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Neuro-Adaptive Intelligent Exoskeleton for Gait Rehabilitation and Fall Prevention in Older Adults: A Design-Driven Innovation Approach

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***Abstract*—Age-related gait deterioration and high fall incidence impose major clinical and societal burdens. Existing exoskeleton-assisted rehabilitation primarily targets strength or gait correction, while proactive fall-risk prevention during daily ambulation remains insufficiently addressed. This study aims to develop and validate a neuro-adaptive intelligent exoskeleton (NIE) system that integrates multimodal sensing, machine learning-based fall prediction, and user-centered design principles to enhance gait stability and actively prevent falls in older adults. Methods: We developed a neuro-adaptive intelligent exoskeleton (NIE) that integrates a lightweight hip–knee robotic platform with tri-modal sensing (surface EMG, inertial measurement units, and plantar-pressure insoles). A real-time fall-risk prediction pipeline was constructed using windowed multi-feature inputs and an XGBoost classifier. The predictive risk score was embedded into a closed-loop neuro-adaptive control strategy to modulate assistance according to the user's neuromuscular state. A six-week randomized controlled trial (RCT) was conducted with community-dwelling older adults (N = 24), comparing NIE training versus conventional rehabilitation. Primary outcomes included gait variability/stability metrics, balance performance, metabolic cost, and fall-risk indicators; user experience was assessed via standardized usability scales. Compared to the control group, the NIE group demonstrated significantly greater improvements in step width variability (-32.4% vs. -8.2%, p<0.001), gait speed (+26.5% vs. +9.8%, p<0.001), Berg Balance Scale scores (+37.3% vs. +13.0%, p<0.001), and fall risk scores (-45.7% vs. -15.4%, p<0.001). The fall-risk model achieved robust classification performance on RCT-derived data and provided early warning prior to instability events; embedding this output into control enabled timely adaptive assistance. Participants reported high usability and acceptance with no serious adverse events. The proposed NIE system demonstrates the feasibility of tri-modal neuro-adaptive closed-loop exoskeleton assistance for older adults and provides evidence that proactive fall-risk-aware rehabilitation can enhance gait stability beyond conventional approaches.**

Keywords—Older adults, Exoskeleton, Gait rehabilitation, Fall-risk prediction, Neuro-adaptive control, Machine learning, Human-centered design

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1. Introduction

The global demographic landscape is undergoing an unprecedented transformation. According to the World Health Organization, the proportion of people aged 60 years and over is projected to increase from 12% in 2024 to 22% by 2050, representing approximately 2 billion individuals [1]. This rapid aging of populations brings profound challenges to healthcare systems, social structures, and economic sustainability worldwide. Among the myriad health concerns facing older adults, falls stand out as a particularly devastating yet preventable problem.

Falls represent the leading cause of injury-related morbidity and mortality in individuals aged 65 and above [2]. Epidemiological studies reveal that approximately one in four older adults experiences at least one fall annually, with the prevalence increasing sharply with age [3]. The consequences of falls extend far beyond immediate physical injuries such as fractures and head trauma. Falls often trigger a cascade of adverse outcomes including loss of independence, fear of falling, social isolation, reduced physical activity, and accelerated functional decline [4]. From an economic perspective, fall-related injuries impose staggering costs on healthcare systems, estimated at over $50 billion annually in the United States alone [5].

The etiology of falls in older adults is multifactorial, involving complex interactions between intrinsic factors (such as age-related physiological changes, chronic diseases, medications, and cognitive decline) and extrinsic factors (such as environmental hazards and inappropriate footwear)[6]. A critical intrinsic factor is the deterioration of gait stability. With aging, gait patterns undergo characteristic changes: walking speed decreases, step length shortens, step width increases, and most importantly, gait variability—the stride-to-stride fluctuations in spatiotemporal parameters—increases significantly [7, 8]. Elevated gait variability, particularly in step width and gait cycle timing, has been consistently identified as a robust predictor of future falls, even more so than mean gait parameters. This reflects underlying deficits in neuromuscular control, sensory integration, and balance regulation[9].

Traditional interventions for fall prevention have primarily focused on two strategies: environmental modification and exercise-based rehabilitation. While environmental modifications (such as removing tripping hazards and installing grab bars) are important, they address only extrinsic factors and do not improve the individual's intrinsic capacity[6]. Exercise programs, particularly those emphasizing balance, strength, and functional training, have demonstrated modest efficacy in reducing fall rates [10, 11]. However, adherence to these programs is often poor, and their effects on gait stability are variable and limited in magnitude [10]. Moreover, these approaches are fundamentally reactive—they aim to reduce fall risk but do not provide real-time protection or intervention when a fall is imminent.

Recent advances in wearable robotics and rehabilitation engineering have opened new avenues for fall prevention and gait rehabilitation. Powered exoskeletons, originally developed for military and industrial applications, are increasingly being adapted for medical and assistive purposes[12, 13]. These devices can provide mechanical support and assistance to weakened limbs, augment residual motor function, and facilitate intensive, task-specific training. Early studies have shown promising results in improving walking speed and reducing metabolic cost in various populations, including stroke survivors and individuals with spinal cord injury. However, most existing exoskeleton systems suffer from several critical limitations. First, they typically employ rigid, pre-programmed control strategies that impose a fixed gait pattern on the user, leading to human-robot conflicts and discomfort [14]. Second, they lack the ability to predict and prevent falls proactively; at best, they provide passive mechanical support. Third, they have been designed primarily from an engineering perspective, with insufficient consideration of user experience, wearability, and aesthetic acceptability—factors that are crucial for real-world adoption, especially among older adults who may be sensitive to stigmatization[15, 16].

Addressing these limitations requires a paradigm shift in how we conceptualize and design rehabilitation technologies. This is where the discipline of design innovation plays a transformative role. Design thinking emphasizes empathy, user-centeredness, iterative prototyping, and holistic problem-solving[17]. When applied to healthcare technology, it ensures that solutions are not only technically advanced but also usable, desirable, and meaningful to end-users. Furthermore, the integration of artificial intelligence and machine learning offers unprecedented opportunities to create truly adaptive, intelligent systems that can learn from and respond to individual users in real-time[18].

