Predictive modelling on handgrip strength in adolescents

Modelo Predictivo de la fuerza de prensión manual en adolescentes

Authors

Ricardo Manuel Santos-Labrador [1]
Giulio Bertamini [2]
Alejandra Rebeca Melero-Ventola [1]
Thomas Zandonai [4]

[1] Universidad de Salamanca (Salamanca, Spain)
[2] University of Trento (Rovereto, Italy)
[3] Miguel Hernández University of Elche (Alicante, Spain)

Corresponding author:
Alejandra Rebeca Melero Ventola
amelero@usal.es

Received: 05-12-25
Accepted: 21-01-26

How to cite in APA

Santos Labrador, R. M., Bertamini, G., Melero Ventola, A. R., & Zandonai, T. (2026). Predictive modelling on handgrip strength in adolescents. *Retos, 76*, 668-679. https://doi.org/10.47197/retos.v76.118298

Abstract

Introduction: Handgrip strength represents a key measure of upper limb function and general physical fitness in adolescents, reflecting muscular health and potential risk for future health conditions.
Objetive: This study aimed at developing a predictive model of adolescent handgrip strength using anthropometric variables to identify those at risk of future health issues.
Methods: Sociodemographic data, Body Max Index (BMI), and body fat percentage were collected during Physical Education classes. Handgrip strength was measured twice using the dominant arm, with the best result recorded. Additional data from the Course Navette test, the Physical Activity and Leisure Motivation Scale (PALMS), the International Physical Activity Questionnaire (IPAQ), and the Questionnaire of Health and Well-Being (QHWB) were also collected. A nested 10-fold cross-validation pipeline was used, incorporating Boruta feature selection, and ElasticNet regression. Model evaluation included Mean Average Error, Root Mean Square Error, R^2, and bootstrapped confidence intervals. The sample included 867 secondary school students (mean age = 14.03 ± 1.19 years; 53.9% boys).
Results: The model showed good predictive performance: MAE = 3.76 (0.29), RMSE = 4.73 (0.36), R^2 = 0.48 (0.08), and Average Normalized MAE = 9.90%. Selected predictors included Age (b = 1.86), Sex (b = -1.03), BMI (b = 4.16), Body Fat (b = -3.94), and Navette Stages (b = 1.06).
Conclusions: This study provides preliminary evidence for a predictive model that estimates handgrip strength in adolescents using indirectly measurable predictors, employing a rigorous machine learning approach that retains only robust predictors for population screening.

Keywords

Handgrip strength; adolescents; population screening; physical activity; musculoskeletal health.

Resumen

Introducción: La fuerza de prensión manual representa una medida clave de la función de las extremidades superiores y la aptitud física general en los adolescentes, ya que refleja la salud muscular y el riesgo potencial de padecer problemas de salud en el futuro.
Objetivo: El objetivo de este estudio fue desarrollar un modelo predictivo de la fuerza de prensión manual en adolescentes utilizando variables antropométricas para identificar a aquellos con riesgo de padecer problemas de salud en el futuro.
Métodos: Se recopilaron datos sociodemográficos, el índice de masa corporal (IMC) y el porcentaje de grasa corporal durante las clases de educación física. La fuerza de prensión manual se midió dos veces utilizando el brazo dominante, y se registró el mejor resultado. También se recopilaron datos adicionales de la prueba Course Navette, la Escala de Motivación para la Actividad Física y el Ocio (PALMS), el Cuestionario Internacional de Actividad Física (IPAQ) y el Cuestionario de Salud y Bienestar (QHWB). Se utilizó un proceso de validación cruzada anidada, incorporando la selección de características Boruta y regresión ElasticNet. La evaluación del modelo incluyó el error medio, el error cuadrático medio, R^2 y los intervalos de confianza bootstrapped. La muestra incluyó a 867 estudiantes de secundaria (edad media = 14,03 ± 1,19 años; 53,9 % chicos).
Resultados: El modelo mostró un buen rendimiento predictivo: MAE = 3,76 (0,29), RMSE = 4,73 (0,36), R^2 = 0,48 (0,08) y MAE normalizado medio = 9,90 %. Los predictores seleccionados incluyeron la edad (b = 1,86), el sexo (b = -1,03), el IMC (b = 4,16), la grasa corporal (b = -3,94) y las etapas de Navette (b = 1,06).
Conclusiones: Este estudio proporciona evidencia preliminar para un modelo predictivo que estima la fuerza de prensión manual en adolescentes utilizando predictores medibles indirectamente, empleando un enfoque riguroso de aprendizaje automático, que retiene solo los predictores robustos para el cribado de la población.

Palabras clave

Fuerza de prensión manual; adolescentes; cribado poblacional; actividad física; salud musculoesquelética.

Introduction

Handgrip strength (HGS) is generally recognized as a measure of upper limb muscular strength. It also serves as a functional indicator of this body region (Concha-Cisternas et al., 2022; Vaishya et al., 2024). Most studies on this indicator have been conducted in older adults, where HGS has been linked to physical fitness, frailty, and cognitive decline (López-Camacho et al., 2025). HGS is also a relevant indicator of fine motor skills (Wind et al., 2010), and its use appears appropriate for assessing the physical capacity of adolescents. Furthermore, grip strength is considered a significant health biomarker across different stages of life, including adolescence (Ortega et al., 2012). Specifically, low levels of grip strength have been identified as potential predictors of all-cause premature mortality (Soysal et al., 2020). In contrast, higher HGS has been established as a protective factor against cardiovascular and metabolic diseases across various age groups, including adolescence (Fraser et al., 2020). Several studies have found that HGS is commonly associated with anthropometric variables such as sex, age (Kastrati et al., 2024), body mass index (BMI), and body fat percentage in adolescents (Triana et al., 2022). Other studies have reported that grip strength varies by sex, with males generally exhibiting higher strength across different age ranges (Alqahtani et al., 2023; Cooper et al., 2022). A meta-analysis by Nuzzo (2025) on sex differences in grip strength from birth to 16 years of age, encompassing data from 45 countries, concluded that HGS was consistently higher in males, with the greatest sex-related difference observed at age 16, attributed to biological factors. However, as found by Alvear-Vasquez et al. (2020), both HGS and Peak Expiratory Flow (PEF) can predict bone health in boys and girls, serving as indicators of functional fitness.

