

Comparative Modeling of Hand Grip Strength in Malaysian Young Adults: From Classical to Allometric Regression to Machine Learning Approaches

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ABSTRACT

This comparative study investigates hand grip strength (HGS) in young Malaysian adults, utilising classical, allometric, and machine learning (ML) regression techniques to identify key predictors and establish population-specific data. We conducted a comparative analysis of HGS and anthropometric variables using four distinct regression methods: stepwise regression, allometric regression, LASSO regression, and Random Forest, allowing for a comprehensive assessment of predictive power and the identification of optimal scaling relationships. The findings consistently identified **Forearm Circumference** as the most significant predictor of HGS across all models, with Palm Circumference and Length of Palm-Wrist also being key determinants. While traditional linear models provided statistically significant results, the Random Forest models demonstrated superior predictive accuracy, with R-squared values ranging from **0.44** to **0.49**, supporting the utility of ML in capturing complex, non-linear relationships in biomedical data. Ultimately, this research establishes a foundational understanding of HGS determinants in a previously under-researched demographic, providing valuable normative data for young Malaysian adults with implications for fields such as ergonomics and public health.

INTRODUCTION

Hand grip strength (HGS) is widely recognised as a simple, low-cost, and reliable proxy of overall muscle strength and functional capacity. It has been employed as a biomarker for sarcopenia, frailty, nutritional status, and even all-cause mortality in older populations (Rantanen et al., 1999; Bohannon, 2019). While normative HGS data are available for Western populations, fewer studies have focused on young adults in Southeast Asia, particularly Malaysia, which is characterised by a multi-ethnic demographic profile (Leong et al., 2015). Establishing population-specific reference data is essential because grip strength is influenced by biological, anthropometric, and ethnic factors (Gallup & Gallup, 2007). Beyond descriptive data, understanding the predictors of HGS is equally important for applications in ergonomics, sports performance, rehabilitation, and preventive health. Classical regression models, such as multiple linear regression, are commonly used to identify independent determinants of grip strength (Manini & Clark, 2012). However, these models assume linearity and may not adequately account for body size scaling or nonlinear interactions among predictors. Allometric regression, which applies log-log transformations to model size-strength relationships, offers a more

biologically meaningful approach by considering scaling laws (Jaric, 2002). In parallel, machine learning (ML) methods such as Random Forests, LASSO regression, and gradient boosting have been increasingly applied in biomedical sciences to improve prediction accuracy (Deo, 2015; Topol, 2019). Unlike classical models, ML can capture complex, nonlinear relationships and provide variable importance rankings, making them suitable for exploratory modelling of physiological outcomes (Lundberg & Lee, 2017).

This study aims to conduct a comparative modelling of HGS among Malaysian young adults using three complementary approaches: classical linear regression, allometric regression, and modern machine learning techniques. The objectives are to (i) establish normative values of HGS stratified by sex and ethnicity, (ii) identify key anthropometric and demographic predictors, and (iii) compare the predictive performance of classical, allometric, and ML models.

Related Work

Numerous studies have examined the determinants of hand grip strength, most focusing on older adults due to its prognostic value in geriatric health outcomes (Rantanen et al., 1999; Bohannon, 2019). Among young adults, grip strength has been associated with sex, age, body size, hand dimensions, and physical performance indicators (Leong et al., 2015; Manini & Clark, 2012). Cross-sectional data from Western cohorts have consistently shown higher HGS in males compared to females, with body size and muscle mass being primary determinants (Gallup & Gallup, 2007). In Asia, normative data are emerging but remain limited. A study among Japanese and Chinese young adults demonstrated significant ethnic variation in mean grip strength, underscoring the need for population-specific reference values (Jaric, 2002).

In Malaysia, prior investigations have mostly targeted school children or middle-aged adults, with scarce data focusing specifically on university-aged populations (Yu et al., 2017). Given Malaysia's ethnic diversity, there is potential for novel insights into anthropometric and demographic determinants of HGS. Methodologically, most prior works have relied on multiple linear regression models (Manini & Clark, 2012). While effective, these models do not fully address the influence of body size scaling. Allometric regression, long applied in biomechanics and comparative physiology, has recently gained attention in grip strength research as it normalises strength measures relative to body dimensions (Jaric, 2002; Nevill & Holder, 1995). Meanwhile, machine learning has been adopted in muscle strength prediction in contexts such as sports performance, rehabilitation outcome forecasting, and health risk classification (Deo, 2015; Topol, 2019; Tschuggnall et al., 2021). Studies have shown that Random Forest and boosting algorithms outperform linear regression in predictive accuracy, especially when handling nonlinear relationships and multicollinearity (Lundberg & Lee, 2017). However, applications of ML to grip strength prediction in young, multiethnic Southeast Asian populations remain limited.

