Prediction for prospective falls via gait evaluation using mobile devices for stroke survivors: A markerless motion analysis study

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Abstract

Objective: Stroke survivors often experience hemiparetic lower extremity impairment, which increases fall risk. This study investigates prospective fall risk prediction using gait kinematic markers analyzed through a markerless motion capture system on mobile devices for participants with chronic stroke. **Design**: A prospective cohort study. **Setting:** Laboratory setting, with three iPad Pros positioned at the start, end, and lateral points along a 3-meter walkway. **Participants:** Adults with hemiplegic stroke (Modified Functional Ambulation Classification ≥III) and age-matched healthy controls, all without a recent fall. **Main measures:** Gait parameters including stride length, cadence, step width, stance/swing time, double support time at baseline, and fall history interview over the 18-month period following the walking experiment. **Results:** Fifty healthy adults and 46 participants with chronic stroke were recruited. The 18-month prevalence for fallers in participants with stroke was 13%. Participants with stroke demonstrated a slower walking speed, a shorter step width, and a longer standing time than the healthy adults. Cadence, stride length, stance time, and swing time were strong predictors of fallers among participants with chronic stroke. The relative risks for low cadence, low swing phase, and high stance phase were 2.163, 2.002, and 2.142, respectively. **Conclusion:** Our findings support the importance of using gait parameters obtained from the markerless motion capture system on mobile devices to predict prospective fall risk in the stroke population. Future research with larger, diverse cohorts of the stroke population using markerless motion capture is recommended to validate and refine the fall prediction models.

(Word count: 245 words)

Keywords: Stroke, fall prediction, gait evaluation, mobile device, markerless motion capture

Introduction

The impairment of hemiparetic lower extremity and balance significantly affect the walking gait of stroke survivors and result in gait performance that diverges from that observed in healthy adults (1). Research indicates that 82% of stroke survivors do not achieve full recovery of community ambulation three months or more poststroke (2). This finding suggests that walking difficulties may persist for extended periods. It thereby increases the risk of falls among this population. A previous study showed that the one-year prevalence of falls was 52.6% among individuals with chronic stroke and mild-to-moderate disabilities in community dwellings (3). Falls among stroke survivors can be fatal or cause 'double' disabilities; therefore, there is a need to investigate effective and efficient instrumental fall-risk prediction tools for fall risk detection in the clinical populations.

Medical professionals have focused on assessing the kinematic aspects of gait in stroke patients to identify their fall risk through the evaluation of walking patterns (4). Recent wearable sensor-based devices using inertial measurement units (5) and posturography using motion capture systems (6) have been developed for applications related to falls. While wearable devices and 3D motion capture systems provide accurate and reliable gait analysis (7), their clinical adoption remains limited due to the high cost, the lack of standardized treatment protocols and the insufficient translation of biomechanical data into actionable therapeutic insights (8). Consequently, therapists have utilized observational gait assessment tools, such as the Hemiplegic Gait Analysis Form, the Gait Assessment and Intervention Tool, and the Wisconsin Gait Scale, to identify gait abnormalities in stroke patients (9). However, these observational methods rely on subjective visual analysis, which suffers from poor inter-rater reliability. While scales such as Wisconsin Gait Scale provide standardized scoring (10), they often reduce complex gait patterns to ordinal categories which might lead to the obscuring of continuous and biomechanically meaningful data.

Studies indicates that only the Gait Assessment and Intervention Tool can be regarded as the current benchmark for observational gait analysis in this population (11).

Given the limitations of existing gait assessment tools—particularly their inability to provide objective, effective, and easily adaptable evaluations for stroke patients with mild to moderate mobility impairments, where gait abnormalities may be subtle and difficult to be observed, there is a need for valid and reliable instruments to assess fall risk in this population. Emerging markerless motion capture systems using mobile devices might show promise for portable, cost-effective gait analysis and fall risk prediction in stroke populations (12). However, few studies have validated their efficacy for kinematic-based fall risk assessment (13). Therefore, the aim of this study is to investigate prospective fall risk prediction in terms of fallers among participants with chronic stroke through an 18-month follow-up using gait kinematic markers analyzed through a markerless motion capture system on mobile devices.

