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Statistical index for the diagnosis of sarcopenia in physically active women over 60 years old: a cross-sectional study

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Abstract

Objective: The detection and classification of sarcopenia involves the analysis of many variables (50 to 60), which increases the time and costs required to diagnose and manage this condition. The objective of the study was to develop a synthetic statistical index to diagnose and classify sarcopenia in physically active women over 60 years old.
Methodology: We conducted a cross-sectional study on 100 physically active women (64.88 ±4.4 years) on whom body composition measurements, muscle strength, and gait tests were performed. One thousand random selections of both training and test sets (80% and 20%, respectively) were made, logistic regression was fitted, and the regularization procedure (Elastic net regression) was performed.
Results: the skeletal appendicular mass index (kg/m2), muscle mass (kg/m2) and SAMI (kg/m2) are highly correlated (0.93) and slow gait speed (m/sec) were the variables that contributed the most to the diagnosis of sarcopenia with a visibly high correlation, (94%).
Conclusion: appendicular lean mass, gait speed, and explosive strength sufficiently describe the state of muscle and functional deterioration (sarcopenia) in physically active older women. Also, the precise identification and classification of this condition facilitates comprehensive multidisciplinary intervention, increasing the positive impact of health promotion and disease prevention programs.

----------*Keywords:* Dynapenia, explosive strength, handgrip strength, body composition.

Índice estadístico para el diagnóstico de la sarcopenia en mujeres mayores de 60 años físicamente activas: Un estudio transversal

Resumen

Objetivo: La detección y clasificación de la sarcopenia implica el análisis de muchas variables (50 a 60), lo que aumenta el tiempo y los costes necesarios para diagnosticar y tratar esta afección. El objetivo del estudio fue desarrollar un índice estadístico sintético para diagnosticar y clasificar la sarcopenia en mujeres físicamente activas mayores de 60 años.
Metodología: Se realizó un estudio transversal en 100 mujeres físicamente activas (64,88 ±4,4 años) en las que se realizaron mediciones de composición corporal, fuerza muscular y pruebas de marcha. Se realizaron mil selecciones aleatorias de los conjuntos de entrenamiento y prueba (80% y 20%, respectivamente), se ajustó la regresión logística y se llevó a cabo el procedimiento de regularización (regresión de red elástica).
Resultados: el índice de masa esquelética apendicular (kg/m2), la masa muscular (kf/m2) y el SAMI (kg/m2) muestran que están altamente correacionados (0,93) y la velocidad de marcha lenta (m/seg) fueron las variables que más contribuyeron al diagnóstico de sarcopenia una correlación visiblemente alta de (94%).
Conclusión: la masa magra apendicular, la velocidad de la marcha y la fuerza explosiva describen suficientemente el estado de deterioro muscular y funcional (sarcopenia) en mujeres mayores físicamente activas. Asimismo, la identificación y clasificación precisa de esta condición facilita la intervención multidisciplinar integral, aumentando el impacto positivo de los programas de promoción de la salud y prevención de enfermedades

----------*Palabras clave:* Dinapenia, fuerza explosiva, fuerza de prensión de la mano, composición corporal.

Índice Estatístico para o Diagnóstico de Sarcopenia em Mulheres Idosas Fisicamente Ativas com Mais de 60 Anos de Idade: Um estudo transversal

Resumo

Objetivo: A detecção e a classificação da sarcopenia envolvem a análise de muitas variáveis (50 a 60), o que aumenta o tempo e os custos necessários para diagnosticar e tratar essa condição. O objetivo do estudo foi desenvolver um índice estatístico sintético para diagnosticar e classificar a sarcopenia em mulheres fisicamente ativas com mais de 60 anos de idade.
Metodologia: Foi realizado um estudo transversal em 100 mulheres fisicamente ativas (64,88 ± 4,4 anos), nas quais foram realizadas medidas de composição corporal, força muscular e testes de marcha. Foram feitas mil seleções aleatórias dos conjuntos de treinamento e teste (80% e 20%, respectivamente), a regressão logística foi ajustada e o procedimento de regularização (regressão de rede elástica) foi realizado.
Resultados: o índice de massa esquelética apendicular (kg/m2), a massa muscular (kf/m2) e o SAMI (kg/m2) mostraram-se altamente correlacionados (0,93) e a velocidade de caminhada lenta (m/seg) foram as variáveis que mais contribuíram para o diagnóstico de sarcopenia, com uma correlação visivelmente alta de (94%).
Conclusão: a massa magra apendicular, a velocidade da marcha e a força explosiva descrevem suficientemente o estado de declínio muscular e funcional (sarcopenia) em mulheres idosas fisicamente ativas. Além disso, a identificação e a classificação precisas dessa condição facilitam a intervenção multidisciplinar abrangente, aumentando o impacto positivo dos programas de promoção da saúde e prevenção de doenças.

