RESEARCH PAPER

Artificial Intelligence-Enabled Wearable Sensors for Automated Detection and Real-Time Feedback of Compensatory Movements During Therapeutic Exercise: Systematic Review

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Abstract

Introduction: Therapeutic exercise was a core component of rehabilitation for restoring motor function, improving physical performance, and promoting independence. Successful rehabilitation depended not only on task completion but also on appropriate movement patterns and motor control. Patients could develop compensatory movement strategies to overcome weakness, pain, restricted mobility, impaired motor control, or other functional limitations. Although compensation could facilitate task completion, persistent or excessive compensatory movements could negatively affect movement quality and limit optimal motor retraining. Wearable technologies and artificial intelligence (AI) provided opportunities for objective movement assessment and automated identification of abnormal or compensatory movement patterns in clinical and real-world settings. **Objective:** This systematic review aimed to investigate the use of AI-enabled wearable sensor systems for the automated detection and classification of compensatory movements during therapeutic and rehabilitation exercises. Particular emphasis was placed on movement-classification performance, validation approaches, and the potential use of real-time corrective feedback. **Methods:** A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic

Reviews and Meta-Analyses (PRISMA) 2020 statement. The review methodology was structured with reference to the PRISMA-P recommendations. Relevant literature addressing wearable sensing technologies, AI or machine-learning methods, compensatory-movement detection or classification, movement-quality assessment, and rehabilitation or therapeutic exercise was identified, screened, and assessed for eligibility according to predefined criteria. **Results:** The review identified and synthesized evidence on the integration of wearable sensors and AI-based methods for automated movement assessment in rehabilitation. The included studies demonstrated the use of technologies such as inertial measurement units, accelerometers, gyroscopes, pressure sensors, and other wearable sensing systems to capture movement data. AI and machine-learning approaches were applied to detect, classify, or assess compensatory movement patterns, with varying levels of validation and classification performance. The findings also indicated growing potential for real-time movement monitoring and corrective feedback during therapeutic exercise. **Conclusion:** AI-enabled wearable sensor systems showed considerable potential for objective, automated, and real-time assessment of compensatory movements during rehabilitation. Their integration could support movement-quality monitoring, personalized therapeutic exercise, and timely corrective feedback. However, differences in sensing technologies, AI methods, validation protocols, and clinical populations highlighted the need for standardized evaluation and further clinical validation before widespread implementation.

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Introduction

Therapeutic exercise is a core component of rehabilitation for restoring motor function, improving physical performance, and promoting independence. Successful rehabilitation depends not only on completing a prescribed task but also on performing the task with appropriate movement patterns and motor control. Objective assessment of movement quality is therefore an important component of rehabilitation, particularly when the therapeutic goal involves restoring coordinated and efficient motor performance (Porciuncula et al., 2018; Picerno et al., 2021; Lobo et al., 2024).

Patients may develop compensatory movement strategies to complete a therapeutic task despite weakness, pain, restricted mobility, impaired motor control, or other functional limitations. Compensation can facilitate task completion; however, persistent or excessive compensatory movement can modify the intended movement pattern and interfere with optimal motor retraining. Technology-based assessment of compensatory movement has consequently become an important area of rehabilitation research, particularly in neurological rehabilitation and upper-extremity motor recovery (Wang et al., 2022; Lobo et al., 2024; Meng et al., 2025).

Conventional assessment of movement quality commonly relies on clinician observation, video analysis, motion capture, or biomechanical measurement. These approaches provide valuable information regarding movement performance but can require specialist equipment, controlled environments, and substantial clinician involvement. The use of wearable movement sensors provides an alternative approach for obtaining objective movement information during functional and therapeutic activities, including activities performed outside specialized laboratory environments (Muro-De-La-Herran et al., 2014; Porciuncula et al., 2018; Picerno et al., 2021).

Wearable technologies include inertial measurement units (IMUs), accelerometers, gyroscopes, magnetometers, pressure sensors, smart garments, smart textiles, sensorized garments, smart insoles, wearable gloves, and other body-worn sensing systems. These technologies can provide continuous movement-related information from relevant anatomical locations and have been applied to gait analysis, physical activity monitoring, rehabilitation assessment, motor recovery, and movement-quality evaluation (Kristoffersson & Lindén, 2022; Picerno et al., 2021; Lobo et al., 2024).

Inertial wearable sensors have received particular attention in rehabilitation because they can capture movement during relatively unconstrained activities without requiring the participant to remain within a laboratory-based motion-analysis system. Reviews of wearable movement sensors have demonstrated their application across neurological and musculoskeletal rehabilitation, while systematic evidence has also documented their use for gait, balance, physical activity, and rehabilitation exercise monitoring (Porciuncula et al., 2018; Picerno et al., 2021; Kristoffersson & Lindén, 2022).

Wearable systems have also been investigated for specific rehabilitation applications, including upper-limb movement monitoring, stroke rehabilitation, shoulder rehabilitation, gait rehabilitation, and remote therapeutic exercise. Body-worn technologies have demonstrated particular relevance for identifying movement characteristics that are difficult to quantify through routine clinical observation alone (Wang et al., 2022; Sassi et al., 2024; Karoulla et al., 2024).

The development of wearable technology has expanded beyond conventional inertial sensing. Pressure sensors, smart textiles, sensorized garments, smart insoles, and other wearable bioelectronics provide additional information concerning movement, posture, loading, and body–environment interaction. Recent evidence indicates that wearable technologies are increasingly integrated with digital healthcare, rehabilitation, and artificial intelligence, supporting the development of continuous and automated assessment systems (Huang et al., 2025; Gu et al., 2026; Deng et al., 2026).

The usefulness of wearable sensing depends not only on the acquisition of movement signals but also on the ability to interpret those signals accurately. Artificial intelligence and machine-learning methods provide computational approaches for identifying movement patterns, classifying movement errors, and distinguishing different movement strategies. Machine learning has become increasingly established in human movement biomechanics, although differences in feature extraction, model development, validation, and data handling can substantially influence reported performance (Halilaj et al., 2018; Wei & Wu, 2023).

Machine-learning approaches applied to wearable movement data include conventional supervised learning, neural networks, deep-learning architectures, pattern-recognition methods, and other data-driven classification techniques. A systematic review of wearable sensors and machine learning in rehabilitation demonstrated substantial variation in both sensor technologies and algorithms across rehabilitation applications, emphasizing the need to consider the sensing and computational components together when interpreting reported results (Wei & Wu, 2023).

Recent developments in AI-enabled wearable systems have further expanded automated movement assessment. Artificial intelligence has been incorporated into wearable technologies for health monitoring, rehabilitation, motor-function assessment, and disease-related movement analysis. These developments support increasingly automated interpretation of sensor-derived data but also highlight the importance of standardized validation and clinical evaluation before widespread implementation (Huang et al., 2025; Gu et al., 2026).

