Balneo and PRM Research Journal
English Edition
e ISSN 2734 - 8458 p ISSN 2734 - 844X
ROMANIAN ASSOCIATION OF BALNEOLOGY

Review article

Artificial Intelligence, Wearable Sensors, and Mobile Applications in Postural Assessment and Rehabilitation

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Citation: Mușat C.L., Iordan D.A., Onu I., Petrica S.D., Neagu S.G., Tudor S.S., Tupu A.E. - Artificial Intelligence, Wearable Sensors, and Mobile Applications in Postural Assessment and Rehabilitation
Balneo and PRM Research Journal **2026**, *17(2): 1018*

Academic Editor(s):
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Received: 18.05.2026
Published: 10.07.2026

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Publisher's Note:
Balneo and PRM Research Journal stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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Abstract: The rapid development of digital technologies has led to the emergence of innovative tools for postural assessment and rehabilitation. Artificial intelligence, wearable sensors, and mobile applications provide objective methods for analyzing body alignment, continuous posture monitoring, and delivering real-time feedback. Recent literature shows that these technologies are used in postural screening, musculoskeletal rehabilitation, ergonomics, and the prevention of postural disorders. The aim of this review was to synthesize the available evidence regarding the role of artificial intelligence, wearable sensors, and mobile applications in postural assessment and rehabilitation. A comparative review of the literature published between 2010 and the present was conducted using PubMed, Web of Science, Scopus, and Google Scholar databases. A total of 68 original studies and review articles analyzing digital technologies used for postural assessment, postural control monitoring, or digital rehabilitation interventions were included. Studies were analyzed thematically based on the technology used and the reported applications. The analyzed evidence indicates that artificial intelligence–based systems can identify postural deviations and automate body alignment analysis through image processing or sensor-derived data. Wearable sensors enable continuous monitoring of posture, balance, and movement in real-life conditions and can provide biofeedback for correction. Mobile applications offer accessible solutions for postural assessment, exercise guidance, and remote monitoring. Digital interventions have been associated with improvements in postural alignment, reduction of musculoskeletal pain, and increased adherence to exercise programs. Artificial intelligence, wearable sensors, and mobile applications represent promising directions for postural assessment and rehabilitation, as they support objective evaluation, continuous monitoring, and personalized interventions. Further research is needed to standardize protocols and assess long-term effectiveness.

Keywords: postural assessment; artificial intelligence; wearable sensors; mobile applications; digital rehabilitation; biofeedback; postural control; musculoskeletal disorders

1. Introduction

Body posture is an essential determinant of musculoskeletal function, playing a key role in maintaining balance, stability, and efficiency of functional movements. From an anatomical and physiological perspective, posture reflects the integration of neuromuscular and sensory mechanisms, and its alteration may affect mobility, motor control, and functional performance [1]. In the current context, postural changes are increasingly reported in association with sedentary behavior, prolonged use of digital devices, and behavioral shifts related to work performed at the office or at home [2]. At the same time, advances in digital devices have expanded the possibilities for movement and posture analysis, offering more accessible and standardized alternatives compared to conventional methods [3]. Within this framework, digital rehabilitation has become a major area of interest, as it facilitates objective assessment, continuous monitoring, and remotely guided interventions [4]. Given the rapid development of artificial intelligence, wearable sensors, and mobile applications, a narrative synthesis is needed to clarify the contribution of these technologies to postural assessment and rehabilitation.

The review question guiding this study was: "How are artificial intelligence, wearable sensors, and mobile applications currently used in postural assessment and rehabilitation, and what evidence supports their clinical applicability?

2. Materials and Methods

2.1. Study Design

This study was conducted as a narrative literature review using a structured search and study selection process inspired by PRISMA recommendations to improve transparency and reproducibility. Studies published between 2010 and 2026 were analyzed, focusing on the use of digital technologies for postural assessment, postural control monitoring, or the implementation of postural rehabilitation interventions (Figure 1).

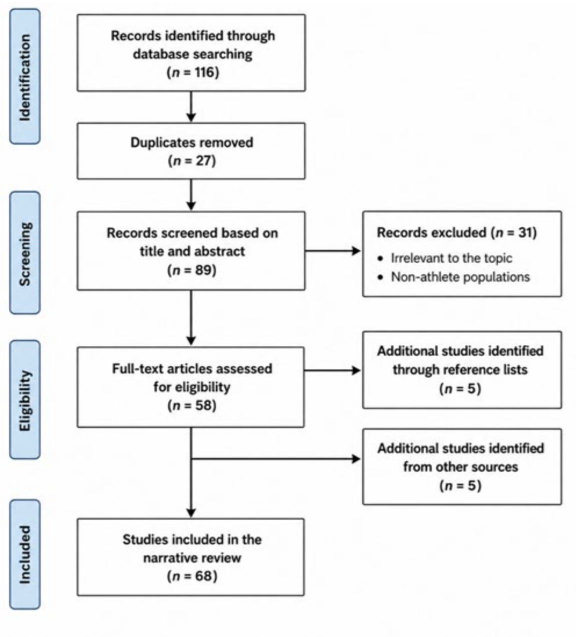

Figure 1. PRISMA Flow Diagram of the Study Selection Process. A total of 116 records were identified through database searches. After removing 27 duplicates, 89 studies were screened based on title and abstract, of which 31 were excluded. Thus, 58 full-text articles were assessed for eligibility. An additional five studies were identified through reference list screening, and five more were identified from other sources. In total, 68 studies were included in the final review.

The study selection process, illustrated in Figure 1, was conducted in accordance with the eligibility criteria and screening procedures described in Sections 2.3 and 2.4.

