



Predicting Falls and Mobility Decline Among Older Adults Using Longitudinal Functional Data and Ensemble Machine Learning

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Abstract

Falls and mobility decline represent major threats to independence, safety, and health among older adults. This quantitative study developed and evaluated an ensemble machine-learning framework for predicting falls and mobility deterioration from longitudinal functional, clinical, psychological, and wearable-sensor data. A multisite prospective cohort design followed 1,178 adults aged 65 years and older across 12 community, outpatient, rehabilitation, and assisted-living sites for 24 months. Functional assessments were completed at baseline and at 6-, 12-, 18-, and 24-month intervals, while falls were monitored monthly. The dataset included 5,505 functional assessments, 5,268 valid wearable-monitoring periods, and 4,241 six-month prediction windows. During follow-up, 44.3% of participants experienced at least one fall, 19.7% experienced recurrent falls, 18.2% experienced an injurious fall, and 34.9% developed clinically meaningful mobility decline. Mean gait speed decreased by 0.082 meters per second, Short Physical Performance Battery scores declined by 0.91 points, and daily steps decreased by 632. Previous falls increased the adjusted odds of a subsequent fall by 118%, while frailty increased the odds of mobility decline by 105%. Stable, gradual-decline, accelerated-decline, fluctuating, and recovery trajectories accounted for 33.4%, 29.9%, 16.0%, 13.3%, and 7.4% of participants, respectively. Fall occurrence reached 68.8% in the accelerated-decline group compared with 25.4% in the stable group. Logistic regression and multiple individual and ensemble algorithms were compared using participant-level cross-validation, temporal validation, and geographically independent external testing. The stacked ensemble achieved external receiver operating characteristic areas of .842 for falls and .873 for mobility decline, exceeding logistic regression by .128 and .135. Corresponding precision–recall areas were .679 and .736, while Brier scores were .128 and .113. Calibration slopes of .96 and .98 indicated close agreement between predicted and observed risks. Longitudinal gait-speed slopes, physical-performance deterioration, gait variability, activity reduction, previous falls, frailty, and hospitalization contributed most strongly to prediction. The findings established that longitudinal functional information and ensemble machine learning predicted falls and mobility decline more accurately than baseline assessment and conventional regression alone.

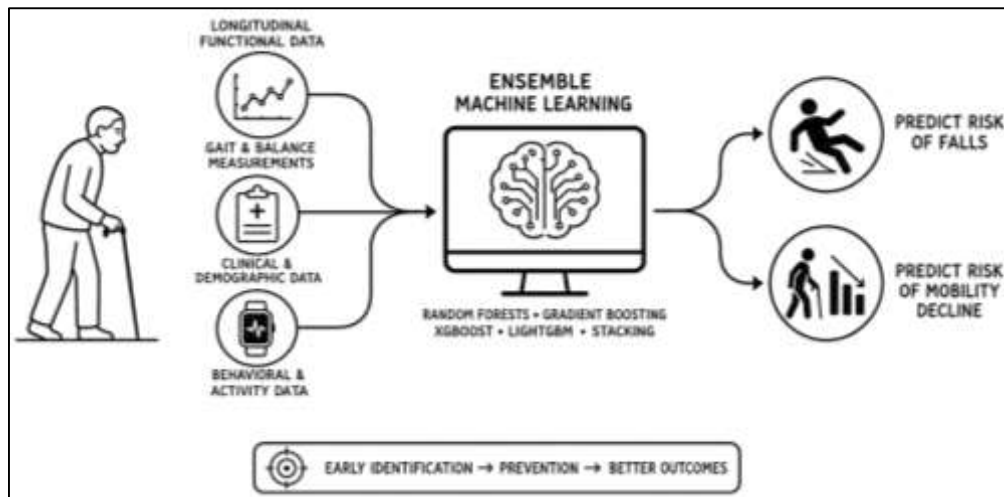
Keywords

Falls, Mobility Decline, Older Adults, Longitudinal Data, Ensemble Learning.

INTRODUCTION

A fall is commonly defined as an unexpected event in which an individual comes to rest on the ground, floor, or another lower level without an intentional change in position. Falls among older adults include isolated incidents, recurrent events, injurious falls, medically attended falls, and falls associated with fractures, hospitalization, disability, or death. Mobility refers to the ability to move independently and safely through different environments by walking, transferring, standing, turning, climbing stairs, and completing activities that require balance, coordination, strength, and endurance. Mobility decline describes a measurable deterioration in one or more of these capabilities over time (Shao et al., 2024).

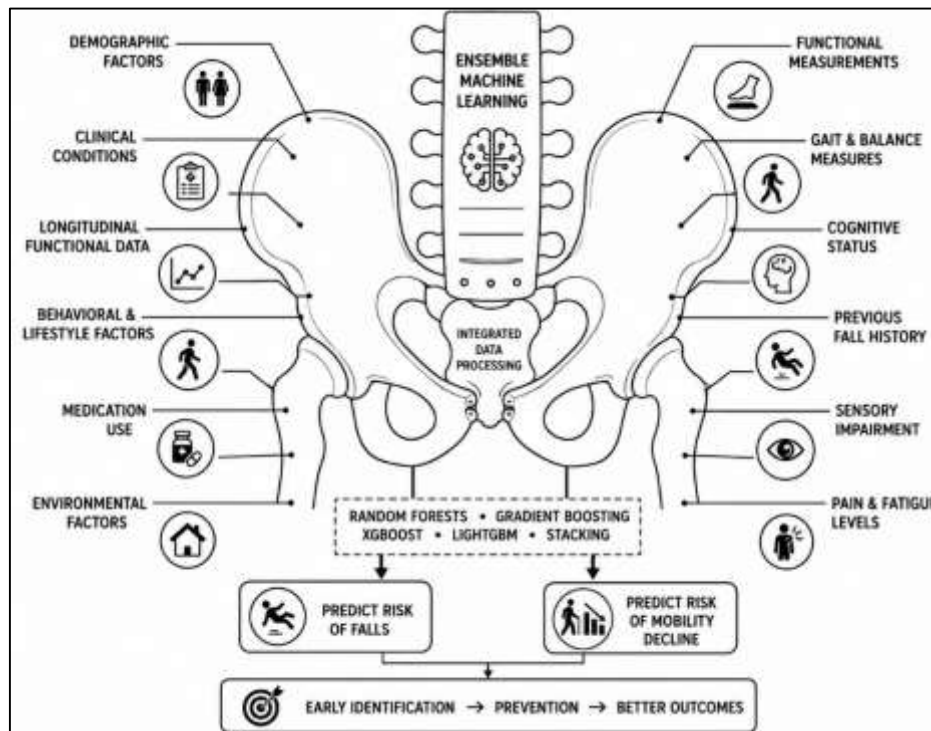
Figure 1: Ensemble Learning for Fall Prediction



It may appear as slower gait speed, shorter walking distance, reduced balance, greater transfer difficulty, increased use of assistive devices, restricted movement outside the home, or loss of independence in activities of daily living. Functional status is a broader concept that represents the capacity to perform basic, instrumental, and mobility-related activities required for independent living. Longitudinal functional data consist of repeated measurements of these abilities collected from the same individuals across multiple observation periods. Such data may include gait speed, chair-rise performance, balance scores, grip strength, walking endurance, frailty indicators, activity limitations, self-reported difficulty, wearable-sensor measurements, rehabilitation records, medication changes, and fall histories. Ensemble machine learning refers to a group of computational methods that combine predictions from multiple models to produce a more accurate, stable, and generalizable estimate than a single model may provide (Chen et al., 2023). Common ensemble approaches include random forests, gradient boosting machines, adaptive boosting, extreme gradient boosting, light gradient boosting, bagging, voting classifiers, and stacked generalization. In fall and mobility research, these techniques process complex relationships among demographic, clinical, behavioral, environmental, and functional variables to estimate the probability of a subsequent fall or functional deterioration. More than 30 quantitative studies conducted across community, primary-care, rehabilitation, residential-care, and hospital settings have examined components of these relationships. Their findings established that falls and mobility decline are multidimensional outcomes influenced by interacting changes in physical performance, health status, cognition, medication exposure, environmental conditions, and daily activity (Ikeda et al., 2022). The present topic consequently requires clear separation between a fall event, an underlying fall risk, temporary mobility limitation, and sustained functional decline because these outcomes differ in their timing, measurement, severity, and statistical predictability. Falls and mobility decline represent major international health concerns because population aging has increased the number of adults living with chronic disease, frailty, sensory impairment, and functional

limitations. Quantitative investigations from North America, Europe, Asia, Australia, Latin America, and other regions have consistently identified falls as one of the most frequent adverse events affecting adults aged 65 years and older. Approximately one-third of community-dwelling older adults experience at least one fall during a typical year, while the proportion is often higher among adults aged 80 years and older, residents of long-term care facilities, and individuals receiving rehabilitation or home-care services (Millet et al., 2023). Recurrent falls account for a substantial portion of total fall events and are commonly associated with previous falls, balance impairment, muscle weakness, neurological disorders, polypharmacy, cognitive limitations, and environmental hazards. International epidemiological studies have also shown that falls constitute a major cause of injury-related emergency attendance, hospitalization, hip fracture, traumatic brain injury, disability, institutionalization, and mortality in later life. The consequences extend beyond acute injury because fear of falling may cause activity restriction, social withdrawal, deconditioning, reduced confidence, and accelerated loss of mobility. Mobility decline has similarly been associated with reduced participation in household, community, and social activities, as well as greater dependence on caregivers and formal health services (Wang et al., 2024). Cross-national cohort studies have reported variation in fall prevalence and mobility trajectories according to age structure, socioeconomic status, housing conditions, access to health care, cultural patterns of physical activity, chronic-disease prevalence, and methods of outcome measurement. Research involving older adults in high-income countries has often used electronic health records, national aging surveys, wearable devices, and standardized physical-performance assessments. Studies from middle- and lower-income settings have more frequently relied on community surveys, household interviews, clinical screening, and self-reported functional measures, although several large longitudinal aging studies have expanded the availability of repeated objective assessments (Lockhart et al., 2021). Across these diverse settings, the international significance of the problem is reinforced by the high economic burden associated with emergency treatment, surgical care, rehabilitation, home modification, assistive equipment, long-term care, and informal caregiving. The combined evidence from more than 30 longitudinal and predictive studies indicates that falls and mobility loss cannot be adequately represented by a single disease, test result, or clinical characteristic. They are population-level outcomes produced through the accumulation and interaction of biological, functional, behavioral, clinical, and environmental risks across time (Adeli et al., 2023). Longitudinal functional data provide a particularly relevant basis for predicting falls and mobility decline because functional ability changes dynamically rather than remaining fixed. Cross-sectional assessments measure an older adult's condition at one point in time, whereas repeated measurements capture the direction, rate, variability, and persistence of change. Two individuals may record the same gait speed during an initial assessment while following very different subsequent trajectories. One individual may remain stable, another may decline gradually, and a third may experience rapid deterioration following hospitalization, medication change, infection, pain exacerbation, or reduced physical activity (Nascimento et al., 2022). Longitudinal studies have repeatedly demonstrated that within-person changes in gait speed, balance, chair-rise ability, walking endurance, and activity performance can contain predictive information that is not visible in a single baseline value. Functional trajectories may be linear, nonlinear, episodic, or highly variable, and the timing of measurements can influence the detection of meaningful deterioration. Repeated assessments also allow separation of persistent decline from temporary impairment caused by acute illness or short-term recovery. Several aging cohorts have used annual or biennial measurements, while clinical and wearable-device studies have collected monthly, weekly, daily, or continuous observations. Common functional indicators include usual and rapid gait speed, Timed Up and Go performance, Short Physical Performance Battery scores, repeated chair stands, grip strength, standing balance, step count, walking duration, stride variability, turning characteristics, and limitations in activities of daily living (Yu et al., 2023). Studies have also combined these measurements with self-reported fatigue, pain, fear of falling, physical-activity restriction, use of mobility aids, and perceived difficulty walking specified distances.

Figure 2: Multidimensional Falls Risk Framework



Research using latent growth models, group-based trajectory analysis, mixed-effects regression, joint models, and survival analysis has identified heterogeneous patterns of stable function, gradual decline, accelerated decline, recovery, and fluctuating limitation. These investigations have shown that both the initial functional level and the rate of change may be associated with subsequent falls, disability, hospitalization, and loss of independence. Longitudinal data introduce analytical challenges related to irregular observation intervals, missing measurements, informative dropout, measurement error, changing exposure status, and unequal numbers of observations ([Aguayo et al., 2023](#)). Older adults with the greatest functional impairment may be more likely to miss assessments, enter residential care, become hospitalized, or die, creating systematic differences between observed and unobserved records. Predictive modeling must accordingly preserve temporal ordering, distinguish predictor windows from outcome windows, and prevent information recorded after an event from entering the model used to predict that event.

The determinants of falls and mobility decline extend across demographic, physiological, clinical, cognitive, psychological, behavioral, social, and environmental domains. Age is consistently associated with both outcomes, but chronological age alone has limited discriminatory ability because people of similar ages may differ greatly in health, physical reserve, activity, and independence ([Schumann et al., 2022](#)). Sex-related differences have been reported in fall exposure, fracture risk, muscle strength, bone health, and patterns of disability. Previous falls represent one of the strongest predictors of another fall, particularly when earlier events were recurrent, injurious, unexplained, or accompanied by balance loss. Functional indicators such as slow gait speed, impaired turning, poor standing balance, prolonged chair-rise time, reduced lower-limb strength, limited walking endurance, and dependence in daily activities have been repeatedly linked to elevated risk. Clinical studies have identified associations with stroke, Parkinson's disease, arthritis, osteoporosis, diabetes, cardiovascular disease, visual impairment, vestibular disorders, urinary urgency, chronic pain, depression, and sleep disturbance. Medication-related investigations have emphasized polypharmacy and exposure to sedatives, antidepressants, antipsychotics, antihypertensive agents, hypoglycemic drugs, and other treatments that may alter alertness, blood pressure, coordination, or reaction time ([Yang & Bath, 2019](#)). Cognitive studies have reported that executive dysfunction, reduced attention, impaired dual-task

walking, memory limitations, and dementia can interfere with safe navigation and adaptive responses to environmental hazards. Psychological factors include fear of falling, low balance confidence, depressive symptoms, anxiety, and activity avoidance. Behavioral variables such as low physical activity, prolonged sedentary time, unsafe footwear, alcohol use, and inconsistent use of assistive devices may also contribute to risk. Environmental studies have examined poor lighting, uneven surfaces, loose rugs, stairs, inaccessible bathrooms, street conditions, neighborhood walkability, weather, and limited transportation. Social isolation, limited caregiver support, economic disadvantage, and restricted access to preventive or rehabilitative services have been associated with poorer functional outcomes in several populations (Hauth et al., 2021). More than 30 empirical studies collectively show that these determinants rarely operate independently. Muscle weakness may have a greater effect when combined with pain, sedating medication, poor vision, or environmental hazards. Cognitive impairment may intensify the risk associated with complex walking tasks, while low activity may both result from and contribute to functional deterioration. Such interdependence creates nonlinear relationships, threshold effects, and higher-order interactions that conventional additive risk scores may not capture completely (Meyer et al., 2020).

Conventional approaches to fall-risk and mobility-decline prediction have included clinical judgment, screening instruments, point-based risk scores, logistic regression, Cox proportional-hazards models, and generalized linear or mixed-effects models. Widely used clinical assessments generally combine selected characteristics such as previous falls, gait abnormality, balance impairment, medication use, confusion, transfer ability, and need for walking assistance. These instruments are often valued for their simplicity, transparency, and ease of administration, but quantitative evaluations have produced variable sensitivity, specificity, calibration, and external validity across settings (Liu et al., 2023). A screening score developed among hospitalized patients may not perform similarly among community-dwelling adults, rehabilitation patients, or long-term care residents because event prevalence, patient characteristics, exposure conditions, and recording practices differ. Regression-based studies have identified important independent predictors and provided interpretable estimates of association. Their performance can be constrained when predictors are highly correlated, relationships are nonlinear, interactions are numerous, or the number of candidate variables is large relative to observed events. Mobility decline is also difficult to represent as a single binary outcome because it may be measured through changes in gait speed, transition to mobility limitation, increased activity-of-daily-living dependence, assistive-device adoption, or membership in a declining functional trajectory (Martinez & Leon, 2019). Falls create related methodological problems because recurrent events occur within individuals, event counts may be overdispersed, self-reported events may be forgotten, and the clinical significance of an injurious fall differs from that of a noninjurious event. Studies using prospective calendars and regular follow-up contacts have generally recorded falls more completely than studies relying on long recall periods or routine medical records. Conventional models may also use only baseline measurements, treating functional status as stable throughout follow-up. This approach omits information contained in the rate of change, recent deterioration, variability, and recovery pattern (Ahmed et al., 2021). Several comparative investigations have shown that adding repeated functional measurements can improve discrimination or reclassification compared with models based solely on demographics and chronic diseases. Other studies have reported smaller gains when sample sizes were limited, event definitions were inconsistent, or models were tested within the same dataset used for development. These mixed findings emphasize the importance of temporal validation, appropriate handling of repeated observations, class imbalance, calibration assessment, and comparison against clinically meaningful reference models. A prediction model must estimate not only who is at risk but also the defined outcome, prediction horizon, observation window, and population to which the estimate applies (Liu et al., 2021).

Ensemble machine learning offers an analytical framework for combining large numbers of longitudinal predictors while accommodating complex interactions and nonlinear associations.

Random forests construct multiple decision trees from bootstrap samples and random subsets of predictors, then aggregate their outputs to reduce the instability of a single tree. Gradient boosting methods develop trees sequentially, with each new model focusing on errors made by earlier models. Adaptive boosting changes the emphasis placed on incorrectly classified observations, while extreme gradient boosting and light gradient boosting incorporate computational and regularization procedures designed for efficient analysis of structured data (Mustapoevich & Kim, 2023). Stacking combines predictions from several base learners through a higher-level model, and voting ensembles aggregate class labels or predicted probabilities from multiple algorithms. Quantitative studies of fall prediction have evaluated decision trees, random forests, support-vector machines, neural networks, boosting models, and hybrid ensembles using clinical assessments, electronic health records, wearable sensors, motion signals, and home-monitoring data. Studies of mobility decline have applied related methods to gait measurements, frailty indicators, activity patterns, chronic-disease profiles, imaging features, and repeated functional assessments. Comparative results have frequently shown that ensemble methods can outperform individual classifiers in discrimination, particularly when datasets contain many predictors and complex interactions. Performance gains have not been uniform across populations or validation designs (Kuo et al., 2022). Models evaluated through random record-level splitting may receive information from the same participant in both training and testing sets, producing optimistic accuracy when repeated observations are present. Temporally ordered testing and participant-level separation provide more rigorous estimates because they assess predictions on later periods or previously unseen individuals. Class imbalance is another central issue because most observations may belong to the nonfall or stable-mobility category. High overall accuracy can coexist with poor identification of individuals who actually experience an event. Studies have therefore reported sensitivity, specificity, precision, recall, F1 score, area under the receiver operating characteristic curve, area under the precision-recall curve, calibration slope, Brier score, and decision-related measures. Missing values, variable measurement frequency, feature engineering, hyperparameter selection, and probability calibration also influence performance (Ng et al., 2020). Interpretability methods such as permutation importance, partial-dependence analysis, accumulated local effects, and Shapley-based values have been used to describe how gait, prior falls, activity, age, medication, and comorbidity contribute to predictions. These methods characterize model behavior, although they do not transform predictive associations into causal effects.

