Assessing Elderly Physical Health Using Motor Function Variability and Bayesian Regression

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***Abstract*—With the global acceleration of population aging, effective health management and disease prevention among the elderly have become critical societal concerns. Skeletal muscle function plays a pivotal role in preserving physical health in older adults, with its decline linked to increased risks of falls and chronic diseases such as diabetes. This study investigates the relationships among motor performance, physical fitness indicators, and overall health status in the elderly, aiming to sustainable monitoring approach. Correlation analysis revealed that a comprehensive motor function indicator-defined as the mean variance in walking-was significantly and positively associated with health metrics such as protein mass (PM) and skeletal muscle mass (SMM). Interestingly, an abnormal negative correlation was observed between Short Physical Performance Battery (SPPB) Test 2 results and InBody health indicators. Bayesian regression further demonstrated that SPPB metrics had limited and statistically insignificant effects on PM and SMM, whereas the motor function indicator exerted a robust positive influence on SMM. These findings suggest that the comprehensive motor function indicator offers a reliable and practical metric for assessing the physical and functional health of elderly individuals.**

***Index Terms*—motor function, elderly health assessment, skeletal muscle mass, bayesian regression, physical performance**

I. Introduction

In the context of global population aging, health management and risk prevention for the elderly have become urgent social issues. With aging, physical functions gradually decline, with skeletal muscle deterioration being a key factor. It not only increases the risk of falls but may also lead to chronic diseases such as diabetes. In our previous studies, we proposed a vision-based edge artificial intelligence method to evaluate the home-based exercise programs of the elderly [1]. Specifically, we integrated pre-trained visual models with edge computing and inferred the health status by analyzing the data of feature points, thus providing a new perspective for the monitoring of physical activities. We also improved the accuracy of human pose detection through preprocessing techniques such as image rotation and scaling [2]. Constructing an optimal process can reduce missed detections, playing a crucial role in the health assessment of the elderly in home settings and enriching the research on health assessment technologies.

The goal and key ideas of this study are to explore the relationships among the elderly's body composition indices, SPPB, and walking distance indicators via correlation and Bayesian regression analyses, aiming to create an evaluation framework based on dynamic motor variability for personalized long-term health monitoring. This study is conducted in three steps. **Step 1**: a composite indicator, `var_mean`, is constructed based on the walking distance in test 2 of the SPPB test. **Step 2**: Spearman's rank correlation analysis is carried out to explore the correlation relationships among the indicator data. **Step 3**: Bayesian regression analysis with a gamma model is utilized to address the issue of a limited sample size and quantify the impacts of various factors on protein mass and skeletal muscle mass.

In our experiment, we found that the walking test score of the Short Physical Performance Battery (SPPB) [3] may fail to truly reflect the physical function of subjects due to the excessively long time taken for the first attempt. In contrast, the mean value of the walking distance variance, a comprehensive indicator, has a significant positive impact on both protein mass (PM) and skeletal muscle mass (SMM).

II. Preliminaries

A. Necessity of Monitoring the Elderly Physical Condition

With the acceleration of the global aging process, a large number of elderly people choose to live independently at home to reduce the burden on their children or avoid the high costs of nursing homes. However, living alone exposes the elderly to higher health risks and emergency difficulties. The decline in physical function and deterioration of health, combined with living alone, cause great concern among family members. Therefore, constructing a system that can effectively monitor the physical condition of the elderly, early-warn risks such as falls, predict health trends, and provide clear and real-time feedback of the monitoring results to both the elderly and their families has become the key to alleviating family anxiety and optimizing elderly health management. At the same time, such monitoring must strictly adhere to the bottom line of privacy protection to ensure that data collection and storage comply with ethical norms, making monitoring a reliable support for maintaining family bonds, facilitating elderly care, and researching health trends.

