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Predicting Falls in Older Adults using AI-Powered Wearable IoT Devices: A Scoping Review

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Abstract. *Background: Falls among older adults are a major global health concern associated with disability, hospitalization, mortality, and reduced independence. Recent advances in artificial intelligence (AI), wearable Internet of Things (IoT), and machine learning have shifted fall prevention from reactive detection toward proactive risk prediction. Objective: This scoping review mapped current evidence on AI-powered wearable IoT devices for predicting falls in older adults, focusing on sensor technologies, AI models, predictive performance, and implementation challenges. Methods: Following PRISMA-ScR guidelines, literature searches were conducted in PubMed, Scopus, IEEE Xplore, Web of Science, and Cochrane Library databases for studies published between 2008 and 2026. Eligible studies involved older adults, wearable IoT sensors, and AI or machine learning models for fall-risk prediction or pre-impact fall detection. Results: Of 1,100 identified records, 170 full-text articles were screened, and 13 studies met the final eligibility criteria. IMUs, accelerometers, gyroscopes, plantar-pressure sensors, and surface electromyography (sEMG) were the most frequently used sensors. Random Forest, XGBoost, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) were the dominant analytical approaches. Several laboratory-based systems achieved accuracies above 95%; however, most studies relied on simulated falls in younger individuals rather than on real-world data from older adults. Conclusion: AI-powered wearable IoT systems show strong potential for proactive fall-risk prediction in older adults. However, translational barriers remain, including limited ecological validation, small sample sizes, and the persistent simulation gap. Future research should prioritize real-world validation, explainable AI, and the integration of multimodal sensing.*

Keywords: *Older Adults; Wearable Sensors; Fall Prediction; Artificial Intelligence; Internet of Things*

1. Introduction

Falls among older adults have emerged as a critical global public health crisis, significantly impacting the structural and functional independence of the aging population. According to the World Health Organization (WHO), falls are the second leading cause of unintentional injury-related deaths worldwide, resulting in an estimated 684,000 fatalities annually (Chen et al., 2025). A rapidly aging global population further compounds this issue; by 2050, approximately 16% of the world's population will be over 65. In this age group, nearly one-third of community-dwelling individuals experience at least one fall each year, with the incidence rate increasing to over 50% for those aged 80 and above. Beyond direct medical costs, these incidents impose significant indirect economic burdens, most notably through productivity loss and the substantial, often uncompensated, strain placed on informal caregivers who provide essential support to injured older adults.

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The consequences of these events extend far beyond immediate physical trauma. While falls often result in serious injuries such as hip fractures, cranioencephalic trauma, and soft tissue damage, they also precipitate a debilitating "post-fall syndrome"(Misaghian et al., 2024). This syndrome is characterized by a profound "fear of falling," which leads to self-imposed activity restriction, social isolation, and muscle atrophy, ultimately initiating a recursive cycle of physical decline that further elevates future fall risk. From a health economics perspective, the burden is staggering, with annual medical expenditures exceeding 2 billion in Canada (Howland et al., 2018). Furthermore, the escalating economic pressure and the inherent limitations of conventional fall prediction models, which often prioritize isolated biological indicators such as gait or visual acuity while failing to address the complex, multifactorial nature of fall etiology, necessitate a paradigm shift toward more integrated, technological solutions.

Historically, technological interventions have relied on Fall Detection Systems (FDS), such as Personal Emergency Response Systems (PERS), which often require manual activation or employ reactive, threshold-based algorithms (Ishaq et al., 2026). However, these "afterward" approaches are inherently limited: they only alert caregivers after an injury may already have occurred, and they are often ineffective if the individual loses consciousness. Furthermore, traditional clinical assessments (e.g., the Berg Balance Scale or Timed Up and Go tests) are often subjective and inconsistent, relying on single time-point measurements that fail to capture the dynamic, "messy" movement characteristics of daily life.

Consequently, there has been a fundamental shift in research from reactive detection to proactive fall-risk prediction. This evolution is driven by advancements in Micro-Electromechanical Systems (MEMS) and the Internet of Things (IoT), which enable continuous, objective monitoring of gait and postural sway using wearable Inertial Measurement Units (IMUs). By integrating Artificial Intelligence (AI) and Deep Learning (DL) architectures such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), researchers can now analyze complex time-series sensor data to identify subtle neuromuscular abnormalities that precede a fall(Bhatti et al., 2025).

These predictive frameworks facilitate early screening and targeted clinical interventions, effectively identifying high-risk individuals before traumatic impact events occur. Such predictive systems prioritize identifying latent postural instability and specific gait biomarkers, offering a more nuanced risk profile than historical incident reporting.