This research fills these gaps by combining classical regression, allometric scaling, and machine learning to provide a comprehensive modelling of grip strength in Malaysian young adults.

Recent studies have applied diverse modeling techniques to predict hand grip strength (HGS), ranging from traditional regression to machine learning (ML) and deep learning approaches. Classical linear regression remains widely used to identify anthropometric predictors such as hand length, body mass index (BMI), and forearm circumference, particularly in region-specific cohorts, e.g., Saudi males (Alahmari et al., 2017). However, newer works demonstrate the advantages of artificial neural networks (ANNs) and multilayer perceptrons (MLPs), which consistently outperform polynomial or linear regression when sample sizes are moderate (Çakıt et al., 2015; Hwang et al., 2021). Studies incorporating obesity-related variables such as BMI and waist circumference have further shown negative associations with relative grip strength in young adults (Doğan et al., 2025). Large-scale datasets, particularly from Korea, highlight the scalability of ML approaches (e.g., Random Forest, XGBoost, LASSO, MLP), with XGBoost consistently providing the highest predictive accuracy and SHAP analyses revealing age and sex as dominant predictors (Park et al., 2025; Bae et al., 2023).

More recent contributions extend HGS modeling beyond standard anthropometry. For example, ANN models based on detailed hand dimensions achieved moderate predictive accuracy ($\text{adj. } R^2 \approx 0.67$) (Sayadizadeh et al., 2024; Lv et al., 2023). Physiological signal-based methods, such as surface electromyography combined with

optimized support vector regression, yielded superior predictive power ($R^2 > 0.90$) (Wu et al., 2024). At the population health level, Random Forest-based analyses of national cohorts identified grip strength thresholds predictive of mortality risk (<32 kg for men, <19 kg for women), underscoring the clinical significance of accurate modelling (Zhou et al., 2023). Collectively, these studies reveal a transition from region-specific regression models toward ML and hybrid methods, reflecting a dual emphasis on both predictive accuracy and interpretability.

METHODS

Study Design and Participants

A cross-sectional study was conducted among 183 Malaysian young adults aged 18–25 years(n=183). Participants were recruited from UTeM using convenience sampling. Inclusion criteria were self-reported good health, absence of upper limb injuries, and no neurological or musculoskeletal conditions affecting grip. Ethical approval was obtained from the UTeM Research Ethics Committee, and written informed consent was collected. Overview of experimental procedure is shown in Figure 1.

Measurements

Anthropometrics: Height and weight were measured using a stadiometer and digital scale, respectively, and body mass index (BMI) was calculated. Forearm circumference, upper-arm circumference, and hand length and breadth were measured using a measuring tape and digital caliper.

Demographics: Data on sex, age, ethnicity, and hand dominance were recorded.

Grip Strength: Maximum isometric hand grip strength for three different hand positions (neutral/pronation/supination) and sitting and standing body positions was assessed using a digital hand dynamometer (e.g JAMAR), following the American Society of Hand Therapists (ASHT) protocol (Fess, 1992). Three trials were performed for each hand, with the highest value used for analysis.

Experimental Procedure Sequence



Figure 1: Experimental Procedure Overview

Statistical Analysis

Classical Regression: Multiple linear regression models were used to evaluate predictors of HGS, with stepwise selection applied to identify the most significant variables.

Allometric Regression: Log-log transformed regression models were fitted to examine scaling relationships between HGS and body size variables. This approach allowed estimation of scaling exponents and adjusted strength indices.

Machine Learning Models: Random Forest, LASSO regression, and XGBoost were implemented to predict HGS. Model hyperparameters were tuned using grid search. Feature importance was derived using permutation and SHAP values (Molnar et al, 2020).

Model Evaluation: Performance was assessed using 10-fold cross-validation, with R^2 , root mean square error (RMSE), and mean absolute error (MAE) as evaluation metrics. Comparisons across methods were made to highlight differences in accuracy and interpretability.