B. Technical Challenges

In terms of monitoring accuracy and individual differences, the individual heterogeneity of the elderly , such as medical history and living habits, and the interference from complex environments (such as occlusions in home scenes) may lead to deviations in gait data. Meanwhile, the small sample size, consisting of only 19 elderly people from a certain region in Japan, may cause the effects of some variables to be insignificant, reducing the reliability of the results and the generalizability of the conclusions. In terms of data privacy and ethics, there are challenges in collecting data on gait features and body composition data. It is necessary to protect privacy while avoiding data distortion.

Moreover, it is necessary to deal with the problem of multicollinearity. The high correlation between time-related variables and score variables gives rise to the problem of multicollinearity. Although the study mitigates the interference through the setting of prior distributions and credible interval analysis in Bayesian regression, the potential linear dependence among variables may still affect the accuracy of parameter estimation, resulting in deviations in the interpretation of the true effects. In the future, it is necessary to explore more effective dimensionality reduction techniques or causal inference models to further optimize the analytical framework.

C. Human Pose Estimation

The MoveNet model [4] is a human pose estimation model based on deep learning, developed by Google. It utilizes convolutional neural networks (CNNs) to extract and analyze features from input images or videos, thereby identifying the positions of key nodes of the human body, such as the head, shoulders, elbows, knees, etc., and determining the human pose. This model has a wide range of applications in multiple fields. In the field of intelligent security, it can be used for abnormal behavior detection, such as determining whether a person has abnormal actions like falling or fighting. In sports training, coaches can use it to analyze whether athletes' movements are standard and assist in formulating training plans. In virtual reality (VR) and augmented reality (AR) technologies, it can achieve real-time capture of human movements, enhancing the interactive experience of users.

D. Anthropometric Scales in the Health Science Field

The SPPB is a tool used to assess an individual's physical functional status, particularly suitable for older adults. The test comprises three components: a balance test (evaluating balance ability through tandem stance, semi-tandem stance, and feet-together stance), a 4-meter normal gait speed walk test (reflecting gait stability and velocity), and an unassisted 5-time chair stand test. The final score comprehensively reflects an individual's physical function level.

Protein mass (PM) [5], together with body water, is a primary component of muscle. Insufficient protein mass indicates poor nutritional status of cells. Skeletal muscle mass (SMM) refers to striated muscles composed of muscle tissue that enable voluntary movement. While the muscles of the limbs are composed entirely of skeletal muscle, the trunk muscles include a mixture of visceral and cardiac muscles. Therefore, this parameter also represents the value obtained by subtracting the estimated muscle mass of visceral and cardiac muscles from the total body muscle mass.

Inbody is a brand of body composition analyzers. Its equipment utilizes bioelectrical impedance analysis (BIA) technology, which applies multi-frequency micro-currents to the human body. Based on the different impedance values of various body tissues (such as muscle, fat, and water) to the current, it accurately measures body composition, providing powerful data support for comprehensively understanding body composition and health status.

III. Proposed Method

A. Goal and Key Idea

This study focuses on investigating the associations among motor function performance, the body composition indices (e.g., PM, SMM), and the SPPB in older adults. By integrating SPPB test data, InBody-derived body composition metrics, and gait data features from the MoveNet model, this research aims to identify reliable assessment indicators for reflecting elderly health status and provide methods for sustainable health monitoring. Multisource data fusion is employed to quantify the relationships between motor function metrics (such as walking distance variance) and health parameters through correlation analysis and unsupervised Bayesian regression modeling. The study emphasizes privacy protection throughout data collection and analysis processes, addresses the bias limitations of traditional SPPB tests caused by testing duration, and

