A multivariate logistic regression model for fall risk prediction based on physical performance in community-dwelling elderly

Modelo de regresión logística multivariante para la predicción del riesgo de caídas basado en el rendimiento físico en personas mayores que viven en la comunidad

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Abstract

Introduction: Falls among older adults lead to significant morbidity and increased healthcare costs. Physical performance measures like strength, mobility, and balance are crucial for fall risk prediction, but existing assessments often rely on single measures, which may not fully capture fall risk.
Objective: To develop a multivariate logistic regression model for fall risk prediction, integrating the *lower limb muscle strength-to-body weight* (LS/BW) ratio, the variables obtained from *Timed Up and Go Test* (TUGT), and the *Sit-to-Stand Test* (STS).
Methodology: Data from 108 community-dwelling elderly individuals (mean age 65.59 ± 4.32 years) were analyzed. Participants underwent physical performance assessments, including TUGT, lower limb strength, and STS. A binary logistic regression model was used to analyze the relationship between these variables and fall risk, with model performance evaluated using AUC of the receiver operating characteristic (ROC).
Results: The model, incorporating LS/BW ratio, *time to completed TUGT* (T_{TUGT}), and *Power Index of STS* (P_{STS}), explained 70.6% of the variance in fall risk. Significant predictors included lower LS/BW ratio (adj.OR = 0.980), longer T_{TUGT} times (adj.OR = 1.617), and lower P_{STS} values (adj.OR = 0.953). The Fall Risk Score equation provides a practical tool for identifying high-risk individuals.
Conclusion: The multivariate model effectively predicts fall risk, offering a reliable tool for fall risk screening and prevention in older adults, supporting personalized interventions to reduce fall incidence.

Keywords

Fall risk prediction; elderly; lower limb strength; timed up and go test; power sit-to-stand test; multivariate logistic regression.

Resumen

Introducción: Las caídas en las personas mayores ocasionan una morbilidad considerable y un aumento de los costes sanitarios. Las medidas de rendimiento físico, como la fuerza, la movilidad y el equilibrio, son fundamentales para predecir el riesgo de caídas, pero las evaluaciones existentes suelen basarse en un solo indicador, lo que puede no reflejar completamente dicho riesgo.
Objetivo: Desarrollar un modelo de regresión logística multivariante para la predicción del riesgo de caídas, integrando la razón entre la fuerza muscular de las extremidades inferiores y el peso corporal (LS/BW), las variables obtenidas del Timed Up and Go Test (TUGT) y el Sit-to-Stand Test (STS).
Metodología: Se analizaron datos de 108 personas mayores que viven en la comunidad (edad media 65,59 ± 4,32 años). Los participantes realizaron evaluaciones del rendimiento físico, incluyendo TUGT, la fuerza de las extremidades inferiores y el STS. Se empleó un modelo de regresión logística binaria para analizar la relación entre estas variables y el riesgo de caídas, y el rendimiento del modelo se evaluó mediante el área bajo la curva (AUC) de la característica operativa del receptor (ROC).
Resultados: El modelo que incorporó la razón LS/BW, el tiempo para completar el TUGT (T_{TUGT}) y la potencia del STS (P_{STS}) explicó el 70,6 % de la variabilidad del riesgo de caídas. Los predictores significativos incluyeron una menor razón LS/BW (OR ajustado = 0,980), tiempos más largos en el T_{TUGT} (OR ajustado = 1,617) y valores más bajos de PSTS (OR ajustado = 0,953). La ecuación de la puntuación de riesgo de caídas (Fall Risk Score) ofrece una herramienta práctica para identificar a las personas con alto riesgo.
Conclusión: El modelo multivariante predice de manera eficaz el riesgo de caídas y proporciona una herramienta fiable para el cribado y la prevención de caídas en personas mayores, apoyando intervenciones personalizadas para reducir su incidencia.

Palabras clave

Predicción del riesgo de caídas; personas mayores; fuerza de las extremidades inferiores; test timed up and go; test de sentarse y levantarse; regresión logística multivariante.

Introduction

Falls among older adults represent a major global public health challenge, with approximately one-third of individuals aged over 65 and half of those over 80 experiencing at least one fall each year, often resulting in serious consequences such as fractures and, in some cases, death (Lewis & Griffin, 2023). In Thailand, falls are a leading cause of accidental injuries in older populations, contributing substantially to morbidity, mortality, and increased healthcare service utilization. A nationwide study revealed that 38.5% of community-dwelling elderly are at high risk, with osteoporosis and sarcopenia being common comorbidities that further elevate this risk (Asavamongkolkul et al., 2024). The repercussions of falling extend beyond physical injury and include disability, loss of independence, fear of falling, social withdrawal, functional decline, and even death. Among those aging with long-term physical disabilities, nearly 65% report experiencing falls, with more than half sustaining injuries as a result. This group also demonstrates a high prevalence of fear of falling, which significantly hampers their participation in social activities and diminishes overall quality of life (Dashner et al.). Furthermore, recurrent falls are strongly associated with increased reliance on hospital-based care, both acutely and chronically, highlighting the critical need to identify and address modifiable risk factors to reduce fall-related hospitalizations and healthcare costs (Trevisan et al., 2023).

