Analysis of the Relation Between Balance Control Subsystems: A Structural Equation Modeling Approach

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***Abstract*— Balance plays a crucial role in human life and social activities. Maintaining balance is a relatively complex process that requires the participation of various balance control subsystems (BCSes). However, previous studies have primarily focused on evaluating an individual's overall balance ability or the ability of each BCS in isolation, without considering how they influence (or interact with) each other. The first study used clinical scales to evaluate the functions of the four BCSes, namely Reactive Postural Control (RPC), Anticipatory Postural Adjustment (APA), Dynamic Gait (DG), and Sensory Orientation (SO), and psychological factors such as fear of falling (FOF). A hierarchical structural equation modeling (SEM) was used to investigate the relationship between the BCSes and their association with FOF. The second study involved using posturography to measure and extract parameters from the center of pressure (COP) signal. SEM with sparsity constraint was used to analyze the relationship between vision, proprioception, and vestibular sense on balance based on the extracted COP parameters. The first study revealed that the RPC, APA, DG and SO indirectly influenced each other through their overall balance ability, and their association with FOF was not the same. APA has the strongest association with FOF, while RPC has the least association with FOF. The second study revealed that sensory inputs, such as vision, proprioception, and vestibular sensing, directly affected each other, but their associations were not identical. Among them, proprioception plays the most important role in the three sensory subsystems. This study provides the first numerical evidence that the BCSes are not independent of each other and exist in direct or indirect interplay. This approach has important implications for the diagnosis and management of balance-related disorders in clinical settings and improving our understanding of the underlying mechanisms of balance control.**

***Index Terms*— Balance control subsystem (BCS), causal effect, clinical scale, fear of falling (FOF), interaction, posturography, structural equation modeling (SEM).**

I. Introduction

A. Reviews on Balance Evaluation

ACCORDING to the World Health Organization, balance dysfunction-related falls have emerged as the second-leading cause of accidental death [1]. In numerous countries, falls have become the primary cause of unintentional injury-related disability, significantly impacting individuals' physical and mental well-being, as well as overall societal safety. This places a substantial burden on families and society as a whole [2], [3], [4]. Additionally, diseases such as strokes and Parkinson's highlight the importance of balance assessments to predict prognosis and rehabilitation outcomes [5], [6]. Moreover, accurate evaluation of balance ability plays a critical role in candidate selection for specific professions like athletics and aviation [7], [8]. Therefore, assessment of balance ability and exploration of balance control mechanisms hold significant importance across societal domains [9].

Currently, two research methods are commonly used to assess balance: the scale method and the instrumentation method [10], [11], [12]. The scale method includes tests such as the Mini-Balance Evaluation Systems Test (Mini-BESTest) and the Short International Fall Effect Scale (SFES-I) [13], [14]. On the other hand, the instrumentation method involves tests such as the Sensory Organization Test (SOT), which is based on posturography [15].

(1) The scale method is commonly used for assessing balance and involves standardized tests to evaluate an individual's ability to maintain balance in a variety of positions and situations. These tests encompass tasks such as standing on

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Local Ethics Committee of the Federal University of ABC under Application No. #842529/2014.

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one leg, walking on a narrow beam, and performing dynamic movements while maintaining balance. The scores obtained from these tests are then compared to normative data to determine the individual's overall balance ability. In recent years, a subsystem approach, exemplified by the Mini-BESTest, has gained prominence in identifying the underlying causes of balance deficits and designing targeted rehabilitation strategies for specific impairments. The Mini-BESTest incorporates a range of individual balance assessments from various scales, including the Berg Balance Scale [16]. Additionally, it includes a dual-task item and postural response items, enabling measurement of four distinct balance control subsystems (BCSes): Anticipatory Postural Adjustments (APA), Reactive Postural Control (RPC), Sensory Orientation (SO), and Dynamic Gait (DG). The Mini-BESTest consists of 14 homeostasis tasks categorized into these BCSes. In Magnani et al., the combination of Mini-BESTest with Time Up and Go and gait speed achieved 89% accuracy in identifying elderly individuals at high risk of falls [17]. Zhu et al. utilized Mini-BESTest to assess balance in patients with bilateral vestibular lesions and found that the SO subsystem degrades with age in these patients [18]. Phyu et al. demonstrated the high responsiveness of Mini-BESTest in evaluating balance exercise training in patients with type 2 diabetes and peripheral neuropathy [19]. According to King et al., individuals with Parkinson's disease may exhibit abnormal RPC but a normal SO subsystem, allowing them to maintain balance with their eyes closed on an unstable surface. Conversely, those with normal RPC may experience abnormal SO, resulting in difficulties in maintaining balance in that situation [20], [21].

(2) SFES-I is commonly used to assess fear of falling (FOF) and has been found to have good reliability and validity. By measuring and analyzing 751 older individuals living in the community, Kuo et al. established a link between frailty and quality of life in the elderly. Their findings suggest that this scale could enhance the feasibility of falling screening for older individuals [22]. Mehdizadeh et al. measured the scale of Parkinson's disease patients and showed that the SFES-I has good psychometric properties in disease diagnosis [23]. Scholz et al. revealed that the SFES-I was one of the most frequently used scales for multiple sclerosis to evaluate the progression of disease [24].

(3) In the past decade, there has been a significant increase in the availability of clinical tools to enable quantitative assessment of postural sway. As a result, an increasing number of physical therapists and physicians are incorporating posturography into their practice to customize treatments. Sensory perturbations, such as manipulating the visual scene, galvanic vestibular stimulation, and tendon vibration to disrupt proprioception, can be used to selectively manipulate one or more sensory inputs for postural control. These perturbations provide valuable insights into how each subsystem contributes to balance control and how individuals adapt to maintain balance in different environments. The SOT is a commercially available system which allows for systematic evaluation of sensory contributions to balance control in a clinical setting. It enables the visual surroundings or support surface, or both, to be "sway-referenced," meaning tilting in response to body sway, creating conditions in which visual and/or somatosensory inputs suggest that the subject is not swaying, which requires the nervous system to interpret the new sensory conditions and rely more heavily on sensory inputs that provide useful feedback about body sway. For example, when the surface under a subject is sway-referenced while their eyes are closed, or if they are looking at sway-reference visual surroundings, they must rely more on vestibular inputs to maintain balance.

Posturography is a commonly used technique for evaluating balance and postural control, particularly with the use of SOT. It involves measuring the center of pressure (COP) signal of the body while standing on a force plate or other instrumented surface [25], [26]. By analyzing COP data, posturography can detect deficits in the three balance control subsystems: vision, proprioception, and vestibular sense. The visual subsystem provides information about the body's position in relation to the environment, and is particularly important for postural stability when the eyes are open. However, when the eyes are closed, reliance on visual information decreases, and other sensory subsystems become more central. The proprioceptive subsystem provides information about the position and movement of the limbs and joints, which is essential for postural stability, especially in situations with limited visual information or when standing on a hard surface. The vestibular subsystem plays a critical role in postural stability, especially during dynamic movements such as standing on a soft surface with eyes closed [15]. In studies by Prieto et al., differences in the three sensory subsystems (vision, proprioception, and vestibular sense) were found in patients with age-related diseases such as Parkinson's, vestibular dysfunction, and strokes based on COP trajectory measurements obtained through posturography [27]. Alizadeh et al. also used posturography to evaluate vision, proprioception, and vestibular sensation of posture control in patients with chronic neck pain, and found that while no abnormalities were observed in their vestibular or visual subsystems, the proprioceptive subsystem seemed to be affected [28]. Quijoux et al. reviewed COP variables to quantify standing balance in elderly individuals, and concluded that COP has important applications in fall prevention, such as early detection of balance degradation [29].

Previous research has demonstrated the high reliability and effectiveness of scale and instrumentation methods for diagnosing and evaluating an individual's balance ability. However, these studies have solely concentrated on assessing either an individual's overall balance ability or the ability of each BCS in isolation, without taking into account the influence between the BCSes. Consequently, this study employs the structural equation modeling (SEM) method to analyze the relations between BCSes.

B. Structural Equation Modeling

The statistical technique known as SEM utilizes a combination of factor analysis and multiple regression to examine the intricate causal relationships among latent variables. These variables are theoretical constructs that are not directly observable but are believed to underlie the observed variables. Since latent variables cannot be measured using a single indicator, they are inferred from a set of observed variables that are believed to be related to the underlying construct [30], [31], [32]. For instance, in a study of academic achievement, intelligence might be the latent variable, whereas grades and test scores might be the observed variables [33]. SEM enables us to model these relationships, estimate the direction and magnitude of the effects of latent variables on each other and on the observed variables, and provide a comprehensive understanding of the complex relationships among variables.

C. Analysis of the Relations Between Balance Control Subsystems Based on Structural Equation Modeling

Balance is a fundamental aspect of human life and social activities, and it involves a complex process that requires the participation of various BCSes. Although prior studies have assessed an individual's overall balance ability or the ability of each BCS separately, they have not examined how these subsystems influence (or interact with) one another. To bridge this gap, we utilized SEM in this study:

(1) In the initial part of the study, a hierarchical SEM in conjunction with the mini-BESTest scale was utilized to examine the impact of four distinct BCSes - RPC, APA, DG, and SO - on overall balance ability. This approach allowed for a more comprehensive evaluation of each subsystem's contribution to overall balance control, thereby unveiling the indirect influence relationship between different BCSes. In the latter part of the first study, we utilized the SFES-I to evaluate FOF and investigate the impact of psychological factors on overall balance, as well as the reciprocal relationship.