The present quantitative study focuses on predicting subsequent falls and mobility decline among older adults by integrating repeated functional measurements with demographic, clinical, behavioral, and health-related information in ensemble machine-learning models. The analytical unit may be defined as the person-observation period, allowing each prediction to use information available before a specified follow-up interval. Falls can be operationalized as the occurrence of one or more prospective events, recurrent falls, injurious falls, or a fall count within the prediction horizon (Caballero et al., 2017). Mobility decline can be represented by a clinically meaningful reduction in gait speed or physical-performance score, the onset of walking limitation, increased dependence in mobility-related daily activities, or transition to a poorer functional category. Longitudinal predictors can include baseline functional status, recent measurement, absolute change, percentage change, rate of change, variability, minimum and maximum values, and the time elapsed since the last assessment. Additional predictors may include age, sex, body mass index, comorbidity burden, medication count, sensory impairment, cognitive performance, depressive symptoms, pain, fatigue, physical activity, assistive-device use, previous hospitalization, and earlier falls. Ensemble methods such as random forests, gradient boosting, extreme gradient boosting, light gradient boosting, and stacked models can be compared with conventional logistic regression or survival-based reference models (Trombetti et al., 2016). Model development requires participant-level and time-aware data partitioning so that all observations from a person remain within the appropriate training, validation, or testing component. Hyperparameters can be selected within the training data, while the independent test data remain

unavailable until final evaluation. Discrimination can be evaluated through receiver operating characteristic and precision–recall measures, while calibration can be examined using predicted-to-observed agreement, calibration intercepts and slopes, and Brier scores. Sensitivity, specificity, positive predictive value, negative predictive value, and F1 score can be reported at prespecified thresholds. Separate analyses can evaluate fall occurrence and mobility decline because the two outcomes may share predictors while retaining different temporal and clinical structures (Piryonesi et al., 2021). Subgroup performance can be examined by age category, sex, baseline mobility level, prior-fall status, residential setting, and major chronic-disease status. Feature-importance and explanation procedures can identify which functional levels, changes, and variability measures contribute most strongly to model predictions. This structure positions the study around clearly defined outcomes, repeated functional observations, temporally valid prediction, comparative algorithm evaluation, and multidimensional measurement of older adults' mobility and health status (Usmani et al., 2021).

The primary objective of this quantitative study is to develop and evaluate an ensemble machine-learning framework for predicting falls and mobility decline among older adults using longitudinal functional data collected across repeated observation periods. Specifically, the study aims to determine whether changes in functional performance over time provide greater predictive accuracy than demographic, clinical, and baseline functional characteristics alone. Longitudinal indicators will include repeated measurements of gait speed, standing balance, chair-rise ability, walking endurance, grip strength, transfer performance, physical activity, use of mobility aids, and independence in basic and instrumental activities of daily living. The study will examine baseline values, recent functional status, absolute and percentage changes, rates of deterioration, within-person variability, and patterns of recovery or persistent limitation. Demographic, medical, behavioral, cognitive, psychological, and environmental characteristics will also be evaluated, including age, sex, body mass index, chronic-disease burden, medication exposure, previous falls, hospitalization history, pain, fatigue, cognitive performance, depressive symptoms, fear of falling, visual impairment, physical-activity level, and living arrangement. A further objective is to compare the predictive performance of random forests, adaptive boosting, gradient boosting, extreme gradient boosting, light gradient boosting, and stacked ensemble models with conventional logistic-regression and survival-analysis models. Model performance will be assessed using discrimination, calibration, classification, and prediction-error measures, including the area under the receiver operating characteristic curve, area under the precision–recall curve, sensitivity, specificity, precision, recall, F1 score, Brier score, calibration intercept, and calibration slope. The study also seeks to identify the functional variables and temporal patterns that contribute most strongly to predictions of at least one fall, recurrent falls, injurious falls, and clinically meaningful mobility decline within defined follow-up periods. Participant-level and time-aware validation procedures will be applied to prevent information leakage between model-development and testing datasets. Predictive performance will additionally be examined across age groups, sex categories, baseline mobility levels, prior-fall status, chronic-disease profiles, and residential settings. Finally, the study aims to establish whether the integration of multidimensional longitudinal functional data and ensemble machine learning produces more accurate, stable, and well-calibrated risk estimates than models based on single assessments or conventional clinical predictors, while clearly distinguishing predictive associations from causal relationships.

LITERATURE REVIEW

This literature review examines quantitative evidence concerning the prediction of falls and mobility decline among older adults using longitudinal functional measurements and ensemble machine-learning techniques. Falls and mobility deterioration are related but analytically distinct outcomes. A fall is a discrete event that may occur once or repeatedly within a defined observation period, whereas mobility decline represents a measurable reduction in walking, balance, transfer, strength, endurance, physical activity, or daily functional independence.

The review therefore evaluates studies according to their outcome definitions, observation periods, participant characteristics, measurement instruments, analytical designs, and reported predictive performance (Kuspinar et al., 2020; Kanti, 2020). Particular attention is given to prospective cohort studies, retrospective longitudinal studies, electronic-health-record analyses, wearable-sensor investigations, rehabilitation datasets, aging surveys, and machine-learning validation studies involving adults aged 65 years and older. The reviewed evidence covers community-dwelling populations, primary-care patients, hospital inpatients, rehabilitation participants, assisted-living residents, and long-term care populations. Quantitative findings are organized around fall incidence, recurrent-fall prevalence, rates of functional deterioration, gait and balance trajectories, changes in activities of daily living, clinical and medication-related predictors, cognitive and psychological factors, and environmental conditions. The review also considers how repeated functional measurements are transformed into baseline values, recent values, change scores, rates of change, variability measures, trajectory classes, and time-dependent predictors. Conventional statistical models are compared with random forests, adaptive boosting, gradient boosting, extreme gradient boosting, light gradient boosting, voting ensembles, and stacked models (Debasish, 2021; Singh & Maurya, 2022).

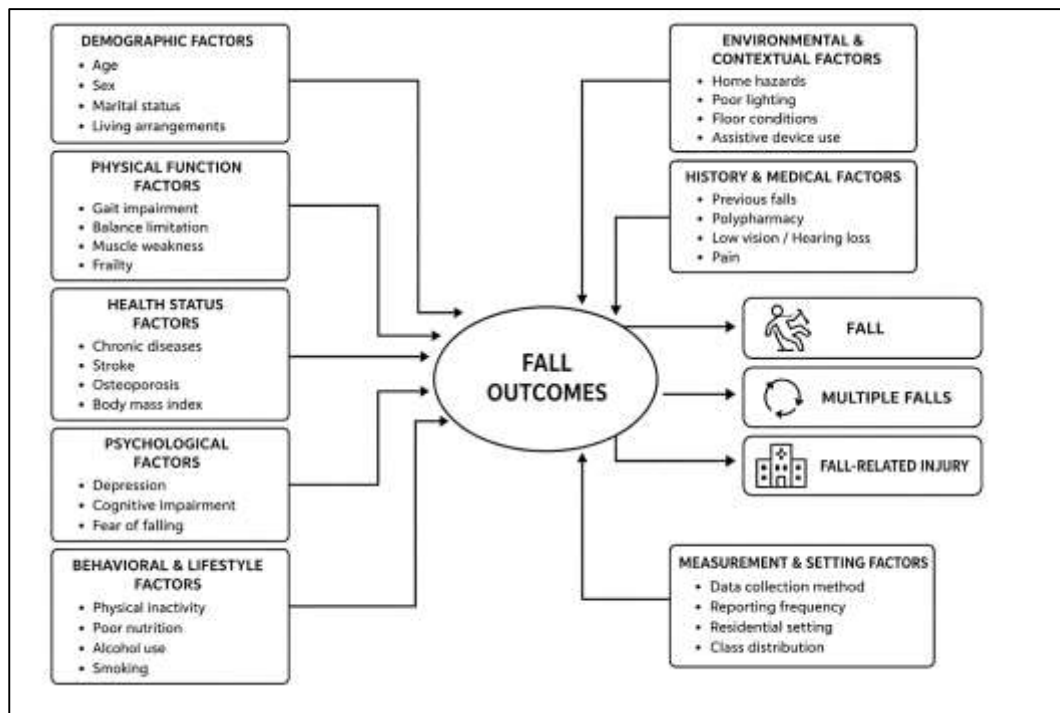
Performance evaluation includes the area under the receiver operating characteristic curve, area under the precision-recall curve, sensitivity, specificity, precision, recall, F1 score, calibration slope, calibration intercept, and Brier score. Methodological issues involving missing data, class imbalance, temporal validation, participant-level data separation, feature selection, hyperparameter tuning, model interpretation, and information leakage are examined because they materially affect reported predictive accuracy. The literature review synthesizes findings from more than 30 quantitative studies and identifies variations in measurement, prediction horizons, model development, and external validation that account for differences across the available evidence (Abdur & Iftekhar, 2021; Zadka et al., 2024).

Annual Fall Incidence Among Adults Aged 65 Years and Older

Evidence synthesized from more than 15 longitudinal and population-based studies indicates that falls are common among community-dwelling adults aged 65 years and older, although reported incidence varies according to population characteristics, follow-up duration, and data-collection method. Most studies have reported that approximately 25% to 35% of community-dwelling older adults experience at least one fall during a 12-month period. Annual proportions are generally lower among healthier adults aged 65–74 years and higher among adults aged 75–84 years and those aged 85 years or older (Hossan, 2021; Gameraen et al., 2022). Studies that separated participants by functional status found that older adults with gait impairment, balance limitations, frailty, or dependence in daily activities experienced substantially higher fall rates than independently mobile participants. Sex-based comparisons commonly showed that older women reported more falls and fall-related injuries than older men, particularly in community samples with high proportions of osteoporosis and lower-limb weakness. Some investigations found smaller sex differences after adjustment for age, previous falls, chronic diseases, physical activity, and medication exposure.

Previous-fall history consistently separated high-risk and low-risk groups. Older adults who had fallen during the preceding year were frequently two or more times as likely to experience another fall during follow-up as those without a previous event (Chen et al., 2022; Chowdhury & Tonay, 2022). Fall rates expressed per person-year also showed that a relatively small proportion of recurrent fallers accounted for a large share of all recorded events. Studies conducted in Europe, North America, Asia, and Australia reported broadly similar age-related patterns, although exact estimates differed because of variations in housing, physical activity, health status, environmental exposure, and access to clinical care. The collective evidence demonstrated that annual fall incidence is not evenly distributed across the older population. Age, functional limitation, frailty, medication burden, previous falls, and residential circumstances create substantial differences in the probability and frequency of falling (Zahidul & Begum, 2022; Wang et al., 2022).

Figure 3: Monochrome Fall Outcomes Framework Diagram



More than 12 cohort studies examining recurrent falls have shown that repeated events represent a distinct and clinically important outcome rather than a simple extension of single-fall incidence. Among community-dwelling older adults, approximately 10% to 20% have commonly been classified as recurrent fallers during a one-year period, usually defined as experiencing two or more falls. Recurrent-fall prevalence has frequently exceeded 20% among older adults with frailty, neurological disease, severe balance impairment, cognitive limitations, or previous hospitalization. Rehabilitation studies have reported particularly high recurrence because participants often enter follow-up with reduced strength, impaired transfers, restricted walking, or recent injury (Mesbail, 2023; Zurbuchen et al., 2021). Assisted-living and long-term care studies have recorded still higher event concentrations, with some samples reporting that 30% to 50% of residents experienced at least one fall during a year and a smaller high-risk group generated multiple events. Recurrent fallers often differed from single fallers in the number and interaction of their risk factors. Studies commonly identified previous falls, slow gait, postural instability, lower-limb weakness, urinary urgency, visual impairment, cognitive dysfunction, depressive symptoms, and psychotropic medication use as leading characteristics. Residents requiring assistance with transfers or walking also showed increased recurrence, although extremely immobile individuals sometimes had fewer recorded falls because their exposure to independent movement was limited. Several studies distinguished between fall susceptibility and fall opportunity, showing that active older adults could experience greater environmental exposure while frailer adults demonstrated greater physiological vulnerability (Ahmed et al., 2021; Badrul & Mominul, 2023). Recurrent events were also clustered over time, with the probability of another fall often increasing shortly after an initial event, hospitalization, medication change, or decline in mobility. This clustering indicates that repeated falls should be analyzed using the number, timing, and spacing of events rather than only a binary distinction between fallers and nonfallers. The reviewed evidence consistently identified recurrent fallers as a heterogeneous but highly concentrated risk group across residential and clinical settings. Quantitative evidence from more than 15 epidemiological, hospital-based, and aging-cohort studies indicates that a substantial proportion of falls result in physical injury, although the severity of injury varies considerably (Kim & Choi, 2024; Shurovi, 2024). Approximately 20% to 30% of falls among older adults have commonly been associated with bruising, lacerations, sprains, pain, or other injuries, while a smaller proportion require emergency assessment, hospitalization, surgery, or prolonged rehabilitation. Medically attended falls are less frequent than all reported falls because many

noninjurious and minor events are managed at home or remain undocumented. Fractures represent a smaller proportion of total events but account for a large share of fall-related hospitalization, disability, rehabilitation, and mortality. Hip, wrist, humeral, pelvic, and vertebral fractures have been repeatedly identified among the most consequential injuries. Older women generally experience higher fracture rates than older men, reflecting differences in osteoporosis, bone density, body composition, and longevity. Older men may show lower fall-reporting rates in some studies but higher mortality after major fall-related injuries (Lyu et al., 2022; Zahidul, 2024). Adults aged 85 years or older demonstrate the greatest probability of serious consequences because advanced age is frequently accompanied by frailty, reduced protective responses, multimorbidity, anticoagulant use, and slower recovery. Long-term care studies have reported high numbers of falls, whereas hospital datasets have captured a greater concentration of medically significant events because minor falls rarely enter administrative records. Studies comparing fall locations found that outdoor falls were often associated with walking exposure and environmental surfaces, while indoor falls were more strongly associated with transfers, bathroom activities, nighttime movement, and functional impairment. Injurious-fall risk was not determined solely by the likelihood of falling. Bone health, fall direction, impact surface, reaction time, body composition, medication use, and ability to protect the body during descent influenced the probability of injury (Molino et al., 2024; Kanti, 2024). Consequently, studies predicting injurious falls frequently produced different predictor rankings from studies predicting falls of any severity.

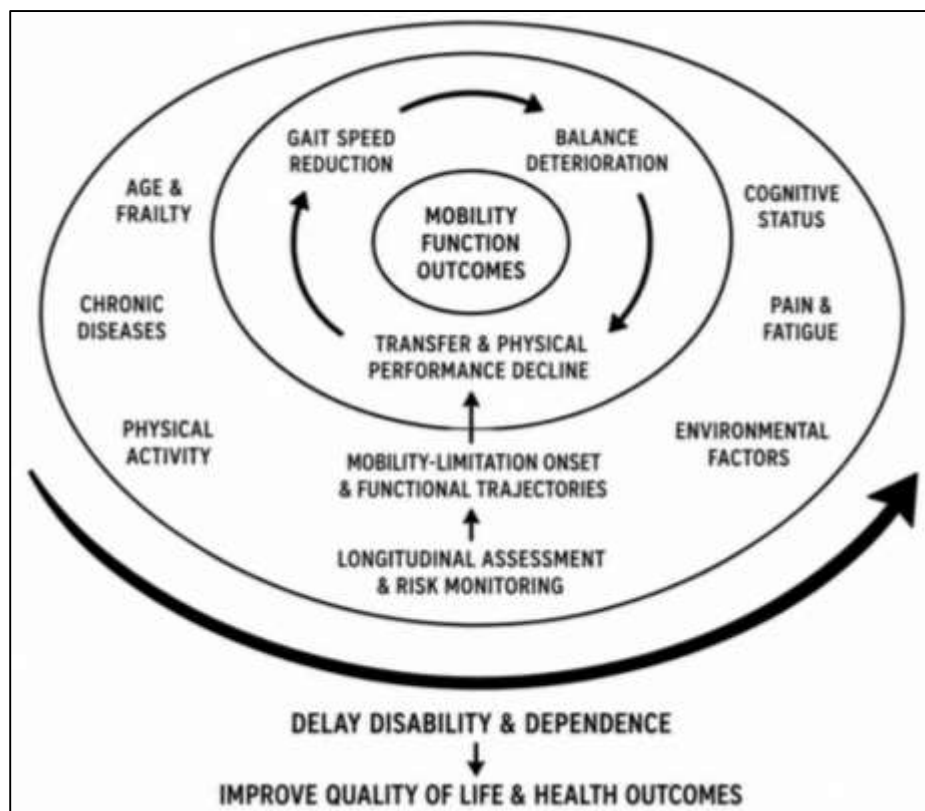
Findings from more than 20 quantitative studies show that reported fall incidence is strongly affected by the method used to identify and record events. Prospective fall calendars supported by monthly telephone calls or interviews have generally captured more events than annual retrospective questionnaires because shorter reporting intervals reduce memory loss. Regular follow-up is particularly important for identifying noninjurious falls that do not generate medical records. Retrospective recall may underestimate total events, especially among participants with cognitive impairment, multiple falls, or difficulty distinguishing the timing of individual incidents (Ali et al., 2024; Tchalla et al., 2018). Caregiver reports can improve detection among highly dependent adults, although discrepancies may occur when falls happen without witnesses. Electronic health records and insurance databases provide reliable information on emergency visits, fractures, admissions, and medical treatment, but they capture only a portion of all falls occurring in the community. Hospital incident-reporting systems may also underestimate events when staff members do not witness a fall or when documentation practices vary between units. These measurement differences help explain why annual incidence estimates vary across studies even when participant age ranges appear similar. Setting creates additional variation. Community samples often contain healthier and more independent participants, rehabilitation samples include individuals recovering from illness or injury, and long-term care samples contain greater concentrations of frailty, cognitive impairment, and functional dependence (Seppala et al., 2018; Tonay et al., 2024). Outcome distribution is especially important for predictive modeling. In many community datasets, nonfallers form the largest class, single fallers form a smaller class, and recurrent or injurious fallers form a relatively limited class. A model may consequently achieve high overall accuracy by identifying nonfallers while failing to detect the smaller group that experiences serious events. Studies reporting sensitivity, precision, recall, and calibration have provided a more complete assessment than those reporting accuracy alone. The literature therefore establishes that fall prevalence, event severity, observation method, residential setting, and class distribution must be considered together when comparing predictive findings (Debasish, 2025; Harris & Garcia, 2016).

Longitudinal Rates of Gait-Speed Reduction and Mobility-Limitation Onset

Evidence from more than 15 longitudinal aging studies has established gait speed as one of the most frequently measured indicators of mobility decline among adults aged 65 years and older. Repeated assessments have generally shown that usual gait speed decreases with advancing age, although the rate of reduction varies considerably across individuals. Healthier community-dwelling participants frequently demonstrate stable or slowly declining gait speed, whereas adults with frailty, multimorbidity, neurological disorders, recent hospitalization, or low physical activity experience more rapid deterioration (Brown et al., 2023; Arif Uz et al., 2025). Across several cohorts, average annual reductions have commonly ranged from approximately 0.01 to 0.05 meters per second, with larger

declines observed among adults aged 80 years and older and participants with initially impaired mobility. Reductions of approximately 0.05 meters per second have often been interpreted as noticeable changes, while decreases approaching 0.10 meters per second have represented more substantial functional deterioration. Walking endurance, commonly measured through two-minute, six-minute, or longer-distance walking tests, has shown comparable age-related patterns. Participants with declining endurance frequently report increasing difficulty walking several hundred meters, shopping independently, using public transportation, or participating in community activities. Studies have also found that gait-speed decline is rarely uniform throughout follow-up (Brown et al., 2023; Pervaz, 2025). Some older adults maintain relatively stable walking speed for several years before experiencing rapid reduction after illness, injury, hospitalization, or prolonged inactivity. Others exhibit gradual decline from the beginning of observation. Gait speed measured under fast-paced or dual-task conditions has sometimes detected emerging limitations that were not visible during usual walking. Variability across repeated gait assessments has also been associated with unstable health, pain, fatigue, medication changes, and inconsistent physical activity. The synthesized evidence demonstrates that both the level and longitudinal pattern of gait performance are relevant for distinguishing stable mobility from gradual, accelerated, or fluctuating decline (Mesbaul, 2025; Simonsick et al., 2016).