----------*Palavras-chave:* Dinapenia, força explosiva, força de preensão manual, composição corporal.

Introduction

Sarcopenia is characterized by the progressive loss of skeletal muscle mass and strength, which can increase the risk of falls, fractures, and decreased functional capacity [1]. Sarcopenia is a common condition among older adults (≥65 years), with a reported prevalence ranging between 6% and 22%, being higher in institutionalized older adults (14%-38%) and geriatric inpatients (10%) [2], but especially in those with hip fractures or some type of physical limitation (60.1%) [3].

However, it is worth noting that some studies have warned that sarcopenia should not only be considered an age-related condition, as it can occur in other stages of the human life cycle due to nutritional problems, immobilization, and having an unhealthy and sedentary lifestyle (e.g., prolonged sitting, physical inactivity, alcohol consumption, smoking, among others) [4]. In this regard, Burgos-Peláez [5] and Gutiérrez-Cortés et al. [6] have reported that muscle mass decreases between 3-8% per decade after the age of 35, reaching approximately 28% and 52% of muscle mass loss in males and females aged over 70 years, respectively. In addition, it has been suggested that sarcopenia will affect more than 200 million people in the next 40 years worldwide [7]. Also, it has been reported that sarcopenia is associated with a 3-to-4-fold increased risk of disability, regardless of age, sex, body mass index, race, socioeconomic level, and comorbidities [8].

Likewise, it has been suggested that in older adults, sarcopenia should be defined as primary (or age-related) when there is no other apparent cause, or secondary when more than two causal factors, such as those mentioned above, are present [7]. In this line of analysis, a conceptual structure that makes it possible to identify and classify the process of muscle deterioration has been proposed as follows [9]: pre-sarcopenia (low muscle mass without effects on muscle strength or physical performance), mild or acute sarcopenia (low muscle mass and low muscle strength without an evident association with poor physical performance), and severe or chronic sarcopenia (low muscle mass, low muscle strength, and poor physical performance). Although there are several direct and indirect diagnostic tests, their heterogeneity affects their sensitivity and specificity to confirm the presence and classification of sarcopenia, leading to an underestimation or overestimation of the patient's condition.

Considering the above, the question arises: Which body composition, muscle strength, and gait variables allow the diagnosis and classification of sarcopenia in active women over 60 years? To answer this question, this study aimed to develop a synthetic statistical index to diagnose and classify sarcopenia in physically active women over 60 years old. This index could be helpful not only in the identification and classification of sarcopenia, but also in establishing cut-off points and reducing costs in terms of time, money and effort used to diagnose and treat this condition. Furthermore, the precise identification and classification of this condition facilitates comprehensive multidisciplinary intervention, increasing the positive impact of health promotion and disease prevention programs.

Methodology

Study design

An analytical cross-sectional study was conducted on women participating in Medellin, Colombia's community-based physical activity programs.

Study population and sample

The study population consisted of all the women participating in three community-based physical-activity programs in Medellín, Colombia, in 2019 (N=280). The following eligibility criteria were considered: being a woman aged between 55 and 76, having a physical activity level higher than 600 METs (metabolic equivalent) according to the International Physical Activity Questionnaire (IPAQ) [10], having participated in physical-activity programs for more than one year, and having been authorized by a physician to engage in physical activity. On the other hand, participants with any spinal and/or upper or lower limb deformity, those using prostheses, those receiving steroid treatment, those with cardiovascular diseases (e.g., angina pectoris, heart failure, venous insufficiency, among others), and those with joint injuries in whom physical activity was contraindicated were not considered.

