Artificial Intelligence-Assisted Fall Prevention in Older Adults - Risk Identification, Individualized Intervention, and Clinical Translation

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Abstract. Falls are a leading cause of disability, hospitalization, and mortality in later life. Although traditional fall-prevention assessment already includes relatively mature scales and physical examination, it is still largely based on one-time screening and may miss fluctuating risks in home and community settings. By reviewing published work, this paper discusses how AI may shift traditional fall prevention from post-event recognition to pre-event prediction and what applications this may enable in VR and AR training, robot rehabilitation, and closed-loop management across home, community, and hospital settings. Current clinical use still requires stronger external validation, better explainability, clearer privacy and bias safeguards, more persuasive cost-effectiveness evidence, and smoother workflow integration. AI has real potential for objective assessment and dynamic management, but its current clinical soundness remains uncertain.

Keywords: Artificial intelligence; older adults; fall risk assessment; wearable sensors; virtual reality; clinical translation.

1. Introduction

With population aging, falls are no longer seen as occasional events in elder care. Falls are often linked to fractures, head injury, hospitalization, restricted activity, functional decline, and a greater need for long-term care. Falls are a major public health problem that affects independent living and quality of life [1]. The World Guidelines for Falls Prevention and Management also state that falls in older adults are not a problem of a single organ or symptom but a syndrome of multifactorial origin involving gait, balance, cognition, medication, environment, and behavior. Fall prevention should move from single-point screening to multifactorial management [2].

Common clinical pathways include Timed Up and Go, Berg Balance Scale, fall history, medication review, and home-environment inspection. They are among the most frequently used measures in practice. However, they are still largely based on a single clinical visit, a single timed test, or one assessor's judgment. They may indicate that a patient appears to be at high risk at a certain moment, but they cannot indicate in a stable way when, why, and under what circumstances that same patient is more likely to fall in daily life. Fall risk is dynamic. Getting up in the middle of the night, fatigue, hypotension, infection, sleep deprivation, or dizziness after a medication change may all push that same person into a very different state of fall risk [2-5].

For that reason, the value of AI in this field goes far beyond digitizing existing scales or generating alarms faster after an event occurs. Its main value lies in transforming a dispersed, static, and post-event approach into a closed loop of continuous sensing, dynamic stratification, individualized intervention, and feedback [2-10].

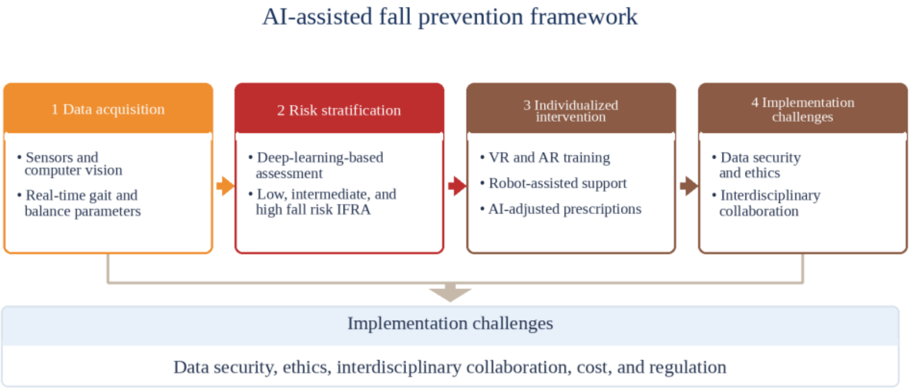

Fig 1. AI-assisted fall prevention, a technology-to-clinical-translation framework.

2. The Clinical Complexity of Fall Risk in Older Adults and the Logic of AI Intervention

Falls in older adults rarely result from a single cause. Most falls are not caused by one clearly poor indicator, but by a combination of multiple moderate risks that occur simultaneously. For instance, weakening lower-limb strength may not yet be severe on its own, but if it occurs together with polypharmacy, orthostatic hypotension, poor nighttime lighting, and mild cognitive decline, the risk of falling increases substantially. That is also why a single static scale often fails to capture a person's true ability to navigate everyday life.