(2) In the second part of the study, the researchers aim to assess the direct influence of vision, proprioception, and vestibular sense on each other in relation to balance. This evaluation is based on the parameters extracted from the COP curve using SEM with sparsity constraint, which facilitates the identification of the most relevant COP parameters to describe how vision, proprioception, and vestibular sense function together to impact balance.

II. METHODS

A. Data Collection and Processing

In this study, a public Human Balance Evaluation Database was implemented, and it can be accessed and downloaded through the website: https://physionet.org/content/hbedb/1.0.0/. A total of 163 subjects (116 female and 47 male) participated in the experimental data collection [34]. The evaluation process involved interviews with the subjects to gather information regarding their socio-cultural, demographic, and health characteristics. The subjects spanned a range of ages from 18-85, with 72 subjects over 60 years old. Their body masses were between 44.0-75.9 Kg, heights between 140.0-189.8 cm, and body-mass indexes (BMI) between 17.2-31.9 Kg/m2. Additionally, each subject underwent an interview with clinical doctors who evaluated their medical history and current health status, along with other qualitative assessments. It is important to note that all subjects met the qualifications for this test. Scale evaluations were conducted on each subject

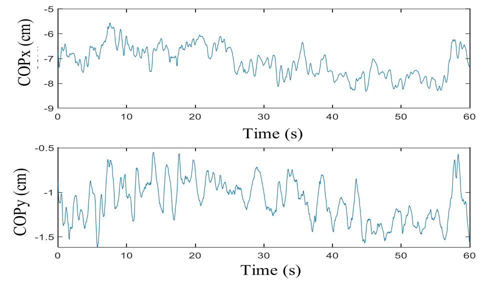

Fig. 1. The time-dependent coordinate position of the COP signal for one subject in the x-axis direction on top and in the y-axis direction at the bottom.

using the mini-BESTest and the SFES-I (the assessments were conducted through individual interviews in a well-illuminated room measuring 7.5 × 5.7 m, following the specific guidelines of the test). The SFES-I comprises seven items, each scored on a four-point scale (1)-4 points). A higher score indicates greater concern about falling. Please refer to Appendix for details on the scale items. The mini-BESTest comprises 14 items scored on a three-point scale (0-(2), which assesses four balance subsystems: APA, RPC, SO, and DG. Each BCS is reflected in the corresponding scale item, as shown in Appendix.

The balance of all participants was evaluated by collecting COP signals using a commercial force platform (40 × 60.132 cm, OPT400600-1000, AMTI, U.S.) and amplifier (Optima Signal Conditioner, AMTI, U.S.) at a sampling frequency of 100 Hz. The foam balance board contained a 6-cm height foam block (Balance Pad, Airex, U.S, stiffness: 69.4kg/m^3). Signal acquisition was performed for each participant under four different conditions to assess balance (Each trial lasts for 60 seconds). These conditions were defined as follows:

Condition 1: Standing with eyes open on a rigid surface
Condition 2: Standing with eyes closed on a rigid surface
Condition 3: Standing with eyes open on an unstable surface
Condition 4: Standing with eyes closed on an unstable surface

Participants were randomly assigned to four experimental conditions, with three acquisitions per condition. In all conditions, participants were instructed to stand barefoot at a 20-degree angle, as still as possible, with arms at their sides and gaze fixed on a 5 cm circular black target positioned 3m above their eyes on the wall. During Condition 3 and Condition 4 experimental conditions, participants stood on a 6 cm high foam balance board. To account for noise in the COP signal during acquisition, a 10 Hz Butterworth low-pass filter was utilized for processing [35]. After denoising the COP signal, Fig. 1 illustrates an example of the trajectory coordinates of the COP signal in the x and y-axis directions over a 1-minute period. Figure 2 depicts the corresponding COP trajectory in the x-y axis plane.

To extract COP features, the COP signal recorded in the x and y-axis directions, as well as their corresponding COP trajectory in the x-y axis plane, were analyzed. The specific COP features under each experimental condition are presented in

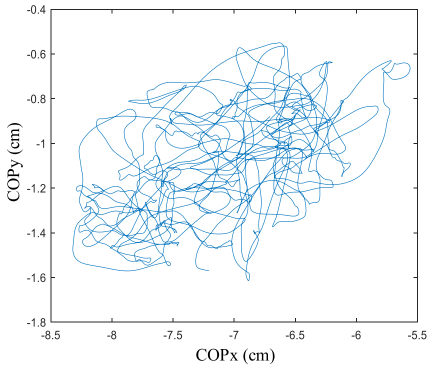

Fig. 2. The COP signal trajectory for one subject is plotted in the x-y axis plane.

TABLE I
THE FEATURES EXTRACTED FROM COP SIGNALS FOR EACH EXPERIMENTAL CONDITION

Features	Definitions
$F(1)$	The total length of COP trajectory in the x-y axis plane
$F(2)$	Enveloping area of COP trajectory in the x-y axis plane
$F(3)$	Maximum swing amplitude of COP signal in the x-axis direction
$F(4)$	Maximum swing amplitude of COP signal in the y-axis direction
$F(5)$	Standard deviation of speed derived from COP signal in the x-axis direction
$F(6)$	Standard deviation of speed derived from COP signal in the y-axis direction
$F(7)$	Standard deviation of acceleration derived from COP signal in the x-axis direction
$F(8)$	Standard deviation of acceleration derived from COP signal in the y-axis direction
$F(9)$	The ratio between feature $F(1)$ and $F(2)$

TABLE II
SOT TESTING AND ITS CORRESPONDING BALANCE CONTROL MECHANISM REVELATION

Conditions	Balance Control Mechanism
1. Eye Open, Hard Surface	Vision, Proprioception and Vestibular Sense
2. Eye Closed, Hard Surface	Proprioception
3. Eye Open, Soft Surface	Vision
4. Eye Closed, Soft Surface	Vestibular Sense

Table I. During the signal acquisition process, three repeated measurements were taken for each subject under each of the four experimental conditions. The three values obtained under the same experimental conditions were averaged to represent the overall performance under those conditions.

According to the previous observations on the human perception system: vision, proprioceptive and vestibular sense jointly maintain the balance of the human body, and different experimental conditions describe different perception subsystems. Among them, the balance control mechanism of experimental condition 2 (eyes closed, hard surface) is mainly proprioceptive; the balance control mechanism of condition 3 (eyes open, soft surface) is mainly vision, and the balance control mechanism of condition 4 (eyes closed, soft surface) is vestibular sense (see Table II). Therefore, based on the COP features obtained in Table I for each SOT condition and [36], [37], [38], [39], we can derive newly constructed COP features to characterize the vision, proprioceptive, and vestibular sense abilities of individuals.

$$Pro\ (i) = \frac{F_{condition2}(i)}{F_{condition1}(i)} \qquad (i = 1, \ldots, 9) \tag{1}$$

$$Vis(i) = \frac{F_{condition3}(i)}{F_{condition1}(i)} \qquad (i = 1, \ldots, 9) \tag{2}$$

$$Ves\ (i) = \frac{F_{condition4}(i)}{F_{condition1}(i)} \qquad (i = 1, \ldots, 9) \tag{3}$$

where $Pro(i)$, $Vis(i)$ and $Ves\ (i)$ represent the newly constructed COP features, which can describe the proprioception, vision, and vestibular sense abilities of individuals, respectively. For example, the newly constructed parameter $Pro\ (1)$ is determined by computing the ratio of $F_{condition2}(1)$ to $F_{condition1}(1)$. $F_{condition2}(1)$ and $F_{condition1}(1)$ represent the COP features extracted from the first row of Table I during SOT conditions 2 and 1, respectively.

B. SEM Construction

SEM is a statistical technique that examines the relationships between variables by analyzing their covariance matrices. SEM comprises two components: the structural model and the measurement model. The measurement model comprises latent and observed variables and serves as a measurement tool to assess the appropriateness of using observed variables as indicators of latent variables. The structural model, on the other hand, describes the causal relationships between latent variables.

Given $\boldsymbol{\eta} = [\eta_1, \cdots, \eta_m]^T$ is the vector of an endogenous latent variable with the dimension of $m \times 1$, and $\mathbf{y} = [y_1, \cdots, y_p]^T$ is the vector of an observational variable with the dimension of $p \times 1$, i.e. an indicator of the endogenous variable $\boldsymbol{\eta}$, and then the general formula of the measurement model is as follows:

$$\mathbf{y} = \boldsymbol{\Lambda}_{\mathbf{y}}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{4}$$

where $\boldsymbol{\Lambda}_{\mathbf{y}}$ refers to the coefficient matrix from $\boldsymbol{\eta}$ to $\mathbf{y}$, namely the factor loading matrix of exogenous observational variables on exogenous latent variables; $\boldsymbol{\varepsilon}$ is the $p \times 1$ measuring error of $\mathbf{y}$, $\boldsymbol{\varepsilon} \sim N(0, \boldsymbol{\Theta}_{\boldsymbol{\varepsilon}})$, and $\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}}$ is the covariance matrix of measuring error.