Despite the high accuracy reported in controlled laboratory settings (often >95%), a critical "simulation gap" persists: 98.5% of studies still rely on falls simulated by young volunteers rather than on real-world data from the target demographic(Broadley et al., 2018). There is an urgent need to map the current technological landscape and identify how to transition AI-powered IoT devices from lab-based prototypes to reliable clinical tools. This scoping review aims to synthesize recent evidence on sensor modalities, computational models, and validation strategies to provide a comprehensive framework for proactive fall-prevention interventions for older adults. Specifically, this synthesis examines how leveraging multimodal sensor fusion by combining wearable inertial measurement units with ambient environmental monitoring can address existing inconsistencies in measurement parameters and modeling techniques. The novelty of this scoping review lies in the critical appraisal of translational maturity for wearable systems, specifically distinguishing between validation in simulated environments and the emerging need for longitudinal data collection in real-world geriatric settings. Beyond the optimization of diverse computing architectures ranging from edge-based processing to hybrid cloud configurations, this review critically maps how essential pillars of clinical translation, specifically system interoperability, data privacy, and end-user acceptance, influence the long-term feasibility and scalability of these wearable IoT ecosystems. This scoping review aims to synthesize evidence on AI-powered wearable IoT systems for proactive fall-risk prediction in older adults, thereby supporting Sustainable Development Goal 3 of ensuring healthy lives and promoting well-being for all at all ages.

2. Methods

This scoping review adheres to the Joanna Briggs Institute methodology for scoping reviews and is reported in accordance with the PRISMA-ScR guidelines. A comprehensive search strategy was implemented across five major electronic databases. The review process followed the population-concept-context framework to systematically identify and categorize sensor-based technologies used to assess and predict fall risk in older populations. Specifically, the protocol adopts the PCC framework to characterize the intersection of wearable sensors, ambient technology, and medical tools designed for community-dwelling adults, ensuring a holistic analysis of current fall-risk assessment strategies.

2.1. Study Design

This study employed a scoping review methodology following the PRISMA Extension for Scoping Reviews (PRISMA-ScR). A scoping review approach was selected because the objective was to map the broad technological evidence, identify research trends, and characterize wearable AI systems, rather than to evaluate intervention effectiveness alone. We chose a scoping review over a systematic review because our goal was to explore a broad range of sensor types and AI models rather than answer a single, narrow clinical question.

2.2. Search Strategy and Information Sources

A comprehensive literature search was conducted in PubMed, Scopus, IEEE Xplore, Web of Science, and the Cochrane Library for studies published between January 2008 and May 2026.

Search terms combined four major domains:

1. Population: “older adults,” “elderly,” “aging,” “geriatric”;
2. Wearable technology: “wearable sensor,” “IoT,” “accelerometer,” “gyroscope,” “IMU,” “smartwatch,” “plantar pressure,” “sEMG”;
3. Artificial intelligence: “machine learning,” “deep learning,” “artificial intelligence,” “LSTM,” “CNN,” “Random Forest,” “XGBoost”;
4. Outcome: “fall prediction,” “fall-risk assessment,” “pre-impact fall detection,” and “gait analysis.”

Boolean operators (AND/OR) and wildcard terms were used to maximize retrieval sensitivity.

2.3. Eligibility Criteria

During the literature selection process, the eligibility criteria were divided into specific inclusion and exclusion parameters. The inclusion criteria focused on original, English-language empirical studies involving older adult populations or systems designed for older-adult fall-risk prediction. These studies were strictly required to utilize wearable or body-worn IoT sensor systems and apply predictive models based on Artificial Intelligence (AI), machine learning, or deep learning.

Conversely, articles were excluded if they consisted of non-health engineering or unrelated AI studies, non-wearable systems lacking wearable integration, review articles intended for primary synthesis, editorials, conference abstracts, opinion papers, or duplicate studies.

2.4. Screening and Selection Process

Two reviewers independently screened titles, abstracts, and full-text articles. Discrepancies were resolved through discussion and consultation with a senior reviewer.

2.5. Data Extraction and Synthesis

To ensure a systematic review process, data extraction from the included studies was conducted using a standardized form that captured bibliometric, methodological, and technical dimensions. This involved recording baseline tracking information—such as the author, publication year, country of origin, and study design—alongside specific sample characteristics to properly contextualize the target demographics. Crucially, detailed technical parameters regarding both hardware and software implementations were extracted, focusing on the specific types of IoT or body-worn sensors, their precise anatomical placements, and the exact AI, machine learning, or deep learning architectures utilized. Furthermore, the ultimate predictive outcomes and the models' clinical or technical efficacy were captured through standardized performance metrics (such as accuracy, sensitivity, and AUC-ROC), which were extracted alongside the primary findings and acknowledged study limitations to help map out current research gaps.

Following data extraction, the final synthesis was conducted narratively and descriptively due to the high heterogeneity in sensor configurations, machine learning models, and outcome measures across the literature, which precluded a formal quantitative meta-analysis. This narrative approach allowed for a structured, qualitative evaluation of the extracted data, organizing the findings into logical themes based on technology types, algorithmic frameworks, and predictive capabilities. By pairing descriptive commentary with comprehensive tabular layouts, this synthesis provides a clear, scannable overview of the current state of art, effectively mapping out overarching technological trends and highlighting critical pathways for future research in eldercare technology.

3. Results and Discussion

3.1. Results

The results of this scoping review consist of a systematic categorization of 13 eligible studies, identifying inertial measurement unit-based wearables as the predominant technological stream. These investigations highlight a clear methodological trend: the majority of studies position sensors exclusively on the lower back to capture localized biomechanical metrics. Conversely, a subset of emerging research has begun to explore the utility of multi-sensor fusion, incorporating wrist-worn and shoe-integrated nodes to enhance the precision of spatiotemporal gait parameters.