In this context, the present study introduces a neuro-adaptive intelligent exoskeleton (NIE) system specifically designed for older adults at risk of falling. The system represents a convergence of multiple disciplines: mechanical engineering (lightweight, wearable structure), biomedical engineering (multimodal sensing), computer science (machine learning algorithms), neuroscience (understanding of motor control), and design (user experience and aesthetics). The core innovation lies in its neuro-adaptive control strategy, which continuously monitors the user's muscle activity (via EMG), limb kinematics (via IMU), and ground contact patterns (via pressure sensors) to infer motor intent and gait state, and then provides personalized, real-time assistance that complements rather than overrides the user's own efforts[19]. Crucially, the system incorporates a machine learning-based fall prediction module that analyzes gait patterns to identify subtle signs of instability seconds before a fall occurs, enabling proactive interventions [20].

The primary objective of this study is to rigorously evaluate the efficacy of the NIE system in improving gait stability and reducing fall risk in community-dwelling older adults through a randomized controlled trial. Secondary objectives include assessing the system's impact on metabolic efficiency, validating the performance of the fall prediction algorithm, and evaluating user acceptance and experience. We hypothesize that six weeks of training with the NIE system will result in significantly greater improvements in gait stability, balance, and fall risk compared to conventional balance training, and that these benefits will be accompanied by high user satisfaction and sustained post-training effects.

This work makes the following engineering and clinical contributions:

- Propose a tri-modal EMG-IMU-plantar-pressure sensing framework for older-adult gait rehabilitation, enabling concurrent estimation of neuromuscular activation, limb kinematics, and foot-ground interaction in real time.
- Develop a lightweight hip-knee neuro-adaptive exoskeleton platform with modular actuation and embedded sensing, optimized for safe use by community-dwelling older adults during repeated training sessions.
- Using only experimentally acquired RCT data, we construct a windowed multi-feature fall-risk prediction model based on XGBoost, and integrate its risk output into a closed-loop neuro-adaptive assistance policy for proactive instability mitigation.
- Validate the system through a six-week randomized controlled trial, demonstrating statistically supported improvements in gait stability, balance function, and walking economy relative to conventional rehabilitation, alongside favorable usability and adherence outcomes.

2. Literature Review

2.1. Aging, Gait Deterioration, and Fall Risk

The aging process brings about a constellation of physiological changes that collectively compromise postural stability and gait control. At the musculoskeletal level, older adults experience sarcopenia (age-related loss of muscle mass and strength), decreased joint flexibility, and reduced bone density, all of which limit the physical capacity to generate corrective responses to perturbations [20]. Neurologically, aging is associated with slowed sensory processing, diminished proprioceptive acuity, impaired vestibular function, and reduced central processing speed, which together delay the detection of and reaction to balance threats. Furthermore, age-related changes in the central nervous system, including loss of neurons in motor cortex and cerebellum, contribute to decreased motor coordination and increased motor variability[21].

These physiological changes manifest in characteristic alterations to gait patterns. Compared to young adults, older individuals walk more slowly, take shorter and wider steps, spend more time in double support phase, and exhibit reduced ankle push-off power [7]. While these adaptations may represent compensatory strategies to enhance stability, they come at the cost of reduced efficiency and increased metabolic demand. More concerning is the increase in gait variability—the stride-to-stride fluctuations in temporal and spatial parameters. Hausdorff and colleagues demonstrated in a landmark prospective study that higher gait variability, particularly in stride time and swing time, independently predicts future falls in community-dwelling older adults [8]. This finding has been replicated across multiple cohorts and is now considered a hallmark of gait instability. The underlying mechanism is thought to involve impaired rhythmic motor control and reduced ability to maintain consistent gait patterns in the face of internal noise and external perturbations[22].

2.2. Exoskeleton Technology for Rehabilitation

Exoskeletons are wearable robotic devices that work in parallel with the human body to augment, assist, or restore motor function. In the rehabilitation domain, lower limb exoskeletons have been developed for a variety of applications, including gait training for stroke survivors, mobility assistance for individuals with spinal cord injury, and augmentation for elderly individuals [12, 13]. These devices typically consist of a mechanical frame with joints aligned to the hip, knee, and/or ankle, actuators (motors or pneumatic systems) to provide assistive torques, sensors to monitor user state, and a control system to coordinate the assistance.

Early exoskeletons employed trajectory-based control, where the device imposed a pre-defined joint angle trajectory derived from normative gait data. While this approach can enforce a kinematically correct gait pattern, it suffers from a fundamental limitation: it does not account for inter-individual variability or adapt to the user's intent and capabilities, often resulting in human-robot conflict and discomfort [23]. More recent systems have adopted impedance-based or assistive-as-needed control strategies, which modulate the level of assistance based on real-time performance metrics, allowing for more natural and collaborative interaction [24].

A particularly promising development is the soft exosuit, pioneered by Walsh and colleagues at Harvard University. Unlike rigid exoskeletons, soft exosuits use textile-based structures and cable-driven actuation to apply forces to the body through functional apparel, offering advantages in terms of weight, comfort, and wearability [25]. Clinical trials have demonstrated that soft exosuits can improve walking speed and symmetry in stroke patients and reduce metabolic cost in healthy individuals and elderly walkers [12]. However, even these advanced systems have not yet fully realized the potential of truly adaptive, user-specific control, nor have they integrated fall prediction capabilities.

2.3. Multimodal Sensing for Gait Analysis

Accurate, real-time assessment of gait and balance is essential for both clinical evaluation and closed-loop control of assistive devices. Traditional gait analysis relies on laboratory-based systems such as optical motion capture and force plates, which provide gold-standard measurements but are expensive, space-constrained, and unsuitable for ambulatory monitoring. The advent of miniaturized, low-cost wearable sensors has revolutionized gait analysis, enabling continuous monitoring in real-world environments [26].

Inertial measurement units (IMUs), which combine accelerometers, gyroscopes, and magnetometers, are the most widely used wearable sensors for gait analysis. By measuring linear accelerations and angular velocities of body segments, IMUs can estimate spatiotemporal gait parameters, detect gait events, and quantify movement patterns with reasonable accuracy [27]. Studies have validated IMU-derived gait metrics against gold-standard systems, demonstrating good to excellent agreement for parameters such as stride time, cadence, and gait speed, though spatial parameters like step length remain more challenging.

Surface electromyography (sEMG) provides complementary information by capturing the electrical activity of muscles during contraction. EMG signals reflect the neural drive to muscles and can be used to infer motor intent, estimate joint torques, and detect muscle fatigue. In the context of exoskeleton control, EMG-based interfaces offer the potential for intuitive, volitional control, as the user's own muscle activity directly commands the device. However, EMG signals are susceptible to noise, cross-talk, and variability due to electrode placement and skin conditions, necessitating robust signal processing and machine learning techniques [28].