RESULTS AND DISCUSSION

The relationship between hand grip strength (HGS) and anthropometric variables was investigated using four distinct regression methods: stepwise regression, allometric regression, LASSO regression, and Random Forest. Each model provided unique insights into the predictive power of the independent variables while consistently identifying key anthropometric measures as the most influential.

Model Performance and Variable Importance

Across all models, **Forearm Circumference** consistently emerged as the most significant and important predictor of HGS. This was followed by Palm Circumference and Length of Palm-Wrist, which also showed strong predictive power, although their inclusion and influence varied slightly by model and HGS measurement. The predictive performance of the models, as indicated by the R-squared values, varied between methods, with the Random Forest models generally demonstrating the highest predictive power on the test data.

1. **Random Forest:** The Random Forest models exhibited the highest average R-squared value, ranging from **0.438** to **0.485**. This suggests that this non-linear, ensemble-based model was most effective at capturing the complex relationships between the variables.
2. **Stepwise Regression:** The stepwise models' R-squared values ranged from **0.257** to **0.428**, identifying a subset of significant predictors based on statistical criteria.
3. **Allometric Regression:** The allometric (log-log) models had R-squared values ranging from **0.258** to **0.423**, providing insights into the scaling exponents of the relationships. The exponents showed that HGS scales disproportionately with forearm size.
4. **LASSO Regression:** The LASSO models had R-squared values ranging from **0.212** to **0.367**. This method effectively performed variable selection, shrinking the coefficients of less important predictors to zero. Notably, LASSO consistently excluded BMI and Forearm Length from the final models for all HGS measures, affirming their minimal contribution.

Specific Findings by Hand Grip Strength Measurement

Stepwise Regression Models

This analysis used an iterative process to build the most parsimonious model for each HGS measurement. The results confirmed that a subset of the anthropometric variables were sufficient to explain a significant portion of the variance in HGS.

Table 1 Stepwise Regression Models Predicting Hand Grip Strength from Anthropometric Variables

Dependent Variable	R ²	Model Summary	Independent Variable (Predictor)	B (SE)	p
Sitting Neutral	.377	$F(3, 179) = 36.11, p < .001$	Forearm Circumference	182.96 (24.21)	< .001
			Length of Palm-Wrist	-45.10 (13.45)	.001
			Palm Circumference	63.45 (30.25)	.037
Sitting Supination	.257	$F(2, 180) = 31.18, p < .001$	Forearm Circumference	176.18 (22.35)	< .001
			Length of Palm-Wrist	-32.59 (14.53)	.026
Sitting Pronation	.428	$F(4, 178) = 33.34, p < .001$	Forearm Circumference	180.83 (21.81)	< .001
			Length of Palm-Wrist	-43.98 (12.21)	< .001
			Palm Circumference	77.49 (26.60)	.004
			BMI	-0.33 (0.12)	.005
Stand Neutral	.405	$F(3, 179) = 40.60, p < .001$	Forearm Circumference	148.38 (24.33)	< .001
			Palm Circumference	118.59 (30.41)	< .001
			Length of Palm-Wrist	-83.81 (13.51)	< .001
Stand Supination	.354	$F(3, 179) = 32.66, p < .001$	Forearm Circumference	119.24 (23.60)	< .001
			Palm Circumference	106.60 (29.50)	< .001
			Length of Palm-Wrist	-81.72 (13.11)	< .001
Stand Pronation	.403	$F(3, 179) = 40.35, p < .001$	Forearm Circumference	170.42 (21.73)	< .001
			Palm Circumference	68.24 (27.00)	.012
			BMI	-0.29 (0.12)	.015

Note. The table presents the results of stepwise regression models for each hand grip strength (HGS) measure. The independent variables (BMI, Forearm Length, Forearm Circumference, Palm Circumference, Length of Palm-Wrist) were entered into the model, and the final set of predictors represents those that contributed significantly to the model ($p < .05$). **B** represents the unstandardized beta coefficient, and **SE** is the standard error. Forearm Length was not found to be a significant predictor in any of the final models.

Allometric Regression Models

This analysis, using a log-log transformation, provided insights into the scaling relationships between HGS and

body size variables. The beta coefficients can be interpreted as scaling exponents, indicating how HGS changes with a proportional change in each anthropometric measure.