Methodology

Study Design

Ethical approval of this study was obtained from the Human Subjects Research Ethics Committee of the Hong Kong Polytechnic University (Reference No.: HSEARS20230214010). All participants who met the inclusion criteria were required to provide informed and written consent before entering the study. This study was a prospective cohort study of participants with chronic stroke and their age- and gender-matched healthy counterparts recruited from the community through convenience sampling to establish reference values for gait parameters. The control group of healthy adults provided a normative gait performance for comparison. Gait parameters were measured in the control group to derive average values, which served as the benchmark for classifying performance levels for the stroke survivors. Before the experiment, the Montreal Cognitive Assessment (cutoff < 22/30) (14) was used to assess participants' cognitive ability. The Modified Functional Ambulation Classification (15), the Fugl-Meyer Assessment of Lower Extremity (16), and the Berg Balance Scale (17) were administered to the stroke participants by registered occupational therapists before the walking trial for gait analysis. Participants from both groups were then instructed to walk a distance of 3 meters at their usual pace three times. The 3-meter walking distance was adopted from the 3-meter walk test. It was selected for this study primarily due to its suitability for clinical environments with space constraints and its established reliability for measuring walking speed in chronic stroke populations (18). The three walking trials were captured using a customized markerless motion capture system in iPad Pro that has undergone a reliability test for joint angle calculation (19). Kinematic information extracted from the markerless motion capture system was used to calculate the gait parameters of the participants at the baseline. An 18-month follow-up was conducted with the participants who were stroke survivors through telephone interviews to record fall incidents, if any, after the walking experiment.

Participants

To be eligible to participate in the study, participants with stroke had to 1) be adults aged 18 years old or above, 2) have been diagnosed with a hemiplegic stroke, 3) have no history of previous neurological or orthopedic diseases/congenital disorders of the upper, lower extremities and spine, 4) have adequate cognitive ability to comprehend simple instructions, 5) be able to walk continuously for at least 3 meters with or without walking aids, 6) have had no falls in the past 3 months before joining the study and 7) have mild to moderate mobility disability (Modified Functional Ambulation Classification category III or above).

Participants were excluded if they 1) were medically unstable or 2) had an Modified Functional Ambulation Classification (15) score of category II or below.

Equipment

The markerless motion capture system was developed using Xcode on the basis of the ARKit6 and RealityKit framework supported by an iPad Pro with a LiDAR scanner. The detection of the human body and the joint positions were extracted and realized through computer-vision algorithms using convolutional neural networks (20). A total of 14 3D body joint positions and the timestamp of the motion detection were captured by our motion tracking platform. The capture frequency of the markerless motion capture system was set at 30 Hz. The normalized coordinates were relative to the center of the pelvis and defined as the origin of the ARKit's coordinate system (21). The adjacent 3D joint coordinates extraction calculated the angles of interest. Angle θ was calculated by three joints (hip, knee, and ankle), namely $A, B, C \in R^3$or associated vectors $\overrightarrow{v_1} = A - B$ *and* $\overrightarrow{v_2} = C - B$, with the formula

$$\theta = \arccos \frac{v_1 \cdot v_2}{||v_1||_2 ||v_2||_2}.$$

Gait Capture

The gait motion capture session was performed in the laboratory of the Hong Kong Polytechnic University, with the floor being covered with vinyl to prevent it from being slippery. Participants were asked to walk for 3 meters at their usual pace for three trials. They were allowed to use their own walking aids, such as cane, that they used during daily ambulation. The start and stop points were indicated by a cone placed on the floor. Three iPad Pros were placed at the starting point, the end point, and the lateral side of the participants, respectively, for capturing the gait patterns of the participants. The environmental setup for the setting of the experiment and the sample motion capture image is illustrated in figure 1a and figure 1b.