Fall risk in community-dwelling elderly is influenced by a multitude of factors, both intrinsic and extrinsic. Intrinsic factors include physical and mental health conditions such as gait and balance disorders, orthostatic hypotension, sensory impairments, and depression. Physical frailty, including the inability to perform functional exercises like the five-time-sit-to-stand test, also contributes to higher fall risk (Esposito et al., 2025; Lage et al., 2023). Extrinsic factors include environmental hazards and medication use, with guidelines recommending interventions such as exercise programs to improve leg strength and balance, and multifactorial risk assessments to address these modifiable risks (Colón-Emeric et al., 2024).

Physical performance measures such as gait, balance, and strength are crucial indicators of fall risk, particularly in older adults and those with specific health conditions (Paredes et al., 2024). For instance, in community-dwelling older adults with chronic obstructive pulmonary disease, balance measures are essential for fall risk screening due to the increased fall risk associated with the condition (Ferragut et al., 2023; Nguyen et al., 2024). Similarly, in older adults with dementia, physical performance measures commonly used in clinical settings can effectively discriminate between fallers and non-fallers, thereby predicting falls (Chan et al., 2024). The *Short Physical Performance Battery* (SPPB), which assesses lower extremity function, has been shown to have a significant inverse association with the incidence of in-hospital falls in high-risk populations, such as patients in geriatric and neurology wards. A lower SPPB score correlates with a higher risk of falls, highlighting the importance of physical performance in fall risk stratification (Tanaka et al., 2023). Collectively, these studies underscore the multifaceted nature of fall risk, which is influenced by various physical performance measures. Accurate assessment and monitoring of these measures are vital for effective fall prevention strategies in diverse populations.

Sit to stand measures are indeed essential for fall risk screening due to their strong association with increased fall risk among older adults. The *Five Times Sit-to-Stand test* (FTSST), for instance, has been shown to be a significant indicator of fall risk, with individuals in the high fall risk group performing significantly worse on this measure compared to those in the low fall risk group (Kim et al., 2024). This test assesses lower body strength and balance, both critical factors in maintaining stability and preventing falls. Additionally, the *Timed Up-and-Go test* (TUGT), which includes a sit to stand component, is widely recognized as a criterion standard for fall risk assessment (Jalayondeja, 2014). These assessments are crucial because they not only help in identifying individuals at risk but also provide a basis for targeted interventions, such as physical therapy, to improve strength and balance, thereby reducing the likelihood of falls. Overall, incorporating sit to stand measures into fall risk screening protocols is a practical and effective approach to mitigate the risk of falls among older adults.

Falls assessment and prevention for older adults are multifaceted, and relying on a single physical performance test such as the FTSST, TUGT, balance tests, or isolated knee strength measures has shown important limitations in predicting future falls (Andrade et al., 2021; Beauchet et al., 2011; Skelton et al., 2002). Existing studies have rarely combined complementary dimensions of physical function into an empirically validated multivariate model and have often failed to control for key confounders such as age, sex, and comorbidities. Therefore, the present study aimed to develop and evaluate a multivariate logistic regression model for fall risk prediction that integrates *lower limb muscle strength-to-body weight ratio* (LS/BW), *time to complete the Timed Up and Go Test* (T_{TUGT}), and the *Power Indexo f Sit-to-Stand Test* (P_{STS}). By combining strength, mobility, and power into a single predictive equation, this model is intended to fill the current gap in fall risk assessment and provide clinicians with an empirically based, integrated tool for identifying community-dwelling older adults at increased risk of falls.

Method

Study Design and Participants

This was an analytical cross-sectional study using a multivariate logistic regression model conducted among community-dwelling older adults. The required sample size was estimated a priori using G*Power 3.1. Based on previous studies reporting moderate associations between physical performance measures and fall status, we assumed a medium effect size corresponding to a correlation of r = 0.30, with α = 0.05 and a desired statistical power of 0.95. This calculation indicated that at least 84 participants were required. In addition, we ensured that the final sample met general recommendations for logistic regression by considering the events-per-variable (EPV) criterion. With 108 community-dwelling older adults, including 42 fallers, and three main predictors in the final model (LS/BW, T_{TUGT}, and P_{STS}), the study achieved an EPV of 14, which exceeds the commonly recommended minimum of 10 events per variable for stable logistic regression estimates.