3.1.1. PRISMA-ScR Screening Process

The PRISMA screening process demonstrated a rigorous eligibility audit across all uploaded records. Although 170 full-text records were initially screened, only 13 studies fulfilled the operational criteria for core synthesis involving wearable IoT devices integrated with AI-based fall prediction. 1.100 studies were identified through database searching, and 930 records were removed before screening due to duplication. 157 studies were excluded primarily due to unrelated engineering topics, the absence of wearable IoT components, or AI predictive systems. This finding highlights the fragmented and heterogeneous nature of the current evidence landscape.

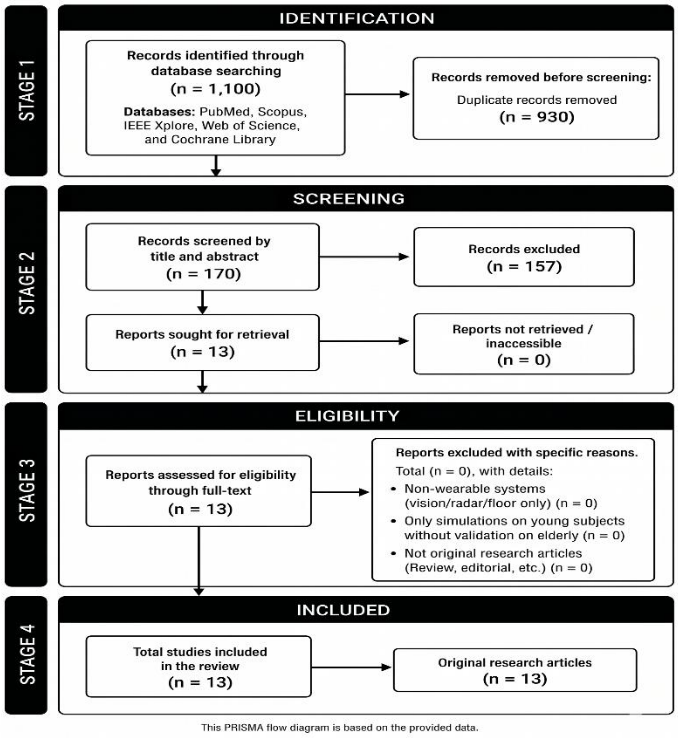

Figure 1. PRISMA-ScR Screening Summary

3.1.2. Operational Eligibility Criteria

Table 2. Eligibility Criteria Applied in the Review

Domain	Inclusion Criteria	Exclusion Criteria
Population	Older adults or the geriatric population	Non-health or unrelated engineering population
Technology	Wearable IoT or body-worn sensors	Non-wearable systems only
AI Component	AI/ML/deep learning predictive models	No predictive AI model
Outcome	Fall prediction or fall-risk assessment	Unrelated outcomes
Evidence Type	Primary empirical studies	Reviews/editorials/duplicates

The eligibility framework ensured methodological consistency across studies. The operational criteria emphasized the integration of wearable sensing technologies with AI-based predictive analytics. Importantly, studies that used hospital databases or questionnaire-only prediction systems without wearable sensors were excluded from the primary synthesis, as the review focused specifically on wearable IoT ecosystems.

3.1.3. Characteristics of Included Studies

Table 3. Final Included Primary Studies (n = 13)

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/Sensitivity/Specificity/AUC	Main Findings	Limitations
Saha et al. (n.d.) - BlockTheFall - PDF 2	United States	Prototype/framework development with experimental ML classification and blockchain-secured architecture	11,935 sensor-event records: 3,528 actual/simulated fall events and 8,407 artificially generated non-fall/fake events in controlled laboratory conditions	Wearable device-based fall detection application connected to cloud/server and blockchain smart-contract layer	Accelerometer, gyroscope, and magnetometer	Naive Bayes, Logistic Regression, Neural Network, and K-means clustering	Real-time fall event detection and emergency alert generation	Balanced accuracy: K-means 0.9570 (70/30), 0.9267 (75/25), 0.9350 (80/20); Neural Network 0.9170, 0.8967, 0.9050; Naive Bayes 0.8932, 0.8430, 0.8315; Logistic Regression 0.7973, 0.7484, 0.7872	Blockchain-enabled wearable architecture supports secure fall-event storage, data integrity, and automated alerting; K-means showed the strongest balanced accuracy across splits.	Controlled/simulated data; unclear participant demographics and older-adult validation; blockchain improves data security but not necessarily clinical validity; prospective real-world validation needed.
Ruiz-Garcia et al. (2023) - CareFall - PDF 3	Spain; public datasets from Erciyes University and UMAFall	Experimental validation of smartwatch-based fall detection using public datasets; threshold vs	Two public datasets: Erciyes University: 17 participants, 3,060 samples; UMAFall: 17 participants, public ADL/fall samples; many participants were young adults	Smartwatch-based fall detection system	3-axis accelerometer and 3-axis gyroscope	Threshold-based approaches; RF for Erciyes; SVM for UMAFall	Fall detection vs activities of daily living	Erciyes: ML Acc+Gyr accuracy 98.4%, sensitivity 98.9%, specificity 96.7%; UMAFall: ML Acc+Gyr accuracy 95.5%, sensitivity 98.6%, specificity 93.7%.	Combining accelerometer and gyroscope features improved overall performance and reduced false positives compared with threshold-only methods.	Validation used public datasets with small sample sizes and simulated tasks; limited evidence in frail/older target populations and naturalist