Fall History Interview

Follow-up phone call interviews were conducted with the participants to obtain their fall history over the 18-month period following the walking experiment. The number, dates, and nature of the fall accidents they experienced and the number of fall accidents that led to hospitalization were recorded. This is a standard method for prospective falls evaluation (22).

Data Extraction

The video data were processed using frame rate normalization and background subtraction to minimize noise. A Butterworth low-pass filter at 10 Hz was used to filter the data. The 3D coordinates of the joint positions were tracked and detected across consecutive video frames. Spatiotemporal gait parameters were computed using the tracked landmark positions. The stride length was calculated as the distance between consecutive heel strikes of the same foot. Cadence was derived from the temporal frequency of steps and was calculated as steps per minute. The step width was measured as the lateral distance between the ankles during the stance phase. The temporal parameters, including the stance time, swing time, and double support time, were extracted on the basis of the timing of the heel strike and toe-off identified from the landmark trajectories.

Data Analysis

Average values of the gait parameter from the three walking trials of each participant were extracted. The data from healthy participants served as the reference for comparison. The stride length, cadence, step width, stance time, swing time, and double support time of the participants with stroke were evaluated relative to the average values of the healthy group. Parameters with values falling below 10% of the healthy group's average were classified as indicating lower-than-average performance, while values exceeding 10% of the healthy group's average were classified as higher-than-average performance. For instance, stroke participants with a cadence below 10% of the healthy group's average were categorized as having low cadence, whereas those with a cadence exceeding 10% of the healthy group's average were categorized as having high cadence. Risk ratios using the formula $\text{Risk ratios} = \frac{\textit{Fall incidence in exposed group}}{\textit{Fall incidence in unexposed group}}$ were calculated to assess the relative risk of fall incidents in terms of fallers (with at least one fall during the prospective 18-month period). To further examine the predictive power of these parameters, Cox Proportional Hazards Models were utilized to estimate hazard ratios ($\text{Hazard ratios} = e^{coefficient}$) and regression coefficients (β), which quantify the impact of each gait parameter on the presence of fall. All analyses included age, gender, and years of education. The final models also included the following baseline covariates: fall history in the year prior to entry, the Berg Balance Scale score, the Montreal Cognitive Assessment score, and the the Fugl-Meyer Assessment of Lower Extremity score. A forward stepwise procedure (P-to-enter = 0.05 and P-to-remove = 0.10; retention criteria, $P < 0.05$) was performed to select the variables most strongly associated with falls and derive a predictive equation. Receiver operating characteristic (ROC) curve analysis was conducted to determine the optimal cutoff values for each gait parameter. The true positive, false positive, true negative, and false negative rates based on participants' fall interview records were calculated. The area under the curve was calculated to evaluate the overall predictive performance of each gait parameter. An area under the curve value of 0.5 indicated no discrimination, while values closer to 1.0 indicated excellent discrimination. The cutoff points that maximized the balance between sensitivity and specificity for each gait parameter were identified using Youden's Index (Sensitivity+Specificity−1) (23), the cutoff values indicated a higher fall risk. The discriminative power of the final model was assessed using the area under the receiver operating characteristic curve. All the descriptive statistics were performed using IBM SPSS 26, while the regression analysis and metric were run using the Scikit-learn package in Python.

Results

Fifty healthy adults and 50 participants with stroke were recruited into the study. Three of the participants with stroke dropped out, and one stroke patient passed away during the follow-up period. Hence, a total of 50 healthy adults (mean age = 60.2, SD = 8.3) and 46 patients with stroke (mean age = 58.1; SD = 11.5) were included in the final data analysis. The gender distribution did not differ significantly between the stroke and healthy adult groups ($p = 0.144$). Thirteen percent of the participants with stroke experienced only one fall accident, while 4.3% of the participants experienced recurrent falls during the follow-up period, and two participants experienced falls that required hospitalization. The demographics of the participants are shown in Table 1.