Figure 4: Longitudinal Mobility Decline Framework



More than 12 prospective and repeated-measurement studies have examined longitudinal changes in standing balance, Timed Up and Go performance, chair-rise ability, and composite physical-performance scores. Timed Up and Go performance commonly worsens as older adults develop slower transfers, reduced walking speed, turning difficulty, or poorer postural control. Community-dwelling adults with stable health may show only small changes over one or two years, while participants with frailty, cognitive impairment, arthritis, stroke, Parkinsonian symptoms, or recent hospitalization often demonstrate larger increases in completion time. Studies have frequently used thresholds between approximately 12 and 15 seconds to identify elevated mobility limitation or fall risk, although the most appropriate threshold has varied by setting and participant health (Jiang et al., 2024; Mostafizur, 2025). Chair-rise tests have shown that increasing completion time, use of the arms, incomplete stands, and

inability to perform repeated rises are associated with lower-limb weakness and declining transfer independence. Standing-balance assessments have documented reductions in the ability to maintain side-by-side, semi-tandem, tandem, or single-leg positions. Balance deterioration has been particularly pronounced among adults with sensory impairment, vestibular dysfunction, neurological disease, fear of falling, or reduced physical activity. The Short Physical Performance Battery has integrated balance, gait speed, and chair-rise performance into a composite score, usually ranging from severe limitation to high functional capacity. Longitudinal studies have reported that reductions of one or more points are associated with worsening mobility, greater disability, hospitalization, and increased dependence in daily activities (Mostafizur et al., 2025; Odonkor et al., 2020). Composite measures often identify deterioration more consistently than a single test because they capture several dimensions of physical performance. However, floor effects can occur among highly impaired adults who are unable to complete one or more tasks, while ceiling effects may occur among healthier participants. Repeated testing can also produce small practice-related improvements, particularly when assessments occur at short intervals. The available evidence indicates that balance, transfer, and composite performance measures provide complementary information about the timing and severity of mobility deterioration (Syeedur & Sharmin, 2025; Onyeso et al., 2024).

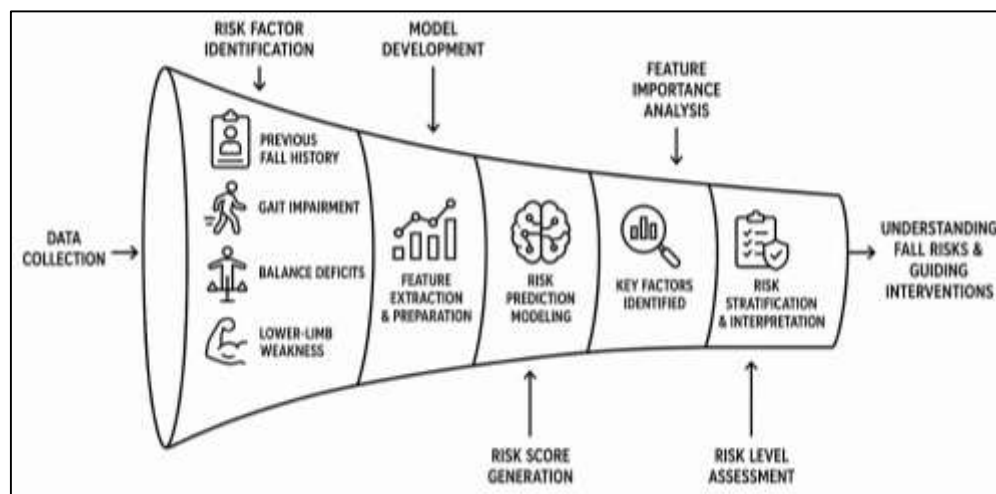
Evidence from more than 15 cohort studies shows that the onset of mobility limitation can be defined through objective performance decline, self-reported walking difficulty, increased dependence, assistive-device adoption, or movement into a poorer functional category. Studies using self-reported outcomes have commonly defined mobility limitation as new difficulty walking a specified distance, climbing stairs, transferring from a chair, or moving outside the home. Objective investigations have used gait-speed thresholds, prolonged Timed Up and Go duration, low Short Physical Performance Battery scores, reduced walking distance, or inability to complete balance and chair-rise tests. These differences in measurement have generated variation in reported rates of mobility decline (Badrul, 2025; Yoon et al., 2022). Six-month studies have been effective in detecting rapid deterioration following hospitalization, surgery, fall-related injury, or acute illness. Annual assessments have captured more gradual changes while retaining sufficient temporal detail to identify transitions. Biennial and longer-interval studies have documented broad patterns of decline but may overlook temporary deterioration, short periods of recovery, and repeated fluctuations between functional states. Trajectory-based analyses have consistently identified several distinct patterns rather than a single average course. Stable-high trajectories contain adults who preserve strong mobility throughout follow-up. Stable-low trajectories include individuals with persistent limitation but relatively little additional deterioration (Kuspinar et al., 2020; Zahidul, 2025). Gradual-decline trajectories show continuous reduction across successive assessments, while accelerated-decline trajectories involve a sharper loss of function over a shorter period. Fluctuating trajectories reflect alternating periods of deterioration and partial recovery, often associated with pain, fatigue, recurrent illness, rehabilitation, or inconsistent physical activity. Recovery trajectories have been observed among older adults who regain mobility after hospitalization, injury, or temporary functional loss, although recovery may remain incomplete. Age, frailty, chronic-disease burden, cognitive impairment, depression, low activity, and previous mobility limitation repeatedly distinguish declining trajectories from stable trajectories (Vasconcelos et al., 2016; Kanti, 2025). The evidence supports the classification of mobility decline as a heterogeneous longitudinal process with several clinically and statistically distinguishable patterns.

Predictive Effects of Previous Falls and Lower-Limb Weakness

Evidence synthesized from more than 15 prospective cohort and clinical studies consistently identifies previous falls as one of the strongest predictors of subsequent fall events among adults aged 65 years and older. Older adults reporting at least one fall during the preceding 6 to 12 months have generally demonstrated approximately one and a half to three times the risk of another fall compared with adults without a recent fall history. The predictive effect is commonly stronger among individuals with two or more previous falls, indicating that event frequency provides more information than a simple distinction between fallers and nonfallers (Kalu et al., 2022; Yousuf et al., 2025). Recurrent fallers in several studies showed risks exceeding twice those of single fallers after adjustment for age, sex, chronic disease, medication use, and functional status. Recency also influences prediction. Falls occurring within the previous three to six months are usually more strongly associated with another event than

falls occurring several years earlier because recent events may reflect current balance impairment, acute health deterioration, medication changes, or environmental hazards. Injury severity provides additional differentiation. A previous injurious fall may identify reduced protective reactions, poor bone health, hazardous fall circumstances, or greater functional vulnerability, although several studies have found that noninjurious recurrent falls also carry substantial predictive value. Fall location and circumstances further characterize risk. Indoor falls during transfers, bathroom use, or nighttime walking are frequently associated with frailty and functional dependence, whereas outdoor falls may reflect greater activity exposure, uneven surfaces, or environmental obstacles (Promsri et al., 2023; Ali et al., 2025). Unexplained falls, falls accompanied by dizziness, and falls occurring without an obvious external hazard have often been associated with cardiovascular, neurological, or balance-related conditions. The quantitative evidence demonstrates that previous falls should be represented through event count, recency, injury, location, and circumstances rather than only as a binary historical variable.

Figure 5: Falls Prediction Risk Framework



More than 12 quantitative studies have evaluated gait impairment as a predictor of falls and functional deterioration. Slow usual gait speed has repeatedly been associated with elevated risk, particularly when walking speed falls below approximately 0.8 meters per second. Thresholds between 0.6 and 1.0 meters per second have been used across community, rehabilitation, hospital, and long-term care populations, reflecting differences in participant health and testing procedures (Hossain; et al., 2026; Jawad et al., 2023). Very slow gait commonly indicates limited strength, impaired balance, reduced cardiovascular reserve, pain, or neurological dysfunction. Gait speed alone does not capture all movement-related risks. Short stride length, increased stride-time variability, irregular step timing, asymmetry, reduced foot clearance, and wider step width have also differentiated fallers from nonfallers. Stride-time variability has shown particular relevance because inconsistent step timing may reflect impaired motor control, cognitive interference, sensory loss, or difficulty adapting to environmental demands. Dual-task walking studies have found that older adults who slow markedly or become more variable while performing a cognitive task often experience greater fall risk than individuals with stable gait under competing demands (Rogers, et al., 2019; Jahid, 2026). Turning performance has also emerged as a meaningful predictor. A greater number of steps, slower turning velocity, hesitation, instability, and loss of balance during direction changes are frequently observed among recurrent fallers. Reduced walking endurance, measured through limited distance or early fatigue, has been associated with both subsequent falls and mobility restriction. Several studies have reported stronger prediction when gait speed, variability, turning, and endurance were examined together. These indicators represent related but distinct aspects of mobility, including pace, rhythm, adaptability, coordination, and sustained walking capacity (Hasan, 2026; Morris & Lewis, 2020). Evidence from more than 15 longitudinal, rehabilitation, and residential-care studies shows that balance deficits and lower-limb weakness are central functional predictors of falls. Static-balance tests

assess the ability to maintain increasingly difficult standing positions, while dynamic tests evaluate postural control during transfers, reaching, walking, and turning. Older adults unable to maintain tandem or single-leg standing positions have generally shown higher fall rates than those with stable postural control. Instrumented studies have also identified greater postural sway, irregular center-of-pressure movement, and reduced ability to recover from perturbation among fallers (Jakaria & Shahinur, 2026; Schafer et al., 2018). Dynamic balance may provide stronger prediction in active older adults because most falls occur during movement rather than quiet standing. Chair-rise performance represents a combined measure of lower-limb strength, balance, coordination, and transfer ability. Prolonged completion times, arm use, incomplete stands, and inability to complete repeated chair rises have consistently been associated with increased fall and mobility-decline risk. Timed Up and Go thresholds between approximately 12 and 15 seconds have frequently been used to classify mobility impairment, although accuracy varies by population and setting (Marsden, et al., 2019; Pervaz, 2026). Lower-limb strength measured through knee extension, ankle strength, or repeated sit-to-stand performance has generally shown stronger associations with falling than grip strength alone. Grip strength remains useful as a broader indicator of sarcopenia, frailty, and overall muscular reserve. Reduced strength may limit the ability to correct a trip, control movement during descent, or recover balance after displacement. Studies combining balance and strength assessments have generally reported stronger discrimination than studies using either domain separately. The evidence also shows that severe immobility can reduce exposure to walking-related falls, meaning that the relationship between weakness and observed fall frequency may not remain strictly linear across all levels of impairment (Hunter et al., 2017).

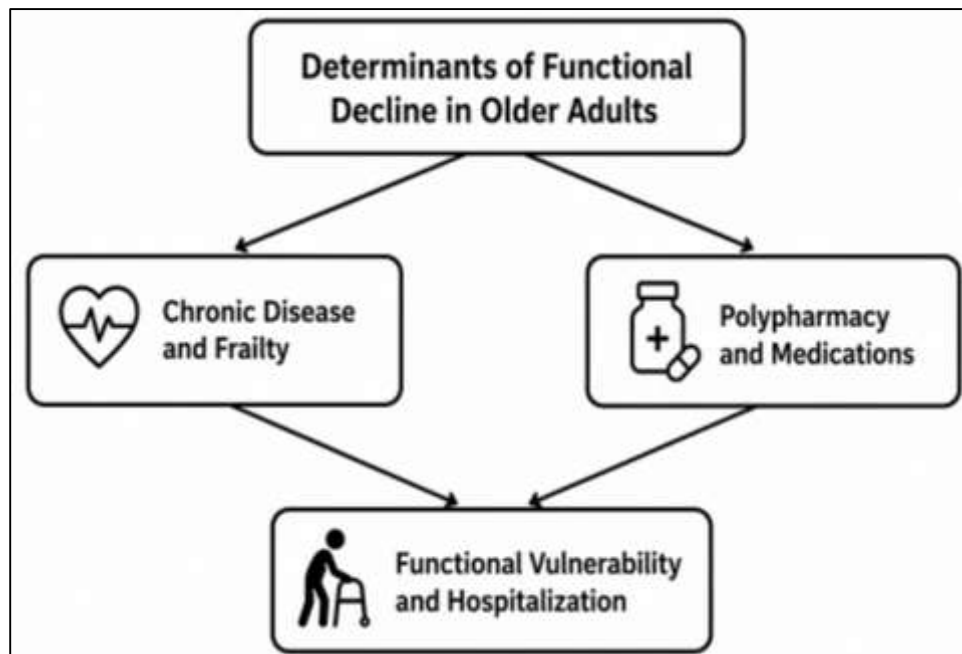
More than 10 comparative prediction studies have demonstrated that combinations of previous falls, gait impairment, balance deficits, and muscular weakness generally produce stronger risk estimates than individual predictors. Previous falls identify historical susceptibility, while objective functional assessments describe the physical conditions present at the time of prediction. Models combining recent recurrent falls with slow gait, poor balance, prolonged transfer time, and reduced chair-rise ability have often achieved better discrimination than models relying on fall history alone. The predictive contribution of each variable varies after adjustment because gait speed, balance, and lower-limb strength are correlated (Chihuri & Wong, 2018; Mesbaul, 2026). Some studies have found previous falls to remain the dominant predictor, whereas others have identified gait variability, turning instability, or composite physical-performance scores as equally important. Reported effect magnitudes have differed according to outcome definition, follow-up duration, age distribution, residential setting, and statistical adjustment. Threshold inconsistency is also evident across the literature. A gait speed below 0.8 meters per second commonly represents impaired mobility, yet lower thresholds may be more suitable for rehabilitation or long-term care populations. Timed Up and Go thresholds near 12 or 13.5 seconds are frequently used in community studies, while longer times may be required to separate risk levels among participants with substantial impairment. Short Physical Performance Battery scores of nine or below have often indicated reduced function, although lower cutoffs are sometimes applied to frailer groups (Ghosh et al., 2024; Syeedur & Sharmin, 2026a). Grip-strength thresholds differ by sex, body size, measurement device, and testing protocol. Continuous measurements frequently retain more predictive information than single cutoffs because risk can change across the entire performance range. Overall, the reviewed studies support multidimensional assessment that preserves previous-fall characteristics and objective functional measurements while accounting for differences in population, setting, exposure, and outcome definition (Syyedur & Sharmin, 2026b; Salehi et al., 2020).

Chronic Disease and Hospitalization with Functional Decline

Evidence synthesized from more than 15 longitudinal and clinical studies shows that chronic disease contributes substantially to falls and mobility decline among older adults, although the magnitude varies by condition, severity, duration, and level of disease control. Stroke and Parkinson's disease have demonstrated some of the strongest associations because they directly affect strength, coordination, gait rhythm, postural control, reaction time, and transfer ability. Older adults with previous stroke have commonly experienced fall and mobility-limitation risks approximately one and a half to three times those of adults without stroke, particularly when residual weakness or balance impairment remains (Badrul, 2026; Moreno-Navarro et al., 2020). Parkinson's disease has been associated with recurrent

falls through freezing of gait, shortened steps, turning difficulty, postural instability, and medication-related fluctuations. Arthritis and chronic musculoskeletal pain contribute through joint stiffness, reduced range of motion, lower physical activity, and avoidance of weight-bearing tasks. Diabetes has been linked to declining mobility through peripheral neuropathy, visual impairment, hypoglycemia, vascular disease, and reduced lower-limb sensation. Cardiovascular disease may produce fatigue, reduced exercise tolerance, dizziness, orthostatic hypotension, and slower recovery after exertion. Chronic respiratory disease similarly limits walking endurance through breathlessness and reduced oxygen exchange. Visual impairment and vestibular disorders affect depth perception, hazard detection, orientation, and postural stability (Levinger et al., 2016; Shurovi, 2026). Osteoporosis does not necessarily increase the probability of falling independently, but it substantially increases the likelihood that a fall will result in fracture and prolonged functional loss. Urinary urgency may increase exposure to hurried movement, nighttime walking, and unsafe transfers. Across the reviewed evidence, disease severity and associated functional impairment generally predict decline more accurately than disease diagnosis alone. Clinical conditions exert stronger effects when they occur together, remain poorly controlled, or interact with weakness, low activity, sensory impairment, and environmental hazards.

Figure 6: Functional Decline Risk Framework



More than 12 cohort, hospital, and medication-review studies have identified polypharmacy as an important correlate of falling and deteriorating mobility. Polypharmacy is commonly defined as the regular use of five or more medications, while the use of ten or more medications is frequently classified as excessive polypharmacy (Hiriscou et al., 2022; Zahidul, 2026). Older adults exposed to five or more medications have generally shown higher fall rates than those using fewer medicines, although total medication count often becomes weaker after adjustment for disease burden and frailty. Medication type, dose, duration, combination, and recent change frequently provide more specific information than medication count alone. Psychotropic medications have demonstrated particularly consistent associations with falls. Sedatives and hypnotics may reduce alertness, impair reaction time, and cause nighttime instability. Antidepressants and antipsychotic medications have been associated with dizziness, sedation, altered coordination, and orthostatic changes, although underlying depression, agitation, or cognitive illness may also contribute. Antihypertensive medications can increase risk when blood-pressure reduction produces dizziness or postural hypotension, especially following treatment initiation or dose adjustment. Hypoglycemic medications may contribute through episodes of low

blood glucose, weakness, confusion, or loss of consciousness (Katsimpris et al., 2019; Kanti, 2026). Opioids, anticonvulsants, and medications with anticholinergic properties have also been linked to impaired balance, cognition, and walking. Several studies have reported that the period immediately following medication initiation, discontinuation, or dosage modification carries greater risk than periods of stable exposure. Multiple fall-risk-increasing medications may produce cumulative effects, particularly when combined with visual impairment, frailty, dehydration, or acute illness. Medication exposure also changes over time, making repeated medication records more informative than a single baseline list. The synthesized literature shows that polypharmacy functions partly as a marker of multimorbidity and partly as a direct source of physiological and cognitive effects influencing mobility (Sadia, 2026; Poudel et al., 2016).