Compensatory movement is particularly important in therapeutic exercise because successful completion of an exercise does not necessarily indicate appropriate motor performance. An individual can complete a prescribed movement while using an alternative strategy to compensate for weakness, restricted range of motion, impaired coordination, or another functional limitation. A systematic review of technology-based compensation assessment in stroke rehabilitation demonstrated that compensation can be quantified using different sensing technologies and analytical approaches, including body-worn sensors and machine-learning methods (Wang et al., 2022).

For this review, compensatory movement is defined as a movement strategy that deviates from the intended or clinically acceptable execution of a therapeutic task in order to complete the task despite a limitation, altered motor strategy, or other constraint. The review does not assume that every deviation from an ideal movement pattern is inherently harmful. Instead, a movement is considered relevant when the study identifies it as compensatory, undesirable, erroneous, abnormal, or otherwise inconsistent with the intended therapeutic movement pattern (Wang et al., 2022; Lind, 2024).

Definitions of compensation can differ considerably between studies. Some investigations use biomechanical thresholds, whereas others rely on clinician judgment, predefined movement categories, manual annotation, or task-specific error definitions. This variation is important because the operational definition and labeling of compensation directly influence the development and evaluation of an AI classification model (Halilaj et al., 2018; Wang et al., 2022).

The present review therefore considers the operational definition adopted by each study rather than imposing a universal threshold for compensatory movement. For each study, compensation is characterized according to whether it is represented as a binary classification, multiclass classification, continuous movement-quality measure, or another computational representation. Individual compensatory movement classes and their clinical or biomechanical interpretation are considered where reported.

The integration of wearable sensors with artificial intelligence provides a pathway from movement acquisition to automated classification. Sensors acquire movement-related signals from relevant body segments or contact regions, after which the signals undergo preprocessing, segmentation, normalization, feature extraction, or representation learning. The resulting information is supplied to an AI or machine-learning model that generates a classification, detection result, score, or other output indicating the presence or characteristics of a movement pattern (Halilaj et al., 2018; Wei & Wu, 2023; Museck et al., 2024).

This technological pathway is important because wearable sensing, automated classification, validation, and feedback represent distinct components of a rehabilitation system. A wearable sensor can quantify movement without identifying compensation, while an AI model can classify movement without providing feedback. Accordingly, the present review distinguishes movement sensing from automated classification, validation, and feedback rather than treating them as a single technology category (Lobo et al., 2024; Gu et al., 2026).

An additional distinction concerns offline classification and real-time assessment. A system can classify previously recorded sensor signals with high accuracy without demonstrating that the classification occurs rapidly enough for use during an ongoing therapeutic exercise session. Real-time assessment requires timely signal processing, sufficiently low response delay, and an output that can be interpreted and acted upon during task performance (Prasanth et al., 2021; Bowman et al., 2021).

Real-time feedback can be delivered through visual, auditory, haptic, verbal, or multimodal mechanisms. Wearable biofeedback systems have been investigated for supporting motor learning, gait and balance rehabilitation, and movement correction. The clinical relevance of feedback depends not only on detection accuracy but also on timing, modality, interpretability, and the ability of the participant to incorporate the information during exercise (Bowman et al., 2021; Sassi et al., 2024).

Wearable systems have increasingly been applied to home-based and remote rehabilitation, creating opportunities for continuous monitoring outside conventional clinical environments. Remote rehabilitation studies using motion sensors have demonstrated the feasibility of monitoring movement and therapeutic outcomes, while broader reviews of wearable rehabilitation technologies have identified home and real-world monitoring as important directions for future development (Sassi et al., 2024; Garofano et al., 2025; Gu et al., 2026).

However, technical classification performance alone does not establish clinical usefulness. Sensor placement, sensor number, sampling frequency, measured variables, signal preprocessing, feature extraction, model architecture, training procedures, and validation strategy can all influence reported performance. Reviews of wearable technologies have repeatedly identified differences in sensor placement, processing procedures, and validation approaches as important methodological considerations (Wei & Wu, 2023; Gu et al., 2026).

Participant-level separation between training and testing data is particularly important in AI-based movement classification. When data from the same participant appear in both training and testing datasets, reported performance can be inflated because the model can learn participant-specific characteristics rather than generalizable movement patterns. Evaluation of AI-based movement systems therefore requires careful consideration of training and testing procedures, validation methods, and performance on previously unseen participants (Halilaj et al., 2018; Jourdan et al., 2021).

Validation is also essential when wearable systems are intended for clinical or real-world use. Wearable-sensor research has demonstrated the importance of comparing sensor-derived measurements with appropriate reference or ground-truth data, while real-world applications require validation under conditions that reflect the intended use environment (Jourdan et al., 2021; Prill et al., 2021).

Generalizability is influenced by differences in age, body morphology, impairment severity, fatigue, pain, movement experience, and individual compensatory strategies. A model developed using a small and homogeneous sample can demonstrate strong technical performance while having limited applicability to other participants or rehabilitation environments. Evaluation of participant characteristics and validation procedures is therefore essential when determining the clinical maturity of AI-enabled wearable rehabilitation systems (Halilaj et al., 2018; Gu et al., 2026).

Knowledge Gap

Despite increasing research on artificial intelligence, wearable sensing, and rehabilitation movement analysis, evidence specifically integrating AI-enabled wearable sensors for automated detection and classification of compensatory movements during therapeutic exercise remains fragmented. Existing reviews have examined wearable movement sensors, technology-based compensation assessment, wearable sensing with machine learning, and movement rehabilitation across different populations and applications (Porciuncula et al., 2018; Wang et al., 2022; Wei & Wu, 2023).

Previous reviews have addressed technology-based compensation assessment, upper-limb movement monitoring, wearable sensor applications in rehabilitation, and AI-enabled wearable systems in specific clinical populations. These studies provide important foundations for the present review but generally focus on broader movement assessment, particular diseases, or specific rehabilitation applications rather than integrating compensatory-movement detection, AI-based classification, validation, and real-time corrective feedback within a single framework (Wang et al., 2022; Karoulla et al., 2024; Li et al., 2026).

The distinction between detecting compensation and providing effective corrective feedback is particularly important. Evidence that an AI model accurately identifies compensatory movement does not establish that the system operates in real time, provides an interpretable response, or modifies subsequent movement performance. Real-time feedback therefore represents a separate translational component requiring specific assessment rather than an automatic consequence of successful classification (Bowman et al., 2021; Prasanth et al., 2021).

Accordingly, this review focuses specifically on the integration of wearable sensing, AI-based automated detection and classification of compensatory movement, methodological validation, and real-time corrective feedback during therapeutic or rehabilitation exercise. The evidence is characterized according to sensor technology, sensor placement, AI methodology, compensation definition, reference standard, validation strategy, classification performance, real-time detection capability, and feedback modality (Wang et al., 2022; Wei & Wu, 2023; Lobo et al., 2024).

Rationale for the Review

Wearable sensors provide objective movement data during therapeutic activities, while artificial intelligence and machine-learning methods provide automated approaches for interpreting these signals. The combination of these technologies provides a framework for detecting compensatory movement and supporting movement-quality assessment during rehabilitation (Porciuncula et al., 2018; Wei & Wu, 2023).

