

Low-Cost Gait Analysis Technologies for Clinical and Real-World Assessment: A Scoping Review of Validity, Reliability, and Clinical Utility

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Systematic Review

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Abstract

Background

Low-cost gait technologies are proposed as alternatives to specialist gait laboratories, but evidence remains fragmented across devices, outcomes and intended uses. This review examined whether performance, affordability and implementation evidence supports clinical and real-world uses.

Methods

We conducted a JBI-guided scoping review reported according to PRISMA-ScR. Six databases were searched to 20 May 2026, with citation searching. Eligible human studies evaluated a low-cost gait technology and reported validity, reliability, measurement error or clinical utility. Technologies, settings, intended uses and seven gait-outcome domains were mapped. Validity used an agreement-first hierarchy; reliability was separated into relative reliability, absolute measurement error and responsiveness; affordability and clinical utility used prespecified frameworks; and a limited COSMIN-informed appraisal contextualised the evidence.

Results

Of 7,745 records, 120 studies were included. Wearable sensors (35.0%) and video-based systems (27.5%) predominated. Spatiotemporal outcomes were reported in 86 studies (71.7%) and kinematics in 56/46.7%. Validity evidence was reported in 104 studies and reliability in 101, but only 63 reported absolute measurement error and one assessed responsiveness. Research measurement dominated intended use (117 studies, 97.5%); 53 studies (44.2%) addressed clinical assessment and 23/19.2% rehabilitation monitoring, whereas only 5/4.2% involved home monitoring and 2/1.7% telehealth-supported assessment. Five studies directly evaluated clinical utility, and one verified a complete setup below US\$1,000. Methodological confidence was higher in 6 studies (5.0%), moderate in 26/21.7%, lower in 87/72.5% and insufficiently reported in 1/0.8%. No study had an African primary setting. Overall, performance evidence was extensive, whereas affordability and real-world implementation evidence was sparse.

Conclusions

Low-cost gait technologies show technical evidence for spatiotemporal and selected kinematic outcomes, but evidence of absolute precision, responsiveness, affordability and implementation remains limited. Technical capability should not be equated with measurement credibility, nor measurement credibility with implementation readiness. Several systems appear promising for selected parameters, but none had sufficient evidence for unrestricted clinical adoption. The absence of African studies limits

transferability to settings with different infrastructure, workforce, connectivity and resources, highlighting the need for context-specific validation and implementation research in Africa. This review derived a six-stage framework knowledge-translation output to support readiness assessment but requires prospective validation before clinical use.

Registration:

Open Science Framework: <https://archive.org/details/osf-registrations-z6ekr-v1>.

INTRODUCTION

Accurate gait assessment is a fundamental component of clinical rehabilitation, biomechanics, and functional outcome evaluation because gait performance provides objective information for diagnosis, treatment planning, monitoring of disease progression, evaluation of rehabilitation outcomes, and assessment of recovery across neurological, musculoskeletal, paediatric, and age-related conditions [1–3]. In routine clinical practice, gait assessment informs decisions related to therapeutic prioritisation, assistive device prescription, fall-risk management, and discharge readiness [3].

Although observational gait assessment remains widely used due to its simplicity and low cost, it is inherently subjective, demonstrates only moderate inter-rater reliability, and may be insufficiently sensitive to detect subtle but clinically meaningful changes in gait performance. Consequently, there has been increasing emphasis on objective and technology-assisted approaches to gait analysis that improve measurement precision, reproducibility, and clinical decision-making [4–8]. Laboratory-based gait analysis systems, including three-dimensional motion capture, force platforms, pressure-sensitive walkways, and instrumented treadmills, are widely regarded as reference-standard methods in controlled research and specialist clinical environments because they provide comprehensive spatiotemporal, kinematic, and kinetic data [2,3,5]. However, these systems require specialised infrastructure, technical expertise, and substantial financial investment, limiting their routine use in primary care, community rehabilitation, and resource-constrained settings [4–8]. In response to these limitations, research has increasingly focused on low-cost and portable gait assessment technologies. These include wearable inertial measurement units (IMUs), smartphone-based applications, depth cameras, markerless motion capture systems, and other emerging digital health tools designed to support accessible and scalable gait evaluation outside laboratory environments [6–10]. Recent evidence also highlights the growing integration of artificial intelligence and machine learning approaches for automated gait classification and remote mobility monitoring, further expanding the scope of digital gait assessment [8–10]. The increasing adoption of these technologies reflects the global demand for accessible rehabilitation services. More than 2 billion people worldwide are estimated to require rehabilitation at some point in their condition trajectory, with a disproportionate burden of unmet need in low- and middle-income countries (LMICs), where shortages of rehabilitation professionals, infrastructure, and assistive technologies remain significant barriers to care [11,12]. Portable gait assessment technologies therefore

represent a potential opportunity to improve access to objective mobility evaluation, particularly in community and remote settings.

Despite rapid technological advancement, the evidence base for low-cost gait analysis technologies remains fragmented. Studies vary considerably in definitions of 'low cost,' target populations, outcome measures, validation approaches and intended application contexts. For clinicians and health systems, the practical problem is not simply whether a portable device can generate a gait variable, but whether that variable is sufficiently valid, reliable and precise for the intended decision; whether observed change exceeds measurement error; whether the technology has been tested in the target population and environment; whether the full operational cost is genuinely affordable; and whether home or telehealth deployment has been evaluated rather than merely proposed. Technology-specific reviews have advanced understanding of markerless systems, wearable inertial sensors, smartphone applications and machine-learning approaches [6–10], but they do not collectively resolve this cross-technology decision problem. The field therefore lacks a unified synthesis that separates technical capability, measurement credibility and implementation readiness.

A scoping review was therefore considered the most appropriate methodology to achieve this because it enables systematic mapping of a broad, heterogeneous and rapidly evolving evidence base, facilitates identification of key concepts and evidence gaps, and accommodates multiple study designs without forcing inappropriate quantitative pooling [13–16]. Unlike previous reviews focused on individual device classes or measurement accuracy, this review integrates measurement performance, affordability evidence, intended-use context, clinical utility, home and telehealth readiness, and methodological confidence across the full range of low-cost gait technologies. It asks not only *'Does the technology measure gait?'* but also *'Is the evidence sufficient to support the way the technology is being promoted or intended to be used?'* The review provides clinicians, researchers and health systems with a framework for distinguishing technologies that are technically promising from those with credible evidence for clinical or real-world implementation. The overarching review question was: What is the nature and extent of the available evidence on low-cost gait analysis technologies used for clinical and real-world assessment, particularly regarding their validity, reliability and clinical utility? Specifically, the review aimed to: (1) identify the range of low-cost gait analysis technologies reported in the literature; (2) describe the clinical populations, settings and contexts in which these technologies have been evaluated; (3) map evidence relating to their validity, reliability and clinical utility; and (4) identify gaps in the evidence to inform future research, clinical implementation and equitable adoption of gait assessment technologies.

METHODS

Study Design

This review was conducted as a scoping review in accordance with the methodological framework originally proposed by Arksey and O'Malley [13], subsequently refined by Levac et al. [14], and guided by

the Joanna Briggs Institute (JBI) methodology for scoping reviews [15]. Reporting was informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [16]. A review protocol was developed a priori to enhance methodological transparency, consistency, and reproducibility and was registered in the Open Science Framework (OSF) (<https://archive.org/details/osf-registrations-z6ekr-v1>). No substantive deviations from the registered protocol occurred during the conduct of the review. A scoping review methodology was considered most appropriate because the literature on low-cost gait analysis tools is broad, heterogeneous, and multidisciplinary, encompassing diverse technologies, populations, settings, and outcome domains. Furthermore, the evidence base includes substantial variation in the assessment of validity, reliability, and clinical utility. Rather than evaluating intervention effectiveness or generating pooled effect estimates, the review sought to systematically map the extent, range, and nature of the available evidence, clarify key concepts, and identify gaps in knowledge, research, and implementation.

Eligibility Criteria

Eligibility criteria were developed using the Population Concept Context (PCC) framework recommended for scoping reviews [15].

Population

Studies involving human participants of any age, sex, or health status were eligible for inclusion. Studies based exclusively on anthropomorphic phantoms, mannequins, robotic limbs, simulated motion, or other non-human technical models were excluded. This human-only criterion was applied consistently to all records. Two studies previously retained during data charting were reclassified as ineligible during the final eligibility audit because they used a robotic leg phantom or an experimental lower-limb model without human participants.

To avoid conflating age, diagnosis, health status and activity, population characteristics were coded independently across four dimensions. Age group was classified as children and adolescents, adults, older adults, or mixed age. Health status was classified as healthy, clinical, or mixed. Diagnostic category was classified as neurological, musculoskeletal, cardiopulmonary, amputee, frailty or ageing, other, none for healthy populations, or mixed diagnostic categories. Activity group was classified as general population, recreational runners, athletes, or clinical rehabilitation population. Studies containing both healthy controls and a clinical group were coded as mixed for health status while retaining the relevant clinical diagnosis. The original single population category was retained only as a legacy field and was not used for synthesis.

Concept

The concept of interest was low-cost gait analysis technology. For this review, “low cost” was operationalised using a pragmatic, reproducible working threshold and an explicit hierarchy of affordability evidence. A technology qualified when its minimum functional assessment setup either had a reported total cost below US\$1,000 or met a prespecified descriptive route when complete cost information was unavailable.

1. The minimum functional assessment setup comprised the essential hardware, software, acquisition interface and accessories required to produce the reported gait outcomes. A reported price for a single component was not treated as the total system cost unless the primary report clearly indicated that the amount represented the complete operational setup.
2. Affordability evidence was classified into five mutually exclusive categories: C1, total functional setup explicitly reported as below US\$1,000; C2, partial or component cost reported with sufficient information to suggest that the complete setup was below US\$1,000, although the total was not fully documented; C3, no numerical cost reported but the primary authors explicitly described the technology as low cost or affordable; C4, reviewer-classified as accessible or consumer-grade without complete cost confirmation; and C5, cost unclear, commercial price unreported, or inconsistent with the working threshold.

For each included technology, the review charted device cost, software cost, licence or subscription cost, required computer or smartphone, accessories and consumables, treadmill or walkway requirements, maintenance and calibration costs, currency and price year, and whether the reported amount represented the complete operational setup. Items absent from the primary report were coded as not reported rather than assumed to be free.

The US\$1,000 threshold was selected pragmatically to distinguish resource-conscious systems from conventional laboratory-based gait-analysis infrastructure. It was used as a transparent evidence-mapping criterion rather than a universal standard of affordability. Affordability is dependent on country, purchasing power, existing infrastructure, recurrent software charges, maintenance, connectivity and the availability of technical support; therefore, C3-C5 classifications were not interpreted as empirical confirmation that the complete system cost less than US\$1,000.

Table 1
Affordability-evidence classification used for low-cost gait-analysis technologies

Code	Affordability evidence	Interpretation in this review
C1	Total functional setup explicitly reported as < US\$1,000	Cost-confirmed below the working threshold
C2	Partial/component cost reported; complete setup likely < US\$1,000 but not fully costed	Partially cost-confirmed; interpreted cautiously
C3	No numerical cost; authors explicitly described the technology as low cost or affordable	Author-claimed affordability; not cost-confirmed
C4	Reviewer-classified as accessible or consumer-grade without complete cost confirmation	Reviewer-inferred accessibility; not cost-confirmed
C5	Cost unclear, commercial price unreported, or inconsistent with the working threshold	Uncertain or conflicting; requires clarification

Eligible technologies were required to generate gait-related outcomes, including spatiotemporal parameters, kinematic measures, kinetic proxies, gait symmetry, gait variability, balance-related gait characteristics, or algorithm-derived gait metrics. Studies were eligible when they evaluated at least one of the following domains: validity; reliability or measurement error; or empirically assessed clinical utility. These domains were alternative routes to eligibility; a study was not required to report all three.

Clinical utility was conceptualised as the practical value of a gait-analysis technology in its intended clinical or research context. To avoid equating technical performance with implementation readiness, each study was assigned one mutually exclusive evidence level: U1, directly evaluated clinical utility; U2, clinical potential stated by the study authors; U3, reviewer-inferred implementation potential; or U0, no clinical-utility information. Portability, affordability, simplicity, commercial availability, validity or reliability alone were not accepted as direct evidence of clinical utility.