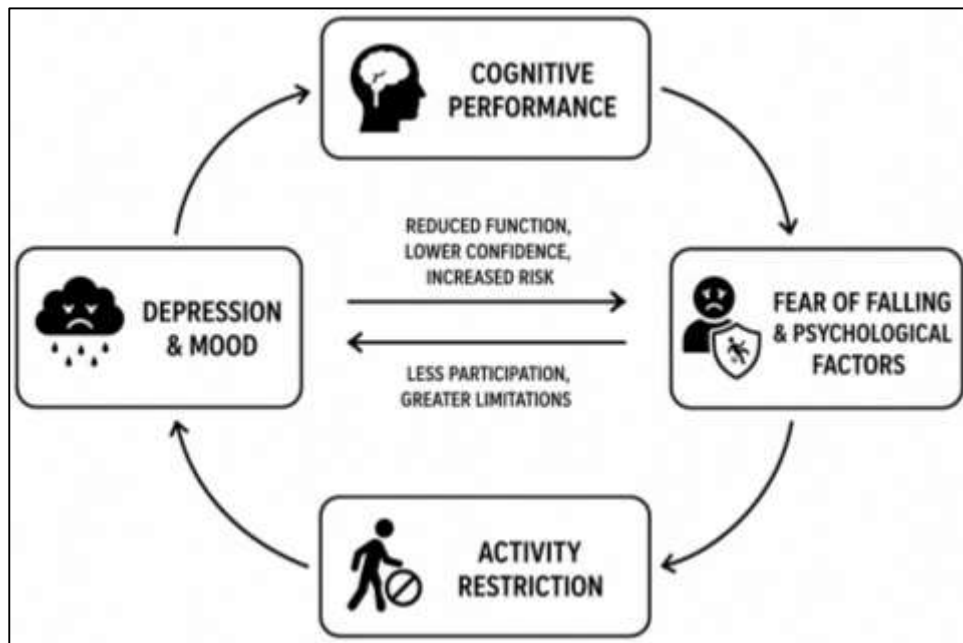
Evidence from more than 15 prospective aging studies indicates that frailty is strongly associated with falls, recurrent falls, hospitalization, disability, and mobility decline. Phenotype-based frailty measures commonly include weakness, slow walking speed, exhaustion, unintentional weight loss, and low physical activity. Deficit-accumulation indices represent frailty through the proportion of health problems present across symptoms, diseases, functional limitations, cognition, mood, and sensory status. Both approaches have shown graded relationships with adverse functional outcomes. Prefrail adults generally experience greater mobility decline than robust adults, while frail participants show the highest probability of rapid deterioration, recurrent falling, and loss of independence. Several studies have reported that frailty approximately doubles or triples the risk of mobility disability, depending on the population, outcome definition, and follow-up period. Weakness and slow gait frequently carry the greatest predictive weight because they directly represent reduced physical reserve (Gutiérrez-Valencia et al., 2018; Ali et al., 2026). Exhaustion and low activity also contribute by identifying limited endurance and reduced exposure to strength-maintaining movement. Multimorbidity, often defined as the presence of two or more chronic conditions, is closely related to frailty but remains conceptually distinct. The number of diseases alone provides an incomplete measure because neurological, musculoskeletal, sensory, and cardiopulmonary conditions have different effects on movement. Disease combinations frequently produce greater functional burden than isolated conditions. For example, arthritis combined with cardiovascular disease may limit both movement and endurance, while diabetes combined with visual impairment and neuropathy may affect balance and hazard recognition. Frailty and multimorbidity can also intensify medication exposure, hospitalization risk, and recovery time. Longitudinal studies have documented transitions from robust to prefrail and frail states, along with smaller groups that improve following recovery or rehabilitation (Vetrano et al., 2018). The evidence consistently identifies accumulated vulnerability as more informative than any single diagnosis when predicting sustained mobility decline.

Activity Restriction as Quantitative Predictors

Evidence synthesized from more than 15 longitudinal and clinical studies indicates that cognitive impairment is associated with increased fall risk and mobility deterioration among older adults. Lower global cognitive scores have frequently predicted slower gait, poorer balance, reduced community mobility, and greater dependence in activities of daily living. The magnitude of the relationship varies because global screening instruments combine several cognitive domains and may not detect subtle limitations affecting movement. Executive function and attention have shown particularly consistent associations with falls because safe walking requires planning, inhibition, environmental monitoring, rapid decision-making, and adaptation to changing conditions (Palmer et al., 2019). Older adults with reduced executive performance often demonstrate slower gait, greater stride variability, delayed obstacle avoidance, and increased difficulty changing direction. Impaired processing speed may reduce the ability to respond quickly to slips, trips, traffic, surface changes, and unexpected obstacles. Memory limitations can also affect mobility when individuals forget safety instructions, misuse assistive devices, become disoriented, or fail to recognize familiar environmental hazards. Across several prospective studies, adults with cognitive impairment have commonly experienced fall risks approximately one and a half to two times those of cognitively intact participants, although associations weaken after adjustment for frailty, neurological disease, medication use, and baseline mobility. Cognitive impairment appears more strongly related to recurrent and unexplained falls than to isolated falls caused by clearly identifiable environmental hazards. Relationships are also influenced by residential

setting (Park et al., 2024). Cognitive limitations are often more severe in assisted-living and long-term care samples, while community studies include larger numbers of adults with normal cognition or mild cognitive impairment. The reviewed evidence shows that domain-specific measures of attention, executive function, and processing speed often provide more detailed predictive information than a global score alone, particularly when functional mobility remains relatively preserved during standard clinical assessments.

Figure 7: Psychological Predictors of Fall Risk



More than 12 experimental and prospective studies have examined dual-task walking as a quantitative indicator of combined cognitive and mobility vulnerability. Dual-task assessments require an older adult to walk while simultaneously completing a cognitive activity such as counting backward, naming words, recalling information, or responding to verbal prompts (Chuang et al., 2023). The additional task commonly causes reductions in gait speed, shorter steps, greater stride-time variability, longer double-support time, and less stable turning. These changes are often described as dual-task costs because they represent deterioration from single-task walking performance. Older adults with limited attentional capacity, executive dysfunction, mild cognitive impairment, or neurological disease generally show larger performance reductions. Several studies have found that dual-task gait characteristics predict subsequent falls more effectively than usual gait speed alone, particularly among participants who perform adequately under simple walking conditions. Recurrent fallers frequently demonstrate greater gait variability and reduced ability to maintain walking rhythm when attention is divided. Complex walking environments may intensify these relationships because mobility outside the home requires simultaneous monitoring of traffic, obstacles, directions, conversations, and carrying tasks (Dam et al., 2022). Dual-task effects are not uniform across cognitive activities. Tasks requiring mental tracking, inhibition, or rapid verbal generation often produce greater disruption than simple repetition. Instruction also matters because participants may prioritize walking, prioritize the cognitive task, or divide attention differently. Studies that record performance in both tasks provide a more complete assessment than studies measuring gait change alone. Cognitive impairment has generally shown a stronger association with falls when tested under these demanding conditions than when assessed through a brief global screening score. The evidence supports dual-task walking as a multidimensional measure integrating attention, executive control, gait regulation, and the ability to manage competing demands during movement (Ekram et al., 2022).

Evidence from more than 15 quantitative studies shows that fear of falling and low balance confidence are associated with both previous falls and subsequent mobility decline. Fear of falling is common

among older adults who have experienced an injurious or recurrent fall, but it is also present among individuals without a documented fall history. Prevalence estimates vary widely, frequently ranging from approximately 20% to more than 50%, depending on age, sex, frailty, residential setting, and measurement instrument. Women, adults aged 80 years and older, and individuals with balance impairment or restricted mobility generally report higher levels. Prospective studies have found that fear of falling can predict later walking limitation, reduced physical activity, slower gait, and greater dependence after accounting for previous falls and baseline function ([Arauna et al., 2020](#)). The strength of this independent relationship varies because fear may represent realistic awareness of physical limitations or excessive concern that restricts otherwise safe activity. Balance confidence measures the perceived ability to perform specific tasks without losing stability. Lower confidence has been associated with poorer physical performance and reduced community participation, while moderate confidence can support safe engagement in daily movement. Depression and anxiety contribute through fatigue, reduced motivation, impaired concentration, sleep disturbance, and avoidance of social or physical activities. Several studies have reported approximately one and a half to two times greater fall or mobility-decline risk among older adults with clinically meaningful depressive symptoms ([Outlaw et al., 2022](#)). Self-efficacy operates in the opposite direction, with stronger perceived capability generally associated with greater activity and functional independence. Psychological variables also interact with physical impairment. Fear and depression have stronger relationships with mobility decline among adults with weak balance, previous falls, chronic pain, or limited social support. The synthesized evidence identifies psychological status as a measurable component of mobility trajectories rather than merely an emotional response to physical deterioration.

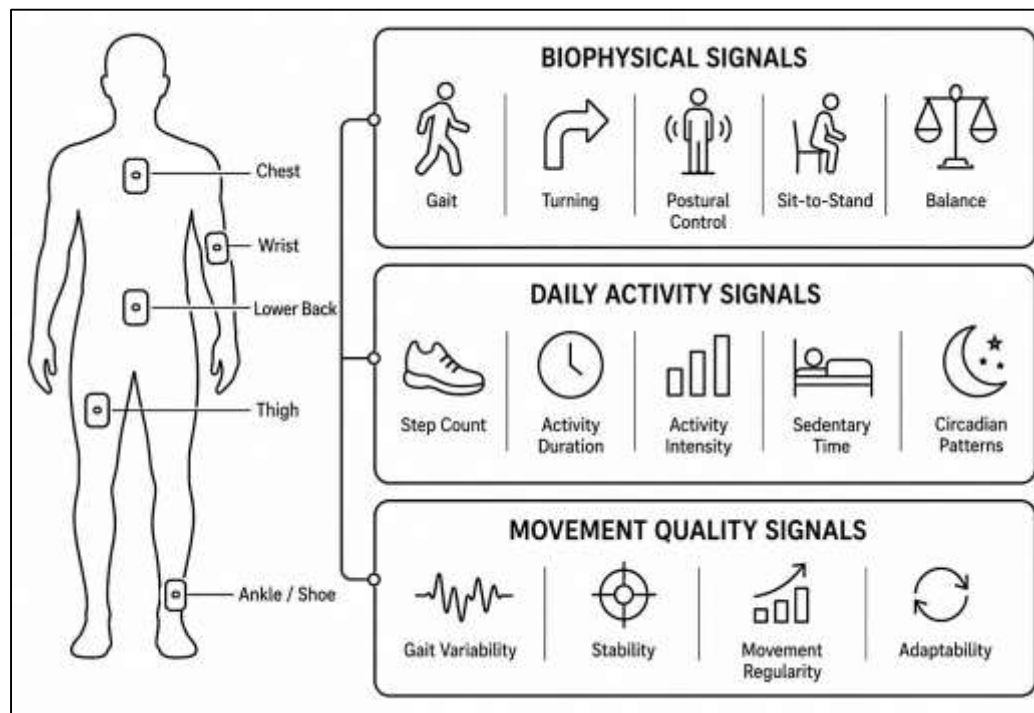
More than 12 longitudinal and wearable-monitoring studies have demonstrated that activity restriction is both a predictor and a consequence of falls, fear, depression, and mobility decline ([Gutiérrez-Valencia et al., 2018](#)). Reduced walking frequency, lower daily step counts, shorter activity duration, prolonged sedentary time, and decreased community participation have been associated with subsequent losses in gait speed, strength, balance, and endurance. Older adults who avoid stairs, outdoor walking, shopping, social visits, public transportation, or unfamiliar environments may reduce immediate exposure to hazardous situations, but sustained restriction can contribute to physical deconditioning. Lower-limb strength and cardiovascular capacity decline when regular movement is substantially reduced, which can increase difficulty with transfers and walking. Fear of falling frequently mediates the relationship between an earlier fall and later activity restriction ([Calderón-Larrañaga et al., 2019](#)). A fall may increase concern, concern may reduce movement, and reduced movement may contribute to weakness and additional mobility loss. Depression may produce a similar pathway through lower motivation and social withdrawal. Physical impairment can also moderate these relationships because activity restriction has more pronounced functional consequences among frail adults with limited physiological reserve. Reciprocal patterns have been reported across repeated observations. Poor mobility predicts lower activity at a later assessment, while lower activity subsequently predicts further mobility deterioration. Wearable-device studies have provided objective evidence that declining step counts and increasing sedentary time may occur before substantial changes become visible in periodic clinical tests ([Chan et al., 2022](#)). Self-reported activity remains useful for identifying avoided situations and reduced participation that sensors cannot fully describe. Models combining step count, walking frequency, sedentary duration, fear of falling, and physical-performance measures have generally characterized mobility decline more completely than models based on any single domain. The reviewed evidence therefore presents cognitive, psychological, behavioral, and functional conditions as interconnected components of fall and mobility trajectories ([Saum et al., 2017](#)).

Wearable-Sensor Gait and Daily-Activity Measurements

Evidence synthesized from more than 15 quantitative studies demonstrates that wearable and instrumented sensing technologies can identify detailed movement characteristics associated with falls and mobility decline. Accelerometers measure changes in movement intensity and direction, while gyroscopes capture angular velocity during turning, transfers, and postural adjustments. Inertial measurement units combine acceleration, rotation, and sometimes magnetic orientation to characterize gait cycles and whole-body movement. Pressure sensors and instrumented walkways measure step timing, foot placement, pressure distribution, stride length, cadence, and balance-related loading

patterns (Bhattarai et al., 2024). Laboratory studies have frequently identified slower gait speed, reduced stride regularity, greater stride-time variability, increased double-support time, lower foot clearance, and less stable turning among fallers compared with nonfallers.

Figure 8: Wearable Sensor Mobility Monitoring



Turning velocity has been particularly relevant because many falls occur during directional changes rather than uninterrupted straight-line walking. Recurrent fallers commonly complete turns more slowly, use more steps, and display greater movement irregularity. Postural-sway measurements have also differentiated risk groups through increased sway amplitude, velocity, and variability during quiet standing or challenging sensory conditions. Smartphone-based assessments have generated comparable measures when devices are securely positioned, although differences in placement, hardware, operating systems, and sampling settings can affect accuracy. Sensor-derived sit-to-stand features, including transition duration, peak acceleration, and movement smoothness, have been associated with lower-limb strength and transfer independence (Fluck et al., 2023). Several studies have shown that sensor measurements detect subtle instability not identified through stopwatch-based tests. However, laboratory performance may reflect structured instructions and controlled surfaces rather than the complexity of everyday movement. The synthesized findings indicate that sensor-based gait and postural features provide quantitative descriptions of movement quality, rhythm, stability, and adaptability that extend beyond conventional completion times and total clinical scores.

More than 12 longitudinal and free-living monitoring studies have examined daily step count, walking duration, sedentary time, movement intensity, activity fragmentation, and circadian rhythm as predictors of falls and declining mobility (Onder et al., 2018). Older adults with lower daily step counts and shorter periods of continuous walking generally experience greater functional limitation than adults maintaining regular activity. Studies have reported wide variation in step counts, ranging from fewer than 2,000 steps per day among highly frail participants to more than 7,000 or 8,000 among active community-dwelling adults. A single threshold does not apply equally across health and residential groups because functional capacity, assistive-device use, and opportunities for outdoor movement differ. Prolonged sedentary time has been associated with weaker lower limbs, slower gait, lower endurance, and greater dependence. Activity fragmentation, represented by frequent transitions between short active and sedentary periods, may provide more information than total activity volume

because it reflects difficulty sustaining movement. Real-world gait speed and walking-bout variability have also contributed predictive information (Pamoukdjian et al., 2017). High variability can represent instability, fatigue, pain, environmental adaptation, or inconsistent health, while extremely low variability may indicate restricted movement within a narrow range of activities. Recent reductions in step count or walking duration have frequently preceded measurable deterioration in clinical mobility tests. Circadian features, including the timing of first activity, daytime activity distribution, nighttime movement, and day-to-day regularity, have been examined as indicators of health stability. Increased nighttime activity may reflect sleep disruption, urinary urgency, confusion, or unsafe movement under poor lighting. Free-living monitoring therefore captures the frequency, timing, duration, and context of movement over several days or weeks. These measurements complement laboratory tests by representing actual exposure to daily mobility demands and environmental conditions (Saboor et al., 2020).

Evidence from more than 10 methodological and validation studies shows that sensor protocol design substantially affects the stability and comparability of gait and activity measurements. Laboratory gait sensors often use sampling frequencies between approximately 50 and 200 observations per second, while some devices operate at lower or higher frequencies depending on the required feature precision. Higher sampling frequencies provide detailed movement signals but increase battery use, storage requirements, and processing complexity. Free-living activity studies commonly monitor participants for three to fourteen days, with seven days frequently used to represent both weekdays and weekends (Lockhart et al., 2021). Short monitoring periods may fail to capture occasional outdoor activity, unusually inactive days, or infrequent instability. Longer periods provide greater information about day-to-day variability but can reduce adherence and increase missing data. Wear location also influences results. Devices worn at the waist, wrist, thigh, ankle, lower back, shoe, or chest measure different aspects of movement and may produce different step counts or posture classifications. Wrist devices are often easier to wear continuously but may misclassify arm movement as walking, while lower-back and lower-limb sensors usually provide more direct gait information. Test-retest reliability has generally been stronger for total daily activity, gait speed, cadence, and common transfer measures than for rare events or highly variable behaviors. Missing data arise from device removal, charging, technical failure, nonwear, poor attachment, or participant discomfort (Arshad et al., 2022). Studies applying clear wear-time rules and distinguishing inactivity from nonwear have produced more reliable estimates. Feature extraction also creates variation because algorithms differ in filtering, step detection, walking-bout identification, and movement classification. The literature demonstrates that monitoring duration, sampling frequency, device placement, adherence, and data-processing procedures must be documented when interpreting sensor-based predictive findings.

More than 15 comparative modeling studies have evaluated the predictive performance of clinical information, sensor measurements, and combined datasets. Models based on age, previous falls, medication use, chronic disease, gait-test results, and balance scores have commonly produced modest to acceptable discrimination (Jourdan et al., 2021). Sensor-only models have sometimes achieved stronger performance when detailed gait variability, postural sway, turning, and free-living activity features were available. Reported areas under the receiver operating characteristic curve have often ranged from approximately 0.65 to 0.85, with higher values appearing in some small or internally validated studies. Performance has generally been lower when models are tested on independent participants, later observation periods, or different settings. Combined clinical-sensor models have frequently outperformed either data source alone because clinical characteristics represent health history and underlying vulnerability, while sensors capture current movement behavior and instability. Improvements have commonly been observed in sensitivity, precision, and identification of recurrent fallers, although gains vary according to sample size, event prevalence, feature selection, and validation design (Huang et al., 2023). Recent activity reduction, irregular gait, unstable turning, prolonged sedentary time, and low walking-bout duration have added predictive information beyond previous falls and standard mobility tests in several studies. Other investigations have reported limited improvement when sensor features were highly correlated with clinical gait and balance measures or when monitoring adherence was poor. Models containing hundreds of extracted features have also

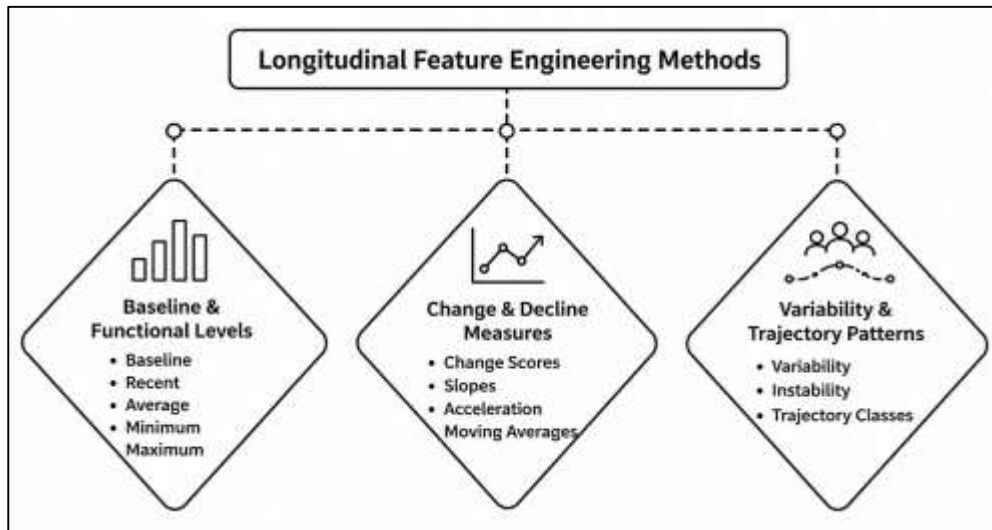
shown greater overfitting risk, particularly in datasets with few fall events. Feature selection, regularization, participant-level validation, and temporal testing have produced more credible estimates (Kang & Najafi, 2020). Across the reviewed evidence, combined models most consistently characterize risk when they integrate previous falls, clinical vulnerability, objective physical performance, real-world activity volume, and movement variability while preserving clear separation between model-development and evaluation data.