The gait parameters associated with fall accidents, which were deduced by univariate analyses, are presented in Table 2. In model 1, the analysis was adjusted for age and gender. In model 2, the analysis was further adjusted for cognitive state, years of education, lower limb functioning level, and previous fall history. Among the gait parameters analyzed, only the presence of a higher cadence was considered to be insignificant in terms of the risk ratios for fall in model 2. The presence of low cadence, low swing phase percentage, and high stance phase percentage contributed to the highest relative risk (risk ratio = 2.163, 2.002 and 2.142, respectively, in model 1) among the fall parameters.

A Cox Proportional Hazards Model was conducted to assess the impact of various gait parameters on the risk of falls among the participants with stroke (Table 3). Model 1 included the gait parameters, while model 2 included the gait parameters along with potential confounders, including gender, years of education, cognitive state, lower limb functioning level, side of hemiplegia, and fall history. All the gait parameters except for low walking speed in model 2 (p =0.054) showed a significant association with prospective fall risk. Low cadence, low stride length, long stance phase, low swing phase, and long double support phase showed the highest Hazard Ratios in association with prospective fallers (Hazard Ratios = 2.17, 2.20, 3.88, 4.39, and 2.10, respectively, in model 2). With the exception of walking speed, all other the gait parameters were strong predictors of fallers, while gender and side of hemiplegia were not significant factors in the prediction of prospective falls (p = 0.092 and 0.057, respectively).

Receiver operating characteristic analysis was conducted for each gait parameter to determine the optimal cutoff values for predicting prospective fall risk (Table 4). The receiver operating characteristic curve for the final model included all the listed gait parameters. The area under the curve for the combined model was 0.81, with a sensitivity of 0.84 and a specificity of 0.79 (Figure 2).

Discussions

In our study, the 18-month prevalence of fallers with mild-to-moderate mobility disability is 13%. While some studies reported fall rates as high as 25–40% in stroke survivors (24), these often include higher-risk subgroups such as the older adults, those with prior fall history, cognitive impairments or severe mobility disability. Our cohort had only 2 prior fallers at baseline, and we focused on participants with mild to moderate mobility disability. It may represent a lower-risk subset, which could explain the fewer observed falls. Our results suggested that cadence, stride length, stance time, and swing time are strong predictors of fallers among stroke survivors, whereas potential contributing factors such as age, gender, and side of hemiplegia were found to be insignificant in the prediction of prospective falls among the participants with stroke. Cognitive score, years of education, and fall history, which were suggested to have a significant association with falls for older adults (25-27), were found to be less strong predictors of fallers among our stroke survivors. This could be due to the fact that stroke can lead to various neurological deficits, such as lower limb movement deficit and impairment in balance (28), which may overshadow the effects of cognitive scores and years of education, making them less prominent in predicting prospective falls among individuals after a stroke. Although lower limb functioning ability contributed to the prediction of prospective falls in our Cox Proportional Hazards Model, the gait parameters appeared to be stronger predictors compared to considering lower limb functioning alone. A possible reason for this finding is that the gait parameters reflect an integration of neuromuscular coordination, sensory feedback, cognitive processing, dynamic movement, lower limb muscle strength, and balance (29). Given that stroke is a neurological disease that can affect different body parts, survivors might have other deficits that influence their walking gait, such as sensory or coordination issues, besides lower limb functioning ability (30). Compared with purely the overall score of the lower limb functioning assessment, the gait patterns indicate the components of walking performance which could be more relevant to fall accidents. Studies have shown that lower limb functional ability is one of the factors, but not the only factor, contributing to fall risk in patients with stroke (31). Our results aligned with the findings of previous studies (31-33), and our fall prediction model further suggested that gait parameters should be evaluated using motion capture, particularly for the purpose of predicting fall risk in the stroke population.

The swing and stance times were found to be the strongest fall risk predictors in our model. Stroke survivors with shorter swing times and prolonged stance/double-support phases have a greater risk of experiencing fall accidents. Due to lower limb muscle weakness, rigidity, and spasticity after a stroke, these individuals have difficulty in making a hip and knee movement for the leg to swing during the swing phase (35). Such difficulty in executing hip/knee flexion during the swing phase (35) and the fear of fall (36) lead to cautious and short steps with extended weight-bearing periods (37). This gait pattern reduces dynamic stability during phase transitions which increases the risks of fall, particularly in dynamic environments (38). Early identification of these temporal gait abnormalities is critical for fall prevention.