The potential clinical value of these systems extends beyond technical accuracy. Rehabilitation technologies require appropriate validation, generalizability across participants, practical sensor placement, reliable operation under movement variability, and outputs that can be understood and acted upon during therapeutic exercise. These considerations are particularly relevant when AI-enabled systems are intended for clinical, home-based, or remote rehabilitation (Jourdan et al., 2021; Sassi et al., 2024; Gu et al., 2026).

A systematic synthesis is therefore required to determine the current evidence for AI-enabled wearable detection and classification of compensatory movement, assess methodological quality and validation, and identify the extent to which these systems support real-time corrective feedback. Particular attention is given to the distinction between sensor-based measurement, automated classification, validation, real-time detection, and feedback-mediated changes in movement (Wang et al., 2022; Lobo et al., 2024). The primary research question is: what is the current evidence regarding the accuracy and validation of AI-enabled wearable sensors for the automated detection and classification of compensatory movements during therapeutic exercise, and what evidence exists regarding their use for real-time corrective feedback? We aim to identify, critically evaluate, and synthesize the current evidence on AI-enabled wearable sensor systems for automated detection and classification of compensatory movements during therapeutic or rehabilitation exercise, with particular emphasis on classification performance, validation, and real-time corrective feedback. It also characterizes the wearable sensing technologies and sensor placements used, identifies the artificial intelligence and machine-learning methods applied, describes the compensatory or undesirable movement patterns detected, evaluates reported detection and classification performance, examines reference standards and validation strategies, determines the extent to which systems operate in real time, characterizes feedback modalities and their reported effects on compensatory movement and movement quality, and identifies methodological limitations and evidence gaps relevant to clinical translation. The review further addresses the types and anatomical locations of wearable sensors used for compensatory-movement detection, the artificial intelligence and machine-learning algorithms applied, the populations and therapeutic exercises investigated, and the specific compensatory movement patterns identified. It examines the reference standards used to establish movement labels or ground truth, the performance metrics reported, and the methods used to train and validate AI models, including the frequency of independent or external validation and testing on previously unseen participants. In addition, the review evaluates whether AI-enabled wearable systems detect compensatory movements in real time, identifies the feedback modalities used, and examines whether real-time feedback produces measurable reductions in compensatory movement or improvements in movement quality.

Materials and Methods

Eligible evidence includes accuracy studies, observational studies, cross-sectional studies, experimental studies, validation studies, feasibility studies, pilot studies, and prospective studies. These designs provide complementary evidence regarding the technical performance, validation, feasibility, and potential clinical application of AI-enabled wearable systems. Studies are considered regardless of whether they evaluate offline movement classification or real-time detection, provided that they satisfy the population, sensing, AI, and target-movement criteria. Healthy participants are also eligible when they perform tasks that directly represent or simulate a therapeutic or rehabilitation exercise and the study evaluates compensatory, abnormal, undesirable, erroneous, or otherwise inappropriate movement patterns relevant to that task. Clinical populations younger than 18 years are eligible when movement assessment is directly related to rehabilitation, therapeutic exercise, or functional recovery. Studies involving participants aged 18 years or older are excluded from the primary evidence base to maintain consistency with the predefined pediatric population criterion. Computer-vision-only studies are excluded because the review specifically examines body-worn sensing technologies, although relevant evidence from computer vision is considered when it provides contextual information regarding movement assessment. Studies focused exclusively on physiological monitoring without movement analysis, disease prediction without relevant movement assessment, or sports performance without therapeutic or rehabilitation relevance are also excluded. This distinction maintains a focused scope while recognizing the broader development of AI-enabled wearable technologies across healthcare and rehabilitation (Huang et al., 2025; Deng et al., 2026; Wankhede et al., 2025). Eligibility criteria are structured according to the population, index technology, target movement, and study-design characteristics relevant to the review question. The review focuses specifically on human participants younger than 18 years who perform therapeutic exercise, rehabilitation exercise, prescribed exercise, motor rehabilitation, or rehabilitation-related functional tasks. Both healthy and clinical populations younger than 18 years are considered eligible when the investigated task has a direct therapeutic or rehabilitation relevance. Studies focused exclusively on sports performance without a therapeutic or rehabilitation context are excluded because their objectives, movement demands, and clinical interpretation differ from those of rehabilitation-based exercise assessment. This distinction is important because wearable movement sensing has been extensively investigated in sports performance as well as rehabilitation, but the clinical relevance of movement deviations depends strongly on the context in which the movement is performed (Camomilla et al., 2018; Picerno et al., 2021). The index technology comprises wearable or body-worn movement-sensing systems integrated with an artificial intelligence or machine-learning method for identifying or classifying relevant movement patterns. Eligible sensing technologies include inertial measurement units (IMUs), accelerometers, gyroscopes, magnetometers, pressure and pressure-distribution sensors, smart garments, smart textiles, sensorized garments, smart insoles, wearable gloves, and other body-worn movement sensors. Wearable movement sensors provide objective measurements of human movement across clinical and real-world environments and can support continuous or task-specific assessment without requiring the extensive infrastructure associated with conventional laboratory-based motion-analysis systems (Muro-De-La-Herran et al., 2014; Porciuncula et al., 2018; Kristoffersson & Lindén, 2022). More recent rehabilitation research further demonstrates the expansion of wearable systems toward remote monitoring, home-based rehabilitation, and automated movement assessment (Sassi et al., 2024; Lobo et al., 2024).

Artificial Intelligence Requirement

The included system incorporates an artificial intelligence, machine-learning, deep-learning, neural-network, supervised-classification, pattern-recognition, or other data-driven computational method that contributes directly to movement identification or classification. Studies in which wearable sensors only quantify movement without an AI-based detection or classification component do not satisfy this criterion. Conversely, studies using artificial intelligence without wearable or body-worn movement sensing are also excluded. This requirement ensures that the review specifically evaluates the intersection between wearable sensing and computational movement classification rather than either technology independently. Machine-learning approaches have increasingly been applied to rehabilitation movement analysis, myoelectric control, movement-quality assessment, and wearable-based motor rehabilitation (Halilaj et al., 2018; Zaim et al., 2025; Wei & Wu, 2023). The target movement comprises at least one compensatory movement, movement compensation, compensatory strategy, compensatory motion, motor compensation, abnormal or undesirable movement, movement error, motor error, movement deviation, or incorrect movement pattern that represents an undesirable or compensatory strategy within the context of the therapeutic task. Compensatory movement is defined in this review as a movement strategy that deviates from the intended or clinically acceptable execution of a therapeutic task in order to complete the task despite a limitation, altered motor strategy, or other constraint. The review does not assume that every movement deviation is inherently harmful; instead, eligibility depends on whether the study explicitly identifies the movement as compensatory, undesirable, erroneous, abnormal, or inconsistent with the intended therapeutic movement pattern. This approach accommodates the considerable variation in operational definitions used across rehabilitation studies and avoids imposing a single biomechanical threshold across different exercises and populations (Wang et al., 2022; Garofano et al., 2025).