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/ Sensitivity/Specificity/AUC	Main Findings	Limitations
		ML comparison	rather than older adults					Threshold sensitivity 100%, but lower specificity (68.4% and 66.3%).		ic environments.
González-Castro et al. (2025) - PDF 7	Spain	Original research: ML comparison using accelerometric, non-accelerometric, and combined datasets	146 older adults	Wearable accelerometric monitoring; exact device type not fully specified in extracted text	Accelerometric movement variables plus demographic/clinical variables	Random Forest, XGBoost, AdaBoost, LightGBM, SVR, Decision Trees, Bayesian Ridge Regression	Fall-risk prediction in older adults	Combined data outperformed single data sources—XGBoost had the lowest MSE (0.0267); Bayesian Ridge had the highest R2 (0.9941). Accelerometric-only/SVR reported poor performance (MSE 1.5243; R2 -2.2532).	Integration of accelerometric and clinical variables improved explanatory/predictive value; age and comorbidities contributed important clinical context beyond movement data.	Small sample (n=146); observational design; limited external validation; feature-importance analysis not fully reported due to high dimensionality and small sample.
Noh et al. (2021)	Republic of Korea	Cross-sectional predictive modeling study using gait tests and XGBoost classification.	746 older adults aged 63-89 years.	Shoe-type wearable data loggers/insole-mounted IMU system.	Inertial measurement unit sensors embedded in both shoe outsoles; gait parameters from a 20-m walkway at slow, preferred, and fast speeds.	Extreme Gradient Boosting (XGBoost).	High vs. low fall-risk level based on fall history and fear-of-falling questions.	Accuracy 67-70%; sensitivity 43-53%; specificity 77-84%.	Stride length, walking speed, and stance phase were the most informative gait features across walking speeds; XGBoost demonstrated potential for objective gait-based fall-risk	Moderate sensitivity; fall-risk labels derived from history/fear rather than prospective falls; controlled walkway assessment may not represent free-living gait; external

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/ Sensitivity/Specificity/AUC	Main Findings	Limitations
									stratification.	validation not emphasized.
Fatima et al. (2025) - PDF 13	India	Prototype development and feasibility testing of a real-time wearable fall-risk prediction system	Feasibility/ prototype data; precise human sample size not clearly reported in extracted text	ESP-32-based wearable module with mobile/cloud interface	MPU6050 accelerometer, force pressure sensor; gyroscope suggested for future/expanded fusion	LSTM time-series model	Real-time fall-risk classification/early warning	Training over 3 epochs: accuracy 82.4%, 85.1%, 88.6%; precision 0.79, 0.83, 0.87; recall 0.81, 0.85, 0.89. The abstract also reports PSNR of 10.3 dB and SSIM of 0.4 for signal preservation.	Low-cost wearable sensor system demonstrated feasibility for real-time fall-risk monitoring and caregiver alerts via app/SMS /WhatsApp.	Hardware limitations restricted training to three epochs; dataset size and clinical validation unclear; needs larger, longitudinal testing in older adults and edge/cloud optimization.
Nkizi & Thamsuwan (2024) - PDF 14	Canada	Cross-sectional pilot balance-assessment study using IMUs and logistic regression	14 active participants from diverse age/health backgrounds; middle-aged to older adults	Wearable inertial measurement units positioned on the head, sternum, and lower back	Tri-axial accelerometer, gyroscope, and magnetometer sampled at 128 Hz	Logistic regression using IMU-derived kinematic variables	Poor balance /balance loss related to fall risk; BBS-linked assessment	Final lower-back model AUC 0.73. Significant predictors: area under acceleration curve (p=0.002), RMS angular velocity (p=0.004), total path length (p=0.0006), movement volume (p=0.02).	Lower-back IMU measures captured balance-related movement patterns; sensor location and task type influenced model coefficients.	Very small sample; active participants rather than frail older adults; balance proxy rather than actual falls; needs larger ecological validation.
Ma et al.	China	Portable wearable-	94 older adults for modeling (57 non-	Portable dual-modal	sEMG from eight lower-limb	PCA and LDA feature	Fall-risk classific	Best model LDA + SVM:	LDA improved class separabilit	Moderate sample; independent