Our receiver operating characteristic curve analysis suggested that the cutoff values for cadence, walking speed, and stride length were 75.1 step/min, 0.77 m/s, and 0.75 m, respectively. These cutoff values were slightly lower than the cutoff value for fall in the healthy older adults (39). A possible explanation is that individuals with stroke often adopt compensatory strategies to maintain stability, such as walking more cautiously or using assistive devices (1), these adaptative methods might help them to prevent falls even with a slower and unstable gait pattern. This might explain the lower cutoff values in the stroke population when compared with the cutoff values for older adults from other studies (40). It might reflect a need to have routine gait performance screening and fall prevention intervention for stroke survivors in the clinic or community to address their unique fall risk factors.

In this study, we extracted the gait parameters from the markerless motion capture system in mobile devices, and the extracted variables demonstrated a significant contribution to the prediction of fall risk in the stroke population. Markerless motion capture systems address key limitations of traditional fall risk tools (41) by enabling a fast and natural gait analysis without the use of reflective markers. The integration of markerless motion capture system into smart devices (13,42) helps to provide objective, noninvasive gait measurements which address the limitations of using conventional methods, such as checklists, observational scales, or even marker-based motion capture systems (43). Combined with machine learning (44), these systems may enhance fall prediction accuracy and efficiency in stroke survivors by automating risk detection.

This study has three major limitations. First, the relatively small sample size of 46 participants with stroke may limit the generalizability of the findings. A larger, more diverse cohort of the stroke population would enhance the robustness and external validity of the results. Second, the reliance on phone interviews to collect fall history over the previous 18 months may have introduced potential recall bias; although participants had been screened for potential cognitive impairment using the Montreal Cognitive Assessment, some patients still may have inaccurately remembered or wrongly reported the date of fall incidents. This could lead to misclassification of fall risk and affect the reliability of the data. Future studies should consider incorporating other objective methods of prospective fall monitoring, such as using wearable sensors, to improve the accuracy of the documentation of fall history. Third, the use of a 3-meter walking distance (18) may have influenced the results of the gait parameters by limiting the number of complete gait cycles analyzed and inherently includes both acceleration and deceleration phases. Future studies should consider longer walking distance to better assess gait endurance and variability.

This study highlights the potential of using gait parameters captured through mobile devices as a predictive tool for prospective fall risk in stroke patients. The findings suggest that specific gait characteristics, such as a reduced swing time, increased double support phase, and low cadence, are associated with prospective fall risk in terms of fallers in the stroke population. Future research using a larger database with more diverse cohorts is recommended to validate these findings and further refine the predictive models. Our findings paves the way for using machine learning via markerless motion capture system through mobile devices in fall risk prediction in the future.

(Word count: 3,333 words)

Clinical Messages

- A mobile markerless motion capture system can objectively quantify gait abnormalities and offer clinicians a portable, cost-effective, alternative solution to using lab-based motion capture or subjective observational scales.
- Our findings demonstrate that stroke survivors with reduced swing time, prolonged double-support phase, and low cadence (<75.1 steps/min) had a higher fall risk in 18-month.
- Our markerless motion capture-derived cutoffs (e.g., stride length <0.75 m, stance time >10% above healthy norms) can be used for fall risk predication in stroke survivors with mild-moderately impaired mobility (Modified Functional Ambulation Classification ≥III),.

DECLARATION STATEMENT

Ethics approval and consent to participate

Experimental procedures were approved by the Human Subjects Research Ethics Committee of the Hong Kong Polytechnic University (Reference No.: HSEARS20230214010). The work was carried out in accordance with The Code of Ethics of the World Medical Association (Declaration of Helsinki). After the nature, purpose, risks and benefits of the study were explained, participants gave written informed consent to participate in the study.

Funding

This research project was funded by Research Centre for Assistive Technology (Ref. no.: CE0E) to KNKF, The Hong Kong Polytechnic University, Hong Kong SAR.