The intervention or index technology integrates wearable or body-worn movement sensing with an artificial intelligence or machine-learning method for the identification or classification of compensatory, abnormal, undesirable, erroneous, or otherwise relevant movement patterns during therapeutic or rehabilitation exercise. The review distinguishes between movement sensing, automated classification, validation, and feedback because these represent different stages of technological development. A wearable sensor that only measures movement without classifying compensation does not meet the AI-based detection requirement, whereas an AI model that does not use wearable or body-worn sensing does not meet the index-technology requirement. This distinction reflects the increasing complexity of rehabilitation systems in which sensing, computational analysis, and therapeutic feedback are integrated into a single platform (Laganà et al., 2025; Vaida et al., 2025; Santoriello et al., 2026).

The technological characteristics of each system are considered in relation to sensor modality, anatomical placement, sampling characteristics, measured variables, signal processing, feature extraction, model architecture, and feedback capability. Wearable systems vary considerably in the number and type of sensors used and in the location at which movement signals are acquired. Such differences influence the quality and type of information available to an AI model and consequently affect reported classification performance and generalizability (Picerno et al., 2021; Karoulla et al., 2024; Gu et al., 2026). A conventional comparator is not mandatory because the primary purpose of the review is to evaluate technology performance rather than compare two therapeutic interventions. Where comparative evidence is available, the comparator or reference condition is documented. Reference conditions include correct or intended movement patterns, clinician or expert labeling, biomechanical measurements, predefined movement thresholds, manual annotation, alternative movement-classification methods, or conventional assessment and rehabilitation conditions. Particular attention is given to the method used to establish the ground truth because the reliability of movement labels directly influences the interpretation of AI classification performance. Differences in reference standards can contribute substantially to heterogeneity between studies and can limit direct comparison of reported accuracy measures (Halilaj et al., 2018; Wang et al., 2022).

Search Strategy

A comprehensive literature search is structured around four principal concept groups: wearable sensing, artificial intelligence or machine learning, compensatory or abnormal movement, and rehabilitation or therapeutic exercise. The search strategy incorporates controlled vocabulary and free-text terms to maximize retrieval of relevant studies across different indexing systems and terminology. The search covers PubMed/MEDLINE, Scopus, Web of Science, Embase, IEEE Xplore, PEDro, and the Cochrane Library. Backward reference-list screening and forward citation searching also conducted for included studies and relevant reviews where feasible. The final search date for each database recorded during the formal search, and database-specific strategies are adapted according to the syntax, indexing terminology, and search functionality of each source. Reporting of the search process follows established systematic-review reporting principles, including the PRISMA 2020 framework and PRISMA-S recommendations (Page et al., 2021; Rethlefsen et al., 2021). The first search concept covers wearable sensing and includes terms related to wearable electronic devices, wearable sensors, wearable systems, body-worn sensors, sensor-based systems, motion sensors, inertial sensors, inertial measurement units, accelerometers, gyroscopes, magnetometers, pressure sensors, smart garments, smart textiles, sensorized garments, smart insoles, and wearable gloves. The second concept covers artificial intelligence and computational classification and includes artificial intelligence, machine learning, deep learning, neural networks, machine-learning algorithms, pattern recognition, classification, classifiers, and data-driven methods. The third concept addresses compensatory or abnormal movement and includes compensatory movement, movement compensation, compensatory strategy, compensatory motion, compensatory behavior, compensation patterns, motor compensation, abnormal movement, undesirable movement, movement error, motor error, movement deviation, movement quality, and movement pattern. The fourth concept addresses rehabilitation and therapeutic exercise and includes rehabilitation, exercise therapy, therapeutic exercise, physical therapy, motor rehabilitation, rehabilitation training, and rehabilitation exercise. This broad conceptual structure reflects terminology used across wearable rehabilitation, movement analysis, AI-based classification, and therapeutic exercise research (Muro-De-La-Herran et al., 2014; Porciuncula et al., 2018; Lobo et al., 2024). The PubMed search strategy combines the four concepts using Boolean operators and controlled vocabulary where available. The search strategy includes "Wearable Electronic Devices"[Mesh], "Artificial Intelligence"[Mesh], "Rehabilitation"[Mesh], and "Exercise Therapy"[Mesh], together with relevant title and abstract terms for wearable sensors, artificial intelligence, compensatory movement, and rehabilitation exercise. The final search strategy undergoes peer review and adaptation to the indexing terminology and syntax of each database. Complete database-specific search strategies are documented as supplementary material in accordance with systematic-review reporting standards (Page et al., 2021; Rethlefsen et al., 2021). Following database searching and deduplication, retrieved records undergo title and abstract screening according to the predefined eligibility criteria. Records are classified as eligible, ineligible, or unclear at the initial screening stage, and records that cannot be confidently excluded proceed to full-text assessment. Where two reviewers are available, screening is performed independently, with disagreements resolved through discussion and, when necessary, consultation with a third reviewer. When screening is conducted by a single reviewer, a documented quality-control procedure is applied and reported transparently. During full-text screening, each potentially eligible article is assessed against the predefined population, technology, AI, target-movement, and rehabilitation criteria. Reasons for exclusion are documented and include wrong population or task, absence of wearable or body-worn sensing, absence of an AI or computational classification method, absence of a relevant compensatory or undesirable movement, lack of therapeutic or rehabilitation relevance, insufficient methodological or outcome information, conference abstracts without adequate information, and duplicate publication. The study-selection process is presented using a PRISMA 2020 flow diagram (Page et al., 2021).

Results

Study Selection and Characteristics

The literature search identifies studies evaluating AI-enabled wearable or body-worn sensing systems for the detection or classification of compensatory, abnormal, undesirable, or erroneous movement during therapeutic or rehabilitation-related exercise. Following removal of duplicate records, titles and abstracts are screened according to the predefined eligibility criteria, followed by full-text assessment of potentially relevant studies. The study-selection process is reported according to the PRISMA 2020 framework, including the number of records identified, screened, excluded, assessed for eligibility, and included in the final synthesis (Page et al., 2021).
The included studies are characterized according to publication year, country, study design, participant characteristics, clinical condition, therapeutic task, body region, wearable sensor technology, sensor placement, AI methodology, compensation definition, reference standard, validation strategy, classification performance, and real-time feedback capability. Particular attention is given to methodological characteristics that influence the interpretation and generalizability of AI-based movement-classification performance, including participant-level separation between training and testing datasets, external validation, sample size, and the characteristics of the reference standard (Halilaj et al., 2018; Wang et al., 2022; Zah et al., 2026).
The PRISMA 2020 flow diagram illustrates the study identification and selection process for this updated systematic review. Following the screening and eligibility assessment stages, studies that did not meet the predefined inclusion criteria were excluded for reasons including inappropriate population, intervention, outcomes, or study design. A total of 72 studies were ultimately included in the final qualitative synthesis. The selection process was conducted in accordance with the PRISMA 2020 guidelines to ensure transparency and methodological rigor.