Eligible participants included community-dwelling older adults, both male and female, who were generally healthy or had manageable chronic conditions such as diabetes or hypertension, and were capable of ambulating independently without the use of walking aids. Participants were excluded if they had musculoskeletal disorders affecting the lower limbs, including osteoarthritis, rheumatoid arthritis, or fractures, as well as neurological conditions that impair balance, mobility, or muscle strength (e.g., stroke, spinal cord injury, Parkinson's disease). Additionally, individuals with significant communication, visual, or auditory impairments were not included. Ethical approval for this study was granted by the Human Research Ethics Committee of the University of Phayao, Thailand (Approval Code No. HREC-UP-HSST 1.2/011/68), and the study adhered to the principles outlined in the Declaration of Helsinki.

The study population consisted of adults aged 60 years and older residing in Muang Phayao Province, Thailand. Recruitment efforts engaged community leaders and local healthcare volunteers, resulting in 120 potential participants. After applying the inclusion and exclusion criteria, 108 participants were retained for analysis, while 12 were excluded. The reasons for exclusion included knee pain (n = 6), rheumatoid arthritis (n = 1), lower-limb prosthesis (n = 1), requirement for walking aids (n = 2), and a history of stroke (n = 2). Ultimately, the final sample comprised 108 older adults with a mean age of 65.59 ± 4.32 years.

Procedure

All participants were thoroughly briefed regarding the objectives of the study and the procedures for data collection by the research team. Informed consent was obtained from each participant prior to enrollment. The study protocol involved an initial screening to determine eligibility, during which demographic information (including age, sex, body weight, and height), vital signs, pre-existing medical conditions, and the necessity for assistive walking devices were recorded. Following this assessment, participants were classified into two categories: non-fallers and fallers, with the latter defined as individuals who had experienced one or more falls within the past six months (Poncumhak et al., 2023).

Prior to commencing the experimental assessments, participants were given a five-minute familiarization period to practice the movements. After ensuring adequate understanding and execution of the tasks, the formal testing began. Measurements included the maximum voluntary isometric contraction (MVIC) of the lower limb muscles, the FTSST, and the TUGT. A minimum rest interval of five minutes was provided between each assessment to reduce fatigue. All physical performance assessments were carried out by trained physical therapists. Each test was administered by one dedicated assessor, and the same assessor performed that specific test for all participants (i.e., one assessor per test). Before data collection, all assessors were familiarized with a detailed testing protocol and practiced the procedures to ensure consistent administration. Standardized verbal instructions and demonstrations were used, the same equipment and chair height were applied throughout, and a fixed order of tests with predefined rest intervals between trials was followed. These procedures were implemented to minimize inter-rater variability and to ensure consistency and reliability of the measurements across participants. The procedures for measurement, including the sequence of tests, were standardized and adhered to throughout the study as follows:

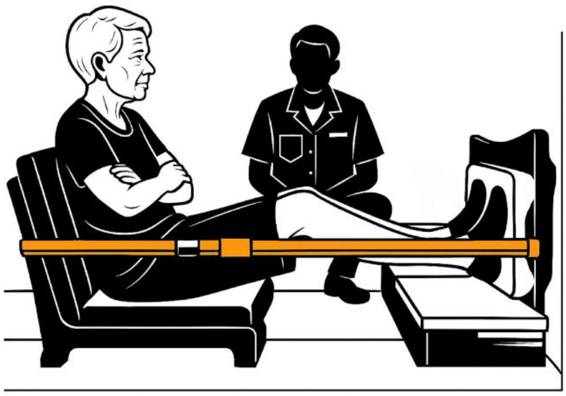
Maximum voluntary isometric contraction (MVIC) of the lower limb muscle strength assessed by Nintendo Wii Balance Board (NWBB)

The *Nintendo Wii Balance Board* (NWBB) is equipped with four vertical strain gauge sensors, each located at the corners of the rigid platform. Data acquisition was performed using a Windows laptop, which received signals from the NWBB through Bluetooth and the device's proprietary software. Sensor outputs from the four channels were recorded at approximately 100 Hz and subsequently filtered using a 20 Hz low-pass filter.

Before the testing protocol, participants completed a 5-minute submaximal jogging warm-up. Seated comfortably with the backrest inclined at 110 degrees, participants placed both feet on the NWBB and crossed their arms over the chest. Knee joint angles were adjusted to 120 degrees of flexion using a universal goniometer (Gronbech Jorgensen et al., 2015), and the seatbelt connecting the NWBB to the backrest was adjusted to ensure stability. The NWBB was mounted on a custom-built platform, oriented at 90 degrees relative to the floor (Fig. 1).

Participants were instructed to press down on the NWBB as forcefully and as quickly as possible for a duration of four seconds until the command to stop was given. Each participant performed two maximal attempts, with a 2-minute rest interval between trials to minimize fatigue. For data analysis, the highest value recorded from the two trials was selected as the representative maximal force.