2.2. Data Sources and Search Strategy

Electronic searches were conducted in PubMed, ScienceDirect, Scopus, Web of Science, and Google Scholar, using combinations of relevant terms related to postural assessment and digital technologies. Search strategies were adapted to each database and included Boolean operators. An example of the search strategy used was:
("posture assessment" OR "postural assessment" OR "postural control") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "wearable sensors" OR "wearable devices" OR "IMU" OR "mobile applications" OR "smartphone" OR "mobile health") AND ("rehabilitation" OR "posture correction" OR "digital rehabilitation").

2.3. Eligibility Criteria

Studies investigating the use of digital technologies for postural assessment, postural control monitoring, or postural rehabilitation were included. Studies conducted on human participants, published in English, and with full-text availability were considered. Research involving artificial intelligence–based systems, wearable sensors, mobile applications, or digital rehabilitation programs was included. Studies without direct relevance to postural assessment or rehabilitation, animal-only studies, articles without full-text availability, and publications focusing exclusively on gait without a relevant postural component were excluded.

2.4. Study Selection

The selection process included two stages: title and abstract screening, followed by full-text eligibility assessment. Of the 116 records initially identified, 27 were removed as duplicates. Of the remaining 89 studies screened, 31 were excluded after title and abstract evaluation. A total of 58 full-text articles were assessed, and an additional 10 studies were identified through reference lists and other sources. Ultimately, 68 studies were included.

Two independent reviewers performed study selection. Titles and abstracts were screened for relevance according to the predefined eligibility criteria. Full-text articles were subsequently assessed for eligibility. Any disagreements regarding study inclusion were resolved through discussion and consensus among the reviewers.

2.5. Data Extraction and Synthesis

From each study, information was extracted regarding the type of technology, postural assessment method, analyzed parameters, study population, type of intervention, and main outcomes. The data were synthesized thematically to highlight the role of artificial intelligence, wearable sensors, and mobile applications in postural assessment and rehabilitation.

Data extraction was performed using a standardized extraction framework. The extracted variables included publication year, study design, technology type, assessment method, study population, intervention characteristics, and main outcomes related to postural assessment or rehabilitation. The findings were synthesized narratively and grouped according to the primary technology investigated. As this study was designed as a narrative review, no formal risk-of-bias assessment or methodological quality scoring system was applied. Nevertheless, preference was given to peer-reviewed studies, systematic reviews, meta-analyses, randomized controlled trials, and validation studies.

3. Results

3.1. Artificial Intelligence in Postural Assessment

Artificial intelligence has emerged as one of the most dynamic directions in postural analysis, particularly through the use of body pose estimation algorithms, machine learning methods, and deep learning networks for the automatic detection of postural deviations and quantification of segmental alignment [5,6]. Recent studies indicate that these systems can approximate postural angles and alignment parameters with clinically relevant accuracy, including in comparison with imaging methods used as reference standards [7]. In addition to conventional video analysis, artificial intelligence has been integrated with alternative motion capture technologies. The use of radar signals for postural assessment has demonstrated the feasibility of automatic posture detection without direct contact, while deep learning–based solutions applied in occupational environments have highlighted the possibility of real-time posture monitoring in teleworking and sedentary contexts [8,9]. Other applications have employed machine learning models for biomechanical analysis of body alignment, focusing on identifying postural imbalances and interpreting kinematic parameters [10].

A distinct area of application is posture assessment outside laboratory settings, through markerless systems and algorithms capable of operating in natural environments or at home [11]. Moreover, recent literature has expanded the use of artificial intelligence toward the assessment of postural control and fall risk, particularly in older adults or neurological patients, where automated models can support functional screening and risk stratification [12,13]. However, results are not uniform across studies. Trend analyses in posture recognition suggest that algorithm performance largely depends on dataset quality, acquisition conditions, and the level of external validation, which limits the transferability of some systems into routine clinical practice [14]. Table 1 summarizes the included studies regarding the use of artificial intelligence in postural assessment and rehabilitation.

Table 1. Studies on the Use of Artificial Intelligence in Postural Assessment and Rehabilitation

Author, Year	Technology	Population	Method	Application	Conclusion
Stenum et al., 2021 [5]	Markerless pose estimation	Human populations	Review	Automated postural assessment	Markerless estimation shows clinical promise
Jiang et al., 2023 [6]	AI-based posture recognition	General populations	Review	Posture classification	AI enables automatic posture detection
Park et al., 2025 [7]	AI vs. radiography	Adults	Comparative study	Postural estimation	Accuracy comparable to imaging
De Vittorio et al., 2024 [8]	Radar + AI	Adults	Experimental study	Contactless detection	Feasible for automated assessment
Martins et al., 2025 [9]	Deep learning	Workers	Automated analysis	Ergonomics	Real-time monitoring possible
Roggio et al., 2024 [10]	Machine learning	Adults	ML analysis	Deviation identification	ML improves analytical accuracy
Piñero-Fuentes et al., 2021 [11]	Deep learning	Workers	Video detection	Monitoring	Remote monitoring is feasible
González-Castro et al., 2024 [12]	AI for fall risk	Elderly	Review	Screening	Useful for prediction
Lin et al., 2025 [13]	AI for postural control	Adults	Automated screening	Assessment	Objective screening method
Yan & Du, 2025 [14]	AI trends	Literature	Bibliometric analysis	Synthesis	Further validation needed
Band et al., 2025 [27]	AI for falls	Elderly	Review	Fall detection	High potential
Gattani et al., 2026 [30]	AI fall detection	Older adults	Review	Monitoring	Prevention potential
Köroglu et al., 2026 [65]	AI postural management	Literature	Critical review	Management	Clinical potential

Note: AI = artificial intelligence; ML = machine learning; deep learning = deep learning; review = narrative review; critical review = critical review; bibliometric analysis = quantitative evaluation of the literature; screening = rapid assessment; markerless = without markers; radar + AI = radar combined with artificial intelligence.