Once the participants meeting the eligibility criteria were screened, they were contacted directly at the locations where the physical activity programs were taking place to invite them to participate in the study. All of them received information about the objectives of the study, as well as the procedures to be performed and the possible risks. A total of 200 women meeting the eligibility criteria agreed to participate after signing an informed consent form. Of these, 100 were excluded for the following reasons: being considered unsuitable to participate in the study during the clinical assessment (n=22), having failed to attend any of the sessions of the physical activity program, having incomplete data on the variables considered, and having failed to complete any of the physical activity tests under the required procedural conditions (n=78). Thus, the sample consisted of 100 physically active women with a mean age of

65 years (±4.4), a mean body mass index (BMI) of 26.8 (±4.1), and a mean waist-to-height ratio of 0.56 (±0.07). Data were collected between January and August 2019.

Finally, a pilot test was conducted on 15 individuals with similar characteristics to those of the sample, where all protocols and procedures were carried out to adjust and control the selection, memory, confusion, and procedural biases reported in the literature for this type of study [11].

Measurements:

Outcome variable:

The number and typology of variables included follow what was suggested by Cruz-Jentoft et al. [7].The variables were organized into three groups for analysis to obtain the synthetic statistical index for the diagnosis and classification of sarcopenia. The first group included body composition data obtained through dual-energy X-ray absorptiometry (DEXA). The cut-off points proposed by Janssen et al., [12] were used to classify muscle deterioration (≥6.6 without sarcopenia, from 7.76 to 6.5 moderate sarcopenia, and ≤5.5 severe sarcopenia). The second group of variables included the speed, height, time, and power of explosive action in the lower limbs, using power values below the 25th quartile (q25) for each group as an indicator of muscle weakness, as well as the prehensile strength of the dominant upper limb, considering a cut-off value of 16 kg or more [13]. Finally, gait pattern kinematic parameters and gait speed (cutoff point ≤ 0.80 m/s) [7] were included in the third group; these data were obtained by using a 5-meter walk test.

Predictors:

Health status and physical activity level: The PARmed-X physical activity readiness screening checklist [14] and the Physical activity fitness questionnaire [15] were used to identify health conditions. Physical activity level was determined using the International Physical Activity Questionnaire (IPAQ) [10].

Body composition: The following body composition indicators were measured using DEXA (DXA system, Hologic Discovery Wi, and APEXTM Software, version 4.5.3): total body mass, total bone mass, total lean body mass, total body fat mass, body mass index (BMI), body fat percentage, and appendicular lean mass (upper and lower limbs).

Explosive strength assessment: The Optogait® infrared ray system [16] was used to assess explosive strength when performing different jumps: squat jump (SJ), countermovement jump (CMJ), and countermovement jump with arm swing (CMas) [17].

***Assessment of prehensile strength (handgrip test)*:** To assess prehensile strength, participants were asked to sit and to hold a dynamometer in position II with a cylindrical claw, which was slightly supported from its base by the evaluator, while keeping their arm adducted, with the elbow flexed at 90º and the wrist in neutral position. Three attempts were made per arm, with a 30-second pause between each attempt, and the highest value in kilograms was recorded for both dominant hand grip strength (HGS) and non-dominant HGS [18].

Gait kinematic parameters*:* The Optogait RX Microgate ® system and the Racetime 2 Microgate ® Optical Data-Collection system were used to assess gait pattern (slow vs. fast) by recording the following data: Displacement duration, stride width, speed per stride, postures, swings, and speed reached during the walk (m/s) [19].

Proposed statistical analysis model:

The development of the synthetic statistical index for the diagnosis and classification of sarcopenia was based on the variables included in the three groups described above (i.e., body composition, gait parameters, lower limb strength, and prehensile strength). A logistic regression analysis with a *logit link* function where sarcopenia was considered a binary response was performed, obtaining a total of 54 covariates as candidates for predicting sarcopenia.

In the case of variables with missing records, data imputation was performed using statistical procedures. Variables were imputed using predictive mean matching (PMM) [20]. For each missing data entry, this method considered a small set of candidate donors (typically with 3, 5, or 10 members). A donor was randomly drawn from the set of candidates, and the observed value of the donor was used to replace the missing value. The assumption was that the distribution of the missing cell was the same as that of the observed value of the donor. Age, weight, height, and BMI were variables that required data imputation.