Figure 1. Setup of the Nintendo Wii Balance Board (NWBB) for assessing maximum voluntary isometric contraction (MVIC) of lower limb muscle strength



Five Times Sit-to-Stand Test (FTSST) and Power Index Calculation (P_{STS})

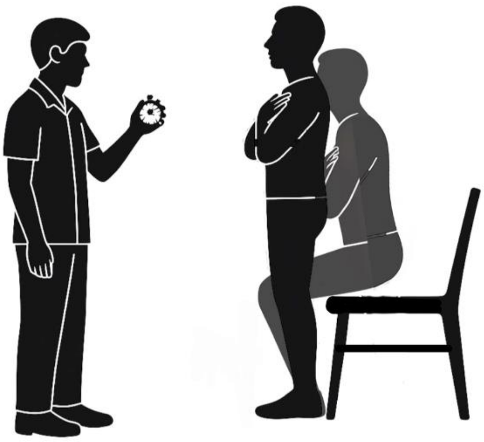
Participants were positioned on a standard armless chair (seat height ≈ 43 cm) with their knees flexed to approximately 100° and their arms crossed over the chest (Takai et al., 2009). At the verbal cue "Start," they were instructed to rise to full hip and knee extension and then return to the seated position, completing this cycle five times as quickly and safely as possible. The total time required to perform the five repetitions (T_{STS}) was measured with a stopwatch, starting from the initial movement until the participant's back made contact with the chair after the fifth repetition, as illustrated in Figure 2. Each participant performed three trials, and the mean of these trials was used for subsequent analysis.

To evaluate lower-limb power during the sit-to-stand task, we calculated the Power Sit-to-Stand index (P_{STS}) using the original equation proposed by Takai et al., 2009. In this model, P_{STS} represents the average mechanical power produced during the five sit-to-stand repetitions and is computed as:

$$P_{STS} = \frac{Body\ mass\ x\ (L - 0.43)\ x\ g\ x\ 5}{T_{STS}}$$

where Body mass is expressed in kilograms (kg), L (m) is the leg length measured from the greater trochanter of the femur to the lateral malleolus, 0.43 m corresponds to the standardized chair height used in this study, g is the acceleration due to gravity (9.81 m·s^{-2}), 5 is the number of sit-to-stand repetitions, and TSTS (s) is the total time required to complete the FTSST. This equation estimates the mean power output of the lower limbs during repeated sit-to-stand movements (Takai et al., 2009).

Figure 2. Demonstration of the Five Times Sit-to-Stand Test (FTSST) setup and procedure for measuring lower limb power



Timed Up and Go Test (TUGT)

For evaluating balance function using the TUGT, the participants took a seat on chairs that lacked armrests, and upon receiving the "Start" command, they rose from the chairs and walked around a cone placed 3 meters away before returning to their seats in a quick and safe manner, without running (Kear et al., 2017). Three rounds of the TUGT were conducted, with a 5-minute rest period between each round. The test parameters were timed to complete TUGT (TTUGT) and recorded by the assessor in seconds.

Data analysis

The data distribution was assessed using the Kolmogorov–Smirnov test, confirming normal distribution across all variables. Descriptive statistics were used to characterize the sample. Univariable analysis was conducted using independent t-tests to compare variables between fall and non-fall groups. Variables with significant differences ($p < 0.05$) were included in the multivariable analysis.

Six significant variables from the univariable analysis were entered into the multivariate logistic regression model to develop the fall risk prediction equation. Adjusted odds ratios (adj.OR) and 95% confidence intervals (95% CI) were reported. The model with the highest Nagelkerke R^2 and lowest multicollinearity was selected as the best-fitting model. The significance of each independent variable coefficient was examined to identify the most influential predictors.

To evaluate the discriminative ability of each logistic regression model, Receiver Operating Characteristic (ROC) curve analysis was performed. The area under the curve (AUC) and corresponding 95% CI were calculated to assess overall classification performance. Optimal cutoff points for the fall risk prediction scores were determined using the Youden Index, which maximizes the difference between sensitivity and 1-specificity. Sensitivity, specificity, and Youden Index values were computed at these optimal thresholds.

Subsequently, a new binary classification variable was created for each model based on the optimal cutoff score. This allowed for the construction of a 2×2 confusion matrix comparing predicted and actual fall statuses. From this matrix, additional diagnostic metrics—accuracy, true positives, true negatives, false positives, and false negatives—were calculated to validate model classification performance. All statistical analyses were performed using SPSS version 21 (SPSS Inc., Chicago, IL, USA), with a significance level set at 0.05.

Results

The study enrolled a sample of 108 elderly individuals, consisting of 42 fallers and 66 non-fallers, with a mean age of 65.59 ± 4.32 years. The participants' mean mass was 56.70 ± 9.28 kg, mean height was 157.32 ± 6.58 cm, and mean body mass index (BMI) was 22.92 ± 3.59 kg/m2. The MVIC of LS was found to be 92.78 ± 29.55 kilograms, while the lower limb muscle strength to body weight ratio (LS/BW ratio) was 165.23 ± 48.98 %. Additionally, the PSTS had an average value of 133.48 ± 47.15 Nm/s. The average T was 11.95 ± 1.86 seconds as shown in Table 1.