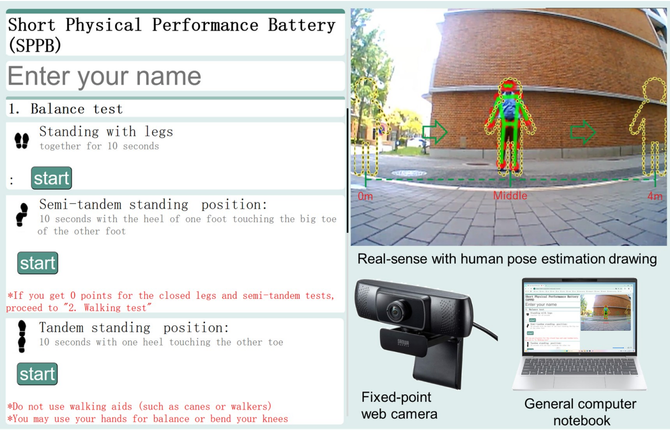

Fig. 1: The proposed system component with a sample scene.

proposes an evaluation framework centered on dynamic motor variability metrics. This approach facilitates personalized long-term health monitoring in home or healthcare facility settings.

B. System Description

this system utilizes Google's MoveNet model in conjunction with TensorFlow.js. It takes a USB camera as the image input device and conducts real-time human pose recognition in the browser, outputting the coordinate results of 17 body parts and their respective scores. With the aid of Raspberry Pi 3B, in combination with tools such as OpenCV and Node-Canvas, data is collected at one-second intervals and processed using Spark Streaming technology. By analyzing the skeletal region information output by the MoveNet model, the system enables the assessment of in-home physical activity quality and location sensing. Additionally, a Web visualization system has been developed to process the collected data in the cloud and display it in the form of charts, ultimately achieving fine-grained and continuous physical activity monitoring and simple in-home positioning functions. Figure 1 illustrates the proposed system component with a sample scene.

Furthermore, Python is employed to extract the JSON data converted from the SPPB test videos of the subjects. This data, combined with the Inbody body composition data of the subjects, is processed and then analyzed using Spearman's correlation analysis and Bayesian analysis to explore the relationships between variables and quantify the impacts of various factors on indicators such as protein mass and skeletal muscle mass.

C. Step 1: Basic Analysis and Index Construction

In this step, a composite indicator was constructed to capture gait variability. The study focused on subjects' foot movement distances during test2 of the SPPB test. Using the Euclidean distance algorithm, the movement distances were calculated. The variance of these distances and the average variance across steps were then computed to form the composite indicator `var_mean`. This indicator effectively reflects gait fluctuation patterns and provides a reliable foundation for subsequent analyses.

D. Step 2: Correlation Analysis

In this step, Spearman's rank correlation analysis was employed to integrate multi-source data from subjects, including basic demographic information, body composition data from InBody measurements, and gait fluctuation indicators. A comprehensive correlation analysis was conducted to validate and interpret the relationships among these indicators by comparing them with actual physical conditions and gait patterns. Heatmap visualization further revealed significant associations between key variables, helping to uncover the underlying connection between gait variability and physical function.

E. Step 3: Bayesian Regression Analysis

In this step, Bayesian regression analysis was applied to address challenges such as the small sample size and the unclear distribution features of certain health indicators. Reasonable prior distributions were assigned to key variables, and a gamma regression model was used for analysis. This approach examined the impact of various factors on protein mass and skeletal muscle mass by estimating coefficients and credible intervals, thereby quantifying their influence. This method not only effectively mitigated issues arising from the limited sample size but also validated the scientific value of the gait fluctuation indicators.

IV. Experimental Evaluation

This study employs an integrated data collection system combining Google's MoveNet model with TensorFlow.js, a fixed-point web camera to capture real-time movement features data from 19 elderly subjects. Data collection is conducted in professional settings using general computer notebook and InBody devices, ensuring the reliability and safety of the dataset.

A. Basic Information of Subjects

As shown in Figure 2, the age distribution of the subjects ranges from 45 to 88 years old, with an average age of 75.1 years old, mainly concentrated between 68 and 84 years old. In terms of the gender ratio, males account for 78.9%, and females account for 21.1%. The height range of this sample group is from 146 cm to 175 cm, with an average value of 161.2 cm; the weight ranges from 40.8 kg to 85 kg, with an average value of 59.2 kg, which overall reflects the relatively uniform basic features of the elderly population.

