# Technology of Center of Gravity Trajectory Sensing for Assessing Balance of the Elderly

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**Abstract.** As the global population ages, older adults face increased fall risks due to physical decline, leading to severe consequences such as fractures and head injuries. Dynamic balance is crucial for maintaining stable gait and preventing falls, yet age-related factors like muscle weakness and vision impairments make it more challenging. Traditional balance assessment methods, such as the Berg Balance Scale (BBS) and Short Physical Performance Battery (SPPB), primarily focus on static balance and rely on subjective observations, leading to inconsistent evaluations. This study developed an innovative balance assessment system that integrates pressure sensing technology and center of gravity (COG) trajectory tracking. Using standardized stepping tasks inspired by the stepping patterns of the Japan Square Step Association, the system ensures data stability and consistency. The experiment recorded total stepping time and COG sway amplitude and compared these metrics with traditional balance assessment results. Due to the complexity and time requirements of the original BBS, a simplified version (SF-BBS) was adopted alongside the SPPB to facilitate efficient screening of older adults' balance capabilities, reducing the burden on participants. Results showed that the system effectively reflects dynamic balance abilities in older adults, with total stepping time and COG sway amplitude strongly correlating with SF-BBS and SPPB outcomes. This method offers a reliable and objective tool for dynamic balance assessment, supporting fall risk pre-diction and rehabilitation program development.

**Keywords:** Elderly · Balance ability assessment · Center of gravity


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## 1 Introduction

Population aging has emerged as a critical concern worldwide. According to the United Nations [1], the proportion of people aged 65 and older is expected to reach 11.7% by 2030 and rise further to 16.4% by 2050. By then, the elderly population will be more than twice the size of children under five years old. This demographic shift poses significant challenges, particularly in societies like Taiwan, where the combined trends of population aging and declining birth rates are reshaping family structures. Smaller family sizes have diminished the traditional caregiving role of families, even as the demand for elder care continues to grow. As a result, the need for social and medical resources has surged significantly [2]. One of the most prevalent health issues faced by older adults is the decline in balance ability. Research indicates that balance deterioration accelerates significantly after the age of 60 [3]. This decline increases the risk of falls and related injuries, such as fractures and head trauma, which can have severe consequences for older individuals [4]. Maintaining good balance is essential for the elderly to remain independent in their daily lives. Two key indicators used to measure balance ability are static balance, which refers to the ability to maintain stability while stationary, and dynamic balance, which involves maintaining stability during movement [5].

Currently, in hospitals and day care centers, the assessment of balance ability in the elderly primarily relies on occupational therapists using visual observation and simple scales, such as the Berg Balance Scale (BBS) [6]. However, these traditional methods are limited by environmental conditions and subjective judgment, leading to insufficient reliability and accuracy in measurement results. Although existing pressure sensing technologies can record static balance abilities, their high costs and hardware limitations prevent a comprehensive assessment of the overall balance abilities of older adults. To address these issues, this study aims to develop an algorithm focused on evaluating the dynamic balance abilities of older adults, based on the force plate module designed by Yoshida et al. [7].

The research aims to create an algorithm specifically designed to assess dynamic balance in older adults. The system works by recording the coordinates of the body's center of gravity (COG) and plotting its trajectory over time. By analyzing COG movement, this approach offers a more detailed and precise understanding of an individual's balance condition. The primary goal of this innovation is to support occupational therapists in making more accurate assessments of balance ability. By providing objective and quantifiable data, the system can help therapists identify specific balance issues and recommend targeted interventions. This, in turn, can improve the quality of care provided to older adults and reduce the risk of falls and injuries.

## 2 Literature Review

The development of a dynamic balance assessment algorithm has the potential to transform how balance ability is evaluated in older adults. The literature review examines three key areas related to the development of a dynamic balance assessment algorithm: balance ability in older adults, methods for assessing balance, and technology integration in balance assessment.