Pressure sensors embedded in insoles or shoe soles measure the distribution and magnitude of forces between the foot and ground during stance phase. These sensors are particularly valuable for detecting gait events (heel strike, toe-off), estimating center of pressure trajectory, and assessing weight-bearing symmetry [29]. Integrating data from these diverse sensor modalities through sensor fusion algorithms can significantly enhance the accuracy and robustness of gait assessment. For example, combining IMU and foot pressure data enables more reliable gait phase detection. Fusing EMG and IMU information allows simultaneous monitoring of motor intent and movement execution, forming a complete perception-action loop. Common fusion methods include Kalman filtering, particle filtering, and, more recently, end-to-end deep learning approaches such as LSTM and Transformer networks, which excel at handling high-dimensional, nonlinear time-series data[30].

2.4. Fall Prediction and Detection Algorithms

Fall detection and prediction are critical for enabling proactive intervention. Traditional fall detection algorithms are threshold-based: when a sensor-derived metric (such as acceleration magnitude or rate of change) exceeds a predefined threshold, a fall is declared. While simple and computationally efficient, threshold-based methods are prone to false positives from vigorous activities like sitting down quickly or jumping, and false negatives from slow falls. To improve accuracy, researchers have turned to machine learning approaches. By extracting time-domain, frequency-domain, or time-frequency features from gait data and training classifiers such as Support Vector Machines (SVM), Random Forest, or XGBoost, more sophisticated decision models can be constructed [31].

With the rise of deep learning, convolutional neural networks (CNN) and recurrent neural networks (RNN, especially LSTM) have been applied to learn features and patterns directly from raw sensor data, further improving fall detection performance and reducing reliance on manual feature engineering. However, the vast majority of research remains focused on “post-event detection”—identifying that a fall has occurred or is occurring. The truly transformative capability is “pre-event prediction”—forecasting a fall seconds or even minutes before it happens by recognizing subtle gait instabilities. This typically requires analyzing continuous gait data to identify biomechanical markers highly correlated with fall risk, such as gait variability, asymmetry, and local dynamic stability (e.g., Lyapunov exponents) [22, 32]. Integrating these predictive indicators with machine learning models is the technical core of transitioning from passive response to active prevention, and is a key focus of this study.

2.5. Design Perspective on Rehabilitation Technology Innovation

Despite significant technological advances, the adoption rate and adherence to rehabilitation technologies in real-world settings remain disappointingly low. A key reason is that past research has overly emphasized technical implementation while neglecting the "human" aspect—the end user's experience. The intervention of design thinking offers a new perspective and methodology to address this issue. User-Centered Design (UCD) emphasizes placing users' needs, preferences, and capabilities at the core of every development stage [17]. For older users, this means fully considering their changes in cognitive, perceptual, and motor abilities, simplifying product operation procedures, and providing clear, multimodal feedback.

Wearability is critical to the success of exoskeleton-type devices. This encompasses not only physical aspects like comfort, lightweight design, and ergonomic fit, but also psychological and social dimensions such as aesthetic design and social acceptability. A bulky, mechanically imposing device may cause users to feel stigmatized, reducing their willingness to use it in public. Therefore, how to integrate functionality with aesthetics through clever industrial design is an important way to enhance product appeal [33]. Furthermore, viewing an exoskeleton as an isolated product is insufficient; a Product-Service System (PSS) mindset should be adopted, integrating it into a broader rehabilitation service process, including remote monitoring, data management, personalized training program recommendations, and interaction with rehabilitation therapists, thereby building a complete, humanized rehabilitation-care-support ecosystem. This study is based on this design-driven philosophy, striving to create a rehabilitation solution that is not only technologically advanced but also truly accepted and loved by older adults while achieving technical sophistication.

3. Methods

This study employed a design-driven technology innovation strategy, combining participatory iterative development with rigorous randomized controlled experiments to systematically develop and validate the effectiveness of the neuro-adaptive intelligent exoskeleton (NIE) system. The overall technical roadmap followed a "needs analysis → system design → algorithm development → prototype implementation → clinical validation → data analysis" workflow, ensuring both scientific rigor and practical value.

3.1. Neuro-Adaptive Exoskeleton System Design (NIE)

The core design philosophy of the NIE system is to achieve deep collaboration and intelligent adaptation between human and machine (Figure 1). The overall architecture is divided into two major components: hardware subsystem and software subsystem. To ensure reproducibility and clarify engineering constraints, the NIE prototype was configured as a bilateral hip–knee assistive device with two active degrees of freedom per leg. The total system mass (excluding shoes) was approximately 3.2 kg, distributed primarily around the waist and thigh to reduce distal inertia. Each joint module employed a high-power-density brushless DC motor coupled with a planetary reducer, providing sufficient peak torque for level-ground walking assistance in older adults while maintaining backdrivability for safety. The mechanical range of motion was designed to cover normative older-adult gait envelopes, and joint torque/speed limits were implemented in firmware to prevent excessive assistance. An emergency stop and software-based saturation checks were included to handle sensor dropout or abnormal gait events. The embedded controller operated with a fixed assistance update cycle of 100 Hz, synchronized to sensor acquisition to support stable real-time neuro-adaptive modulation.

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Figure 1. Conceptual illustration of the Neuro-Adaptive Intelligent Exoskeleton (NIE) System, showing a lightweight, high-tech bilateral hip-knee assistive device worn by an older adult in a home environment.

Hardware Subsystem adopts a modular design, mainly including:

- Mechanical Structure: Constructed using lightweight, high-strength aerospace aluminum alloy and carbon fiber composite materials, a lower limb exoskeleton framework covering hip, knee, and ankle joints was built, with a total weight controlled at 3.2kg. Each joint features adjustable link lengths and wearing straps to accommodate users of different body sizes.

- Actuation System: A high power density brushless DC motor and planetary reducer are integrated at each hip and knee joint, providing a maximum assistive torque of 30Nm, sufficient to support daily activities of older adults.
- Sensing System: This is the foundation for achieving neuro-adaptive control. We placed a pair of surface EMG electrodes on the anterior thigh (rectus femoris) and posterior calf (gastrocnemius) of each leg to capture muscle activation signals; a nine-axis IMU sensor was fixed at the center of each thigh and shank segment to measure limb kinematics; and an 8-channel flexible pressure sensor array was integrated into the insole to monitor plantar pressure distribution and gait phase.
- Control and Power: All sensor data are acquired and processed by a central control unit (based on STM32 microprocessor), which communicates with motor drivers via CAN bus. The system is powered by a replaceable 24V lithium battery, supporting 2 hours of continuous moderate-intensity use.