3.2. Wearable Sensors for Posture and Postural Control Monitoring

Wearable sensors represent one of the most robust approaches for continuous monitoring of posture and postural control in real-life conditions. Inertial measurement units (IMUs), accelerometers, and gyroscopes have been widely used to assess balance, stability, and segmental orientation [15,16]. Available evidence indicates that these systems can provide reliable measurements of both static and dynamic balance, including in clinical and functional settings [17,18].

In addition to quantifying balance parameters, wearable sensors are used for analyzing static and dynamic postures, detecting poor postural positions, and classifying motor behavior during daily activities [19,20]. Studies integrating sensors into garments or less restrictive configurations have reported that monitoring can also be performed in ecological conditions without substantially compromising posture classification accuracy [21].

A further step involves combining sensor-derived signals with machine learning algorithms. This approach has enabled more refined biomechanical analysis of the spine and automatic classification of postural deviations, including anatomically oriented models [22,23]. In parallel, the literature on wearable biofeedback highlights that vibratory, auditory, or visual signals can enhance posture awareness and facilitate active correction of improper positions, both in musculoskeletal rehabilitation and ergonomics [24,25].

The clinical relevance of these technologies is particularly evident in the assessment of populations at increased risk of postural instability. Wearable sensors have been used to characterize gait and mobility in aging and Parkinson's disease, demonstrating utility in detecting subtle functional changes [26]. At the same time, research on fall monitoring in older adults shows that systems based on artificial intelligence and inertial sensors can support risk prediction and early identification of balance deterioration [27–30]. In Parkinson’s disease, dedicated mobile monitoring platforms have been proposed as useful tools for longitudinal tracking of mobility and postural control [31].

Although the advantages are clear, methodological limitations remain significant. Recent reviews highlight variability in sensor placement, differences between devices, lack of standardized protocols, and heterogeneity of indicators used to define correct or pathological posture [32,33]. These challenges should also be interpreted in the context of the historical evolution of motion sensors, where sensitivity, sampling rate, and processing strategies have varied considerably across device generations [34]. In addition, the performance of classification systems depends on the choice of supervised algorithms and the quality of initial data labeling [35].

In occupational settings, however, their use continues to expand, including applications in ergonomic assessment within industrial environments [36].Table 2 summarizes the included studies regarding the use of wearable sensors in postural assessment and rehabilitation.

Table 2. Studies on the Use of Wearable Sensors in Postural Assessment and Rehabilitation

Author, Year	Technology	Population	Method	Application	Conclusion
Johnston et al., 2019 [15]	Inertial sensors	Adults	Review	Postural control	Robust tools
Simpson et al., 2019 [16]	Spinal wearables	Adults	Review	Spinal posture	Clinical utility
Ghislieri et al., 2019 [17]	IMU for balance	Adults	Experimental	Balance	Valid approach
Figueira et al., 2024 [18]	Wearables with feedback	Workers	Review	Ergonomics	Useful feedback
Museck et al., 2024 [19]	Wearables + ML	Adults	Classification	Monitoring	Enables automation
Doshi et al., 2023 [20]	Smartphone-based wearable	Adults	Monitoring	Posture	Accessible solution
Jayasinghe et al., 2023 [21]	Smart clothing sensors	Adults	Classification	Static postures	Eco-friendly
Koca & Koca, 2025 [22]	IMU + ML	Adults	Spine analysis	Posture	High accuracy
Del Din et al., 2016 [23]	Gait sensors	Parkinson’s patients	Monitoring	Mobility	Effective detection

Battis et al., 2024[24]	Wearable biofeedback	MSK conditions	Scoping review	Control	Supports correction
Lind, 2024 [25]	Biofeedback	Ergonomics	Review	Feedback	Useful tool
Picerno et al., 2021 [26]	Inertial sensors	Clinical populations	Review	Movement	Monitoring capability
Lai & Fong, 2025 [28]	Waist-worn sensor	Elderly	Prediction	Falls	Predictive potential
Song et al., 2025[29]	Wearable fall risk systems	Elderly	Assessment	Screening	Effective detection
Mancini & Horak, 2016 [31]	APDM Mobility system	Parkinson's patients	Monitoring	Postural control	Longitudinal tracking
Liguori et al., 2026 [32]	Wearables in adolescents	Adolescents	Review	Posture	Promising results
Caixeiro et al., 2026[33]	Wearable correctors	Adults	Review	Correction	Moderate effectiveness
Naranjo et al., 2025 [36]	Industrial wearables	Workers	Ergonomic analysis	Posture	Useful in workplace
Chen et al., 2022 [61]	Wearables for fall risk	Elderly	Review	Prediction	Effective
Bonanno et al., 2025 [62]	Neurological wearables	Neurological patients	Review	Falls	Useful
Motta et al., 2024 [66]	Wearables for MSK	Workers	Review	Ergonomics	Detection capability
Vermander et al., 2024 [67]	Sitting wearable devices	Sedentary individuals	Monitoring	Sitting posture	Feedback provided
Zhang et al., 2022 [68]	Deep learning wearable systems	Adults	Recognition	Postures	High accuracy

Note: IMU = Inertial Measurement Unit; ML = machine learning; wearables = wearable sensors; biofeedback = real-time biological feedback; MSK = musculoskeletal; APDM = APDM Mobility Lab wearable system; review = narrative review; scoping review = exploratory review; balance = postural balance.