One way AI enters this problem is not by replacing the clinic, but by turning information that clinicians can often sense but cannot easily quantify, or would like to observe continuously but cannot, into data. Walking speed, step length, step-to-step variability, turning time, sit-to-stand quality, sway of the center of mass, and plantar-pressure distribution were traditionally measured only locally in laboratories or rehabilitation centers. They can be measured over longer periods and under more life-like conditions with wearable inertial sensors, pressure mats, depth cameras, and environmental sensors [3-6]. When continuous signals are combined with clinical variables such as age, medication use, comorbidities, and previous falls, the time and context dimensions of risk assessment begin to exceed a one-time score.

A large body of studies has focused on fall detection, meaning rapid recognition and alarm after a fall has occurred. What clinicians care more about, however, is fall-risk prediction, namely identifying high-risk individuals before a fall and changing that course. The two may share part of the sensor and algorithm pipeline, but not all of it, nor necessarily their study design, evaluation metric, or clinical value.

AI intervention in fall prevention can be considered at three levels, risk identification and stratification, translation into training and rehabilitation, and barriers to safe implementation in real-world settings.

3. Wearable Sensors, Turning Subtle Changes into Continuous Signals.

3.1. Wearable Sensors, Turning Subtle Changes into Continuous Signals

Wearable solutions appear frequently in fall-risk research because they are close to the body. Accelerometers, gyroscopes, inertial measurement units, and plantar-pressure sensors can output gait rhythm, turning speed, center-of-mass transfer, and many other signals, and hence can provide objective measures of gait deterioration and balance impairments. Compared with a brief one-time test in the clinic, they are more likely to reflect high-risk situations such as getting up at night, gait changes after fatigue, or instability when going up or down stairs. Hence, they are more promising for detecting problems before a fall event.

The current reviews suggest that performance is very sensitive to sensor placement, sampling frequency, task protocol, and feature engineering. If study A places the sensor on the waist and study B places the sensor on the foot dorsum or wrist, the time-series features extracted from these two studies may not be directly interchangeable. Likewise, if training data come mainly from relatively healthy community-dwelling older adults and the model is later applied to hospitalized patients, post-stroke groups, or residents in long-term care facilities, performance may change dramatically [3, 6].

3.2. Contactless Vision Based Monitoring, From Action Recognition to Scene Understanding.

If patients are poorly adherent to wearing a device, have cognitive impairment, or need to wear it continuously at night, contactless vision provides another route. RGB video, depth cameras, and ambient-perception cameras can detect difficulty rising, unusual pauses, gait dragging, near-fall pauses, and indoor environmental features such as narrow passages, obstacles, and lack of light that may precede falls, without any active cooperation from the patient. Compared with systems based only on wearables, the strength of vision is that it can preserve contextual information. It can indicate not only that a person fell, but also that it happened while turning, while stepping over a threshold, while walking to the bathroom at night, or after tripping over something on the floor.

On the other hand, vision-based systems also reveal their limitations quickly in practice. Complex lighting, occlusion, multiple people in the same scene, furniture, changes in camera angle, and boundary conditions can all reduce model robustness. Video data also sit close to a privacy boundary, and continuous recording in the home may reduce user acceptance [4, 11-12]. A more practical approach is to use vision as one component of a multimodal system. Such systems can provide contextual information when needed and rely on less intrusive approaches when privacy is a concern.

3.3. Machine Learning Stratification Models, From Binary Classification to Actionable Risk Spectra

If sensors answer the question of whether continuous data exists, machine learning addresses a different question, namely how clinically usable patterns can be extracted from noisy, high-dimensional data. In the past few years, random forests, support vector machines, gradient boosting, convolutional networks, and sequential deep-learning models have all been applied to jointly analyze gait parameters, balance indicators, and clinical variables in order to better discriminate high-risk candidates. It is better suited to analyzing high-dimensional, nonlinear relationships than conventional linear statistics.

Stratification, rather than binary classification alone, is of real importance here. Clinicians need to know whether a patient falls into a low-risk, intermediate-risk, or high-risk category, whether stronger intervention is needed immediately, whether additional environmental assessment is required, and whether reassessment should be scheduled soon. The IFRA study is representative because it did not end with an abstract prediction score. Based on instrumented Timed Up and Go data, it tried to build an interpretable low-risk, intermediate-risk, and high-risk hierarchy such that the model output is more aligned with the language of clinical decision-making [7].