Similarly, as for n-dimensional exogenous latent variable $\boldsymbol{\xi}$ and its corresponding q-dimensional observational variable $\mathbf{x}$, the general formula of the measurement model is as follows:

$$\mathbf{x} = \boldsymbol{\Lambda}_{\mathbf{x}}\boldsymbol{\xi} + \boldsymbol{\delta} \tag{5}$$

where, $\boldsymbol{\Lambda}_{\mathbf{x}}$ refers to the $q \times n$ coefficient matrix from $\boldsymbol{\xi}$ to $\mathbf{x}$, namely the factor loading matrix of endogenous observational variables on endogenous latent variables; $\boldsymbol{\delta}$ is the $q \times 1$ measuring error of $\mathbf{x}$, $\boldsymbol{\delta} \sim N(0, \boldsymbol{\Theta}_{\boldsymbol{\delta}})$, and $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ is the covariance matrix of measuring error.

The structural model contains various latent variables only, and the relationship between latent variables is simultaneously estimated with the measurement model. For example, the

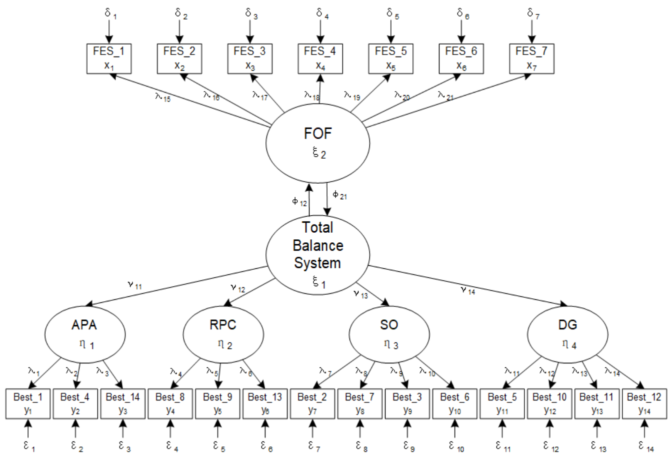

Fig. 3. The proposed SEM model for the first study.

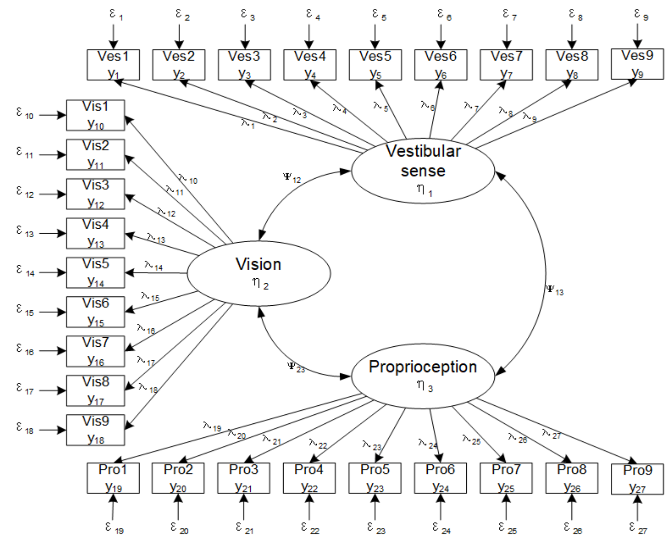

Fig. 4. The proposed SEM model for the second study.

relationship between the endogenous variable η_1 and the exogenous variable ξ_1 can be expressed as:

$$\eta_1 = \gamma_{11}\xi_1 + \zeta_1 \tag{6}$$

The endogenous variable η_2 is associated with η_1 and ξ_1, and it can be expressed as:

$$\zeta_2\zeta_1\eta_2 = \beta_{21}\eta_1 + \gamma_{21}\xi_1 + \zeta_2 \tag{7}$$

where and are the residuals for the above two equations.

Equation (6) and (7) can be expressed as a matrix:

$$\begin{pmatrix}\eta_1\\ \eta_2\end{pmatrix} = \begin{pmatrix}0 & 0\\ \beta_{21} & 0\end{pmatrix}\begin{pmatrix}\eta_1\\ \eta_2\end{pmatrix} + \begin{pmatrix}\gamma_{11}\\ \gamma_{21}\end{pmatrix}(\xi_1) + \begin{pmatrix}\zeta_1\\ \zeta_2\end{pmatrix} \tag{8}$$

or the general form of the structural model:

$$\boldsymbol{\eta} = \mathrm{B}\eta + \Gamma\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{9}$$

where B refers to the coefficient matrix of influence relations between endogenous variables. Γ refers to the coefficient matrix of influence relations of exogenous variables on endogenous variables. The vectors $\boldsymbol{\eta}$, $\boldsymbol{\xi}$ and $\boldsymbol{\zeta}$ refer to the endogenous variables, exogenous variables and residuals for (9).

In this study, two models are established to explore the complex relationship between various factors related to balance control. Model 1 is used to study the effects of APA, RPC, SO, DG on FOF (see Fig. 3). In Model 1, the higher-order SEM is used; firstly, four BCSes are set, i.e. APA (η_1), RPC (η_2), SO (η_3) and DG (η_4), and their co-influence source "total balance system (ξ_1)" is a higher-order factor, which is an exogenous latent variable in this model, and there is no subordinate observational variable [40]. In order to study the relationship between balance and FOF, and the latent variable - FOF (ξ_2) is set. The observational variables $y_1, \cdots, y_{14}$, $x_1, \cdots, x_7$ measured by Mini-BESTest and SFES-I can be taken as the indicators for describing the corresponding latent variables. The factor loadings $\lambda_1, \cdots, \lambda_{21}$ are used to describe the relationship between latent variables and observational variables, $\gamma_{11}, \cdots, \gamma_{14}$ are used to describe the relationship between exogenous and endogenous latent variables, and ϕ_{12}, ϕ_{21} are used to describe the relationship between total balance ability and FOF. At the same time, the measuring error of each observational variable is also quantified, such as δ_1, ε_1.

Model 2 intends to study the mutual relation between three sensory subsystems affecting balance (see Fig. 4). In Model 2, three latent variables are set, i.e. the vestibular sense (η_1), vision (η_2) and proprioception (η_3); and the posturography-derived COP features serve as observational variables for describing the three latent variables [41].

The estimation of the SEM is the relationship between minimized sample variance/covariance and the variance/covariance estimated by the model. Σ is the overall variance/covariance matrix representing observational variables $\mathbf{y}$ and $\mathbf{x}$, and the key to estimation of the SEM is to express matrix Σ as a function of the free parameter $\boldsymbol{\theta}$ in the hypothetical model, with the underlying assumption of $\Sigma = \Sigma(\boldsymbol{\theta})$, in which, $\Sigma(\boldsymbol{\theta})$ is the variance/covariance matrix estimated by the model. The objective of model estimation is to find a set of model parameters ($\boldsymbol{\theta}$), and then minimize $\Sigma - \Sigma(\boldsymbol{\theta})$. Maximum likelihood is a common estimation method, but the premise is that the data conform to multivariate normal distribution. Since the data in this study do not conform to multivariate normal distribution, MLR (Maximum likelihood with robust standard error) is selected, which can better process the categorical data in violation of the multivariate normal hypothesis. MLR estimation adopts an asymptotically unbiased estimation method and corrects the standard error and chi-square statistics. It is calculated as follows:

$$acov\,(\boldsymbol{\theta}) = N^{-1}(\Delta'\mathrm{I}_{ob}\boldsymbol{\Delta})^{-1}\Delta'\mathrm{I}_{ob}\boldsymbol{\Gamma}\mathbf{I}_{ob}\boldsymbol{\Delta}(\Delta'\mathrm{I}_{ob}\boldsymbol{\Delta})^{-1} \tag{10}$$

where,

$$\mathrm{I}_{ob} = \mathbf{D}'\left\{\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta}) \otimes \left[\Sigma^{-1}(\boldsymbol{\theta})\mathbf{S}\Sigma^{-1}(\boldsymbol{\theta}) - \frac{1}{2}\Sigma^{-1}(\boldsymbol{\theta})\right]\right\}\mathbf{D}$$

Here, N is the sample size, Γ is estimated asymptotic covariance matrix of $\mathbf{S}$, $\boldsymbol{\Delta}$ is the first-order derivative of the parameter vector, $\otimes$ is the Kronecker product, and $\mathbf{D}$

is a "repetition matrix" in the process of Kronecker product operation.

Furthermore, in the second study, the sparsity constraint is added to SEM:

$$\hat{\xi}_i = \arg\min \left\{ lsm + \lambda_1 \sum_{j=1}^{27} \xi_{ij}^2 + \lambda_2 \sum_{j=1}^{27} \left|\xi_{ij}\right| \right\} (i = 1, 2, 3) \tag{11}$$

where,

ξ : (27×3) loading factor

lsm : the error sum of squares

λ_1, λ_2 : penalty factors

After model estimation, in order to determine whether the proposed theoretical hypothetical model can be used to describe the relationships between latent variables, the model fitting evaluation is carried out for the constructed model. In this study, six fit indices are used, as illustrated below [42].

(1) Standardized Root Mean Square Residual

The Standardized Root Mean Square Residual (SRMR) is a residual-based index, which is unique in its direct dependence on residuals. In contrast, the Root Mean Square Residual (RMR) is calculated using the sample gap, and its magnitude is influenced by the scale of the indices used. SRMR, however, employs standardized metrics, which provides greater comparability across studies. This leads to greater ease of interpretation of standardized SRMR values. SRMR is calculated as follows:

$$SRMR = \sqrt{\frac{2 \sum_{i=1}^{p} \sum_{j=1}^{i} (s_{ij} - \hat{\sigma}_{ij})^2 \Big/ (s_{ii} s_{jj})}{p(p+1)}} \tag{12}$$

where, $s_{ij} - \hat{\sigma}_{ij}$ is the sample residual of the covariance of x_i and x_j, and s_{ii} is the sample variance of x_i.