Univariable Analysis of Demographic and Physical Performance Variables Associated with Fall History

Demographic characteristics, including weight, height, and BMI did not differ significantly between faller and non-faller group (p > 0.05) as shown in Table 1. The faller elderly showed significantly higher ratio of female (85.7% vs. 54.5%) and older than non-faller group (66.71 ± 4.52 vs. 64.88 ± 4.06 years). The faller elderly showed significantly lower MVIC of LS measured by NWBB (73.34 ± 21.19 vs. 105.16 ± 27.47 kg), LS/BW ratio (133.48 ± 38.18 vs. 185.44 ± 44.30 %), and PSTS (99.37 ± 20.35 vs. 155.19 ± 46.56 Nm/s), but higher TTUGT (13.56 ± 1.32 vs. 10.92 ± 1.42 seconds) than the non-falling risk group (p < 0.01) as shown in Table 1.

Table 1. Univariate analysis for investigating factors associated with fall risk

Variables		Total (n=108)	Fall Group		*p*-value	95% C.I.
			Non-Faller (n=66)	Faller (n=42)		
Gender, n (%)	Male	36 (33.3%)	30 (45.5%)	6 (14.3%)	<0.001**	0.07 to 0.54
	Female	72 (66.7%)	36 (54.5%)	36 (85.7%)		
Age (years)		65.59 ± 4.32	64.88 ± 4.06	66.71 ± 4.52	0.031*	-3.50 to -0.17
Weight (kg)		56.70 ± 9.28	57.26 ± 9.50	55.83 ± 8.98	0.438	-2.21 to 5.07
Height (cm)		157.32 ± 6.58	156.96 ± 5.35	157.88 ± 8.19	0.482	-3.50 to 1.66
BMI (kg/m^2)		22.92 ± 3.59	23.29 ± 3.98	22.35 ± 2.81	0.184	-0.46 to 2.34
MVIC of LS (kg)		92.78 ± 29.55	105.16 ± 27.47	73.34 ± 21.19	<0.001**	21.95 to 41.69
LS/BW ratio (%)		165.23 ± 48.98	185.44 ± 44.30	133.48 ± 38.18	<0.001**	35.50 to 68.41
T_{TUGT} (s)		11.95 ± 1.86	10.92 ± 1.42	13.56 ± 1.32	<0.001**	-3.16 to -2.11
P_{STS} (Nm/s)		133.48 ± 47.15	155.19 ± 46.56	99.37 ± 20.35	<0.001**	40.71 to 70.92

Note: * indicates a significant difference at *p* < 0.05, ** indicates a significant difference at *p* < 0.01, BMI; body mass index, MIVC; maximal voluntary isometric contraction, LS; lower limb muscle strength, LS/BW ratio; lower limb muscle strength to body weight ratio n, T_{TUGT}; time to completed TUGT, T_{STS}; time to completed *the Five Times Sit-to-Stand Test*, P_{STS}; power index of the sit to stand test.

Multivariate Analysis of Factors Associated with Fall Risk and Regression Model for Fall Risk Prediction

The binary logistic regression analysis of fall risk revealed the results for three predictive models, as summarized in Table 2. In Model 1, only the TTUGT variable emerged as a significant predictor of fall risk. Model 2 incorporated the LS/BW ratio, while Model 3 further included the PSTS variable. Among these, Model 3 demonstrated the strongest statistical association with fall risk (χ^2 = 79.457, p < 0.05) and exhibited the highest explanatory power, with a Nagelkerke R^2 of 0.706. This indicates that the combined contribution of LS/BW ratio, TTUGT, and PSTS accounted for approximately 70.6% of the variance in predicting fall risk.

In the final model (Model 3), three variables were significantly associated with fall status: LS/BW, TTUGT, and PSTS. LS/BW showed an inverse association with falls (adj.OR = 0.980, 95% CI 0.96 to 1.00, p = 0.019), indicating that older adults with a lower strength-to-body-weight ratio had a higher likelihood of falling. In contrast, longer TTUGT times (adj.OR 1.617, 95%CI 1.05 to 2.50, p = 0.030) and lower

PSTS values (adj.OR 0.953, 95% CI 0.92 to 0.99, p = 0.022) (Table 2) were associated with increased fall risk. As a result, the equation for fall risk's predictive accuracy was 2.382 – 0.020(%LS/BW ratio) + 0.481(TTUGT) – 0.045(PSTS), where A value calculated from this equation approaching 1 or higher indicates an increased fall risk.