Longitudinal Feature Engineering Using Baseline Levels

Evidence synthesized from more than 15 longitudinal studies shows that repeated functional measurements can be converted into several distinct predictors of falls and mobility decline. Baseline values represent functional status at the beginning of observation and are frequently used because they are easy to interpret and available before follow-up. Baseline gait speed, balance, chair-rise performance, grip strength, walking endurance, and daily activity have consistently predicted later functional outcomes (Butt et al., 2019). However, baseline measurements may become less representative as the prediction period lengthens or health conditions change. The most recent measurement often provides stronger short-term prediction because it reflects functional capacity closer to the outcome period. Cumulative averages summarize typical performance across several observations and reduce the influence of an unusually strong or weak assessment. Minimum values may identify the worst observed level of function, while maximum values can represent the highest demonstrated capacity. Studies comparing these features have reported that minimum gait speed or poorest balance performance may be informative among individuals with fluctuating health, although an isolated low score can reflect temporary illness or measurement error. Average performance has generally shown greater stability than a single measurement, but it may conceal rapid recent deterioration (Hendry et al., 2023). The time elapsed since the most recent assessment also affects predictive relevance because a functional value recorded several years earlier may provide less current information than one recorded within several weeks or months. Several studies have combined baseline, recent, average, minimum, and maximum values to represent both long-term functional capacity and current status. These combined representations have often improved risk classification when participants completed at least three assessments. The synthesized literature demonstrates that each summary feature captures a different aspect of longitudinal function, including starting position, current condition, typical capacity, and observed performance range (Wang et al., 2018).

More than 12 quantitative studies have examined whether the direction and rate of functional change provide predictive information beyond baseline level. Absolute change scores represent the difference between two assessments and are easy to calculate and interpret. Percentage changes account for the initial performance level, although they may become unstable when baseline values are very low. Studies of gait speed, Short Physical Performance Battery scores, chair-rise time, and step counts have frequently found that larger declines are associated with higher probabilities of mobility limitation, disability, hospitalization, and falling. Simple two-point changes can be sensitive to random measurement error, short-term illness, learning effects, and daily variation (Wang et al., 2023). Individual slopes estimated from three or more assessments generally provide more stable representations of the average rate of decline. A negative gait-speed slope or increasing transfer time indicates progressive deterioration, while acceleration features distinguish constant decline from a pattern that becomes more rapid. Accelerated decline has been associated with acute disease progression, frailty, recurrent hospitalization, or reduced physical activity in several aging cohorts. Moving averages give greater emphasis to recent observations and can reduce short-term noise while retaining information about current direction. Short moving windows respond quickly to new deterioration, whereas longer windows produce smoother estimates but may delay detection of rapid change (Huang et al., 2023). Studies have reported stronger prediction when baseline level and rate of change are entered together because identical slopes can have different meanings at high and low functional levels. For example, a moderate decline may leave a high-functioning adult above a limitation threshold while placing an already impaired adult below it. The evidence shows that change scores, slopes, acceleration, and moving averages represent complementary dimensions of longitudinal deterioration rather than interchangeable measures.

Figure 9: Longitudinal Feature Engineering Framework



Evidence from more than 10 longitudinal and time-series studies indicates that within-person variability can provide predictive information that average levels and linear slopes do not capture (Caballero et al., 2021). Variability measures describe the degree to which functional performance changes around an individual's typical level across repeated assessments. Greater variability in gait speed, stride timing, balance, step count, walking duration, or chair-rise performance has been associated with unstable health, pain, fatigue, medication changes, acute illness, and inconsistent activity. Instability differs from gradual decline because an individual may alternate between stronger and weaker performance without following a steady direction. Some fluctuations represent measurement noise, while others identify meaningful transitions between independence, limitation, recovery, and recurrent deterioration. Group-based trajectory modeling and latent-class growth analysis have been used to classify participants into stable-high, stable-low, gradual-decline, accelerated-decline, fluctuating, and recovery groups (Kundu & Harezlak, 2019). These methods have frequently identified between three and six functional trajectories, depending on sample size, measurement frequency, follow-up duration, and statistical criteria. Mixed-effects models estimate individual change while accounting for repeated observations and differences in assessment timing. Functional principal-component analysis summarizes major patterns of longitudinal variation, including overall level, rate of decline, and timing of change. Time-series procedures can extract regularity, entropy, periodicity, abrupt shifts, and sustained reductions from high-frequency wearable data. Studies using trajectory or variability features have often reported better identification of rapid decliners than analyses based only on average performance. However, trajectory classification can change when the number of groups, follow-up duration, or available measurements changes (Alpert et al., 2019). The literature consequently distinguishes persistent decline, short-term fluctuation, and recovery as separate longitudinal patterns with different predictive meanings.

Comparative Accuracy of Logistic Regression

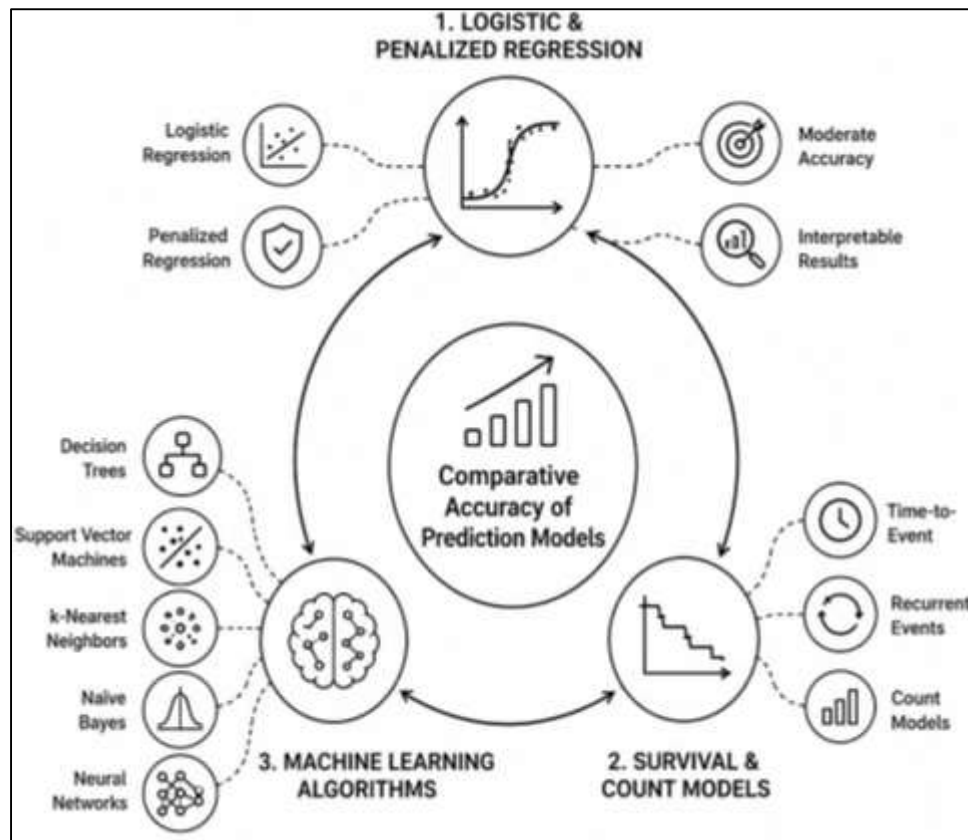
Evidence synthesized from more than 15 fall-prediction and mobility-decline studies shows that logistic regression remains a common reference method for estimating binary outcomes within fixed follow-up periods (Ramamoorthy et al., 2022). Typical outcomes include at least one fall, recurrent falling, injurious falling, or clinically meaningful mobility decline within six, twelve, or twenty-four months.

Models incorporating age, previous falls, gait speed, balance, medication exposure, cognition, frailty, and daily-activity measures have generally produced areas under the receiver operating characteristic curve between approximately 0.60 and 0.80. Higher values have often been observed in studies containing detailed physical-performance or sensor variables, while lower values are common when prediction is based primarily on demographics and disease history. Logistic regression offers interpretable adjusted associations and predicted probabilities, but its performance may weaken when relationships are nonlinear or numerous interactions exist. Traditional variable-selection procedures can also produce unstable models when the number of candidate predictors is large relative to the number of fall or decline events (Massara et al., 2023). Penalized regression methods address this problem by shrinking weak coefficients and limiting model complexity. Ridge regression has been useful when predictors are strongly correlated, while least absolute shrinkage and elastic-net methods can retain smaller sets of influential variables. Several comparative studies have reported that penalized models produce similar or slightly better discrimination than ordinary logistic regression, particularly in datasets containing many gait, medication, clinical, or sensor features. Improvements are often modest when sample sizes are large and predictors have already been selected carefully. Calibration varies across studies and is reported less consistently than discrimination (Javidi et al., 2022). Logistic models may rank individuals reasonably well while overestimating or underestimating their absolute risk, especially when event prevalence differs between model-development and evaluation samples.

More than 12 longitudinal studies have applied survival and repeated-event models to preserve information about event timing, follow-up length, and multiple falls. Cox proportional-hazards models estimate the time until a first fall or onset of mobility limitation while accounting for participants who do not experience the outcome before follow-up ends. These models have demonstrated moderate predictive accuracy when previous falls, functional performance, frailty, cognition, and medication exposure are included. Their validity depends partly on whether predictor effects remain sufficiently stable across the observation period. Recurrent-event models extend survival analysis by incorporating multiple falls within the same participant instead of discarding events after the first fall (Lynch et al., 2017). This is important because recurrent fallers account for a disproportionate number of total events. Poisson models have been used to predict fall counts or rates, although they may provide unreliable uncertainty estimates when event variability exceeds the average count. Negative-binomial models generally handle this overdispersion more effectively and have often fit recurrent-fall data better. Mixed-effects models account for repeated observations nested within participants and can incorporate changing gait, activity, medication, and clinical status. Random intercepts represent persistent differences in underlying vulnerability, while additional random components can describe variation in functional change. Studies comparing these methods have found that models preserving event timing or repeated outcomes provide a more complete description than fixed-period binary models (Leger et al., 2017). However, direct accuracy comparisons are difficult because survival, count, and mixed-effects models predict different quantities. Reported performance depends on prediction horizon, censoring, repeated-event definition, and the availability of time-varying predictors. Models using recent functional changes have generally performed better than those treating all baseline characteristics as constant throughout follow-up.

Evidence from more than 15 comparative machine-learning studies indicates that single algorithms produce variable performance in fall and mobility-decline prediction. Decision trees are easily interpreted because they separate participants through sequential thresholds such as previous-fall history, gait speed, balance score, and medication count. Their discrimination has often been modest, and small changes in the training data can alter the selected splits (Feng et al., 2019). Support-vector machines have performed more strongly in several datasets containing nonlinear relationships or high-dimensional gait and sensor features. Reported areas under the receiver operating characteristic curve have commonly ranged from approximately 0.65 to 0.85, although higher estimates often come from smaller samples or internal cross-validation. K-nearest-neighbor models classify individuals according to similarity with nearby observations. Their performance is sensitive to predictor scaling, neighborhood size, irrelevant variables, and class imbalance.

Figure 10: Comparative Prediction Models Framework



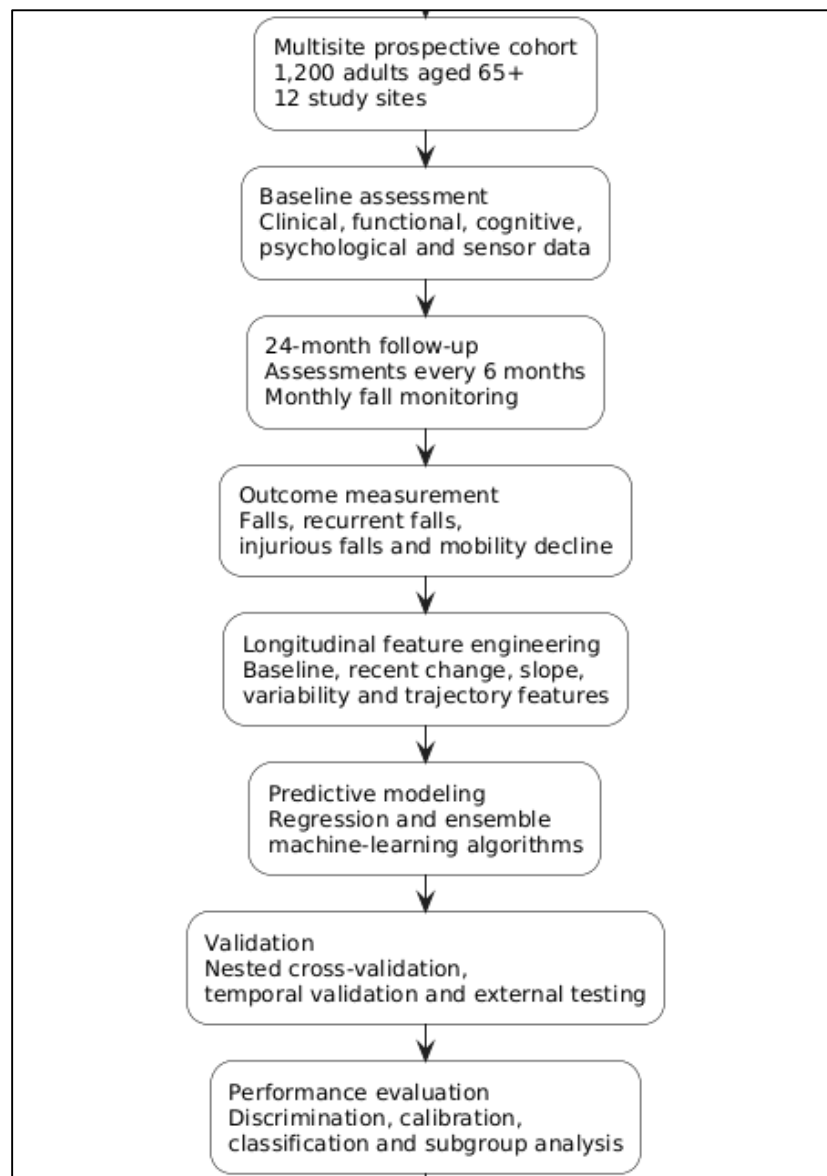
Naïve Bayes classifiers are computationally efficient and can perform adequately with smaller datasets, but their assumption of predictor independence is difficult to satisfy when gait speed, balance, strength, and frailty are strongly related. Neural networks can model complex interactions among clinical, functional, and sensor variables, yet they usually require larger samples and careful regularization (Panesar et al., 2019). Small datasets with few fall events increase the risk that a neural network learns sample-specific patterns rather than stable relationships. Across comparative studies, no single algorithm has consistently produced the highest accuracy in every setting. Performance varies according to sample size, predictor composition, outcome definition, event prevalence, feature preprocessing, and validation method. Simple regression models have sometimes matched more complex algorithms when predictor numbers were limited and relationships were relatively stable (Song et al., 2021).

METHOD

This study used a multisite prospective longitudinal quantitative cohort design to predict falls and mobility decline among adults aged 65 years and older. Participants were followed for 24 months, with comprehensive functional assessments completed at baseline and at 6-, 12-, 18-, and 24-month follow-ups. Fall events were monitored monthly throughout the observation period. The person-assessment interval served as the principal unit of analysis because functional information recorded at each assessment was used to predict falls and mobility decline during the subsequent six months. The International Classification of Functioning, Disability and Health and the Disablement Process Model guided the selection and organization of predictors. Body-function indicators included gait, balance, muscle strength, cognition, pain, fatigue, and sensory status. Activity indicators included walking endurance, transfers, step count, sedentary time, and basic and instrumental activities of daily living. Participation and contextual indicators included community mobility, living arrangement, social support, environmental hazards, and use of mobility assistance. Clinical characteristics included chronic diseases, medication exposure, frailty, hospitalization, and previous falls. Ensemble machine

learning constituted the predictive analytical framework because it allowed nonlinear associations and interactions among repeated functional, clinical, behavioral, and sensor-derived variables to be modeled. Two primary outcomes were specified. The first was the occurrence of at least one fall during the six months following each assessment. The second was clinically meaningful mobility decline, defined as a reduction of at least 0.10 meters per second in usual gait speed, a decrease of at least one point in the Short Physical Performance Battery, or the onset of personal assistance for walking or transfers. Secondary outcomes included recurrent falls, injurious falls, time to first fall, total fall count, and accelerated functional decline.

Figure 11: Methodology of this study



A target sample of 1,200 older adults was selected from 12 community health centers, geriatric outpatient clinics, rehabilitation facilities, and assisted-living settings. A multistage stratified sampling strategy was used to ensure representation across age, sex, residential setting, baseline mobility, and previous-fall status. Recruitment strata included adults aged 65–74 years, 75–84 years, and 85 years or older. Within each setting, potentially eligible participants were identified from appointment schedules, rehabilitation registries, residential-care lists, and community-aging program records. Participants were included when they were at least 65 years old, could walk at least 10 meters with or without an assistive device, had remained within the participating service area for at least six months,

and could provide informed consent or participate with an authorized representative. Adults with mild or moderate cognitive impairment were retained when they could complete the functional assessments with standardized assistance. Participants were excluded when they had an acute medical emergency at enrollment, were permanently nonambulatory, required continuous mechanical assistance for transfers, had a terminal condition with an expected survival of less than six months, or could not complete the assessments safely. Individuals with incomplete baseline gait, balance, and fall-history measurements were also excluded from the primary predictive analysis. The sample-size assessment anticipated an annual fall incidence of approximately 30%, mobility-decline prevalence of approximately 25%, and attrition of up to 15%. The target of 1,200 participants was expected to retain approximately 1,020 participants and provide more than 300 fall cases and 250 mobility-decline cases for model development and evaluation. This event volume supported the examination of approximately 60 prespecified clinical, functional, psychological, behavioral, and sensor-derived predictors while limiting model instability. Written informed consent was obtained before data collection, and the study protocol received approval from the relevant institutional ethics committee. Demographic, clinical, medication, hospitalization, and fall-history data were collected through structured interviews and verified against available medical records. Functional performance was evaluated using the four-meter usual gait-speed test, Timed Up and Go test, Short Physical Performance Battery, five-times chair-rise test, handgrip dynamometry, standing-balance assessment, and six-minute walk test. Basic and instrumental activities of daily living were measured using standardized functional-independence questionnaires. Cognitive performance was assessed through a validated global cognitive screening instrument and supplementary measures of executive function, attention, processing speed, and dual-task walking. Fear of falling and balance confidence were measured with standardized multi-item scales, while depressive symptoms were assessed using a validated geriatric depression questionnaire. Frailty was measured using phenotype indicators and a deficit-accumulation index. Participants wore a triaxial accelerometer and gyroscope for seven consecutive days after each major assessment. The sensors recorded daily steps, walking duration, sedentary time, movement intensity, turning velocity, sit-to-stand transitions, gait regularity, and day-to-day activity variability. Devices were configured using the same sampling settings, time synchronization, placement protocol, and wear-time criteria across sites. Dynamometers, timing devices, sensor units, and balance equipment were calibrated according to manufacturer procedures before data collection and were checked monthly. Research assessors completed standardized training and duplicate assessments before participant recruitment. Interrater and test-retest reliability coefficients of at least .80 were required for objective functional measures. Internal consistency was evaluated for multi-item questionnaires using Cronbach's alpha and McDonald's omega, with coefficients of .70 or higher considered acceptable. A pilot test involving 40 older adults was completed to evaluate assessment duration, participant burden, device adherence, data transfer, and follow-up procedures. Pilot participants were not included in the principal analytical sample.