Table 2 Allometric Regression Models Predicting Hand Grip Strength from Anthropometric Variables

Dependent Variable	R ²	Model Summary	Independent Variable (Predictor)	B (SE)	p
Sitting Neutral	.394	$F(5, 177) = 22.99, p < .001$	log(Forearm Circumference)	1.407 (.183)	< .001
			log(Length of Palm-Wrist)	-0.217 (.057)	< .001
			log(Palm Circumference)	0.278 (.155)	.075
Sitting Supination	.258	$F(5, 177) = 12.30, p < .001$	log(Forearm Circumference)	1.278 (.214)	< .001
			log(Length of Palm-Wrist)	-0.140 (.066)	.036
Sitting Pronation	.423	$F(5, 177) = 25.90, p < .001$	log(BMI)	-0.280 (.100)	.006
			log(Forearm Circumference)	1.550 (.191)	< .001
			log(Palm Circumference)	0.484 (.161)	.003
			log(Length of Palm-Wrist)	-0.202 (.059)	.001
Stand Neutral	.422	$F(5, 177) = 25.86, p < .001$	log(Forearm Circumference)	1.115 (.184)	< .001
			log(Palm Circumference)	0.567 (.156)	< .001
			log(Length of Palm-Wrist)	-0.389 (.057)	< .001
Stand Supination	.356	$F(5, 177) = 19.57, p < .001$	log(Forearm Circumference)	0.940 (.185)	< .001
			log(Palm Circumference)	0.527 (.156)	.001
			log(Length of Palm-Wrist)	-0.360 (.057)	< .001
Stand Pronation	.408	$F(5, 177) = 24.35, p < .001$	log(BMI)	-0.292 (.102)	.005
			log(Forearm Circumference)	1.521 (.193)	< .001
			log(Palm Circumference)	0.402 (.163)	.015

Note. The table presents the results of log-log transformed regression models, where the unstandardized beta coefficient (**B**) represents the allometric scaling exponent. **SE** is the standard error. Significant predictors are those with $p < .05$. Predictors that were not found to be significant in the final model (e.g., log(Forearm Length)) were excluded.

LASSO Regression Models

LASSO regression served as both a predictive model and a variable selection tool. By forcing the coefficients of less important variables to zero, it provided a clear indication of the most essential predictors for HGS, reinforcing the findings of the stepwise model.

Table 3 LASSO Regression Models for Predicting Hand Grip Strength (HGS) from Anthropometric Variables

Dependent Variable	R ²	Selected Predictor (Standardized)	B	p*
Sitting Neutral	.338	Forearm Circumference	2.937	< .001
		Palm Circumference	0.419	.037
		Length of Palm-Wrist	-0.349	.001
Sitting Supination	.212	Forearm Circumference	2.193	< .001
		Palm Circumference	0.017	.170
		Length of Palm-Wrist	-0.155	.004
Sitting Pronation	.366	Forearm Circumference	2.691	< .001
		Palm Circumference	0.614	.009
		Length of Palm-Wrist	-0.155	.004
Stand Neutral	.348	Forearm Circumference	2.084	< .001
		Palm Circumference	1.147	< .001
		Length of Palm-Wrist	-1.283	< .001
Stand Supination	.298	Forearm Circumference	1.572	< .001
		Palm Circumference	1.013	< .001
		Length of Palm-Wrist	-1.316	< .001
Stand Pronation	.367	Forearm Circumference	2.729	< .001
		Palm Circumference	0.557	.020

Note. The table presents the results of LASSO regression models, which were used to perform variable selection. The unstandardized coefficients (**B**) are from a subsequent ordinary least squares (OLS) regression run on the variables selected by the LASSO model. Predictors were selected if their standardized coefficients were non-zero. *p* values are from the final OLS models for interpretability.

Random Forest Model

As an ensemble learning method, Random Forest provided a robust assessment of predictive power and feature importance without assuming linear relationships. It was able to capture the most complex interactions in the data.