Competing interests

The author(s) declare no potential conflicts of interest with respect to this article' research, authorship, and/or publication that might be perceived to influence the results and/ or discussion reported in this paper.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Consent for publication

All authors have approved this manuscript for publication. It has not been previously published, nor is it pending publication elsewhere.

Contributorship

We confirm that all authors have contributed to the work presented in this manuscript and agree with the following contributorship statement:

1. Winnie W. T. Lam: Conceptualized the study, designed the methodology, writing of the manuscript, data collection. Contributed to data analysis and interpretation.
2. Ang, Wei Tech: Conducted the literature review, contributed to study design
3. Kenneth N. K. Fong: Supervised the project, conceptualized the study, designed the methodology. Drafting the manuscript and reviewed the final version. Reviewed and edited the manuscript for intellectual content.

All authors have approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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Tables

Table 1

Demographics of the Participants

Participants	Participants with stroke (n = 46)	Healthy participants (n = 50)
Mean Age (years)	58.1 (11.5)	60.2 (8.3)
Gender ratio (males: females)	61.3:38.7	46:54
Time since stroke onset (Months)	72.3 (28.4)	NA
MFAC (n)		
Levels 3-5	14	NA
Levels 6-7	32	NA
Hemiplegic side (n)		
Right	19	NA
left	27	NA
Dominant side (Pre-onset) **(n)**		
Right	45	49
Left	1	1
Years of education (Mean)	9.2	11.8
MoCA Score (0-30) (Mean)	25.8 (3.1)	26.4 (2.2)
FMA-LE Score (0-34) (Mean)	23.0 (7.2)	NA
BBS Score (0-56) (Mean)	38.4 (6.7)	NA
Experienced fall accident in the year prior to entry (n)	2	1
Experienced only 1 fall during the 18-month follow-up period (n)	6	NA
Experienced more than 1 fall during the 18-month follow-up period (n)	2	NA
Experienced fall that needed hospitalization	2	NA

BBS: **Berg Balance Scale**, *FMA-LE*: **Fugl-Meyer Assessment of Lower Extremity**, *MFAC:* **Modified Functional Ambulation Classification**, *MoCA:* **Montreal Cognitive Assessment**

Table 2

Risk Ratio of the Gait Parameters for Prospective Fall Risk

Gait parameters	Reference (Mean value from healthy group)	Mean value of the stroke group	Model 1 Risk ratio (95% CI)	p	Model 2 Risk ratio (95% CI)	p
Cadence	100.4 step/min	80.1 step/min				
Low cadence			2.162 (1.820 - 2.251)	<0.001	2.033 (1.805 – 2137)	<0.001
High cadence			1.009 (1.002 – 1.013)	0.030	1.071 (1.012 – 1.090)	0.053
Walking speed	0.92 m/s	0.63 m/s				
Low walking speed			1.358 (1.212 – 1.452)	0.003	1.361 (1.249 – 1.477)	0.029
High walking speed			1.539 (1.290 – 1.663)	0.016	1.558 (1.313 – 1.680)	0.011
Stride length	1.12 m	0.89 m				
Low stride length			1.931 (1.725 – 1.994)	<0.001	1.892 (1.700 – 1.987)	<0.001
High stride length			1.158 (1.021 – 1.294)	0.004	1.119 (1.008 – 1.213)	0.024
Step width	4.33 cm	3.59 cm				
Low step width			1.874 (1.705 – 1. 993)	0.021	1.786 (1.639 – 1.818)	0.019
High step width			1.098 (1.002 – 1.179)	0.025	1.052 (1.021 – 1.077)	0.033
Stance phase	57.2%	70.2%				
Low stance phase			1.034 (1.004 - 1.090)	0.001	1.031 (1.005 – 1. 058)	<0.001
High stance phase			2.002 (1.966 – 2.181)	<0.001	1.989 (1.823 – 2.000)	<0.001
Swing phase	42.8%	29.8%				
Low swing phase			2.142 (2.010 – 2.300)	0.002	2.112 (2.094 – 2. 259)	<0.001
High swing phase			1.012 (1.001 – 1.036)	0.001	1.007 (1.001 - 1.028)	<0.001
Double support phase	28.1%	46.7%				
Low double support phase			0.225 (0.190 – 0.312)	0.033	0.213 (0.091 – 0.308)	0.045
High double support phase			1.557 (1.419 – 1.673)	0.042	1.326 (1.215 – 1.509)	0.034

