ScienceDirect

Gait & Posture

Volume 92, February 2022, Pages 455-460

Factors influencing gait speed in community-dwelling older women: A Bayesian approach

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https://doi.org/10.1016/j.gaitpost.2021.12.022

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Highlights

- Human gait is a complex task dependent on sensory-motor integration.
- Gait speed declines with aging due to impaired sensory-motor integration.
- The influence of sensory-motor integration on gait speed is not well established.
- Age, explosive force, and stabilometric parameters influence gait speed.

Abstract

Background

Human gait is a complex task resulting from the interaction of sensory perception, muscle force output, and sensory-motor integration, which declines with the aging process and impacts gait speed in older women.

Research question

What are the separate and combined impacts of sensory-motor factors on gait speed of older women?

Methods

Sixty healthy older women (69.3 ± 5.9 years) volunteered for this study. A previous screening using Pearson's correlation selected variables significantly correlated with gait speed: age, plantar tactile perception, lower limb explosive force, and mean velocity (MV) of the center of pressure (CoP). Simple and multivariate regression models were performed with selected variables. The magnitude of evidence was obtained using Bayesian inference, determining posterior probabilities based on our data.

Results

Gait speed was negatively correlated with age and positively correlated with plantar tactile perception, MV (Romberg index), and lower limb explosive force. The coefficient of determination (R^2) varied between 0.06 for plantar tactile perception and 0.22 for explosive force ($p < 0.05$). The multivariate model, including age, MV (Romberg index), and lower limb explosive force, explained 44% ($R^2 = 0.44$) of the variance in gait speed, with a small standard error of estimate (0.14 m/s). Bayesian inference confirmed the good posterior probability of the model.

Significance

Age, plantar tactile perception, MV (Romberg index), and lower limb explosive force impact gait speed, whereas the combination of the first three factors has an excellent posterior probability of predicting or affecting gait speed.

Previous

Next

Keywords

Rate of force development; Stabilometry; Bayesian statistics; Aging

1. Introduction

Walking is an inherent ability of humans, but it is a complex task resulting from the interaction of several systems (e.g., skeletal muscle system, sensory systems, and sensory-motor integration) that allow balance and locomotion in different environments. Limitations in sensory input from other sources (e.g., visual, tactile plantar, proprioceptive, and vestibular) and deficiencies in sensory-motor integration or muscle strength [1] are the main factors associated with gait impairments, especially in older adults [2].

Gait speed is essential for older adults since it is a limiting factor for performing instrumental daily living activities and maintaining functional independence [3]. However, it declines with advancing age and is associated with adverse health outcomes in older adults [4].

Since gait speed is a clinical outcome influenced by several factors, knowledge regarding the impact of each determinant on gait speed of older adults may contribute to the development of intervention programs with higher probabilities of success. In this context, previous studies suggested that plantar sensitivity [5], [6], [7], the ability to integrate sensory-motor information in the central nervous system [8], [9], and the ability to produce muscle strength in short time intervals (i.e., explosive force) [10], [11], [12] directly impact gait speed and mobility of older adults.

However, the proportion in which each factor contributes to gait speed performance is not well established. Thus, this study aims to investigate the impact, separate and combined, of sensory-motor factors on gait speed of older women using a frequentist and Bayesian approach. We investigated this issue in two steps. First, we estimated the amount of variance of gait speed explained by age, plantar sensitivity, sensory-motor integration, and ability to produce explosive force. Then, we evaluated which variables, separate or combined, better explained gait speed in older women. We used frequentist and Bayesian approaches to define the better multivariate model since a predictive variable could be significantly associated with gait speed in a bivariate test but have an insignificant contribution to predicting gait speed when considered in a multivariate model.

2. Methods

Sixty community-dwelling older women (69.3 ± 5.9 years old) with no diagnosis of diabetes mellitus or vestibulopathies volunteered for this study. Since cognitive deficit is associated with gait impairments [13], we used the Mini-Mental State Examination instrument adapted by Bertolucci et al. [14] to assess cognitive performance, and only older women without cognitive deficit were included. All participants presented independent ambulation, absence of claudication, or another abnormal gait pattern. The local research ethics committee approved (protocol nº 3.932.381) all procedures according to the Declaration of Helsinki.