Context

No restrictions were placed on geographic location, income setting, healthcare level, or assessment environment. Studies conducted in hospitals, outpatient clinics, rehabilitation centres, universities, research laboratories, community settings, and home environments were all eligible. This broad contextual scope was adopted to capture the diversity of settings in which low-cost gait analysis tools have been evaluated. Intended-use context was coded independently from physical assessment setting using nine non-mutually exclusive categories: diagnostic or clinical assessment; treatment planning; rehabilitation monitoring; gait retraining; screening; research measurement; home monitoring; remote or telehealth-supported assessment; and sports or running analysis. A study could contribute to more than one intended-use category when this was supported by its stated objective, population, setting, gait task, or implementation description.

To facilitate evidence mapping, contextual information was charted at multiple levels, including the country reported for each study, country-income classification, assessment setting, and intended use context. For geographic frequency reporting, each study was assigned one mutually exclusive primary country and one primary region. The primary country was defined as the principal country of data collection or study setting. Where an extracted record listed more than one country and the principal data-collection site could not be distinguished from the available report, the first-listed country was retained as the primary country and the remaining country or countries were recorded separately as collaborators. Multinational studies were therefore counted once in regional totals. Country-income classifications were assigned according to the World Bank classification [17].

Outcomes

Studies were eligible if they reported at least one outcome relating to validity, reliability or measurement error, or empirically assessed clinical utility. Measurement performance outcomes included validity and reliability.

Validity evidence was classified as criterion validity, concurrent validity, construct validity, discriminative or known-groups validity, diagnostic accuracy, or classification agreement. Criterion and concurrent validity were distinguished according to the role and timing of the comparator. Studies without a formal validity assessment were coded as not assessed.

Reliability evidence was separated into relative reliability, absolute reliability or measurement error, and responsiveness. Relative reliability included ICC, kappa, Gwet coefficients and related consistency indices. Absolute reliability and measurement error included SEM, MDC or SDD, coefficient of variation, Bland-Altman bias and limits of agreement, typical error, and within-day, between-day, inter-rater and intra-rater error. Responsiveness was charted separately using sensitivity-to-change indices or explicit comparisons with clinically meaningful change thresholds. A high ICC was not treated as evidence of small absolute error or ability to detect change.

Validity statistics were interpreted using a prespecified hierarchy. Greatest weight was given to Bland-Altman bias and limits of agreement and to absolute-error indices such as RMSE, RMSD, MAE and percentage error. Sensitivity, specificity and AUC were used for diagnostic performance; kappa, Gwet coefficients and related indices were used for classification agreement. Correlation coefficients were interpreted as evidence of association only and were not described as agreement or interchangeability. A non-significant difference between methods was not treated as evidence of equivalence unless a formal equivalence or non-inferiority design with a prespecified margin was used.

Clinical utility was operationalised across five predefined domains and graded using the U1-U0 evidence hierarchy shown in Table 2.

Table 2
Clinical-utility evidence classification

Level	Meaning	Editorial interpretation
U1	Directly evaluated clinical utility	A measured or observed implementation outcome is reported. Claims are restricted to the measured domain, population and setting.
U2	Clinical potential stated by study authors	Potential application is described, but implementation is not directly evaluated.
U3	Reviewer-inferred implementation potential	Potential is inferred only from technical attributes; it is not empirical clinical-utility evidence.
U0	No clinical-utility information	No clinical-utility claim is made.

1. **Feasibility** – including completion rate, setup burden, technical failures, testing burden, portability, and workflow compatibility.
2. **Ease of use** – including time requirements, training demands, calibration burden, and operational simplicity.
3. **Interpretability** – including clarity of outputs, usefulness of reports, and applicability for clinical or research decision-making.
4. **Acceptability** – including user satisfaction, perceived usability, preference, comfort, and clinician or participant uptake.
5. **Cost-related practicality** – including affordability, maintenance burden, equipment accessibility, and resource implications.

Clinical-utility evidence was classified as U1 only when a study directly measured or observed an implementation outcome, such as setup or processing time, completion or technical-failure rate, training requirement, clinician or participant usability, acceptability, workflow compatibility, output interpretability, effect on clinical decision-making, home adherence, or data-transmission success. *U2 was used* when primary authors stated clinical, home or telehealth potential without directly measuring implementation. *U3 was reserved* for reviewer inference based only on technical attributes, and *U0 indicated* no utility information. Formal cost-effectiveness was not inferred unless supported by an economic evaluation.

Types of Evidence Sources

The review considered original empirical studies of any design, including validation, observational, methodological, feasibility, usability, pilot, diagnostic-accuracy and mixed-methods studies. Eligible evidence sources comprised peer-reviewed journal articles, complete conference proceedings papers, theses or dissertations, and full technical reports, provided that a complete report containing sufficient methods and original empirical results was available and all other eligibility criteria were met.

Systematic reviews, scoping reviews, meta-analyses, editorials, opinion papers, commentaries, letters and protocols were excluded. Conference abstracts, posters and meeting summaries without an available complete report were also excluded. Review articles were used only for backward citation screening to identify potentially eligible primary studies.

Only studies published in English were included. This restriction was applied because of resource limitations associated with translation and full-text assessment and is acknowledged as a potential source of language bias in a field characterised by international and technology-driven research.

Information Sources

A comprehensive literature search was conducted in PubMed/MEDLINE, Scopus, Web of Science Core Collection, CINAHL, Embase, and IEEE Xplore from database inception to 20 May 2026. These databases were selected to ensure broad coverage of the rehabilitation, clinical, biomechanical, engineering, and digital health literature relevant to low-cost gait analysis technologies. In addition to electronic database searching, backward citation screening was undertaken by reviewing the reference lists of all included studies and relevant review articles to identify additional eligible records not retrieved through the primary database search. Grey-literature databases were not systematically searched. However, potentially eligible full-text theses, technical reports or complete conference proceedings papers identified incidentally through citation searching were considered when they contained sufficient original empirical data. The included evidence sources were coded as journal article (JA), full conference paper (FCP), thesis or dissertation (TD), technical report (TR), or other (OTH). This distinction separates the search strategy from the eligibility of incidentally identified full reports.

Search Strategy

Search strategies were developed iteratively using PubMed/MEDLINE as the reference database. The PubMed strategy was structured around four core concepts: (1) gait and walking; (2) accessible gait analysis technologies; (3) measurement and implementation properties; and (4) affordability and accessibility. Because many relevant studies do not explicitly describe technologies as “*low cost*,” the search combined affordability-related terms with technology-specific terms commonly used for portable or consumer-accessible gait analysis systems, including wearable sensors, inertial measurement units, accelerometers, smartphone-based applications, video-based systems, and markerless motion analysis tools. Measurement and implementation concepts included validity, reliability, reproducibility, feasibility, usability, acceptability, clinical utility, and related outcomes. The PubMed search combined Medical Subject Headings (MeSH) and free-text terms and was subsequently translated for the other databases by adapting controlled vocabulary, field tags, truncation symbols, phrase searching, and platform-specific syntax as appropriate. Database-specific indexing terms were used where available, including MeSH in PubMed, Emtree in Embase, and CINAHL Headings in CINAHL, while equivalent keyword-based strategies were employed for Scopus, Web of Science, and IEEE Xplore. A comprehensive search was conducted across all selected databases using controlled vocabulary and free-text keywords combined

with Boolean operators (AND/OR). Database-specific search strategies were adapted to the indexing structure and search functionality of each platform. Where supported, searches were limited to human studies and English-language publications. No date restrictions were applied. The complete search strategies for all databases, including platform-specific adaptations, limits, filters, and the final PubMed/MEDLINE search string, are provided in Appendix A.

Study Selection

All records identified through database and supplementary searching were imported into EndNote before screening. The database-specific counts were treated as pre-deduplication counts. The materials available for this revision did not include the original database export files, the EndNote library, or a contemporaneous deduplication log; consequently, the reported removal of 172 duplicate records could not be independently reproduced during editorial audit and has been retained provisionally. Before submission, the search records should be re-audited using a documented two-stage procedure: automated matching on title, author, publication year and reference type, supplemented by DOI and PMID matching, followed by manual review of near-duplicate titles, online-first and final publications, and conference-to-journal versions. Only true duplicate reports should be removed; distinct reports from the same study should be linked rather than deleted. Two reviewers independently screened all records against the predefined eligibility criteria. Before formal screening, they independently assessed a calibration set of 20 title-and-abstract records. A separate calibration set of 20 full-text reports was then assessed before full-text screening. Cohen's kappa was calculated as $\kappa = (Po - Pe)/(1 - Pe)$, where Po is the observed proportion of agreement and Pe is the agreement expected by chance. Two reviewers independently assessed calibration sets of 20 title-and-abstract records and 20 full-text reports before formal screening. Cohen's kappa was calculated for binary include/exclude decisions. In the calibration exercises, agreement was $\kappa = 0.80$ at title-and-abstract screening and $\kappa = 0.78$ at full-text screening. Both exceeded the prespecified operational threshold of $\kappa \geq 0.70$. Disagreements were discussed, the eligibility guidance was refined, and unresolved cases were referred to a third reviewer.

Table 3
Two-by-two agreement table for the title-and-abstract screening calibration exercise (n = 20)

Reviewer 1	Reviewer 2: Include	Reviewer 2: Exclude	Total
Include	6	1	7
Exclude	1	12	13
Total	7	13	20

At both screening stages, disagreements between reviewers were resolved through discussion and, where necessary, consultation with a third reviewer. Reasons for exclusion at the full-text stage were recorded and documented. At full-text assessment, each excluded report was assigned one mutually exclusive principal reason using the following hierarchy: (1) not an eligible primary empirical study; (2) non-human or technical model outside the eligibility scope; (3) wrong technology; (4) technology not

meeting the low-cost criterion; (5) no gait-related outcome; (6) no eligible validity, reliability, measurement-error, or empirically assessed clinical-utility evidence; (7) protocol only; (8) review article; and (9) full text unavailable. A report was not excluded for lack of clinical-utility evidence when it contained eligible validity or reliability evidence. Non-human technical models were excluded consistently under the human-only population criterion. The study selection process was reported using a PRISMA-ScR flow diagram, detailing the numbers of records identified, duplicates removed, records screened, full-text articles assessed for eligibility, reports excluded, and studies included in the final review.

Data Charting

A structured data charting form was developed in accordance with Joanna Briggs Institute (JBI) guidance [16] and piloted on 20 included studies prior to full data extraction. The pilot exercise was used to refine variable definitions, improve consistency in coding, and clarify procedures for charting complex studies involving multiple technologies, populations, or outcome domains. Three reviewers independently charted data from the included studies. To enhance accuracy and consistency, extracted data were cross-checked by another reviewer, with each reviewer verifying studies extracted by a colleague. Any discrepancies identified during verification were resolved through discussion and consensus. Where agreement could not be reached, a third reviewer provided adjudication. Modifications made to the charting framework following pilot testing were documented to maintain methodological transparency and an audit trail. To enhance reproducibility, the charting process distinguished between directly reported study findings and reviewer-classified descriptors. Where studies reported multiple technologies, populations, or outcome domains, data were charted in a manner that preserved the structure of the original study while allowing descriptive mapping across categories.

Data Items

Data extracted from each included study comprised bibliographic information, study aims and design, sample size and participant characteristics, primary country, primary geographic region, additional collaboration countries, country-income classification, and assessment setting. Population characteristics were coded independently by age group, health status, diagnostic category and activity group so that overlapping characteristics were preserved rather than collapsed into a single category. Contextual data included both the physical assessment environment and the intended-use context. Intended-use categories were diagnostic or clinical assessment, treatment planning, rehabilitation monitoring, gait retraining, screening, research measurement, home monitoring, remote or telehealth-supported assessment, and sports or running analysis. These categories were coded independently and were non-mutually exclusive.

