural progression in the Osteoarthritis Initiative cohort [10]. Importantly, the KL system was not designed to detect grade 0-1 disease, so radiography alone will miss precisely the population that these criteria define. Early symptoms also appear first during demanding, knee-loading activities such as stair use rather than level walking [11].

Movement may reveal joint dysfunction earlier than structure does. Joint pathology can change how a person walks before it alters radiographic findings: patients tend to avoid deep knee flexion, shorten stance on the painful limb, and adopt lateral trunk lean to reduce load on the medial compartment [12,13]. Biomechanical assessments using optical motion capture, force plates, and laboratory-based electromyography (EMG) accurately measure such changes; however, they are costly, time-consuming, and confined to the laboratory. Wearable sensors are small, body-worn devices that record movement (accelerometers and gyroscopes), muscle electrical activity (surface EMG), or plantar pressure (sensing insoles) continuously during everyday activities such as walking, stair climbing, and rising from a chair. A digital biomarker is an objective, quantifiable physiological or behavioral measure collected by such a device that indicates a biological process, disease state, or response to treatment. Like any biomarker, it must be shown to be analytically valid (it measures what it claims to measure), clinically valid (it relates to a clinical state or outcome), and clinically useful before it can be adopted [14].

Inertial sensors are promising for remote monitoring and risk assessment in hip and KOA [15], and, in a large cohort study, wearable-derived gait parameters were associated with worsening knee pain and physical function over two years [16]. Nevertheless, most of the available evidence compares established or end-stage KOA with healthy controls, and no sensor-derived marker has yet been validated for diagnosing early disease. This narrative review therefore (1) summarizes current wearable sensor technologies; (2) describes candidate movement markers (“kinematic signatures”) of early KOA and the criteria against which they should be judged; (3) outlines machine learning (ML) methods and the key primary studies; (4) discusses clinical applications and the problem of diagnostic specificity; and (5) sets out the evidence required before wearable gait measures can be used clinically. Throughout, the abbreviation KOA refers specifically to KOA, and OA refers to osteoarthritis in general.

Review

Methods

Literature Search and Selection

This is a narrative (non-systematic) review prepared in accordance with the Scale for the Assessment of Narrative Review Articles (SANRA) [17]. PubMed, Scopus, and IEEE Xplore were searched from January 2010 to October 2026 using combinations of the terms “knee osteoarthritis” AND (“wearable” OR “inertial sensor” OR “accelerometer” OR “insole” OR “electromyography” OR “digital biomarker” OR “gait” AND “machine learning”). Seminal articles published before 2010 that define the disease, its grading, or its biomechanics were retained. English-language, peer-reviewed studies involving adults with or at risk of KOA that used body-worn sensors were eligible. Conference abstracts and studies that used only laboratory-fixed equipment (optical motion capture or force plates) were excluded unless they provided the biomechanical rationale for a wearable measure or served as a reference standard. Reference lists of included reviews were hand-searched. Two authors independently screened titles and abstracts, and disagreements were resolved through discussion with a third author.

For each primary study of wearable sensors in people with or at risk of KOA, the population and KOA definition, sample size, sensor type and placement, extracted features, analytical model, validation design (internal or external), and reported accuracy were extracted into a summary table below. Because this is a narrative review, no formal risk-of-bias tool was applied; instead, the validation design of each study is reported explicitly, and the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool is recommended for any future systematic synthesis [18]. Findings were summarized narratively by sensor type and gait domain. The final narrative draws on 59 references, of which 12 are primary studies of wearable sensors in people with or at risk of KOA.

Early KOA: pathology and the case for functional markers

Early Pathological Changes

Early KOA begins with disruption of cartilage homeostasis. Aging, abnormal mechanical loading, obesity, previous injury, and metabolic or inflammatory factors shift the balance between matrix synthesis and degradation; pro-inflammatory cytokines, matrix metalloproteinases, and aggrecanases drive catabolism, and low-grade synovitis contributes to both structural changes and symptoms [3,19,20]. Concurrently, subchondral bone remodels, and the meniscus degenerates, losing its ability to distribute load [21]. These processes are mutually reinforcing: stiffer subchondral bone alters cartilage loading, and a damaged meniscus concentrates contact stress. Early KOA is therefore best understood as an iterative cycle of tissue

change, pain, altered load distribution, and compensatory movement (Figure *1*) [22]. The present review focuses on the movement component of that cycle because it is the part that body-worn sensors can measure.

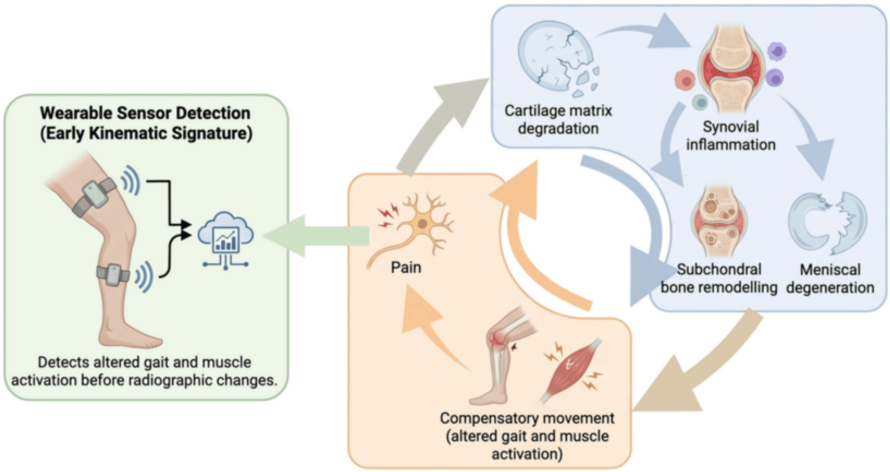


FIGURE 1: Biological-biomechanical feedback loop of early KOA.

KOA, knee osteoarthritis

This figure was created by Sankalp Yadav using BioRender (BioRender, Toronto, Canada).

Criteria for a Clinically Useful Functional Marker

A functional marker of early KOA should be safe and noninvasive; sensitive enough to detect small changes; reliable on repeated measurement; associated with clinically relevant endpoints such as pain, function, or structural progression; feasible in outpatient or home settings; able to track changes over months to years; robust to minor variations in testing conditions; and interpretable by clinicians. These criteria are used in the following sections to assess each candidate wearable measure. Wearables meet several of them in principle: they produce quantitative data without ionizing radiation, and they record movement in the environments where patients actually live. Their key advantage is not portability as such but the capacity for repeated, longitudinal measurement of function in the same individual.

Wearable sensor technologies

Table *1* summarizes the main classes of wearable sensors relevant to KOA, their typical placement, the parameters they capture, and their principal limitations.