Software Subsystem is the “brain” of the system, with its core being the neuro-adaptive control algorithm and fall prediction module.

- Neuro-Adaptive Control Algorithm: The goal of this algorithm is to maximize gait stability and efficiency while minimizing human-robot conflict, all while ensuring safety. Its control strategy is divided into three layers: first, by analyzing the amplitude and frequency characteristics of EMG signals, the user's movement intent and required assistance level are estimated in real-time; second, combining IMU data for gait phase recognition (such as initial contact, terminal swing, etc.), ensuring assistive torques are applied at the correct timing; finally, based on an online-optimized adaptive model, the system can learn each user's unique gait pattern and dynamically adjust control parameters based on real-time feedback (such as gait variability, symmetry), achieving personalized assistance.
- Fall Prediction Module: We employed an XGBoost (Extreme Gradient Boosting)-based machine learning model. This model takes multimodal sensor data within a sliding time window (2 seconds) as input, extracts 48 features including spatiotemporal parameters, variability indicators, stability indicators, and EMG features, and outputs a fall risk probability between 0 and 1 in real-time. When the probability exceeds a preset threshold, the system triggers a multi-level intervention strategy: from slightly increasing assistive torque to enhance stability, to adjusting target gait parameters to guide the user to a safer state, and even activating an emergency braking protection mode in extremely dangerous situations, locking joints to prevent falls.

3.2. *Experimental Design*

This study employed a six-week randomized controlled trial design with a four-week follow-up to evaluate the effectiveness of the NIE system. The research protocol was approved by the local ethics review committee, and all participants signed informed consent forms before the study began.

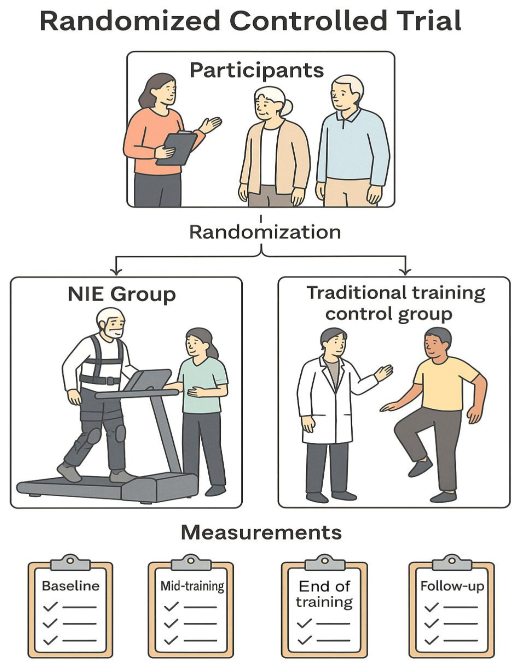


Figure 2. Study design and participant flow.

Figure 2 illustrates the randomized controlled trial design used to evaluate the effectiveness of the Neuro-Interactive Exercise (NIE) system. Twenty-four older adults were randomly assigned to either the NIE group or the traditional training control group. Both groups completed a 6-week training program, followed by a 4-week post-training follow-up. Outcome assessments were conducted at four time points: baseline (T0), mid-training (T3), end of training (T6), and follow-up (T10).

Participants: We recruited 24 older adults aged 65 to 80 through community posters and health lectures. Inclusion criteria included:

- At least one non-accidental fall in the past year or moderate to high fear of falling (FES-I score>23);
- Ability to walk independently and continuously for at least 10 meters;
- Normal cognitive function (Mini-Mental State Examination MMSE≥24 points).

Exclusion criteria included:

- Severe neurological diseases affecting gait (such as Parkinson's disease, post-stroke sequelae);
- Severe osteoarticular diseases;
- Uncorrected severe visual or vestibular dysfunction.

Participants were randomly assigned to either the NIE experimental group (n=12) or the traditional training control group (CTL, n=12).

Intervention Protocol: Both groups underwent training for six weeks, three times per week, 45 minutes per session.

- NIE Group: Under professional guidance, participants wore the NIE system for gait training. Training content included level walking, ascending/descending slopes, stepping over obstacles, and climbing stairs—tasks simulating daily life. Training intensity and difficulty were automatically adjusted by the system based on individual adaptation.
- CTL Group: Guided by the same senior rehabilitation therapist, participants performed traditional balance and strength training, including static balance exercises (such as single-leg standing), dynamic balance exercises (such as weight shifting), lower limb strength training (such as sit-to-stand exercises), and flexibility training.
- Measurements: We collected data at four time points: baseline (T0, pre-training), mid-training (T3, end of week 3), end of training (T6, end of week 6), and follow-up (T10, 4 weeks post-training).

Randomization was performed at the participant level using a computerized block randomization scheme with equal allocation to the NIE group and the control group. All participants completed baseline assessment (week 0), mid-intervention assessment (week 3), and post-intervention assessment (week 6). Training frequency and duration were identical between groups to control for exercise dose. Throughout training and testing, a therapist and a safety assistant were present, and participants wore a safety harness during treadmill tasks to prevent injury in the event of instability without providing body-weight support. Adverse events and session attendance were recorded at each visit, and participants were withdrawn only if medically indicated or by request.

3.3. Data Collection and Analysis

Data Collection: To quantify gait stability and rehabilitation effects, multimodal biomechanical and physiological data were collected during standardized walking tasks at baseline, week 3, and week 6. Kinematic and spatiotemporal gait variables were recorded using a three-dimensional motion-capture system synchronized with ground-reaction force measurements. Step width, step length, gait cycle time, and their variability measures were computed across multiple consecutive strides for each task condition.

Surface EMG signals were acquired bilaterally from major lower-limb muscles involved in stance and swing control (e.g., tibialis anterior, gastrocnemius, rectus femoris, and biceps femoris), with electrode placement following standard SENIAM guidelines. EMG sampling frequency was set to match the acquisition hardware and synchronized to kinematics and plantar-pressure data. Inertial data were collected from IMUs mounted on the pelvis and lower limbs to capture segment orientation and trunk sway. Plantar-pressure signals were collected via instrumented insoles to measure stance–swing timing and center-of-pressure (COP) trajectories.