As shown in Figure 3, the distribution features of the body composition indices of the 19 subjects vary. Fat mass (FAT) and body mass index (BMI) reflect body weight and body fat composition. Most subjects' BMI values fall within the healthy range of 18.5-24.9 as defined by the World Health Organization (WHO), but some individuals have abnormal FAT levels, suggesting potential metabolic or nutritional problems. The recommended healthy range for SLM is 70%-75% of the

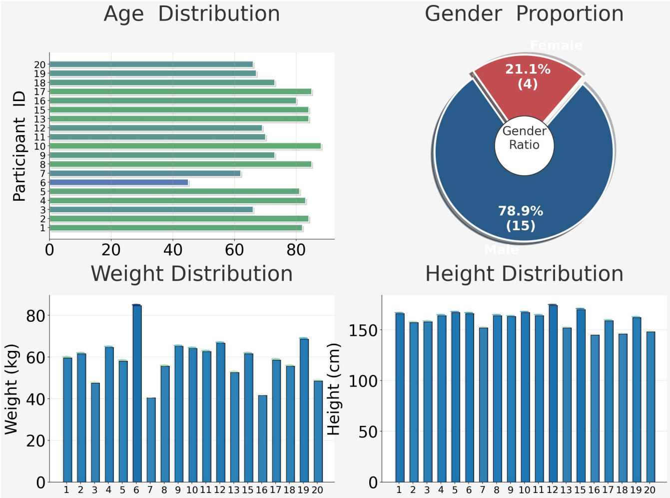

Fig. 2: Basic physical features of subjects.

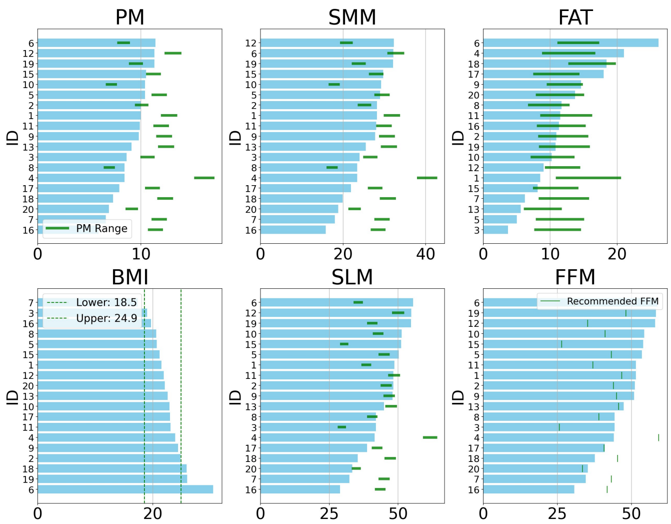

Fig. 3: Distribution and comparison of InBody health indicators among subjects.

total body weight, and most subjects do not meet this standard. The recommended range for PM is 18%-20% of the total body weight for men and 16%-18% for women. Most subjects' PM values are close to or even lower than the lower limit of the recommended range, indicating a potential risk of insufficient protein intake. For 70-year-old individuals, the recommended percentage of FFM is 69.6% of body weight for men and 62.8% for women [6], and most subjects' FFM percentages deviate from the recommended values. In terms of SMM, the healthy range for men is 40%-45% of body weight, and for women it is 35%-40%. Many subjects' SMM values are close to or at the lower limit of the healthy range, indicating a common problem of insufficient muscle mass in this group, which is consistent with the age-related muscle loss commonly observed in the elderly.