Body mass index (BMI = weight/heigh^2) was calculated, and gait speed, plantar tactile sensitivity, stabilometric parameters, and explosive strength were assessed as described in the following sections.

2.1. Gait speed

Gait speed (meters/second) was measured using the timed 3-meter walk test [15]. Volunteers were asked to walk at a normal pace in a straight line on a flat surface, as recommended by Mehmet et al. [16]. They started from a standing position without previous distance from the start line because the investigated distance reproduces most daily dislocations performed in the household environment, including acceleration phase, which is dependent on explosive force.

2.2. Plantar tactile perception

Cutaneous tactile perception was assessed at ten sites on the plantar surface of each foot: first toe, third toe, fifth toe, first metatarsal head, third metatarsal head, fifth metatarsal head, interphalangeal region between the first and second toes, calcaneus region, and medial and middle-lateral region of plantar surface of the midfoot. All assessments were performed using Semmes–Weinstein monofilaments (SORRI®, Bauru, SP, Brazil).

The examiner randomly performed six trials at each site of both feet, one for each monofilament degree. One of the six trials at each site was “sham”, in which the examiner did not touch the participant but still asked for a response. Each correct response (including the “no” from sham trial) scored one point, and total cutaneous tactile score ranged from 0 to 60 points per foot. The mean score between right and left foot was used for statistical analysis.

2.3. Stabilometric parameters

Coordinates of the body center of pressure (CoP) were recorded during 30 s of quiet barefoot standing (sampling frequency of 100 Hz) using a BIOMEC 400® (EMG System Brazil) force plate. Volunteers remained with arms relaxed alongside the body and were asked to keep bipedal support with heels 6-cm apart and a 30º angle between feet (a reference was used over the force plate to ensure adequate feet position). They were instructed to remain immobile during the recording and look at a fixed point placed 2 m (eye height) on a wall for visual reference [17]. Six 30-second recordings were performed with 1-min intervals between them; three recordings were randomly carried out with eyes open (EO) and three with eyes closed (EC). The ratio between sway with EC and EO was measured and reported as Romberg index [18].

Body CoP displacement was analyzed in MATLAB® software using routines developed to obtain stabilometric parameters: area (AREA) and mean velocity (MV) of CoP displacement [19]. Both parameters were used to obtain Romberg index (AREA_RI and MV_RI).

2.4. Explosive force (rate of force development)

Ground reaction force (GRF) was measured during the single chair-stand test using a force plate (BIOMEC 400®, EMG System Brazil). Volunteers stayed seated on a chair (~43 cm) and were instructed to stand up as quickly as possible with feet over the force plate. They were also asked to stay seated with hands crossed over chest to avoid “swing hands” or “push off the chair using hands” during the test [12].

GRF data were smoothed using a digital fourth-order zero-lag Butterworth filter with cutoff frequency of 15 Hz [20], [21]. The average slope of the force-time curve (Δforce/Δtime) over 0–200 ms time interval (i.e., RFD200ms = force at 200 ms/0.2) relative to onset of force-time curve was calculated as representative of RFD. Onset was defined as the time when the force curve exceeded baseline values.

Peak force and the moment at which it was achieved were used to calculate RFDpeak and normalize RFD200ms (i.e., relative RFD200ms [RFDr200ms = RFD200ms/RFDpeak]). This procedure was adopted to normalize explosive force since body mass influences GRF.

2.5. Statistical analysis

Descriptive data are presented as mean ± SD. Pearson's correlation was applied between gait speed and the following potential variables for inclusion in the multivariate analysis: age, BMI, plantar tactile perception, RFDr200ms, and stabilometric parameters (AREA and MV obtained during EO and EC conditions and AREA_RI and MV_RI). Variables with statistically significant correlation ($p < 0.05$) were used to generate a multivariate linear regression model, as described below.

Associations among selected independent variables (i.e., age, plantar sensibility, total mean velocity of CoP, and RFDr200ms) and gait speed were verified using simple and multivariate linear regression models. A stepwise method was used for the multivariate linear regression model ($p < 0.05$ and $p > 0.1$ as criteria for inclusion and exclusion of a variable, respectively). Adequacy of each regression model (simple and multivariate) was verified by analyzing residues using Shapiro-Wilk test; visual inspection was also conducted to identify extreme observations in histograms of residues. The coefficient of determination (R^2) was calculated and represented the amount of variance of the dependent variable explained by one predictor (simple linear regression) or group of predictors (multivariate linear regression). We also presented adjusted R^2 from each regression model since it is more conservative than R^2.