Balance refers to the ability to maintain the body's center of gravity (COG) within a controllable range [8]. COG is a point on the ground representing the vertical projection of the body's center of mass (COM) [9, 10]. The COM is a theoretical point calculated by weighing the positions of various body segments [11]. Since the COG was initially defined as the point of ground reaction force measured by a force plate, it is also referred to as the center of pressure (COP). Balance can be categorized into static and dynamic balance. Static balance refers to the ability to maintain an upright posture in a stationary position, while dynamic balance involves maintaining balance during movement or posture changes [12]. Static and dynamic balance are independent, and static balance cannot predict dynamic balance [13]. Walking is a typical dynamic balance activity, requiring head and trunk stability as well as coordinated steps [14, 15].

Assessing balance ability is critical for patients with balance disorders, helping therapists identify underlying causes and develop rehabilitation plans. During assessment, patients perform basic daily movements while therapists observe their responses and performance. Using validated and reliable methods, therapists can estimate fall risk and its potential consequences. Common tools include the Berg Balance Scale (BBS) and the Short Physical Performance Battery (SPPB). The BBS, developed by Berg in 1989, is suitable for older adults and stroke patients. It includes 14 daily activities, each scored from 0 to 4 based on performance, with total scores below 20 indicating a high fall risk [6, 16]. To simplify the testing process, a short-form BBS (SF-BBS) was developed, consisting of 7 tests scored from 0 to 4, with a total score of 28. Scores below 10 indicate a high fall risk [17]. The SPPB, developed by the U.S. National Institute on Aging in 1994, quantifies lower-limb function in older adults, assessing standing balance, gait speed, and the ability to rise from a chair. Each component is scored from 0 to 4, with a total score of 12 indicating optimal balance, and scores below 10 reflecting insufficient balance ability [18, 19]. These tools provide comprehensive and reliable clinical diagnoses and form an essential part of rehabilitation plans for older patients with balance disorders.

With technological advancements, balance testing has become more accurate and diverse, aiding in predicting fall and mortality risks. Wearable devices and computer-assisted systems improve testing sensitivity and, by integrating patient health data, offer personalized treatment recommendations [20, 21]. Observing the center of mass (COM) is a critical indicator in balance assessment, and force plate methods are widely used for gait analysis due to their high accuracy [22]. Portable force plates demonstrate accuracy comparable to laboratory-grade equipment, making them a potential choice for convenient balance assessment tools [23]. Pressure-sensing technology further simplifies the testing process and reduces equipment barriers, making it particularly suitable for assessing older adults. Yoshida et al. [7] developed a floor module embedded with 36 pressure sensors, enabling measurement without wearable or external imaging devices. This ensures privacy and is suitable for clinical and home environments. Compared to traditional laboratory force plates, this technology offers advantages such as low cost, high flexibility, and ease of deployment, making it an ideal choice for assessing balance abilities in older adults. The integration of these technologies not only enhances testing efficiency but also provides more insightful data support for clinical applications.

## 3 System Implementation

This study selected the pressure-sensitive floor module developed by Yoshida et al. [7], considering its ease of measurement and cost-effectiveness. The device consists of a 50 × 50 × 5 cm elevated floor casing, 36 pressure sensors, and a customized PCB board, with a total weight capacity of up to 200 kg. To achieve the research goals and calculate the COG position, this study referred to relevant previous studies to identify and adopt the most suitable algorithm for COG coordinate calculation. This extended the application of the pressure-sensitive floor module, enabling its effective use in balance ability testing and analysis. Schmidt et al. [24] installed pressure sensors at the four corners of a tabletop, placing the system within a two-dimensional coordinate system. The pressure sensor at the top-left corner was set as the origin (0,0), while the coordinates of the other three corners were defined as (Xmax,0), (0,Ymax), and (Xmax,Ymax) based on the distribution of the X and Y axes. Assuming the total force applied on the four sensors is Fx, the pressure values measured by the four corner sensors are denoted as F1, F2, F3, and F4. By analyzing the initial pressure data without force loading are recorded by the sensors are F01, F02, F03, and F04, the initial background forces acting on the four sensors (F0x) can be calculated. These initial values are used to calibrate the weight and position calculations of newly added objects. Based on this, the X-axis and Y-axis coordinates of the object position can be accurately calculated using the algorithms provided by Schmidt et al. [24].