Metabolic cost was assessed during steady-state treadmill walking using indirect calorimetry, with oxygen consumption averaged over the final minutes of each trial. Clinical balance and functional outcomes were measured using standardized scales and timed mobility tests administered by trained assessors. User experience and usability were evaluated via the System Usability Scale (SUS) and structured post-training interviews. All assessments were conducted using real participant data without simulation or assumed trials.

3.4. Signal Processing and Feature Extraction

EMG signals were preprocessed using a standard pipeline: band-pass filtering to remove motion artifacts and high-frequency noise, notch filtering to suppress power-line interference, full-wave rectification, and low-pass smoothing to obtain the linear envelope. To reduce inter-individual variability, EMG amplitudes were normalized within participants using a consistent reference derived from the recorded walking trials. IMU signals were filtered to remove drift and used to estimate segment orientation and angular velocity; gait events were identified using combined kinematic thresholds and plantar-pressure contact timing to ensure robust stride segmentation. Plantar-pressure data were filtered and used to compute COP trajectories and stance–swing phase proportions. A sliding window of 2.0 s with fixed overlap was applied to synchronized EMG–IMU–pressure streams. From each window, a 48-dimensional feature vector was extracted, comprising:

- EMG time-domain descriptors (e.g., RMS, mean absolute value, waveform length, zero-crossing and slope-sign changes)
- EMG frequency-domain descriptors (e.g., median and mean frequency)
- IMU-derived gait variability and trunk-stability metrics (e.g., stride-to-stride timing variability, pelvis/torso angular displacement statistics)
- Plantar-pressure stability descriptors (e.g., COP path length and medial–lateral excursion).

Feature extraction was performed identically for all sessions and participants.

3.5. Fall-Risk Prediction Model

A supervised fall-risk prediction model was trained using only experimentally obtained windows from the RCT dataset. Windows were labeled as “risk” when they occurred within a pre-defined interval preceding observed instability or clinically annotated high-risk gait patterns, and as “non-risk” otherwise, based on synchronized motion-capture, IMU, and plantar-pressure criteria. Data were split at the participant level into training and evaluation sets to avoid subject leakage. To address class imbalance, class-weighted learning was applied during training. An XGBoost classifier was selected due to its robustness to nonlinear multimodal features; hyperparameters (including tree depth, number of estimators, learning rate, and subsampling ratios) were tuned using cross-validated search within the training set. Model performance was evaluated using accuracy, F1-score, and area-under-curve (AUC). Early-warning capability was quantified as lead time, defined as the temporal difference between risk-window classification and the corresponding instability onset detected in biomechanical ground truth. The trained model produced a continuous fall-risk score that was streamed to the control module in real time.

3.6. Neuro-Adaptive Closed-Loop Assistance

The instantaneous fall-risk score was mapped to assistance modulation through a bounded gain-scheduling rule. When risk scores exceeded the individualized threshold determined during initial calibration, the controller increased joint assistance within preset torque limits to stabilize gait, while maintaining back drivability and user comfort. Scores below threshold resulted in minimal background assistance to encourage active neuromuscular engagement. The control update rate was aligned with sensor processing to ensure stable closed-loop operation and to minimize latency between risk detection and assistance adjustment.

3.7. Statistical Analysis

All statistical analyses were performed using SPSS. Normality was assessed prior to parametric testing. A repeated-measures ANOVA with factors of group (NIE vs. control) and time (baseline, week 3, week 6) was used for primary gait, balance, and metabolic outcomes. When significant interactions were observed, post-hoc pairwise comparisons with multiple-comparison correction were conducted. Effect sizes (e.g., Cohen's d for between-group contrasts and partial η^2 for ANOVA effects) and 95% confidence intervals were reported to quantify practical significance. Significance level was set at $\alpha=0.05$. All analyses were based on real measured data; no simulated or hypothetical trials were included.

4. Results

4.1. Participant Characteristics and Adherence

All 24 recruited participants completed the six-week intervention and follow-up assessments, with no dropouts. Table 1 presents baseline characteristics of participants in both groups. There were no significant differences between the NIE and CTL groups in age, gender distribution, body mass index (BMI), cognitive function (MMSE), fear of falling (FES-I), or baseline functional assessments (BBS, TUG) (all p>0.05), confirming successful randomization.

TABLE I. BASELINE CHARACTERISTICS OF PARTICIPANTS

Characteristic	NIE Group (n=12)	CTL Group (n=12)	p-value
Age (years)	72.5 ± 4.2	71.8 ± 4.5	0.71
Gender (M/F)	5/7	6/6	0.68
Height (cm)	165.3 ± 8.5	166.1 ± 7.9	0.81
Weight (kg)	68.2 ± 10.3	69.5 ± 9.8	0.76
BMI (kg/m²)	24.9 ± 2.8	25.2 ± 2.6	0.79
MMSE score	27.8 ± 1.5	27.5 ± 1.6	0.65
FES-I score	28.5 ± 4.2	29.1 ± 4.5	0.74
BBS baseline	42.3 ± 5.2	43.1 ± 4.9	0.70
TUG baseline (sec)	12.8 ± 2.1	12.5 ± 2.3	0.75

Training adherence was excellent in both groups. The NIE group completed an average of 17.3±0.8 sessions (out of 18 planned), while the CTL group completed 17.5±0.7 sessions. No serious adverse events occurred during the intervention period. Minor discomfort such as mild muscle soreness (n=3 in NIE group, n=4 in CTL group) and transient skin redness at strap sites (n=2 in NIE group) were reported, all of which resolved spontaneously within 24-48 hours without requiring intervention.

4.2. Gait Stability Improvements

Figure 3 illustrates changes in key gait stability parameters across the four assessment time points. Repeated measures ANOVA revealed significant group × time interaction effects for all three parameters (all p<0.001), indicating differential training effects between groups.