Several HGS studies indicated that age also influences muscle strength, with the difference becoming more pronounced over time. Therefore, the pubertal stage is crucial in the development of strength among adolescents (Reig et al., 2019). Other factors influencing HGS include metabolic profile and body weight (Blakeley et al., 2018). Specifically, HGS tends to be greater in individuals with normal weight compared to those with obesity. Additionally, fat mass is negatively correlated with grip strength (Cossio-Bolaños et al., 2020), likely because excessive adiposity may impair muscular performance.

However, although there is scientific literature supporting the associations between the variables mentioned, these studies are mainly descriptive and correlational and have mainly explored these predictors in isolation. Therefore, given the limitations of previous studies, there is a need to use predictive approaches based on objective and easily accessible anthropometric variables that allow for the estimation of HGS in adolescents.

Recently, Lima et al. (2025) developed a mathematical model to predict HGS in quilombola children and adolescents, identifying the following as relevant predictive variables: age, height, and lean mass. This study highlights the current interest in developing predictive models of muscle strength in this type of population, although it uses a classical regression approach with a small sample size and focuses on a very specific and vulnerable population.

To consolidate and expand upon these findings, the aim of the present study was to develop a predictive model capable of estimating adolescents' HGS using anthropometric variables (sex, age, BMI, and body fat percentage) as predictors. The hypothesis was that these objective anthropometric variables would demonstrate significant predictive capacity for HG.

Since HGS requires a direct strength assessment, the ability to estimate it using indirect measures, such as questionnaires or self-reported information, would enable wider application of this parameter for large-scale screening purposes. This would allow the identification of adolescents with low muscular strength, who may therefore be at increased risk of developing musculoskeletal or cardiovascular diseases in adulthood or old age. . In this regard, it was decided to include physiological (maximal oxygen consumption) and self-reported measures such as motivation towards PA using the PALMS scale, physical activity levels using the IPAQ questionnaire, and health-related quality of life measured using the QHWB instrument. All of these were administered for exploratory and comparative purposes, without expecting them to act as primary predictors of HGS. However, their inclusion allowed us to examine their possible contribution to the model, as well as to compare them with the objective anthropometric predictors commonly used in epidemiological research.

Method

Design

This is a cross-sectional observation study that followed the STROBE Statement, using the checklist for cross-sectional studies.

Participants

The sample consisted of 867 students enrolled in Compulsory Secondary Education (ESO) from the province of Salamanca, Spain. The mean age was 14.03 ± 1.19 years, ranging from 12 to 16 years, with 53.9% boys (n = 467) and 46.1% girls (n = 400) (see Table 1). Of the total sample, 54.3% (n = 471) attended schools located in urban areas (<10,000 inhabitants), according to the criteria of Chillón et al. (2011). With regard to predictive models, recent literature indicates that considerations regarding sample size should focus on model stability and minimising overfitting, rather than being based exclusively on traditional power calculations. In particular, the required sample size depends on the number of candidate predictors and the expected performance of the model, usually quantified by the predicted R^2, which can be difficult to specify accurately a priori (Riley et al., 2020). In the present study, the initial set of candidate predictors consisted of 34 variables, representing an approximate ratio of 25 participants per predictor (n = 867), which is higher than the usual methodological recommendations for ensuring model stability. In addition, the use of variable selection procedures (Boruta), nested cross-validation, and ElasticNet penalised regression helps to reduce the risk of overfitting and reinforce the robustness of the estimates (Steyerberg, 2019).

The inclusion criteria for the study were: being enrolled in compulsory secondary education, being between 12 and 16 years of age, and regularly attending physical education classes.

On the other hand, the exclusion criteria for the study were: adolescents with recent musculoskeletal injuries, neuromuscular diseases, physical disabilities that prevented them from performing the tests correctly, and those who were undergoing pharmacological treatment that could influence muscle strength.

Participants were selected randomly through a two-stage cluster sampling procedure with proportional allocation. All students in the selected classes were invited to participate. The participation rate was 100% of the students invited to participate, all of whom completed all assessments. Participation was entirely voluntary and without academic or monetary compensation. The study was conducted in accordance with the ethical guidelines established in the current Declaration of Helsinki (Helsinki, 2024), thereby ensuring professional ethics and participant safety. Informed consent was obtained from the participants' parents or legal guardians, and authorization and cooperation were secured from the school. In addition to the informed consent of parents or legal guardians, verbal informed consent was obtained from all participants prior to data collection, in accordance with ethical recommendations for research involving minors. The study was also endorsed by the Pontifical University of Salamanca.

Procedure

The tests were administered in the following order: collection of sociodemographic data, anthropometric measurements, assessment of handgrip strength, and finally, completion of the questionnaires.

Sociodemographic data, Body Mass Index (BMI), and body fat percentage were collected in a single session lasting approximately 30 minutes, during regular Physical Education class hours. Before data collection began, participants received brief instructions and were informed about the confidentiality of their responses.

The measurements were taken by a single, previously trained researcher with specialised training, following a standardised protocol.

At the time of HGS measurement, the dynamometer was calibrated in advance according to the manufacturer's recommendations and the grip width was adjusted to the size of each participant's hand. Participants were then asked to stand upright, with their dominant arm stretched out alongside their body (without bending the elbow), without touching their torso and with their wrist in a neutral position.

They were then instructed to exert maximum grip strength for three seconds, which was performed twice, and the best result was recorded.

During the assessment, the assessor was unaware of the participants' anthropometric characteristics.

To estimate maximal oxygen consumption (VO_2 max), the Course Navette Test, commonly referred to as the 20-meter shuttle run test, was administered. This test serves as an indirect measure of maximal aerobic capacity and allows for the estimation of VO_2 max, expressed in milliliters per kilogram per minute (ml/kg/min) (Jódar, 2003).). For this purpose, the following formula, developed by Léger, Mercier, Gadoury and Lambert (1988) [19], should be applied to children aged 6 to 17.9 years to convert the achieved stages into VO_2 max: VO2 max = 31.025 + (3.238 × VFA) − (3.248 × A) + (0.1536 × VFA × A), where A represents the age of the participant in years, and VFA is the final running speed (velocity) attained, expressed in kilometers per hour (km/h).