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/ Sensitivity/Specificity/AUC	Main Findings	Limitations
(2026)		system modeling study with leave-one-out cross-validation and small independent clinical validation.	fallers, 37 ICD-10 propensity-to-fall) plus 10 older adults for independent clinical validation.	ity wearable system: bilateral sEMG electrodes plus plantar-pressure insoles; wireless central acquisition.	muscles bilaterally; plantar pressure from eight anatomical foot regions; features included muscle contribution, mean frequency, mean power frequency, and pressure impulse.	reduction; SVM, Random Forest, XGBoost classifiers; Leave-One-Out Cross-Validation.	ation during natural overground walking.	accuracy 0.88, precision 0.92, recall/sensitivity 0.85, F1-score 0.87.	y; dual sEMG and wearable plantar-pressure sensing produced clinically interpretable fall-risk predictions.	validation had only 10 participants; AUC/specificity not emphasized in abstract; real-world long-term prediction still needs testing.
Lockhart et al., 2021	United States / South Korea collaboration	Prospective wearable-system fall-risk prediction study using random forest classification and blind testing.	171 community-dwelling older adults; 127 used for model training, and 44 followed for 6 months for blind testing; 9 fallers in the test set.	A wearable inertial measurement unit was affixed to the sternum during a 10-m walking test.	Sternum-mounted IMU; linear and nonlinear gait variability, complexity, smoothness, and recurrence features.	Random Forest classifier with feature engineering/principal components; linear and nonlinear gait features.	Future faller classification/fall-risk prediction over a 6-month follow-up.	Best model: 81.6 ± 0.7% accuracy, 86.7 ± 0.5% sensitivity, 80.3 ± 0.2% specificity.	Combining linear and nonlinear gait features improved prediction; nonlinear complexity and recurrence features were strong predictors, supporting IMU-based ambulatory fall-risk screening.	Moderate sample size; short 10-m test; faller definition and follow-up period may limit generalizability; needs larger external validation.
Hua et al., 2018	United States	Pilot predictive modeling study	67 older women, mean age 77.5 years; high fall risk n=19 and low fall risk n=48 based on SPPB and fall history.	Hip-worn wearable accelerometer during a timed	Hip triaxial accelerometer, 30 Hz; traditional gait measures plus signal-	Random Forest classifiers; 10-fold cross-validation; 11 feature-	Classification of high vs low fall risk amo	Average: 73.7% accuracy, 81.1% precision, AUC 0.706. Best model: 78.9% accuracy,	Mediolateral accelerometer features and gait measures improved fall-risk classificati	Small pilot sample, women only, laboratory walking task, composit

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/Sensitivity/Specificity/AUC	Main Findings	Limitations
				400-m walk.	based accelerometer features.	set models.	ng older women.	84.4% precision, AUC 0.846.	on; accelerometer-derived walking features appear promising for screening.	e risk labels rather than prospective falls, and no external validation.
Hauth et al., 2021	United States	Preliminary real-world observational machine-learning study	8 community-dwelling older adults with a history of falls; >290 hours of real-world walking data.	Body-worn inertial measurement unit system for real-world monitoring.	Three wearable IMUs; spatiotemporal gait metrics derived from real-world walking; voice-recorded LOB event timestamps.	Machine-learning classifiers with leave-one-participant-out validation.	Automated identification of loss-of-balance (LOB) events during real-world walking.	Best model achieved AUROC >=0.87 for every held-out participant; AUPR was 4-20 times the LOB event incidence rate; at least 65.7% of data filtered while detecting >=87.0% of events on average.	Wearable IMUs can support retrospective identification of real-world LOB events and reduce manual review burden in high-volume monitoring datasets.	Very small sample; LOB events were self-reported; outcome was LOB detection rather than future fall prediction; highly imbalanced event data and limited generalizability.
Greene et al., 2021	Ireland	Real-world observational deployment study of a smart phone app for unsupervised balance and falls-risk assessment.	594 smartphone assessments from 147 unique phones; reference dataset of 277 participants (178 female; age 74.7 ± 6.6 years) used for comparison /algorithm background.	Smartphone-based mHealth assessment held against the torso during the standing balance test.	Smartphone inertial sensors (accelerometer and gyroscope) and questionnaire-based clinical fall-risk factors.	Previously trained /validated machine-learning /statistical fall-risk algorithms; classifier fusion using questionnaire and inertial-sensor data.	Balance impairment and falls-risk estimate from self-directed standing balance	No standard accuracy/ sensitivity /specificity/AUC reported for deployment sample; falls-risk/balance scores showed a strong association with self-reported fall history.	Unsupervised smartphone-based balance assessment was feasible in real-world deployment and produced clinically meaningful fall-risk/balance measures.	Relies on self-reported falls and unsupervised data quality; not a prospective fall-outcome validation in the deployment sample; smartphone handling variability may affect signals.