3.3. Mobile Applications in Postural Assessment and Monitoring

Mobile applications have become accessible tools for postural assessment due to their portability, low cost, and the possibility of use both in clinical settings and at home. Early applications designed to measure body position using smartphones demonstrated the feasibility of obtaining clinically useful measurements through digital images and photogrammetry [37,38]. Subsequently, applications incorporating automated image processing or algorithm-assisted analysis were also proposed [39]. Validity and reliability studies have shown that certain mobile applications can provide measurements comparable to established clinical methods for assessing standing posture [40]. Good intra- and inter-rater agreement has also been reported for applications used in static postural analysis, supporting their use in screening and clinical follow-up contexts [41,42]. Additional data regarding PostureScreen indicated acceptable accuracy for evaluating segmental alignment under standardized conditions [43].

More recently, meta-analyses of smartphone applications for spinal posture assessment have confirmed a promising level of reliability and reproducibility, particularly when image capture protocols and analysis procedures are rigorously controlled [44]. At the same time, interest has expanded to pediatric populations, where dedicated software and digital screening tools have been applied for detecting postural disorders in children and adolescents [45]. The utility of mobile applications is not limited to static alignment analysis. Some tools have been developed as professional resources for posture assessment and range of motion measurement [46], while others have been validated for quantifying joint position in regional contexts, such as the knee [47]. Additionally, reproducible digital assessments based on mobile devices have supported the possibility of monitoring progress over time and using standardized images for serial comparisons [48]. In younger populations, recent literature suggests that digital tools may also have preventive value by enabling early detection of factors associated with postural disorders and supporting corrective interventions [49].

3.4. Digital Rehabilitation and Technology-Based Interventions

Beyond their evaluative role, digital technologies have been actively integrated into postural rehabilitation. Interventional studies show that combining therapeutic exercises with support from mobile applications can lead to improvements in neck pain, head posture, and muscular endurance in individuals with nonspecific neck pain [50]. Similarly, biofeedback applications for postural education have demonstrated feasibility and acceptability, suggesting that immediate feedback can facilitate correction of inadequate motor behaviors [51]. The effectiveness of digital interventions has also been reported in adolescents, where digitally assisted corrective programs were associated with improvements in head and shoulder alignment [52]. At a broader level, systematic reviews and meta-analyses on digital self-management of spinal musculoskeletal disorders indicate that mobile technologies can contribute to symptom reduction and functional improvement, particularly when integrated into a structured therapeutic program [53]. Technology-supported home rehabilitation represents another important direction. Scoping reviews indicate that digital solutions for home-based rehabilitation can improve access to interventions, continuity of monitoring, and user engagement [54]. In the same vein, literature on digital technologies in physiotherapy highlights that mobile tools and remote monitoring systems can support the clinical process through feedback, documentation, and therapeutic communication [55]. Similar results have been reported for other musculoskeletal conditions, including elbow pain and musculoskeletal pain in young individuals, where personalized digital interventions have proven useful for self-management and adherence [56,57]. At a conceptual level, the role of biofeedback in rehabilitation remains central to understanding the effectiveness of these interventions. External feedback provided in real time can accelerate motor learning, increase posture awareness, and support the consolidation of corrective strategies. This explains why digital rehabilitation is increasingly integrated into the management of postural disorders [58]. Table 3 summarizes the included studies on the use of mobile applications, digital rehabilitation, and technology-based interventions in postural assessment and rehabilitation.

Table 3. Studies on the Use of Mobile Applications, Digital Rehabilitation, and Technology-Based Interventions in Postural Assessment and Rehabilitation

Author, Year	Technology	Population	Method	Application	Conclusion
Szucs & Brown, 2018 [37]	Mobile application	Adults	Validation	Posture	Valid tool
Milani et al., 2014 [38]	Smartphone posture analysis	Adults	Photogrammetry	Position	Useful
Moreira et al., 2020 [39]	Automated application	Adults	Feasibility study	Posture	Automated approach
Hopkins et al., 2019 [40]	Orthostatic posture app	Adults	Validation	Posture	Comparable results
Boland et al., 2016 [41]	Mobile posture tool	Adults	Reliability study	Screening	Good reliability
Timurtaș et al., 2022 [42]	Postural app	Adults	Validation	Posture	Feasible
Iacob et al., 2020 [43]	PostureScreen app	Adults	Accuracy study	Alignment	Acceptable accuracy
Karbalaeimahdi et al., 2025 [44]	Meta-analysis	Literature	Meta-analysis	Spine	Reliable
Neves et al., 2023 [45]	PosturAll app	Children	Screening	Pediatric posture	Effective detection
Healy, 2020 [46]	Posture app	Clinicians	Evaluation	Posture	Useful
Sabino et al., 2021 [47]	Knee assessment app	Adults	Validation	Joint assessment	Clinically applicable
Trovato et al., 2022 [48]	Digital assessment	Adults	Serial evaluation	Monitoring	Reproducible

Iordan et al., 2025 [49]	Digital screening	Children	Interventions	Posture	Preventive potential
Abadiyan et al., 2021 [50]	App + exercise program	Cervical conditions	RCT	Rehabilitation	Improvement observed
García-Luna et al., 2026 [51]	Mobile biofeedback	Adults	Feasibility study	Education	Acceptable
Baek et al., 2025[52]	Digital program	Adolescents	RCT	Correction	Improvement observed
Cargnin et al., 2023 [53]	Digital self-care	MSK conditions	Meta-analysis	Management	Symptom reduction
Arntz et al., 2023 [54]	Home-based digital rehab	Adults	Review	Telerehabilitation	Improved access
Merolli et al., 2022 [55]	Digital physiotherapy	MSK conditions	Review	Monitoring	Supportive tool
Janela et al., 2022 [56]	Digital rehabilitation	Elbow conditions	Interventions	Self-management	Useful
Slater et al., 2020 [57]	Digital pain management	Young individuals	Evaluation	Self-management	Good adherence
Fontenele et al., 2023 [59]	Smartphone posture use	Adolescents	Observational study	Posture	Associated outcomes
Toko et al., 2025[60]	Digital posture study	General populations	Study	Poor posture	Association identified

Note: RCT = randomized controlled trial; meta = meta-analysis; MSK = musculoskeletal; app = mobile application; tele-rehab = telerehabilitation; self-care = self-care; biofeedback = biological feedback; screening = rapid assessment; photogrammetry = image-based postural analysis.