The imputation procedure was carried out using the multiple imputation chained equations (MICE) method [20]. The algorithm used for data imputation is described below:

Specify an imputation model P(Yjmis|Yjobs,Y-j,R) for the variable Yj with j=1,…,p, j=1,…,p.

For each j, the initial imputations yj0 were completed by random draws from Yj0.

- Repeat for t = 1,…,M
- Repeat for j = 1,…,p.
- Define y-jt = y1t,…,yj-1t,yj+1t-1,…Ypt-1 with the newly completed data, except for the data of interest Yj
- Extract yjt~P(jt)/Yjobs,yt-j,R)
- Extract the imputations yjt~P(Yjmis/Yjobs,Y-jt, Rjt)

- Finish repeating j.
- Finish repeating t.

In this algorithm, **y-jt** means a set of all variables, except for the j^{th} variable; **t** corresponds to a step in the algorithm, and **j** is a subscript of a variable. Once the variables have been imputed, the probability of occurrence of sarcopenia is estimated. This condition is predicted using logistic regression as follows:

$$\frac{Pi}{1-Pi} = \beta_0 + \beta_0 xi + \beta 1 X_1 + \beta 1 X_1$$

Where:

p_i= the individual's probability of having sarcopenia

$x_1,\ldots x_p$ are covariates

Initially, the logistic regression analysis was performed with 40 covariates. However, there were many highly correlated covariates, so a variable selection procedure was necessary to obtain a parsimonious model. Given the high number of variables available to predict the occurrence of sarcopenia, a regularization procedure was used to select the most relevant variables. The *Ridge and Lasso* regression is a common regularization procedure for selecting relevant variables. In our study, we used an intermediate model between the named procedures, called *Elastic Net,* that generalizes the *Ridge and Lasso* penalties [21]. The objective function for the estimation of the logistic-regression parameters through Elastic Net regularization was:

$$min_{(\beta_0,\beta)\in R^{p+1}}\left(-\frac{1}{N}\sum_{i=1}^{n} y_i-(\beta_0+x_i^T\beta)-log(1+e^{(\beta_0+x_i^T\beta)})+\lambda(1-\alpha)\sum_{j=1}^{p}\beta_p^2/2+\alpha\sum_{j=1}^{p}|\beta_p|\right)$$

First, we imputed a set of variables with missing data using essential variables (age, weight, height, BMI, and lean mass) to take advantage of the observed correlation among all the variables included in the model and, in this way, maintain adequate processing times. Then, the imputation procedure was performed via the *MICE* method [20] using the sets of variables that had complete information. Imputation was carried out through the MICE package of the R statistical software. In addition, the PMM method was chosen.

The first set of variables to be imputed were obtained from the DEXA records: android mass (kg or %), genoid mass (kg or %), lean mass/height (kg/cm), appendicular lean mass/height (kg or %), lean mass (kg or %), appendicular lean mass (kg or %), fat mass (kg or %), bone mass (kg or %), total mass (kg or %), and BMI (kg/m). The second group of variables to be imputed were those in which information was recorded using the Takei tkk5401® hand dynamometer, that is, those related to hand grip strength. The last group of variables were those in which data were obtained with the Optogait® photocell system: SJ flight (s), SJ height (cm), SJ speed (m/s), CMJ flight, CMJ height, CMJ speed, CMJas flight, CMJas height, and CMJas speed.