The Bayes factor hypothesis testing was used to check qualitative outcomes and the probability of replicating results (i.e., magnitude of the evidence). Bayes factor (BF_{10}) represents the change from prior to posterior odds of the model given a set of data. In regression models, it indicates the difference between prior odds and posterior odds [22], [23], indicating the relative predictive performance of the model for the analyzed data (i.e., ratio of marginal likelihoods) [24]. Interpretation of Bayes factor is intuitive: $BF_{10} = 5$ indicates that data are 5-fold more likely under alternative hypothesis than null hypothesis, whereas $BF_{10} = 0.2$ indicates that the observed data are 5-fold more likely under null hypothesis than under alternative hypothesis [24], [25]. It is worth emphasizing that, in linear regression models, the null hypothesis states that the true slope of the line (i.e., beta) is zero [26].

Bayes factor analysis was carried out using JAMOVI®, and the parameter Jeffreys-Zellner-Siow prior (JZS prior) was set as r scale = 0.001 due to the relatively small sample size. Inclusion Bayes factor ($BF_{inclusion}$) was reported only for variables present in the multivariate model since it quantifies the probability of the observed data under models including a particular predictor (i.e., independent variable) relative to models without that predictor. We choose to compute and report parameter estimates from the best model obtained (i.e., highest BF_{10}). Then, the reported $BF_{inclusion}$ for each predictor was exclusively related to the best model.

3. Results

Characteristics of the studied population are presented in Table 1.

Table 1. Sample characteristics.

Variables	Mean ± SD	95% CI
Age (years)	69.3 ± 5.9	67.8–70.8
BMI (weight/heigh^2)	26.6 ± 4.4	25.4–27.7

Variables	Mean ±SD	95% CI
Gait speed (m/s)	0.82 ± 0.18	0.8–0.9
Plantar tactile perception (score)	38.4 ± 5.3	37.0–39.7
AREA EO	0.73 ± 0.49	0.60–0.87
AREA EC	0.92 ± 0.62	0.75–1.09
AREA_RI	1.39 ± 0.62	1.25–1.54
MV EO	2.44 ± 0.41	2.33–2.55
MVEC	2.60 ± 0.55	2.45–2.75
MV_RI	1.07 ± 0.08	1.04–1.09
RFDr200ms (%MVIF·s^{-1})	3.5 ± 1.4	3.2–3.9

Data reported as mean and standard deviation (SD) and 95% confidence interval (CI). BMI = Body mass index; EO = eyes opened; EC = eyes closed; MV = mean velocity; AREA_RI = Romberg index from area of CoP displacement; MV_RI = Romberg index from MV of CoP displacement; RFDr200ms = relative rate of force development at 200 ms; MVIF = maximal isometric voluntary force.

Gait speed was negatively correlated with age and positively correlated with plantar tactile perception, MV_RI, and RFDr200ms (Table 2).

Table 2. Correlation coefficients between gait speed and measured variables.

Variables	Correlation coefficient	P-value
Age (years)	-0.45	< 0.001*
BMI (weight/heigh^2)	0.08	0.546
Plantar tactile perception (score)	0.266	0.040*
AREA EO	-0.177	0.188
AREA EC	0.028	0.835
AREA_RI	0.217	0.105
MV EO	-0.24	0.071
MV EC	-0.05	0.712
MV_RI	0.339	0.001*
RFDr 200 ms (%MVIF·s^{-1})	0.483	< 0.001*

BMI = body mass index; EO = eyes opened; EC = eyes closed; MV = mean velocity; AREA_RI = Romberg index from area of CoP displacement; MV_RI = Romberg index from MV of CoP displacement; RFDr200ms = relative rate of force development at 200 ms; MVIF = maximal isometric voluntary force.

*

$p < 0.05$

Results from the linear regression model (Fig. 1) indicated that all selected variables were significantly associated with gait speed, and adjusted R^2 ranged from 0.06 for plantar sensibility to 0.22 for RFDr200ms (all $p < 0.05$). The multivariate model included age, MV_RI, and RFDr 200 ms and explained ~44% (adjusted $R^2 = 0.44$) of the variance in gait speed from the studied sample, with a small standard error of estimation (0.14 m/s). Table 3 presents parameters from simple and multivariate regression models.