Data on gait outcomes were coded non-mutually exclusively across seven prespecified domains: spatiotemporal parameters; kinematic measures; kinetic or kinetic-proxy measures; gait symmetry; gait variability; balance-related gait characteristics; and algorithm-derived gait metrics. Spatiotemporal measures included speed, cadence, step and stride dimensions and timing, stance and swing

characteristics, support phases, contact or flight time, step count and walking distance. Kinematic measures included joint, segment, posture and centre-of-mass angles, positions, trajectories, displacement and range of motion. Kinetic or kinetic-proxy measures included ground-reaction force, pressure, centre of pressure, impulse, force-development, stiffness and related force-derived variables. Symmetry and variability were coded only when explicitly reported. Balance-related measures included gait stability, margin of stability, postural stability, sway, TUG/ETGUG components, irregular-surface or obstacle balance, and dual-task metrics. Algorithm-derived measures were restricted to named computed indices, ratios or costs, nonlinear metrics, automated gait-event or gait-phase outputs, step-count algorithms, or automated markerless trajectory or classification outputs; routine sensor-estimated spatiotemporal measures were not automatically classified as algorithm-derived. For validity, the comparator, validity domain, outcome domain, reported statistic and parameter-specific result were charted separately. The extraction form distinguished author-reported conclusions from the review's editorial interpretation and recorded whether numerical interchangeability was established. The final charting framework was designed to support evidence mapping across technologies, populations, settings, outcome domains, measurement properties, and implementation-related characteristics.

Methodological appraisal and certainty of evidence

Consistent with scoping-review methodology, formal critical appraisal was not considered mandatory for evidence mapping. However, because validity, reliability and measurement error were central review domains, a limited methodological appraisal was undertaken using selected COSMIN-informed criteria and design-specific JBI items. The appraisal was used to contextualise reported findings rather than to exclude studies or generate certainty ratings. The appraisal was applied to all 120 included studies. General items addressed sample-size adequacy, description of the population and testing procedure, assessor independence or blinding, handling of missing data or technical failures, and applicability to the intended setting. Validity studies were appraised for the appropriateness of the comparator or reference standard, the use of agreement-, error-, diagnostic- or classification-based analyses rather than correlation or difference testing alone, and the use of prespecified hypotheses where relevant. Reliability studies were appraised for repeated-measure design, interval and participant stability, the appropriateness and specification of ICC, kappa or other reliability statistics, and reporting of SEM, MDC/SDD, coefficient of variation, Bland-Altman bias or limits of agreement, or comparable absolute-error indices. Direct clinical-utility evidence and real-world evaluation were appraised separately [15,138]. Sample-size adequacy was categorised as very good (at least 100 participants), adequate (50–99), doubtful (30–49), inadequate (fewer than 30), or unclear when the usable sample could not be established. Study-level criteria were rated as adequate, doubtful, inadequate, unclear, or not applicable. Domain-level methodological confidence was then described as higher, moderate, lower, insufficiently reported, or not appraised. These categories are contextual methodological-confidence descriptors rather than GRADE certainty ratings. The appraisal was completed from the extracted and source-verified review dataset by one reviewer; independent second-reviewer verification against the primary reports remains required before submission. Detailed study-level ratings are provided in Supplementary Table S9.

Synthesis of Results

Extracted data were synthesised using descriptive numerical summary and narrative synthesis, consistent with scoping review methodology [15]. Frequencies and percentages were calculated separately for publication period, mutually exclusive primary geographic region, study design, each of the four population dimensions, setting, technology category, gait domain and outcome type. Multinational collaboration was summarised separately and did not contribute additional counts to regional totals. Population counts from different dimensions were not combined because each dimension described the same set of included studies from a different perspective. Narrative synthesis was organised directly around the four review aims: (1) the range of low-cost gait-analysis technologies; (2) the clinical populations, physical settings and intended-use contexts represented; (3) reported validity, reliability, measurement-error and clinical-utility evidence; and (4) gaps relevant to future research, clinical implementation and equitable adoption. Synthesis wording was certainty-controlled: the review used terms such as *“reported validity evidence”*, *“studies reported favourable reliability”*, *“evidence concentration”*, and *“apparent measurement performance”*, and avoided claims of strong or high-quality evidence, proven validity, comparative superiority, or recommendations for adoption. Variations in terminology, measurement approaches, comparator standards, reporting practices, and implementation characteristics were identified inductively during data charting and synthesised narratively. Findings were presented using narrative summaries, tables, and evidence maps where appropriate. Evidence maps were generated for variables with sufficient coverage and comparability, including technology category by population type, technology category by setting, and technology category by outcome domain, to illustrate areas of evidence concentration and evidence scarcity. Subgroup descriptions according to technology type, each independent population dimension, setting and country-income classification were descriptive and were not intended to support statistical or inferential comparisons.

Review Aim Traceability

To make the relationship between the prespecified aims and the synthesis transparent, each aim was linked prospectively to a Results subsection, principal figure or supplementary table, and corresponding Discussion subsection (Table 4).

Table 4
Alignment of review aims with the Results, figures/tables and Discussion

Review aim	Results subsection and principal output	Discussion subsection	Implementation
1. Identify the range of low-cost gait-analysis technologies	Technology categories; gait outcomes and measurement domains; Figs. 2–3; Tables S2 and S7	Interpretation by technology category	Explicit closing sentence added to Results
2. Describe clinical populations, settings and contexts	Populations and settings; intended-use contexts; geographic and equity distribution; Fig. 6; Figure S1; Tables S1 and S8	Clinical, remote-monitoring, and equity implications	Physical setting and intended use reported separately
3. Map validity, reliability and clinical utility	Validity evidence; reliability and measurement error; clinical utility; Figs. 4–5; Tables S3–S5	Measurement and implementation implications	Validity, reliability and utility mapped separately
4. Identify gaps for research, clinical implementation and equitable adoption	Three evidence-gap subsections; Figure S5; Table S6	Research, clinical and equity implications	Gap reporting divided into the three prespecified components

RESULTS

Study Selection

A total of 7,687 records were identified through database searching, comprising PubMed/MEDLINE (n = 1,842), Scopus (n = 2,156), Web of Science (n = 1,428), Embase (n = 1,217), CINAHL (n = 684), and IEEE Xplore (n = 360). An additional 58 records were identified through citation searching, yielding 7,745 records overall. Following the provisionally reported removal of 172 duplicate records, 7,515 records remained for title and abstract screening. Of these, 6,518 records were excluded because they did not meet the eligibility criteria. A total of 997 reports were sought for full-text retrieval from the database search, of which 960 were retrieved and 37 were unavailable. Citation searching identified 58 additional reports, of which 54 were retrieved and 4 were unavailable. In total, 1,014 reports were assessed for eligibility. Following the human-only and evidence-source audits, 894 reports were excluded after assignment of one principal reason per report: technology not meeting the low-cost criterion (n = 268), no eligible validity, reliability, measurement-error, or empirically assessed clinical-utility evidence (n = 284), wrong technology type (n = 98), no gait-related outcome (n = 85), review article (n = 103), protocol only (n = 28), non-human or technical-model study outside the eligibility scope (n = 27), and conference abstract without an available complete report (n = 1). Consequently, 120 studies were included in the review. Ultimately, 120 human studies met the eligibility criteria and were included in the scoping review. Two technical-model studies and one conference abstract without an available complete report were

excluded during the final eligibility audits. The study-selection process is illustrated in the PRISMA 2020 flow diagram (Figure 1), while the complete characteristics of all included studies are presented in the supplementary tables. Eligibility-audit consequence: exclusion of the conference abstract increased total full-text exclusions from 893 to 894 and reduced the included total from 121 to 120. All study identifiers, reference assignments, evidence-source codes, tables and percentages were recalculated from the final master dataset.

Figure 1: PRISMA Flow Diagram

Characteristics of the Included Studies

A concise summary of study-level characteristics is presented in Table 5; full individual-study details remain in Supplementary Table S1. A total of 120 human studies published between 1995 and 2026 met the eligibility criteria and were included in this scoping review. Publication activity increased substantially over time, with 98 studies (81.7%) published between 2015 and 2026 and 22 (18.3%) published before 2015. The greatest number of publications occurred during 2020-2026 (n = 53, 44.2%), followed by 2015-2019 (n = 45, 37.5%).

Figure 2. Growth and technological evolution of low-cost gait-analysis research.

Panel A shows the annual publication trend from 1995 to 2026. **Panel B** shows the distribution of technology categories across four publication periods: before 2010, 2010–2014, 2015–2019, and 2020–2026.

Using one mutually exclusive primary geographic classification per study, Europe contributed 57 of 120 studies (47.5%), followed by North America (n = 28, 23.3%), Asia (n = 25, 20.8%), Oceania (n = 7, 5.8%), and South America (n = 3, 2.5%). No eligible study had an African country as its primary setting. Six studies (5.0%) listed more than one country and were recorded separately as multinational collaborations; they were counted only once in the regional totals. The rounded percentages sum to 99.9% because of rounding. Geographic classification was derived from the final study-level dataset; mutually exclusive regional counts were verified to sum exactly to the 120 included human studies.

Evidence-source composition: 114 studies (95.0%) were journal articles, 5 (4.2%) were complete conference proceedings papers, and 1 (0.8%) was a thesis. No technical reports or other source types were included. One meeting abstract lacking an available complete report was excluded during the final source audit.

Methodologically, nearly half of the included studies were designed as validation and reliability studies (n = 59, 48.0%), while 43 studies (35.0%) focused exclusively on validation and 15 studies (12.2%) investigated reliability alone. Only a small number of studies employed validation and feasibility (n = 1, 0.8%), observational (n = 3, 2.4%), experimental or machine-learning validation (n = 1, 0.8%), or case-control (n = 1, 0.8%) designs, indicating that the evidence base has been dominated by methodological evaluations of measurement performance.

Population characteristics differed according to the dimension examined. By age, 95 studies (79.2%) involved adults, 11 (9.2%) older adults, 9 (7.5%) mixed-age samples and 5 (4.2%) children or adolescents. By health status, 74 studies (61.7%) involved healthy participants, 24 (20.0%) clinical populations and 22 (18.3%) mixed healthy and clinical samples. Diagnostic coding identified 28 neurological studies (23.3%), 13 musculoskeletal studies (10.8%), 9 frailty or ageing studies (7.5%) and 4 other diagnostic groups (3.3%); 66 studies (55.0%) involved healthy populations without a diagnosis. By activity group, 64 studies (53.3%) involved the general population, 44 (36.7%) clinical rehabilitation populations, 9 (7.5%) recreational runners and 3 (2.5%) athletes. These dimensions describe the same 120 studies independently and should not be combined into a single total.

Most studies were conducted under controlled laboratory conditions (n = 72, 60.0%). Twenty-nine studies (24.2%) combined laboratory and clinical assessment, 7 (5.8%) were conducted in clinical settings alone, and 12 (10.0%) used community, home, mixed laboratory-community, mixed clinical-home, or other settings. Thus, validation remained predominantly laboratory based despite the intended real-world application of many technologies.

Table 5. Characteristics of the 120 included studies

Characteristic	Category	Studies, n	Studies, %
Publication period	Before 2010	8	6.7
	2010–2014	14	11.7
	2015–2019	45	37.5
	2020–2026	53	44.2
Study evidence design	Validity and reliability study	85	70.8
	Validity study only	19	15.8
	Reliability study only	16	13.3
Primary region	Europe	57	47.5
	North America	28	23.3
	Asia	25	20.8
	Oceania	7	5.8
	South America	3	2.5
	Africa	0	0.0
Age group	Children and adolescents	5	4.2
	Adults	95	79.2
	Older adults	11	9.2
	Mixed age	9	7.5
Health status	Healthy	74	61.7
	Clinical	24	20.0
	Mixed	22	18.3
Diagnostic category	None (healthy population)	66	55.0
	Neurological	28	23.3
	Musculoskeletal	13	10.8
	Frailty or ageing	9	7.5
	Other	4	3.3
Activity group	General population	64	53.3
	Clinical rehabilitation population	44	36.7
	Recreational runners	9	7.5

	Athletes	3	2.5
Assessment setting	Laboratory only	72	60.0
	Clinical only	7	5.8
	Combined laboratory and clinical	29	24.2
	Community, home or mixed real-world setting	9	7.5
	Other or not reported	3	2.5
Evidence source	Journal article	114	95.0
	Full conference paper	5	4.2
	Thesis or dissertation	1	0.8

Note: Percentages are based on 120 studies. Categories within each characteristic are mutually exclusive. The median usable sample size was 23.5 participants (interquartile range 14.0–34.8; range 3–572).

Technology categories

The 120 included studies covered seven technology categories. Wearable sensor systems were most frequent (n = 42, 35.0%), followed by video-based systems (n = 33, 27.5%), depth-camera systems (n = 13, 10.8%), mobile or smartphone systems (n = 11, 9.2%), machine-learning or markerless systems (n = 8, 6.7%), hybrid or other systems (n = 7, 5.8%), and pressure-sensing systems (n = 6, 5.0%). The first review aim was therefore addressed by identifying and categorising the range of low-cost video-based, wearable, mobile, pressure-sensing, depth-camera, markerless, consumer-device and hybrid gait-analysis technologies represented in the literature.