Below, the reader can consult the full list of covariates: Muscle mass/body height (kg/m), Appendicular mass (Kg), Sex, Physical activity level -NAF-, MET (ml O2/kg x min), Physical Activity classification (kcals*week), Age (years), Weight (kg), Size (cm), BMI, (kg/height), Waist(cm), Waist/hip ratio (m), Waist/height index (m), Lean mass (kg), Grip Strength (kg), Flight Time SJ, Height SJ, Velocity SJ (s), Flight Time CMJ, height CMJ, Velocity CMJ (s), Flight Time CMJas (s), CMJas Height (cm), Velocity AB (s), Distance Slow Gait (m), Time Slow Gait (s), Velocity Average Slow Gait (m/s), Average Stride Slow Gait (m), Double Support Medium Slow Gait (s), Medium Contact Phase Slow Gait (s), Propulsion Slow Gait (s), Distance Maximum Slow Gait (m), Time Fast Gait (s), Velocity Fast Gait (m/s), Acceleration Fast Gait (s), Step Fast Gait (m), Normal Step Fast Gait (m), Stride Fast Gait (m), Imbalance Fast Gait (s), Double Support Fast Gait (s), Time Average Fast Gait (s), Contact Average Fast Gait (s), Propulsion Fast Gait, Lean Mass DEXA (% or kg), Fat Mass (% or kg), Power Squat Jump (Watt), Power Counter Movement Arm Swing (Watt), Power Counter Movement Swing (Watt), Body Fat (DXA= kg or %)), Total Muscle Mass (DXA=Kg or %), Android Mass (DXA= kg or %), Genoid Mass (DXA= kg or %)).

In short, the analysis model allows the identification of the variables with the most significant contribution to the diagnosis of sarcopenia, those with redundant contributions, and those with insignificant contributions. At the end of the process, it is possible to extract an equation that integrates the variables with the most outstanding diagnostic contribution. With this equation model, it is possible to determine cut-off points in line with the characteristics of the subjects, as well as confidence intervals that allow the classification of the state of sarcopenia.

The study protocol was approved by the Ethics Committee of the Institution Universidad de Antioquia (Bioethical Registry Number CE 001-2019). Likewise, the ethical principles for conducting biomedical research involving human beings established in the Declaration of Helsinki [22] were followed at all times

Results

Table 1 summarizes the sample profile of active women between 60 and 70 years old with an apparently healthy appendicular mass and walking speed. Considering the number of possibilities, a previous selection of variables was necessary for creating the sarcopenia prediction model.. To achieve this, 1000 random selections of both training and test sets were made (80% training and 20% test data sets selected from the full data set). For each of those 1000 data sets, logistic regression was fitted, and the regularization procedure (Elastic et regression) was performed, which allowed the selection of the relevant variables to be used in each model run[23]. The summary of the performance of each of the resulting 1000 models is described with the statistical values for precision (first quartile = 0.80; median = 0.85; mean = 0.86; third quartile = 0.90), specificity (first quartile = 0.80; median = 0.85; mean = 0.86; third quartile = 0.90) and sensitivity (first quartile = 0.78; median = 0.89; mean = 0.86; third quartile = 1.00), showing an acceptable performance in these three metrics. Then, to preselect strong candidate variables for predicting sarcopenia, we looked at the variables retained in each of the 1000 runs. The candidate variables that were most frequently retained are presented in Table 2.

Variables appearing in more than 60% of the models were considered initially strong candidate variables to predict sarcopenia. However, we checked mul-

Table 1. Characteristics of the Sample.

Variable	Mean	Standard deviation	CI 95%
Age (years)	65.05	4.39	64.3 - 65.7
Height (cm)	154.7	6.58	153.6 - 155.8
Body weight (kg)	63.73	11.01	61.9 - 65.5
Body mass index	26.81	4.05	26.1 - 27.5
Skeletal appendicular mass index (kg/m^2)	6.32	0.95	6.1 - 6.5
Slow gait speed (m/s)	1.32	0.73	1.2 - 1.5

Table 2. Variables Retained in the 1000 Elastic Net Logistic Regression Models.

Variable	Frequency	Importance
Skeletal appendicular mass index (kg/m^2)	1000	100
Lean mass/height (kg/m^2)	1000	100
CMJ power (watts)	955	95.5
Slow gait speed (m/s)	895	89.5
Total body mass (kg)	892	89.2
Fast-gait speed (m/s)	828	82.8
Lean mass (kg)	749	74.9
Gait distance (m)	726	72.6
Android mass (kg)	723	72.3
Lean mass (%)	367	36.7
CMJas power (watts)	349	34.9
Android mass (%)	144	14.4
Fast gait step time (s)	121	12.1
Squad jump flight time (s)	103	10.3
Fast gait - double support (s)	100	10

CMJ: countermovement jump; CMJas: countermovement jumps with arm swing

Note: We calculated the proportion of appearance of each variable in 1000 elastic net logistic regression models. The most frequent variables in each model are presented (variables appearing in less than 10% of the models are omitted).

ticollinearity to assess redundancies in these variables until the variables best suited to predict the outcome of sarcopenia occurrence were preselected. Then, we performed a stepwise procedure [24] on the previously preselected variables. The estimates of the parameters are shown in Table 3.