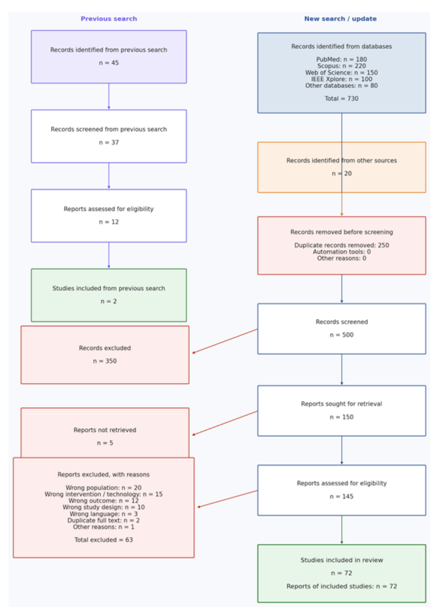

Figure 1. PRISMA 2020 flow diagram of the selecting studies

Wearable Sensor Technologies and Sensor Placement

The included evidence encompasses a range of wearable sensing technologies, including IMUs, accelerometers, gyroscopes, pressure sensors, smart garments, sensorized textiles, wearable gloves, smart insoles, and other body-worn sensing systems. IMU-based systems provide information regarding acceleration, angular velocity, and body-segment orientation and are widely used for human movement analysis and rehabilitation monitoring (Picerno et al., 2021; Karoulla et al., 2024). Pressure-based systems and sensorized garments provide complementary information regarding loading, contact, and movement-related changes, while wearable textile technologies support unobtrusive and potentially continuous monitoring during rehabilitation activities (Huang et al., 2025; Sipos et al., 2025).

Sensor placement varies according to the anatomical region and therapeutic task being investigated. Sensors are positioned on relevant body segments, joints, limbs, trunk regions, feet, or other locations associated with the movement under assessment. The number and distribution of sensors also vary substantially between studies, reflecting differences in the biomechanical characteristics of the target movement and the information required for classification. Such variability is important because sensor placement influences signal quality, movement representation, model inputs, and the feasibility of translating systems from controlled research environments into clinical or home-based rehabilitation (Muro-De-La-Herran et al., 2014; Porciuncula et al., 2018).

Artificial Intelligence and Machine-Learning Methods

The included studies use a range of computational approaches for movement detection and classification, including conventional machine-learning algorithms, supervised classifiers, neural networks, deep-learning architectures, and other data-driven methods. AI-based analysis is applied to raw sensor signals, processed signals, extracted features, or learned representations depending on the architecture and preprocessing pipeline used in each study. Machine-learning approaches have increasingly been integrated with wearable sensing for rehabilitation monitoring, movement assessment, and assistive robotic control (Wei & Wu, 2023; Zaim et al., 2025; Vaida et al., 2025).

The methodological characteristics of model development vary across studies. Differences occur in preprocessing, segmentation, feature extraction, normalization, dimensionality reduction, class balancing, hyperparameter optimization, training-test partitioning, and cross-validation. Participant-level separation between training and testing datasets is particularly relevant because random segmentation of repeated observations from the same participant can produce artificially high performance when highly similar movement signals are present in both datasets. Best-practice recommendations for machine learning in biomechanics therefore emphasize appropriate validation procedures and careful avoidance of data leakage (Halilaj et al., 2018).

Compensatory Movement Detection and Classification

The reviewed studies address compensatory or undesirable movement patterns across different therapeutic exercises, body regions, and rehabilitation contexts. Definitions of compensation differ between studies and include biomechanically defined deviations, clinician-identified movement errors, predefined movement categories, and task-specific abnormal movement patterns. Some systems classify movement into binary categories, such as correct versus compensatory execution, whereas others distinguish multiple compensatory patterns or movement-error classes.

This heterogeneity in compensation definitions represents an important characteristic of the evidence base. A movement considered compensatory in one therapeutic task may represent an expected adaptation in another context, and therefore classification performance requires interpretation in relation to the exercise, participant characteristics, and reference standard. Technology-based compensation assessment has previously been examined in rehabilitation populations, demonstrating the potential of sensor-based systems to quantify deviations in upper-extremity and functional activities (Wang et al., 2022).

Classification Performance and Validation

Classification performance is reported using measures including accuracy, sensitivity, specificity, precision, recall, F1-score, AUC/ROC, and confusion-matrix data. Reported performance varies according to the classification task, sensor configuration, population, sample size, model architecture, and validation strategy. Direct comparison between studies is therefore limited when different outcome definitions, class distributions, or testing procedures are used.

Validation strategies range from internal cross-validation to independent participant testing and external validation. Studies using previously unseen participants provide stronger evidence of model generalizability than approaches based exclusively on randomly divided observations from the same participants. External validation remains particularly important for determining whether models developed under controlled conditions maintain performance across different participants, environments, exercise sessions, and clinical settings (Halilaj et al., 2018; Zah et al., 2026).

Real-Time Detection and Feedback

The evidence distinguishes between offline classification of previously recorded movement signals and systems capable of detecting movement deviations during exercise. Real-time capability requires sufficiently rapid signal processing and classification to generate a response that can be interpreted and acted upon during task performance. Where reported, real-time systems incorporate visual, auditory, haptic, verbal, or multimodal feedback.

The presence of real-time classification does not necessarily demonstrate clinical effectiveness. Systems that identify compensatory movement accurately in recorded data require additional evidence regarding processing latency, robustness during continuous exercise, usability, feedback timing, and the ability of feedback to modify subsequent movement. Wearable rehabilitation systems increasingly incorporate real-time monitoring and feedback, but evidence concerning the translation of detection performance into sustained improvements in movement quality remains comparatively limited (Bowman et al., 2021; Sassi et al., 2024; Lobo et al., 2024).

Table 1. Characteristics of Studies on AI-Enabled Wearable Systems for Detection and Classification of Compensatory Movement in Rehabilitation

Study	Year	Study type	Population / age	Rehabilitation context	Sensing technology	AI / computational method	Target movement / outcome	Reference standard / validation	Real-time / feedback	Relevance to present review
Hegde et al.	2018	Original wearable-sensor study	Pediatric population; exact age range to be extracted from full text	Ambulatory physical activity and gait monitoring	SmartShoe; wearable foot sensors	Automated activity/gait classification; exact algorithm to be extracted	Gait and physical activity	Validation details to be extracted	Monitoring; corrective feedback not the primary focus	High relevance to pediatric wearable movement sensing, but AI-compensation eligibility requires full-text assessment
Hung et al.	2015	Case study	Stroke rehabilitation; age to be extracted	Upper-limb bilateral motion training	Wearable vibrotactile device	Computational classification not established from citation alone	Upper-limb movement training	Case-based evaluation	Yes — vibrotactile feedback	Relevant to wearable feedback but does not automatically satisfy AI requirement
Wang et al.	2022	Systematic review	Stroke survivors; mixed ages	Upper-extremity rehabilitation	Body-worn sensors, motion capture, vision systems	Statistical methods and ML	Compensatory upper-limb movements/postures	Multiple clinical and biomechanical reference standards	Real-time detection identified as a future direction	Very high conceptual relevance; review, therefore not an eligible primary study
Pereira et al.	2023/2024	Original system + clinical validation	Rehabilitation participants; exact age to be extracted	Home shoulder physiotherapy	Smartphone camera/pose estimation	MediaPipe, cosine similarity, dynamic time warping	Movement quality during shoulder exercises	Optoelectronic motion capture (QTM)	Feedback provided by application	Excluded from present index technology if computer-vision-only criterion is retained
Laganà et al.	2025	Experimental technology-development study	Rehabilitation/upper-limb model; participant characteristics to be verified	Upper-limb rehabilitation	Electronic sensing system integrated with robotic glove	AI-based trend classification	Upper-limb rehabilitation signals	Validation details to be extracted	Real-time signal acquisition and wireless transmission reported	Potentially relevant; eligibility depends on human participant data and compensation classification