Table 2. Multivariate analysis for investigating factors associated with fall risk and Model of regression analysis for fall risk prediction

Model	Variables in the Equation	β	p-value	Chi-square	Nagelkerke r^2	Adj.Odds ratio	95% C.I. of Adj.Odds ratio
Model 1	T_{TUGT} (s)	1.131	<0.001**	61.255	0.587	3.100	2.11 to 4.55
	Constant	-14.229	<0.001**			0.000	
Model 2	LS/BW ratio (%)	-0.022	0.007**	69.866	0.646	0.978	0.96 to 0.99
	T_{TUGT} (s)	0.907	<0.001**			2.476	1.71 to 3.59
	Constant	-8.143	0.004**			0.000	
Model 3	LS/BW ratio (%)	-0.020	0.019*	79.457	0.706	0.980	0.96 to 1.00
	T_{TUGT} (s)	0.481	0.030*			1.617	1.05 to 2.50
	P_{STS} (Nm/s)	-0.045	0.022*			0.953	0.92 to 0.99
	Constant	2.382	0.612			10.821	

Note: * Correlation is significant at p < 0.05, ** Correlation is significant at p < 0.01, LS/BW ratio; lower limb muscle strength to body weight ration, T_{TUGT}; time to completed TUGT, T_{STS}; time to completed FTSST, P_{STS}; power index of the sit to stand test

Model Discrimination, Optimal Cutoff, and Diagnostic Accuracy

To further evaluate the predictive accuracy of the three regression models, ROC curve analysis was conducted. The Area Under the Curve (AUC) for Model 1 was 0.893 (95% CI: 0.827 to 0.959), for Model 2 was 0.900 (95% CI: 0.832 to 0.968), and for Model 3 was the highest at 0.936 (95% CI: 0.887 to 0.986), indicating excellent discriminative ability of all models, particularly Model 3 (Table 3, Figure 3).

Each model's optimal cut-off point for the Fall Risk Score was determined based on the maximum Youden Index. The best threshold for Model 1 was -0.144, yielding a sensitivity of 95.2% and specificity of 87.9% (Youden Index = 0.831). For Model 2, the optimal cut-off was -0.605, resulting in 95.2% sensitivity and 86.4% specificity (Youden Index = 0.816). Similarly, Model 3's best cut-off was identified at -0.231 with the same sensitivity and specificity values (95.2% and 86.4%, respectively), also achieving a Youden Index of 0.816.

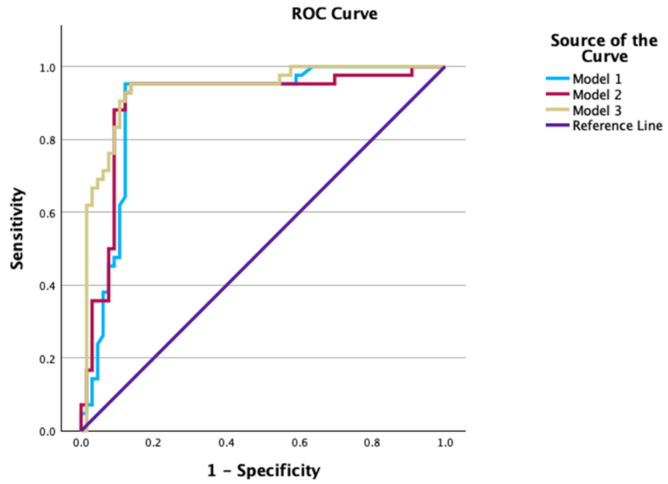
The confusion matrix at the optimal cut-off for Model 3 (cut-off = -0.231) demonstrated high classification accuracy: 40 of 42 fallers were correctly classified (true positives), and 57 of 66 non-fallers were correctly identified (true negatives), yielding an overall accuracy of 89.8%. These findings support the robustness of Model 3 in correctly identifying older adults at risk of falling based on physical performance metrics.

Table 3. Cut-off points, sensitivity, specificity, and area under the ROC curve (AUC) for the fall risk prediction models

Model	Cut-off of Fall Risk Score from prediction equation model	Sensitivity (%)	Specificity (%)	Youden Index	AUC (95% CI)
Model 1 (T_{TUGT} only)	-0.813	0.952	0.864	0.816	0.893 (0.827 to 0.959)
	-0.144	0.952	0.879	0.831	
	-0.041	0.929	0.879	0.807	
Model 2	-1.012	0.952	0.848	0.801	0.900 (0.832 to 0.968)
	-0.605	0.952	0.864	0.816	
	-0.245	0.929	0.864	0.792	
Model 3	-0.472	0.952	0.848	0.801	0.936 (0.887 to 0.986)
	-0.231	0.952	0.864	0.816	
	-0.053	0.929	0.864	0.792	

Note: AUC; area under the receiver operating characteristic (ROC) curve, 95% CI; 95% of confidence interval

Figure 3. Receiver Operating Characteristic (ROC) curves illustrating the discriminative ability of the three logistic regression models for fall risk prediction.



Note: Model 3 demonstrated the highest AUC (0.936; 95% CI: 0.887–0.986), followed by Model 2 (AUC = 0.900; 95% CI: 0.832–0.968) and Model 1 (AUC = 0.893; 95% CI: 0.827–0.959). All models showed excellent classification performance, with Model 3 exhibiting the strongest overall diagnostic accuracy.