Although the previous logistic model is parsimonious (it is adjusted to four variables), with a visibly high correlation, (94%), between the variables; muscle mass (kg/m^2) and SAMI (kg/m^2) (Figure 1). In addition,

Table 3. Parameter variations of the logistic regression model were obtained after performing the stepwise procedure.

Predictors	Log-Odds	CI	p-value
Intercept	-25.03	-35.92 – -14.14	<0.001
SAMI (kg/m^2)	-0.85	-2.42 – 0.72	0.283
Muscle mass (kg/m^2)	2.07	0.99 – 3.15	<0.001
CMJ power (watts)	0	-0.00 – 0.00	0.115
SGS (m/s)	-1.62	-2.81 – -0.43	0.007

SAMI (kg/m^2) = Skeletal appendicular mass index; SGV: Slow gait speed; CMJ: Countermovement jump.

CMJ power (in Newtons) was not statistically significant in the model (Figure 1).

Muscle mass (kg/m^2) and SAMI (kg/m^2) are highly correlated (0.93), and the inclusion of both variables in the model is statistically redundant. DEXA total mass (g) and DEXA lean mass T-value are highly correlated with muscle mass (kg/m^2) and SAMI (kg/m^2) (0.84 and 0.82, respectively). There were many highly correlated paired variables, so to obtain a model as parsimonious as possible, we performed a stepwise procedure on the preselected variables to eliminate redundant variables. The step-by-step procedures resulted in the following estimates (Table 4).

To evaluate the logistic regression model obtained after the stepwise procedure in terms of its ability to predict sarcopenia in new data, a cross-validation was performed on selected variables, and a well-functioning final model of performance metrics was obtained based on the following metrics: precision (mean = 0.8375, standard error = 0.0590727, k = 10), area under the curve (AUC) (mean = 0.9544643, standard error = 0.027096410, k = 10), sensitivity (mean = 0.8871429, standard error = 0.06203101, k = 10), and specificity (mean = 0.8416667, standard error = 0.07291336, k = 10).

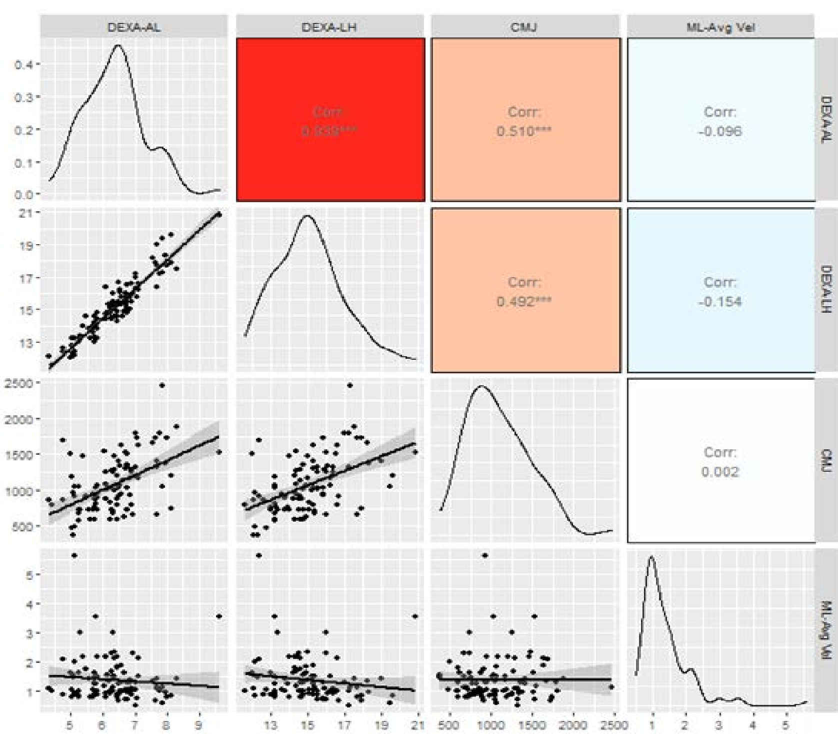

Figure 1. Correlation between the variables retained in the model after the stepwise procedure was performed.