Gait outcomes and measurement domains

All 120 included studies reported at least one eligible gait-related outcome. Because studies could contribute to more than one domain, frequencies were non-mutually exclusive. Spatiotemporal parameters were reported in 86 studies (71.7%) and kinematic measures in 56 (46.7%). Kinetic or kinetic-proxy outcomes were reported in 6 studies (5.0%), gait symmetry in 7 (5.8%), gait variability in 10 (8.3%), balance-related gait characteristics in 8 (6.7%), and algorithm-derived gait metrics in 17 (14.2%). Spatiotemporal outcomes included gait speed, cadence, step and stride length or width, step and stride time, stance and swing duration, support phases, contact or flight time, step count and walking distance. Kinematic outcomes included joint and segment angles, posture, trajectories, displacement and range of motion. Kinetic and kinetic-proxy outcomes included ground-reaction force, centre-of-pressure, impulse, stiffness and other force-derived measures. Symmetry outcomes comprised explicit bilateral symmetry or asymmetry measures; variability outcomes included step-to-step or stride-to-stride variability, coefficient of variation, entropy and fractal measures. Balance-related outcomes included gait stability

ratio, margin of stability, postural stability, sway, TUG/ETGUG components and selected irregular-surface, obstacle or dual-task measures. Algorithm-derived outcomes included named computed indices or ratios, nonlinear features, automated gait-event or phase outputs, step-count algorithms and automated markerless trajectories or classifications. The distribution by technology category is shown in Figure 3 and study-level coding is provided in Supplementary Table S7.

Figure 3. Evidence map of technology category by gait-measurement domain

The heatmap covers: *spatiotemporal outcomes; sagittal, frontal, and transverse-plane kinematics; kinetic proxies; gait-event detection; classification outcomes.*

Populations and settings

The multidimensional classification showed that the apparent dominance of healthy adults in the former single-category approach concealed important overlap. Twenty-two studies included both healthy and clinical groups, and clinical diagnoses were retained separately from health-status coding. Evidence nevertheless remained concentrated in controlled environments: 72 studies were laboratory-only and 29 combined laboratory and clinical assessment, whereas only a small minority included home or community assessment.

Intended-use contexts

Technology categories, gait-outcome domains and intended-use contexts are summarised together in Table 6, with study-level detail retained in Supplementary Tables S2, S7 and S8.

Intended-use categories were non-mutually exclusive. Research measurement was the most frequent intended use (n = 117, 97.5%), followed by diagnostic or clinical assessment (n = 53, 44.2%), rehabilitation monitoring (n = 23, 19.2%), sports or running analysis (n = 14, 11.7%), home monitoring (n = 5, 4.2%), screening (n = 3, 2.5%), gait retraining (n = 2, 1.7%), remote or telehealth-supported assessment (n = 2, 1.7%), and treatment planning (n = 1, 0.8%). Study-level coding and supporting evidence are provided in Supplementary Table S8. Intended-use contexts included routine clinical assessment, rehabilitation outcome monitoring, gait retraining, screening, sports and running analysis, research measurement, home assessment and proposed remote-monitoring applications. However, most evaluations remained laboratory based, and direct testing in routine clinical, community, home and telehealth workflows was limited.

Table 6. Technology categories, gait-outcome domains and intended-use contexts

Domain	Category	Studies, n	Studies, %
Technology category	Wearable IMUs/accelerometers	42	35.0
	Video-based systems	33	27.5
	Depth-camera systems	13	10.8
	Smartphone/tablet systems	11	9.2
	Markerless/AI-based systems	8	6.7
	Hybrid/other systems	7	5.8
	Pressure-sensing systems	6	5.0
Gait-outcome domain	Spatiotemporal parameters	86	71.7
	Kinematic measures	56	46.7
	Kinetic or kinetic-proxy measures	6	5.0
	Gait symmetry	7	5.8
	Gait variability	10	8.3
	Balance-related gait characteristics	8	6.7
	Algorithm-derived gait metrics	17	14.2
Intended-use context	Research measurement	117	97.5
	Diagnostic or clinical assessment	53	44.2
	Rehabilitation monitoring	23	19.2
	Sports or running analysis	14	11.7
	Home monitoring	5	4.2
	Screening	3	2.5
	Gait retraining	2	1.7
	Remote or telehealth-supported assessment	2	1.7
	Treatment planning	1	0.8

Note: Gait-outcome and intended-use categories were non-mutually exclusive; a study could contribute to more than one category.

Validity Evidence

Editorial interpretation rule: “valid,” “accurate,” “agreement,” “equivalent,” and “interchangeable” were used only when supported by the corresponding design and statistics. Author language that exceeded the

reported evidence was retained only in the supplementary author-reported field and was qualified in the editorial interpretation field. Validity evidence was available for 104 of 120 studies and was heterogeneous in comparator, outcome and statistical method. Evidence was classified as criterion or concurrent validity, construct validity, discriminative validity, diagnostic accuracy or classification agreement. At least one agreement or absolute-error statistic was reported in 57 studies, while 11 relied on correlation or association statistics alone and 3 relied primarily on difference testing. Correlations were therefore reported as associations, not agreement, and non-significant differences were not treated as equivalence. No technology was treated as interchangeable with a reference system solely on the basis of a high correlation coefficient.

Reliability and measurement error

Table 7 summarises the structure and interpretive adequacy of reported validity, reliability and measurement-error evidence; parameter-level statistics remain in Supplementary Tables S3 and S4. Reliability was assessed in 101 studies. Relative reliability was reported in 77 studies, whereas 63 reported at least one absolute-error index and 43 reported both relative and absolute evidence. In 34 studies, reliability conclusions relied on relative coefficients without SEM, MDC/SDD, coefficient of variation, Bland-Altman limits or comparable error estimates. Responsiveness was reported in 1 study. Accordingly, favourable ICCs were interpreted as rank-order consistency rather than evidence of small measurement error. Suitability for detecting intervention-related change or longitudinal monitoring remained uncertain unless measurement error was compared with an MCID, expected change, or accepted parameter-specific tolerance. Within-day performance was often better than between-day performance, and sensor repositioning, camera placement and rater-dependent landmark selection contributed additional error for some outcomes.

Table 7. Summary of reported validity, reliability and measurement-error evidence

Evidence domain	Evidence category	Studies, n	Studies, %	Editorial interpretation
Validity	Any reported validity evidence	104	86.7	Evidence was reported, but methodological confidence varied.
	Agreement or absolute-error analysis	57	47.5	Provides the strongest basis in this dataset for judging numerical agreement; interchangeability still requires acceptable limits.
	Association/correlation only	11	9.2	Shows association, not agreement or interchangeability.
	Difference testing only	3	2.5	A non-significant difference does not establish equivalence.
	Classification-agreement analysis	2	1.7	Supports categorical concordance rather than numerical interchangeability.
	Validity basis unclear or incompletely reported	29	24.2	Limits interpretation of favourable validity claims.
Reliability	Any reliability assessment	101	84.2	At least one reliability or repeatability result was reported.
	Relative and absolute reliability/measurement error	42	35.0	Most informative combination for repeated clinical measurement.
	Relative reliability only	34	28.3	High ICC or kappa alone does not quantify absolute error.
	Absolute reliability/measurement error only	20	16.7	Quantifies error but does not establish relative ranking consistency.
	Relative, absolute and responsiveness evidence	1	0.8	Only one study evaluated the full sequence needed to support change detection.
	Reliability reported; statistical domain unclear	4	3.3	Insufficient detail for confident interpretation.
	No reliability assessment	19	15.8	No evidence on reproducibility or measurement error.

Note: Evidence categories describe reporting patterns. They do not constitute formal certainty-of-evidence ratings, and favourable association or relative-reliability statistics should not be interpreted as agreement, interchangeability or responsiveness.

Figure 4. Validity, reliability and measurement-error evidence by technology category-

Panel A: criterion/concurrent, construct, discriminative, diagnostic, classification-agreement, and unassessed validity. **Panel B:** relative reliability, absolute error, combined evidence, responsiveness, and no reliability assessment.

Clinical utility

Direct clinical-utility evidence was limited. Five studies (4.17%) were classified U1 because they directly measured or observed a defined implementation outcome. The remaining 115 studies (95.83%) were classified U2 because clinical usefulness was proposed by the primary authors but implementation was not directly tested. No studies were classified U3 or U0. Portability, affordability, simplicity, commercial availability and favourable validity or reliability were therefore treated as technical attributes rather than proof of clinical utility. The third aim was addressed by mapping the types and statistical bases of reported validity and reliability evidence and by distinguishing directly evaluated clinical utility from author-stated or inferred implementation potential.

Figure 5. Clinical utility, home use, and telehealth readiness of low-cost gait-analysis technologies.

Panel A shows the distribution of studies according to clinical utility evidence levels (U0–U1). **Panel B** summarizes the implementation outcomes directly evaluated among studies classified as U1. **Panel C** presents the home-use and telehealth-readiness classifications of the included technologies.

Limited methodological appraisal

Across the 120 included studies, 6 (5.0%) were classified as having higher overall methodological confidence, 26 (21.7%) moderate confidence, 87 (72.5%) lower confidence, and 1 (0.8%) insufficient reporting for an overall judgement. These categories contextualise the credibility and transferability of reported findings; they are not certainty-of-evidence grades and were not used to exclude studies. Among the 104 studies with validity evidence, 6 were rated higher, 16 moderate, 74 lower, and 8 insufficiently reported. Fifty-eight studies used an accepted or appropriate reference standard, and 59 used agreement-, absolute-error, diagnostic-accuracy, or classification-agreement analyses. However, correlation-only analysis, weak or unclear comparators, and small samples frequently reduced methodological confidence. Among the 101 reliability studies, 4 were rated higher, 34 moderate, and 63 lower. Sixty-three reported an absolute measurement-error index, whereas 38 reliability studies did not report SEM, MDC/SDD, coefficient of variation, limits of agreement, or a comparable absolute-error measure. Seventy studies (58.3%) had usable samples smaller than 30 and sample size was unclear in 14 (11.7%). Seventy-two studies (60.0%) were conducted exclusively in laboratory settings. Assessor independence or blinding was explicitly reported in only 2 studies and was unclear in 118 (98.3%). Direct implementation evidence was available in 5 studies; 1 had moderate and 4 had lower implementation confidence. Study-level ratings and the prespecified appraisal rules are presented in Supplementary Table S9 and the Methodological Appraisal Summary.

Home use and remote-monitoring readiness

Home use was classified as reported for 57 studies, potential or conditional for 44, and absent for 19. Telehealth readiness was classified as reported for 64, potential for 41, and absent for 15. These classifications largely reflected technical capability or author-stated suitability; only a small subset directly evaluated unsupervised home assessment, remote transmission, longitudinal monitoring or telehealth review.

Cost evidence

Affordability evidence was dominated by descriptive rather than complete operational costing. Only 1 of 120 studies (0.83%) met C1 by explicitly reporting a complete functional setup below US\$1,000. Four studies (3.33%) were classified C2 because they reported a component price suggesting affordability but not the complete setup. Most studies were classified C3 (n = 101, 84.17%) because authors described the technology as low cost or affordable without reporting a numerical total. Eight studies (6.67%) were classified C4 on the basis of consumer-grade hardware or reviewer judgement without complete cost confirmation, and 6 (5.00%) were classified C5 because cost was unclear or inconsistent with the working threshold. Across categories, recurrent software fees, required computers or smartphones, accessories, treadmill or walkway infrastructure, maintenance, calibration, connectivity and replacement costs were frequently unreported. Consequently, the review distinguishes cost-confirmed technologies from reported or inferred affordability and does not treat portability, free software or consumer-grade hardware as proof that the complete operational setup costs less than US\$1,000.

Geographic and equity distribution

The evidence base remained geographically concentrated: 85 of 120 studies (70.8%) were assigned to Europe or North America, whereas only 3 (2.5%) were assigned to South America and none to Africa. Six studies involved multinational collaboration, but collaboration status did not increase regional counts. The absence of a systematic grey-literature search may have reduced retrieval of locally disseminated research; however, complete theses and conference proceedings identified incidentally were eligible and were coded separately from journal articles.