(2) Root Mean Square of Error of Approximation

The Root Mean Square of Error of Approximation (RMSEA) is one of the indices proposed earlier but still favored by the researchers. It is calculated as follows:

$$RMSEA = \max \left[\sqrt{\frac{\chi^2 - df}{(N-1)\big/df}}, 0 \right] \tag{13}$$

where df is the degree of freedom of chi-square. RMSEA measures the normative property of the off-center parameter $(\chi^2 - df)$. It is slightly affected by sample size, and it penalizes complex models.

(3) Comparative Fit Index

The Comparative Fit Index (CFI) assesses the degree of discrepancy between the postulated model and the null model, which lacks any covariance relationships. CFI also accounts for the spread of the evaluated model and the central chi-square distribution. The calculation of CFI is as follows:

$$CFI = 1 - \frac{\max\left[(\chi_T^2 - df_T), 0\right]}{\max\left[(\chi_T^2 - df_T), (\chi_N^2 - df_N), 0\right]} \tag{14}$$

where χ_N^2 and χ_T^2 respectively refer to the chi-square values obtained by the virtual fit model and hypothetical model.

(4) Tucker-Lewis Index

The Tucker-Lewis Index (TLI) is a measure of relative fit that compares the hypothetical model to a nested model without any covariance assumptions between observed variables. TLI is calculated using the comparison principle of nested models. The formula for TLI is as follows:

$$TLI = \frac{\chi_N^2 / df_N - \chi_T^2 / df_T}{\chi_N^2 / df_N - 1} \tag{15}$$

The main shortcoming of TLI is the high sample volatility, especially when the virtual model can better fit the sample data. Nevertheless, it is still a more commonly used relative index.

(5) Chi-Square to Degrees of Freedom Ratio

In SEM, the Chi-Square to Degrees of Freedom Ratio (χ^2/df) is a metric used to evaluate the model's fit to the data. It calculates the ratio of the model's chi-square value to its degrees of freedom, providing a measure of how well the theoretical model aligns with the observed data.

(6) Incremental Fit Index

The Incremental Fit Index (IFI) is a commonly used measure of SEM to assess the overall model fit. It quantifies the improvement in observed data fit relative to a perfectly fitting model. The IFI is calculated as follows:

$$IFI = \left[1 - \left(\chi_M^2 \Big/ \chi_F^2\right)\right]^{\frac{1}{2}} \tag{16}$$

where χ_M^2 represents the model's chi-square value, and χ_F^2 represents the chi-square value of a hypothetical model which perfectly fits the observed data. The IFI ranges from 0 to 1, with values closer to 1 indicating better fit.

III. Results

In this study, the fit statistics of our proposed models are shown in Table III and IV, respectively. As can be seen, we observed a good fitting model by several goodness-of-fit indices. In the full models (see Fig. 5 and 6), we found that the RPC, APA, DG, and SO BCSes indirectly influenced each other through their overall balance ability, and their association with FOF varied. APA has the strongest association with FOF, while RPC has the least association with FOF. Additionally, we discovered that sensory inputs, such as vision, proprioception, and vestibular sensing, directly affected each other, but their associations were not uniform. Among them, proprioception plays the most important role in the three sensory subsystems.

IV. Discussion

A significant proportion of individuals aged 65 and above experience challenges with balance or walking, with those affected by neurological or musculoskeletal disorders at an even higher risk of mobility issues. The intricacies of balance control result in a range of balance problems that necessitate BCS clinical assessment for effective treatment. However, previous studies have focused solely on evaluating an individual's overall balance ability or the ability of each BCS in isolation, without considering the interplay between BCSes that characterizes an individual's balance as a whole. This

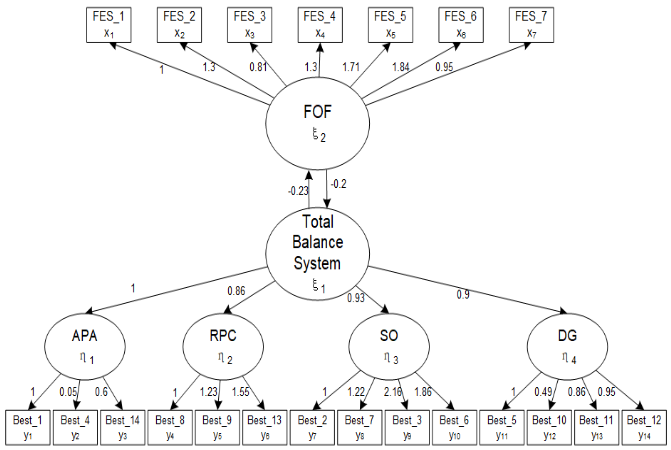

Fig. 5. Model of the first study using a SEM approach.

TABLE III
THE FIT STATISTICS OF SEM MODEL FOR THE FIRST STUDY

Index	Value	Explanations
SRMR	0.025	< 0.08 The fit is good
RMSEA	0.032	< 0.05 The fit is good
		0.05-0.08 Interpretation is acceptable
		> 0.08 The fit is not good
CFI	0.966	> 0.95 The fit is good
		0.9-0.95 Interpretation is acceptable
		< 0.9 The fit is not good
TLI	0.960	> 0.95 The fit is good
		0.9-0.95 Interpretation is acceptable
		< 0.9 The fit is not good
χ^2/df	1.136	2-5 The fit is acceptable
		< 2 The fit is good
IFI	0.918	> 0.9 The fit is acceptable
		> 0.95 The fit is good

TABLE IV
THE FIT STATISTICS OF SEM MODEL FOR THE SECOND STUDY

Index	Value	Explanations
SRMR	0.046	< 0.08 The fit is good
RMSEA	0.014	< 0.05 The fit is good
		0.05-0.08 Interpretation is acceptable
		>0.08 The fit is not good
CFI	0.927	> 0.95 The fit is good
		0.9-0.95 Interpretation is acceptable
		< 0.9 The fit is not good
TLI	0.913	> 0.95 The fit is good
		0.9-0.95 Interpretation is acceptable
		< 0.9 The fit is not good
χ^2/df	4.327	2-5 The fit is acceptable
		< 2 The fit is good
IFI	0.927	> 0.9 The fit is acceptable
		> 0.95 The fit is good

study aims to address this gap by exploring the interplay between BCSes.

The results shown in the Fig. 5 have several comments: (1) The relationship between FOF and balance abilities has been a topic of interest for researchers for many years. While many studies have explored the correlation between these two factors, few have examined their causal effects on each other. Recently, there has been an increasing interest in investigating the causal effects of FOF on balance abilities, and vice versa. For example, Gazibara et al. found that FOF is one of the factors that can cause falls in individuals over the age of 65, while Kendrick et al. demonstrated that exercise can enhance balance control ability and further reduce FOF in patients [43], [44]. However, most studies have analyzed the causal effects between FOF and balance ability separately, rather than simultaneously. Given that FOF and balance abilities coexist in individuals, it is reasonable to investigate their causal effects simultaneously. In this study, we aimed to explore the simultaneous influence of FOF and balance abilities on each other. Our findings suggest that balance ability has a stronger impact on FOF than vice versa. (2) This study also aimed to investigate the relationship between FOF and BCSes. Our results revealed for the first time from a data-driven perspective that the APA subsystem has the closest relationship with FOF. Early clinical observations have revealed a notable correlation between FOF and APA. Among the main findings, individuals with FOF exhibit a significant increase in APA latency: the time gap between receiving an activity instruction and executing the corresponding postural adjustment [45]. This suggests that individuals with FOF adopt more conscious postural control, carefully regulating their movements to prevent falls. However, this cautious strategy can lead to incomplete movement execution and reduced ability to adjust to interference, increasing the risk of falling. A study of individuals with FOF performing a rise-to-toes task at the edge of a high platform found a decrease in APA magnitude due to this cautious strategy [46]. The influence of FOF on APA may be linked to the co-contraction mechanism proposed by Uemura et al. Individuals with FOF adopt stiff postural strategies through simultaneous contraction of antagonistic muscles to reduce the risk of falls, which influences APA to generate autonomous movements to anticipate and correct for upcoming body disturbances [47]. Moreover, we found that the relationship between RPC and FOF was the weakest among the four subsystems. This is mainly because RPC refers to an automatic movement of the trunk and limbs when an individual is suddenly stimulated by external factors to change their center of gravity, causing the center of gravity to return to its original stable state or establish a new equilibrium state. In contrast, FOF mainly describes an individual's concern about losing balance in the future, rather than the fear of losing balance due to sudden interruptions. (3) This study employed a second-order SEM to investigate the relationships among BCSes. This approach was chosen for several reasons. First, the Mini-BESTest scale used in this study is hierarchical, with the first layer representing the function of individual BCSes and the second layer representing overall balance control ability. Secondly, previous clinical observation studies have suggested indirect, rather than direct interactions between BCSes. As such, we selected a second-order SEM, i.e. fork structure, which is a typical model for studying indirect causal relationships between variables. (The second-order SEM is a type of graphical model, which can represent causal relationships among variables in a system. It consists of a central variable influenced by two or more other variables, which may not be directly related to each other [48]). Additionally, we also explored the direct causal relationships among these four BCSes. Our findings suggest that balance subsystems mainly affect each other indirectly through the entire balance system, rather than through direct causal relationships. Finally, it should be emphasized that the aforementioned assertion is based on a mathematical modeling approach, which merely alludes to the indirect relationships among the four subsystems. From a physiological standpoint, the functions of the four subsystems are regulated by musculoskeletal factors, which can also be deemed as overall contributing elements to the four subsystems. Consequently, it is possible that the four balance subsystems could engage in indirect physiological interactions through musculoskeletal factors. (4) In this study, we used items of the scale as observation variables to quantify the FOF and the functions of BCSes. Our findings revealed significant differences in the factor loadings between these observation variables. As is well known, an individual's balance ability is affected by two important issues: the center of gravity and the support surface [49]. A larger support surface leads to smoother movements, while a stable and appropriate center of gravity results in better balance. For instance, the item "walking on a slope" in the FOF FES_6 item was found to have a relatively large loading weight due to the unstable support surface and the difficulty for individuals to maintain balance while walking on a slope. On the other hand, the item "stand up and sit down on a chair" in the FOF FES_3 item involves less movement of the center of gravity compared to other items, and the support surface is relatively stable, resulting in a small loading weight in the SEM model. Furthermore, in the Mini-BESTest scale, RPC refers to the pre-activation of corresponding posture muscles before the body produces a target action or foreseeable external force interference. Our results indicate that there is a difference in the loading weights between Best_1, namely "from sitting to station", and Best_4, namely "compensatory forward posture adjustment". This loading weight difference may be due to the fact that actions occurring in the former are known in advance, while actions occurring in the latter are unpredictable and cannot be proactively grasped by testers. (5) It would be helpful to include other questions in the FOF assessment such as confidence in not falling when being pulled by a dog or bumped by a child, or ability to walk on unstable surfaces. These questions would provide a more comprehensive evaluation of an individual's FOF. However, the SFES-I is currently widely established and standardized for evaluating FOF. Therefore, this study used the original SFES-I for our SEM. Moreover, SFES-I is commonly used among elderly individuals, but it can also be applied to subjects of all ages without restriction. Its application orientation does not provide any information indicating age limitations [50]. Therefore, it is entirely reasonable for this study to use SFES-I to measure the participants of ages 18-85.