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/ Sensitivity/Specificity/AUC	Main Findings	Limitations
							testing.			
Lee et al., 2023	United States	Experimental device development and deep-learning fall-monitoring study using skin-wearable electronics.	Four groups, each with 5 participants; one older-adult group aged 65+ and three young-adult groups aged 21-30; activity/fall data collected across device placements.	Wireless flexible skin-wearable motion monitoring device laminated to skin; Bluetooth-connected to an Android device.	Six- or nine-axis inertial measurement unit; acceleration and gyroscope channels; device placements included chest, wrist, and necklace.	LSTM, 1D-CNN, ConvLSTM-1D, Bi-LSTM, and CNN-LSTM; LSTM with XYZ acceleration and gyroscope performed best.	Fall detection/monitoring among older adults and activities of daily living.	LSTM with XYZ acceleration + gyroscope: approximately 98.5% accuracy in older adults; chest placement approximately 97.6% accuracy in placement comparison.	Chest placement and older-adult-specific data improved performance; flexible skin-wearable electronics can support comfortable and accurate fall monitoring.	Very small sample; falls were simulated in controlled conditions; limited battery life/real-world continuous validation; detection rather than prospective prediction.
Mohan et al., 2025	New Zealand	AI model-development study using public datasets	45 subjects meeting inclusion criteria from public repositories; 30 for training and 15 for testing; ADL data included about 75 hours of monitoring.	Proposed cooperative AI model implementable in wearable health care/ home automation monitoring; uses physiological and behavioral streams.	Vital signs: blood pressure, heart rate, blood oxygenation; ADL/behavioral movement-pattern data.	AI1 Fuzzy Logic model for vital signs; AI2 Deep Belief Network for ADLs; cooperative/meta-model with ensemble learning/random-forest decision layer.	Future fall-risk prediction and classification into low, moderate, and high risk categories aligned with the Morse	Cooperative meta-model: 90.00% accuracy, 100% specificity, 85.71%-85.75% sensitivity. AI1: 95.24% accuracy, 100% specificity, 93.75% sensitivity. AI2: 91.67% accuracy, 100% specificity, 90% sensitivity.	Combining physiological and ADL-based AI outputs can support proactive fall-risk prediction and continuous monitoring for older adults.	Small sample; indirect pairing of ADL and vital-sign datasets; no k-fold/hold-out cross-validation beyond limited testing; not validated on large synchronized real-time data; only four of five ADLs included.

Author & Year	Country	Study Design	Sample	Type of IoT Wearable	Sensor Used	AI/ML Algorithm	Outcome Prediction	Accuracy/ Sensitivity/Specificity/AUC	Main Findings	Limitations
							Fall Scale.			

The included studies demonstrated substantial heterogeneity in both sensor architecture and AI methodologies. IMUs and accelerometers were the dominant sensing technologies due to their portability, low energy consumption, and ability to capture gait variability. Deep learning approaches such as LSTM and CNN-LSTM consistently produced high classification performance in laboratory environments, particularly for real-time monitoring applications.

Several studies integrated multimodal sensing approaches, combining physiological, biomechanical, and clinical features to improve predictive capability. Studies utilizing combined accelerometric and clinical data generally demonstrated superior predictive performance compared with single-modality systems.

3.1.4. Hardware and Wearable IoT Infrastructure

Regarding hardware, Inertial Measurement Units (IMUs)—which combine 3-axial accelerometers and gyroscopes—were the most commonly used sensors across the reviewed systems. Some advanced setups expanded on this standard by incorporating 72 surface electromyography (sEMG) features and four plantar-pressure features; when combined with demographic data, this created a high-dimensional input space of 81 features. For data transmission, the ESP-32 microcontroller was frequently chosen as the core IoT node because of its integrated Wi-Fi and Bluetooth capabilities, enabling raw sensor data to stream directly to cloud platforms such as Google Firebase for real-time processing. Sensor placement also presented distinct trade-offs depending on the study's goal. The waist or lower back (lumbar L3/L5) was the preferred location for analyzing balance and postural sway. Alternatively, placing sensors on the chest or sternum proved highly effective at detecting fall-specific peaks, yielding accuracies of 97.6%- 98.5%. Wrist placement offered better user compliance but suffered from signal noise due to daily arm movements. In contrast, foot or shank placements were critical for capturing step-level temporal features such as stride-time variability and swing time.

Table 4. Sensor Modalities and Placement

Sensor Type	Common Placement	Main Function
IMU	Sternum, waist, lower back	Gait and balance monitoring
Accelerometer	Hip, wrist, chest	Motion and fall detection
Gyroscope	Chest, smartwatch	Angular movement analysis
Plantar pressure sensors	Insoles/feet	Step variability and load distribution
sEMG	Lower limbs	Muscle activation monitoring

IMUs remained the most dominant wearable technology because they simultaneously capture acceleration and rotational movement. Sensor placement substantially influenced predictive performance. Chest and sternum placements achieved higher detection accuracy due to stable trunk-movement signals, whereas wrist placement increased usability but introduced more signal noise from non-fall arm activities. Hybrid wearable systems that combine plantar pressure and sEMG sensing have shown promise in capturing neuromuscular instability before overt gait deterioration occurs.

3.1.5. Artificial Intelligence Architectures

Computationally, the field has moved away from simple threshold-based triggers, which typically yield high sensitivity but low specificity. Instead, Deep Learning (DL) architectures such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) have become prominent for their ability to capture long-term dependencies in time-series gait data. Studies reported LSTM accuracies ranging from 88.6% to 98.5%. In classical machine learning approaches, Random Forest (RF) was often favored for its feature-ranking capabilities, which identified tasks such as "turn 360 degrees" and "sit-to-stand" as highly informative for fall risk prediction. Furthermore, newer "Cooperative AI" frameworks are emerging; these combine Fuzzy Logic for vital signs with Deep Belief Networks (DBN) for activities of daily living, ultimately relying on a Random Forest meta-classifier to synthesize a final risk score.