This study utilizes the pressure-sensitive floor module developed by Yoshida et al. [7] as the foundation, further integrating the Unity engine to construct a data processing system. The floor module includes 36 pressure sensors and a customized PCB board. Pressure sensor data are read at a frequency of 10 Hz using an HX711 analog-to-digital converter and output in string format after being processed by Teensy 4.1 firmware. Each module is equipped with a USB-A cable extending from the micro-controller, which connects to a USB hub and aggregates data to a computer for centralized management and analysis. During the process of calculating COG coordinates, we identified inconsistencies in the distribution of pressure sensors. Given the emphasis in previous literature on the importance of accurate relative positioning of pressure sensors, we repositioned the sensors within a virtual two-dimensional coordinate system and measured the actual distances between sensors. This adjustment aimed to correct the effects of actual force and moments on the accuracy of COG coordinate calculations. In designing the COG calculation algorithm, we referred to existing studies and made adjustments based on the hardware configuration.

The formula is as follows:

$$\mathrm{cog\,X} = \mathrm{j} * (\mathrm{float})\mathrm{floor\,Data}[\mathrm{i}]\big[\mathrm{j}\big]/\mathrm{totalWeight} \tag{1}$$

$$\mathrm{cog\,Y} = \mathrm{i} * (\mathrm{float})\mathrm{floor\,Data}[\mathrm{i}]\big[\mathrm{j}\big]/\mathrm{totalWeight} \tag{2}$$

The total weight (totalWeight) is defined as the total weight detected by the system's sensors. The variables y and x represent the number of pressure sensors in the vertical and horizontal directions, respectively. A for loop is used to sum all pressure values. To prevent errors in the COG calculation algorithm when the device is unoccupied (i.e., the total pressure sum is 0), the totalWeight is set to 1 if the total pressure sum is 0, ensuring the system operates normally. Here, cogX and cogY represent the calculated COG coordinates (x, y) in Eq. (1) and Eq. (2), while floor-Data[i][j] represents the pressure value detected by a specific sensor. The parameters i and j in the matrix indicate the sensor's position, and their product reflects the influence of the pressure value in the horizontal and vertical directions. The for loop iterates through all calculations, where m and n represent the number of sensors in the vertical and horizontal directions within the floor module during the experiment.

Due to the uneven distribution of sensors (as illustrated in Fig. 1) within the pressure-sensitive floor modules, cogXmm in Eq. (3) and Eq. (4) represent the x-direction coordinate, where the x-direction is defined as the long edge coordinate. A vernier caliper with a minimum measurement value of 0.01 mm was used to measure the actual distances between pressure sensors, with 113.83 mm and 51.83 mm representing two types of distances between sensors along the long edge. Accordingly, based on the sensor arrangement and parameter settings, the COG coordinate in the x-direction (cogX) was converted into the actual distance in the x-direction. In Eq. (5) and Eq. (6), cogYmm represents the y-direction coordinate, where the y-direction is defined as the short edge coordinate. The parameters 119.14 mm and 47.4 mm represent two types of distances between sensors along the short edge. Accordingly, based on the sensor arrangement and parameter settings, the COG coordinate in the y-direction (cogY) was converted into the actual distance in the y-direction.