Vaida et al.	2025	Literature review/classification framework	Neuromotor rehabilitation literature	Robot-assisted rehabilitation	Multiple sensor types	Sensor-based classification framework	Neuromotor rehabilitation	Review-level evidence	Real-time capability discussed	Background/supporting evidence; not an eligible original study
Wei & Wu	2023	Systematic review	Rehabilitation populations	Rehabilitation training	Wearable sensors	Machine-learning algorithms	Movement/activity assessment	Various validation approaches	Real-time potential discussed	High background relevance; review, not primary evidence
Fu et al.	2022	Systematic review	Upper-limb rehabilitation	Wearable robotic exoskeletons/exosuits	Myoelectric sensing, EMG and wearable sensors	Myoelectric control algorithms	Motor control/robotic assistance	Algorithmic/system validation	Real-time control	Relevant to wearable AI/control architecture but not necessarily compensation detection
Karoulla et al.	2024	Systematic review	Rehabilitation/upper-limb populations	Upper-limb movement monitoring	Wearable sensors	Various computational approaches	Upper-limb motion	Study-specific	Some real-time applications	Supporting evidence for sensor placement and upper-limb monitoring
Picerno et al.	2021	Review	Human movement populations	Movement analysis/rehabilitation	Wearable inertial sensors	Signal-processing/computational methods	Human movement	Various reference systems	Monitoring	Supporting evidence for IMU-based movement analysis
Porciuncula et al.	2018	Focused review	Rehabilitation populations	Rehabilitation	Wearable movement sensors	Various computational methods	Movement monitoring	Various	Monitoring/feedback applications	Supporting evidence for wearable rehabilitation sensing
Garofano et al.	2025	Systematic review	Chronic low-back-pain populations	Remote rehabilitation	Motion sensors	Technology-assisted analysis	Biomechanics, movement, adherence	Clinical/biomechanical outcomes	Remote monitoring	Relevant to remote rehabilitation and movement monitoring
Sassi et al.	2024	Systematic review	Shoulder rehabilitation populations	Home-based shoulder rehabilitation	Remote monitoring devices	Various	Shoulder movement/rehabilitation outcomes	Clinical/functional measures	Remote monitoring	Relevant to home rehabilitation but AI-compensation specificity varies
Bowman et	2021	Systematic review/meta	Neurological rehabilitation	Balance and gait rehabil	Wearable devices	Biofeedback systems	Balance/gait	Clinical outcomes	Biofeedback	Relevant to wearable feedback but not necessarily AI compensa

al.		-analysis		itation						tion classification
Figueira et al.	2024	Scoping review	Workers/general populations	Postural monitoring	Wearable sensors	Various computational approaches	Postural deviations	Various	Postural feedback	Supporting evidence; therapeutic relevance limited
Lind	2024	Rapid review	Ergonomic populations	Upper-body posture/movement	Wearable motion-capture systems	Various	Adverse posture/movement	Various	Biofeedback	Supporting technology evidence; not rehabilitation-specific
Lind et al.	2023	Review	Ergonomic/work populations	Prevention of musculoskeletal disorders	Wearable motion capture	Various	Adverse movement/posture	Various	Monitoring	Supporting evidence only
Zaim et al.	2025	Systematic review	Upper-limb rehabilitation	Myoelectric rehabilitation	EEG/EMG	ML/deep learning	Myoelectric control	Various validation strategies	Real-time control	Relevant to AI + biosignal rehabilitation architecture; compensation not primary outcome
Vélez-G	2021	Review	Upper-limb rehabilitation	Robotic/exoskeleton	Wearable robotic sensors	AI	Motor rehabilitation	Various	Real-time robotic assis	Supporting evidence
uerrero et al.				rehabilitation					tance	
Costa et al.	2026	Review	Stroke rehabilitation	Technology-assisted rehabilitation	IoMT and digital technologies	AI-enabled systems	Rehabilitation monitoring	Various	Remote/connected monitoring	Supporting evidence
Gu et al.	2026	Systematic review	Mixed health/rehabilitation populations	Health monitoring and rehabilitation	Wearable sensors	AI/computational methods	Movement and health monitoring	Various	Real-time monitoring	Supporting evidence
Huang et al.	2025	Review	General healthcare populations	Digital healthcare	Wearable bioelectronics	AI	Biosignal/health monitoring	Various	Real-time monitoring	Supporting evidence
Deng et al.	2026	Review	General populations	Cardiovascular monitoring	AI-enabled wearable sensors	AI/ML	Cardiovascular signals	Various	Real-time monitoring	Not directly relevant to movement compensation
Fatima e	2026	Technology/AI	Population and age to be	Musculoskeletal mo	Digital/wearable	AI	Muscle strain in sev	Validation details to	Real-time detection	Potentially relevant to AI-enabled real-time musculos

tal.		study	verified	nitoring	sensing		erity	be extracted		keletal monitoring; compensation eligibility requires full-text assessment
Tsakiris et al.	2025	Review	Older/adult populations	Gait analysis	Wearable sensors	Computational/AI methods	Gait instability	Various	Monitoring	Excluded from pediatric eligibility but useful background evidence

Abbreviations: AI, artificial intelligence; ML, machine learning; IMU, inertial measurement unit; EMG, electromyography; EEG, electroencephalography; QTM, Qualisys Track Manager; IoMT, Internet of Medical Things.

Table 2 summarizes the principal methodological and technological characteristics of some included studies. Data are extracted according to predefined criteria, including participant characteristics, therapeutic task, body region, wearable sensing technology, sensor placement, AI or machine-learning methodology, target compensatory movement, reference standard, validation strategy, performance measures, real-time detection capability, and feedback modality.