As shown in Figure 4, from the distribution of first-test scores and total scores in Test 2, it can be observed that

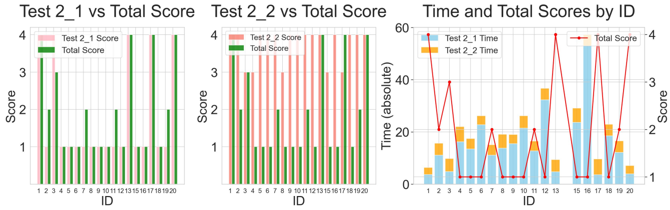

Fig. 4: Walking test scores and time distribution by subject in SPPB Test 2.

the two distributions are quite similar, indicating that the first test contributed significantly to the overall score and had an important influence on it. In contrast, the distribution of second-test scores relative to the total score showed notable differences. Specifically, the scores from the second test were generally higher than the total scores, suggesting a relatively smaller impact of the second test on the total score.

Further analysis combining test duration and total scores reveals that the proportion of time spent on the first test in Test 2 was significantly higher compared to the total testing duration, while the second test required much less time. This suggests that the total score was largely influenced by the duration of the first test. However, the longer duration of the first test may be attributed to subjects' need to adapt to the testing environment or procedures. The shorter time and higher scores in the second test may reflect improved performance due to prior adaptation, rather than fully reflecting the subjects' true physical condition.

B. Experimental Method and Scale

In this study, the experimental method aims to explore the relationships among the motor function performance, physical fitness indicators, and overall health status of the elderly. First, Body composition indicators of the subjects, including FAT, BMI, SLM, PM, FFM, and SMM, were measured using InBody devices. Meanwhile, the movement distances of the left and right feet during Test 2 of the SPPB test were measured in centimeters. The Euclidean distance algorithm was used to calculate their variances (in cm^2/frame) and the average variance (`var_mean`, in cm^2/frame) to capture gait variability. For data analysis, Python (used in different versions in Spyder 6 and Google Colaboratory) was employed. Spearman's rank correlation analysis was used to integrate multi-source data and explore the relationships between variables, and heatmap visualization was used to present the results. Bayesian regression analysis was also applied, using a gamma regression model and reasonable prior distributions to address issues such as small sample size and unclear distribution features of certain indicators.

In terms of the scale, the data in this study were sourced from a small sample of 19 elderly individuals. Although the sample size is limited, it still has research value. The measured variables cover multiple aspects. The body composition variables are measured in kilograms or derived units, reflecting different health components of the body. The SPPB test-

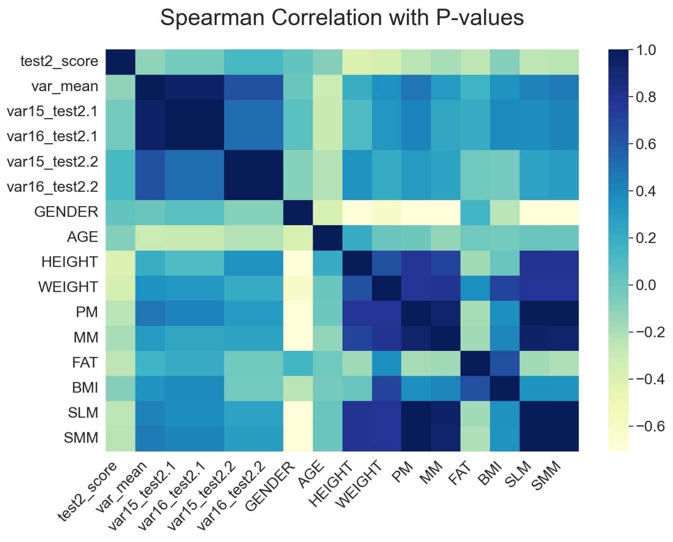

Fig. 5: Spearman correlation analysis of walking variability, movement means, variance means, and body features.