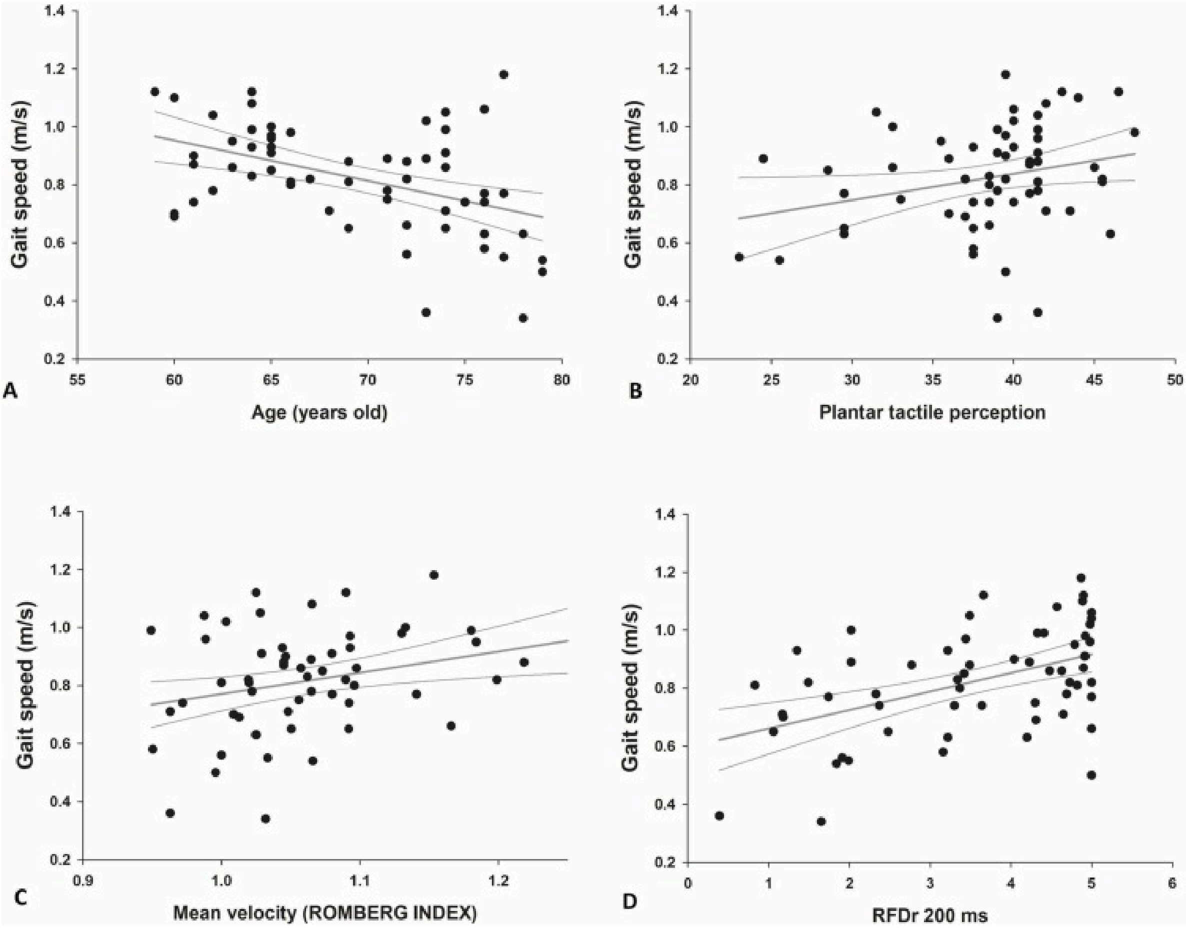

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Fig. 1. Regression lines and 95% confidence intervals between gait speed and age (A), plantar tactile perception (B), mean velocity [Romberg index] (C), and RFDr200ms (D).

Table 3. Statistical parameters obtained from regression models and Bayes factors.