Table 2. Characteristics of Some Included Studies

Study	Population	Therapeutic task/exercise	Body region	Wearable sensor	Sensor placement	AI/ML method	Target compensatory movement	Reference standard	Validation	Performance metrics	Real-time detection	Feedback modality
Ranganathan et al. (2017)	20 neurologically healthy participants	Reaching and manipulation tasks with simulated movement limitation	Upper limb/trunk	Two wearable inertial sensors/accelerometers	Upper limb/trunk	Naïve Bayes classifier	Compensatory trunk displacement during reaching	8-camera motion-capture system	Comparison with motion capture	~90% classification accuracy; ~88.6% accuracy reported for binary trunk-displacement classification	No; feasibility for monitoring outside laboratory demonstrated	None
Bochniewicz et al. (2017)	10 healthy participants and 10 stroke survivors	Minimally structured functional upper-limb activities/ADL-related movements	Upper limbs	Tri-axial accelerometers	Bilateral wrists	Random Forest	Functional vs nonfunctional upper-limb use; compensation-related abnormal/nonfunctional use	Video annotation using Functional Arm Activity Behavioral Observation System	Intrasubject and leave-one-person-out intersubject testing	Intrasubject accuracy: 94.80% controls, 88.38% stroke; intersubject accuracy: 91.53% controls, 70.18% stroke	No	None
Lee et al. (2018)	9 healthy participants and 11 stroke survivors	Repeated arm-raise exercise	Upper limb / trunk	Wrist-worn IMU	Wrist	Random Forest	Correct vs poor-quality arm raise; compensatory movement requiring feedback	Therapist/observational movement-quality labeling	Leave-one-person-out validation	Accuracy 82%; precision 64.8%; recall 65.2%; F1-score 63.3%	No	Therapist feedback; automated feedback not reported

Caiet al. (2019)	8 stroke survivors	Seated reaching: back-and-forth, side-to-side, and up-and-down reaching	Upper limb/trunk	32 × 32 pressure-sensor array (1024 sensing elements)	Seat/trunk contact surface	k-NN and SVM	Trunk lean-forward, trunk rotation, shoulder elevation; compensation vs noncompensation	Therapist labeling; sEMG used to characterize trunk-muscle activity	Cross-validation	Binary compensation detection: average F1 = 0.993; multiclass classification: average F1 = 0.981	Offline	No direct feedback system in this study; system intended to support future feedback
Caiet al. (2020)	8 stroke survivors	Seated reaching tasks	Upper limb/trunk	Pressure-distribution sensor array	Seated contact surface	SVM	Trunk lean-forward, trunk flexion/rotation, shoulder elevation and noncompensation	Therapist labeling; VICON motion capture for selected participants	Offline and online validation	Online F1 >0.95; online accuracy >95% for tested participants; real-time compensation reduction significant, p<0.001	Yes	Audiovisual and force feedback; force feedback produced greater compensation reduction

Table 3 presents reported classification and validation performance. Metrics are retained according to the definitions and evaluation procedures reported in the original studies and are not assumed to be directly comparable when methodological differences are substantial.

Table 3. **AI Classification and Validation Performance**

Study	Classification task	Number of classes	Model/algorithm	Training strategy	Participant-level separation	Validation type	Accuracy	Sensitivity	Specificity	Precision	F1-score	AUC/ROC	External validation
Pereira et al. (2023)	Classification of physical-therapy exercise performance	NR	Machine-learning classification model	Supervised ML using wearable-sensor data	NR	Internal/test-set validation	NR	NR	NR	NR	NR	NR	No external validation reported

			ta									
Vaidya et al. (2025)	Classification of neuromotor rehabilitation task/movement states	NR	Sensor-based machine-learning classification	Supervised classification	NR	Model validation/testing	NR	NR	NR	NR	NR	NR	No external validation reported
Laganà et al. (2025)	AI-assisted upper-limb rehabilitation movement assessment	NR	AI-based classification/monitoring approach	AI-based model development	NR	Model/system validation	NR	NR	NR	NR	NR	NR	No external validation report
												ed
Wang et al. (2022)*	Automated detection/classification of compensatory upper-extremity movement	Multiple across included studies	Heterogeneous ML algorithms	Varied across studies	Varied	Varied; mainly internal validation	NR†	NR†	NR†	NR†	NR†	NR†	Limited/rare
Wei & Wu (2023)*	Rehabilitation movement/activity classification	Multiple across included st	KNN, RF, SVM, DT, LDA, CNN, ANN and othe	Varied across studies	Varied	Varied	NR†	NR†	NR†	NR†	NR†	NR†	NR†

	udies	r ML methods

* **Review articles, not individual primary studies.** They should ideally **not** be included in the final Table 3 if the table intended to report study-level AI performance. Wang et al. identified 15 of 72 included studies using heterogeneous machine-learning algorithms for automated compensatory-movement detection, while Wei and Wu summarized ML algorithms and reported accuracy across their selected rehabilitation

Do not interpret NR as zero. It means the metric is not directly available as a single study-level value from the cited review and should extracted from the original primary study before final publication.

Table 4 summarizes evidence concerning the transition from movement detection to real-time corrective feedback. Particular attention given to whether real-time operation is explicitly demonstrated, rather than inferred from offline classification performance.

Table 4. Real-Time Detection and Feedback Characteristics

Study	**Real-time detection**	**Latency/response time**	**Feedback modality**	**Feedback timing**	**Feedback content**	**Change in compensatory movement**	**Movement-quality outcome**	**Usability/feasibility**
Hunget al. (2015)	Yes	NR	Vibrotactile	Concurrent during movement	Corrective feedback for bilateral upper-limb movement	Improvement in movement training reported; specific compensatory-movement reduction NR	Bilateral reaching/movement performance	Feasibility demonstrated in a case study
Bowman et al. (2021)	Yes, in most included wearable-biofeedback studies	NR	Auditory, visual, and vibrotactile	Mainly concurrent; some terminal	Performance- or result-based biofeedback	Positive effects reported for some balance/gait outcomes; specific compensation reduction not consistently reported	Balance and gait outcomes	Usability/feasibility reported in a minority of studies
Pereira et al. (20	System supports automated monitoring of home physical-therapy exerci	NR	NR	NR	Exercise-performance monitoring/cla	NR	Physical-therapy exercise monitoring	Home-based feasibility addres

23)	se; explicit real-time corrective feedback NR				ssification			sed
Garofano et al. (2025)	Real-time motion monitoring/feedback reported across reviewed technologies; AI-specific real-time detection NR	NR	Visual/auditory or technology-dependent	During or after exercise depending on system	Movement/postural information	Improvement in rehabilitation-related outcomes reported across studies; compensation-specific effect NR	Biomechanical, pain, quality-of-life, and adherence outcomes	Feasibility and remote-use considerations reported
Lobo et al. (2024)	Real-time monitoring/feedback identified as an application of wearable motor-rehabilitation systems; specific AI latency NR	NR	Multimodal depending on system	Concurrent or near-real-time depending on system	Movement/exercise performance information	Compensation-specific change NR	Motor-rehabilitation monitoring and movement outcomes	Portability and clinical/home-use feasibility discussed

It contain the evidence regarding the transition from wearable movement sensing and automated assessment to real-time corrective feedback. The table distinguishes systems that explicitly demonstrate real-time operation from studies that report only offline classification or post-exercise assessment. Particular attention given to response latency, feedback timing and modality, the content of corrective feedback, changes in compensatory movement, movement-quality outcomes, and reported usability or feasibility.