Table 3

Cox Proportional Hazards Model for the Analysis of Impacts of Various Factors on Prospective Fall Risk in Stroke Survivors

Factors	Model 1 Hazard Ratio (95% CI)	*P*	*β*	Model 2 Hazard Ratio (95% CI)	*P*	*β*
Age						
<65 years old	NA	-	-	1		
≥65 years old	NA	-	-	1.38 (1.22 – 1.47)	0.056	0.32
Gender						
Male	NA	-	-	1.41 (1.33 – 1.48)	0.092	0.34
Female	NA	-	-	1		0
Years of education	NA	-	-			
<6 years	NA	-	-	1.23 (1.01 – 1.33)	0.036	0.21*
≥6 years	NA	-	-	1		0
MoCA score						
<22	NA	-	-	1.52 (1.41 – 1.63)	0.008	0.41***
≥22	NA	-	-	1		0
FMA_LE score						
<21	NA	-	-	1.67 (1.52 – 1.79)	0.026	0.51**
≥21	NA	-	-	1		0
Side of hemiplegia						

Right	NA	-	-	1.55 (1.40 – 1.61)	0.057	0.44
Left	NA	-	-	1		0
Presence of fall prior to the study						
Yes	NA	-	-	1.89 (1.76 – 2.05)	0.002	0.62**
No	NA	-	-	1		0
Cadence						
Low cadence	2.13 (1.99 – 2.28)	<0.001	0.76***	2.17 (2.00 – 2.31)	<0.001	0.79***
Average cadence	1		0	1		0
High cadence	1.31 (1.18 – 1.41)	<0.001	0.27***	1.30 (1.18 – 1.40)	<0.001	0.26***
Walking speed						
Low walking speed	1.51 (1.43 – 1.59)	0.044	0.41**	1.51 (1.43 – 1.60)	0.054	0.41**
Average walking speed	1		0	1		0
High walking speed	1.64 (1.48 – 1.72)	0.029	0.49**	1.65 (1.50 – 1.73)	0.032	0.49**
Stride length						
Low stride length	2.15 (1.97 – 2.33)	<0.001	0.77***	2.20 (2.00 – 2.38)	0.002	0.79**
Average stride length	1		0	1		0
High stride length	1.12 (1.02 – 1.19)	0.011	0.11*	1.11 (1.01 – 1.19)	0.018	0.10**
Step width						
Low step width	1.90 (1.83 – 1.98)	<0.001	0.64***	1.97 (1.84 – 1.99)	0.001	0.68**

Average step width	1		0	1		0
High step width	1.03 (1.02 – 1.19)	0.022	0.03**	1.09 (1.02 – 1.19)	0.032	0.09**
Stance phase						
Low stance phase	1.03 (1.00 – 1.12)	0.002	0.03**	1.03 (1.00 – 1.13)	0.008	0.03**
Average stance phase	1		0	1		0
High stance phase	3.88 (3.69 – 3.94)	<0.001	1.3***	3.88 (3. 67 – 3.95)	<0.001	1.36***
Swing phase						
Low swing phase	4.53 (4.44 – 4.60)	<0.001	1.50***	4.39 (4.32 – 4.58)	<0.001	1.49***
Average swing phase	1		0	1		0
High swing phase	1.10 (1.02 – 1.24)	0.007	0.10**	1.10 (1.03 – 1.24)	0.034	0.10**
Double support phase						
Low double support phase	1.36 (1.22 – 1.40)	<0.001	0.31***	1.36 (1.21 – 1.43)	<0.001	0.31***
Average double support phase	1		0	1		0
High double support phase	2.09 (2.00 – 2.13)	<0.001	0.74***	2.10 (2.02 – 2.21)	<0.001	0.74***