Technology	Typical placement	Key parameters captured	Main advantages	Main limitations
IMUs	Foot, shank, thigh, pelvis, trunk	Walking speed, cadence, step/stride length, knee flexion-extension, symmetry, postural sway	Portable, inexpensive, suited to prolonged monitoring	Drift, magnetic interference, placement sensitivity
Wearable surface EMG	Quadriceps, hamstrings, gastrocnemius, gluteals	Activation timing/amplitude, co-contraction, fatigue	Captures neuromuscular strategy	Electrode/artifact sensitivity; compensatory versus pathological ambiguity
Pressure-sensing insoles	Inside footwear (plantar surface)	Regional plantar pressure, center-of-pressure trajectory, contact time, loading rate	Worn in normal shoes; captures daily loading	Indirect surrogate for tibiofemoral load
Flexible goniometers/smart knee sleeves	Knee joint (brace or sleeve)	Knee flexion-extension angle, ROM	Easy to fit; intuitive output	Sensor deformation, garment migration, calibration needs
Smart textiles	Garment-embedded (leg, trunk)	Joint movement, muscle activity, posture, activity	Comfortable for long-duration wear	Signal durability through washing/stretching
Multimodal systems	Combined IMU + EMG + pressure	Integrated kinematic, neuromuscular, and loading profile	Richer, more complete mechanistic picture	Added complexity; validation still limited

TABLE 1: Overview of wearable sensor technologies relevant to early KOA assessment.

EMG, electromyography; IMUs, inertial measurement units; KOA, knee osteoarthritis; ROM, range of motion

Inertial Measurement Units (IMUs)

IMUs are among the most commonly used wearable sensors for gait analysis [15]. An IMU typically combines a triaxial accelerometer, a gyroscope, and, in some devices, a magnetometer to measure linear acceleration, angular velocity, and heading, respectively. Depending on their location (foot, shank, thigh, pelvis, or trunk), IMUs can measure walking speed, cadence, step and stride length, double-support time, gait symmetry, knee flexion-extension, trunk and pelvic motion, turning characteristics, and postural sway.

A single pelvis- or foot-worn sensor provides an adequate overview of temporal gait parameters and is well suited to detecting heel strike and toe-off, whereas knee kinematics require two segment sensors (thigh and shank) and correction for soft-tissue artifacts and gyroscope drift. Reviews comparing IMUs with optical motion capture generally support their validity, although accuracy depends on sensor placement and the parameter measured [23]. In KOA specifically, a single pelvic IMU differentiated 20 patients with end-stage disease awaiting arthroplasty from 30 healthy controls during gait, sit-to-stand, and step-up tasks. It should be noted that this and most comparable studies enrolled patients with established or severe KOA rather than early disease. An agreed-upon, clinically meaningful core set of IMU-derived gait measures for KOA would enhance comparability between studies [24,25]. Large, multicohort technical validation of real-world gait outcomes using a single lower-back sensor has recently been published by the Mobilise-D consortium, with mean absolute errors for walking speed of about 0.1 m/s and lower accuracy in short or slow walking bouts. KOA was not among the validated cohorts, so these algorithms still require confirmation in this population [26,27]. IMUs are portable and ideal for long-term use; however, they are susceptible to drift, magnetic interference, and sensitivity to sensor placement and algorithm choice.

Wearable EMG

Surface EMG records the electrical activity of contracting muscles, typically the quadriceps, hamstrings, gastrocnemius, and gluteals; it is a skin-mounted muscle sensor, not a footwear device. Wearable EMG can detect changes in activation timing, intensity, duration, agonist-antagonist co-contraction, fatigue, and side-to-side differences [28]. Increased co-contraction at the knee may be an attempt to stabilize or compress the joint, while decreased or delayed activation of the quadriceps may impair shock absorption and joint stability. These patterns have been characterized in people with severe KOA awaiting joint replacement [29].

However, EMG is sensitive to electrode position, skin impedance, movement artifacts, subcutaneous fat, and

cross-talk among neighboring muscles [28]. Newer wearable EMG devices have been validated against laboratory-grade equipment, with promising results [30]. Interpretation is difficult because an altered activation pattern could be compensatory rather than disease-related. EMG is therefore more likely to contribute to a multimodal assessment than to serve as a stand-alone diagnostic signal.

Pressure-Sensing Insoles

Pressure-sensing insoles contain arrays of force or pressure sensors that record plantar loading during standing, walking, and other weight-bearing tasks. They provide information on the regional distribution of pressure under the foot, the trajectory of the center of pressure during stance, contact time, and loading rate. Because the foot is the final point of contact with the ground, plantar pressure patterns are altered by pain avoidance, malalignment, and limited proximal knee motion. For example, sensing insoles have been used to quantify plantar pressure patterns in medial KOA and their changes with lateral-wedge insoles [31], and insole-derived vertical ground reaction force signatures have been used to classify knee arthropathy using ML [32]. Insoles have the practical advantage of fitting inside regular footwear during everyday activities. Their principal limitation is that plantar pressure is only an indirect surrogate for tibiofemoral contact force and is influenced by footwear, walking surface, speed, body weight, and foot shape.

Flexible Goniometers and Smart Knee Sleeves

Flexible, stretch-sensitive sensors attached to a knee brace, sleeve, or garment may be used to measure knee flexion-extension angles based on changes in length and electrical resistance during movement [33]. They can track range of motion (ROM) over time, quantify reduced flexion during walking, support the progression of rehabilitation programs, and provide real-time feedback on movement. The devices are simple to fit and usually straightforward to interpret; however, they may be susceptible to sensor deformation, garment migration, and the need for recalibration.

Smart Textiles

Smart textiles incorporate conductive fibers, strain sensors, pressure sensors, or EMG electrodes directly into fabrics, allowing more comfortable extended wear than straps [34]. In principle, a single garment could record joint movement, muscle activity, posture, and activity simultaneously. In practice, maintaining signal stability through repeated washing and daily use remains an unsolved engineering problem and a major barrier to clinical application [35].

Multimodal Wearable Systems

Combining several sensors, such as an IMU to measure movement, EMG to measure muscle activity, and a pressure sensor to measure plantar loading, can provide a more complete picture of joint movement, muscle activation, and external loading than any single device [36]. Current systems can record gait, posture, and muscular activity concurrently; however, it is unclear whether this added complexity improves diagnostic accuracy over simpler, single-sensor approaches because comparative studies are lacking.

Candidate kinematic signatures of early KOA

Kinematic signatures are measurable patterns of movement associated with a physiological or pathological state. No single gait parameter is specific to KOA; a useful signature is more likely to be a composite of temporal, spatial, angular, symmetry, and variability measures (Table *2*). The candidate parameters below are assessed against the criteria set out above.