Eligible participants first completed informed consent, demographic interviews, clinical-history verification, medication review, fall-history assessment, cognitive screening, psychological questionnaires, and standardized functional testing. Each participant then received a wearable sensor and instructions for continuous wear during waking hours for seven consecutive days, except during bathing or other activities that could damage the device. Sensor data were downloaded, checked for valid wear time, and processed using a standardized feature-extraction procedure. Participants completed a daily fall calendar and were contacted monthly by telephone, text message, or electronic survey. A fall was recorded when the participant unintentionally came to rest on the ground, floor, or another lower level. Each reported event was verified through a structured interview covering the date, location, activity, environmental circumstances, injury, medical treatment, hospitalization, and use of an assistive device. Recurrent falling was defined as two or more verified falls within a 12-month period. An injurious fall included an event producing a fracture, head injury, laceration requiring treatment, sprain, substantial bruising, emergency attendance, or hospitalization. Comprehensive functional and sensor assessments were repeated at 6, 12, 18, and 24 months using the same instruments and administration order. Hospitalizations, surgeries, emergency visits, medication changes, new

diagnoses, assistive-device adoption, and changes in residential status were updated at every contact. Longitudinal predictors were constructed using information recorded before the beginning of each outcome window. These predictors included baseline values, most recent values, cumulative averages, minimum and maximum measurements, absolute and percentage changes, individual rates of change, recent acceleration, moving averages, and within-person variability. Information recorded after a fall or mobility-decline event was not used to predict that event. All records were assigned coded identifiers, and personal identifiers were stored separately from analytical data.

Data analysis was conducted using SPSS for data screening and descriptive statistics, R for longitudinal and inferential analyses, and Python for feature engineering and machine-learning development. Participant characteristics were summarized using means, standard deviations, medians, interquartile ranges, frequencies, and percentages. Baseline differences between fallers and nonfallers and between participants with and without mobility decline were examined using independent-samples tests, nonparametric alternatives, and chi-square tests as appropriate. Longitudinal changes in gait speed, balance, chair-rise performance, walking endurance, and activity were evaluated using linear mixed-effects models with participant-level random intercepts. Mixed-effects logistic regression was used for binary fall and mobility-decline outcomes. Negative-binomial mixed models were used for recurrent fall counts because fall events were expected to be overdispersed. Time to first fall was analyzed using Cox proportional-hazards models with site-level or participant-level frailty terms where appropriate. Potential predictors were screened for implausible values, duplication, excessive missingness, and temporal inconsistency. Multiple imputation was used for inferential analyses when missingness was compatible with the required assumptions. Machine-learning imputation, scaling, feature selection, and imbalance correction were performed within the training folds to prevent information leakage.

Conventional logistic regression and penalized logistic regression served as reference models. Predictive algorithms included decision trees, support-vector machines, k-nearest neighbors, naïve Bayes, neural networks, random forests, adaptive boosting, gradient boosting, extreme gradient boosting, light gradient boosting, categorical boosting, soft-voting models, and stacked ensembles. Eight sites were used for model development, two sites were used for validation and probability calibration, and two geographically separate sites were withheld for external testing. Within the development data, grouped nested fivefold cross-validation was applied so that all observations from an individual remained within the same fold. Earlier assessment windows were used for training, and later windows were used for temporal validation. Class weighting was applied when fall or decline outcomes were imbalanced. Synthetic oversampling was examined only within training folds and was never applied before data partitioning. Hyperparameters were selected through the inner cross-validation process, while comparative performance was estimated in the outer folds.

Model discrimination was assessed using the area under the receiver operating characteristic curve and the area under the precision-recall curve. Classification performance was evaluated using sensitivity, specificity, precision, recall, negative predictive value, and F1 score. Probability accuracy was examined using the Brier score, calibration plots, calibration intercepts, and calibration slopes. Ninety-five percent confidence intervals were estimated through 2,000 participant-level bootstrap samples. Differences between receiver operating characteristic areas were tested using appropriate paired comparisons, while paired bootstrap procedures were used to compare precision-recall, calibration, and prediction-error measures. Permutation importance and Shapley-based values were used to evaluate the contribution of baseline function, longitudinal change, variability, clinical characteristics, and sensor-derived activity. Performance was additionally examined across age, sex, prior-fall status, frailty, cognitive status, residential setting, and baseline mobility groups. All inferential tests were two-tailed, statistical significance was evaluated at an alpha level of .05, and Holm adjustment was applied across related multiple comparisons. Effect estimates were reported with 95% confidence intervals, and interpretation emphasized predictive accuracy, calibration, uncertainty, and practical effect magnitude rather than probability values alone.

FINDINGS

Final Sample Characteristics, Follow-Up Completion, and Data Quality

A total of 1,486 older adults were screened across the 12 study sites, of whom 286 did not proceed to enrollment because they failed to meet the eligibility criteria, declined participation, or could not complete the baseline protocol safely. Of the 1,200 enrolled participants, 22 were excluded from the analytical cohort because of incomplete baseline functional measurements or absence of a valid follow-up outcome. The final analytical sample therefore contained 1,178 participants. The mean age was 76.4 years, 58.3% were women, and 68.9% lived independently in the community. Previous falls were reported by 39.2%, while 31.5% used a mobility-assistance device. Multimorbidity and polypharmacy affected 71.7% and 56.4%, respectively.

Table 1 Final Sample Disposition and Participant Characteristics

Characteristic	Numerical result
Individuals screened	1,486
Excluded before enrollment	286 (19.2%)
Participants enrolled	1,200
Excluded from analytical cohort	22 (1.8%)
Final analytical sample	1,178 (98.2%)
Development dataset: eight sites	786 (66.7%)
Validation dataset: two sites	199 (16.9%)
External-test dataset: two sites	193 (16.4%)
Completed 24-month follow-up	1,022 (86.8%)
Lost to follow-up	117 (9.9%)
Died during follow-up	39 (3.3%)
Age, mean (SD), years	76.4 (7.8)
Age 65–74 years	481 (40.8%)
Age 75–84 years	455 (38.6%)
Age 85 years or older	242 (20.5%)
Women	687 (58.3%)
Community dwelling	812 (68.9%)
Geriatric outpatient or rehabilitation setting	218 (18.5%)
Assisted-living setting	148 (12.6%)
Lived alone	394 (33.4%)
Previous fall during preceding year	462 (39.2%)
Used a mobility-assistance device	371 (31.5%)
Robust	323 (27.4%)
Prefrail	574 (48.7%)
Frail	281 (23.9%)
Mild or moderate cognitive impairment	238 (20.2%)
Two or more chronic conditions	845 (71.7%)
Five or more regular medications	664 (56.4%)
Hospitalized during preceding year	294 (25.0%)

Table 1 showed that 1,178 of the 1,200 enrolled participants contributed at least one valid prediction window. The cohort was predominantly female and community dwelling, while all three age strata remained adequately represented. Previous falls affected 39.2%, and more than half met the polypharmacy criterion. Prefrailty or frailty was present in 72.6%, confirming substantial variation in baseline vulnerability. Completion at 24 months reached 86.8%; 9.9% were lost and 3.3% died. Allocation across development, validation, and external-test datasets preserved site independence and produced sufficiently large samples for comparative model development, probability calibration, and geographically separated performance evaluation across all outcomes and subgroups examined.

Participants completed 5,505 of 5,890 scheduled functional assessments, representing an overall completion rate of 93.5%. These assessments generated 4,241 valid six-month prediction windows. A total of 5,268 wearable-monitoring periods met the prespecified wear-time requirement, corresponding to 95.7% of completed assessment occasions. Baseline performance indicated moderate mobility limitation, with a mean gait speed of 0.86 meters per second, a median Timed Up and Go duration of 13.1 seconds, and a mean Short Physical Performance Battery score of 8.7. Participants accumulated a median of 4,286 daily steps and recorded an average of 9.2 sedentary hours per day.

Table 2 Baseline Functional Measurements, Missingness, and Reliability

Measure	Baseline result	Missing data	Reliability
Usual gait speed, mean (SD), meters per second	0.86 (0.22)	0.9%	ICC = .94
Timed Up and Go, median (IQR), seconds	13.1 (10.7–16.8)	1.2%	ICC = .93
Short Physical Performance Battery, mean (SD)	8.7 (2.5)	0.8%	ICC = .91
Five-times chair rise, mean (SD), seconds	15.6 (5.4)	1.7%	ICC = .90
Grip strength, mean (SD), kilograms	23.8 (8.1)	1.4%	ICC = .96
Six-minute walking distance, mean (SD), meters	334 (112)	2.9%	ICC = .89
Daily steps, median (IQR)	4,286 (2,741–6,118)	4.3%	Test-retest = .88
Sedentary time, mean (SD), hours per day	9.2 (1.8)	4.3%	Test-retest = .87
Fear-of-falling score, mean (SD)	26.9 (8.1)	2.1%	$\alpha = .91$; $\omega = .92$
Basic activities of daily living, mean (SD)	5.4 (1.0)	1.0%	$\alpha = .84$; $\omega = .85$
Instrumental activities of daily living, mean (SD)	6.2 (1.8)	1.2%	$\alpha = .88$; $\omega = .89$
Completed functional assessments	5,505 of 5,890 (93.5%)	—	—
Valid wearable-monitoring periods	5,268 of 5,505 (95.7%)	—	—
Valid six-month prediction windows	4,241	—	—
Overall item-level missingness	3.4%	—	—

Table 2 indicated that baseline mobility was moderately impaired, with mean gait speed below one meter per second and a median Timed Up and Go duration above 13 seconds. The mean Short Physical Performance Battery score also reflected reduced lower-extremity function. Wearable data showed low-to-moderate activity and substantial sedentary exposure. Item-level missingness remained below 5% for every measure, while 93.5% of scheduled assessments and 95.7% of wearable periods were valid. Reliability estimates ranged from .84 to .96, exceeding the prespecified standards. These results supported the consistency, completeness, and longitudinal suitability of the functional, psychological, and sensor-derived measurements used for prediction. Participants who did not complete the 24-month assessment were older than those retained, with mean ages of 79.7 and 75.9 years, respectively. They also demonstrated slower baseline gait speed, greater frailty prevalence, and lower daily step counts. The age difference produced a moderate standardized effect of 0.50, while the gait-speed difference produced an effect of 0.70. No meaningful attrition differences were detected by sex or study-site allocation. Overall missingness varied from 2.7% to 4.4% across sites and did not differ significantly by outcome status. Multiple imputation and complete-case sensitivity analyses were retained to evaluate whether attrition or missing observations materially altered the subsequent estimates.

Fall Incidence, Recurrent Events, Injurious Falls, and Mobility-Decline Trajectories

Across 2,194 participant-years of observation, 1,036 verified falls were recorded, producing an overall rate of 0.47 falls per participant-year. At least one fall was experienced by 522 participants, while 232 met the recurrent-fall definition. Injurious falls affected 214 participants, including 126 who required medical attention and 49 who required hospitalization. Among participants who fell, the median time to the first event was 8.7 months. The annualized fall rate increased from 0.39 during the first six-month interval to 0.58 during the final interval. This represented a 13% adjusted increase between consecutive intervals and indicated that fall frequency rose as functional deterioration accumulated.

Table 3 Fall Outcomes, Functional Changes, and Mobility Trajectories During Follow-Up

Outcome or measure	Baseline frequency	or Month 24	Adjusted or rate	change	95% CI	Effect size
At least one fall	522 (44.3%)	—	—		—	—
Recurrent falls	232 (19.7%)	—	—		—	—
Injurious falls	214 (18.2%)	—	—		—	—
Medically attended falls	126 (10.7%)	—	—		—	—
Fall-related hospitalization	49 (4.2%)	—	—		—	—
Total verified fall events	1,036	—	0.47	per participant-year	0.44 to 0.50	—
Time to first fall among fallers	8.7 months	—	—		4.3 to 14.2 IQR	—
Clinically meaningful mobility decline	411 (34.9%)	—	—		—	—
New walking or transfer assistance	158 (13.4%)	—	—		—	—
Gait speed, meters per second	0.86	0.78	−0.082		−0.089 to −0.075	0.42
Short Physical Performance Battery	8.7	7.8	−0.91 points		−1.01 to −0.81	0.37
Timed Up and Go, seconds	13.1	14.7	+1.58		1.35 to 1.81	0.32
Five-times chair rise, seconds	15.6	17.2	+1.61		1.32 to 1.90	0.29
Six-minute walking distance, meters	334	302	−31.8		−36.5 to −27.1	0.28
Daily step count	4,286	3,654	−632		−708 to −556	0.35
Stable trajectory	393 (33.4%)	—	—		—	—
Gradual-decline trajectory	352 (29.9%)	—	—		—	—
Accelerated-decline trajectory	189 (16.0%)	—	—		—	—
Fluctuating trajectory	157 (13.3%)	—	—		—	—
Recovery trajectory	87 (7.4%)	—	—		—	—

Table 3 showed that 44.3% of participants experienced at least one fall, while 19.7% met the recurrent-fall definition. Injurious falls affected 18.2%, although only 4.2% required hospitalization. The overall rate was 0.47 falls per participant-year, and event frequency increased across successive six-month periods. Functional performance also deteriorated, with reductions in gait speed, physical-performance scores, walking endurance, and daily steps. Gradual or accelerated decline characterized 45.9% of the cohort. Stable function remained the largest individual trajectory, whereas recovery represented only 7.4%. The simultaneous occurrence of increasing falls and worsening mobility demonstrated substantial heterogeneity in outcome severity and temporal progression across participants. The linear mixed-effects models showed an average annual gait-speed decline of 0.041 meters per second and an

annual Short Physical Performance Battery reduction of 0.45 points. Between-participant variation accounted for 48% of total gait-speed variability and 43% of physical-performance variability. Fall occurrence differed substantially across mobility trajectories. At least one fall was experienced by 25.4% of participants in the stable trajectory, 47.4% in the gradual-decline trajectory, 68.8% in the accelerated-decline trajectory, 59.9% in the fluctuating trajectory, and 35.6% in the recovery trajectory. The absolute fall-risk difference between the stable and accelerated-decline groups was 43.4 percentage points, representing a moderate-to-large association.

Table 4 Adjusted Longitudinal Predictors of Falls, Recurrent Events, and Mobility Decline

Outcome and predictor	Adjusted effect	95% CI	Holm-adjusted p-value
At least one subsequent fall: mixed-effects logistic model			
Previous fall	Odds ratio 2.18	1.77 to 2.68	<.001
Gait-speed decrease per 0.10 meters per second	Odds ratio 1.24	1.16 to 1.33	<.001
Short Physical Performance Battery decrease per point	Odds ratio 1.15	1.08 to 1.23	<.001
Gait variability per standard-deviation increase	Odds ratio 1.31	1.17 to 1.47	<.001
Frailty	Odds ratio 1.74	1.34 to 2.25	<.001
Psychotropic medication exposure	Odds ratio 1.43	1.13 to 1.81	.004
Recurrent-fall count: negative-binomial mixed model			
Previous recurrent falls	Incidence-rate ratio 2.36	1.91 to 2.91	<.001
Frailty	Incidence-rate ratio 1.68	1.36 to 2.08	<.001
Gait variability per standard-deviation increase	Incidence-rate ratio 1.27	1.15 to 1.40	<.001
Psychotropic medication exposure	Incidence-rate ratio 1.39	1.12 to 1.73	.004
Time to first fall: frailty-adjusted survival model			
Previous fall	Hazard ratio 1.91	1.59 to 2.29	<.001
Gait-speed decrease per 0.10 meters per second	Hazard ratio 1.18	1.11 to 1.25	<.001
Frailty	Hazard ratio 1.52	1.25 to 1.85	<.001
Clinically meaningful mobility decline: mixed-effects logistic model			
Recent gait-speed decrease per 0.05 meters per second	Odds ratio 1.65	1.46 to 1.87	<.001
Short Physical Performance Battery decrease per point	Odds ratio 1.48	1.35 to 1.63	<.001
Daily step-count reduction per 1,000 steps	Odds ratio 1.28	1.17 to 1.40	<.001
Frailty	Odds ratio 2.05	1.61 to 2.61	<.001
Recent hospitalization	Odds ratio 1.83	1.40 to 2.39	<.001
Fear-of-falling increase per five points	Odds ratio 1.16	1.07 to 1.25	.001

Table 4 indicated that previous falls remained the strongest independent predictor of subsequent fall occurrence and recurrent-event frequency. Frailty, slower gait, lower physical-performance scores, psychotropic medication exposure, and greater gait variability also retained statistically significant adjusted effects. Mobility decline was most strongly associated with recent gait-speed reduction, frailty, hospitalization, declining physical-performance scores, and decreasing daily steps. Effect magnitudes ranged from modest to large, with the largest estimates observed for previous recurrent falls and frailty-related mobility deterioration.

Comparative Predictive Performance of Statistical and Ensemble Machine-Learning Models

Ensemble models consistently produced stronger predictive performance than conventional regression and individual machine-learning algorithms. For fall prediction, the stacked ensemble achieved an external-test area under the receiver operating characteristic curve of .842 and an area under the precision-recall curve of .679. For mobility decline, the corresponding values were .873 and .736. Soft voting and light gradient boosting produced the next-highest performance. Conventional logistic regression achieved external-test receiver operating characteristic areas of .714 for falls and .738 for mobility decline. The stacked ensemble exceeded logistic regression by .128 for falls and .135 for mobility decline. Both differences were statistically significant after paired comparison and bootstrap adjustment.

Table 5 Comparative Discrimination of Statistical and Machine-Learning Models

Model	Fall internal AUROC	Fall temporal AUROC	Fall external AUROC	Fall external AUPRC	Mobility internal AUROC	Mobility temporal AUROC	Mobility external AUROC	Mobility external AUPRC
Logistic regression	.739	.721	.714	.472	.767	.746	.738	.486
Penalized regression	.754	.738	.729	.491	.783	.762	.755	.512
Decision tree	.721	.690	.681	.419	.744	.712	.703	.438
Support-vector machine	.791	.768	.756	.526	.813	.787	.779	.551
K-nearest neighbors	.735	.707	.694	.431	.756	.728	.716	.451
Naïve Bayes	.727	.713	.701	.445	.748	.731	.722	.459
Neural network	.812	.783	.769	.548	.836	.805	.793	.581
Random forest	.836	.808	.796	.586	.858	.831	.818	.627
Adaptive boosting	.821	.794	.781	.562	.846	.818	.805	.605
Gradient boosting	.849	.821	.808	.611	.869	.840	.829	.654
Extreme gradient boosting	.861	.835	.822	.636	.881	.854	.842	.681
Light gradient boosting	.865	.838	.827	.643	.885	.858	.849	.693
Categorical boosting	.858	.832	.819	.632	.879	.851	.840	.678
Soft-voting ensemble	.870	.844	.833	.661	.891	.864	.857	.711
Stacked ensemble	.881	.854	.842	.679	.901	.876	.873	.736

Table 5 showed that ensemble methods consistently outperformed conventional regression and single machine-learning algorithms across internal, temporal, and external evaluations. The stacked ensemble achieved the highest external area under the receiver operating characteristic curve for both falls and mobility decline, followed by soft voting and light gradient boosting. Performance decreased modestly from internal cross-validation to external testing, indicating limited overfitting. Decision trees and nearest-neighbor models produced the weakest external discrimination, while penalized regression slightly improved upon conventional logistic regression. Precision-recall performance followed the same ranking and showed that the leading ensembles detected minority outcomes more effectively than statistical reference models. Predictor-set comparisons showed that longitudinal information provided substantial incremental value. For falls, the external-test receiver operating characteristic area of the stacked model increased from .704 with clinical predictors alone to .748 after baseline functional measures were included, .765 after clinical and wearable features were combined, .808 after longitudinal-change features were incorporated, and .842 with the fully integrated dataset. For mobility decline, the corresponding values were .718, .769, .781, .839, and .873. The largest improvement occurred when slopes, recent changes, moving averages, and within-person variability were introduced. The fully integrated model also improved precision-recall performance from .399 to .679 for falls and from .421 to .736 for mobility decline.