The findings presented in Fig. 6 provide several noteworthy observations: (1) It is important to note that the visual, proprioceptive, and vestibular sensory subsystems play simultaneous roles in inputting sensations into the neural center during the process of maintaining balance. If one of these sensory subsystems is damaged, the other subsystems will compensate and play a greater role in balance control [51]. To model these complex interactions, we employed the models of sensory subsystems that directly affect each other, and our model fits well. This supports the validity of our approach and is consistent with preliminary clinical observations. (2) Based on graph theory, the importance of hidden variables in a SEM model is often assessed by examining the values of the path coefficients connected to these variables. If the coefficients on a given variable are large, it tends to play a more critical role in the overall model. In our study, the respective path coefficients between proprioception and the other two variables are 0.4 and 0.49, the highest values among all the paths. Therefore, based on graph theory, it can be inferred that proprioception has the greatest influence on balance control within the sensory subsystems. (3) Previous clinical studies suggest that proprioception plays a significant role in the sensory systems of healthy individuals. Specifically, it relies on proprioceptive (70%), visual (10%), and vestibular (20%) information [51]. During postural control, proprioceptors in muscles, joints, ligaments, and other areas collect information about body changes in response to the environment, and transmit it through sensory pathways. In the case of nerve injury or abnormalities in plantar skin and lower limb proprioception, individuals may lose the ability to perceive the supporting surface, leading to compromised postural stability, highlighting the critical role of proprioception in balance control [52]. (4) We used parameters $F(1) - F(9)$ in Table I as observation variables to quantify various sensory subsystems (i.e., latent variables) and simultaneously adopted sparse constraint methods. As such, the results only show observed variables that best reflect the properties of latent variables. From the results, we can see that parameters $F(1) - F(4)$ is related to the distance traveled, while parameters $F(5) - F(8)$ is related to velocity and acceleration. The parameters used to describe the visual system are mainly concentrated in parameters $F(1) - F(4)$, while the other two subsystems have a strong association with distance, velocity, and acceleration. These observations may be related to the mechanism of action of the three major sensory subsystems. For instance, the vestibular subsystem is known to be sensitive

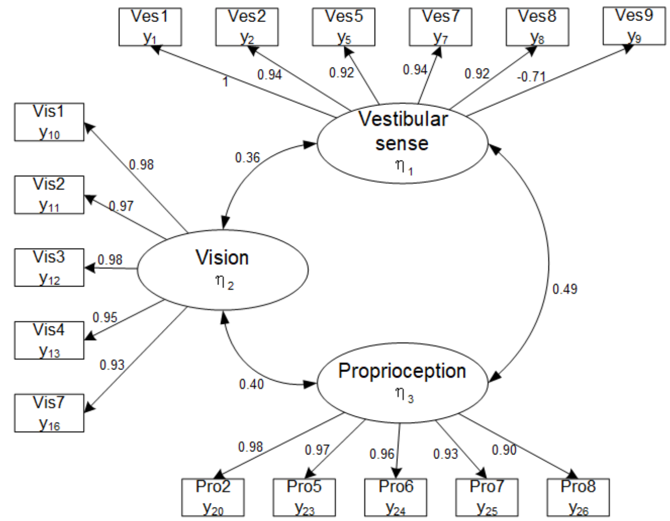

Fig. 6. Model of the second study using a SEM approach.

to velocity and acceleration, while the visual subsystem is mainly sensitive to distance [53].

The following points need to be clarified: (1) In SEM, randomly setting a path loading coefficient to 1 creates a reference point or standard scale for other path coefficients. This practice, commonly referred to as fixing the scale of the model, allows for easier interpretation and comparison of the magnitudes of the path coefficients. By fixing one path loading to 1, all other coefficients are estimated relative to this path, simplifying the analysis and facilitating meaningful comparison. This computing strategy is widely recognized as a standard operation in SEM and has been extensively utilized across disciplines, including prestigious journals such as Nature [54], [55]. (2) SEM is a statistical technique utilizing multiple regression equations developed using data from a large sample of subjects, rather than from just one. However, only one multiple regression equation model can be created, even when working with a dataset that includes many subjects. Each dependent variable in this model has a unique coefficient, rather than being a set. In SEM, each path is assigned a loading coefficient that corresponds to a single coefficient in the multiple regression model. This uniqueness can make it challenging to identify meaningful differences in loading values between different paths within the SEM framework, since statistical comparisons such as the t test should involve two sets of coefficients, rather than two different variables. It should be noted that researchers often assess the relative importance of specific paths in SEM by comparing their respective loading values. For instance, Kar et al. employed SEM to investigate the impact of personal, habitual, and work-related factors on work-related musculoskeletal disorders (WRMSDs) [56]. Their findings revealed a moderate positive correlation between WRMSDs and personal factors (path coefficient = 0.313), but a weak correlation between WRMSDs and work-related factors (path coefficient = 0.296). Despite the slight difference of 0.017 in the two coefficients, their study suggested that the relationship represented by the path with the larger coefficient was stronger. Similarly, Nouri-Keshtkar et al. employed SEM to investigate the factors contributing to prevalence of metabolic syndrome (MetS) across different populations [57]. Their results showed that BMI had the most significant influence on the occurrence of MetS, with path coefficients of 0.915 for men and 0.631 for women. Their study concluded that BMI had a greater impact on the incidence of MetS in men compared to women. Likewise, Bountress et al. utilized SEM to explore the relationship between alcohol use, alcohol use disorder (AUD), and life satisfaction [58]. Their results indicated a modest negative correlation between AUD and life satisfaction (path loading: -0.17), while a substantial positive correlation was observed between AUD and alcohol use (path loading: 0.72). These previous studies have not conducted statistical tests on the loading coefficients of different paths in SEM.

We also incorporated age variables into these two models and reconducted a detailed analysis of the results, which can be found in the Appendix (see Fig. 7 and 8). The key findings can be summarized as follows: (1) The inclusion of age variables did not alter the primary conclusions regarding

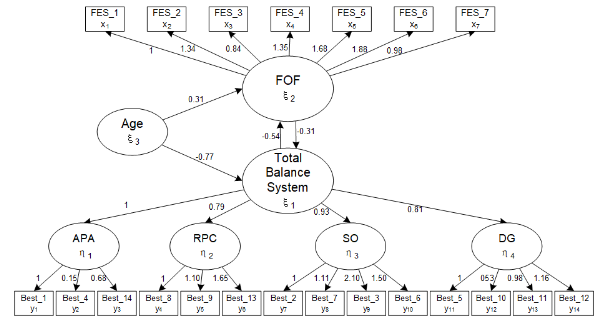

Fig. 7. Model of the first study using a SEM, while incorporating age as a modeling factor.