Domain	Representative parameters	Proposed clinical significance
Temporal	Walking speed, cadence, stance/swing time, double-support duration	Pain-related unloading, reduced limb confidence, compensatory timing changes
Spatial	Step length, stride length	Reduced knee excursion and peak joint moments
Angular/ROM	Peak knee flexion, knee ROM, angular velocity	Stiffness, pain avoidance, quadriceps dysfunction, reduced shock absorption
Symmetry and variability	Inter-limb asymmetry indices, stride-to-stride variability	Unilateral unloading, impaired motor control, instability
Trunk, pelvic, and balance	Trunk lean angle, pelvic obliquity, postural sway	Compensatory offloading strategy, reduced KAM
Functional task performance	Stair descent kinematics, sit-to-stand time, Timed Up and Go, single-leg stance	Sensitivity beyond level walking; eccentric quadriceps control deficits

TABLE 2: Candidate kinematic signatures ("digital biomarkers") proposed for early KOA.

KAM, knee adduction moment; KOA, knee osteoarthritis; ROM, range of motion

Walking speed is the simplest parameter to measure and the most consistently altered. People with KOA walk more slowly because of pain, stiffness, muscle weakness, or low confidence in the joint, but speed also varies with age, fitness, mood, and environment [12]. Shorter steps and strides accompany reduced knee flexion ROM and lower peak joint moments, and both are strongly dependent on walking speed and leg length. KOA also alters cadence, stance and swing time, and the duration of single and double support. A longer double-support phase may indicate reduced limb confidence, whereas shorter stance time on the affected side suggests pain-related unloading; therefore, between-limb comparisons aid interpretation. Meta-analyses of level walking in established KOA confirm reduced walking speed, reduced knee flexion excursion, and altered neuromuscular patterns compared with controls; whether the same deviations are present and detectable in early (KL 0-1) disease is much less certain [37,38].

Reduced knee flexion during the loading response impairs shock absorption, and reduced flexion during the swing phase reduces foot clearance; these patterns are well described in severe KOA [29]. Lower angular velocities may indicate a cautious gait, and jerk-based smoothness measures have been proposed but are not yet standardized for clinical use. Inter-limb asymmetry and stride-to-stride variability in step length and timing can indicate unilateral pathology or impaired motor control, although bilateral involvement complicates their use [22].

Trunk and pelvic motion are important because they represent active compensations: lateral trunk lean toward the stance limb reduces the external knee adduction moment (KAM), a surrogate for medial compartment load [13]. Wearables can also quantify postural sway and sit-to-stand performance, which level-walking tests do not capture. Because knee pain in early OA first appears during stair use, tasks that demand eccentric quadriceps control through a large flexion range, such as stair descent, chair rise, step-down, the Timed Up and Go test, and single-leg stance, may reveal abnormalities that are absent during level walking [11]. These tasks form part of the Osteoarthritis Research Society International (OARSI)-recommended performance test set [39], and sensor-derived measures from sit-to-stand and step-up transfers showed good discriminative capacity in end-stage KOA [24]. A structured battery of such tasks is therefore likely to be more sensitive than level-walking gait analysis alone, although this has yet to be demonstrated in early KOA.

Differential diagnosis and the specificity of gait markers

None of the kinematic deviations described above is unique to KOA. Slower walking, shorter steps, reduced knee flexion, and an antalgic pattern also occur with aging, obesity, muscle weakness, general deconditioning, and, importantly, diseases of neighboring joints and the nervous system. Hip pathology, including avascular necrosis of the femoral head in older adults, may present with gait changes and knee-region pain [40]. Lumbar spinal stenosis and spondylolisthesis can also alter gait and lower-limb function, producing leg symptoms, walking intolerance, and slower gait that resemble knee-driven changes [41]. Knee pain and gait disturbance may arise from cervical myelopathy or nerve root disease and have been reported even after total knee arthroplasty [42]. Peripheral neuropathy, Parkinson's disease, stroke, and vestibular disorders produce further overlapping gait phenotypes. These conditions are real-world sources of false-positive classifications for any knee-focused algorithm trained only on KOA cases and healthy controls, and they limit the specificity of wearable gait markers. Future diagnostic studies should therefore include disease

controls with hip, spinal, and neurological causes of altered gait and should report specificity against these conditions rather than only against healthy volunteers.

Wearable sensors and ML

Wearable devices generate large amounts of time-series data, which can be analyzed using ML techniques to identify patterns that may not be detected by traditional statistical approaches [43]. The typical pipeline comprises data collection from sensors; preprocessing, such as filtering and time alignment; detection of events, such as steps, gait cycles, or functional tasks; feature extraction; model training and selection; internal and, ideally, external validation; and, finally, clinical interpretation (Figure *2*). Common features include mean acceleration, peak angular velocity, temporal gait parameters, symmetry indices, variability measures, and frequency-domain properties, which are used as inputs to algorithms [32,44].

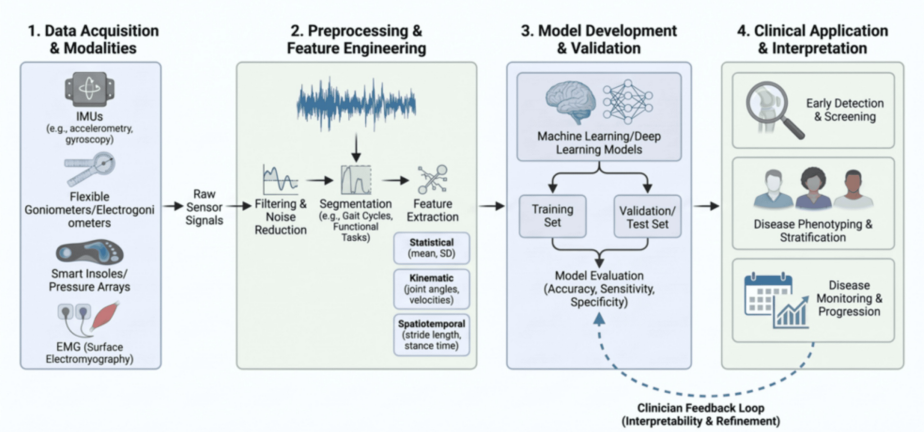


FIGURE 2: Analytical pipeline linking wearable sensor data to clinical decision-making in early KOA.

EMG, electromyography; IMUs, inertial measurement units; KOA, knee osteoarthritis

This figure was created by Madhan Jeyaraman using BioRender (BioRender, Toronto, Canada).