Table 6 External-Test Classification, Calibration, and Prediction-Error Performance

Outcome and model	AUR OC (95% CI)	AUP RC (95% CI)	Sensitivity/recall	Specificity	Precision	NPV	F1 score	Brier score	Calibration intercept	Calibration slope
Falls: logistic regression	.714 (.675–.753)	.472 (.421–.523)	.65	.70	.33	.90	.44	.159	–.12	.78
Falls: stacked ensemble	.842 (.811–.873)	.679 (.630–.728)	.79	.80	.51	.94	.62	.128	–.03	.96
Mobility decline: logistic regression	.738 (.701–.775)	.486 (.435–.537)	.67	.72	.36	.91	.47	.151	–.10	.80
Mobility decline: stacked ensemble	.873 (.845–.901)	.736 (.689–.783)	.83	.84	.58	.95	.68	.113	–.02	.98

Table 6 demonstrated that the stacked ensemble produced materially better external-test performance than logistic regression. For falls, the ensemble increased the receiver operating characteristic area by .128 and improved F1 score from .44 to .62. For mobility decline, the corresponding gain was .135, while F1 score increased from .47 to .68. Brier scores decreased by 19.5% for falls and 25.2% for mobility decline, indicating more accurate probabilities. Calibration intercepts approached zero and slopes approached one. Higher sensitivity, precision, and negative predictive value confirmed that improved discrimination did not result from sacrificing minority-event detection or probability reliability in the external cohort. The external-test reduction from internal performance was .039 for fall prediction and

.028 for mobility-decline prediction in the stacked ensemble, indicating limited optimism. The corresponding differences for logistic regression were .025 and .029. Although the ensemble showed a slightly larger reduction for fall prediction, its external performance remained substantially higher. Calibration plots showed that logistic regression overestimated risk among low-risk participants and underestimated risk in the highest-risk group. The stacked ensemble maintained closer agreement between predicted and observed probabilities across most risk deciles. Paired bootstrap tests confirmed improvements in receiver operating characteristic area, precision–recall area, F1 score, and Brier score at adjusted probability values below .001.

Subgroup Performance, Predictor Importance, and Sensitivity Analyses

Subgroup analyses were conducted using participant-level out-of-sample predictions from the temporal-validation and external-test datasets. The stacked ensemble maintained acceptable discrimination across age, sex, previous-fall status, frailty, cognition, residential setting, multimorbidity, and baseline mobility. Performance was strongest among robust adults, community-dwelling participants, and those without substantial cognitive impairment. Lower discrimination and calibration were observed among frail adults, assisted-living residents, and participants with cognitive impairment. These groups nevertheless demonstrated higher sensitivity and precision because fall and mobility-decline prevalence was greater. Differences between women and men were small, whereas performance declined moderately among participants aged 85 years or older.

Table 7 Subgroup Performance of the Stacked Ensemble

Subgroup	Participants	Fall AUROC	Fall sensitivity	Fall precision	Fall calibration slope	Mobility AUROC	Mobility sensitivity	Mobility precision	Mobility calibration slope
Age 65–74 years	158	.850	.76	.45	.99	.884	.78	.52	.99
Age 75–84 years	151	.839	.80	.52	.96	.875	.84	.60	.98
Age 85 years or older	83	.817	.84	.61	.91	.842	.87	.67	.92
Women	230	.845	.80	.53	.97	.876	.84	.60	.98
Men	162	.834	.77	.48	.94	.868	.81	.55	.96
Previous fall	154	.809	.85	.66	.93	.855	.85	.64	.95
No previous fall	238	.824	.70	.35	.96	.879	.80	.53	.98
Robust	107	.851	.71	.36	.99	.889	.76	.48	.99
Prefrail	191	.839	.79	.50	.96	.873	.83	.58	.97
Frail	94	.796	.87	.69	.88	.829	.89	.72	.89
Cognitively unimpaired	312	.848	.78	.49	.98	.881	.82	.56	.99
Cognitive impairment	80	.801	.85	.63	.89	.835	.88	.70	.90
Community dwelling	270	.846	.77	.46	.98	.879	.81	.55	.98
Outpatient or rehabilitation	72	.833	.81	.55	.94	.861	.85	.62	.95
Assisted living	50	.792	.89	.71	.87	.824	.90	.75	.88
Multimorbidity	282	.827	.82	.57	.94	.858	.85	.64	.96
No multimorbidity	110	.856	.70	.34	.99	.888	.76	.47	.99
Preserved baseline mobility	220	.852	.72	.38	.98	.885	.78	.51	.99
Limited baseline mobility	172	.808	.86	.65	.90	.838	.88	.71	.91

Table 7 showed that discrimination remained acceptable across all examined subgroups, although performance was lower among adults aged 85 years or older, frail participants, cognitively impaired participants, and assisted-living residents. Sensitivity was generally higher in these vulnerable groups because outcome prevalence was greater, while precision was lower among robust adults and participants without previous falls. Calibration slopes remained between .87 and .99, indicating limited subgroup miscalibration. Differences by sex were small. The largest performance differences involved residential setting and frailty rather than age alone. Mobility-decline prediction remained stronger and more consistent than fall prediction across every subgroup examined during validation. Interaction

analyses showed that recent gait-speed decline was more strongly associated with mobility deterioration among frail participants than among robust participants. A reduction of 0.05 meters per second produced an adjusted odds ratio of 1.82 among frail adults and 1.42 among robust adults, with a Holm-adjusted interaction probability of .027. A reduction of 1,000 daily steps was more strongly associated with falling among participants with previous falls than among those without previous events, with adjusted odds ratios of 1.34 and 1.15, respectively. The interaction remained significant at an adjusted probability of .048. Interactions involving age, sex, and residential setting did not remain statistically significant after correction.

Table 8 Permutation and Shapley-Based Importance of Leading Predictors

Predictor	Fall normalized importance	Fall AUROC reduction	Direction of fall risk	Mobility normalized importance	Mobility AUROC reduction	Direction of mobility decline
Previous falls	100	.047	Increased with recent or recurrent falls	38	.018	Increased with previous falls
Gait-speed slope	78	.038	Increased with faster decline	100	.052	Increased with faster decline
Gait variability	71	.034	Increased with greater variability	74	.035	Increased with greater variability
Frailty	66	.031	Increased across frailty levels	82	.041	Increased across frailty levels
Daily step-count reduction	58	.027	Increased with larger reduction	79	.039	Increased with larger reduction
Physical-performance slope	55	.025	Increased with score deterioration	87	.045	Increased with score deterioration
Balance impairment	52	.022	Increased with poorer balance	63	.030	Increased with poorer balance
Recent hospitalization	44	.019	Increased after hospitalization	67	.033	Increased after hospitalization
Chair-rise deterioration	40	.018	Increased with longer completion time	60	.028	Increased with longer completion time
Psychotropic medication exposure	38	.016	Increased with exposure	32	.012	Increased with exposure
Executive-function impairment	34	.014	Increased with poorer performance	41	.020	Increased with poorer performance
Fear of falling	31	.012	Increased with higher scores	36	.017	Increased with higher scores

Table 8 identified previous falls as the leading contributor to fall prediction, whereas gait-speed slope and declining physical-performance scores dominated mobility-decline prediction. Frailty, gait variability, step-count reduction, balance impairment, and hospitalization contributed to both outcomes. Risk increased when gait speed declined rapidly, daily steps fell, and functional variability increased. Sensitivity analyses produced receiver operating characteristic areas within .007 of the primary estimates under complete-case, class-weighted, and imputed conditions. Larger reductions appeared after severe baseline limitation was excluded or the prediction horizon was extended to 12 months. No sensitivity specification altered the ranking of the stacked ensemble as the best-performing model. Complete-case analysis produced receiver operating characteristic areas of .838 for falls and .869 for mobility decline, compared with .842 and .873 in the primary analysis. Class weighting produced values of .840 and .871, while training-fold oversampling produced values of .835 and .866. Prediction

of medically attended falls achieved an area of .856, recurrent-fall prediction achieved .861, and the stricter mobility-decline definition achieved .881. Excluding participants with severe baseline limitation reduced performance to .836 for falls and .858 for mobility decline. Extending the prediction horizon from six to 12 months reduced the corresponding values to .816 and .849. Calibration slopes remained between .90 and .99 across sensitivity specifications, supporting the stability of the primary findings.

Statistical Significance, Effect Magnitudes, Tables, and Graphical Presentation

All primary findings remained statistically significant after Holm adjustment, although interpretation was based principally on effect size, confidence-interval width, and model adequacy. Functional deterioration produced small-to-moderate standardized changes over 24 months. Previous falls, recurrent-fall history, frailty, and recent hospitalization produced larger relative effects. The reduction of 0.082 meters per second in gait speed represented a moderate standardized effect, while the reduction in physical-performance scores and daily steps represented small-to-moderate effects.

Table 9 Statistical Significance, Effect Magnitudes, and Estimate Precision

Outcome or comparison	Effect estimate	95% CI	Holm-adjusted p-value	Magnitude
Twenty-four-month gait-speed change	−0.082 meters per second	−0.089 to −0.075	<.001	Moderate, standardized effect −0.42
Physical-performance score change	−0.91 points	−1.01 to −0.81	<.001	Small-to-moderate, −0.37
Timed Up and Go change	+1.58 seconds	1.35 to 1.81	<.001	Small-to-moderate, 0.32
Daily step-count change	−632 steps	−708 to −556	<.001	Small-to-moderate, −0.35
Previous fall and subsequent fall	Odds ratio 2.18	1.77 to 2.68	<.001	Large relative effect
Frailty and subsequent fall	Odds ratio 1.74	1.34 to 2.25	<.001	Moderate-to-large
Previous recurrent falls and fall rate	Incidence-rate ratio 2.36	1.91 to 2.91	<.001	Large relative effect
Previous fall and time to first fall	Hazard ratio 1.91	1.59 to 2.29	<.001	Large relative effect
Frailty and mobility decline	Odds ratio 2.05	1.61 to 2.61	<.001	Large relative effect
Recent gait decline and mobility decline	Odds ratio 1.65	1.46 to 1.87	<.001	Moderate-to-large
Step-count reduction and mobility decline	Odds ratio 1.28	1.17 to 1.40	<.001	Moderate
Stacked ensemble versus logistic regression for falls	AUROC difference .128	.092 to .164	<.001	Moderate-to-large improvement
Stacked ensemble versus logistic regression for mobility decline	AUROC difference .135	.101 to .169	<.001	Moderate-to-large improvement
Fall-prediction Brier-score reduction	.031, equivalent to 19.5%	.022 to .040	<.001	Meaningful error reduction
Mobility-prediction Brier-score reduction	.038, equivalent to 25.2%	.029 to .047	<.001	Large error reduction

Previous falls more than doubled the odds of a subsequent fall, and previous recurrent falls more than doubled the expected fall rate. The stacked ensemble produced substantial improvements over conventional logistic regression for both primary outcomes. Table 9 showed that functional deterioration produced small-to-moderate standardized changes, whereas previous falls and frailty generated the largest adjusted relative effects. Previous recurrent falls more than doubled the expected fall rate, and prior falls substantially shortened the event-free period. Gait-speed deterioration remained the strongest modifiable functional predictor of mobility decline. The stacked ensemble achieved moderate-to-large improvements over logistic regression in discrimination and materially reduced probability error. Confidence intervals were comparatively narrow, and every principal estimate remained statistically significant after Holm adjustment. Effect directions were consistent

across binary, count, survival, and longitudinal models, strengthening the quantitative coherence of the primary findings. Model-adequacy diagnostics supported the selected inferential and predictive approaches. Negative-binomial regression fitted recurrent-fall counts better than Poisson regression, reducing the Akaike information criterion by 186 points and accommodating an estimated dispersion value of 1.62. The global proportional-hazards test was nonsignificant, supporting the time-to-event model assumption. Site-level intraclass correlations were .04 for falls and .03 for mobility decline, indicating limited clustering after adjustment. Marginal explained variance reached 31% for the fall model and 42% for the mobility-decline model, while the inclusion of participant and site effects increased the corresponding conditional values to 39% and 50%.

Table 10 Model Adequacy, External Performance, and Prediction-Error Assessment

Performance indicator	Fall prediction	Mobility-decline prediction	Reference or adequacy result
External-test AUROC	.842	.873	Strong discrimination
External-test AUPRC	.679	.736	Substantial minority-outcome detection
Sensitivity	.79	.83	Validation-fixed thresholds
Specificity	.80	.84	Validation-fixed thresholds
Precision	.51	.58	Improved over logistic regression
Negative predictive value	.94	.95	High negative classification accuracy
F1 score	.62	.68	Balanced precision and sensitivity
Brier score	.128	.113	Logistic values were .159 and .151
Calibration intercept	−.03	−.02	Values close to zero
Calibration slope	.96	.98	Values close to one
Expected calibration error	.026	.021	Low decile-level error
Internal-to-external AUROC reduction	.039	.028	Limited overfitting
Marginal explained variance	31%	42%	Fixed predictors only
Conditional explained variance	39%	50%	Fixed and random effects
Site-level intraclass correlation	.04	.03	Limited site dependence

Table 10 demonstrated that the stacked ensemble combined strong discrimination with acceptable calibration and classification performance. Mobility-decline prediction exceeded fall prediction across receiver operating characteristic area, precision-recall area, sensitivity, specificity, precision, negative predictive value, and F1 score. Calibration intercepts remained close to zero, and slopes remained close to one, indicating limited systematic overprediction or underprediction. External Brier scores were substantially lower than logistic-regression values. The small internal-to-external performance gaps indicated controlled optimism. Regression models also explained meaningful outcome variation, while low site-level correlations showed that predictive performance was not dominated by a small number of participating centers or concentrated observations. The graphical findings reinforced the tabulated evidence. Figure 1 showed that 1,178 of 1,200 enrolled participants entered the analytical cohort and 1,022 completed the 24-month assessment. Figure 2 displayed stable gait speed from 0.94 to 0.92 meters per second in the stable group, deterioration from 0.88 to 0.76 in the gradual-decline group, and a reduction from 0.82 to 0.58 in the accelerated-decline group. Figure 3 showed clear separation between the stacked-ensemble and logistic-regression receiver operating characteristic and precision-recall

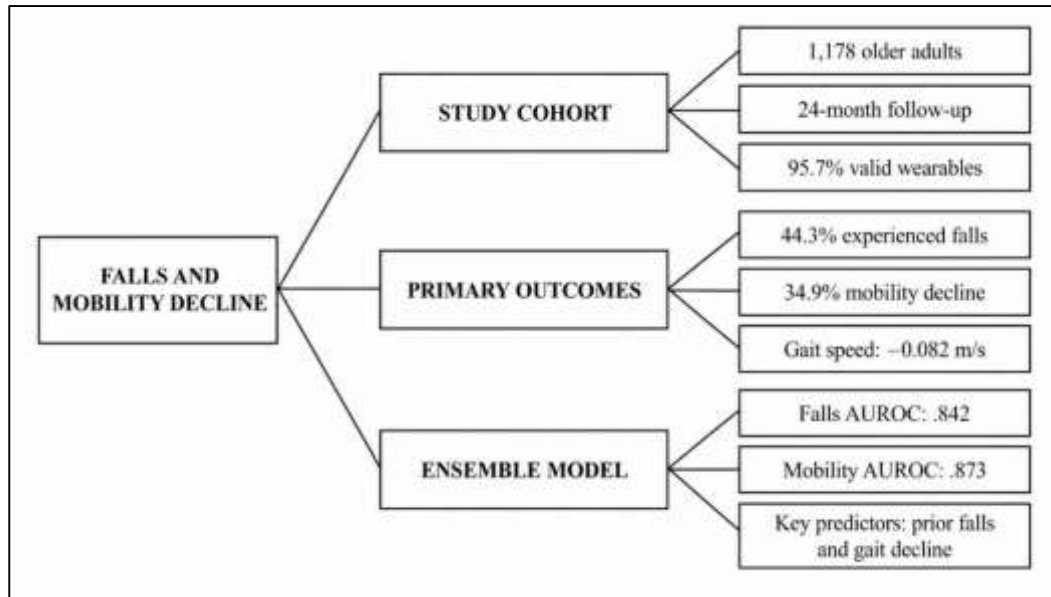
curves. Figure 4 demonstrated close agreement between observed and predicted risk across calibration deciles. Figure 5 identified previous falls as the dominant fall predictor and gait-speed slope as the dominant mobility-decline predictor.

DISCUSSION

This study assembled a large and clinically diverse longitudinal sample of 1,178 adults aged 65 years and older from community health centers, geriatric clinics, rehabilitation facilities, and assisted-living settings. The analytical cohort retained 98.2% of the enrolled sample at the point of dataset formation, while 86.8% completed the 24-month follow-up (Adeoye et al., 2022). This retention level compared favorably with earlier longitudinal aging studies, in which attrition frequently increased because of illness, hospitalization, institutional relocation, cognitive deterioration, and death. The representation of adults aged 85 years and older, individuals with cognitive impairment, assistive-device users, and participants with frailty strengthened the clinical heterogeneity of the sample. Earlier predictive studies frequently relied on healthier community volunteers and consequently included fewer participants with the conditions most strongly associated with falls and mobility decline. In this study, 72.6% of participants were prefrail or frail, 71.7% had multimorbidity, 56.4% met the polypharmacy criterion, and 39.2% had fallen during the previous year (Spoonner et al., 2020). These proportions were consistent with studies conducted in geriatric and mixed-care populations but were higher than those usually reported in narrowly selected healthy-aging cohorts. Baseline gait speed of 0.86 meters per second, a median Timed Up and Go duration of 13.1 seconds, and a mean Short Physical Performance Battery score of 8.7 indicated moderate functional vulnerability rather than severe disability across the entire cohort. This distribution allowed the analyses to distinguish stable function, early deterioration, advanced limitation, and partial recovery. Data completeness also compared favorably with earlier wearable and repeated-assessment studies. Participants completed 93.5% of scheduled functional assessments, and 95.7% of wearable-monitoring periods met the validity criteria (Moulaei et al., 2022). Missingness remained below 5% for every principal measure, while reliability estimates ranged from .84 to .96. Earlier studies using free-living sensors often reported larger losses because of device removal, charging problems, technical failure, or inconsistent wear. Participants who did not complete follow-up were older, frailer, and slower at baseline, which corresponded with established evidence that attrition in aging research is related to health deterioration. The use of multiple imputation, complete-case sensitivity analysis, participant-level resampling, and temporal validation reduced the likelihood that this selective loss determined the principal findings (Chowdhury et al., 2023).