$*P \leq 0.05$; $**P \leq 0.01$; and $***P \leq 0.001$

Table 4

ROC Analysis for Each Gait Parameter to Determine the Optimal Cutoff Values for Predicting Fallers

Gait parameter	AUC (95% CI)	Optimal Cutoff	Sensitivity	Specificity
Cadence	0.82 (0.77 – 0.84)	75.1 step/min	0.74 (0.69 – 0.78)	0.86 (0.80 – 0.91)
Walking speed	0.71 (0.65 – 0.78)	0.77 m/s	0.70 (0.63 – 0.75)	0.73 (0.67 – 0.77)
Stride length	0.74 (0.68 – 0. 81)	0.75 m	0.72 (0.63 – 0.78)	0.81 (0.75 – 0.84)
Step width	0.81 (0.75 – 0.84)	3.40 cm	0.76 (0.70 – 0.81)	0.77 (0.71 – 0.82)
Stance Phase	0.83 (0.78 – 0.87)	70.2%	0.80 (0.74 – 0.86)	0.79 (0.72 – 0.85)
Swing Phase	0.88 (0.80 – 0.93)	25.8%	0.91 (0.83 – 0.95)	0.88 (0.80 – 0.93)
Double support Phase	0.89 (0.80 – 0.94)	58.7%	0.93 (0.83 – 0.96)	0.89 (0.83 – 0.95)

Figures

Figure 1.

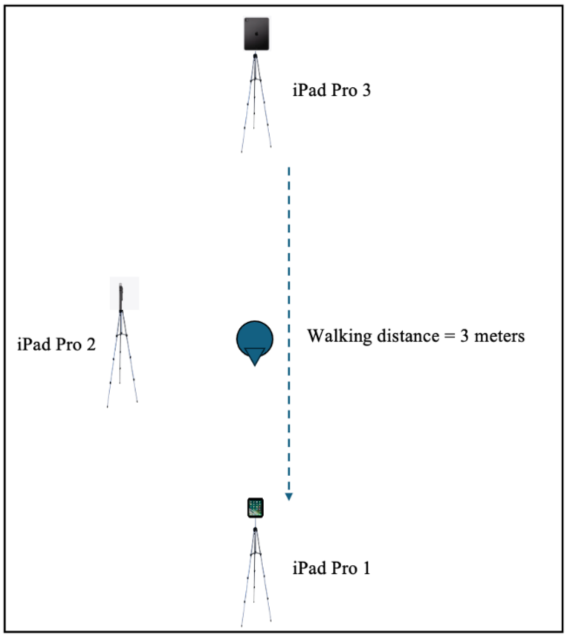
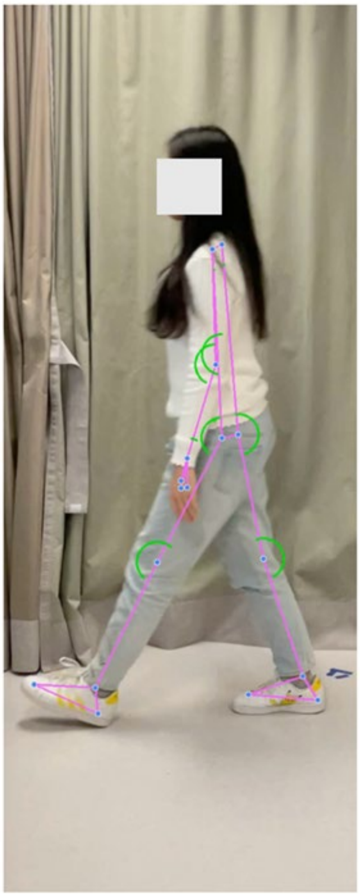
A) Environmental setup for the experiment	*B) Example of the motion capture image by the iPad Pro placing on the lateral side*
	

Figure 2.

ROC Curve for the Final Model Combining All Gait Parameters (The optimal cutoff point is marked, balancing sensitivity and specificity)