Table *3* summarizes the key primary studies. Several groups have shown that wearable-derived features can differentiate people with KOA from healthy controls: a single pelvic IMU used across gait and transfer tasks in patients with end-stage KOA [24]; foot-worn sensors in patients awaiting arthroplasty; a support vector machine trained on force-plate data that classified knee arthropathy using digital insole recordings in an independent dataset, with an area under the receiver operating characteristic curve (AUC) of 0.83-0.93; and dual thigh-shank IMUs with ensemble classifiers in a very small sample [32,45,46]. In an at-risk population, IMU-derived knee kinematics discriminated between 12 people with anterior cruciate ligament reconstruction and 19 controls, with 80.7% accuracy (sensitivity, 92%; specificity, 74%) [47]. Wearables combined with ML have also been used to estimate knee-loading variables that previously required a gait laboratory: artificial neural networks fed by two IMUs reproduced the knee flexion moment well, and the KAM moderately during walking [48], and a single tibial IMU with a deep-learning model reconstructed the KAM waveform, with correlations of about 0.6 for peak KAM and 0.75 for KAM impulse in an independent hold-out sample of 45 participants that included KL 0-4 knees [49]. Finally, multisensor accelerometry has been used to predict responses to exercise therapy (classification accuracy, 74%-82%) and to track individual changes in movement patterns after intervention [44,50].

Study	Population and KOA definition	n	Sensor and placement	Features	Model/analysis	Validation	Reported performance
Bacon et al. (2024) [16]	MOST cohort: adults with or at risk of KOA; outcomes included worsening pain and function over two years	2,324	IMUs on the lower back and both ankles; 20-meter walk	Spatiotemporal gait parameters, asymmetry, and dominant frequency	Super learner (ensemble) for variable selection; log-binomial regression	Internal CV	Associations (risk ratios) for asymmetry, step length, and dominant frequency (pain) and cadence (function); no diagnostic AUC reported
Bolink et al. (2012) [24]	End-stage KOA (KL grades 3-4) awaiting TKA vs. healthy controls	20 KOA; 30 controls	Single IMU on the pelvis	Spatiotemporal gait parameters, pelvic ROM, sit-	Group comparison; discriminative	None (cross-sectional)	Significant group differences; time-based measures were the most discriminative; no AUC

			(lower back)	to-stand and step-up timing	capacity		reported
Hubley-Kozey et al. (2008) [29]	Severe KOA within one week of TKA	51	Laboratory surface EMG of seven knee muscles	EMG waveform principal patterns	Principal component analysis; ANOVA	None	Descriptive coactivation patterns; no classifier
Wipperman et al. (2024) [32]	Knee arthropathy (force-plate dataset: 625 knee injury cases vs. 211 controls); independent insole dataset: KOA with KL grade ≥2, ACR criteria, and WOMAC pain score ≥4	Insole dataset: 38 KOA; 22 controls	Pressure-sensing digital insoles (vertical ground reaction force)	Stance-phase force waveform features	Support vector machine trained on force-plate data	Internal CV, hold-out set, and external insole dataset	AUC of 0.86 (hold-out) and 0.83 (independent insole dataset); per-knee models: AUC of 0.92-0.95
Hu et al. (2025) [36]	KOA (engineering validation of the system)	Not stated as a diagnostic cohort	Multimodal: surface EMG, pressure sensors, and IMU	Gait and EMG features	Feature extraction and rehabilitation system	Technical validation	Mean relative error of gait features <8%; no diagnostic accuracy reported
Kobsar and Ferber (2018) [44]	KOA before and after an exercise intervention	8	Accelerometers on the lower back, thigh, and shank	Three-dimensional acceleration per stride (treadmill)	One-class support vector machine (outlier strides)	None	Change in outlier percentage correlated with changes in pain and function; no diagnostic metrics reported
Kluge et al. (2018) [45]	End-stage unilateral KOA before and one year after TKA, plus matched controls	24 KOA; matched controls	Foot-worn IMUs	Spatiotemporal gait parameters	ML prediction of functional responder status	Internal CV	Responder prediction accuracy of up to 89%; stride time and stride length were the most important features
Bharanidivya and Dhanalakshmi (2026) [46]	KOA (definition not stated) vs. healthy controls	15 participants (637 gait cycles)	Dual IMUs on the femur and tibia	Orientation, angular velocity, and acceleration per gait cycle	Random forest and other ensemble classifiers	Internal (cycle-level) validation	Accuracy of 97% (random forest); risk of an optimistic estimate due to cycle-level splitting
Butler et al. (2025) [47]	ACLR (at risk of early KOA) vs. healthy controls	12 ACLR; 19 controls	IMU-based three-dimensional knee kinematics	468 knee time-series features across daily tasks	LASSO regression classifier	Internal CV	Accuracy, 80.7%; sensitivity, 92%; specificity, 74%
Stetter et al. (2020) [48]	Healthy adults (method development for KOA loading)	13	Two IMUs on the thigh and shank	Raw IMU signals	Artificial neural network estimating knee flexion moment and KAM	LOSO CV	Walking: KFM r ≥ 0.69; KAM r = 0.71 (rRMSE, 22%); weaker performance for cutting and running
Sakamoto et al. (2026) [49]	Healthy controls (KL grade 0) and participants with KOA (KL grades 1-4)	50 for development; 45 for independent hold-out	Single IMU on the tibial tuberosity	Stance-phase IMU waveforms	1D U-Net with GRU bottleneck for reconstructing the KAM waveform	Internal validation and independent hold-out (same protocol)	Peak KAM: r = 0.60 (internal) and 0.62 (hold-out); KAM impulse: r = 0.74-0.75
Kobsar et al. (2017) [50]	Clinically diagnosed KOA; 6-week hip-strengthening program	39	Accelerometers on the back, thigh, shank, and foot	Gait acceleration features and KOOS	Discriminant analysis of principal components (responder prediction)	Internal CV	Accuracy of 74.4% (thigh alone) to 81.7% (back + thigh + shank)

TABLE 3: Key primary studies of wearable sensors in people with or at risk of KOA.

Where a 95% CI was not reported in the source, none is given.