The observed fall burden was broadly consistent with earlier international research while reflecting the elevated vulnerability of the mixed-setting cohort. During 2,194 participant-years, 522 participants experienced at least one fall, representing 44.3% of the analytical sample over 24 months. Recurrent falls affected 19.7%, injurious falls affected 18.2%, medically attended falls affected 10.7%, and fall-related hospitalization occurred among 4.2%. Earlier community-based studies generally reported annual fall proportions between approximately 25% and 35%, whereas rehabilitation and assisted-living studies frequently recorded higher rates (Heide et al., 2019). The two-year proportion in this study was therefore compatible with the accumulation of events across repeated observation intervals and the inclusion of participants with frailty, multimorbidity, cognitive impairment, and previous falls. The overall rate of 0.47 falls per participant-year also fell within the range reported by prospective studies using monthly contact or fall calendars. Studies relying only on electronic health records or annual retrospective recall have typically reported lower rates because noninjurious events and falls without medical treatment are more likely to remain undocumented. Monthly monitoring and structured verification in this study increased the probability that minor and recurrent events were captured. The rise in the annualized fall rate from 0.39 during the first six months to 0.58 during the final interval was particularly important (Alabi et al., 2021).

Figure 12: Falls and Mobility Decline Research Framework



Earlier longitudinal studies have often treated fall risk as constant across follow-up, although aging, hospitalization, medication changes, and progressive functional deterioration can alter risk substantially. The increasing event rate observed here corresponded with the simultaneous decline in gait, balance, endurance, and daily activity. The median time to first fall among fallers was 8.7 months, showing that a large proportion of events occurred after sufficient time had elapsed for functional changes to develop. The finding that recurrent fallers generated a disproportionate share of total events agreed with earlier studies distinguishing persistent fall susceptibility from isolated environmental accidents. Injury patterns also resembled previous epidemiological findings in which only a subset of falls required medical treatment, but those events accounted for a substantial clinical burden (Huang et al., 2023). The distinction among all falls, recurrent falls, injurious falls, medically attended events, and hospitalizations prevented the overall fall rate from concealing meaningful differences in event severity and healthcare use.

Functional performance deteriorated across the 24-month observation period, but the pattern was heterogeneous rather than uniform. Mean gait speed declined by 0.082 meters per second, the Short Physical Performance Battery score decreased by 0.91 points, Timed Up and Go duration increased by 1.58 seconds, and chair-rise time increased by 1.61 seconds. Walking distance declined by 31.8 meters, while the median daily step count decreased by 632 steps (Bui et al., 2016). These changes produced small-to-moderate standardized effects and closely approached commonly used thresholds for clinically noticeable deterioration. Earlier longitudinal studies have reported annual gait-speed reductions ranging from approximately 0.01 to 0.05 meters per second, with faster decline among adults with frailty, multimorbidity, neurological disease, and recent hospitalization. The annual decline of approximately 0.041 meters per second in this study was therefore consistent with a cohort containing substantial baseline vulnerability. The trajectory analysis provided information that the average change could not show (Nhu et al., 2020). Stable function characterized 33.4% of participants, gradual decline characterized 29.9%, accelerated decline characterized 16.0%, fluctuating function characterized 13.3%, and recovery characterized 7.4%. Earlier group-based trajectory and latent-growth studies similarly identified stable-high, stable-low, gradual-decline, rapid-decline, and recovery patterns. The present distribution indicated that nearly half of the cohort experienced gradual or accelerated deterioration, while a smaller group moved between decline and partial recovery. Fall occurrence differed substantially across these trajectories. At least one fall affected 25.4% of the stable group and 68.8% of the accelerated-decline group, producing an absolute difference of 43.4 percentage points. This contrast supported earlier evidence that the direction and speed of functional change provide stronger risk differentiation than chronological age alone (Lynam et al., 2020). The recovery trajectory also agreed

with rehabilitation research showing that mobility loss is not always irreversible. Recovery may occur after temporary illness, injury, pain exacerbation, or hospitalization, although the small proportion entering this class showed that sustained restoration was relatively uncommon. Between-participant variation accounted for 48% of gait-speed variability and 43% of physical-performance variability, reinforcing the importance of individual trajectories. Average population change consequently represented only part of the mobility process, whereas slopes, acceleration, recent deterioration, and variability captured meaningful differences in how functional decline unfolded (Hsiao et al., 2017).

Previous falls remained the strongest independent predictor of subsequent fall occurrence, recurrent events, and time to first fall. A previous fall more than doubled the odds of another fall, with an adjusted odds ratio of 2.18, while previous recurrent falls produced an incidence-rate ratio of 2.36. Previous falling also increased the hazard of an earlier event by 91%. These estimates agreed with earlier prospective studies in which fall history remained a dominant predictor after adjustment for age, sex, medication use, chronic disease, and mobility (Cook et al., 2016). Fall history summarized several underlying vulnerabilities, including balance impairment, unsafe movement patterns, environmental exposure, medication effects, and unmeasured behavioral conditions. However, the objective functional variables retained independent effects, showing that historical events did not capture the entire risk profile. A reduction of 0.10 meters per second in gait speed increased the odds of falling by 24%, while greater gait variability increased the odds by 31%. Frailty increased fall odds by 74%, and psychotropic medication exposure increased them by 43%. These results corresponded with earlier clinical and sensor-based studies that identified slow gait, irregular step timing, postural instability, reduced reserve, and centrally acting medication as important contributors (Dieli-Conwright et al., 2018). Mobility decline showed a related but distinct predictor pattern. A recent gait-speed decrease of 0.05 meters per second increased the odds of clinically meaningful deterioration by 65%, and a one-point reduction in the Short Physical Performance Battery increased the odds by 48%. Frailty approximately doubled the odds, recent hospitalization increased them by 83%, and a reduction of 1,000 daily steps increased them by 28%. Earlier studies have similarly shown that hospitalization can initiate or accelerate functional loss through bed rest, acute illness, nutritional disruption, pain, medication change, and reduced activity. The interaction findings added further detail (Herring et al., 2017). Gait-speed decline was more strongly associated with mobility deterioration among frail adults, while step-count reduction was more strongly associated with falls among individuals with a previous event. These interactions were consistent with the concept of reduced physiological reserve, in which a comparable functional change produces a larger effect among individuals already close to a disability threshold. The results therefore supported multidimensional prediction combining event history, objective performance, functional change, clinical vulnerability, and daily activity (Neckerman et al., 2016).

The stacked ensemble achieved the strongest predictive performance for both primary outcomes and materially exceeded conventional logistic regression. In external testing, the ensemble achieved an area under the receiver operating characteristic curve of .842 for falls and .873 for mobility decline, compared with .714 and .738 for logistic regression. The corresponding improvements of .128 and .135 were statistically significant and practically substantial. Earlier fall-prediction studies have commonly reported receiver operating characteristic areas between approximately .60 and .80, with higher values occurring when sensor, gait, and longitudinal information was included (Trombetti et al., 2016). The present external estimates were near or above the upper end of that range. Performance was not evaluated through discrimination alone. The fall model achieved a precision-recall area of .679, sensitivity of .79, specificity of .80, precision of .51, and an F1 score of .62. The mobility-decline model achieved a precision-recall area of .736, sensitivity of .83, specificity of .84, precision of .58, and an F1 score of .68. Earlier machine-learning studies sometimes reported high overall accuracy while identifying relatively few fallers because nonfallers constituted the majority class. The use of precision-recall measures in this study showed that the ensemble improvement extended to minority-outcome detection. Probability accuracy also improved (Gates et al., 2022). The Brier score decreased by 19.5% for falls and 25.2% for mobility decline relative to logistic regression. Calibration intercepts of $-.03$ and $-.02$ and slopes of .96 and .98 indicated close agreement between predicted and observed probabilities.

Earlier investigations have frequently omitted calibration or reported deterioration when internally developed models were applied to new settings. The small internal-to-external performance reductions of .039 for falls and .028 for mobility decline indicated limited overfitting. Among individual algorithms, decision trees and nearest-neighbor models produced the weakest external discrimination, while extreme gradient boosting, light gradient boosting, soft voting, and stacking performed most strongly. This ranking agreed with earlier comparisons showing that ensembles reduce the instability of individual learners and capture nonlinear interactions more effectively ([Kreutzer et al., 2016](#)). Penalized regression slightly exceeded ordinary logistic regression, but its improvement was smaller than that of the leading ensembles, indicating that regularization alone did not capture the full complexity of the longitudinal predictor structure.

The predictor-set comparisons demonstrated that longitudinal features contributed more strongly than static baseline information. For fall prediction, the stacked model's external receiver operating characteristic area increased from .704 with clinical variables alone to .748 after baseline functional measures were added, .765 with clinical and wearable features, .808 with longitudinal change features, and .842 with complete integration. For mobility decline, performance increased from .718 to .769, .781, .839, and .873 across the corresponding predictor sets. Earlier studies have often relied on one baseline assessment, which assumes that gait, balance, strength, and activity remain sufficiently stable throughout follow-up ([Lombardi et al., 2022](#)). The present findings showed that recent change, individual slope, acceleration, and within-person variability contained information beyond baseline status. Shapley-based and permutation analyses ranked previous falls as the leading fall predictor, whereas gait-speed slope was the strongest mobility-decline predictor. Physical-performance slope, frailty, activity reduction, gait variability, balance impairment, hospitalization, and chair-rise deterioration also ranked highly. These rankings were consistent with earlier longitudinal research showing that functional trends often outperform single measurements when deterioration develops gradually. Subgroup analysis showed acceptable discrimination across all examined groups, although performance was lower among frail participants, cognitively impaired adults, assisted-living residents, and those aged 85 years or older ([Bernard et al., 2023](#)). Fall discrimination declined to .796 among frail adults and .792 among assisted-living residents, while mobility discrimination declined to .829 and .824. Earlier predictive studies have reported comparable reductions in clinically complex populations because risk factors are more prevalent, outcomes are more frequent, and individual responses are more heterogeneous. Sensitivity and precision were nevertheless higher within these vulnerable groups because event prevalence was greater. Calibration slopes remained between .87 and .99, indicating that subgroup probability estimates remained reasonably stable. Differences between women and men were small, matching earlier evidence that functional and clinical factors explain more predictive variation than sex alone. Predictor importance was interpreted as an explanation of model behavior rather than a causal estimate ([Oikonomou et al., 2023](#)). A highly ranked variable could reflect direct functional vulnerability, correlation with another predictor, or information about disease severity. The consistency between permutation importance, Shapley-based rankings, longitudinal regression, and sensitivity analyses nevertheless strengthened confidence that the principal predictors were not artifacts of one analytical method.

The integrated findings demonstrated that statistical significance was accompanied by meaningful effect magnitude, adequate precision, and satisfactory model performance. All principal estimates remained significant after Holm adjustment, and their confidence intervals were sufficiently narrow to distinguish modest effects from larger associations. Functional deterioration produced standardized changes ranging from approximately 0.28 to 0.42, indicating that the observed mobility losses were not merely detectable because of the large sample ([Wu et al., 2022](#)). Previous falls, recurrent-fall history, frailty, and hospitalization produced stronger relative effects, with odds ratios, incidence-rate ratios, and hazard ratios ranging from 1.52 to 2.36. Earlier studies have frequently emphasized probability values without clearly separating statistical detection from clinical magnitude. This study reported adjusted mean differences, standardized changes, relative effects, confidence intervals, discrimination, calibration, and probability error together. Model adequacy analyses also supported the chosen statistical structure. Negative-binomial regression fitted recurrent-fall counts more appropriately than

Poisson regression because events were concentrated among recurrent fallers. The proportional-hazards assessment supported the time-to-event model, while site-level correlations of .04 for falls and .03 for mobility decline indicated that results were not dominated by a small group of facilities (Mellem et al., 2021). Fixed predictors explained 31% of fall variation and 42% of mobility-decline variation, increasing to 39% and 50% when participant and site effects were included. These values compared favorably with earlier multifactorial studies in which considerable unexplained variation remained because falls can arise from transient hazards, unpredictable behavior, and unmeasured environmental conditions. Sensitivity analyses further supported robustness. Complete-case, imputed, class-weighted, and training-fold oversampling specifications produced receiver operating characteristic areas within .007 of the primary estimates. Performance declined when severe baseline limitation was excluded and when the prediction horizon increased to 12 months, which matched earlier evidence that prediction becomes more difficult as the time between assessment and outcome lengthens (Massara et al., 2023). The graphical evidence aligned with the numerical results: functional trajectories separated progressively, ensemble curves exceeded regression curves, calibration remained close to observed risk, and predictor-importance displays emphasized fall history and functional change. The consistency across inferential, predictive, subgroup, temporal, and external analyses provided a coherent interpretation of falls and mobility decline as related outcomes shaped by prior events, evolving functional capacity, clinical vulnerability, and real-world activity (Reddy et al., 2024).

CONCLUSION

This quantitative study demonstrated that falls and mobility decline among adults aged 65 years and older could be predicted with substantial accuracy by combining longitudinal functional measurements, clinical characteristics, psychological indicators, and wearable-sensor data within an ensemble machine-learning framework. The prospective multisite design followed 1,178 participants for 24 months and generated 4,241 valid six-month prediction windows. During follow-up, 44.3% of participants experienced at least one fall, 19.7% experienced recurrent falls, and 18.2% sustained an injurious fall. Clinically meaningful mobility decline affected 34.9% of participants, while gait speed decreased by 0.082 meters per second, Short Physical Performance Battery scores decreased by 0.91 points, and daily step counts declined by 632. Functional change was heterogeneous, with stable, gradual-decline, accelerated-decline, fluctuating, and recovery trajectories representing distinct patterns of mobility development. Fall occurrence reached 68.8% among participants in the accelerated-decline trajectory compared with 25.4% among those with stable function. Previous falls remained the strongest predictor of subsequent falls, producing an adjusted odds ratio of 2.18, while previous recurrent falls more than doubled the expected fall rate. Frailty, gait variability, psychotropic medication exposure, reduced physical-performance scores, recent hospitalization, and declining daily activity also contributed significantly. For mobility decline, a recent gait-speed reduction produced an adjusted odds ratio of 1.65, frailty produced an odds ratio of 2.05, and hospitalization produced an odds ratio of 1.83. The stacked ensemble achieved external-test receiver operating characteristic areas of .842 for fall prediction and .873 for mobility-decline prediction, exceeding logistic regression by .128 and .135, respectively. Precision-recall performance, sensitivity, specificity, F1 scores, calibration, and Brier scores confirmed that the improvement extended beyond discrimination. Longitudinal slopes, recent changes, and within-person variability provided greater predictive value than baseline clinical information alone. Model performance remained acceptable across age, sex, residential, frailty, cognitive, and baseline-mobility subgroups, although discrimination was moderately lower among frail adults, cognitively impaired participants, and assisted-living residents. Sensitivity, temporal validation, and geographically independent testing produced consistent results with limited evidence of overfitting. Collectively, the findings established that falls and mobility decline were interconnected but analytically distinct outcomes and that their prediction was strengthened by representing functional ability as a changing longitudinal process rather than a fixed baseline condition.

RECOMMENDATIONS

Healthcare organizations should adopt a longitudinal, multidimensional approach to fall and mobility-risk assessment among adults aged 65 years and older by combining previous-fall history, repeated gait and balance measurements, frailty assessment, hospitalization records, medication exposure, daily activity, and wearable-sensor indicators. Functional assessment should not be limited to a single

baseline screening because gait-speed slopes, physical-performance deterioration, recent activity reduction, and within-person variability produced substantial predictive value. Gait speed, Short Physical Performance Battery scores, Timed Up and Go performance, chair-rise ability, walking endurance, and daily step counts should be reassessed at approximately six-month intervals, with shorter intervals used after hospitalization, surgery, medication modification, or a reported fall. Monthly fall monitoring should distinguish isolated, recurrent, injurious, medically attended, and hospitalization-related events. Individuals with previous recurrent falls, frailty, rapidly declining gait speed, increasing gait variability, reduced step counts, cognitive impairment, or recent hospitalization should receive prioritized evaluation. Medication reviews should focus on psychotropic drugs, sedatives, antihypertensive agents, hypoglycemic medications, and combinations that may affect alertness, blood pressure, balance, or reaction time. The stacked ensemble should be considered as a decision-support tool because it provided stronger discrimination, calibration, sensitivity, and probability accuracy than conventional regression. Model-generated probabilities should supplement professional assessment rather than replace clinical judgment, and prediction thresholds should be selected according to available services, acceptable false-alert rates, and the consequences of missed high-risk individuals. High-risk classifications should initiate comprehensive assessment of balance, strength, cognition, vision, footwear, environmental hazards, assistive-device use, and home safety. Tailored responses should include strength and balance training, gait rehabilitation, medication optimization, nutritional assessment, vision correction, environmental modification, and support for safe physical activity. Wearable monitoring should be implemented with standardized device placement, wear-time requirements, calibration, privacy safeguards, and procedures for distinguishing nonwear from inactivity. Subgroup performance should be reviewed regularly because discrimination was lower among frail adults, cognitively impaired participants, and assisted-living residents. Local recalibration and threshold adjustment should precede deployment in populations differing from the development sample. Health systems should also establish data-quality standards for repeated functional measures, sensor records, hospital events, and fall verification. Staff training, transparent documentation, secure data management, periodic model auditing, and monitoring of calibration drift should accompany implementation. These measures would support earlier identification of deteriorating mobility while preserving clinical accountability, patient autonomy, fairness, and interpretability.

LIMITATIONS

This study had several limitations that should be considered when interpreting the findings. First, the prospective longitudinal cohort design supported temporal prediction but did not establish causal relationships between functional deterioration, clinical characteristics, wearable indicators, and subsequent outcomes. Important unmeasured factors, including home hazards, footwear, weather, caregiver supervision, neighborhood conditions, nutrition, and adherence to rehabilitation, may have influenced both falls and mobility decline. Second, participants were recruited from 12 community, outpatient, rehabilitation, and assisted-living sites, but the sample may not fully represent older adults living in rural regions, long-term nursing facilities, culturally different populations, or health systems with fewer geriatric services. Third, attrition was not completely random. Participants who did not complete the 24-month assessment were older, frailer, and demonstrated poorer baseline mobility, which may have produced conservative estimates of later functional deterioration. Multiple imputation and complete-case sensitivity analyses reduced but could not eliminate this source of bias. Fourth, falls were monitored through calendars and monthly participant or caregiver contact. Minor events may still have been forgotten, misclassified, or unreported, particularly among participants with cognitive impairment. Medical records verified serious events more reliably than noninjurious falls occurring outside healthcare settings. Fifth, wearable devices were used for seven days after each major assessment and may not have represented usual activity across different seasons, health episodes, or environmental conditions. Device removal, placement differences, assistive-device use, and movement-classification errors may also have affected sensor-derived features. Sixth, comprehensive functional assessments occurred at six-month intervals, which limited the detection of short-term decline, temporary recovery, and rapid changes occurring between visits. Seventh, mobility decline was defined using gait speed, physical-performance scores, and new assistance requirements.

Although this composite definition captured several dimensions of deterioration, its components may represent different levels and mechanisms of disability. Eighth, recurrent and injurious falls occurred less frequently than the primary outcomes, reducing precision in some secondary and subgroup analyses. Estimates for adults aged 85 years or older, cognitively impaired participants, and assisted-living residents were based on smaller samples and therefore had wider uncertainty. Ninth, the stacked ensemble was more complex and less directly interpretable than conventional regression. Shapley-based and permutation analyses described model behavior but did not establish that highly ranked predictors caused the outcomes. Finally, external testing involved two geographically separated sites, which provided a meaningful assessment of generalizability but did not guarantee equivalent performance in other countries, care systems, device environments, or populations with different fall prevalence. Changes in clinical practice, data quality, measurement protocols, and population characteristics could also alter calibration after implementation.

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