Instruments

HGS(HGS) was assessed using a JAMAR hydraulic hand dynamometer (model J00105, Lafayette Instrument Company, USA; capacity: 90kg, weight: 727g), following the protocol established by Roberts et al. (2011).

Body Mass Index (BMI) and body fat percentage were measured using a Tanita body composition monitor, model MC780MA. To obtain reliable measurements with the body composition monitor, subjects must perform the test standing up, without shoes and wearing light clothing, with their legs and arms apart and extended, on an empty stomach and without having exercised for at least the previous three hours.

To assess participants' self-perceived health, the Questionnaire of Health and Well-Being (QHWB) (Torsheim, Välimaa, & Danielson, 2004) was used. We included three questions from QHWB: 1) Would you say your health is (from 1 = poor to 4 = excellent)? 2) In the past 6 months, how often have you experienced any of the following: headache, stomachache, backache, feeling low, irritability, bad mood, nervousness, trouble falling asleep, or dizziness? (from 1 = almost every day to 5 = never or almost never). 3) If on a scale where 10 represents the best possible life for you and 0 represents the worst possible life, where would you say you personally stand at this time? (from 0 = worst possible life to 10 = best possible life).

To assess motivations for engaging in physical activity (PA), we used the Physical Activity and Leisure Motivation Scale (PALMS), originally developed by Morris and Rogers (2004), in its version adapted for Spanish adolescents (PALMS-e). This instrument consists of a total of 25 items grouped into eight motivational factors, with responses recorded using a 5-point Likert scale, where 1 indicates "strongly disagree" and 5 "strongly agree." The eight factors and their corresponding items are as follows: Ego (items 11, 19, and 25), Appearance (items 6, 15, and 22), Others' expectations (items 3, 13, and 18), Affiliation (items 2, 4, 12, and 24), Physical condition (items 5, 9, and 20), Psychological condition (items 1, 8, and 14), Mastery (items 10, 16, and 21), Enjoyment (items 7, 17, and 23). Validation studies of the PALMS in adult populations, such as that by Molanorouzi et al. (2014), reported high internal consistency, with a Cronbach's alpha of 0.82. Similarly, Zach et al. (2012) found satisfactory reliability in an earlier version applied to participants aged 9 to 69 years, with subscale Cronbach's alpha values ranging from 0.63 to 0.96. Santos-Labrador et al., 2021 created and validated a PALMS-e 25 items with adequate fit indices, CFI = 0.933, TLI = 0.918, SRMR = 0.042, RMSEA = 0.052 (90% CI 0.048; 0.056) and good reliability for each of the dimensions, ranging from 0.625 to 0.835.

On the other hand, to assess the level of physical activity engagement, the International Physical Activity Questionnaire (IPAQ) was employed, specifically the version adapted for European adolescents (IPAQ-A) by Hagströmer et al. (2008). This questionnaire divides physical activity into four domains: PA at school, household chores, transport-related PA, and leisure-time PA, sports, and free time, which is further subdivided into walking, moderate, and vigorous activities. In the present study, the sections related to physical activity performed at school (IPAQ-1) and to activity associated with commuting (IPAQ-3) were used.

In the present sample, the self-reported instruments showed adequate internal consistency, with Cronbach's alpha values above 0.70 on the scales analysed.

On the other hand, it is important to note that the PALMS, IPAQ and QHWB instruments were included for exploratory and comparative purposes. Although they were initially collected, they were not incorporated into the final model as they did not improve its predictive capacity, thus avoiding the inclusion of irrelevant variables and reducing the risk of overfitting.

Data analysis

A comprehensive data analysis pipeline was implemented to ensure robust and reproducible predictive modeling. A nested cross-validation procedure was employed to perform feature selection, hyperparameter tuning, and model evaluation, while strictly preventing information leakage.

An external 10-fold cross-validation repeated 10 times was used to partition the data into training and independent test sets. At each external iteration, test samples were completely held out and never accessed during either feature selection or model optimization. All analytical steps described below were performed exclusively on the training data within each external split.

Within each external training set, an internal 10-fold cross-validation loop was implemented to perform robust feature selection using the Boruta algorithm (Kursa et al., 2010) and to tune ElasticNet hyperparameters. Boruta is a wrapper feature selection method based on Random Forests (RF) that identifies relevant predictors by explicitly testing their importance against randomized shadow features. Specifically, shuffled copies of all predictors (shadow features) were appended to the original dataset, and a RF model (100 trees, maximum depth = 5) was trained on this extended feature space. Feature importance scores derived from the RF were then compared between original variables and their corresponding shadow features. Predictors that consistently exhibited higher importance than the maximum shadow importance were confirmed as relevant, whereas those that did not were rejected. This procedure was iterated until a stable set of features was identified within each internal fold.

Feature selection was entirely driven by the Boruta algorithm within the internal cross-validation loop. To further enhance stability and reduce selection variability, features were retained for the final model only if they were selected in at least 80% of the internal cross-validation folds. This frequency-based criterion ensured that only robust predictors consistently supported by the data were included.

Following feature selection, ElasticNet regression was used as the predictive model. ElasticNet was chosen for its ability to simultaneously handle multicollinearity among predictors and enforce model sparsity through the combination of L1 and L2 regularization. Hyperparameter tuning was performed via grid search within the internal cross-validation loop, exploring a logarithmic range of alpha values (regularization strength) and multiple L1 ratio values to balance between ridge-like and lasso-like behavior.

After completion of the internal loop, the most frequently selected hyperparameters across folds were retained. The final ElasticNet model was then retrained on the entire external training set using the features selected in at least 80% of internal folds and the optimized hyperparameters. This final model was evaluated on the left-out external test set, yielding unbiased estimates of predictive performance.

Model performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). In addition, the Average Normalized MAE was computed by normalizing MAE by the observed range of the outcome variable. Performance metrics were aggregated across external test folds, and their mean, standard deviation, and interquartile range were reported.

To assess the stability and interpretability of the models, regression coefficients obtained across external iterations were aggregated. The distribution of coefficients was examined to evaluate consistency, and statistical inference was performed using nonparametric bootstrapping (N = 10000 resamples) to derive 95% confidence intervals and test whether coefficients differed significantly from zero. This procedure allowed assessment of both effect directionality and robustness across resampled datasets.