Variables	Constant (95% CI)	Beta (95% CI)	Adjusted R^2	SEE	P-value	BF_{10}	$BF_{inclusion}^{\phi}$
Age (years)	1.79 (1.28–2.30)	-0.014 (−0.02 to −0.006)	0.19	0.16	<0.001	1.45	–
Plantar tactile perception	0.47 (0.14–0.81)	0.009 (0.0001–0.018)	0.06	0.18	0.04	1.01	–
MV_RI	0.04 (−0.54 to 0.63)	0.73 (0.19–1.28)	0.10	0.17	0.01	1.04	–
RFDr200ms	0.60 (0.48–0.71)	0.06 (0.03–0.09)	0.22	0.16	<0.001	2.15	–
Multivariate Model							
Age (years)	0.97 (0.34–1.60)*	-0.013 (−0.02 to −0.006)	0.44*	0.14*	<0.001*	162.84*	26.03
RFDr200ms		0.05 (0.02–0.08)					18.78
MV_RI		0.53 (0.07–0.99)					2.75

MV = mean velocity; MV_RI = Romberg Index from MV of CoP displacement; RFDr = normalized rate of force development; SEE = Standard error of estimation; BF10 = Bayes factor; (*) General parameters from the multivariate model with best performance; (ϕ) BFinclusion is reported only for multivariate model.

Results from Bayesian analysis (Table 3) indicated modest BF_{10} for simple linear regression, including age (BF_{10} = 1.45), plantar sensitivity (BF_{10} = 1.01), and MV_RI (BF_{10} = 1.04), suggesting a modest probability favoring the alternative hypothesis. RFDr200ms exhibited the highest probability among simple regression models favoring the alternative hypothesis (BF_{10} = 2.15). In contrast, the multivariate model showed a probability 162.84-fold higher for the alternative hypothesis than for the null hypothesis, suggesting greater magnitude of evidence favoring the capacity of variables included in the multivariate model to predict gait speed from the studied sample. Results from $BF_{inclusion}$ indicated that the multivariate model including age is, on average, 26.03-fold more likely than the model without age. In contrast, RFDr200ms and MV are, on average, 18.78-fold and 2.75-fold ($BF_{inclusion}$ = 18.78 and 2.75 for RFDr200ms and MV_RI, respectively) more likely than the model without this variable, respectively.

4. Discussion

The present study investigated the impact, separate and combined, of sensory-motor factors on gait speed of older women using a frequentist and Bayesian approach. Age, plantar tactile perception, MV_RI, and RFDr200ms were significantly associated with gait speed; however, the multivariate analysis indicated that age, MV_RI, and RFDr200ms combined explained approximately 44% of the variance in gait speed of the studied sample. Bayesian analysis indicated that age and RFDr200ms presented high posterior probability of influencing gait speed, whereas age, RFDr200ms, and MV_RI combined have a posterior probability 162.84-fold higher for the alternative hypothesis than for null hypothesis.

Gait speed decreases with aging [27], [28], and our results corroborate this hypothesis since age explained approximately 19% of the variance in gait speed. However, when analyzed alone, the posterior probability of age influencing gait speed was only 1.45 times higher in favor of the alternative hypothesis. Nonetheless, considering the Bayesian inference applied to the multivariate regression model, we infer that age contributed most to the model because $BF_{inclusion}$ was the largest among studied variables ($BF_{inclusion}$ = 26.03). This may be explained by the influence of aging over sensory-motor integration and explosive force, which also composed the multivariate regression model [1], [12], [29], [30], [31].

Plantar tactile perception was also associated with gait speed but with small potential to explain its variance. In addition, the magnitude of evidence was only anecdotal (BF_{10} = 1.01) in favor of the alternative hypothesis. This explains the exclusion of plantar tactile perception from the multivariate regression model. Indeed, despite a reasonable prior probability of influencing gait speed [30], plantar tactile perception was not promising, either using frequentist or Bayesian approach.

Deshpande et al. [30] showed that the strength of association between plantar tactile perception and gait speed varied according to type of sensitivity evaluated (i.e., vibratory or tactile/pressure). However, they obtained gait speed in a 6-meter corridor, twice the distance covered in our study. Additionally, Cruz-Almeida et al. [7] demonstrated that the association between plantar tactile perception and gait speed varied according to plantar region used as reference, which may explain the low R^2 value found for plantar tactile perception once we scored tactile perception in 10 foot sites.