Figure 6. Geographic distribution and equity gaps in the evidence base.

Panel A shows the geographic distribution of included studies by primary region. **Panel B** presents the distribution of studies according to World Bank income group classifications.

Evidence gaps

Gaps for future research

Research gaps included limited responsiveness evidence, incomplete reporting of clinically interpretable measurement error, sparse transverse-plane and kinetic assessment, and limited evidence concerning gait symmetry, gait variability, balance-related outcomes, pathological gait, paediatric and older-adult populations, longitudinal validation, external validation and head-to-head comparisons. Future studies

should report parameter-specific agreement and error and should validate technologies in the populations and settings for which they are intended.

Gaps for clinical implementation

Clinical-implementation gaps included limited direct evidence on feasibility, setup burden, clinician training, workflow integration, acceptability, report interpretability, clinical decision impact, technical failure, home adherence, unsupervised operation, telehealth transmission, remote clinician review, and cybersecurity and data governance. Most implementation claims were based on portability, affordability or apparent measurement performance rather than evaluation in routine care.

Gaps affecting equitable adoption

Table 8 integrates clinical utility, affordability, methodological confidence and the principal implementation and equity gaps; full study-level evidence is retained in Supplementary Tables S2, S5, S6 and S9. Equity gaps included the absence of an eligible primary study from Africa, concentration of evidence in Europe and North America, limited LMIC representation, incomplete reporting of full operational cost, and dependence on smartphones, computers, software licences, internet connectivity, reliable electricity and replacement capacity. Little evidence addressed local calibration, workforce requirements, infrastructure constraints or sustainable adoption in resource-limited settings. The fourth aim was therefore addressed by separating gaps relevant to future research, clinical implementation and equitable adoption and linking them to the corresponding Discussion implications, Supplementary Figure S5 and Table S6.

Table 8. Clinical utility, affordability, methodological confidence and principal evidence gaps

Domain	Category/code	Studies, n	Studies, %	Meaning or implication
Clinical utility	U1	5	4.2	Directly evaluated clinical utility
	U2	115	95.8	Clinical potential stated by authors without direct implementation evaluation
	U3	0	0.0	Reviewer-inferred potential only
	U0	0	0.0	No clinical-utility information
Affordability evidence	C1	1	0.8	Complete functional setup explicitly reported below US\$1,000
	C2	4	3.3	Partial cost evidence; full setup probably below threshold but not completely costed
	C3	101	84.2	Author-described as low cost or affordable without complete numerical costing
	C4	8	6.7	Reviewer-classified as accessible/consumer-grade without cost confirmation
	C5	6	5.0	Cost unclear or conflicting
Methodological confidence	Higher	6	5.0	Limited COSMIN-/JBI-informed appraisal; contextual rating, not a certainty grade.
	Moderate	26	21.7	Limited COSMIN-/JBI-informed appraisal; contextual rating, not a certainty grade.
	Lower	87	72.5	Limited COSMIN-/JBI-informed appraisal; contextual rating, not a certainty grade.
	Insufficiently reported	1	0.8	Limited COSMIN-/JBI-informed appraisal;

				contextual rating, not a certainty grade.
Key implementation/evidence gap	Sample size <30	70	58.3	Small samples reduce precision and generalisability.
	Laboratory-only evaluation	72	60.0	Real-world workflow performance remains uncertain.
	Assessor independence/blinding unclear	118	98.3	Potential measurement and interpretation bias was poorly documented.
	Direct clinical utility evaluated	5	4.2	Very limited direct evidence of feasibility, usability or workflow integration.
	Responsiveness evaluated	1	0.8	Ability to detect clinically meaningful change was rarely established.
	Complete operational cost confirmed	1	0.8	Most affordability claims did not include total ownership or recurrent costs.
	Primary study setting in Africa	0	0.0	No direct evidence from African settings.

Note: Methodological-confidence ratings were generated through a limited COSMIN- and JBI-informed appraisal and were used to contextualise reported findings rather than to exclude studies or generate formal certainty grades.

DISCUSSION

This review provides a cross-technology account of a field that is expanding rapidly but remains dominated by technical validation and research measurement (Table 4; Fig. 2). The central result is a translation gap: the literature is rich in studies showing that low-cost systems can generate selected gait variables, but sparse in studies demonstrating that those systems are affordable as complete operational packages, interpretable within clinical workflows, usable by patients and clinicians, responsive to meaningful change, or successfully implemented in home and remote-care settings (Tables 5 and 7; Fig. 5). Research measurement was the stated or inferred use in 97.5% of studies, whereas home monitoring and remote or telehealth-supported assessment were represented in only 4.2% and 1.7%, respectively. Only five studies directly evaluated a clinical-utility outcome. The field has accumulated considerable technical validation evidence, but very little evidence that these technologies

are usable, affordable, interpretable or successfully implemented in the clinical, home and remote settings for which they are promoted (Tables 5 and 7; Fig. 5).

The review therefore advances a three-stage translational framework. Technical capability asks whether a system can generate a gait-related output. Measurement credibility asks whether that output is valid, reliable, sufficiently precise and responsive for the intended decision. Implementation readiness asks whether the technology can be deployed effectively, acceptably, sustainably and equitably in the setting for which it is proposed. Technical capability does not equal measurement credibility, and measurement credibility does not equal implementation readiness. High correlation does not establish agreement between measurement methods because correlation describes association rather than the magnitude and distribution of measurement differences [141]. A high ICC indicates favourable relative reliability but does not establish small absolute measurement error, responsiveness or the ability to detect clinically meaningful change [142,143]. Portability is a technical characteristic rather than evidence of usability or implementation readiness; those claims require direct evaluation of user burden, training, acceptability, workflow compatibility, technical failure and sustained use in the intended setting [144]. An author's description of a device as "*low cost*" does not establish affordability of the complete operational setup, which may also require software, licences, host devices, accessories, calibration, maintenance, training and connectivity (Table 7; Supplementary Table S2).

The limited methodological appraisal further shows why evidence volume should not be confused with evidence credibility. Most studies had lower overall methodological confidence because of small samples, laboratory-only testing, incomplete reporting of assessor independence, weak or unclear comparator standards, and absent absolute measurement-error estimates (Table 7; Supplementary Table S9). Evidence concentration or favourable reported findings cannot be equated with high-quality or certain evidence. Lower-confidence ratings do not imply that a technology is ineffective; they indicate that the available report does not yet justify strong inferences about interchangeability, detection of clinical change, comparative superiority or implementation readiness.

Interpretation by technology category

The distribution of evidence is broadly consistent with contemporary technology-specific reviews, while extending them in clinically important ways. Recent reviews of wearable inertial sensors have reported promising but heterogeneous validity across gait outcomes, with substantial variation in sensor placement, signal selection, algorithms and statistical validation methods [8]. A recent smartphone review in older adults reported generally favourable findings for gait speed and selected spatiotemporal parameters, but its evidence was population- and parameter-specific [138]. A recent markerless-system review found comparatively favourable performance for spatiotemporal parameters and sagittal-plane hip and knee measures, but weaker evidence for ankle and frontal- or transverse-plane kinematics [7]. The present review confirms the concentration of favourable evidence in spatiotemporal measurement, but shows that such performance rarely translated into direct evidence of usability, workflow integration,

home adherence or telehealth delivery. It also shows why optimistic conclusions from a single device class cannot be generalised across low-cost gait technologies as a whole.

Positioning within contemporary literature

Contemporary syntheses have generally concentrated on a single technology family, population or application - for example, wearable IMUs, markerless camera systems, smartphone assessment in older adults, or real-world digital mobility outcomes in Parkinson's disease [7,8,138,140]. Wearable-sensor reviews have concentrated on benchmarking IMU outputs against laboratory systems [8,9], markerless reviews on accuracy and reliability relative to marker-based motion capture [6,7], smartphone reviews on selected populations and predominantly spatiotemporal parameters [138], and telerehabilitation reviews on treatment delivery using remote monitoring and guidance rather than on the measurement readiness of gait-assessment technologies themselves [139]. A recent review of real-world digital mobility outcomes in Parkinson's disease distinguished supervised mobility capacity from everyday mobility performance and identified persistent protocol heterogeneity [140]. The present review complements and extends these literatures by evaluating multiple technology classes within one framework and by linking measurement performance to intended use, complete affordability evidence, directly evaluated clinical utility, home and telehealth readiness, methodological confidence and geographic equity. The concentration of favourable spatiotemporal findings is consistent with recent wearable-sensor reviews [8], but the present review extends this literature by showing that favourable measurement performance rarely translated into direct evidence of usability, workflow integration, home adherence or telehealth delivery (Tables 5 and 7; Fig. 5). Previous markerless-system reviews have reported comparatively favourable performance for spatiotemporal parameters and selected sagittal-plane measures, while identifying weaker evidence for other joints and movement planes [7]. The present findings show that even where accuracy is promising, evidence remains sparse for representative clinical populations, non-laboratory environments and longitudinal monitoring. The findings challenge the frequent use of '*portable*,' '*consumer-grade*' or '*low cost*' as proxies for implementation readiness, because only one study verified a complete setup below the review threshold and only five directly evaluated clinical utility (Table 7; Supplementary Tables S2 and S5).

Scientific contribution and practical usefulness

The review's principal scientific contribution is conceptual and methodological. It integrates nine elements that have usually been considered separately: multiple technology categories, seven gait-outcome domains, validity, relative reliability, absolute measurement error, responsiveness, intended use, affordability and clinical utility, while also incorporating home and telehealth readiness, methodological confidence and equity. This integrated architecture reveals not only where evidence exists, but whether it is aligned with the claims made for the technology. It therefore provides a reproducible framework for future reviews, validation studies and technology evaluations. For clinicians, the framework converts a heterogeneous evidence base into a practical sequence of questions: What clinical decision is being made? Which gait parameter is required? Was the parameter validated against an appropriate reference

standard in a comparable population and task? What are the SEM, MDC or limits of agreement? Is the expected treatment-related change larger than measurement error? Has the system been tested in the intended clinic, community, home or telehealth workflow? What equipment, software, training, calibration and recurrent costs are required? Together, these questions discourage adoption decisions based solely on portability, correlation or relative reliability, because none of these characteristics independently establishes agreement, sensitivity to change, usability or implementation readiness [141–144]. For researchers and developers, the review identifies the evidence needed to move a device along the translation pathway: from proof of technical capability, through parameter-specific measurement credibility, to prospective demonstration of implementation readiness. For health services and policymakers, the C1–C5 affordability framework and U1–U0 clinical-utility hierarchy offer a transparent preliminary structure for local technology assessment, procurement deliberation and prioritisation of implementation research. These frameworks have not yet been prospectively tested in procurement or service-delivery decisions. For LMIC settings, the review makes explicit that affordability must include the full operational ecosystem rather than the purchase price of a sensor or free application alone.

Translating the Evidence into Clinical Decision-Making

Drawing on the mapped evidence, we developed a review-derived framework to help clinicians, researchers and health systems distinguish technical capability from measurement credibility and implementation readiness. The framework is not a validated clinical decision rule; rather, it provides a structured sequence for evaluating whether a low-cost gait technology is suitable for a defined parameter, population, task and service context. The framework arose from the major evidence domains examined in the review. It links intended use, gait-outcome requirements, comparator and validity evidence, reliability and absolute measurement error, responsiveness, population and task comparability, clinical utility, affordability and methodological confidence.

Clinician's question	Evidence generated by the review
What clinical decision is being made?	Intended-use categories: diagnosis, screening, treatment planning, rehabilitation monitoring, gait retraining, home monitoring and telehealth.
Which gait parameter is required?	Seven gait-outcome domains: spatiotemporal, kinematic, kinetic/kinetic proxy, symmetry, variability, balance-related and algorithm-derived metrics.
Was the parameter validated appropriately?	Validity mapping by criterion, concurrent, construct, discriminative, diagnostic and classification evidence.
Was the comparator appropriate?	Extraction of reference systems such as 3D motion capture, force platforms, instrumented walkways and clinical comparators.
Is the measurement reproducible?	Relative reliability statistics, including ICC and kappa.
Is measurement error clinically acceptable?	SEM, MDC/SDD, coefficient of variation, Bland-Altman bias and limits of agreement.
Can the tool detect treatment-related change?	Responsiveness evidence and comparison of measurement error with expected clinical change.
Was it evaluated in a comparable population and task?	Multidimensional population coding, gait task, setting and intended-use context.
Has it been tested in the intended workflow?	U1-U0 clinical-utility classification, home-use assessment and telehealth-readiness evidence.
What resources are required?	C1-C5 affordability classification, hardware, software, host device, accessories, calibration, training and recurrent costs.
Is the evidence methodologically credible?	Limited COSMIN-informed and JBI-informed methodological appraisal.