At every stage of the pipeline, predictors were independently standardized using parameters estimated from the corresponding training data only. This ensured complete separation between training and test information and prevented data leakage. All analyses were implemented in Python using established machine learning libraries.

Results

The initial feature set in our data analysis plan consisted of 34 variables showed in Table 1 which are: Sex (male and female), Age (years), Type of Sport, Tanita BMI, Tanita BodyFat, PALMS questionnaire categories (Ego, Appearance, Others' Expectations, Affiliation, Physical Condition, Psychological Condition, Mastery, Enjoyment/Fun), IPAQ1 categories (School Physical Activity (day per week), School Physical Activity Time (min), School Recess Walking (days per week), School Recess Walking Time (min), School Recess Moderate (days per week), School Recess Moderate Time (min), School Recess Vigorous (days per week), School Recess Vigorous Time (min)), IPAQ3 categories (School Transport Walking (days per week), School Transport Walking Time (min), School Transport Bike (days per week), School Transport Bike Time (min), School Transport Motor Vehicle (days per week), School Transport Motor Vehicle Time (min)), WHWB (question 1, 2, 3), Course Navette Test (Stages, Speed, VO2 max).

Table 1. Characteristics of participants by sex.

Variables	Total	Male	Female
Participants (n) (%)	867 (100)	467 (53.9)	400 (46.1)
Age (years)	14.03 ± 1.19	14.10 ± 1.19	13.96 ± 1.19
Weight (kg)	56.84 ± 11.86	59.66 ± 13.48	53.55 ± 8.93
Height (cm)	163.46 ± 8.33	167.06 ± 8.89	159.28 ± 6.27
Tanita BMI (%)	21.20 ± 3.54	21.25 ± 3.93	21.14 ± 3.04
Tanita Body Fat (%)	23.32 ± 6.65	19.70 ± 6.50	27.67 ± 5.26
HGS(kg)	20.98 ± 6.15	23.93 ± 7.13	17.62 ± 3.91
Type of Sport (%)			
No sport	0.33 ± 0.47	0.26 ± 0.44	0.40 ± 0.49
Individual	0.29 ± 0.45	0.23 ± 0.42	0.35 ± 0.48
Team	0.39 ± 0.49	0.51 ± 0.50	0.24 ± 0.43
PALMS			
Ego	2.52 ± 0.59	2.73 ± 0.55	2.28 ± 0.62
Appearance	3.60 ± 0.49	3.61 ± 0.49	3.60 ± 0.50
Others' Expectations	2.03 ± 0.68	2.10 ± 0.67	1.95 ± 0.69
Affiliation	3.63 ±0.47	3.68 ± 0.47	3.58 ± 0.46
Physical Condition	4.12 ± 0.48	4.10 ± 0.48	4.14 ± 0.48
Psychological Condition	3.68 ± 0.52	3.71 ± 0.53	3.65 ± 0.51
Mastery	3.72 ± 0.53	3.83 ± 0.54	3.59 ± 0.52
Enjoyment/Fun	3.81 ± 0.49	3.95 ± 0.49	3.65 ± 0.48
IPAQ1			
School Physical Activity (dpw)	1.85 ± 0.63	1.84 ± 0.64	1.87 ± 0.62
School Physical Activity Time (min)	88.5 ± 37.21	89.18 ± 36.78	87.71 ± 37.75
School Recess Walking (dpw)	2.06 ± 2.08	1.96 ± 2.05	2.18 ± 2.12
School Recess Walking Time (min)	20.17 ± 27.14	22.36 ± 30.94	17.61 ± 21.64
School Recess Vigorous (dpw)	1.12 ± 1.50	1.42 ± 1.65	0.77 ± 1.22
School Recess Vigorous Time (min)	19.58 ± 31.59	24.23 ± 35.85	14.16 ± 24.70
School Recess Moderate (dpw)	0.92 ± 1.46	0.95 ± 1.47	0.89 ± 1.45
School Recess Moderate Time (min)	17.78 ± 34.78	18.36 ± 35.37	17.12 ± 34.11
IPAQ3			
School Transport Walking (dpw)	2.75 ± 2.62	2.60 ± 2.60	2.92 ± 2.64
School Transport Walking Time (min)	35.88 ± 49.75	38.97 ± 54.96	32.27 ± 42.65
School Transport Bike (dpw)	1.22 ± 1.92	1.44 ± 2.01	0.96 ± 1.79
School Transport Bike Time (min)	32.46 ± 55.85	39.44 ± 59.93	24.34 ± 49.53
School Transport Motor Vehicle (dpw)	3.88 ± 2.92	3.42 ± 2.92	4.43 ± 2.84
School Transport Motor Vehicle Time (min)	47.32 ± 54.45	47.42 ± 58.82	47.20 ± 48.94
QHWB			
Question 1	2.98 ± 0.62	3.06 ± 0.61	2.88 ± 0.63
Question 2	3.69 ± 1.30	3.89 ± 1.24	3.46 ± 1.33
Question 3	7.37 ± 1.55	7.49 ± 1.54	7.22 ± 1.56
Course Navette Test			
Stages	5.38 ± 2.21	6.22 ± 2.33	4.39 ± 1.58
Speed	10.58 ± 1.11	11.01 ± 1.17	10.09 ± 0.80
VO2max	42.54 ± 6.06	44.73 ± 6.28	39.98 ± 4.63

Note: PALMS: Physical Activity and Leisure Motivation Scale, IPAQ: International Physical Activity Questionnaire, QHWB: Questionnaire of Health and Well-Being; dpw: days per week; min: minutes.

Feature consistency

The feature selection procedure selected a total of N=5 features. Age, Sex, and Tanita BMI were selected in 100% of cases. Additionally, Tanita BodyFat was selected in 86% of cases, and Navette Test Stages in

17% of cases. Therefore, Age, Sex, Tanita BMI, and Tanita BodyFat were strongly associated with the outcome variable.

Predictive modeling

Model evaluation on the left-out test sets indicated a good predictive fit, with MAE=3.76 (0.29), IQR=[3.56; 3.95]; RMSE=4.73 (0.36), IQR=[4.46; 4.96]; and R^2=0.48 (0.08) IQR=[0.44; 0.54]. Average Normalized MAE was 9.90 (0.76) indicating that model predictive errors are in the order of 10% on average.