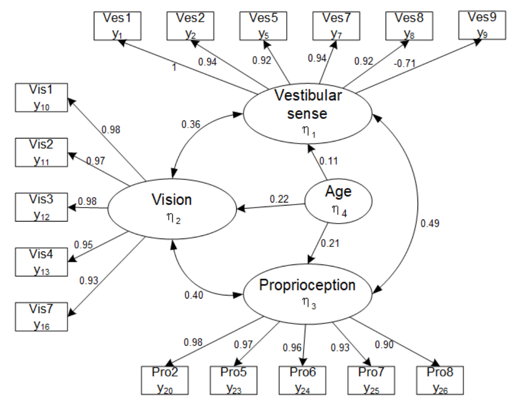

Fig. 8. Model of the second study using SEM, while incorporating age as a modeling factor.

the relationships between the balance control subsystems. In Model 1, the relationships between these subsystems were primarily influenced by overall balance rather than direct interactions. Notably, a significant relationship was observed between FOF and APA. In Model 2, proprioception emerged as the most important of the sensory-related subsystems. These findings suggest that age has a limited impact on the relationships between the balance subsystems. (2) However, Model 1 introduced age as a variable, finding that as individuals age, their FOF tends to increase. This result aligns with previous studies indicating that older adults are more susceptible to FOF compared to younger individuals. FOF is recognized as a specific health concern among the elderly, with a significant proportion experiencing falls and functional decline as a result [59], [60], [61]. Additionally, the study found a significant decline in balance ability with age. Previous research has also shown that age affects multiple balance subsystems, including APA, RPC, SO, and DG [62], [63], [64], [65], [66]. Furthermore, it should be emphasized that age has a greater impact on balance ability than on FOF. This is also in line with expectations, since as individuals age, their various physiological functions decrease, inevitably degrading balance ability. FOF, in contrast, is mainly influenced by the falling experiences of the elderly, followed by factors such as physical activity limitations and gait impairments. These factors vary among individuals, thus FOF also varies. In addition, FOF can be avoided, but the decline in individual physiological functions is unavoidable. These are all possible reasons why

TABLE V
THE SFES-I SCALE USED TO ASSESS FOF

Latent variable	Observation variables	Explanation
FOF	FES-1	Assisting with dressing or undressing
	FES-2	Taking a shower or bath and conversing
	FES-3	Sitting down or rising from a chair
	FES-4	Ascending or descending a flight of stairs
	FES-5	Retrieving an object from above or below
	FES-6	Climbing or descending an inclined surface
	FES-7	Attending social gatherings, such as religious services, family reunions, or meetings

TABLE VI
THE MINI-BESTEST SCALE USED TO ASSESS BCSES

Latent variables		Observation variables	Expound
BCS	APA	Best-1	Sit to stand
		Best-4	Compensatory stepping correction-forward
		Best-14	Timed up & go with dual-task
	RPC	Best-8	Eyes closed, foam surface (feet together)
		Best-9	Incline-eyes closed
		Best-13	Step over obstacles
	SO	Best-2	Raise toes
		Best-3	Stand on one leg
		Best-6	Compensatory stepping correction-backward
		Best-7	Eyes open firm surface (feet together)
	DG	Best-5	Compensatory stepping correction-backward
		Best-10	Change in gait speed
		Best-11	Walk with head -horizontal
		Best-12	Walk with pivot turns

age has a greater impact on balance ability than on FOF. (3) In Model 2, we utilized COP features to describe the functions of the three sensory subsystems. Higher values of the latent variables associated with these subsystems indicated poorer function. Consequently, age exhibited a positive correlation with the latent variables representing each of the three sensory subsystems, indicating that as individuals age, their ability to utilize these subsystems diminishes. This finding is supported by the existing literature, which highlights age-related declines in proprioceptive function, vestibular function, and visual acuity, thereby increasing the risk of balance disorders. Furthermore, the results from Model 2 underscore the strong relationship between age and proprioception function, as well as the importance of age and vision in the balance control process. This aligns with previous research indicating that postural stability in older individuals is particularly vulnerable to visual impairments [67], [68]. We also found that age has a relatively small impact on the vestibular system, which may be due to the following reasons. First, the vestibular system plays a relatively small role in balance control, accounting for only about 20% of the entire process. For young people, proprioception plays an important role in balance, while older people rely more on visual compensation. Second, degeneration of the vestibular system occurs relatively late. For example, vestibular ocular reflex function begins to decline after the age of 75, and primary vestibular afferent nerve degeneration mainly occurs in the population aged 70-85 [69]. In contrast, Hurley et al. found a significant difference in the sensitivity of proprioception between young and middle-aged individuals, indicating that degradation of proprioception occurs relatively early [70].

The limitations and future works are as follows: (1) Along with the Mini-BESTest, the Physiological Profile Approach (PPA) is a tool that assesses five physiological functions that have been shown to differentiate between fallers and non-fallers in institutional and community settings [71]. The PPA is structured around the physiological impairments that contribute to fall risk. In the future, SEM may be utilized to explore the interplay among different physiological functions measured by the PPA. This could yield a more comprehensive understanding of how these functions contribute to fall risk and inform the development of more targeted interventions. (2) Recently, multi-modal wearable devices have been implemented that include the measurement of electroencephalogram, electrocardiogram, electromyography, acceleration signal, and other physiological signals for balance evaluation [72]. In future studies, it may be possible to employ these multi-modal physiological signals and SEM methods together to investigate the interaction effect among these physiological signals during balance control. This could provide a more complete understanding of the underlying mechanisms of balance control and could inform the development of more effective interventions for individuals with balance deficits. (3) In future research, SEM can be utilized to investigate the variations in interactions among distinct BCSes in patients with different diseases, such as Parkinson's, amyotrophic lateral sclerosis, stroke, and others. This study might hold paramount importance in comprehending how diseases affect individual BCS capabilities and their interaction effect [73]. (4) In principle, a variety of techniques exist for extracting COP features, including frequency domain analysis, time-frequency analysis, and nonlinear dynamic analysis. These techniques often aid in automated detection of balance disorders, typically facilitated by artificial intelligence. Our approach involves extracting COP features using these methods and subsequently introducing them into a classifier for disease detection. While artificial intelligence offers advantages such as conserving medical resources and enabling large-scale early screening for balance disorders, it may not adequately uncover potential relationships among diverse balance control subsystems. To address this, our study has employed a SEM. It is worth noting that although more sophisticated nonlinear methods are available for COP feature extraction, we opted for linear features due to their broader applicability in the medical domain, particularly when interpreting physiological mechanisms [29], [74], [75]. It is important to clarify that the primary purpose of artificial intelligence is often geared towards practical applications like automatic disease detection, rather than elucidating balance mechanisms. This rationale guided our selection of linear-based COP features for SEM construction, as presented in Table I. In future studies, we aim to explore the incorporation of nonlinear COP features as observation parameters within the SEM framework. The broader applicability of these COP features may however require deeper examination and analysis. Additionally, SEM has a mathematical foundation rooted in linear methods, further justifying our reliance on linear features. (5) The study involved 163 participants, ranging from 18 to 85 years old, with 72 individuals aged over 60. This dataset is currently the largest in the public field of balance control research. However, creating separate models for the younger (under 60) and elderly (over 60) groups is challenging due to the relatively small sample sizes in each group, both having fewer than 100 participants, which is insufficient for SEM. SEM typically requires a sample size of at least 100 participants [76]. Therefore, future research aims to gather larger datasets to establish separate models for the young and elderly groups, enabling a more comprehensive investigation of their distinct characteristics and differences. (6) We attempt to incorporate FOF into the SEM model to assess its influence on the sensory subsystems of individuals. By exploring the relationship between FOF and the three sensory subsystems, we found that FOF mainly inhibits proprioception and to a lesser extent vision. When people are in a state of fear, their body muscles may become tense, affecting the sensory input of proprioceptors distributed in muscles and tendons. Previous studies have demonstrated a significant correlation between FOF and proprioception. For instance, Shao et al. compared the proprioception and FOF levels of elderly and young people and found that the elderly had poorer ankle proprioceptive discrimination sensitivity and higher FOF levels during walking, indicating a close relationship between the two [77]. Additionally, we found that FOF can enhance the vestibular system's ability. This may be attributed to FOF increasing sensitivity to self-motion through noradrenergic and serotonergic inputs to the vestibular nuclei [78]. A study has shown that FOF can exacerbate vestibular balance responses, aligning with our findings [79]. However, it should be noted that our results indicate a relatively weak relationship between FOF and the sensory subsystems.

V. Conclusion

By utilizing SEM, we provided numerical evidence of the interdependence among various BCSes, which is a departure from relying solely on clinical observations. Our findings revealed that the RPC, APA, DG, and SO indirectly influenced each other through their overall balance ability, and their association with FOF varied. Among them, APA had the strongest association with FOF, while RPC had the weakest. Moreover, we identified that sensory inputs, such as vision, proprioception, and vestibular sensing, directly affected each other, but their associations were not uniform. Proprioception was found to be the most crucial factor in the three sensory subsystems. The examination of the relationships between BCSes has significant implications for diagnosing and managing balance-related disorders in clinical settings, as well as for enhancing our understanding of the fundamental mechanisms of balance control.

Appendix

See Tables V and VI, Figures 7 and 8.

References

[1] *Falls*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/falls

[2] S. Kobayashi et al., "Relationship of dual task performance ability and balance ability in community-dwelling elderly," *Physiotherapy*, vol. 101, p. e771, May 2015.

[3] E. Burns and R. Kakara, "Deaths from falls among persons aged ≥65 years—United States, 2007–2016," *MMWR. Morbidity Mortality Weekly Rep.*, vol. 67, no. 18, pp. 509–514, May 2018.

[4] D. L. Sturnieks, R. St George, and S. R. Lord, "Balance disorders in the elderly," *Neurophysiologie Clinique/Clinical Neurophysiol.*, vol. 38, no. 6, pp. 467–478, Dec. 2008.