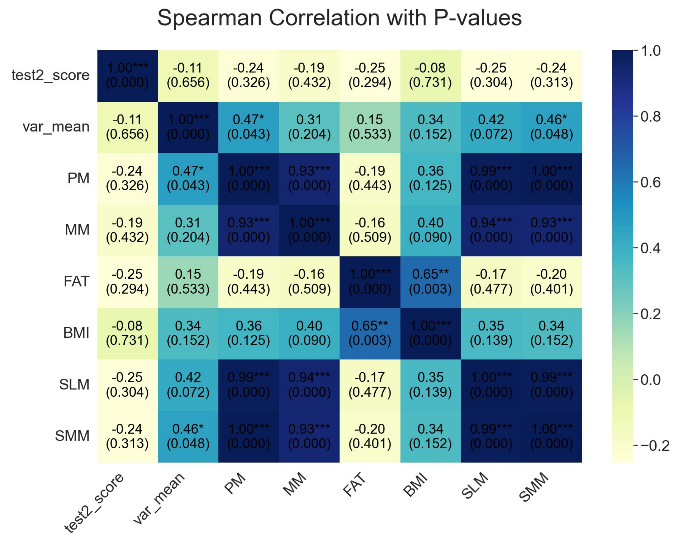

Fig. 6: Detailed correlation analysis of walking variance means, test 2 scores, and body features with significance.

related variables, such as test duration (in seconds) and scores (unitless), reflect the physical performance during the test. The movement-related variables, namely the movement distances of the left and right feet (in centimeters) and their variances (in cm^2/frame), reflect the gait features, where "frame" represents a time interval of one second for analyzing the variance of distances.

C. Results

*1) Result 1: **Correlation Analysis**:* In the context of limited data, this study preliminarily explored the relationship between gait fluctuation, measured as variability in walking distance, and physical function in older adults. As shown in Figure 5, the variance and average variance of walking distance were generally positively correlated with body composition indicators-greater gait variability was associated with higher levels of physical indicators such as PM and SMM. This suggests that older adults with greater walking fluctuations may possess better physical function and vitality [7]. At the same time, gait variability showed a negative correlation with age and gender (male = 1, female = 0), indicating reduced walking stability among older individuals and females [8].

To further refine the analysis, we examined the correlations between the average walking distance variance and key body composition indicators (see Figure 6). The results showed significant positive relationships between the average walking variance and both PM (r = 0.47) and SMM (r = 0.46), both statistically significant at p ¡ 0.05.

*2) Result 2: **Outlier Correlation Analysis**:* As shown in the correlation heatmap in Figure 6, the score from the walking test (Test 2) in the SPPB is generally negatively correlated with body composition indicators [9]. This observation contradicts common expectations, as higher scores are usually associated with better physical function and should therefore show positive correlations with physical indicators. The Score is Heavily Influenced by Test Duration: The total test2 score is calculated based on the time taken to complete each task. In this study, the first trial (Test 2_1) took significantly longer than the second, contributing more heavily to the total time and thereby lowering the overall score [10]. As shown in the bar chart in Figure 4, the distribution of scores from the first trial closely resembles that of the total scores, indicating that the first trial had the greatest impact on the final scoring.

*3) Result 3: **Bayesian Regression Analysis: PM** in Relation to Gait Fluctuation, test 2 Scores, and Task Duration:* Under the gamma distribution, the percentage change in the mean response associated with a one-unit increase in the predictor variable is calculated using the following formula:

If the regression coefficient $\beta < 0$, the percentage change is given by:

$$\text{Percentage Change} = (1 - e^{\beta}) \times 100\% \tag{1}$$

If the regression coefficient $\beta > 0$, the percentage change is given by:

$$\text{Percentage Change} = (e^{\beta} - 1) \times 100\% \tag{2}$$

As shown in Figures 7, time-related variables have minimal effects on PM. Bayesian regression analysis reveals that the total time taken for Test 2 has a regression coefficient (β_{Time}) of -0.0025, indicating an extremely small effect size that is practically negligible. Similarly, the regression coefficients for both the first trial (Test 2_1) and second trial (Test 2_2) are nearly zero.

The mean regression coefficient for the average walking distance variance ($\beta_{\text{var\_mean}}$) is 0.076, with a 94% HDI of $[0.015, 0.14]$. After transformation, this implies that a one-unit increase in the average variance leads to approximately a 7.9% increase in PM. As the HDI does not include zero, the effect is considered statistically significant.