Model coefficients for Age (b=1.86 (0.19); CI=[1.82; 1.90]), Sex (b=-1.03 (0.75); CI=[-1.18; -0.90]), Tanita BMI (b=4.16 (0.98); CI=[3.97; 4.35]), Tanita BodyFat (b=-3.94 (0.24); CI=[-3.99; -3.89]), and Navette Test Stages (b=1.06 (0.22); CI=[0.97; 1.17]) indicated that Age and Tanita BMI are directly associated with HGS. On the contrary, Tanita Body Fat and Sex (males higher than females) are inversely associated with Hand grip strength. Navette Test Stages seems not to be a reliable and generalizable predictor of the dependent variable, despite having a positive effect. In general, models predicted a consistent amount of the observed variance even when tested on previously unseen data, indicating good generalization and robust estimates. In summary, the most relevant features emerged from the analysis were Tanita MBI, and Tanita BodyFat, with positive and negative effects on the HGS outcome variable, respectively. Higher Tanita BMI and lower Tanita BodyFat consistently predicted higher values in HGS. Further, Age and Sex was also associated with the outcome variable, with higher age associated with higher HGS, as well as being male.

Figure 1. Best fit

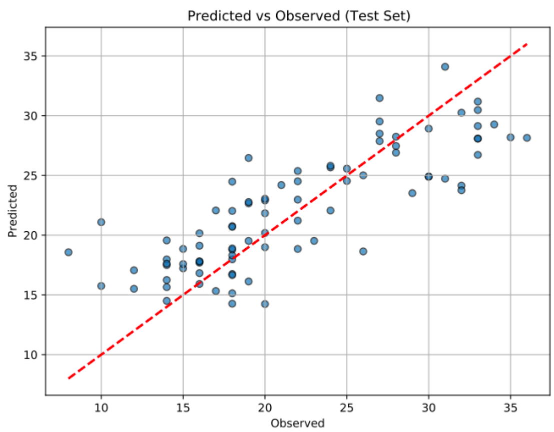
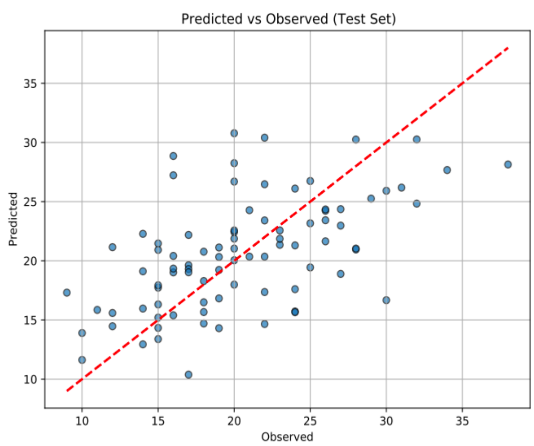


Figure 2. Worst fit



Discussion

The aim of the present study was to develop a predictive model of HGSin an adolescent sample by using a set of anthropometric variables, including sex, age, BMI, and body fat percentage. Specifically, the objective was to develop a predictive model capable of generating robust estimates of HGS based on easily obtainable variables, while also identifying the key factors influencing this parameter. The results of the predictive model showed a good fit, with BMI and body fat percentage emerging as the most significant predictive variables. Therefore, the findings of this study align with growing research in this area. In fact, previous studies had already found associations between sex, age, body composition, and HGS (Martínez-Torres et al., 2022), as well as between HGS and body fat percentage (Méndez-Cornejo et al., 2024), highlighting that lower levels of body fat are related to better HGS performance.

The main contribution of this study lies in the rigorous methodology applied, which involved the use of nested cross-validation. Moreover, models were selected employing a robust machine-learning based complementary technique to perform feature selection in a nested cross-validation procedure through permutation analysis. The controlled procedure and bootstrapping allowed to compute metric distribution and confidence intervals, to further complete model evaluation. Finally, regularized regression ensured model sparcity and addressed potential collinearity (Hajihosseinlou et al., 2024). It is important to note that the analytical strategy was explicitly designed to maximise model stability and generalisation performance at the population level, rather than optimising prediction accuracy at the individual level.

The results of this study have important practical implications, as the proposed model can serve as an effective tool for the early identification of adolescents with low muscle strength, a factor associated with an increased risk of future musculoskeletal and cardiovascular diseases. This underscores the value of timely preventive interventions, such as specific exercise and nutrition programmes aimed at improving muscle strength, to potentially reduce the burden of non-communicable diseases. Grip strength is widely recognised as a reliable indicator of muscle and overall health and has been proposed as a biomarker for various pathological conditions. From a practical perspective, the model is not intended to replace direct assessment of HGS at the individual level, but rather to support population-level screening in educational or public health settings where direct dynamometry may not be feasible.

In such contexts, the model could be used to flag adolescents most likely to have low HGS, leading to further confirmatory assessment. The establishment of specific cut-off points, as well as acceptable thresholds for sensitivity and specificity, was beyond the scope of the present study and should be addressed in future validation research.

In line with these findings, a recent study published by Lima et al. (2025) developed a mathematical model to predict HGS in children and adolescents from quilombola communities, identifying age, height, and lean mass as significant predictors of HGS. Although this study was conducted in a specific vulnerable population and employed a classical regression approach with a relatively small sample size (n = 82), its results support the relevance of anthropometric variables in explaining variability in HGS during childhood and adolescence. Compared to this work, the present study extends previous evidence by utilising a substantially larger sample and adopting a machine learning-based predictive framework with variable selection and penalised regression, which improves model stability and reduces the risk of overfitting, potentially improving its applicability to broader adolescent populations.

Although the proposed model explains approximately 48% of the variance in handgrip strength, this level of explained variance is consistent with previous predictive models developed in adolescent populations using anthropometric and readily obtainable variables. Conversely, when the objective is indirect estimation using widely accessible variables, moderate R^2 values are commonly observed, which are considered acceptable for population-level screening but not for individual diagnosis.