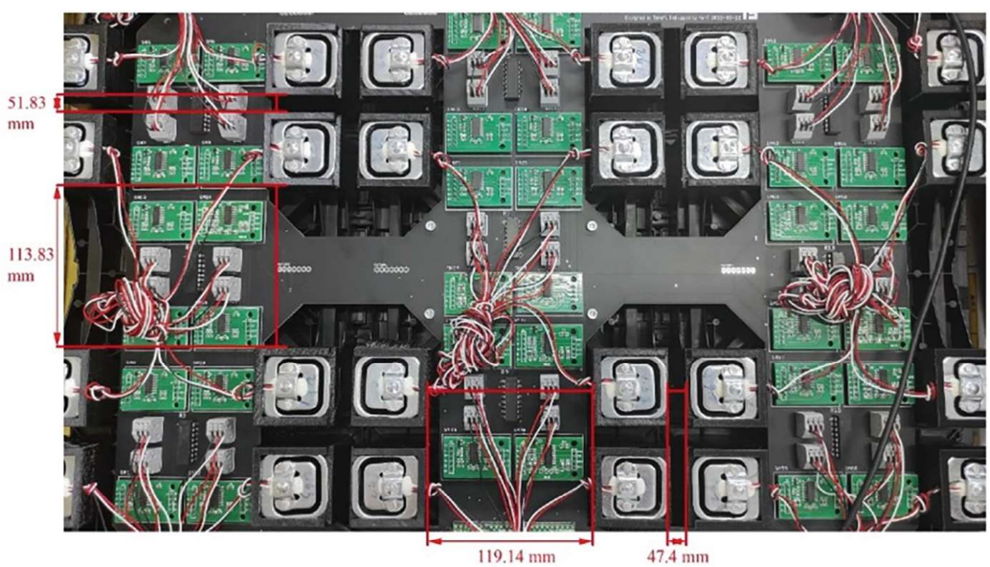


**Fig. 1.** Distribution of Pressure Sensors.

$$cogXmm = (113.83 * (cogX/2)) + (51.83 * (cogX/2)) + (cogX\%1) * 113.83 \quad (3)$$

$$\text{cogXmm} = (113.83 * (\text{cogX}/2)) + (51.83 * (\text{cogX}/2)) + (\text{cogX}\%1) * 51.83 \quad (4)$$

$$\text{cogYmm} = (119.14 * (\text{cogY}/2)) + (47.4 * (\text{cogY}/2)) + (\text{cogY}\%1) * 119.14 \quad (5)$$

$$\text{cogYmm} = (119.14 * (\text{cogY}/2)) + (47.4 * (\text{cogY}/2)) + (\text{cogY}\%1) * 47.14 \quad (6)$$

To verify the accuracy and stability of the COG recording algorithm, a weight test was conducted in this study. Multiple sets of calibrated weights ranging from 20 to 140 lb (approximately 9 to 63.5 kg) were prepared and measured using the pressure-sensitive floor modules. During the testing process, the weights were sequentially placed on individual sensors, and the sensor readings were recorded to evaluate their weight detection capabilities. The experimental results were presented in a line chart, demonstrating a strong linear correlation between the sensor readings and the actual weights. In Fig. 2, linear regression analysis showed an $R^2$ value of 0.9953, and the regression results were statistically significant ($p < 0.001$), indicating a high level of consistency between the sensor data and the actual weights. This confirms the reliability and accuracy of the pressure sensors in measuring body weight and highlights their suitability for accurately recording and analyzing weight-related data.