3.5. Clinical Applications and Contexts of Use

The analysis of the literature highlights that these technologies are used across a wide range of clinical and functional contexts. In musculoskeletal practice, they support postural screening, progress quantification, and intervention adjustment. In neurology and geriatrics, they are relevant for assessing postural control, mobility, and fall risk. In ergonomics, they contribute to identifying harmful postural exposures and providing corrective feedback. In telerehabilitation, they facilitate the extension of monitoring beyond the clinical environment, which is particularly valuable for individuals with limited access to specialized services.

4. Discussion

4.1. Summary of Main Findings

This review indicates that artificial intelligence, wearable sensors, and mobile applications converge toward the same clinical objective: transforming postural assessment from a predominantly observational process into one that is quantifiable, repeatable, and longitudinally monitorable. The results suggest that the value of these technologies lies not only in measurement accuracy but also in their ability to support clinical decision-making, self-correction, and remote monitoring.

4.2. Artificial Intelligence and Digital Assessment Compared to Traditional Methods

Compared to conventional assessments based on clinical observation, manual photogrammetry, or laboratory-based optical systems, current digital solutions offer clear advantages in terms of automated processing and scalability. However, comparison with earlier video analysis and markerless technologies shows that accuracy must be interpreted in relation to the type of system used, the acquisition environment, and the anatomical segment analyzed.

For example, earlier markerless systems, such as those based on Microsoft Kinect or passive home visual monitoring, paved the way for ecological functional assessment but were limited by sensor resolution and sensitivity [63,64]. Similarly, recent critical evaluations of artificial intelligence in postural management indicate that clinical implementation still depends on standardized datasets and rigorous external validation [65].

4.3. Clinical Implications for At-Risk Populations and Prevention

An important clinical implication is the extension of these technologies to populations exposed to harmful postural behaviors. Available data in adolescents and young adults suggest an association between excessive smartphone use, digital device dependency, and the development of postural changes, supporting the usefulness of digital tools for early screening and preventive interventions [59,60].

In addition, clinical relevance is particularly high in geriatrics and neurology. Systematic reviews focusing on fall risk assessment using wearable sensors indicate that continuous monitoring can contribute to early identification of postural instability, while studies on neurological disorders confirm the utility of these systems in populations with increased functional vulnerability [61,62].

4.4. Implications for Ergonomics and Rehabilitation Practice

In clinical rehabilitation and occupational health, these technologies provide the opportunity to move from point-in-time assessment to continuous monitoring. Wearable systems and intelligent applications can be integrated into ergonomic interventions, particularly in environments involving sedentary work or repetitive activities, where musculoskeletal load is persistent [66,67].

At the same time, the integration of automated human activity classification can refine the interpretation of the functional context in which postural deviations occur, which is relevant for personalizing therapeutic recommendations and feedback [68].

4.5. Limitations and Future Directions

Although the synthesized data are promising, limitations persist regarding methodological heterogeneity, inconsistent definitions of postural parameters, and limited comparability between devices and protocols. Future research should aim at standardizing digital postural assessment, conducting multicenter clinical validation, and achieving more coherent integration of different data sources, so that algorithms, sensors, and mobile applications can function complementarily within a mature clinical digital ecosystem.

The present findings are consistent with recent studies showing that technology-assisted interventions can improve balance and postural control. Ungur and Badau reported significant improvements in dynamic balance after a 12-week Blazepod-based training program, while Alecu et al. demonstrated enhanced trunk mobility and upper trunk stability following core stability training [69-70].

Similarly, Moraru et al. highlighted the usefulness of the APECS artificial intelligence–based mobile application for identifying postural deviations and trunk asymmetries, supporting the growing role of digital technologies in objective postural assessment and rehabilitation [71].

From a clinical perspective, these technologies may facilitate earlier detection of postural deviations, support individualized rehabilitation planning, improve adherence through real-time feedback, and extend monitoring beyond traditional clinical environments. Their increasing accessibility may also contribute to broader implementation of preventive and rehabilitation strategies in musculoskeletal, neurological, geriatric, and occupational health settings.

5. Conclusions

AI, wearable sensors, and mobile applications outline an emerging and highly relevant direction in postural assessment and rehabilitation. Available evidence shows that these technologies enable objective quantification of body alignment, continuous posture monitoring in functional contexts, and real-time biofeedback delivery. By automating postural analysis and facilitating monitoring in daily life, they support the development of personalized, accessible, and scalable interventions.

The integration of AI–based systems, wearable sensors, and mobile applications expands the possibilities for assessment and intervention in clinical settings, as well as in telerehabilitation and ergonomics. Overall, these solutions contribute to increased objectivity of assessment, improved adherence to interventions, and enhanced long-term monitoring. However, further studies are needed to standardize protocols, validate clinical applications on large samples, and clarify their impact on long-term functional outcomes.

From a practical perspective, these technologies may support clinicians in the early detection of postural deviations, facilitate individualized rehabilitation planning, and improve patient engagement through real-time feedback and remote monitoring. Their integration into clinical practice, ergonomics, and telerehabilitation programs may contribute to more accessible and data-driven postural assessment and rehabilitation strategies.

Funding. This research received no external funding.

Acknowledgments. All authors have equally contributed to this article.

Conflicts of Interest. The authors declare no conflict of interest.