In this regard, Park et al. (2025) developed machine learning models, including polynomial regression, multilayer perceptron (MLP), and Extreme Gradient Boosting (XGBoost), to estimate HGS in healthy adults using demographic, anthropometric, and physical activity data. Among these, the XGBoost model demonstrated the best performance, based on easily measurable variables such as weight, age, height, and waist circumference (Park et al., 2025). Focusing on younger populations, Alshahrani et al. (2025)

applied machine learning techniques, including decision tree and regression models, to predict dominant HGS in children aged 6 to 15 years. Their models identified age, weight, hand span, and BMI as key predictors, explaining up to 66% of the variance in HGS and confirming the utility of computational methods based on simple anthropometric data. Further supporting the role of HGS as a health biomarker, Nazarzadeh et al. (2025) introduced a novel ΔHGS score, calculated as the difference between actual and predicted HGS, using machine learning models. This score was found to correlate strongly with brain structure and neurological changes associated with stroke and major depression, suggesting its potential as a sensitive biomarker for brain health. Additionally, higher HGS has been associated with improved cognitive performance, greater life satisfaction, and lower levels of depression and anxiety, reinforcing its relevance as a biomarker for mental health (Jiang et al., 2022). In pediatric populations, higher relative HGS is linked to lower risks of elevated blood pressure and hypertension, whereas significant asymmetry in HGS between hands (greater than 30%) is associated with increased odds of these conditions (Li & Gu, 2025). Finally, in 18-year-old adolescents, HGS shows a positive correlation with lung function measures such as FEV1 and FVC, suggesting its potential as a surrogate marker for respiratory muscle strength (Hesselberg et al., 2023).

A relevant methodological consideration concerns the inclusion of variables derived from the Course Navette test, a standardised test that allows indirect estimation of maximum oxygen consumption (VO_2 max) and does not assess specific muscle strength. Although these variables were part of the initial set of candidate predictors, their frequency of selection throughout the cross-validation folds was low, indicating a limited and less robust contribution to the final model. However, the fact that the Course Navette involves a structured physical test may reduce the model's viability in contexts where the goal is to minimise the need for physical performance assessments, even when these are indirect.

However, despite its methodological strengths, this study has certain limitations. The first is the type of design, since it is a cross-sectional study and therefore it is not possible to make causal inferences. The second limitation is the absence of external validation in an independent sample, which limits the generalisation of the results. The third limitation is that the sample only comprises adolescents from schools in the province of Salamanca, which may introduce selection bias. Finally, possible seasonal effects were not controlled for, as the time of year may influence body composition and variables related to the physical fitness of adolescents.

Furthermore, the exclusive use of anthropometric variables as predictors of HGS may restrict the model's applicability. Moreover, the relationships identified in this analysis should be interpreted with caution, as the sample includes only adolescents and, therefore, the findings should be generalized solely to this population. Thus, while anthropometric variables are indeed relevant, it must be recognized that HGS is a multifactorial indicator, and other factors could also serve as predictors, including habitual physical activity levels, nutritional status, presence of medical conditions, or individuals' social and economic background (Rodrigues et al., 2017). Additionally, despite machine-learning based feature selection, this study employed a linear approach and was therefore not able to capture potential non-linear associations. Finally, direct hand-related anthropometric measures were not included and have been shown to explain additional variance in related models.

For this reason, and in relation to future research, this study highlights the importance of including other potential predictors in the model, such as lifestyle factors (sleep, physical activity, diet, etc.) or biological markers (e.g., hormonal factors) that may influence HGS prediction in adolescents. The inclusion of such variables could enhance the model's predictive power. Another relevant aspect for future studies would be to assess the effectiveness of interventions or programs designed to improve HGS among adolescents identified as at-risk by the model. Such studies could provide evidence on the most effective strategies to promote adequate HGS and, consequently, better musculoskeletal and cardiovascular health in this population.

Conclusions

In conclusion, this study provides preliminary evidence supporting the development of a predictive model to estimate HGS in adolescents based on anthropometric variables. The findings highlight the relevance of body composition indicators, such as BMI and body fat percentage, in explaining variability in muscle strength during adolescence. However, the moderate proportion of variance explained suggests that the model is more suitable for population-level screening than for establishing an individual diagnosis.

Therefore, the proposed model should be interpreted as a complementary tool for the early identification of adolescents at higher risk of low muscle strength. This means that it needs to be accompanied by other types of confirmatory assessments in cases where this is considered appropriate.

For all the above reasons, the results of this study, which should be considered exploratory, highlight the importance of integrating simple anthropometric information into preventive strategies aimed at improving and promoting cardiovascular and musculoskeletal health in adolescents.

Future research should focus on external validation in independent adolescent populations, refinement of predictive performance, and evaluation of alternative versions of the model.

Finally, the predictive model developed in this study represents a methodological step towards the development of robust and validated tools for adolescent health screening, which may serve as a basis for future large-scale applications once validation and refinement have been completed.

References

Alqahtani, B. A., Alenazi, A. M., Elnaggar, R. K., Alshehri, M. M., Alhowimel, A., Najmi, A. A., Alasraj, M., & Alghadeer, M. (2023). Normative values for hand grip and pinch strength for 6 to 18 year-olds in Saudi Arabia. *BMC Musculoskeletal Disorders*, *24*(1), 96. https://doi.org/10.1186/s12891-023-06197-0

Alshahrani, M. S., Thomas, R. A., Samuel, P. S., Kakaraparthi, V. N., Reddy, R. S., & Dixit, S. (2025). Predictive analysis of dominant handgrip strength among young children aged 6-15 years using machine learning techniques: a decision tree and regression analysis. *Frontiers in pediatrics*, *13*, 1569913. https://doi.org/10.3389/fped.2025.1569913

Alvear-Vasquez, F., Gomez-Campos, R., Pezoa-Fuentes, P., Urra-Albornoz, C., Caceres-Bahamondes, J., Luarte-Rocha, C., Sulla-Torres, J., & Cossio-Bolaños, M. A. (2020). El Flujo espiratorio Máximo y la Fuerza de prensión Manual predicen la salud ósea de niños y adolescentes (Maximum expiratory flow and handgrip strength predict bone health in children and adolescents). *Retos*, *38*, 123-128. https://doi.org/10.47197/retos.v38i38.71786

Blakeley, C. E., Van Rompay, M. I., Schultz, N. S., & Sacheck, J. M. (2018). Relationship between muscle strength and dyslipidemia, serum 25(OH)D, and weight status among diverse schoolchildren: a cross-sectional analysis. *BMC Pediatrics*, *18*(1), 23. https://doi.org/10.1186/s12887-018-0998-x