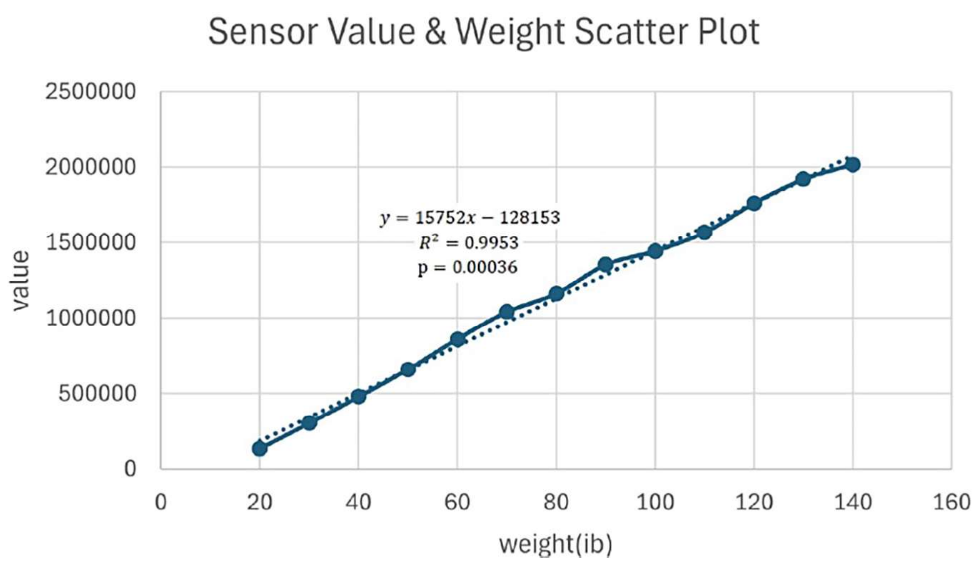


**Fig. 2.** Regression Analysis of Sensor Measurements and Weight ($p < 0.001$).

## 4 Experiment and Data Analysis

This study aimed to test the effectiveness of the algorithm-generated center of gravity (COG) coordinates and movement trajectories in assessing the balance abilities of older adults. Twelve participants aged 65 and above, meeting the inclusion criteria, were recruited. The experiment was conducted and used the Japanese square step exercise as the testing method. Each participant was required to complete the stepping task on the pressure-sensitive floor module following a designated step pattern, with COG coordinates and trajectory data collected for each trial. Data analysis was performed using MATLAB to calculate two key metrics: COG sway amplitude and time spent. This study collaborated with occupational therapists and rehabilitation physicians to select a simple step pattern as shown in Fig. 3 to reduce the learning burden for older adults and minimize errors or fatigue caused by complex step patterns. This ensured that participants could successfully complete the experiment. A stepping diagram compliant with the standards of the Japan Square Step Association was created, using black footprints and numbered markers to indicate the stepping sequence and positions. The diagram was secured to the pressure-sensitive floor module, and participants performed the steps according to the diagram to standardize the trajectory and range.

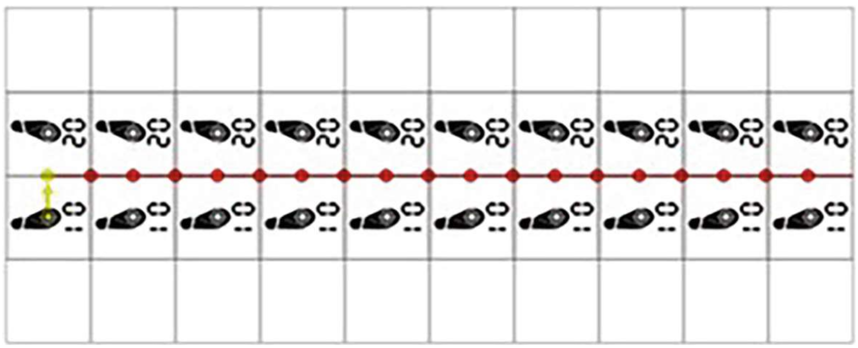

**Fig. 3.** Square Step Pattern Used in This Experiment.

The step pattern incorporated red dots as reference points for the ideal COG movement trajectory envisioned by the occupational therapists, which served as a basis for evaluating the participants' balance performance. Participants in this study were required to be 65 years or older with normal cognitive function (0 to 2 errors on the MMSE). Exclusion criteria included recent participation in balance or strength training, lower limb amputation, central or vestibular system disorders, and the use of psychotropic medications to ensure data accuracy. Before the experiment began, participants were informed of the study's purpose and details, provided written informed consent, and completed balance assessments upon meeting the inclusion criteria. The stepping experiment then proceeded. This study was approved by the Institutional Review Board (IRB), ensuring that its design and implementation adhered to ethical guidelines. During the measurement phase, occupational therapists assisted in assessing participants' balance and cognitive abilities using tools such as the Short Form Berg Balance Scale (SF-BBS), Short Physical Performance Battery (SPPB), Clinical Frailty Scale (CFS), FES-I, and MMSE. These assessments served as critical references for subsequent analyses. Prior to the formal experiment, occupational therapists led a 10-min warm-up session, which included stretching from the major torso and joints to limb extremities. This warm-up ensured participants were not at risk of injury during the exercise and adequately prepared for the square step experiment.