ACLR, anterior cruciate ligament reconstruction; ACR, American College of Rheumatology; AUC, area under the receiver operating characteristic curve; CV, cross-validation; EMG, electromyography; GRU, gated recurrent unit; IMU, inertial measurement unit; KAM, knee adduction moment; KFM, knee flexion moment; KL, Kellgren-Lawrence; KOA, knee osteoarthritis; KOOS, Knee injury and Osteoarthritis Outcome Score; LASSO, least absolute

shrinkage and selection operator; LOSO, leave-one-subject-out; ML, machine learning; MOST, Multicenter Osteoarthritis Study; ROM, range of motion; rRMSE, relative root mean square error; TKA, total knee arthroplasty; WOMAC, Western Ontario and McMaster Universities Osteoarthritis Index

Three cautions apply. First, with the exception of the Multicenter Osteoarthritis Study (MOST) analysis (n = 2,324) and the insole study, the samples in Table *3* are small (8-51 participants), and most studies compare established or end-stage KOA with healthy controls rather than early KOA. Second, overfitting is the major analytical risk: a model may perform well on its training data yet poorly on new data. A systematic review found no performance advantage of ML over logistic regression in clinical prediction models, largely because of small samples and optimistic validation [16,32,51]. Accuracy alone is therefore an inadequate metric; sensitivity, specificity, AUC with 95% CIs, calibration, and performance on an external dataset should be reported, following the TRIPOD and TRIPOD+AI statements [52,53]. Of the studies in Table *3*, only the insole study and the single-IMU KAM study report performance in an independent hold-out or external dataset, and none fully meets TRIPOD reporting standards for calibration [32,49]. Third, interpretability matters: clinicians may be reluctant to act on a risk score that does not indicate which movement features contributed to it. Therefore, explainable models and transparent feature reporting are essential for medical use.

Clinical applications

Early Risk Identification

Wearable monitoring could, in principle, identify abnormal movement patterns before imaging changes become evident, serving as a screening or early-warning signal rather than a diagnostic tool in groups at elevated risk: older adults with intermittent knee pain, people with obesity, those with previous anterior cruciate ligament or meniscal injuries, individuals with a family history of OA, and athletes or workers with high cumulative knee loading. The ACL reconstruction study [47] is a preliminary example of this approach. However, no prospective study has yet shown that a wearable-derived marker predicts incident KOA in such a population; therefore, this application remains hypothetical.

Monitoring Disease Progression

Repeated measurement of gait speed, knee ROM, inter-limb symmetry, and physical activity may capture changes within an individual more sensitively than cross-sectional comparisons with population norms. In the MOST cohort, greater gait asymmetry, longer average step length, and lower dominant frequency were associated with worsening pain, while lower cadence was associated with worsening physical function over two years [16]. These are associations with symptom and functional outcomes rather than with structural (cartilage) progression, but they support the potential of wearable gait measures as prognostic rather than merely descriptive markers.

Rehabilitation and Biofeedback

Wearables can provide real-time feedback on gait parameters and joint motion, which is the basis of gait-retraining strategies (such as increased trunk lean, toe-in or toe-out, or altered step width) that aim to reduce medial knee load [54,55]. Sensor-derived outcomes also allow clinicians to track recovery between visits. Preintervention accelerometry has been used to predict which patients respond to a strengthening program, and preoperative sensor-based gait parameters predicted functional outcomes after total knee arthroplasty with up to 89% accuracy in a cohort of 24 patients [45,50]. Combined with pain scores and questionnaires, such measures could help evaluate exercise therapy, weight management, bracing, orthoses, injection therapy, and neuromuscular training, although controlled trials demonstrating improved outcomes are still awaited.

Remote and Home-Based Care

Home monitoring reduces the need for laboratory visits and captures function in real-world settings, where walking bouts are shorter, surfaces and footwear vary, and fatigue accumulates. The trade-off is greater measurement variability, and real-world algorithms require specific validation [26,27]. A scoping review of real-world wearable use in KOA found that most studies were small and short, and that participants with obesity, multimorbidity, or severe mobility limitations were often excluded [56].

Comparison of conventional diagnostic approaches

Table *4* compares wearables with currently used diagnostic approaches. Clinical examination is low-cost and widely accessible but examiner-dependent; radiography is standardized and readily available but insensitive to early soft-tissue changes; MRI provides comprehensive joint information but is costly and impractical for frequent monitoring; patient-reported outcomes capture the patient's own experience but are inherently subjective; and laboratory gait analysis is accurate but limited to brief, artificial assessments. Wearables offer objectivity, no radiation exposure, lower costs than MRI, suitability for long-term and home

monitoring, measurement during real-world tasks rather than only during treadmill walking, and ready integration with telehealth and ML analytics. Despite these advantages, standardization is limited, and diagnostic thresholds remain undefined. The argument presented here is not for replacing imaging and clinical assessment but for adding a functional dimension that those modalities lack.

Method	Primary information captured	Key advantages	Key limitations
Clinical examination	Symptoms, alignment, tenderness, ROM	Low cost, widely available, no equipment needed	Examiner-dependent; limited objectivity
Radiography (KL)	Osteophytes, joint-space narrowing, subchondral sclerosis, bony deformity	Standardized, accessible, inexpensive	Limited sensitivity to early soft-tissue and functional changes; cannot identify early disease at KL grades 0-1
MRI	Cartilage, menisci, synovium, bone marrow lesions	Detailed whole-joint structural assessment	Expensive, time-consuming; impractical for repeated screening
WOMAC/KOOS (patient-reported) [7,8]	Patient-reported symptoms and function	Patient-centered, low cost, easy to administer	Subjective; influenced by mood and context
Laboratory gait analysis	Detailed kinematics and kinetics	High precision and validity	Expensive, laboratory-restricted; provides only a brief snapshot of movement
Wearable sensors (IMU/EMG/insoles/multimodal systems)	Real-world gait, joint motion, muscle activity, loading, and physical activity	Portable, repeatable, suitable for continuous or long-duration real-world monitoring	Limited standardization; uncertain diagnostic thresholds; no validated marker for early KOA; specificity untested

TABLE 4: Wearable sensors compared with conventional diagnostic approaches for KOA.

EMG, electromyography; IMU, inertial measurement unit; KL, Kellgren-Lawrence; KOA, knee osteoarthritis; KOOS, Knee Injury and Osteoarthritis Outcome Score; ROM, range of motion; WOMAC, Western Ontario and McMaster Universities Osteoarthritis Index

Advantages of wearable biomarkers

Wearable devices offer several advantages, including objective measurement and quantification of movement; noninvasive monitoring without radiation exposure; lower costs than other modalities, such as MRI; long-term monitoring over months or years; and applicability in home, hospital, and clinic settings. They can be used during everyday activities rather than only during treadmill walking and can be readily integrated into telehealth systems. They may also support the development of personalized patient health profiles when combined with ML algorithms. Monitoring patients outside the clinic is particularly important because an hour spent with a patient in a clinical setting provides limited information about their movement patterns and does not reveal the discomfort or fatigue they may experience during their usual daily activities.