[5] R. A. W. Felius, M. Geerars, S. M. Bruijn, N. C. Wouda, J. H. Van Dieën, and M. Punt, "Reliability of IMU-based balance assessment in clinical stroke rehabilitation," *Gait Posture*, vol. 98, pp. 62–68, Oct. 2022.

[6] F. M. Dornas, F. M. M. Bispo, Y. G. Viana, J. M. Vasconcelos, R. D. C. Lana, and J. C. Polese, "Predictors of balance in individuals with Parkinson's disease: A cross-sectional study," *J. Bodywork Movement Therapies*, vol. 35, pp. 64–68, Jul. 2023.

[7] N. Xu, X. Wang, Y. Xu, T. Zhao, and X. Li, "Deep multi-scale residual connected neural network model for intelligent athlete balance control ability evaluation," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–11, May 2022.

[8] G. Clément et al., "Cognitive and balance functions of astronauts after spaceflight are comparable to those of individuals with bilateral vestibulopathy," *Frontiers Neurol.*, vol. 14, Oct. 2023, Art. no. 1284029.

[9] P. Ren et al., "Assessment of balance control subsystems by artificial intelligence," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 3, pp. 658–668, Mar. 2020.

[10] N. Banker, C. Gough, and S. Gordon, "Classification of balance assessment technology: A scoping review of systematic reviews," *Stud. Health Technol. lnform.*, vol. 268, pp. 45–59, Mar. 2020.

[11] S.-H. Park, "Tools for assessing fall risk in the elderly: A systematic review and meta-analysis," *Aging Clin. Experim. Res.*, vol. 30, no. 1, pp. 1–16, Apr. 2017.

[12] L. Abou et al., "Gait and balance assessments using smartphone applications in Parkinson's disease: A systematic review," *J. Med. Syst.*, vol. 45, no. 9, p. 87, Aug. 2021.

[13] F. B. Horak, D. M. Wrisley, and J. Frank, "The balance evaluation systems test (BESTest) to differentiate balance deficits," *Phys. Therapy*, vol. 89, no. 5, pp. 484–498, May 2009.

[14] L. Yardley, N. Beyer, K. Hauer, G. Kempen, C. Piot-Ziegler, and C. Todd, "Development and initial validation of the falls efficacy scale-international (FES-I)," *Age Ageing*, vol. 34, no. 6, pp. 614–619, Nov. 2005.

[15] D. M. Wrisley, M. J. Stephens, S. Mosley, A. Wojnowski, J. Duffy, and R. Burkard, "Learning effects of repetitive administrations of the sensory organization test in healthy young adults," *Arch. Phys. Med. Rehabil.*, vol. 88, no. 8, pp. 1049–1054, Aug. 2007.

[16] A. L. Leddy, B. E. Crowner, and G. M. Earhart, "Functional gait assessment and balance evaluation system test: Reliability, validity, sensitivity, and specificity for identifying individuals with Parkinson disease who fall," *Phys. Therapy*, vol. 91, no. 1, pp. 102–113, Jan. 2011.

[17] P. E. Magnani et al., "Use of the BESTest and the mini-BESTest for fall risk prediction in community-dwelling older adults between 60 and 102 years of age," *J. Geriatric Phys. Therapy*, vol. 43, no. 4, pp. 179–184, Oct. 2020.

[18] M. Zhu et al., "Assessing balance in people with bilateral vestibulopathy using the mini-balance evaluation systems test (Mini-BESTest): Feasibility and comparison with healthy control data," *J. Neurol.*, vol. 270, no. 9, pp. 4423–4433, Jun. 2023, doi: 10.1007/s00415-023-11795-y.

[19] S. N. Phyu, S. Wanpen, and U. Chatchawan, "Responsiveness of the mini-balance evaluation system test in type 2 diabetic patients with peripheral neuropathy," *J. Multidisciplinary Healthcare*, vol. 15, pp. 3015–3028, Dec. 2022.

[20] L. A. King and F. B. Horak, "Lateral stepping for postural correction in Parkinson's disease," *Arch. Phys. Med. Rehabil.*, vol. 89, no. 3, pp. 492–499, Mar. 2008.

[21] F. Franchignoni, F. Horak, M. Godi, A. Nardone, and A. Giordano, "Using psychometric techniques to improve the balance evaluation systems test: The mini-BEStest," *J. Rehabil. Med.*, vol. 42, no. 4, pp. 323–331, Apr. 2010.

[22] C.-T. Kuo, D.-R. Chen, Y.-M. Chen, and P.-Y. Chen, "Validation of the short falls efficacy scale-international for Taiwanese community-dwelling older adults: Associations with fall history, physical frailty, and quality of life," *Geriatric Nursing*, vol. 42, no. 5, pp. 1012–1018, Sep. 2021.

[23] M. Mehdizadeh et al., "Reliability and validity of fall efficacy scale-iInternational in people with Parkinson's disease during on- and off-drug phases," *Parkinsons Dis.*, vol. 2019, Jan. 2019, Art. no. 6505232.

[24] M. Scholz, R. Haase, K. Trentzsch, M. L. Weidemann, and T. Ziemssen, "Fear of falling and falls in people with multiple sclerosis: A literature review," *Multiple Sclerosis Rel. Disorders*, vol. 47, Jan. 2021, Art. no. 102609.

[25] M. Janc, M. Sliwinska-Kowalska, P. Politanski, M. Kaminski, M. Jozefowicz-Korczynska, and E. Zamyslowska-Szmytke, "Posturography with head movements in the assessment of balance in chronic unilateral vestibular lesions," *Sci. Rep.*, vol. 11, no. 1, p. 6196, Mar. 2021.

[26] M. B. Terra, R. A. Da Silva, M. E. B. Bueno, H. B. Ferraz, and S. M. Smaili, "Center of pressure-based balance evaluation in individuals with Parkinson's disease: A reliability study," *Physiotherapy Theory Pract.*, vol. 36, no. 7, pp. 826–833, Jul. 2020.

[27] T. E. Prieto, J. B. Myklebust, R. G. Hoffmann, E. G. Lovett, and B. M. Myklebust, "Measures of postural steadiness: Differences between healthy young and elderly adults," *IEEE Trans. Biomed. Eng.*, vol. 43, no. 9, pp. 956–966, Sep. 1996.

[28] A. Alizadeh, A. S. Jafarpisheh, M. Mohammadi, and A. H. Kahlaee, "Visual, vestibular, and proprioceptive dependency of the control of posture in chronic neck pain patients," *Motor Control*, vol. 26, no. 3, pp. 362–377, Jul. 2022.

[29] F. Quijoux et al., "A review of center of pressure (COP) variables to quantify standing balance in elderly people: Algorithms and open-access code," *Physiol. Rep.*, vol. 9, no. 22, p. e15067, Nov. 2021.

[30] K. Kongwattanakul, V. Hiengkaew, C. Jalayondeja, and Y. Sawangdee, "A structural equation model of falls at home in individuals with chronic stroke, based on the international classification of function, disability, and health," *PLoS ONE*, vol. 15, no. 4, Apr. 2020, Art. no. e0231491.

[31] D. S. Peterson, C. Van Liew, S. Stuart, P. Carlson-Kuhta, F. B. Horak, and M. Mancini, "Relating Parkinson freezing and balance domains: A structural equation modeling approach," *Parkinsonism Relat. Disord.*, vol. 79, pp. 73–78, Oct. 2020.

[32] A. Hidrus, Y. C. Kueh, B. Norsa'adah, Y. Kim, Y.-K. Chang, and G. Kuan, "Structural equation model of psychological constructs of transtheoretical model, motives for physical activity, and amount of physical activity among people with type 2 diabetes mellitus in Malaysia," *PLoS ONE*, vol. 17, no. 3, Mar. 2022, Art. no. e0266104.

[33] I. Mercader-Rubio, N. G. Ángel, N. F. O. Ruiz, and J. J. Carrión Martínez, "Emotional intelligence and its relationship to basic psychological needs: A structural equation model for student athletes," *Int. J. Environ. Res. Public Health*, vol. 19, no. 17, p. 10687, Aug. 2022.

[34] D. A. Santos and M. Duarte, "A public data set of human balance evaluations," *PeerJ*, vol. 4, p. e2648, Nov. 2016.

[35] F. Rojas, I. K. Niazi, P. Maturana-Russel, and D. Taylor, "Exploring the potential of machine learning for the diagnosis of balance disorders based on centre of pressure analyses," *Sensors*, vol. 22, no. 23, p. 9200, Nov. 2022.

[36] C. D. Ford-Smith, J. F. Wyman, R. K. Elswick, T. Fernandez, and R. A. Newton, "Test-retest reliability of the sensory organization test in noninstitutionalized older adults," *Arch. Phys. Med. Rehabil.*, vol. 76, no. 1, pp. 77–81, Jan. 1995.

[37] E. Ionescu, T. Morlet, P. Froehlich, and C. Ferber-Viart, "Vestibular assessment with balance quest: Normative data for children and young adults," *Int. J. Pediatr. Otorhinolaryngol.*, vol. 70, no. 8, pp. 1457–1465, Aug. 2006.

[38] R. Maire et al., "Discussion about visual dependence in balance control: European society for clinical evaluation of balance disorders," *J. Int. Adv. Otol.*, vol. 13, no. 3, pp. 404–406, Dec. 2017.