Chillón P., Ortega F. B., Ferrando J. A., & Casajús J. A. (2011). Physical fitness in rural and urban children and adolescents from Spain. *Journal of Science and Medicine in Sport, 14*(5), 417-423. https://doi.org/10.1016/j.jsams.2011.04.004

Cooper, R., Tomlinson, D., Hamer, M., & Pinto Pereira, S. M. (2022). Lifetime body mass index and grip strength at age 46 years: the 1970 British Cohort Study. *Journal of Cachexia, Sarcopenia and Muscle*, *13*(4), 1995–2004. https://doi.org/10.1002/jcsm.12992

Concha-Cisternas, Y., Petermann-Rocha, F., Castro-Piñero, J., Parra, S., Albala, C., Wyngard, V. V., Vásquez, J., Cigarroa, I., & Celis-Morales, C. (2022). Fuerza de prensión manual. Un sencillo, pero fuerte predictor de salud en población adulta y personas mayores [Handgrip strength as a predictor of adverse health outcomes]. *Revista medica de Chile*, *150*(8), 1075–1086. https://doi.org/10.4067/S0034-98872022000801075

Cossio-Bolaños, M., Gómez-Campos, R., Castelli, L. F., Sulla-Torres, J., Urra-Albornoz, C., & Pires, V. (2020). Fuerza muscular y porcentaje de grasa corporal en niños y adolescentes de la región del Maule, Chile. *Archivos Argentinos de Pediatría*, *118*(3), 216–226. https://www.sap.org.ar/docs/publicaciones/archivosarg/2020/v118n5a07.pdf

Fraser, B. J., Blizzard, L., Buscot, M. J., Schmidt, M. D., Dwyer, T., Venn, A. J., & Magnussen, C. G. (2021). The Association Between Grip Strength Measured in Childhood, Young- and Mid-adulthood and Prediabetes or Type 2 Diabetes in Mid-adulthood. *Sports Medicine*, *51*(1), 175–183. https://doi.org/10.1007/s40279-020-01328-2

Hajihosseinlou, M., Maghsoudi, A., & Ghezelbash, R. (2024). Regularización en modelos de aprendizaje automático para el mapeo de prospectividad de Pb-Zn MVT: aplicación de algoritmos Lasso y Elastic-Net. *Earth Sci Inform*, *17*, 4859–4873. https://doi.org/10.1007/s12145-024-01404-5

Hagströmer, M., Bergman, P., De Bourdeaudhuij, I., Ortega, F. B., Ruiz, J. R., Manios, I., … Sjöström, M. (2008). Concurrent validity of a modified version of the International Physical Activity Questionnaire (IPAQ-A) in European adolescents: the HELENA study. *International Journal of Obesity, 32*(S5), 42–48. https://doi.org/10.1038/ijo.2008.182

Hesselberg, L. M., Kyvsgaard, J. N., Stokholm, J., Chawes, B. L. K., Bønnelykke, I. M., Bisgaard, H., & Vahlkvist, S. (2023). Handgrip strength associates with effort-dependent lung function measures among adolescents with and without asthma. *Scientific Reports*, *13*. https://doi.org/10.1038/s41598-023-40320-4

Jiang, R., Westwater, M. L., Noble, S., Rosenblatt, M., Dai, W., Qi, S., Sui, J., Calhoun, V. D., & Scheinost, D. (2022). Associations between grip strength, brain structure, and mental health in > 40,000 participants from the UK Biobank. *BMC Med, 20*(286). https://doi.org/10.1186/s12916-022-02490-2

Jódar, R. (2003). Revisión de artículos sobre la validez de la prueba de Course Navette para determinar de manera indirecta el VO2 max. *Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte*, 3(11), 173-181. http://cdeporte.rediris.es/revista/revista11/revision.htm

Kastrati, A., Gashi, N., Nazrije, G., Georgiev, G., & Gontarev, S. (2024). Normative Data of Handgrip Strength in Macedonian Children and Adolescents According to Chronological and Biological Age. *International Journal of Morphology*, *42*(1), 147–153. https://www.scielo.cl/pdf/ijmorphol/v42n1/0717-9502-ijmorphol-42-01-147.pdf

Kursa, M. B., Jankowski, A., & Rudnicki, W. R. (2010). Boruta–a system for feature selection. *Fundamenta Informaticae, 101*(4), 271-285. https://doi.org/10.3233/FI-2010-288

Li, H., & Gu, H. (2025). Association between handgrip strength and hypertension in children and adolescents: an analysis of the National Health and Nutrition Examination Survey 2011–2014. *Frontiers in Pediatrics*, *13*. https://doi.org/10.3389/fped.2025.1559556

Lima, L. P., Pontes-Silva, A., Oliveira, I. P., Quaresma, F. R. P., & Maciel, E. (2025). Modelo matemático para predecir la fuerza de prensión manual en niños y adolescentes Quilombolas: un estudio transversal. *Retos*, *62*, 26-30. https://doi.org/10.47197/retos.v62.108681

López-Camacho, M. O., Aguilar-Torres, C. K., Morales-Aguilar, J. J., Cuevas-López, A. A., & Estrada-Díaz, S. A. (2025). Índice de masa muscular esquelética, actividad física, fragilidad y condición física en adultos mayores. *Bioc Scientia*, *1*(1), 2410. https://doi.org/10.63622/RBS.2410

Martínez-Torres, J., Gallo-Villegas, J.A., & Aguirre Acebedo, D.C. (2022). Características antropométricas y de composición corporal asociadas a la fuerza prensil manual en niños y adolescentes. Una Revisión Sistemática Exploratoria. *Andes Pediátrica, 96*(6), 906-917. https://www.andespediatrica.cl/index.php/rchped/article/view/4408/0

Mendez-Cornejo, J., Vidal-Espinoza, R., Alvear-Vasquez, F., Belen-Guzman, A., Gomez-Campos, R., y Cossio, M. (2024). Relación entre adiposidad corporal y fuerza de prensión manual con la preocupación por la alimentación en deportistas universitarios. *Nutrición clínica y dietética hospitalaria, 44*(1),229-236. https://doi.org/10.12873/441mendez

Molanorouzi, K., Khoo, S., & Morris, T. (2014). Validating the Physical Activity and Leisure Motivation Scale (PALMS). *BMC Public Health,* 14(909). https://doi.org//10.1186/1471-2458-14-909

Morris, T., & Rogers, H. (2004). Measuring Motives for Physical Activity. In *Sport and Chance of Life: International Sport Science Congress* (pp. 242–250). The Kansas Association for Health, Physical Education, Recreation, and Dance.