Limitations and challenges

Several limitations restrict the clinical applicability of wearable gait markers in early KOA. The first is definitional: “early KOA” has been operationalized in different studies as symptomatic knees with normal radiographs, KL grade 1 disease, MRI-defined early abnormalities, or merely elevated risk. These are not equivalent populations, and a classifier trained using one definition will not necessarily generalize to another. Adoption of a single consensus definition would allow direct comparison between studies and the eventual derivation of diagnostic cutoff values [9].

The second limitation is methodological heterogeneity. Small differences in sensor position materially affect measurements, so standardized placement protocols are needed. Filtering techniques, gait event detection algorithms, and feature definitions also vary among research groups, producing results that cannot be pooled [23,25]. Third, most published studies are small, enroll participants with established or end-stage KOA, and often exclude people with obesity, multiple comorbidities, or severe mobility impairment, precisely those most likely to be seen in clinical practice [56]. Age, sex, body mass, muscle strength, pain level, and footwear all influence sensor outputs. Fourth, as discussed above, no movement pattern is specific to KOA, and the specificity of wearable markers against hip, spinal, and neurological diseases has not been tested [40-42]. Fifth, external validation is almost entirely absent, and reporting rarely meets TRIPOD standards [52,53].

Practicality matters as much as accuracy: uncomfortable or inconvenient devices will not be worn consistently outside a study setting. Continuous monitoring also raises legitimate concerns about data privacy, informed consent, and accountability. Finally, a diagnostic or risk-prediction tool based on wearable data would probably need regulatory approval as software as a medical device, and adoption will depend on validated cutoff values, integration with electronic health records, and evidence that it improves patient outcomes [57].

Future directions

Progress depends on large, prospective, multicenter studies that enroll participants who meet a consensus definition of early KOA, include disease controls with hip, spinal, and neurological causes of altered gait, and follow participants long enough to relate sensor-derived markers to incident or progressive disease. Such studies should preregister their analysis plans, report diagnostic accuracy with CIs and calibration, and validate models externally. Priorities for the field include an agreed definition of early KOA; standardized sensor placement and calibration; a small, clinically meaningful core outcome set; minimal clinically important differences for longitudinal tracking; and head-to-head comparisons of laboratory and real-world measurements. Multimodal approaches that integrate gait, muscle activity, estimated joint loading, imaging, and patient-reported outcomes may characterize disease state more completely than any single measure. The consensus frameworks developed for digital mobility outcomes [58,59] provide a template that the KOA field has yet to adopt.

Conclusions

Wearable sensors can measure gait, joint motion, postural stability, muscle activity, and plantar loading outside the laboratory. Candidate digital gait biomarkers, such as reduced walking speed, shorter steps, reduced knee flexion, inter-limb asymmetry, increased variability, and compensatory trunk motion, are associated with pain and functional decline in established KOA. However, no sensor-derived marker has yet been validated for diagnosing early KOA. The evidence base consists largely of small studies of established or end-stage disease compared with healthy controls; early KOA is inconsistently defined; sensor protocols are not standardized; external validation is rare; and specificity against other causes of altered gait is untested. At present, wearable gait measures are best regarded as research tools and as adjuncts for monitoring rehabilitation and home-based care. Translation into diagnostic practice will require consensus definitions, standardized protocols, and prospective, externally validated studies in populations that meet accepted criteria for early disease.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sankalp Yadav, Kothakota Bhanutej Kumandan, Navaneetha Krishnan Sekar, Suresh Krishna Lokayah, Rohith Kumaar, Shanmuga Boopathy Gangadharan, Sumesh Subramanian, Siddarth Rangabashyam, Nishanthan Vengappa, Madhan Jeyaraman, Naveen Jeyaraman

Acquisition, analysis, or interpretation of data: Sankalp Yadav, Kothakota Bhanutej Kumandan, Navaneetha Krishnan Sekar, Suresh Krishna Lokayah, Rohith Kumaar, Shanmuga Boopathy Gangadharan, Sumesh Subramanian, Siddarth Rangabashyam, Nishanthan Vengappa, Madhan Jeyaraman, Naveen Jeyaraman

Drafting of the manuscript: Sankalp Yadav, Kothakota Bhanutej Kumandan, Navaneetha Krishnan Sekar, Suresh Krishna Lokayah, Rohith Kumaar, Shanmuga Boopathy Gangadharan, Sumesh Subramanian, Siddarth Rangabashyam, Nishanthan Vengappa, Madhan Jeyaraman, Naveen Jeyaraman

Critical review of the manuscript for important intellectual content: Sankalp Yadav, Kothakota Bhanutej Kumandan, Navaneetha Krishnan Sekar, Suresh Krishna Lokayah, Rohith Kumaar, Shanmuga Boopathy Gangadharan, Sumesh Subramanian, Siddarth Rangabashyam, Nishanthan Vengappa, Madhan Jeyaraman, Naveen Jeyaraman

Supervision: Sankalp Yadav, Kothakota Bhanutej Kumandan, Navaneetha Krishnan Sekar, Suresh Krishna Lokayah, Rohith Kumaar, Shanmuga Boopathy Gangadharan, Sumesh Subramanian, Nishanthan Vengappa, Madhan Jeyaraman, Naveen Jeyaraman

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have

no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Associate Editor authorship:** Sankalp Yadav was an Associate Editor for the Cureus Journal of Medical Science at the time of submission. To minimize potential bias, this manuscript was handled independently by an alternate Associate Editor with no conflict of interest, and the author was blinded to and had no access to the peer review process, reviewer identities, or editorial decision-making for this submission. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