The framework therefore converts the study's separate evidence maps into one ordered clinical question: **Can this specific technology measure the required parameter, with sufficient credibility and precision, in the population, task and workflow in which the clinician intends to use it?**

Stage 1: Define the clinical purpose. The clinician first identifies the decision that the measurement must support, such as screening, diagnosis, treatment planning, rehabilitation monitoring, gait retraining, or home or telehealth monitoring. This stage prevents evidence generated for research measurement from being assumed to support a different clinical purpose.

Stage 2: Match the required gait outcome. Technology selection is then anchored to the required outcome: spatiotemporal, kinematic, kinetic or kinetic-proxy, symmetry, variability, balance-related, or algorithm-derived. The review showed that evidence was concentrated in spatiotemporal and kinematic measures and was comparatively sparse for several other domains.

Stage 3: Evaluate measurement credibility. The next stage examines whether the parameter was evaluated against an appropriate comparator in a comparable population and task, whether agreement or diagnostic performance was demonstrated, and whether relative reliability, absolute measurement error and responsiveness support the intended interpretation. High correlation does not establish agreement between measurement methods because correlation describes association rather than the magnitude and distribution of measurement differences [141]. A high ICC indicates favourable relative reliability but does not establish small absolute measurement error, responsiveness or the ability to detect clinically meaningful change [142,143].

Stage 4: Evaluate implementation readiness. The clinician then asks whether the system has been tested in the intended service workflow. Relevant evidence includes directly evaluated clinical utility, setup and processing time, technical failures, training, interpretability, workflow integration, acceptability, and home or telehealth performance.

Stage 5: Evaluate resource and equity requirements. The framework next considers the complete operational setup, including device and software costs, licences, computing and connectivity, accessories, calibration, maintenance, local technical support, and accessibility in resource-constrained and LMIC settings.

Stage 6: Make a qualified adoption decision. The accumulated evidence supports one of four qualified outcomes: suitable for the specified purpose; promising but requiring local verification; appropriate for research use only; or insufficient evidence for adoption. These outcomes are purpose-specific rather than global ratings of a technology.

Application of the framework may prevent adoption based solely on portability, high correlation, high ICC or manufacturer claims. It also makes evidence gaps explicit, particularly where absolute measurement error, responsiveness, operational cost or workflow evaluation has not been reported. Together, these questions discourage adoption decisions based solely on portability, correlation or relative reliability, because none of these characteristics independently establishes agreement, sensitivity to change, usability or implementation readiness [141–144]. The framework is a conceptual and practice-oriented output of the review that requires prospective validation with clinicians, patients, service managers and technology developers.

Applying the framework to representative technologies

The review did not prospectively classify every individual technology into adoption categories. The four readiness labels were derived from the review-derived framework and were applied here only to representative systems for which the extracted evidence permitted a cautious, purpose-specific interpretation. They are not global ratings of a device, do not establish comparative superiority, and should not be interpreted as recommendations for unrestricted adoption.

Technically promising for selected parameters and contexts, but not proven ready for unrestricted clinical adoption.

No technology had sufficient combined evidence of parameter-specific measurement credibility, responsiveness, complete affordability and real-world implementation to support unrestricted clinical adoption across populations and settings.

Table 8
Readiness classification of representative low-cost gait technologies

Readiness category	Representative tools	Evidence supporting classification	Main reason for caution
Technically promising	Axivity AX3, CvMob, selected Kinovea protocols, Gait&Balance app, selected smartphone gait applications	Higher methodological confidence and parameter-specific agreement or error evidence	Limited clinical utility, responsiveness and workflow testing
Promising but requires local verification	Most IMU, smartphone, 2D video and Kinect systems	Favourable findings for selected parameters	Population-, task-, algorithm- and setup-specific performance
Research or restricted observational use	Video Screen Measurement in cerebral palsy, sagittal video joint-angle systems with wide limits of agreement, correlation-only 2D systems	Some reproducibility or association evidence	Poor agreement, wide error, small samples or no direct utility
Insufficient evidence	Single-participant or early proof-of-concept systems	Technical feasibility only	Inadequate clinical validation and implementation evidence

Clinical implications

Low-cost gait technologies should be selected according to the clinical question rather than treated as interchangeable substitutes for laboratory gait analysis. For screening or broad functional profiling, a portable system may be useful when its classification performance and error are adequate for that purpose. For treatment planning or longitudinal monitoring, clinicians require parameter-specific agreement and measurement-error evidence, not merely association or relative reliability. A tool may show high relative reliability yet have an MDC or limits of agreement too large to detect clinically meaningful change. Clinical adoption should therefore be conditional on population-, task- and setting-specific evidence, clear output interpretation, feasible workflow integration and evidence that observed change exceeds measurement error.

Remote-monitoring implications

The review demonstrates a marked mismatch between the language of remote capability and the evidence of remote implementation. Contemporary telerehabilitation literature shows that remote monitoring and guidance can support gait and balance interventions when communication, feedback and clinical oversight are built into the care pathway [139]. However, the technologies in the present review were rarely evaluated as complete remote-assessment services. Only one U1 study directly examined repeated home assessment under remote supervision, and the available evidence did not establish autonomous use, robust data transmission, clinical action thresholds or sustained integration into care. Remote deployment therefore requires prospective evidence on unsupervised operation, data completeness, adherence, environmental variability, connectivity, privacy, cybersecurity, clinician review and escalation pathways. Real-world digital mobility literature similarly distinguishes supervised mobility capacity from everyday mobility performance and stresses the need to standardise protocols before clinical interpretation [140].

Equity and LMIC Implications

The equity relevance of low-cost gait technology lies in its potential to reduce dependence on specialist laboratories, but that potential remains largely untested in settings with the greatest rehabilitation-access constraints. No eligible study had an African country as its primary setting, and the evidence was concentrated in Europe and North America. Only one study verified a complete setup below the working threshold; most relied on author descriptions of affordability. A consumer device or free application may still require a compatible smartphone or computer, accessories, calibration, paid support, reliable electricity, internet connectivity, data storage, replacement capacity and trained personnel. The C1-C5 framework therefore prevents nominal device price from being mistaken for system affordability. Equitable adoption requires locally conducted studies that assess total cost, workforce requirements, cultural and environmental fit, language, connectivity, data governance, maintenance and sustainable integration into existing rehabilitation pathways.

Research implications

Future work should be designed around the translation pathway established by this review. Early studies should report transparent hardware, software, algorithms and full operational costs. Validation studies should use representative clinical samples, accepted reference standards and parameter-specific agreement analyses. Reliability studies should report the ICC model together with SEM, MDC/SDD, coefficient of variation, Bland-Altman bias and limits of agreement, and within- and between-day error as appropriate. Responsiveness should be evaluated separately against prespecified clinically meaningful change. Implementation studies should then test usability, training burden, workflow compatibility, acceptability, adherence, data transmission, decision impact and sustainability in the intended clinic, community, home or telehealth setting. This staged programme would allow promising devices to progress from technical feasibility to defensible clinical adoption without conflating the stages.

Strengths and Limitations

Strengths of this review include broad multidisciplinary coverage, an explicit operational definition of low cost, mapping across multiple technology classes and seven gait-outcome domains, intended-use coding, separation of association from agreement, separation of relative reliability from absolute error and responsiveness, direct-versus-claimed clinical-utility classification, a complete-cost evidence framework, home and telehealth-readiness assessment, multidimensional population and geographic coding, and a study-level limited methodological appraisal. Together, these elements allow the review to move beyond a catalogue of devices and expose the translation gap between technical capability, measurement credibility and implementation readiness.

Limitations include restriction to English-language reports, no systematic grey-literature search, heterogeneity that precluded quantitative pooling, incomplete reporting of measurement-error statistics, sparse responsiveness and implementation evidence, and dependence on the information available in primary reports and the source-verified extraction dataset. The appraisal was limited rather than a full COSMIN review of every measurement-property result, was not a GRADE certainty assessment, and still requires independent second-reviewer verification. The duplicate-removal count and screening-calibration confidence intervals also remain subject to the previously described source-data limitations.

CONCLUSIONS

This review maps the full low-cost gait-technology landscape and shows where evidence is concentrated, where it remains methodologically weak and where implementation claims exceed direct evaluation. Low-cost technologies are most promising for selected spatiotemporal outcomes, but the field remains dominated by laboratory validation and research measurement. The mismatch between intended application and evaluation context is substantial: home, telehealth, workflow, responsiveness, complete-cost and direct clinical-utility evidence are scarce. Technical capability does not equal measurement credibility, and measurement credibility does not equal implementation readiness. The review's contribution is a unified translational framework that helps clinicians judge whether a tool is fit for a specific decision, helps researchers design the next stage of validation or implementation work, and helps health systems distinguish nominally inexpensive devices from technologies with credible evidence for sustainable and equitable adoption. Future research should progress deliberately from technical feasibility to measurement credibility and then to direct implementation testing in the populations and settings for which these technologies are intended. The review-derived framework is an additional practice-oriented contribution that organises the evidence into six sequential decisions and four qualified adoption outcomes. It was not prospectively applied or validated as a device-level adoption classification and should be refined and validated before being treated as a clinical algorithm or decision-support product. No individual technology was shown to have sufficient combined evidence for unrestricted adoption across settings. The representative readiness classifications in Table 8 are purpose-specific interpretations and require prospective validation before they are used as device-level adoption decisions.

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Authors' contributions

SCI and KEF conceived the study, participated in the study design, methodology development, formal analysis, validation, and manuscript preparation. KEF coordinated the investigation, conducted data curation and visualization, prepared the original draft of the manuscript, and participated in the review and editing of the manuscript. CE, AIO, JLE, CNU, GCI, CNI, BUI and ADE participated in the investigation, data curation, validation, and critically reviewed and edited the manuscript. SCI supervised the study and participated in the review and editing of the manuscript. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The study-level data extraction sheet is provided as Supplementary tables (Microsoft Excel), figures, and additional methodological materials are provided in Supplementary Material 1.

Clinical trial number

Not applicable.

Ethics statement

Ethical approval and informed consent were not required for this study because it is a scoping review based exclusively on data from previously published literature and did not involve human participants or identifiable personal data.