References

1. Carini, F.; Mazzola, M.; Fici, C.; et al. Posture and posturology: anatomical and physiological profiles. Acta Biomed. 2017, 88, 11–16. doi:10.23750/abm.v88i1.5309
2. Susilowati, I.H.; Kurniawidjaja, L.M.; Nugraha, S.; Nasri, S.M.; Pujiriani, I.; Hasiholan, B.P. The prevalence of bad posture and musculoskeletal symptoms originating from the use of gadgets as an impact of the work from home program of the university community. Heliyon. 2022, 8, 10, :e11059. doi:10.1016/j.heliyon.2022.e11059
3. Roggio, F.; Ravalli, S.; Maugeri, G.; Bianco, A.; Palma, A.; Di Rosa, M. et al. Technological advancements in the analysis of human motion and posture management through digital devices. World J Orthop. 2021, 12, 7, 467–484. doi:10.5312/wjo.v12.i7.467
4. Regterschot, G.R.H.; Ribbers, G.M.; Bussmann, J.B.J. Wearable movement sensors for rehabilitation. Sensors (Basel). 2021, 21, 4744. doi:10.3390/s21144744
5. Stenum, J.; Cherry-Allen, K.M.; Pyles, C.O. et al. Pose estimation in human health. Sensors (Basel). 2021, 21, 7315. doi:10.3390/s21217315
6. Jiang, X.; Hu, Z.; Wang, S.; Zhang, Y. Artificial intelligence in posture recognition. Comput Model Eng Sci. 2023, 137, 35–82. doi:10.32604/cmes.2023.027345
7. Park, S.C.; Lee, S.; Yoon, J. et al. AI-based posture estimation vs radiographic imaging. Diagnostics (Basel). 2025, 15, 1340. doi:10.3390/diagnostics15081340
8. De Vittorio, D.; Barili, A.; Danese, G. et al. Artificial intelligence for the evaluation of postures using radar technology: a case study. Sensors (Basel). 2024, 24, 6208. doi:10.3390/s24196208
9. Martins, D.R.; Cerqueira, S.M.; Pombeiro, A. et al. ErgoReport deep-learning posture assessment. Sensors (Basel). 2025, 25, 2282. doi:10.3390/s25072282
10. Roggio, F.; Di Grande, S.; Cavalieri, S. et al. Biomechanical posture analysis using machine learning. Sensors (Basel). 2024, 24, 2929. doi:10.3390/s24092929
11. Piñero-Fuentes, E.; Canas-Moreno, S.; Rios-Navarro, A. et al. Deep learning posture detection in telework environments. Sensors (Basel). 2021, 21, 5236. doi:10.3390/s21155236
12. González-Castro, A.; Leirós-Rodríguez, R.; Prada-García, C.; Benítez-Andrades, J.A. Artificial intelligence for assessing fall risk: systematic review. J Med Internet Res. 2024, 26, e54934. doi:10.2196/54934
13. Lin, K.C.; Wai, R.J.; Chang Chien, H.Y. AI-assisted dynamic postural control screening. JMIR Aging. 2025, 8, e73290. doi:10.2196/73290
14. Yan, L.; Du, Y.; Trends in posture recognition research. Sensors (Basel). 2025, 25, 632. doi:10.3390/s25030632