References

1. Hunter DJ, Bierma-Zeinstra S: Osteoarthritis. Lancet. 2019, 393:1745-59. 10.1016/s0140-6736(19)30417-9
2. Safiri S, Kolahi AA, Smith E, et al.: Global, regional and national burden of osteoarthritis 1990-2017: a systematic analysis of the Global Burden of Disease Study 2017. Ann Rheum Dis. 2020, 79:819-28. 10.1136/annrheumdis-2019-216515
3. Loeser RF, Goldring SR, Scanzello CR, Goldring MB: Osteoarthritis: a disease of the joint as an organ . Arthritis Rheum. 2012, 64:1697-707. 10.1002/art.34453
4. KE JH, LA JS: Radiological assessment of osteo-arthrosis. Ann Rheum Dis. 1957, 16:494-502. 10.1136/ard.16.4.494
5. Bedson J, Croft PR: The discordance between clinical and radiographic knee osteoarthritis: a systematic search and summary of the literature. BMC Musculoskelet Disord. 2008, 9:116. 10.1186/1471-2474-9-116
6. Guermazi A, Roemer FW, Haugen IK, Crema MD, Hayashi D: MRI-based semiquantitative scoring of joint pathology in osteoarthritis. Nat Rev Rheumatol. 2013, 9:236-51. 10.1038/nrrheum.2012.223
7. Bellamy N, Buchanan WW, Goldsmith CH, Campbell J, Stitt LW: Validation study of WOMAC: a health status instrument for measuring clinically important patient relevant outcomes to antirheumatic drug therapy in patients with osteoarthritis of the hip or knee. J Rheumatol. 1988, 15:1833-40.
8. Roos EM, Roos HP, Lohmander LS, Ekdahl C, Beynnon BD: Knee Injury and Osteoarthritis Outcome Score (KOOS)—development of a self-administered outcome measure. J Orthop Sports Phys Ther. 1998, 28:88-96. 10.2519/jospt.1998.28.2.88
9. Luyten FP, Bierma-Zeinstra S, Dell'Accio F, et al.: Toward classification criteria for early osteoarthritis of the knee. Semin Arthritis Rheum. 2018, 47:457-63. 10.1016/j.semarthrit.2017.08.006
10. Mahmoudian A, Lohmander LS, Jafari H, Luyten FP: Towards classification criteria for early-stage knee osteoarthritis: a population-based study to enrich for progressors. Semin Arthritis Rheum. 2021, 51:285-91. 10.1016/j.semarthrit.2020.11.002
11. Hensor EM, Dube B, Kingsbury SR, Tennant A, Conaghan PG: Toward a clinical definition of early osteoarthritis: onset of patient-reported knee pain begins on stairs. Data from the osteoarthritis initiative. Arthritis Care Res (Hoboken). 2015, 67:40-7. 10.1002/acr.22418
12. Astephen JL, Deluzio KJ, Caldwell GE, Dunbar MJ: Biomechanical changes at the hip, knee, and ankle joints during gait are associated with knee osteoarthritis severity. J Orthop Res. 2008, 26:332-41. 10.1002/jor.20496
13. Gerbrands TA, Pisters MF, Theeven PJ, Verschueren S, Vanwanseele B: Lateral trunk lean and medializing the knee as gait strategies for knee osteoarthritis. Gait Posture. 2017, 51:247-53. 10.1016/j.gaitpost.2016.11.014
14. Coravos A, Khozin S, Mandl KD: Developing and adopting safe and effective digital biomarkers to improve patient outcomes. NPJ Digit Med. 2019, 2:14. 10.1038/s41746-019-0090-4
15. Kobsar D, Masood Z, Khan H, Khalil N, Kiwan MY, Ridd S, Tobis M: Wearable inertial sensors for gait analysis in adults with osteoarthritis—a scoping review. Sensors (Basel). 2020, 20:7143. 10.3390/s20247143
16. Bacon KL, Felson DT, Jafarzadeh SR, et al.: Gait alterations and association with worsening knee pain and physical function: a machine learning approach with wearable sensors in the multicenter osteoarthritis study. Arthritis Care Res (Hoboken). 2024, 76:984-92. 10.1002/acr.25327
17. Baethge C, Goldbeck-Wood S, Mertens S: SANRA—a scale for the quality assessment of narrative review articles. Res Integr Peer Rev. 2019, 4:5. 10.1186/s41073-019-0064-8
18. Whiting PF, Rutjes AW, Westwood ME, et al.: QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies. Ann Intern Med. 2011, 155:529-36. 10.7326/0003-4819-155-8-201110180-00009
19. Kapoor M, Martel-Pelletier J, Lajeunesse D, Pelletier JP, Fahmi H: Role of proinflammatory cytokines in the pathophysiology of osteoarthritis. Nat Rev Rheumatol. 2011, 7:33-42. 10.1038/nrrheum.2010.196
20. Sellam J, Berenbaum F: The role of synovitis in pathophysiology and clinical symptoms of osteoarthritis . Nat Rev Rheumatol. 2010, 6:625-35. 10.1038/nrrheum.2010.159
21. Englund M, Guermazi A, Lohmander SL: The role of the meniscus in knee osteoarthritis: a cause or consequence?. Radiol Clin North Am. 2009, 47:703-12. 10.1016/j.rcl.2009.03.003
22. Andriacchi TP, Mündermann A, Smith RL, Alexander EJ, Dyrby CO, Koo S: A framework for the in vivo pathomechanics of osteoarthritis at the knee. Ann Biomed Eng. 2004, 32:447-57. 10.1023/b:abme.0000017541.82498.37
23. Kobsar D, Charlton JM, Tse CT, et al.: Validity and reliability of wearable inertial sensors in healthy adult walking: a systematic review and meta-analysis. J Neuroeng Rehabil. 2020, 17:62. 10.1186/s12984-020-00685-3
24. Bolink SA, van Laarhoven SN, Lipperts M, Heyligers IC, Grimm B: Inertial sensor motion analysis of gait, sit-stand transfers and step-up transfers: differentiating knee patients from healthy controls. Physiol Meas. 2012, 33:1947-58. 10.1088/0967-3334/33/11/1947
25. Boekesteijn RJ, van Gerven J, Geurts AC, Smulders K: Objective gait assessment in individuals with knee osteoarthritis using inertial sensors: a systematic review and meta-analysis. Gait Posture. 2022, 98:109-20. 10.1016/j.gaitpost.2022.09.002
26. Micó-Amigo ME, Bonci T, Paraschiv-Ionescu A, et al.: Assessing real-world gait with digital technology? Validation, insights and recommendations from the Mobilise-D consortium. J Neuroeng Rehabil. 2023, 20:78. 10.1186/s12984-023-01198-5