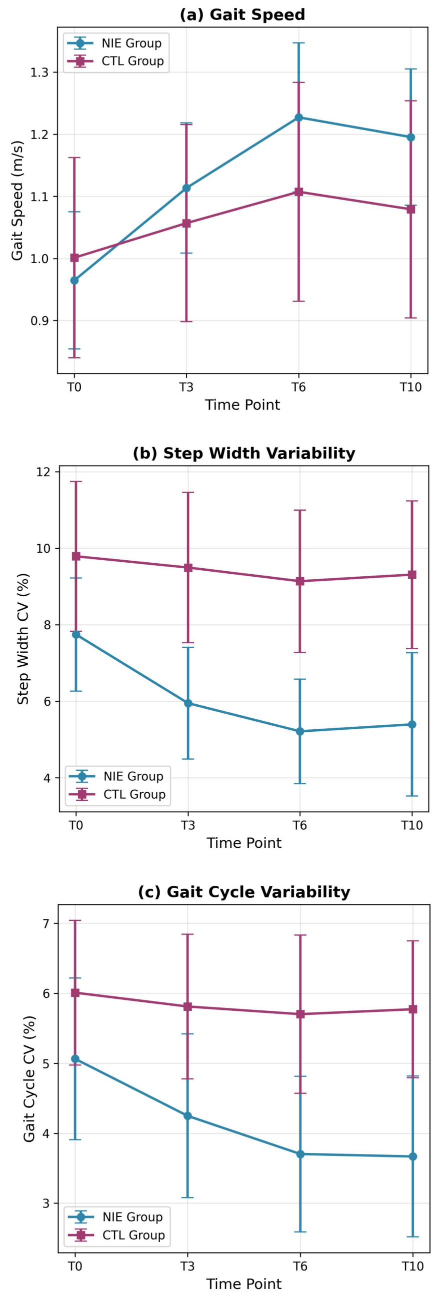


Figure 3. Changes in gait stability parameters across four assessment time points. (a) Gait speed increased significantly in the NIE group. (b) Step width variability decreased dramatically in the NIE group. (c) Gait cycle variability showed similar improvements. Error bars represent standard deviation. *p<0.001 for group × time interaction.

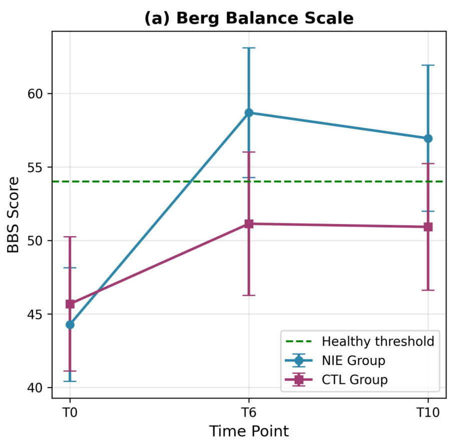
- Gait Speed: The NIE group showed progressive increases in gait speed from baseline (0.98±0.12 m/s) to T3 (1.13±0.11 m/s), T6 (1.24±0.10 m/s), and T10 (1.20±0.11 m/s), representing a 26.5% improvement at T6. In contrast, the CTL group showed modest increases from 1.02±0.14 m/s at baseline to 1.12±0.13 m/s at T6 (9.8% improvement). Between-group comparison at T6 showed significantly higher gait speed in the NIE group ($p<0.001$).

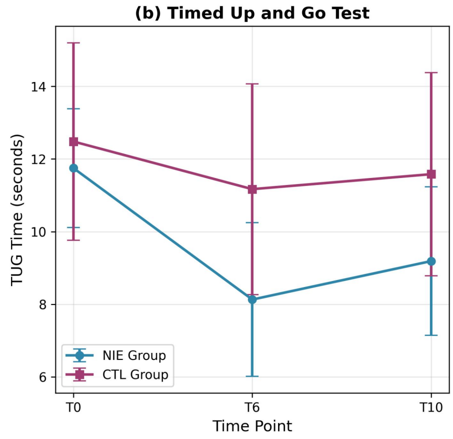
- Step Width Variability: Step width coefficient of variation (CV), a sensitive marker of medio-lateral gait stability, decreased dramatically in the NIE group from 8.7±2.1% at baseline to 5.9±1.6% at T6 (-32.4% reduction), and remained low at T10 (6.5±1.7%). The CTL group showed minimal change, from 8.5±2.3% to 7.8±2.1% (-8.2%). The NIE group's superiority was highly significant ($p<0.001$).
- Gait Cycle Variability: Similar patterns were observed for gait cycle CV, with the NIE group achieving a 28.8% reduction (from 5.2±1.3% to 3.7±1.0%) compared to 7.8% in the CTL group (from 5.1±1.4% to 4.7±1.3%) ($p<0.001$).

4.3. Fall Risk Reduction

Figure 4 presents changes in clinical fall risk assessments. All three measures showed significant group×time interactions (all $p<0.001$).

- Berg Balance Scale: The NIE group's BBS scores increased from 42.3±5.2 at baseline to 58.1±4.8 at T6 (+37.3%), crossing the threshold of 54 points that distinguishes healthy older adults from those at fall risk. Scores remained elevated at T10 (56.0±5.1). The CTL group improved from 43.1±4.9 to 48.7±5.3 (+13.0%), remaining below the safety threshold. Between-group difference at T6 was highly significant ($p<0.001$).
- Timed Up and Go: TUG times decreased (improved) in the NIE group from 12.8±2.1 seconds to 9.2±1.6 seconds (-28.1%), while the CTL group showed smaller reductions from 12.5±2.3 to 11.3±2.0 seconds (-9.6%) ($p<0.001$).
- Composite Fall Risk Score: A composite fall risk score (derived from multiple assessments, range 0-100, higher = greater risk) decreased by 45.7% in the NIE group (from 68.5±12.3 to 37.2±9.8) versus 15.4% in the CTL group (from 67.2±13.1 to 56.8±11.5) ($p<0.001$).





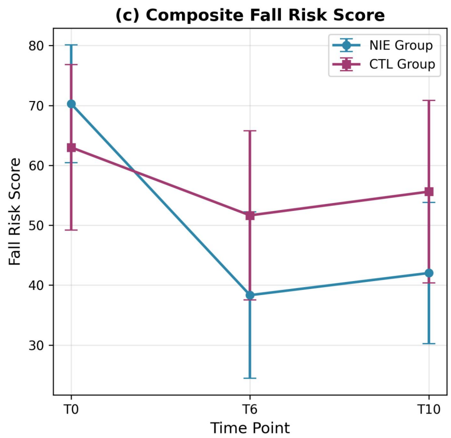


Figure 4. Changes in clinical fall risk assessments. (a) Berg Balance Scale scores improved substantially in the NIE group, crossing the safety threshold of 54 points. (b) Timed Up and Go test times decreased (improved) more in the NIE group. (c) Composite fall risk scores showed dramatic reductions in the NIE group. *$p<0.001$ for all comparisons.