Table 5. AI Algorithms Used in Included Studies

AI Algorithm	Frequency of Use	Main Application
Random Forest	Very common	Fall-risk classification
XGBoost	Common	Predictive modeling
SVM	Common	Pattern recognition
LSTM	Common	Time-series prediction
CNN/CNN-LSTM	Moderate	Deep feature extraction
Logistic Regression	Moderate	Balance-risk prediction
Deep Belief Network	Limited	Cooperative AI systems

The review identified a major methodological transition from conventional threshold-based systems toward advanced machine learning and deep learning architectures. Random Forest and XGBoost remained highly popular for their interpretability and feature-ranking capabilities. However, LSTM-based architectures demonstrated superior performance in temporal gait analysis by effectively capturing long-term dependencies in movement sequences. Emerging cooperative AI frameworks that integrate multiple algorithms have also demonstrated promising performance in multimodal data fusion.

3.1.6. Predictive Performance

The reviewed studies reported diverse metrics to demonstrate model robustness. Many models exceeded 95% accuracy in controlled laboratory settings. For instance, XGBoost achieved high predictive accuracy, with a Mean Squared Error (MSE) of 0.0267, and Bayesian Ridge Regression demonstrated exceptional explanatory power, with an R^2 of 0.9941, when handling high-dimensional clinical and sensor data. However, a critical finding was the presence of a severe "simulation gap." The data revealed that 98.5% of the studies still relied on young volunteers performing simulated falls onto protective mats. When models trained on this younger demographic were tested against actual data from older adults, overall activity classification accuracy dropped drastically, sometimes to as low as 48.3%, highlighting a major failure in cross-demographic generalization.

Table 6. Summary of Predictive Performance Metrics

Performance Indicator	Range
Accuracy	67%–98.5%
Sensitivity	43%–100%
Specificity	66%–100%
AUROC/AUC	0.706–0.87+

Predictive performance varied considerably depending on sensor configuration, validation strategy, and population characteristics. Laboratory-based deep learning systems generally achieved exceptionally high performance metrics above 95%; however, studies involving real-world data from older adults reported lower and more variable predictive accuracy. This discrepancy strongly suggests a simulation gap between controlled environments and real-world geriatric mobility.

3.1.7. Functional Parameters for Prediction

To predict fall risks, these models primarily extracted gait and balance features from 10-second data windows. Significant discriminative features between fallers and non-fallers included temporal metrics such as mean step time, cadence, and stride-time symmetry. Variability measures were also crucial, including the Coefficient of Variation (CoV) of acceleration and Sample Entropy (SaEn), with lower entropy scores often indicating rigid movement patterns associated with disease states. Finally, integrating non-accelerometric clinical context, such as age, BMI, medical history, and cognitive impairments, significantly improved the models' Area Under the Curve (AUC) compared with systems that rely solely on sensor data.

3.2. Discussion

3.2.1. Transition from Reactive Detection to Proactive Prediction

This scoping review demonstrates a major paradigm shift in fall-prevention research from reactive fall detection toward proactive fall-risk prediction. Traditional threshold-based systems primarily detect falls after impact, limiting their ability to prevent injuries. Conversely, wearable AI systems aim to detect subtle biomechanical deterioration that precedes falls. The dominance of IMU-based systems across studies reflects their affordability, portability, and ability to monitor gait and postural sway in real-world settings continuously. Despite these advancements, the field faces significant challenges regarding model generalizability, as current datasets often suffer from insufficient sample sizes and inherent data variation (Lim et al., 2024). Furthermore, the reliance on heterogeneous sensor placements and varied experimental protocols complicates the establishment of a standardized, gold-standard benchmark necessary for cross-study comparison. The prevailing focus on static feature extraction often overlooks the temporal evolution of gait biomarkers, necessitating a transition toward longitudinal risk profiling that tracks individual movement patterns as they deteriorate over time. Integrating transparent algorithmic frameworks, specifically those that use feature attribution techniques, is crucial not only to address the lack of transparency in complex models but also to provide clinicians with a detailed, actionable understanding of the physiological factors influencing a person's fall risk, thereby establishing the confidence required for clinical adoption.

3.2.2. Importance of Multimodal Sensor Fusion

A major finding of this review is the growing emphasis on multimodal sensor fusion. Combining accelerometers, gyroscopes, plantar-pressure sensors, and sEMG improved predictive performance because falls are multifactorial events involving gait instability, muscle weakness, balance impairment, and neurological decline. By aggregating heterogeneous data streams, these integrated systems bridge the gap between clinical functionality and user experience, enabling the derivation of more robust, patient-specific risk profiles. The successful implementation of these fused architectures requires addressing technical hurdles, such as precise data synchronization and cross-sensor calibration, to maintain signal reliability in ambulatory settings (Bao et al., 2023). The simultaneous monitoring of disparate physiological signals such as cardiac and muscular activity via these fused networks can elucidate the underlying etiology of mobility decline, thereby facilitating more precise, informed clinical intervention strategies. Studies integrating clinical variables such as age, body mass index, comorbidities, and cognitive impairment further enhanced predictive capability, supporting a biopsychosocial approach to fall-risk assessment.