27. Kirk C, Küderle A, Micó-Amigo ME, et al.: Mobilise-D insights to estimate real-world walking speed in multiple conditions with a wearable device. Sci Rep. 2024, 14:1754. 10.1038/s41598-024-51766-5
28. Hubley-Kozey CL, Robbins SM, Rutherford DJ, Stanish WD: Reliability of surface electromyographic recordings during walking in individuals with knee osteoarthritis. J Electromyogr Kinesiol. 2013, 23:334-41. 10.1016/j.jelekin.2012.12.002
29. Hubley-Kozey C, Deluzio K, Dunbar M: Muscle co-activation patterns during walking in those with severe knee osteoarthritis. Clin Biomech (Bristol). 2008, 23:71-80. 10.1016/j.clinbiomech.2007.08.019
30. Molina-Molina A, Ruiz-Malagón EJ, Carrillo-Pérez F, Roche-Seruendo LE, Damas M, Banos O, García-Pinillos F: Validation of mDurance, a wearable surface electromyography system for muscle activity assessment. Front Physiol. 2020, 11:606287. 10.3389/fphys.2020.606287
31. Hsu WC, Chou LW, Chiu HY, Hsieh CW, Hu WP: A study on the effects of lateral-wedge insoles on plantar-pressure pattern for medial knee osteoarthritis using the wearable sensing insole. Sensors (Basel). 2022, 23:84. 10.3390/s23010084
32. Wipperman MF, Lin AZ, Gayvert KM, et al.: Digital wearable insole-based identification of knee arthropathies and gait signatures using machine learning. Elife. 2024, 13:e86132. 10.7554/eLife.86132
33. Rivera B, Cano C, Luis I, Elias DA: A 3D-printed knee wearable goniometer with a mobile-app interface for measuring range of motion and monitoring activities. Sensors (Basel). 2022, 22:763. 10.3390/s22030763
34. Angelucci A, Cavicchioli M, Cintorrino IA, Lauricella G, Rossi C, Strati S, Aliverti A: Smart textiles and sensorized garments for physiological monitoring: a review of available solutions and techniques. Sensors (Basel). 2021, 21:814. 10.3390/s21030814
35. Khundaqji H, Hing W, Furness J, Climstein M: Smart shirts for monitoring physiological parameters: scoping review. JMIR Mhealth Uhealth. 2020, 8:e18092. 10.2196/18092
36. Hu J, Wang S, Shen Y, Miao X: A wearable system for knee osteoarthritis: based on multimodal physiological signal assessment and intelligent rehabilitation. Sensors (Basel). 2025, 25:7334. 10.3390/s25237334
37. Mills K, Hunt MA, Ferber R: Biomechanical deviations during level walking associated with knee osteoarthritis: a systematic review and meta-analysis. Arthritis Care Res (Hoboken). 2013, 65:1643-65. 10.1002/acr.22015
38. Mills K, Hunt MA, Leigh R, Ferber R: A systematic review and meta-analysis of lower limb neuromuscular alterations associated with knee osteoarthritis during level walking. Clin Biomech (Bristol). 2013, 28:713-24. 10.1016/j.clinbiomech.2013.07.008
39. Dobson F, Hinman RS, Roos EM, et al.: OARSI recommended performance-based tests to assess physical function in people diagnosed with hip or knee osteoarthritis. Osteoarthritis Cartilage. 2013, 21:1042-52. 10.1016/j.joca.2013.05.002
40. Chu EC: Idiopathic avascular necrosis of the femoral head in an older adult: a case report . Cureus. 2026, 18:e112084. 10.7759/cureus.112084
41. Chu EC, Kong P: Conservative care for L3/L4 spondylolisthesis with severe stenosis in the setting of L5 sacralization. Cureus. 2026, 18:e115887. 10.7759/cureus.115887
42. Chu EC, Lin AF: Knee pain following total knee arthroplasty secondary to cervical spondylotic myelopathy . Curr Health Sci J. 2022, 48:226-9. 10.12865/CHSJ.48.02.13
43. Halilaj E, Rajagopal A, Fiterau M, Hicks JL, Hastie TJ, Delp SL: Machine learning in human movement biomechanics: best practices, common pitfalls, and new opportunities. J Biomech. 2018, 81:1-11. 10.1016/j.jbiomech.2018.09.009
44. Kobsar D, Ferber R: Wearable sensor data to track subject-specific movement patterns related to clinical outcomes using a machine learning approach. Sensors (Basel). 2018, 18:2828. 10.3390/s18092828
45. Kluge F, Hannink J, Pasluosta C, et al.: Pre-operative sensor-based gait parameters predict functional outcome after total knee arthroplasty. Gait Posture. 2018, 66:194-200. 10.1016/j.gaitpost.2018.08.026
46. Bharanidivya M, Dhanalakshmi S: TinyML-enabled wearable system for early detection of knee osteoarthritis using ensemble gait classification. Comput Biol Med. 2026, 200:111345. 10.1016/j.compbiomed.2025.111345
47. Butler BR, Gholami B, Low BZ, et al.: Feasibility of automatic knee kinematic feature learning for discriminating between individuals with and without a history of an anterior cruciate ligament reconstruction. Clin Biomech (Bristol). 2025, 130:106673. 10.1016/j.clinbiomech.2025.106673
48. Stetter BJ, Krafft FC, Ringhof S, Stein T, Sell S: A machine learning and wearable sensor based approach to estimate external knee flexion and adduction moments during various locomotion tasks. Front Bioeng Biotechnol. 2020, 8:9. 10.3389/fbioe.2020.00009
49. Sakamoto H, Yoshihara H, Akiba A, et al.: A single-IMU wearable system with 1D U-Net for knee adduction moment waveform reconstruction during gait. Sensors (Basel). 2026, 26:4421. 10.3390/s26144421
50. Kobsar D, Osis ST, Boyd JE, Hettinga BA, Ferber R: Wearable sensors to predict improvement following an exercise intervention in patients with knee osteoarthritis. J Neuroeng Rehabil. 2017, 14:94. 10.1186/s12984-017-0309-z
51. Christodoulou E, Ma J, Collins GS, Steyerberg EW, Verbakel JY, Van Calster B: A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. J Clin Epidemiol. 2019, 110:12-22. 10.1016/j.jclinepi.2019.02.004
52. Collins GS, Reitsma JB, Altman DG, Moons KG: Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD): the TRIPOD statement. Ann Intern Med. 2015, 162:55-63. 10.7326/M14-0697
53. Collins GS, Moons KG, Dhiman P, et al.: TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024, 385:e078378. 10.1136/bmj-2023-078378
54. Simic M, Hinman RS, Wrigley TV, Bennell KL, Hunt MA: Gait modification strategies for altering medial knee joint load: a systematic review. Arthritis Care Res (Hoboken). 2011, 63:405-26. 10.1002/acr.20380
55. Bowd J, Biggs P, Holt C, Whatling G: Does gait retraining have the potential to reduce medial compartmental loading in individuals with knee osteoarthritis while not adversely affecting the other lower

limb joints? A systematic review. Arch Rehabil Res Clin Transl. 2019, 1:100022. 10.1016/j.arrct.2019.100022

56. Cudejko T, Button K, Willott J, Al-Amri M: Applications of wearable technology in a real-life setting in people with knee osteoarthritis: a systematic scoping review. J Clin Med. 2021, 10:5645. 10.3390/jcm10235645
57. Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan . FDA, Silver Spring, MD; 2021.
58. Rochester L, Mazzà C, Mueller A, et al.: A roadmap to inform development, validation and approval of digital mobility outcomes: the mobilise-D approach. Digit Biomark. 2020, 4:13-27. 10.1159/000512513
59. Kluge F, Del Din S, Cereatti A, et al.: Consensus based framework for digital mobility monitoring. PLoS ONE. 2021, 16:e0256541. 10.1371/journal.pone.0256541