Integrating sensory input at central nervous system level is essential for posture control under static and dynamic conditions [29], [30], explaining the significant association between the stabilometric parameter MV_RI and gait speed. Postural adjustments driven by proprioceptive input occur at a higher frequency than by visual input since the former originates from widespread sources (e.g., mechanoreceptors from skin, synovial membranes, and ligaments), which justify its use as reliable cue source for moment-to-moment adjustments [29], [32]. Thus, proprioceptive-based postural adjustment is characterized by high frequency, with consequent high speed and fast changes in the direction of CoP, which may also be associated with greater co-contraction of postural muscles [29], [33].

MV_RI represents the percentage increase in CoP oscillation velocity from EO to EC condition. Then, high MV_RI may indicate greater capacity to reweight sensory cues used in the absence of visual information, suggesting a good adaptive capacity to maintain adequate postural control. In this context, our findings regarding the significant association between MV_RI and gait speed indicate that a better ability to reweight sensory cues (i.e., better sensorimotor integration) could be necessary for a faster gait speed. However, the posterior probability applied to simple linear regression indicated odds only 1.04 times greater for the alternative hypothesis than null hypothesis. Although the relevance of MV_RI increased when analyzed in the multivariate model, $BF_{inclusion}$ was still low.

Explosive force, measured using RFDr200ms, was the variable that associated most with gait speed. According to the coefficient of determination, RFDr200ms explained approximately 22% of the variance in gait speed, the highest coefficient of determination and highest BF_{10} (posterior probability 2.15-fold higher favoring the alternative hypothesis) obtained in this study. In the multivariate analysis, its importance was confirmed by the high $BF_{inclusion}$ value.

The inability of different muscle groups to increment force in short time intervals is strongly associated with functional decline in older adults [1], [21], [34], [35] and stroke survivors [36], as well as with the risk of fall in this population [12], [31]. Kera et al. [12] identified that explosive force measured using GRF analysis could predict falls in older adults. Da Silva et al. [36] demonstrated that RFD was a better determinant of gait speed than peak torque of knee extensors in stroke survivors. In this context, RFDr200ms could be significantly associated with gait speed since both are closely related in older adults.

Hester et al. [31] observed that explosive force of plantar flexors measured using GRF analysis explained approximately 21.7% of the variance in gait speed of older women, close to our result. This reinforce the notion that explosive maneuvers involving knee extensors and plantar flexors analyzed using GRF may help explain much of the variance in gait speed of older women. Results from Bayesian inference also reinforced our hypothesis.

We highlight that predictive models, such as those generated here, are useful for indicating variables with higher probability of impacting an outcome of interest (e.g., gait speed), increasing the confidence to test hypotheses in randomized clinical trials. The model is also used to predict complex outcomes from variables easy to obtain; however, this does not apply to the present study since some dependent variables demanded specific equipment (e.g., force plate). In this context, results allow us to indicate that 1) interventions to improve sensorimotor integration in older women have a higher prior probability of success to improve gait speed than interventions to improve plantar sensitivity; 2) interventions to increase lower limb explosive force in older women have a higher prior probability of success to improve gait speed than interventions to improve plantar sensitivity and sensorimotor integration; and 3) interventions to improve sensorimotor integration and lower limb explosive strength have an excellent prior probability of success to improve gait speed in older women. Then, future studies must consider these hypotheses based on frequentist and Bayesian inferences.

5. Conclusion

Age, plantar tactile perception, MV_RI, and RFDr200ms are significantly associated with gait speed. Moreover, age, MV_RI, and RFDr200ms combined have an excellent posterior probability to predict gait speed, explaining approximately 44% of the variability of this outcome. Bayesian inference supports the probability of success of interventions aiming to improve gait speed using lower limb explosive force and sensory-motor integration training. In contrast, an anecdotal probability of success of interventions seeks to improve plantar tactile perception.

Ethics approval and consent to participate

All participants provided informed consent. The procedures complied with the Declaration of Helsinki regarding human experimentation. The research project received a positive opinion from the Universidade Estadual do Sudoeste da Bahia Ethics Committee (protocol nº 3.932.381).

Funding

This work was supported by grants from Fundação de Amparo à Pesquisa do Estado da Bahia (FAPESB) (Award Numbers: JCB 0056/2013andAPP0018/2016APP0018/2016).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank all members of Integrative Physiology Research center, Research Group in Neuromuscular Physiology, and Center for Studies in the Epidemiology of Aging for all technical support. The authors thank Probatus Academic Services for providing scientific language revision and editing.

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