Whether considering IFRA in post-stroke patients or sensor-based models for broader older-adult groups, most studies are still limited by small sample sizes, single-center designs, insufficient follow-up, and lack of external validation. AI has shown that it can find latent risk patterns in data. It is still some way from showing that it can generally replace regular assessment methods.

3.4. From Model Performance to Clinical Trustworthiness, What Is Still Missing

Many papers report on AUC, accuracy, sensitivity, and specificity.

In fall-risk papers, labels are sometimes inconsistent. Some studies define high risk by prior fall history. Others define it by prospective follow-up. Some include near-falls, and some use functional decline as a surrogate endpoint. When labels change, what the model learns also changes substantially [5-7].

4. AI-Driven Individualized Intervention and Intelligent Rehabilitation

4.1. From Risk Identification to Prescription Generation, Interventions Must Remain Adjustable

The most difficult aspect of fall prevention is not identifying high-risk people, but turning that identification into an executable, sustainable, and adjustable plan when circumstances change. The most practical role of AI in this process is to link assessment, prescription, and feedback so that intervention can be adjusted as functional status changes.

For instance, training intensity can be adjusted in small and fast steps based on gait stability, sit-to-stand time, fatigue trend, training completion trend, and fall history. Rather than using the same prescription for a long period after one assessment, the system adjusts training intensity continuously. For some patients, this continuous feedback may be more important than the model itself because the feedback directly drives adjustment. It has been shown that when training effects are visible, patients are more likely to continue training, and when movement errors are detected in time, therapists are more likely to adjust risk management [2, 5, 8].

4.2. VR and AR Training, Above All, a Training Medium with High Adherence

An important advantage of VR and AR in fall-prevention settings lies less in replacing balance training than in improving how training is delivered. Standing and weight shifting, lower-limb lifting, reaction drills, and dual-task gait work can be monotonous, exhausting, and easy to discontinue. When these movements are embedded in visual tasks with feedback, participation and adherence may improve. Recent systematic reviews therefore tend to position VR more as a means of modulating training effect and participation than as a modality separate from rehabilitation [8, 9].

Claims about VR should remain cautious. VR setups differ widely across studies. Immersive head-mounted displays are used in some studies, whereas non-immersive screen-based or exergame-type platforms are used in others. Baseline function, training duration, and outcome measures also vary widely, so heterogeneity is the rule [8, 9]. A more consistent conclusion is that VR and AR show promise for balance, gait, lower-limb function, and participation, but long-term effects, optimal dose, ideal target groups, and safety in frail older populations still need clarification through stronger studies.

4.3. Robot-Assisted Gait Training, Better Suited to Some High-Risk Subgroups

Robot-assisted gait training has already accumulated considerable experience in neurorehabilitation, particularly after stroke. High repetition, quantifiability, adjustability, and reduced physical burden on therapists are advantages of this technology for patients with clear gait impairment, limited endurance, and a need for high-intensity input [10]. In fall prevention, this is not equivalent to preventing falls themselves, but it may reduce fall tendency indirectly in some high-risk groups by improving gait symmetry, lower-limb function, and quality of motor learning.

Robotic training devices are expensive, take up space, require special support, and should not be described as part of mainstream community fall-prevention practice. A more practical position is to see them as one intensified option for some high-risk, functionally limited patients with complex rehabilitation needs.

4.4. Closed-Loop Management, What Changes Is the Management Logic, Not a Single Technology

In sum, the value of AI-driven individualized intervention does not lie in any single technology but in new management logic. Risk is not judged once and for all in the outpatient clinic and then settled for the foreseeable future. It is recalculated across home, community, outpatient care, and rehabilitation training. Intervention is not administered once and for all but adjusted according to feedback. The patient is not a passive recipient of advice but may increasingly appreciate how personal risk changes through visible feedback [2, 8-10]. If this logic can be implemented effectively, fall prevention will mean more than identifying those at high risk. It will begin to mean continuously reducing high risk.

5. Key Bottlenecks in Clinical Translation

5.1. Uneven Strength of Evidence, Technical Feasibility Doesn’t Equal Clinical Maturity

The most serious gap in existing AI-for-falls literature is not that nothing works, but that the evidence is dispersed. There are papers showing that a device or a model can discriminate features under controlled conditions, and there are papers reporting good prediction performance in selected groups. What is lacking is long-term real-world evidence showing that the use of a system is associated with fewer falls, fewer hospitalizations, less functional decline, or reduced care burden [2, 5-7].