[39] N. Vanicek, S. A. King, R. Gohil, I. C. Chetter, and P. A. Coughlin, "Computerized dynamic posturography for postural control assessment in patients with intermittent claudication," *J. Visualized Exp.*, no. 82, Dec. 2013, Art. no. e51077.

[40] J. N. Pritikin, M. D. Hunter, T. von Oertzen, T. R. Brick, and S. M. Boker, "Many-level multilevel structural equation modeling: An efficient evaluation strategy," *Struct. Equation Model., A Multidisciplinary J.*, vol. 24, no. 5, pp. 684–698, Sep. 2017.

[41] R. Jacobucci, K. J. Grimm, and J. J. McArdle, "Regularized structural equation modeling," *Struct. Equation Model., A Multidisciplinary J.*, vol. 23, no. 4, pp. 555–566, Jul. 2016.

[42] J. Burnette and L. J. Williams, "Structural equation modeling (SEM): An introduction to basic techniques and advanced issues," in *Research in Organizations: Foundations and Methods of Inquiry*. San Francisco, CA, USA: Berrett-Koehler Publishers, 2005, pp. 143–160.

[43] T. Gazibara et al., "Falls, risk factors and fear of falling among persons older than 65 years of age," *Psychogeriatrics*, vol. 17, no. 4, pp. 215–223, Jul. 2017.

[44] D. Kendrick et al., "Exercise for reducing fear of falling in older people living in the community," *Cochrane Database Systematic Rev.*, vol. 2015, no. 10, Nov. 2014, Art. no. CD009848.

[45] T. J. Ellmers, A. Maslivec, and W. R. Young, "Fear of falling alters anticipatory postural control during cued gait initiation," *Neuroscience*, vol. 438, pp. 41–49, Jul. 2020.

[46] A. L. Adkin, J. S. Frank, M. G. Carpenter, and G. W. Peysar, "Fear of falling modifies anticipatory postural control," *Exp. Brain Res.*, vol. 143, no. 2, pp. 160–170, Mar. 2002.

[47] K. Uemura, M. Yamada, K. Nagai, B. Tanaka, S. Mori, and N. Ichihashi, "Fear of falling is associated with prolonged anticipatory postural adjustment during gait initiation under dual-task conditions in older adults," *Gait Posture*, vol. 35, no. 2, pp. 282–286, Feb. 2012.

[48] J. Pearl and D. Mackenzie, *The Book of Why: The New Science of Cause and Effect* (Science), vol. 361. New York, NY, USA: Basic Books, May 2018, pp. 124–129.

[49] M. van den Bogaart, S. M. Bruijn, J. Spildooren, J. H. van Dieën, and P. Meyns, "Effects of age and surface instability on the control of the center of mass," *Hum. Movement Sci.*, vol. 82, Apr. 2022, Art. no. 102930.

[50] A. Wunderlich et al., "Dual-task performance in hearing-impaired older adults—Study protocol for a cross-sectional mobile brain/body imaging study," *Frontiers Aging Neurosci.*, vol. 13, Nov. 2021, Art. no. 773287.

[51] F. B. Horak, "Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls?" *Age Ageing*, vol. 35, pp. 7–11, Sep. 2006.

[52] R. J. Peterka, "Sensorimotor integration in human postural control," *J. Neurophysiol.*, vol. 88, no. 3, pp. 1097–1118, Sep. 2002.

[53] G. Jull, A. Moore, D. Falla, J. Lewis, C. McCarthy, and M. Sterling, *Grieve's Modern Musculoskeletal Physiotherapy*. Amsterdam, The Netherlands: Elsevier, 2015.

[54] A. D. Grotzinger et al., "Genetic architecture of 11 major psychiatric disorders at biobehavioral, functional genomic and molecular genetic levels of analysis," *Nat. Genet.*, vol. 54, pp. 548–559, May 2022.

[55] R. Maier et al., "Genomic structural equation modelling provides insights into the multivariate genetic architecture of complex traits," *Nat. Hum. Behav.*, vol. 3, no. 5, pp. 513–525, 2019.

[56] M. B. Kar, M. Aruna, and B. M. Kunar, "Structural equation modelling of work related musculoskeletal disorders among dumper operators," *Sci. Rep.*, vol. 13, no. 1, p. 14055, Aug. 2023.

[57] M. Nouri-Keshtkar et al., "Role of gender in explaining metabolic syndrome risk factors in an Iranian rural population using structural equation modelling," *Sci. Rep.*, vol. 13, no. 1, p. 16007, Sep. 2023.

[58] K. E. Bountress et al., "Genetic associations between alcohol phenotypes and life satisfaction: A genomic structural equation modelling approach," *Sci. Rep.*, vol. 13, no. 1, p. 13443, Aug. 2023.

[59] A. C. Scheffer, M. J. Schuurmans, N. van Dijk, T. van der Hooft, and S. E. de Rooij, "Fear of falling: Measurement strategy, prevalence, risk factors and consequences among older persons," *Age Ageing*, vol. 37, no. 1, pp. 19–24, Jan. 2008.

[60] P. C. Fletcher, "Restriction in activity associated with fear of falling among community-based seniors using home care services," *Age Ageing*, vol. 33, no. 3, pp. 273–279, May 2004.

[61] J. Howland, M. E. Lachman, E. W. Peterson, J. Cote, L. Kasten, and A. Jette, "Covariates of fear of falling and associated activity curtailment," *Gerontologist*, vol. 38, no. 5, pp. 549–555, Oct. 1998.

[62] E. Eckstrom, S. Neukam, L. Kalin, and J. Wright, "Physical activity and healthy aging," *Clin. Geriatr. Med.*, vol. 36, no. 4, pp. 671–683, Nov. 2020.
[63] G. D'Onofrio, J. Kirschner, H. Prather, D. Goldman, and A. Rozanski, "Musculoskeletal exercise: Its role in promoting health and longevity," *Prog. Cardiovasc. Dis.*, vol. 77, pp. 25–36, Mar. 2023.
[64] N. Kanekar and A. S. Aruin, "The effect of aging on anticipatory postural control," *Exp. Brain Res.*, vol. 232, no. 4, pp. 1127–1136, Apr. 2014.
[65] N. Kanekar and A. S. Aruin, "Aging and balance control in response to external perturbations: Role of anticipatory and compensatory postural mechanisms," *AGE*, vol. 36, no. 3, p. 9621, Jun. 2014.
[66] M. Y. Osoba, A. K. Rao, S. K. Agrawal, and A. K. Lalwani, "Balance and gait in the elderly: A contemporary review," *Laryngoscope Investigative Otolaryngol.*, vol. 4, no. 1, pp. 143–153, Feb. 2019.
[67] J. J. Jeka, L. K. Allison, and T. Kiemel, "The dynamics of visual reweighting in healthy and fall-prone older adults," *J. Motor Behav.*, vol. 42, no. 4, pp. 197–208, Aug. 2010.
[68] L. Hay, C. Bard, M. Fleury, and N. Teasdale, "Availability of visual and proprioceptive afferent messages and postural control in elderly adults," *Exp. Brain Res.*, vol. 108, no. 1, pp. 129–139, Feb. 1996.
[69] G. Ishiyama, "Imbalance and vertigo: The aging human vestibular periphery," *Seminars Neurol.*, vol. 29, no. 5, pp. 491–499, Nov. 2009.
[70] M. V. Hurley, J. Rees, and D. J. Newham, "Quadriceps function, proprioceptive acuity and functional performance in healthy young, middle-aged and elderly subjects," *Age Ageing*, vol. 27, no. 1, pp. 55–62, 1998.
[71] E. K. Mcmahon, E. Youatt, and S. A. Cavigelli, "A physiological profile approach to animal temperament: How to understand the functional significance of individual differences in behaviour," *Proc. Roy. Soc. B, Biol. Sci.*, vol. 289, Jan. 2022, Art. no. 20212379.
[72] M. Hallett, "Evaluation of movement and brain activity," *Clin. Neurophysiol.*, vol. 132, no. 10, pp. 2608–2638, Oct. 2021.
[73] M. M. Montero-Odasso et al., "Evaluation of clinical practice guidelines on fall prevention and management for older adults: A systematic review," *JAMA Netw. Open*, vol. 4, no. 12, Dec. 2021, Art. no. e2138911.
[74] J. Johansson, E. Jarocka, G. Westling, A. Nordström, and P. Nordström, "Predicting incident falls: Relationship between postural sway and limits of stability in older adults," *Human Movement Sci.*, vol. 66, pp. 117–123, Aug. 2019.
[75] M. Mukaino et al., "Objective measurement of dynamic balance function by the simultaneous measurement of the center of gravity (COG) and center of pressure (COP)," in *Proc. Int. Conf. Intell. Auton. Syst.*, vol. 531, 2017, pp. 69–75.
[76] J. Hair, *Multivariate Data Analysis*, 7th ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2013.
[77] X. Shao et al., "Impaired ankle inversion proprioception during walking is associated with fear of falling in older adults," *Frontiers Aging Neurosci.*, vol. 14, Sep. 2022, Art. no. 946509.
[78] W. R. Young and A. Mark Williams, "How fear of falling can increase fall-risk in older adults: Applying psychological theory to practical observations," *Gait Posture*, vol. 41, no. 1, pp. 7–12, Jan. 2015.
[79] J. L. M. Worms, J. F. Stins, P. J. Beek, and I. D. Loram, "The effect of fear of falling on vestibular feedback control of balance," *Physiological Rep.*, vol. 5, no. 18, Sep. 2017, Art. no. e13391.