Table 4. The Logistic Regression Coefficient of the Reduced Model.

	Model 1
Intercept	-15.048*** -3.83
SAMI (kg/m²)	2.423*** -0.62
SGV (m/s)	-1.796** -0.661
CMJ (watts)	0.002+ -0.001
Num. Obs.	100
(Aikake information criterion) AIC	77.4
(Bayesian information criterion) BIC	87.9
(Logarithm of likelihood) Log. Lik.	-34.72
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001	

SAMI (kg/m^2) = Skeletal appendicular mass index; SGV (m/s) = Slow gait velocity; CMJ (watts) = Countermovement jump power.

Suggested Model

We predicted the occurrence of sarcopenia using SAMI (kg/m^2) and SGS (m/s) variables. The estimates of the logistic regression parameters are shown in Table 5.

Table 5. Parameter Estimation of the Reduced Logistic-Regression Model to Predict Sarcopenia.

Classification			
Predictors	Estimate	CI	P value
Intercept	-13.14	-20.18 – -7.68	<0.001
SAMI (kg/m²)	2.45	1.56 – 3.61	<0.001
SGS (m/s)	-1.66	-2.97 – -0.56	0.007

SAMI: Skeletal appendicular mass index; SGS: Slow gait speed.

Cross-validation was used to estimate the prediction error of the previous model. According to the data presented in Table 6, it is possible to say that the final model has a good performance in different metrics [23].

Table 6. Logistic Regression Model of Cross-Validated Summary Metrics to Predict Sarcopenia.

Metrics	Mean	Standard deviation
Accuracy	0.91	0.06
AUC	0.87	0.09
Precision	0.85	0.09
Specificity	0.76	0.22

AUC: area under the curve

The probability and individual presentation of the sarcopenia diagnosis index were estimated as follows:

$$p_i = \frac{e^{-13.142+2.45\times SAMIn_i-1.663SGV_i}}{1+e^{-13.142+2.45\times SAMIn_i-1.663SGV_i}}$$

Where:
SAMI (kg/m^2) = Skeletal appendicular mass index
SGS (m/s) = Slow gait speed

Once this stage was over, the new prediction model, that is, the model into which SAMI (kg/m2) and SGS (m/s) were integrated, reported a prevalence of sarcopenia of 48%, while the observed prevalence in the sample was 51% using the equations proposed by Janssen et al., 2004.

Discussion

The objective of this study was to develop a synthetic statistical index for the diagnosis and classification of sarcopenia in physically active older adult women. This index was obtained after combining different statistical models in which those variables that best described the impact of sarcopenia in the group of women analyzed were integrated. The resulting index reduced the sarcopenia detection profile from 54 covariates that could predict the outcome of sarcopenia to 3: SAMI, slow gait speed, and countermovement jump.

To begin with, variables such as absolute muscle mass (kg), relative muscle mass (%), muscle mass/height index (kg/height^2), and appendicular skeletal muscle mass/height index (kg/height^2) have been used in different studies about sarcopenia in older adults. However, these variables describe the loss of muscle mass differently, and, therefore, they should not be interpreted separately since doing so can lead to an underestimation or overestimation of the state of sarcopenia [25]. For example, when absolute (kg) or relative (%) muscle mass data are obtained using different tests (direct- or indirectly), the diagnosis of sarcopenia is limited to the quantitative values on muscle quantity that were individually recorded, thus minimizing aspects related to muscle quality, which refers to the decrease in strength per muscle-mass unit, a fairly common mistake [26]. Similarly, several studies report how the size, morphology, and configuration of muscle groups vary between the upper and lower limbs, as well as between the limbs and the rib cage, and by sex, and that they are also conditioned by sedentary behavior [27, 28].