15. Johnston, W.; O'Reilly, M.; Argent, R.; Caulfield, B. Inertial sensor systems for postural control assessment. Sports Med. 2019, 49, 783–818. doi:10.1007/s40279-019-01072-0
16. Simpson, L.; Maharaj, M.M.; Mobbs, R.J. Wearables in spinal posture analysis: systematic review. BMC Musculoskelet Disord. 2019, 20, 55. doi:10.1186/s12891-019-2437-3
17. Ghislieri, M.; Gastaldi, L.; Pastorelli, S. et al. Wearable inertial sensors to assess standing balance. Sensors (Basel). 2019, 19, 4075. doi:10.3390/s19184075
18. Figueira, V.; Silva, S.; Costa, I. et al. Wearables for monitoring and postural feedback in work context: scoping review. Sensors (Basel). 2024, 24, 1341. doi:10.3390/s24041341
19. Museck, I.J.; Brinton, D.L.; Dean, J.C. Wearable sensors and machine learning for posture analysis. Sensors (Basel). 2024, 24, 7280. doi:10.3390/s24227280
20. Doshi, K.B.; Moon, S.H.; Whitaker, M.D.; Lockhart, T.E. Assessment of gait and posture using smartphone wearable system. Sci Rep. 2023, 13, 538. doi:10.1038/s41598-023-27597-3
21. Jayasinghe, U.; Janko, B.; Hwang, F.; Harwin, W.S. Classification of static postures with wearable sensors mounted on loose clothing. Sci Rep. 2023, 13, 131. doi:10.1038/s41598-022-27134-9
22. Koca, R.; Koca, Y.B. Anatomy-based assessment of spinal posture using IMU sensors and machine learning. Sensors (Basel). 2025, 25, 5963. doi:10.3390/s25205963
23. Del Din, S.; Godfrey, A.; Galna, B.; Lord, S.; Rochester, L. Free-living gait characteristics in ageing and Parkinson's disease. J Neuroeng Rehabil. 2016, 13, 46. doi:10.1186/s12984-016-0154-5
24. Battis, A.; Norrie, J.P.; McMaster, H.; Beaudette, S.M. Wearable technology mediated biofeedback to modulate spine motor control: a scoping review. BMC Musculoskelet Disord. 2024, 25, 770. doi:10.1186/s12891-024-07870-5
25. Lind, C.M. Wearable biofeedback motion capture systems in ergonomics. Sensors (Basel). 2024, 24, 3345. doi:10.3390/s24103345
26. Picerno, P.; Iosa, M.; D'Souza, C. et al. Wearable inertial sensors for movement analysis. Expert Rev Med Devices. 2021, 18, 79–94. doi:10.1080/17434440.2021.1862788
27. Band, S.S.; Biyari, M.; Hsu, C.C. et al. A review on AI approaches in elderly fall monitoring systems. Cogn Comput. 2025, 17, 176. doi:10.1007/s12559-024-10279-4
28. Lai, K.M.; Fong, K.N.K. Waist-mounted sensor predicting falls. Sensors (Basel). 2025, 25, 2516. doi:10.3390/s25072516
29. Song, Z.; Ou, J.; Wu, S.; et al. Wearable fall risk assessment. J Neuroeng Rehabil. 2025, 22, 64. doi:10.1186/s12984-025-01364-5
30. Gattani, A.; Dixit, S.; Patil, M.; Gupta, M.; Navghane, A.; Hule, O.; Srinivasan, K. Artificial intelligence for fall detection in older adults: A comprehensive survey of machine learning, deep learning approaches, and future directions. Ageing Res Rev. 2026, 113, 102948. doi:10.1016/j.arr.2025.102948
31. Mancini, M.; Horak, F.B. Potential of APDM Mobility Lab for monitoring Parkinson's disease. Expert Rev Med Devices. 2016, 13, 455–462. doi:10.1586/17434440.2016.1153469
32. Liguori, S.; Moretti, A.; Andreozzi, V.; Catalano, C.; Pontillo, G.; Maresca, L.; Riccio, M.; Breglio, G.; Paoletta, M.; Gimigliano, F.; Iolascon, G Posture evaluation and treatment in adolescents through wearable technology: a systematic review. Front. Rehabil. Sci. 2026, 7, 1587466. doi:10.3389/fresc.2026.1587466
33. Caixeiro, D.; Cordeiro, T.; Constantino, L.; Carreira, J.; Mendes, R.; Silva, C.G.; Castro, M.A. Effectiveness of Wearable Devices for Posture Correction: A Systematic Review of Evidence from Randomized and Quasi-Experimental Studies. Appl. Sci. 2026, 16, 81. doi:10.3390/app16010081
34. Yang, C.C.; Hsu, Y.L. A review of accelerometry-based wearable motion detectors. Sensors (Basel). 2010, 10, 7772–7788. doi:10.3390/s100807772
35. Safi, K.; Attal, F.; Mohammed, S.; Khalil, M.; Amirat, Y. Physical activity recognition using inertial wearable sensors: a review of supervised classification algorithms. In: Proc Int Conf Adv Biomed Eng. 2015, doi:10.1109/ICABME.2015.7323256
36. Naranjo, J.E.; Mora, C.A.; Bustamante Villagómez, D.F. et al. Wearable sensors in industrial ergonomics. Sensors (Basel). 2025, 25, 1526. doi:10.3390/s25051526
37. Szucs, K.A.; Brown, E.V.D. Mobile application for posture analysis validity. J Phys Ther Sci. 2018, 30, 31–36. doi:10.1589/jpts.30.31
38. Milani, P.; Coccetta, C.A.; Rabini, A. et al. Mobile smartphone applications for body position measurement. PM R. 2014, 6, 1038–1043. doi:10.1016/j.pmrj.2014.07.003
39. Moreira, R.; Teles, A.; Fialho, R.; et al. Automatic posture measurement using mobile applications. Med Hypotheses. 2020, 142, 109741. doi:10.1016/j.mehy.2020.109741
40. Hopkins, B.B.; Vehrs, P.R.; Fellingham, G.W.; et al. Validity of standing posture measurements using mobile app. J Manipulative Physiol Ther. 2019, 42, 132–140. doi:10.1016/j.jmpt.2018.11.006
41. Boland, D.M.; Neufeld, E.V.; Ruddell, J.; Dolezal, B.A.; Cooper, C.B. Inter- and intra-rater agreement of static posture analysis using a mobile application. J Phys Ther Sci. 2016, 28, 3398–3402. doi:10.1589/jpts.28.3398