This study used MATLAB for data analysis and processing. To ensure the accuracy and validity of the collected data, MATLAB was first utilized to calculate the weight distribution and stepping time of older participants during the stepping process, verifying whether participants correctly stepped onto the designated positions in the step pattern. After data collection, the ideal COG movement trajectory anticipated by the occupational therapist and the actual COG trajectory generated by older participants during stepping were plotted as two-dimensional line charts for comparative analysis. According to discussions with occupational therapists, traditional balance assessments often rely on visual observation of trunk sway and gait stability. Therefore, this study employed MATLAB to calculate the average deviation between the participants' actual COG movement trajectory and the ideal COG trajectory. This average deviation was used as an indicator of balance ability, representing the amplitude of COG sway. The algorithm, based on a linear formula, calculated the minimum distance between each COG coordinate point output from the participants' stepping trajectories and the ideal trajectory for every frame. The average of these minimum distances was used as the final evaluation result for COG sway amplitude, providing a quantitative analysis of balance ability.

A preliminary stepping test was conducted with a young participant without lower limb disorders to verify the accuracy of the COG recording algorithm and its associated computational logic. The test results showed that the young participant's COG sway amplitude was 63.40, and the stepping time was 9.8 s. The test results are illustrated in Fig. 4, where the blue line represents the ideal trajectory anticipated by the occupational therapist, and the orange line represents the actual trajectory generated during the stepping process. The purpose of this test was to ensure that the data generated in subsequent experiments would be reasonable and to avoid excessive deviations or unreasonable data values.

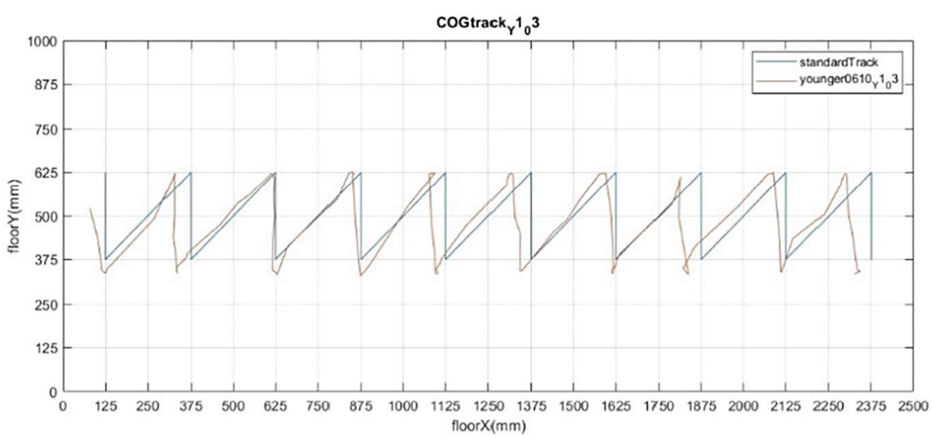


**Fig. 4.** COG Trajectory Chart for Young Participant's Stepping Test.

This experiment recruited a total of 12 older adults aged 65 and above, with an average age of 72.5 years and a median age of 70.5 years. All participants were screened by occupational therapists to ensure they met the inclusion criteria, with none meeting the exclusion criteria. Data from various assessment scales were recorded as critical references for subsequent data analysis, used to quantify the participants' baseline conditions and experimental performance, and to explore the correlation between these factors and COG sway amplitude. The results further revealed the relationship between balance ability and related physiological conditions, providing support for clinical assessment and intervention.