Nazarzadeh, K., Eickhoff, S. B., Antonopoulos, G., Hensel, L., Tscherpel, C., Komeyer, V., Raimondo, F., Müller, V., Grefkes, C., & Patil, K. R. (2024). *Machine Learning-Driven Correction of Handgrip Strength: A Novel Biomarker for Neurological and Health Outcomes in the UK Biobank* (Preprint). medRxiv. https://doi.org/10.1101/2024.11.27.24318057

Nuzzo, J. L. (2023). Sex Differences in Grip Strength From Birth to Age 16: A Meta-Analysis. *European Journal of Sport Science*, *25*(3), 25-e12268. https://doi.org/10.1002/ejsc.12268

Ortega, F. B., Silventoinen, K., Tynelius, P., & Rasmussen, F. (2012). Fuerza muscular en adolescentes varones y muerte prematura: estudio de cohorte de un millón de participantes. *BMJ*, *345*, e7279. https://doi.org/10.1136/bmj.e7279

Park, M., Kim, Y. H., & Lee, J. S. (2025). Machine Learning-Based Model for Grip Strength Prediction in Healthy Adults: A Nationwide Dataset-Based Study. *Journal of Clinical Medicine*, *14*(5), 1542. https://doi.org/10.3390/jcm14051542

Reigl, F., Planas, I., Rosselló, L., Pifarré, J., Ticó, I., & Sans, J. A. (2019). La fuerza dinamométrica en adolescentes: revisión sistemática y percentiles normativos. *Acta Pediátrica Española*, *77*(7-8), e122–e129. https://www.actapediatrica.com/index.php/secciones/originales/1617-la-fuerza-dinamometrica-en-adolescentes-revision-sistematica-y-percentiles-normativos

Riley, R. D., Snell, K. I. E., Ensor, J., Burke, D. L., Harrell, F. E. Jr., Moons, K. G. M., & Collins, G. S. (2019). Minimum sample size for developing a multivariable prediction model: Part II – binary and time-to-event outcomes. *Statistics in Medicine, 38*(7), 1276–1296. https://doi.org/10.1002/sim.7992

Roberts, H. C., Denison, H. J., Martin, H. J., Patel, H. P., Syddall, H., Cooper, C., & Sayer, A. A. (2011). A review of the measurement of grip strength in clinical and epidemiological studies: towards a standardised approach. *Age and ageing*, *40*(4), 423–429. https://doi.org/10.1093/ageing/afr051

Rodrigues, T., Santos, D.A., Chula, J.A., & Destro, D.G. (2017).Handgrip strength and associated sociodemographic and lifestyle factors: A systematic review of the adult population. *Journal of Bodywork and Movement Therapies, 21*(2), 401-413. https://doi.org/10.1016/j.jbmt.2016.08.017

Santos-Labrador, R. M., Melero-Ventola, A. R., Cortés-Rodríguez, M., Sánhez-Barba, M., & Arroyo-Anlló, E. M. (2021). Validation of the Physical Activity and Leisure Motivation Scale in Adolescent School Children in Spain (PALMS-e). *Sustainability,* *13*(14), 7714. https://doi.org/10.3390/su13147714

Soysal, P., Hurst, C., Demurtas, J., Firth, J., Howden, R., Yang, L., Tully, M. A., Koyanagi, A., Ilie, P. C., López-Sánchez, G. F., Schwingshackl, L., Veronese, N., & Smith, L. (2021). Handgrip strength and health outcomes: Umbrella review of systematic reviews with meta-analyses of observational studies. *Journal of Sport and Health Science*, *10*(3), 290–295. https://doi.org/10.1016/j.jshs.2020.06.009

Steyerberg, E. W. (2019). *Clinical prediction models: A practical approach to development, validation, and updating* (2nd ed.). Springer. https://doi.org/10.1007/978-3-030-16399-0

Torsheim, T., Valimaa, R., & Danielson, M. (2004). Health and well-being. En: Currie et al. (eds.). *Young people's health in context. Health behaviour in school-aged children (HBSC): International report from the 2001/2002 survey* (pp. 55-62). Copenague: World Health Organization.

Triana-Reina, H. R., Ortiz-Pacheco, L. E., & Ramírez-Vélez, R. (2022). Menores valores de fuerza de prensión manual se asocian a incremento de los niveles de adiposidad y exceso de peso: un estudio transversal. *Nutricion Hospitalaria*, *39*(4), 752–759. https://doi.org/10.20960/nh.04004

Vaishya, R., Misra, A., Vaish, A., Ursino, N., & D'Ambrosi, R. (2024). Hand grip strenght as a proposed new vital sign of health: a narrative review of evidences. *Journal of health, population, and nutrition*, *43*(1), 7. https://doi.org/10.1186/s41043-024-00500-y

Wind, A. E., Takken, T., Helders, P. J. M., & Engelbert, R. H. H. (2010). Is grip strength a predictor for total muscle strength in healthy children, adolescentes, and young adults? *European Journal of Pediatrics*, *169*(3), 281–287. https://doi.org/10.1007/s00431-009-1010-4

World Medical Association. (2024). World Medical Association Declaration of Helsinki: Ethical principles for medical research involving human participants. Journal of the American Medical Association, 333(1), 71–74.

Zach, S., Bar-Eli, M., Morris, T., & Moore, M. (2012). Measuring motivation for physical activity: an exploratory study of PALMS-the physical activity and leisure motivation scale. *Athletic Insight. 4*(2), 141–152. https://www.proquest.com/docview/1698634442?sourcetype=Scholarly%20Journals

Authors' and translators' details:

Ricardo Manuel Santos Labrador	ricardo.santos@usal.es	Author
Giulio Bertamini	giulio.bertamini@unitn.it	Author
Alejandra Rebeca Melero Ventola	amelero@usal.es	Author
Thomas Zandonai	tzandonai@umh.es	Author and Translator