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Figures

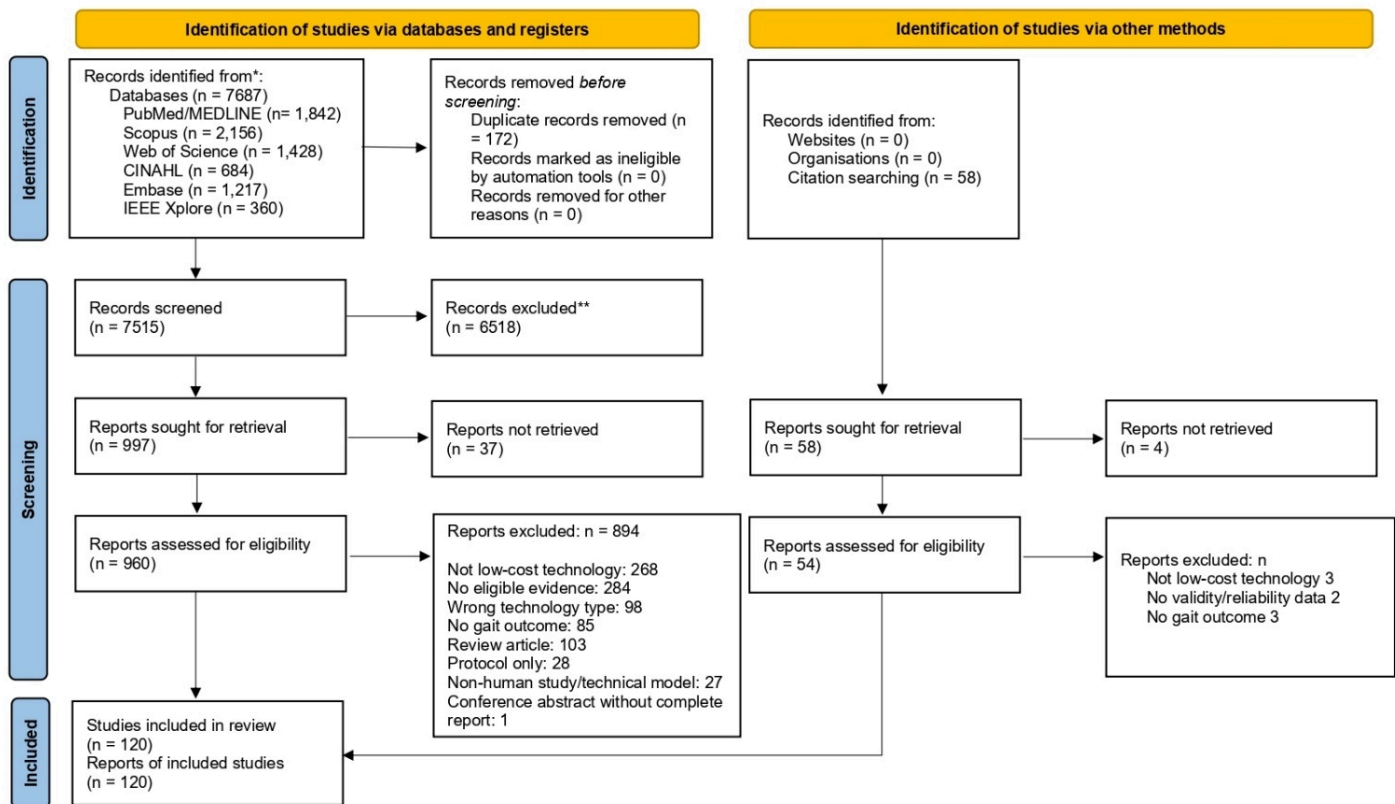


Figure 1

PRISMA Flow Diagram

Figure 2. Growth and technological evolution of low-cost gait-analysis research

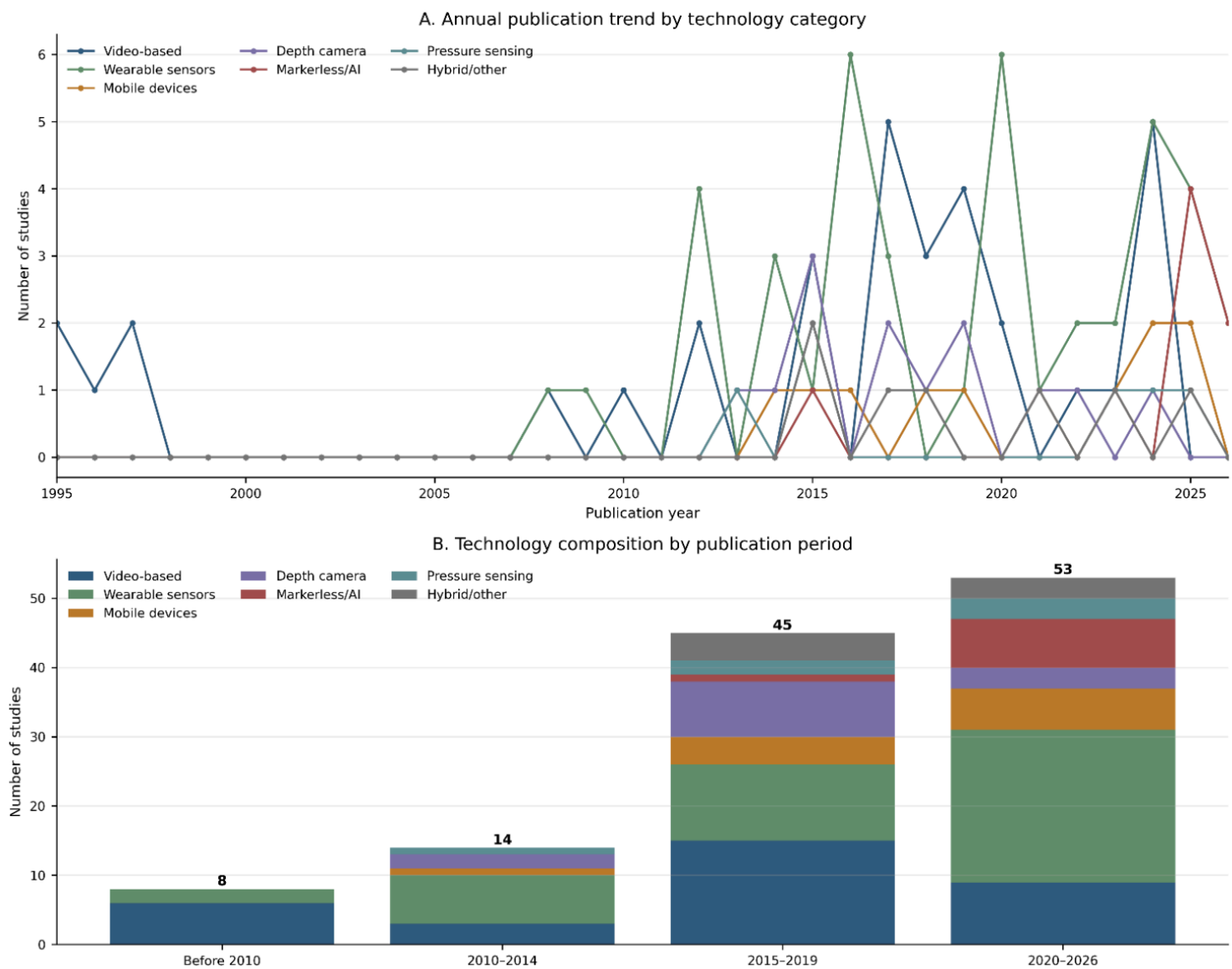


Figure 2

Growth and technological evolution of low-cost gait-analysis research.

Panel A shows the annual publication trend from 1995 to 2026. **Panel B** shows the distribution of technology categories across four publication periods: before 2010, 2010–2014, 2015–2019, and 2020–2026.

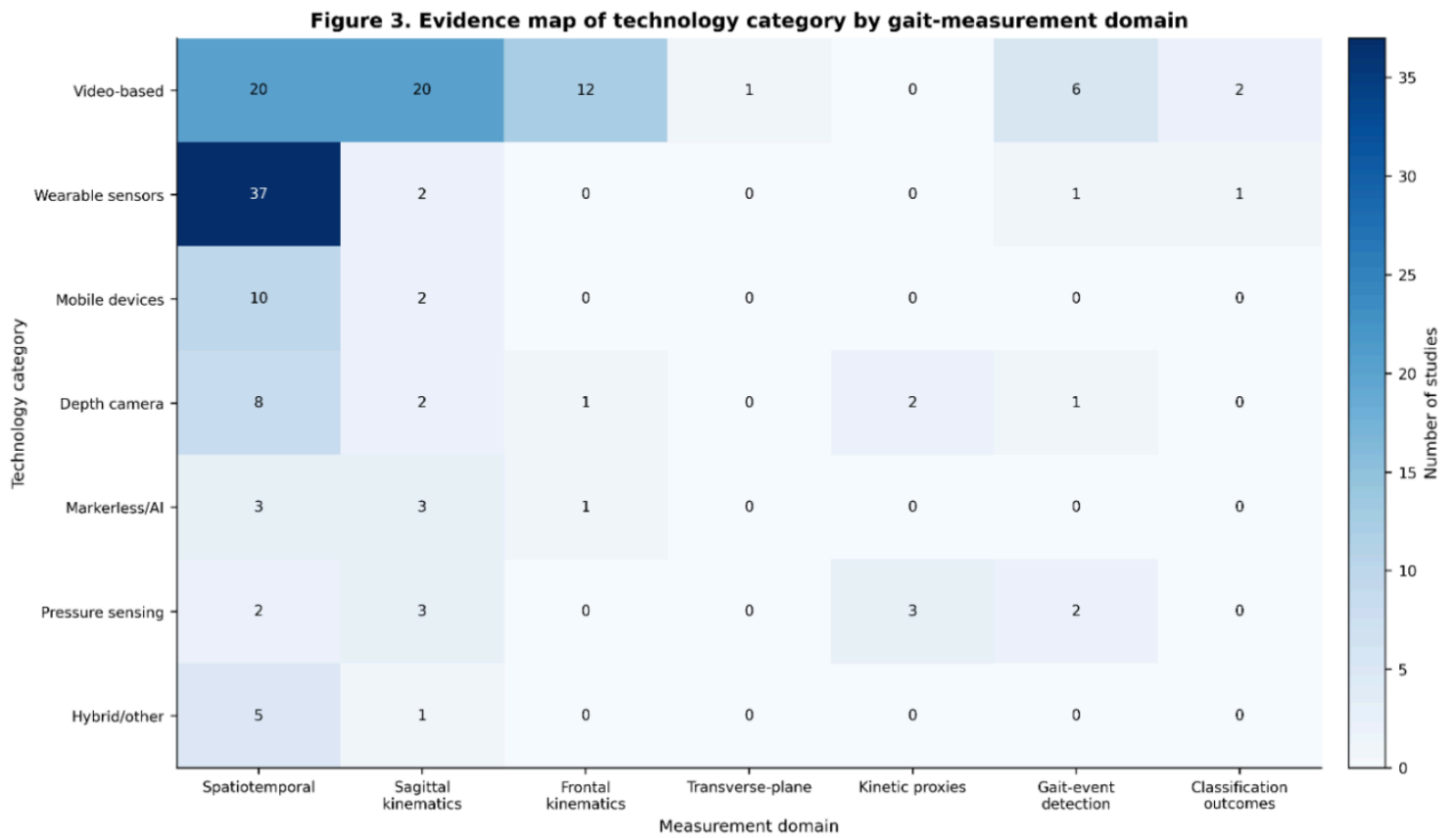


Figure 3

Evidence map of technology category by gait-measurement domain

The heatmap covers: *spatiotemporal outcomes; sagittal, frontal, and transverse-plane kinematics; kinetic proxies; gait-event detection; classification outcomes.*

Figure 4. Validity, reliability and measurement-error evidence by technology category