The results (Table 1) showed that the 12 older participants had an average SF-BBS score of 24.92 and a median score of 25.5. Two participants (c and d) exhibited partial balance impairments. The average and median SPPB scores were both 11, with two participants (g and h) performing relatively poorly in the mobility assessment. In the stepping experiment, the average COG sway amplitude among the 12 participants was 80.45, and the average time spent was 9.86 s. Only the FES-I scores showed a higher degree of data dispersion, indicating significant differences in the participants' subjective perceptions of their fall risk.

**Table 1.** Participant demographics and experimental data.

| Subject | Gender | Age | SF-BBS | SPPB | FES-I | MMSE | CFS | Mean COG Shaking | Mean Time |
|---|---|---|---|---|---|---|---|---|---|
| a | M | 87 | 24 | 11 | 18 | 29 | 2 | 95.93 | 7.67 |
| b | F | 69 | 26 | 12 | 19 | 30 | 1 | 71.65 | 4.76 |
| c | F | 75 | 20 | 11 | 21 | 30 | 3 | 93.52 | 10.07 |
| d | F | 75 | 20 | 11 | 50 | 30 | 3 | 92.76 | 8.23 |
| e | F | 70 | 25 | 12 | 16 | 30 | 1 | 69.92 | 8.50 |
| f | F | 69 | 26 | 11 | 21 | 30 | 1 | 85.76 | 7.75 |
| g | F | 75 | 24 | 9 | 29 | 27 | 2 | 90.28 | 10.90 |
| h | M | 75 | 24 | 9 | 22 | 26 | 3 | 85.63 | 17.11 |
| i | F | 71 | 28 | 11 | 21 | 28 | 1 | 69.10 | 10.60 |
| j | F | 70 | 28 | 12 | 19 | 25 | 1 | 71.98 | 9.17 |
| k | F | 68 | 26 | 11 | 31 | 28 | 2 | 60.35 | 13.50 |
| l | M | 66 | 28 | 12 | 23 | 26 | 1 | 78.57 | 10.08 |
| Mean | | 72.5 | 24.92 | 11.0 | 24.17 | 28.25 | 1.75 | 80.45 | 9.86 |
| Median | | 70.5 | 25.50 | 11.0 | 21.00 | 28.50 | 1.50 | 82.10 | 9.62 |
| SD | | 5.4 | 2.75 | 1.04 | 9.20 | 1.86 | 0.87 | 11.72 | 3.13 |

Considering that balance assessment scales often account for the duration older adults can maintain balance, the average COG sway amplitude of all participants was com-pared against the average total stepping time to examine the correlation between the two indicators. The results showed no significant correlation, indicating that the time spent on the stepping task was not associated with COG sway. This suggests that the duration of the stepping task did not influence the extent of COG sway in this experiment.

## 5 Discussion and Conclusion

This study aims to propose a COG recording algorithm capable of measuring the COG coordinates in elderly individuals and plotting COG movement trajectories. The algorithm-derived COG data provides two key indicators: the COG shaking amplitude and the time spent on stepping. These indicators can be compared with assessment scores from tools like the short-form Berg Balance Scale (SF-BBS) to assist in evaluating dynamic balance abilities. In the future, the algorithm can be used to detect and record stepping indicators in elderly individuals at daycare centers as a pre-assessment screening mechanism before they receive professional evaluation. Professional medical services can be sought if abnormal indicators are found. However, it cannot replace traditional balance assessment methods, the results of this study present an innovative indicator for elderly balance assessment. A limitation of this research is that most elderly participants recruited for the experiment had good short-form Berg Balance Scale (SF-BBS) scores. Further validation with participants of varying balance abilities and COG data is necessary to confirm the reliability and validity of this COG recording algorithm for dynamic balance assessment across diverse steppers.

For future development, from an engineering development perspective, it is recommended to integrate the MATLAB indicator algorithm with the visual interface for the COG recording algorithm. This integration would facilitate real-time visualization to calculate and generate COG shaking amplitude, correlating with balance ability scale scores. In addition, Japanese square stepping patterns with varying difficulty levels could be implemented to further challenge the COG control ability of elderly individuals.

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**Disclosure of Interests..** The authors declare that they have no competing interests.

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