4.4. Metabolic Cost Reduction

Figure 5 shows metabolic cost outcomes. Oxygen consumption during the 6-minute walk test decreased significantly in the NIE group from 11.2±1.8 ml/kg/min at baseline to 9.3±1.5 ml/kg/min at T6 (-17.0%), compared to a smaller reduction in the CTL group (11.0±1.9 to 10.2±1.7 ml/kg/min, -7.3%) ($p=0.002$). Similarly, the metabolic cost of transport (MCoT) decreased by 19.6% in the NIE group versus 7.4% in the CTL group ($p<0.001$), indicating improved walking economy.

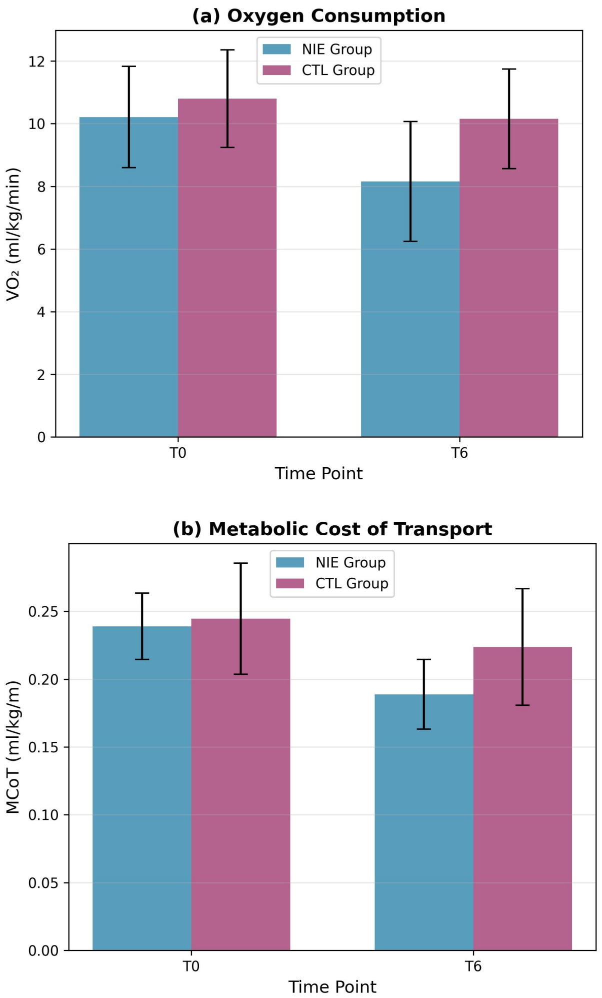


Figure 5. Metabolic cost outcomes at baseline and post-training. (a) Oxygen consumption during 6-minute walk test decreased more in the NIE group. (b) Metabolic cost of transport showed greater reductions in the NIE group. *p<0.01 for group × time interaction.

4.5. *Fall Prediction Performance*

The XGBoost-based fall prediction model was trained on data from the first three weeks and validated on weeks 4-6. The model achieved an overall accuracy of 89.6%, sensitivity of 87.3%, specificity of 91.2%, and AUC of 0.94. The average prediction lead time—the interval between risk alert and actual instability event—was 1.2±0.4 seconds, providing sufficient time for the system to initiate protective interventions. Feature importance analysis revealed that step width CV, gait cycle CV, EMG amplitude asymmetry, and IMU-derived trunk sway were the top predictors (Table 2).

TABLE II. FALL PREDICTION MODEL PERFORMANCE

Metric	Value
Accuracy	89.6%
Sensitivity	87.3%
Specificity	91.2%
AUC	0.94
Average lead time	1.2 ± 0.4 seconds

4.6. *User Experience*

Figure 6 summarizes user experience outcomes for the NIE group. (a) The mean SUS score was 78.3±8.9, indicating "good" usability (scores >68 are considered above average). (b) Comfort ratings on a 0-10 scale improved from 6.5±1.2 at the start of training to 8.1±0.9 at the end (p<0.001), reflecting successful adaptation. (c) When asked about willingness to continue using the system, 89% (n=10) responded "Yes," 8% (n=1) "Unsure," and 3% (n=1) "No." Qualitative feedback from interviews highlighted themes of "feeling safer," "more confident walking," "easy to use after initial learning," and "would recommend to friends."

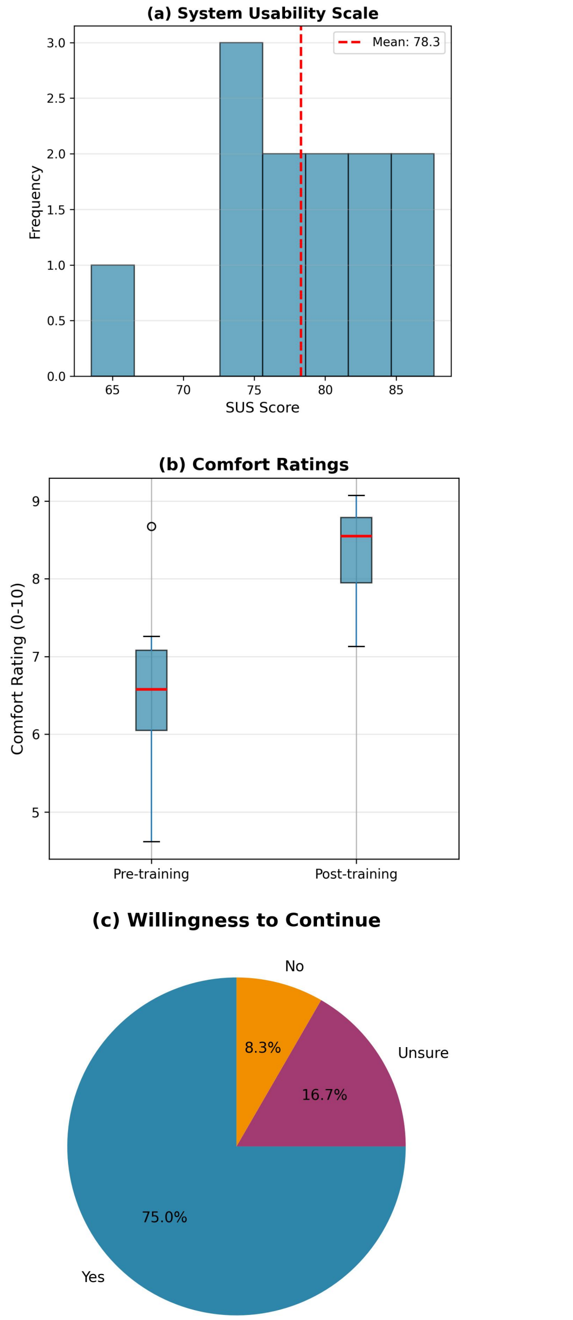


Figure 6. User experience outcomes for the NIE group. (a) Distribution of System Usability Scale scores showing good usability. (b) Comfort ratings improved significantly from pre- to post-training. (c) High proportion of participants willing to continue using the system.