3.2.3. Deep Learning and Temporal Pattern Recognition

Deep learning architectures, particularly LSTM and CNN-LSTM, demonstrated superior ability to process time-series gait signals. Unlike conventional machine learning classifiers, LSTM networks effectively capture long-term temporal dependencies in movement patterns. By learning directly from raw IMU time-series, these models mitigate the manual burden of feature extraction and selection while capturing complex physiological signals that traditional methods often overlook (Bargiotas et al., 2022). The complexity of these architectures introduces technical challenges related to data synchronization, sensor calibration, and algorithmic interpretability that must be addressed to ensure the reliability of the resulting diagnostic outputs. Specifically, reconciling the "black box" nature of these deep architectures with the clinical requirement for interpretable diagnostic indicators remains a primary barrier to widespread adoption. To bridge this gap, incorporating Explainable Artificial Intelligence techniques into deep learning pipelines can provide transparent insights into the biomechanical indices driving a model's decision. Future clinical validation must prioritize large-scale, heterogeneous datasets collected in community-dwelling environments rather than controlled laboratories to ensure the robustness of these models against naturalistic environmental noise. However, many deep learning systems remain "black-box" models with limited explainability, which creates challenges for clinical adoption and trust among

3.2.4. The Simulation Gap

The most important limitation identified in this review was the substantial simulation gap. Most systems were trained using falls simulated by young healthy volunteers under controlled laboratory conditions. When these systems were applied to older adults in practice, predictive performance frequently declined. Older adults demonstrate unique gait biomechanics, slower recovery responses, frailty-related movement patterns, and multimorbidity-related instability that younger participants cannot adequately replicate. Consequently, relying exclusively on simulated datasets compromises the ecological validity of these models, as they fail to capture the nuances of pathological gait associated with elevated fall risk. To overcome this limitation, research must shift to leveraging real-world data from older populations, as these records provide the critical diversity needed to mitigate inter-individual physiological differences and improve model robustness (Liu & Bai, 2024). Moreover, establishing standardized, publicly available databases that include both accelerometer data and synchronized video footage would facilitate a more rigorous, comparative evaluation of different detection methodologies. Therefore, future research must prioritize longitudinal real-world validation involving frail community-dwelling older adults.

3.2.5. Clinical and Technological Implications

The integration of wearable IoT systems with cloud computing, edge AI, and blockchain demonstrates increasing technological maturity. Edge computing may reduce latency for pre-impact interventions, whereas blockchain integration may strengthen the security and privacy of medical data. The establishment of unified evaluation benchmarks is essential for resolving existing methodological inconsistencies and ensuring that researchers can reliably compare algorithmic performance across diverse study populations. Shifting focus toward device-free, privacy-centric monitoring architectures could mitigate user compliance issues while facilitating the seamless, long-term data collection necessary to refine these diagnostic tools (Wang et al., 2020). Addressing the current reliance on fixed thresholds is vital, as shifting toward subject-specific parameters can significantly improve accuracy across diverse patient cohorts. Implementing such adaptive protocols requires careful consideration of device form factor and power consumption, as high-performance hardware often conflicts with the practical need for unobtrusive, long-term wearability. Finally, exploring alternative cost functions that account for individual risk preferences could enable the dynamic adjustment of sensitivity thresholds, thereby aligning automated alerts more closely with specific clinical requirements. The usability of these systems must be balanced against stringent energy constraints, as maintaining continuous operation for at least a full day remains a critical prerequisite for meaningful clinical utility. Implementation barriers remain substantial, including battery limitations, user adherence, sensor discomfort, data privacy concerns, interoperability issues, and limited ecological validation.

Conclusions

This scoping review highlights the accelerating evolution of AI-powered wearable IoT technologies as a transformative approach for proactive fall-risk prediction among older adults. Advanced IMU-based systems, multimodal wearable sensors, and deep learning architectures have demonstrated substantial predictive potential, particularly within controlled laboratory environments. These innovations signify a critical paradigm shift from reactive fall detection to preventive, real-time monitoring that supports safer, more independent aging.

Nevertheless, the current evidence remains constrained by a major translational limitation: the overwhelming reliance on simulated falls conducted by younger individuals, rather than on real-world validation in frail older adults. This "simulation gap" raises important concerns regarding ecological validity, generalizability, and clinical readiness. To advance these technologies from experimental prototypes into reliable clinical solutions, future research must prioritize longitudinal real-world validation, explainable AI frameworks, multimodal sensor fusion, edge AI integration, standardized evaluation protocols, and user-centered wearable design tailored to older populations. If these challenges can be successfully addressed, AI-powered wearable IoT systems have the potential to substantially reduce fall-related injuries, healthcare expenditures, hospitalization rates, and loss of independence, ultimately contributing to healthier and safer aging societies worldwide.

Conflicts of Interest

The authors declare no conflict of interest.

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