5.2. Privacy, Bias, and Explainability, These Are Not Appendix Issues

Privacy and explainability are not issues to be added to the end of a study. Fall-prevention cameras in homes may need to collect videos from the home, activity paths, functional condition, medical history, and long-term behavior, making the data highly sensitive. Unless data governance, permission control, de-identification, and informed consent are done well, even a state-of-the-art system will have a hard time winning long-term trust [11, 12].

In the home setting, acceptance of technology may depend not only on accuracy, but also on whether users feel that they are always being watched. Bias can also be introduced. If training data come mostly from one region, one age group, or a relatively high-functioning population, performance may be biased in other groups. If that bias enters routine screening, it is no longer an error term in a paper. It becomes a question of whether a real patient is identified promptly, misclassified, or exposed to an inappropriate intervention. Therefore, explainability, fairness, and post-deployment evaluation should appear in the main body of a paper, not in a poorly presented future work paragraph.

5.3. Cost, Acceptability, and Workflow Integration

For many systems, the trouble lies not in the inability to build them, but that once built, it is not clear who will continue to use them. Device acceptability among older people, budget constraints in primary healthcare facilities, the cost of training therapists, compatibility with information-system interfaces, and the impact of alarm thresholds on workload may seem minor, yet they often decide the fate of a technology more than the algorithm [2, 10-12].

From a practical point of view, a layered strategy may be more realistic than the continued build-up of high-cost hardware. Low-cost devices and selected key features can be used for initial screening. Then, multimodal assessment and intensive intervention can be applied to high-risk individuals. This strategy is more realistic with respect to clinical resource allocation and the actual capacity of primary care and home-based support.

6. Discussion

Overall, the main contribution of AI to fall prevention in older adults is not that machines are wiser than humans. Instead, AI changes the logic of assessment itself, from one-time, fragmentary, experience-led judgment to continuous sensing, ongoing updating, and more objective risk stratification [2-7]. Attention should focus not on any single technology, but on how AI, within current guideline limits, can compensate for gaps in conventional assessment that do not fully reflect real-life situations.

Table 1. Main technical pathways, clinical value, and translation barriers in AI-supported fall prevention.

Technical pathway	Main data source	Clinical value	Main limitation	Best-suited setting
Wearable inertial and pressure sensors	Acceleration, angular velocity, plantar pressure, gait parameters	Continuous monitoring and relatively easy quantification of gait and balance change	Adherence is limited; sensor position affects results; comparability is insufficient	Community screening, home follow-up, long-term monitoring
Contactless vision and ambient sensing	Video, depth images, spatial-behavior information	Preserves scene information and helps identify environmental triggers and abnormal behavior	Clear privacy concerns; insufficient robustness in complex scenes	Nighttime safety monitoring, institutional care
Machine-learning risk stratification	Sensor features plus clinical variables	Supports low-risk, intermediate-risk, and high-risk tiers and helps resource allocation	External validation remains insufficient; explainability still needs strengthening	Outpatient stratified assessment, rehabilitation reassessment
VR and AR training systems	Training-process data, motion trajectories, interactive feedback	Improves engagement and adherence and supports immediate correction	Systems vary widely; long-term effects and suitable target groups remain unclear	Balance training, enhanced home rehabilitation
Robot-assisted gait training	Gait cycle, joint kinematics, training dose	Suitable for intensified training in high-risk patients with functional limitation	High equipment cost; heavy demand for professional support; limited scalability	Post-stroke patients or those with marked gait impairment

7. Conclusion

Overall, AI offers more technically feasible approaches to fall prevention in older adults. It supports more continuous monitoring, more objective assessment, and more individualized management of risk information. Wearable and vision sensors help generate more risk-related information. Machine learning helps stratify risk. VR and AR, used together with robot-assisted systems, offer new possibilities for adherence and rehabilitation. Based on the available evidence, AI has not replaced conventional assessment. A more cautious conclusion is that AI can reinforce weak links in guideline-driven practice, particularly in dynamic monitoring, objective quantification, and feedback loops. If future work continues to enhance multicenter validation, real-world application, design-based explainability, and ethical governance, AI-enabled fall prevention may transition from technical feasibility to routine clinical applicability.

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