Discussion

Falls in the elderly are a leading cause of morbidity, reduced independence, and increased healthcare costs, underscoring the critical need to identify individuals at high risk effectively (Camp et al., 2024; Colón-Emeric et al., 2024). This study developed a multivariate logistic regression model that integrates LS/BW, T_{TUGT}, and P_{STS} to predict falls in community-dwelling older adults. The final model identified lower LS/BW, longer T_{TUGT} times, and lower P_{STS} values as independent predictors of falls and demonstrated excellent discriminative ability (Nagelkerke R^2 = 0.706, AUC = 0.936). These findings indicate that combining complementary domains of physical performance—strength, mobility, and power—provides a more comprehensive and accurate estimate of fall risk than traditional approaches that rely on single tests such as the TUGT or FTSST alone (Nguyen et al., 2024; Sato et al., 2024; Wu et al., 2024).

The univariate results of this study highlight key physical performance differences between elderly fallers and non-fallers. Significant findings include higher T_{TUGT} and lower values for MVIC of LS, LS/BW ratio, and P_{STS} in fallers. These differences underline the critical role of lower limb strength, power, and functional mobility in fall risk among the elderly (Cebolla et al., 2015; Ishigaki et al., 2014; Sadaqa et al., 2023; Skelton et al., 2002; Wages et al., 2020; Winger et al., 2022). As individuals age, there is a natural decline in physical abilities, which can lead to increased fall risk and associated injuries. Strengthening the lower limbs through targeted exercises can significantly improve muscle mass and strength, balance, mobility, and overall functional capacity, thereby reducing the likelihood of falls (Ishigaki et al., 2014; Nurdin et al., 2025; Sadaqa et al., 2023). Moreover, studies have demonstrated that elderly individuals with a history of falls tend to have reduced lower limb strength, particularly in the knee flexors, which correlates with poorer performance in dynamic balance tests (Cebolla et al., 2015). Higher T_{TUGT} among fallers reflect deficits in dynamic balance and functional mobility (Tan et al., 2023). This aligns with prior research emphasizing TUGT's utility as a quick screening tool, albeit with limitations when used alone (Ibeneme et al., 2022; Oliveira-Zmuda et al., 2022). The fallers' lower MVIC of LS and LS/BW ratio suggest that reduced lower limb strength is a critical factor (Daneshjoo et al., 2023). Similarly, lower P_{STS} values in fallers indicate compromised ability to generate power during functional tasks like standing, which are essential for balance recovery during perturbations (Alcazar et al., 2021; Campitelli et al., 2022). These findings stress the necessity of multifaceted physical performance assessments. While TUGT highlights mobility deficits, integrating strength and power measures like LS/BW ratio and P_{STS} provides a comprehensive risk profile.

The findings from the multivariate logistic regression analysis emphasize the critical importance of adopting a multifactorial approach to predict fall risk among community-dwelling older adults. The predictive model integrates three key physical performance metrics: the lower limb muscle strength as a percentage of body weight (%LS/BW), the T_{TUGT}, and P_{STS} measured in Newton-meters per second (Nm/s). Together, these factors explain 70.6% of the variance in fall risk, demonstrating the superior explanatory power of the combined model compared to single-factor analyses. This underscores the multifaceted nature of fall risk, which is influenced by the interplay of muscle strength, functional mobility, and dynamic balance, necessitating a comprehensive assessment approach in clinical practice.

The predictive equation derived from this study offers a valuable tool for fall risk assessment:

$$\text{Fall Risk Score} = 2.382 - 0.020(\%LS/BW) + 0.481(T_{TUGT}) - 0.045(P_{STS})$$

A score approaching or exceeding 1 indicates an elevated risk of falls. For example, an older adult with %LS/BW of 120%, T_{TUGT} of 12 seconds, and P_{STS} of 100 Nm/s would have the following risk score:

$$\text{Fall Risk Score} = 2.382 - 0.020(120) + 0.481(12) - 0.045(100)$$

$$\text{Fall Risk Score} = 2.382 - 2.4 + 5.772 - 4.5 = 1.254$$

This score indicates a moderately elevated risk of falls. Healthcare providers can use this equation to identify individuals at higher risk and tailor interventions accordingly.

From an analytical standpoint, each variable in the model contributes uniquely to fall risk prediction. The %LS/BW ratio serves as an indicator of relative lower limb strength, a critical determinant of postural stability and functional independence. The inverse association observed between LS/BW and fall risk (adjusted OR < 1) indicates that older adults with relatively lower lower-limb strength for their body weight are more likely to experience falls. Clinically, this finding highlights the importance of not only absolute strength, but also strength relative to body mass when screening for fall risk. Lower values in this measure are associated with an increased likelihood of falls, particularly in tasks requiring strength to counterbalance unexpected perturbations. P_{STS}, reflecting dynamic lower limb power with typical values around 130 Nm/s in older adults, assesses muscular efficiency crucial for activities such as standing from a seated position. Higher P_{STS} values indicate greater dynamic strength and are protective against falls. The T_{TUGT}, a widely used functional mobility test, measures the ability to transition between static and dynamic postures. Elevated T_{TUGT} times are indicative of reduced mobility and compromised balance, significantly increasing fall risk. When combined, these variables provide a nuanced representation of physical function, surpassing the predictive capacity of individual tests.