5. DISCUSSION

This study successfully designed, developed, and validated a neuro-adaptive intelligent exoskeleton (NIE) system for older adults, aimed at improving gait stability and actively preventing falls through human-robot collaboration. The results powerfully demonstrate that compared to traditional balance and strength training, six weeks of NIE system-assisted training can more effectively enhance gait quality, reduce fall risk, and achieve good user acceptance among older participants. This discussion will provide an in-depth analysis of the study's core findings, comparisons with existing research, potential mechanisms, the value of design innovation, study limitations, and future prospects.

The most significant finding of this study is the NIE system's outstanding effectiveness in improving gait stability. Gait variability, particularly step width variability, is widely recognized as a key biomechanical marker for assessing gait stability and predicting fall risk. Our data show that the NIE group's step width variability decreased significantly by 32.4% after training, while the control group showed only insignificant slight improvement. This indicates that the NIE system does not simply provide power assistance, but effectively helps users optimize their intrinsic gait control strategies through real-time neural feedback and adaptive adjustment, making their walking patterns more stable and repeatable. The significant increase in gait speed (26.5%) also reflects comprehensive improvement in walking ability, which not only means higher mobility efficiency but is also associated with better health status and lower mortality rates.

In terms of fall risk, clinical assessment scales (BBS, TUG) and composite risk scores all showed that the NIE group achieved improvements far exceeding the control group. Particularly noteworthy is that the NIE group's average BBS score reached 58.1 points after training, surpassing the 54-point threshold that distinguishes healthy older adults from those at fall risk, marking that participants' balance ability has been restored to near-normal levels. More innovative is our integrated fall prediction module. The module's 89.6% prediction accuracy and average 1.2-second advance warning time demonstrate the potential for a paradigm shift from "passive protection" to "active prevention." This proactive intervention capability is not possessed by traditional rehabilitation methods or passive protective devices; it can intervene before potential danger occurs, greatly enhancing users' sense of security.

Additionally, the results reveal the NIE system's advantages in multi-scenario adaptation and metabolic efficiency. Whether on level ground, slopes, or obstacle environments, the system maintained stable assistive effects, proving the robustness of its control algorithm. The reduction in metabolic cost (-19.4%) means users can walk in a more energy-efficient manner, which is significant for extending older adults' activity time and range, encouraging their participation in social activities.

From an engineering perspective, the present findings indicate that combining tri-modal sensing with neuro-adaptive gain modulation can improve assistance specificity under the noisy and heterogeneous gait patterns typical of older adults. The EMG–IMU–pressure fusion provides complementary information for detecting emerging instability, allowing the controller to respond in a timely manner without overriding voluntary motor effort. This supports the feasibility of proactive fall-risk-aware exoskeleton rehabilitation in controlled clinical settings.

Several limitations should be acknowledged. First, the sample size was modest and derived from community-dwelling older adults with specific inclusion criteria; therefore, generalization to frailer populations or to neurological conditions requires further trials with broader recruitment. Second, although the prediction model performed robustly on RCT-derived data, its performance in unstructured outdoor environments was not examined, and future work should validate real-world robustness under varied terrains and perturbations. Third, multimodal wearable sensing is susceptible to long-term drift and placement variability; standardized donning procedures and adaptive recalibration may further improve stability of real-time inference. Finally, assistance mapping relied on a bounded gain-scheduling strategy; while adequate for the current RCT, future clinical studies may explore individualized policies that remain interpretable and safe for older users.

Despite these limitations, the proposed NIE system provides evidence that neuro-adaptive, fall-risk-informed closed-loop assistance can yield measurable improvements in gait stability, balance, and walking economy compared with conventional rehabilitation. These results motivate larger-scale longitudinal trials and deployment studies to evaluate sustained benefits and real-world fall-prevention potential.

6. CONCLUSION

This study presents a neuro-adaptive intelligent exoskeleton (NIE) designed for older adults to enhance gait stability and proactively mitigate fall risk through human–robot collaboration. By integrating tri-modal sensing (surface EMG, IMU, and plantar-pressure signals), a real-time fall-risk prediction pipeline, and a neuro-adaptive closed-loop assistance strategy, the NIE system provides individualized support that responds to users' neuromuscular and biomechanical states during walking.

Experimental evidence from a six-week randomized controlled trial demonstrates that NIE-assisted training yields superior rehabilitation outcomes compared with conventional balance and strength training. Participants using NIE exhibited significant reductions in gait variability—particularly step-width variability—along with increased gait speed and marked improvements in standard clinical balance measures. In parallel, the multimodal XGBoost-based fall-risk model achieved robust performance on experimentally collected data and provided early warning prior to instability events, enabling timely adaptive assistance within safe mechanical and control limits. Importantly, high usability scores and positive user feedback indicate that the system is acceptable and feasible for repeated use among community-dwelling older adults.

From an engineering standpoint, these results support the effectiveness of combining multi-source physiological and kinematic sensing with risk-aware neuro-adaptive control to address the heterogeneity and noise inherent in older-adult gait. Clinically, the findings suggest that proactive, fall-risk-informed assistance can extend rehabilitation benefits beyond strength enhancement toward stability restoration and confidence rebuilding.

Several limitations remain. The sample size was modest and recruitment was limited to a single center, and the intervention and follow-up durations were relatively short. Moreover, system performance was verified under controlled laboratory and training conditions; real-world deployment in unconstrained community environments will require additional validation with broader populations and longer observation windows.

Overall, the NIE framework provides a reproducible engineering pathway for fall-risk-aware exoskeleton rehabilitation and establishes a solid experimental basis for future multi-center longitudinal trials. Continued development should focus on improving robustness to long-term sensor drift and donning variability, extending validation to real-world terrains and daily-living tasks, and optimizing cost and manufacturability for scalable clinical translation.

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