42. Timurtaş, E.; Avcı, E.E.; Mate, K. et al. Mobile application for standing posture analysis. Ir J Med Sci. 2022, 191, 2123–2131. doi:10.1007/s11845-021-02789-0
43. Iacob, S.M.; Chisnoiu, A.M.; Lascu, L.M. et al. Accuracy of Posture Screen mobile app. Cranio. 2020, 38, 233–239. doi:10.1080/08869634.2018.1549470
44. Karbalaeimahdi, M.; Minoonejad, H.; Mousavi, S.H.; Rajabi, R. Photogrammetry-based smartphone applications for spinal posture assessment: a systematic review and meta-analysis. Sci Rep. 2025, 16, 1, 2885. doi: 10.1038/s41598-025-32708-1.
45. Neves, A.B.; Martins, R.; Matela, N.; Atalaia, T. PosturAll posture assessment software for children. Bioengineering (Basel). 2023, 10, 1171. doi:10.3390/bioengineering10101171
46. Healy, H.S. Posture App (version 2.1.66). J Med Libr Assoc. 2020, 108, 520–522. doi:10.5195/jmla.2020.1001
47. Sabino, G.S.; Ferraz de Souza, L.A.; Ribeiro, T. et al. Smartphone application for knee posture quantification. J Bodyw Mov Ther. 2021, 28, 42–48. doi:10.1016/j.jbmt.2021.05.010
48. Trovato, B.; Roggio, F.; Sortino, M. et al. Digital reproducible posture evaluation. J Funct Morphol Kinesiol. 2022, 7, 98. doi:10.3390/jfmk7040098
49. Iordan, D.A.; Mușat, C.L.; Neagu, S.G.; Nicolescu-Șeușan, N.; Ștefănescu, C.A.; Onu, I et al. Postural disorders of the spine in children and adolescents: risk factors and the effectiveness of corrective interventions. Balneo and PRM Research Journal. 2025, 16, 4, 922. doi:10.12680/balneo.2025.922
50. Abadiyan, F.; Hadadnezhad, M.; Khosrokiani, Z.; Letafatkar, A.; Akhshik, H. Adding a smartphone app to global postural re-education to improve neck pain, posture, quality of life, and endurance in people with nonspecific neck pain: a randomized controlled trial. Trials. 2021, 22, 274. doi:10.1186/s13063-021-05201-1
51. García-Luna, M.A.; García-Jaén, M.; Ruiz-Fernández, D. et al. Mobile biofeedback app for postural education. JMIR Hum Factors. 2026, 13, e79282. doi:10.2196/79282
52. Baek, C.Y.; Ahn, J.H.; Lee, J.; et al. Effect of digital health corrective posture exercise program on head and shoulder posture in adolescents: a cluster randomized controlled trial. Medicine (Baltimore). 2025, 104, e41893. doi:10.1097/MD.0000000000041893
53. Cargnin, Z.A.; Schneider, D.G.; Rosa-Junior, J.N. Digital self-care in the management of spine musculoskeletal disorders: systematic review and meta-analysis. Rev Lat Am Enfermagem. 2023, 31, e3908. doi:10.1590/1518-8345.6260.3908
54. Arntz, A.; Weber, F.; Handgraaf, M. et al. Technologies in home-based digital rehabilitation: scoping review. JMIR Rehabil Assist Technol. 2023, 10, e43615. doi:10.2196/43615
55. Merolli, M.; Gray, K.; Choo, D. et al. Digital health technologies in physiotherapy. Musculoskeletal Care. 2022, 20, 641–659. doi:10.1002/msc.1597
56. Janela, D.; Costa, F.; Molinos, M.; et al. Digital rehabilitation for elbow pain musculoskeletal conditions. Int J Environ Res Public Health. 2022, 19, 9198. doi:10.3390/ijerph19159198
57. Slater, H.; Stinson, J.N.; Jordan, J.E. et al. Evaluation of digital technologies tailored to support young people's self-management of musculoskeletal pain. J Med Internet Res. 2020, 22, e18315. doi:10.2196/18315
58. Giggins, O.M.; Persson, U.M.; Caulfield, B. Biofeedback in rehabilitation. J Neuroeng Rehabil. 2013, 10, 60. doi:10.1186/1743-0003-10-60
59. Fontenele, T.M.O.; Nunes, P.P.B.; Silva, F.V.M. et al. Smartphone addiction and postural alterations in adolescents. Rev Paul Pediatr. 2023, 42, e2023051. doi:10.1590/1984-0462/2023/42/2023051
60. Toko, B.; Parihar, A.; Reddy, P.; Mandlik, R.; Kewalramani, Y.; Patel, M.; Khairwar, A. The modern epidemic-digital era bad posture and its musculoskeletal consequences: A questionnaire-based study. J Family Med Prim Care. 2025, 14, 10, 4187-4192. doi:10.4103/jfmpc.jfmpc_299_25.
61. Chen, M.; Wang, H.; Yu, L.; et al. Wearable sensor-based technologies for fall risk assessment in older adults: systematic review. Sensors (Basel). 2022, 22, 6752. doi:10.3390/s22186752
62. Bonanno, M.; Ielo, A.; De Pasquale, P. et al. Use of wearable sensors to assess fall risk in neurological disorders: systematic review. JMIR Mhealth Uhealth. 2025, 13, e67265. doi:10.2196/67265
63. Stone, E.E.; Skubic, M. Passive in-home measurement of stride-to-stride gait variability comparing vision and Kinect sensing. In: Proc Annu Int Conf IEEE Eng Med Biol Soc. 2011, 6491–6494. doi:10.1109/IEMBS.2011.6091602
64. Clark, R.A.; Pua, Y.H.; Fortin, K. et al. Validity of the Microsoft Kinect for assessment of postural control. Gait Posture. 2012, 36, 372–377. doi:10.1016/j.gaitpost.2012.03.033
65. Köroglu, Y.; Hosseini, E.; Bahadır, Z.; Karakus, B.; Alimoradi, M.; Alghosi, M.; Konrad, A. Artificial intelligence in postural management: a critical review of detection, correction, and clinical applicability. J Orthop Surg Res. 2026, 21, 1, 130. doi:10.1186/s13018-025-06640-z.
66. Motta, F.; Varrecchia, T.; Chini, G. et al. Wearable systems for musculoskeletal risk assessment. Int J Environ Res Public Health. 2024, 21, 1567. doi:10.3390/ijerph21021567
67. Vermander, P.; Mancisidor, A.; Cabanes, I.; Perez, N. Intelligent sitting posture monitoring systems. J Neuroeng Rehabil. 2024, 21, 28. doi:10.1186/s12984-024-01252-5

68. Zhang, S.; Li, Y.; Zhang, S. et al. Deep learning human activity recognition using wearable sensors. Sensors (Basel). 2022, 22, 1476. doi:10.3390/s22041476
69. Alecu, S.; Onea, G.A.; Badau, D. Impact of a 12-Week Core Stability Training on Upper Trunk Stability, Trunk Mobility, and Postural Asymmetries in University Students. Life (Basel). 2025, 15, 12, 1801. https://10.3390/life15121801
70. Ungur, M. & Badau, D. Enhancing Static Balance in Mini-Football Players through a Unique Training Program that Leverages the Innovative Blazepod Technology. Postmodern Openings. 2025, 15, 1, 19-31. doi:10.18662/po15.1/610
71. Moraru, L.; Badau, A.; Litoi, F.M.; Petrescum, A.M.; Manescu, C.O.; Smidu, N. Identification of Postural Deviations and Trunk Asymmetries in Physical Therapy Students Using an AI-Based Mobile Application. Balneo and PRM Research Journal Balneo and PRM Research Journal. 2025, 16, 2 doi:10.12680/balneo.2025.802.