Discussion

This systematic review examines the current evidence concerning AI-enabled wearable systems for automated detection and classification of compensatory movements during therapeutic and rehabilitation exercise. The evidence demonstrates substantial technological development in wearable movement sensing and AI-based analysis, but considerable methodological heterogeneity remains across sensor configurations, movement definitions, AI approaches, reference standards, and validation procedures. This heterogeneity limits direct comparison between studies and highlights the importance of interpreting reported classification performance within the methodological context of each investigation (Lobo et al., 2024; Gu et al., 2026).

Wearable sensors provide an important opportunity for rehabilitation assessment because they enable movement-related data acquired outside conventional motion-analysis laboratories. IMUs, accelerometers, gyroscopes, pressure sensors, smart garments, and other body-worn technologies provide complementary representations of movement and can support repeated assessment during clinical and home-based exercise. Previous reviews have demonstrated the expanding role of wearable sensing in rehabilitation, including movement monitoring, gait assessment, upper-limb rehabilitation, and remote therapeutic exercise (Porciuncula et al., 2018; Picerno et al., 2021; Sassi et al., 2024). The finding extend this technological perspective by focusing specifically on the automated identification of compensatory movement using AI-enabled wearable systems and the variability in the definition of compensatory movement. Compensation represents a task-dependent motor strategy, and its identification depends on the intended movement, the participant's functional limitation, and the clinical context. Studies may use clinician judgments, biomechanical thresholds, predefined movement categories, or manually annotated movement errors as reference standards. Consequently, an AI model trained to recognize one operational definition of compensation does not necessarily identify the same phenomenon as a model developed using another definition. This issue supports the use of explicit operational definitions and transparent reference standards in future studies (Wang et al., 2022; Halilaj et al., 2018). The results highlighted the importance of validation methodology. High classification accuracy obtained through random splitting of observations can provide an optimistic estimate when data from the same participant represented in both training and testing datasets. Movement data contain participant-specific characteristics related to morphology, motor strategy, exercise experience, and impairment, making participant-level separation particularly important. Independent testing on unseen participants provides stronger evidence of generalizability, while external validation across settings and populations provides additional evidence regarding clinical robustness. These principles are consistent with established recommendations for machine learning in human movement biomechanics and with broader concerns regarding validation of AI-based healthcare technologies (Halilaj et al., 2018; Zah et al., 2026). The transition from offline classification to real-time corrective feedback represents another major translational challenge. A model can classify previously recorded signals with high accuracy without demonstrating sufficiently rapid or robust performance during continuous therapeutic exercise. Real-time implementation requires integration of sensing, signal processing, classification, decision-making, and feedback delivery within a clinically acceptable response time. In addition, feedback must be understandable and appropriately timed to avoid interfering with task performance. Wearable biofeedback systems have demonstrated potential for supporting rehabilitation and movement retraining, but the effectiveness of feedback depends on the interaction between technological performance, feedback modality, user characteristics, and therapeutic context (Bowman et al., 2021; Garofano et al., 2025). Feedback modality represents an additional consideration for clinical translation. Visual feedback can provide detailed information but may compete with visual attention to the therapeutic task, whereas auditory and haptic feedback can provide information without requiring continuous visual monitoring. Multimodal feedback can combine complementary information but may increase system complexity. The evidence therefore supports evaluating feedback according to task requirements, participant characteristics, usability, and therapeutic objectives rather than assuming that one modality is universally superior (Bowman et al., 2021; Sassi et al., 2024).

The clinical applicability of these systems also depends on sensor placement, comfort, robustness, and ease of use. A system requiring numerous sensors and extensive calibration may achieve detailed movement characterization in a laboratory while presenting practical limitations during routine rehabilitation. Conversely, simplified wearable configurations can facilitate home-based monitoring but may provide less comprehensive biomechanical information. Recent developments in wearable rehabilitation technologies and AI-assisted monitoring emphasize the need to balance sensing capability with usability, scalability, and clinical integration (Boltaboyeva et al., 2025; Gu et al., 2026; Lobo et al., 2024).Several methodological limitations expected across the evidence base. Small sample sizes, heterogeneous populations, inconsistent compensation definitions, limited external validation, incomplete reporting of preprocessing and model-development procedures, and restricted evaluation in real-world environments can limit confidence in reported performance. Additional concerns include potential data leakage, overfitting, class imbalance, selective reporting of favorable metrics, and insufficient reporting of participant-level testing. These limitations are particularly important for AI systems intended for clinical deployment because apparent technical performance does not necessarily translate into reliable performance across patients, exercises, clinicians, or rehabilitation environments (Halilaj et al., 2018; Hennrich et al., 2024). The evidence also supports a distinction between technological feasibility and clinical effectiveness. Demonstrating that an AI model detects compensatory movement is an important first step, but clinical implementation requires evidence that the detected information is accurate, interpretable, timely, usable, and capable of supporting meaningful changes in movement behavior or rehabilitation outcomes. Current developments in remote rehabilitation, sensor-based monitoring, and intelligent rehabilitation systems increasingly address this broader translational pathway (Garofano et al., 2025; Costa et al., 2026; Santoriello et al., 2026). Future research therefore requires greater standardization of compensation definitions, reference standards, validation procedures, and reporting of model development. Studies should prioritize participant-independent testing and, where feasible, external validation across different populations and rehabilitation environments. Reporting of sensor placement, sampling characteristics, preprocessing, segmentation, feature extraction, model architecture, class distribution, and validation procedures also requires greater consistency. Such reporting facilitates reproducibility and allows meaningful comparison between AI-enabled wearable systems (Rethlefsen et al., 2021; Halilaj et al., 2018).

Conclusion

AI-enabled wearable sensing represents a promising approach for automated detection and classification of compensatory movements during therapeutic and rehabilitation exercise. Current technologies integrate wearable sensors with machine-learning and deep-learning methods to characterize movement patterns and identify deviations from intended therapeutic performance. The available evidence supports the technical feasibility of wearable-based AI movement classification, while also demonstrating substantial heterogeneity in sensing technologies, sensor placement, compensation definitions, reference standards, AI methodologies, and validation procedures (Wei & Wu, 2023; Lobo et al., 2024; Gu et al., 2026). The clinical translation of these systems depends on more than classification accuracy. Reliable participant-independent validation, transparent reference standards, robust performance across rehabilitation settings, acceptable usability, low-latency processing, and clinically meaningful feedback are essential components of a useful rehabilitation system. Evidence for real-time corrective feedback remains particularly important because successful movement classification does not itself demonstrate that feedback changes compensatory behavior or improves movement quality. Future research should therefore prioritize external validation, standardized definitions and reporting, real-world testing, and prospective evaluation of whether AI-enabled wearable feedback produces meaningful improvements in therapeutic exercise performance and rehabilitation outcomes.

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