Therefore, when absolute (kg) or relative (%) muscle mass values are taken as a reference value, the appendicular lean mass index can be used as a complement. This will allow a description of the deterioration of the muscles of the extremities according to the height of the person, where the amount of appendicular lean mass of the lower limbs is of great importance. In addition, these values can be complemented with gait pattern variables (slow vs. fast gait) or the force generated by the lower limbs, thus allowing the description of aspects related to muscle quality and its effect on locomotor function [29].

The second variable integrated into the model refers to the indicators derived from the analysis of gait pattern parameters, kinetic (the forces that occur because of movement) and/or kinematic (the quantification of the movement of body segments in space and time). In this regard, several studies have described how the reconfiguration of body composition and the deterioration of the locomotion pattern [30, 31] are among the causal factors of falls, accidents, fractures, surgeries, and death in older adults [32, 33]. In fact, the findings of the present study are in line with reports [34] where a negative impact of changes in muscle and fat mass on these indicators was identified, a causal factor to be considered within the patient's risk profile and the classification of their risk level.

The third variable integrated into the index proposed here refers to the ability of the muscle to express maximal tension in the shortest possible time, which can be affected by neurological, hormonal, muscle, and periarticular changes, among other factors [35]. These factors have a marked impact on the expression of maximal isometric strength and explosive strength of the lower limbs, which are associated with the risk of injuries and accidents in older adults [36].

On the other hand, it should be taken into account that muscle power loss occurs at a faster rate than muscle mass and muscle strength loss, which reinforces the idea that both the central and peripheral nervous systems play a role in functional deterioration in older people [37]. Despite the above, the CMJ power variable (measured in watts) was not included in the final prediction model, even though it showed moderate correlations in the analysis process, it reduces the precision, sensitivity, and specificity of the index proposed here for the diagnosis and classification of sarcopenia. Another noteworthy aspect is that the handgrip strength test did not pass the analysis stage; therefore, it is a poor predictor of muscle deterioration in women 60 years old. The factors that may explain this analysis go beyond the scope of the present study but can be consulted in a previous study by this team [38].

Considering the above, the findings of this study pave the way for further research on simplifying the diagnosis and classification of sarcopenia, given that the proposed index considerably reduces the variables required for the prediction of sarcopenia, and its predictive capacity has been proven. In addition, it identifies appendicular lean mass, gait speed, and explosive strength as the most sensitive predictors of sarcopenia in women over 55 years, simplifying the process of determining the risk level of sarcopenia. An additional element related to applying these statistical models in the field of public health can strengthen diagnostic proposals and reduce biases related to modeling techniques. Finally, this simplification allows the indices to be incorporated into the software support used in the laboratories.

The main limitation of this study is that we did not include males in the sample; thus, determining sex differences was not possible. In addition, we believe future studies on this topic in older adults should analyze differences according to the level of physical activity (active vs. sedentary), the type of physical activity program they are enrolled in, and their nutritional and hormonal characteristics (e.g., if they are receiving nutritional counseling or are receiving hormone therapy), due to the implications of these variables. : Finally, there is a need to review how using less complex technical actions and movements and a highly sensitive and reliable data capture system "may help" to obtain data on the upper and lower limb strength of those parameters in the statistical index. Also, it is essential to consider that inflammatory processes derived from diseases, drugs, sedentary behavior, and personal history, among other factors, limit the applicability of this index and should be considered in future studies. Likewise, it should be noted that the generalizability of our findings is limited to active older women.

Conclusion and Perspectives

In conclusion, appendicular lean mass and gait speed are variables that sufficiently describe the state of muscle and functional deterioration in physically active older women. The statistical index proposed here simplifies the diagnostic and classification process of sarcopenia by reducing the analysis variables from 54 to 2, which could improve the data registration and processing times, as well as results reporting. In this regard, statistical prediction models efficiently organize, filter, and locate the variables that explain the outcome. Once this analysis stage has been completed, these statistical models can be used to update computer programs, establish new cut-off points, and create mobile applications that simplify diagnosing and treating health conditions.

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Conflict of Interest

The authors declare no conflicts of interest

Statement of Responsibility

The authors assume professional responsibility for the subject matter, methodology, results and professional judgments based on scientific evidence.

Author Contributions

The authors declare that they participated in the construction of this writing and its content.

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