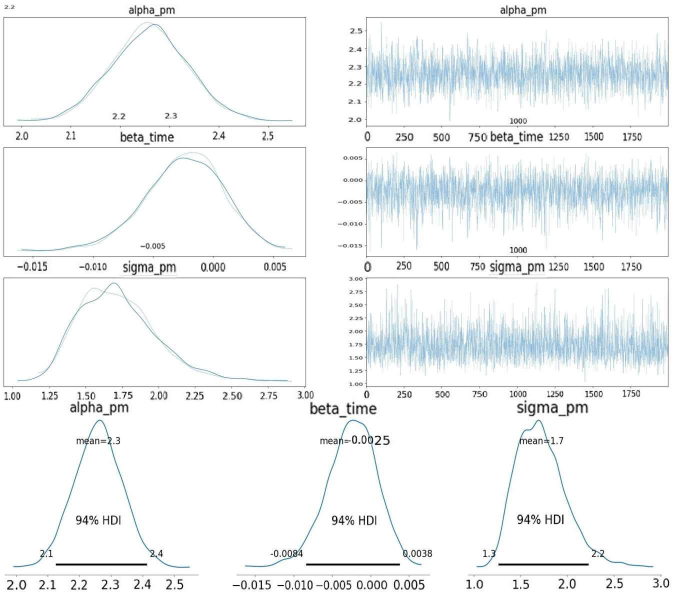

Fig. 7: Results of Bayesian regression: effect of total walking time on PM.

4) Result 4: ***Bayesian Regression Analysis: SMM*** *in Relation to Gait Fluctuation, test 2 Scores, and Task Duration:* Time-related variables (`Time2_1`, `Time2_2`, and `Time`) have minimal and statistically insignificant effects on skeletal muscle mass (SMM). Their mean regression coefficients are -0.0026 for `Time2_1`, -0.013 for `Time2_2`, and -0.0027 for `Time`, and since the 94% HDI for all three variables include zero, these effects are not statistically significant.

The average walking distance variance (`Var_mean`) has a slightly positive but statistically non-significant effect on SMM. The mean regression coefficient ($\beta_{\text{Var\_mean}}$) is 0.081, with a 94% HDI of $[0.025, 0.13]$. This implies that for every one-unit increase in `Var_mean`, the mean SMM increases by approximately 8.1%. However, despite the HDI being mostly concentrated in the positive range, the relatively small effect size and uncertainty suggest that this influence is not strongly supported by the data.

D. Discussion

This experiment found that gait fluctuation is closely related to physical function. The variance and average variance of walking distance are mostly positively correlated with body composition indicators, especially significantly positively correlated with protein mass and skeletal muscle mass. Moreover, gait fluctuation is negatively correlated with age and gender. Nevertheless, an abnormal negative correlation was observed between the scores of SPPB Test 2 and body composition indicators. This is mainly due to the influence of test duration, which caused the total score to fail to accurately reflect the actual physical function of the subjects. Meanwhile, Bayesian regression analysis indicated that time and scores had little impact on body composition indicators, while the average variance of walking distance had a significant positive impact on protein mass and skeletal muscle mass, making it a more suitable indicator for assessing the physical health of older adults.

V. Conclusion

This study focused on exploring the relationships among the motor function, physical fitness indicators, and overall health status of the elderly, as well as developing a new health monitoring method. The findings indicated that gait fluctuation indicators, such as the mean value of the walking distance variance, had significant positive correlations with health indicators like protein mass and skeletal muscle mass. However, the SPPB test scores were affected by test duration, showing complex relationships with body composition indicators. In the future, our efforts will be made to expand the sample size. More composite indicators will be explored, and statistical techniques will be used to address the multicollinearity problem. Machine learning and deep learning techniques will also be introduced to optimize the model, aiming to create a more accurate health monitoring system for the elderly.

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