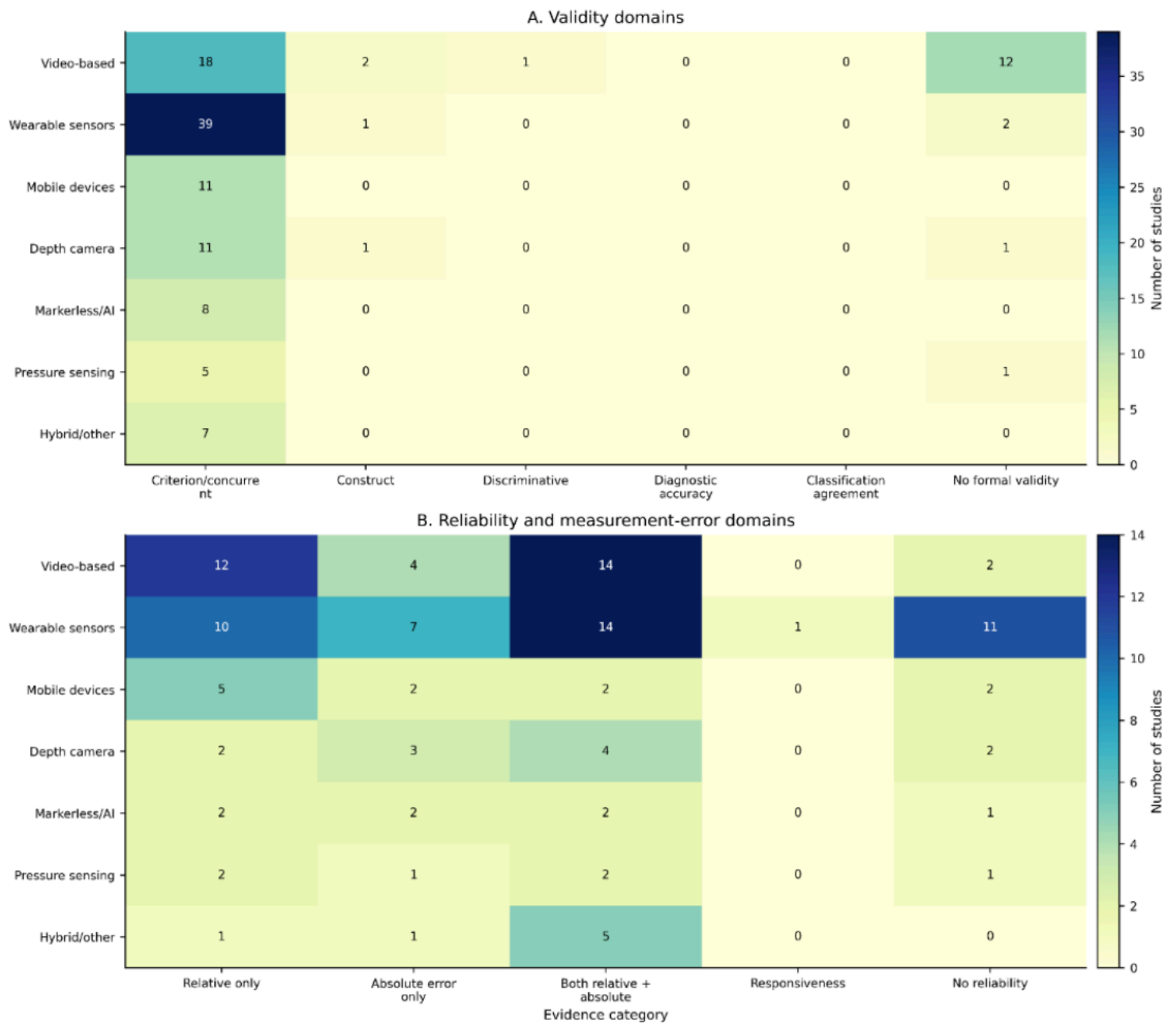


Figure 4

Validity, reliability and measurement-error evidence by technology category-

Panel A: criterion/concurrent, construct, discriminative, diagnostic, classification-agreement, and unassessed validity. **Panel B:** relative reliability, absolute error, combined evidence, responsiveness, and no reliability assessment.

Figure 5. Clinical utility, home use and telehealth readiness

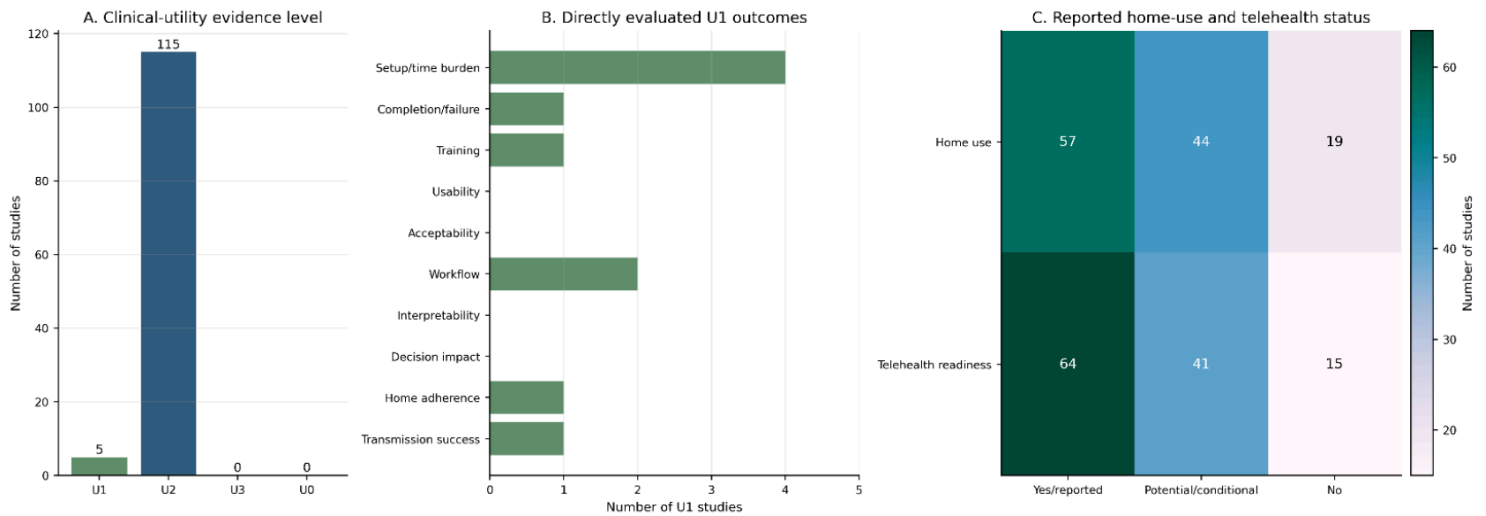


Figure 5

Clinical utility, home use, and telehealth readiness of low-cost gait-analysis technologies.

Panel A shows the distribution of studies according to clinical utility evidence levels (U0–U1). **Panel B** summarizes the implementation outcomes directly evaluated among studies classified as U1. **Panel C** presents the home-use and telehealth-readiness classifications of the included technologies.

Figure 6. Geographic distribution and equity gaps in the evidence base

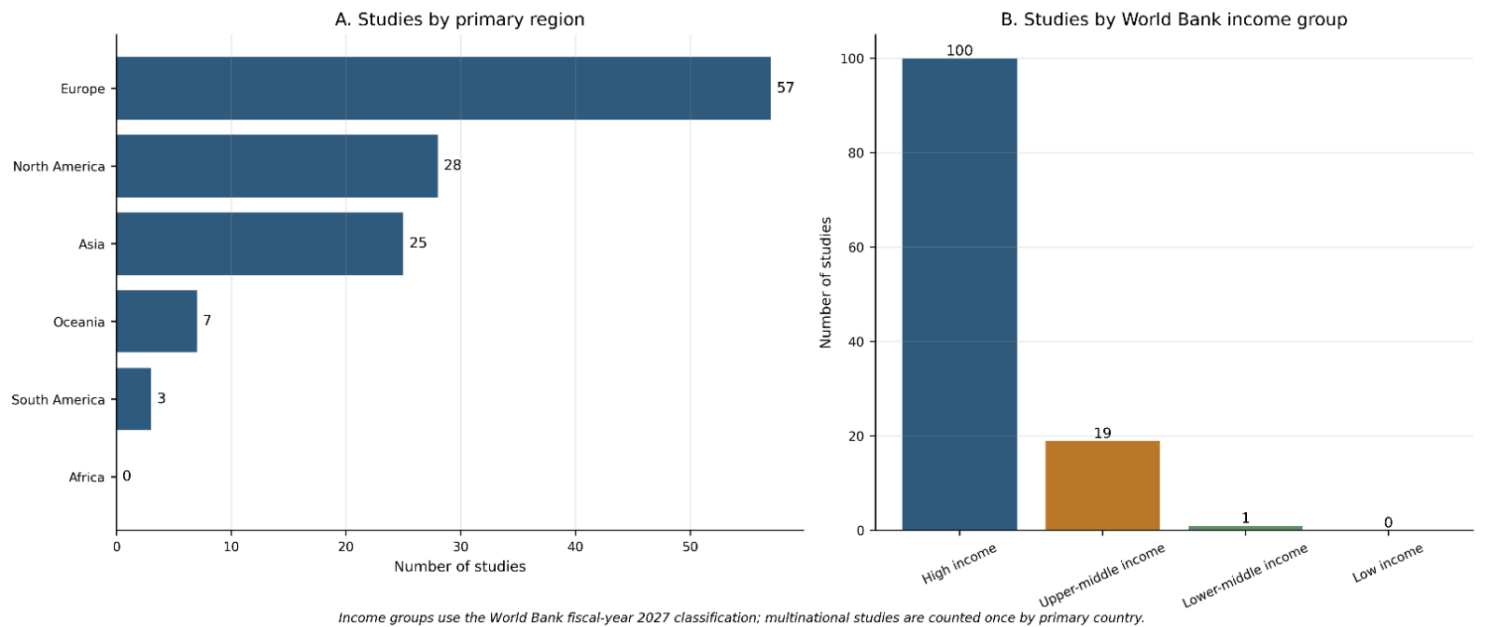


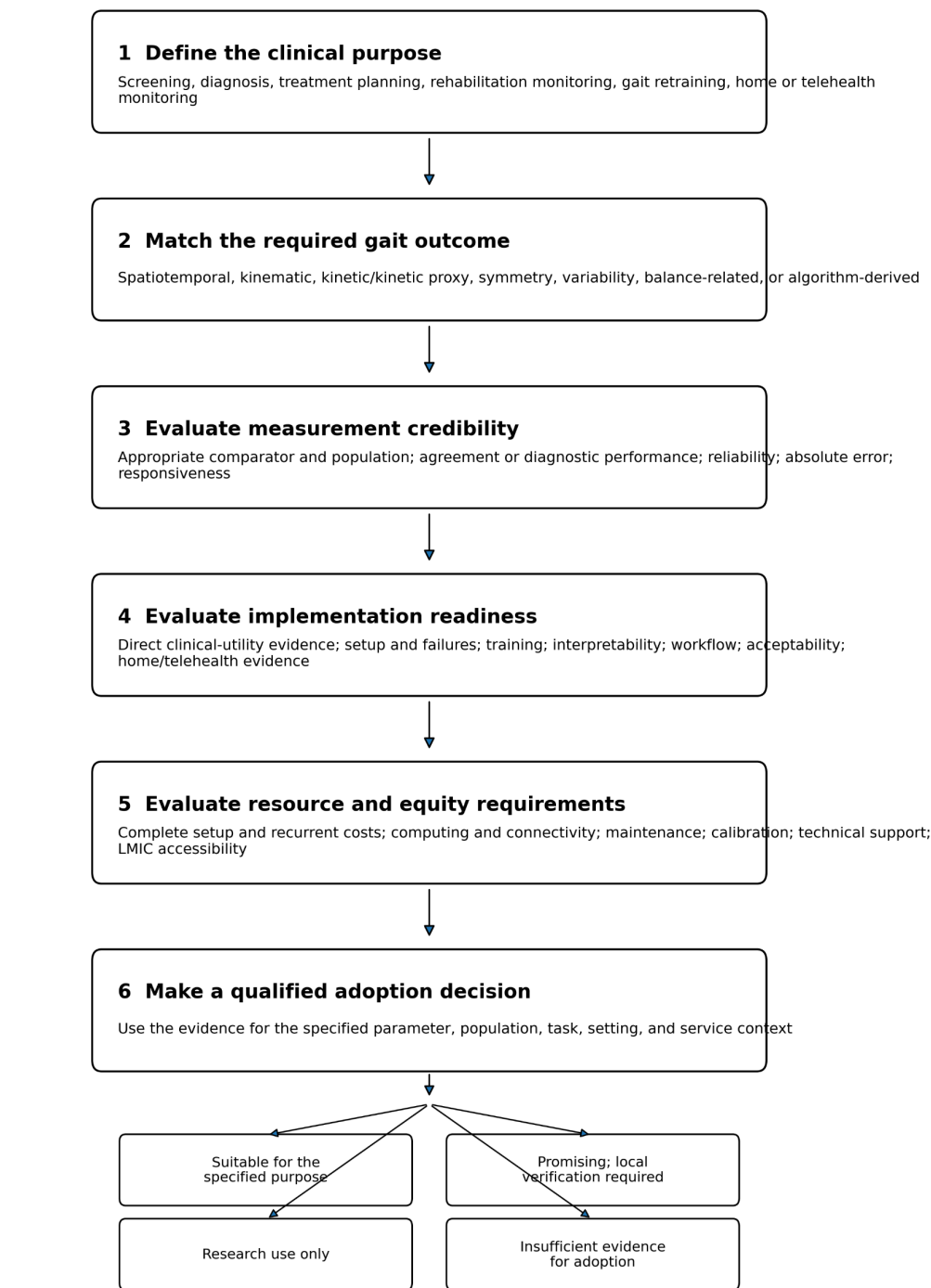
Figure 6

Geographic distribution and equity gaps in the evidence base.

Panel A shows the geographic distribution of included studies by primary region. **Panel B** presents the distribution of studies according to World Bank income group classifications.

Review-derived framework for evaluating the clinical and real-world readiness of low-cost gait-analysis technologies

Technical capability does not equal measurement credibility, and measurement credibility does not equal implementation readiness.



Practice-oriented knowledge-translation framework; prospective validation is required before use as a clinical decision rule.

Figure 7

Review-derived framework for evaluating the clinical and real-world readiness of low-cost gait-analysis technologies.

Supplementary Files

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