The ROC analysis confirmed strong discriminative performance across all models, with Model 3 achieving the highest AUC (0.936), followed by Model 2 and Model 1. At the optimal cutoff score of −0.231, Model 3 demonstrated excellent diagnostic accuracy, with 95.2% sensitivity and 86.4% specificity. Our observation that relatively lower LS/BW was associated with an increased likelihood of falling is in line with the findings of Skelton et al. (2002), who reported that reduced lower-limb strength predicts future falls in community-dwelling older adults. However, whereas Skelton et al. primarily examined absolute strength measures as single predictors, our model incorporates strength relative to body weight alongside mobility (T_{TUGT}) and power (P_{STS}), thereby capturing complementary dimensions of neuromuscular function within a single predictive framework. The association between longer T_{TUGT} times and fall status in our study is also consistent with prior work showing that reduced functional mobility predicts future falls (e.g., Barry et al., 2014). Importantly, T_{TUGT} remained a significant predictor even after adjusting for LS/BW and P_{STS}, suggesting that the dynamic components of gait and turning captured by the TUGT provide information that is not fully explained by strength or power alone. Thus, by combining relative strength (%LS/BW), mobility (T_{TUGT}), and functional power (P_{STS}) into a regression-based equation validated through ROC and confusion matrix analysis, our study offers a multifactorial approach that improves prediction accuracy and provides a clinically applicable threshold for identifying fall risk in community-dwelling older adults. With an overall classification accuracy of 89.8%, the model supports practical implementation for targeted screening and intervention, and the use of the Youden Index ensures an optimal trade-off between sensitivity and specificity, in line with best practices in diagnostic test development.

The practical applications of this model are profound for clinical practice. Instead of relying on isolated measures, clinicians can assess a broader range of functional capacities—strength, mobility, and power—enabling the development of tailored interventions. From a clinical perspective, the fall risk score equation derived from Model 3 can be readily implemented in outpatient clinics and community-based programs. After assessing LS/BW, T_{TUGT}, and P_{STS}, practitioners can enter these values into the logistic regression equation to obtain an individual fall risk score and compare it with the cutoff value identified in this study (−0.231) to classify older adults as being at higher or lower risk of falling. For example, an older adult with a relatively low LS/BW, a prolonged T_{TUGT}, and a reduced P_{STS} would obtain a fall risk score of 1.254, which is above the cutoff and therefore indicates a high risk of falls. In practice, such individuals could be prioritized for targeted interventions, such as progressive resistance training, power-oriented sit-to-stand exercises, or balance-focused programs delivered in primary care or community settings, whereas those with scores below the cutoff may be monitored periodically rather than receiving intensive interventions. The inclusion of P_{STS} adds valuable insights into dynamic lower limb power, further refining intervention strategies. This comprehensive assessment supports proactive screening and early intervention, potentially reducing the incidence of falls and alleviating their associated physical, psychological, and economic burdens.

Despite its strengths, the study has some limitations. The sample size, while adequate for statistical analysis, may not fully represent the diversity of older adult populations, particularly those with comorbidities or varying levels of physical activity. Moreover, participants were community-dwelling older adults from a single province in northern Thailand with generally moderate physical fitness, which may limit the generalizability of our findings to frailer institutionalized populations or older adults in other regions or healthcare systems. Additionally, the cross-sectional nature of the study restricts the ability to infer causal relationships between these predictive factors and fall risk. Variability in the execution of physical performance tests across clinical settings could also affect the generalizability of the model. Furthermore, unmeasured variables such as cognitive function, sensory impairments, or environmental factors may contribute significantly to fall risk but were not accounted for in the model.

Future research should validate this model in larger, more diverse populations and explore its predictive power through longitudinal studies. Incorporating additional variables such as gait variability or cognitive function could further enhance the model's comprehensiveness. Advances in technology, such as wearable sensors, could also improve the accuracy and accessibility of assessing physical performance metrics, making fall risk prediction more practical in diverse healthcare settings. By integrating such a multifactorial assessment framework, clinicians can enhance the precision of fall risk predictions, optimize prevention strategies, and ultimately improve health outcomes for older adults.

Conclusions

This study highlights the superiority of a multifactorial approach to fall risk prediction over single-factor analyses. By integrating LS/BW ratio, T_{TUGT}, and P_{STS}, the model provides a comprehensive tool that captures the complex interplay of strength, balance, and mobility in determining fall risk. Clinically, this model offers significant potential to enhance early detection, personalized interventions, and proactive fall prevention strategies. Addressing the study's limitations and expanding research to validate and refine the model can further strengthen its utility, ultimately contributing to improved health outcomes and quality of life for older adults.

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