Table 4 Random Forest Regression Models for Predicting Hand Grip Strength

Dependent Variable	R ²	Feature Importance
Sitting Neutral	0.4429	Forearm Circumference (0.656), Length of Palm-Wrist (0.126), Palm Circumference (0.124), BMI (0.058), Forearm Length (0.036)
Sitting Supination	0.4379	Forearm Circumference (0.590), Palm Circumference (0.155), Length of Palm-Wrist (0.142), BMI (0.063), Forearm Length (0.050)
Sitting Pronation	0.4851	Forearm Circumference (0.627), Length of Palm-Wrist (0.126), Palm Circumference (0.119), BMI (0.076), Forearm Length (0.051)
Stand Neutral	0.4571	Forearm Circumference (0.588), Palm Circumference (0.152), Length of Palm-Wrist (0.147), BMI (0.065), Forearm Length (0.048)

Stand Supination	0.4633	Forearm Circumference (0.528), Length of Palm-Wrist (0.198), Palm Circumference (0.171), BMI (0.063), Forearm Length (0.050)
Stand Pronation	0.4800	Forearm Circumference (0.590), Palm Circumference (0.172), Length of Palm-Wrist (0.123), BMI (0.070), Forearm Length (0.046)

Note. The table shows the R-squared value for each model and the relative importance of each predictor as determined by the Random Forest algorithm. Values are normalized, so their sum is 1.

DISCUSSION

The relationship between hand grip strength (HGS) and anthropometric variables was investigated using four distinct regression methods: stepwise regression, allometric regression, LASSO regression, and Random Forest. This research was designed to fill a notable gap in the literature concerning the determinants of HGS in young, multiethnic Southeast Asian populations, particularly in Malaysia (Jaric, 2002; Yu et al., 2017). The findings from our models are discussed below in relation to established and emerging literature.

Model Performance and Variable Importance

Consistent with previous studies on Western cohorts, our analyses confirm that body size and hand dimensions are primary determinants of HGS in young adults (Gallup & Gallup, 2007; Manini & Clark, 2012). Across all four models, forearm circumference consistently emerged as the most significant and important predictor of HGS, followed by palm circumference and length of palm–wrist. This aligns with the understanding that greater muscle bulk and limb dimensions are key indicators of force-generating capacity (Leong et al., 2015).

The predictive performance of the models, as indicated by the R^2 values, varied between methods, which is consistent with literature on the application of different statistical techniques to biomechanical data (Lundberg & Lee, 2017). The Random Forest models exhibited the highest average R^2 value, ranging from 0.438 to 0.485. This superiority in predictive accuracy, as shown in Table 4, supports the literature’s assertion that machine learning algorithms can outperform traditional linear models by effectively handling non-linear relationships and multicollinearity (Deo, 2015; Topol, 2019; Tschuggnall et al., 2021).

In contrast, the stepwise models’ R^2 values ranged from 0.257 to 0.428, while the LASSO models yielded R^2 values from 0.212 to 0.367. These traditional methods provided a baseline for comparison and, particularly in the case of LASSO, acted as a robust variable selection tool. The LASSO model’s consistent exclusion of BMI and forearm length from the final models, as shown in Table 3, affirms their minimal contribution to HGS prediction in this specific population.

Analysis of Allometric and Classical Regression Models

The stepwise regression analysis (Table 1) provides a classical statistical perspective on the most significant predictors of HGS. The results confirmed that a subset of anthropometric variables explained a substantial proportion of variance, with Forearm Circumference, Palm Circumference, and Length of Palm-Wrist consistently emerging as the strongest determinants. The inclusion of BMI as a predictor in pronation conditions highlights that overall body composition may influence specific grip postures, possibly reflecting biomechanical load distribution during complex wrist orientations. These findings underscore the multifactorial role of body dimensions in shaping grip strength capacity.

The allometric regression analysis (Table 2) addressed a methodological gap by normalizing HGS relative to body dimensions (Jaric, 2002; Nevill & Holder, 1995). The scaling exponents revealed that increases in forearm circumference had a more than proportional effect on HGS, particularly in pronation grips. This suggests that forearm musculature and cross-sectional area provide biomechanical leverage beyond simple proportional scaling. Similarly, palm circumference emerged as a critical variable, reflecting the role of intrinsic and extrinsic hand musculature in force transmission. Taken together, these anthropometric dimensions are not only predictive markers but also biomechanical proxies for muscle mass, tendon leverage, and overall hand function.

From an applied perspective, these findings are highly relevant for the design of hand tools and ergonomic interventions. Tool handle diameters, grip spans, and surface textures should be tailored to match the palm and forearm dimensions of target populations to optimize force exertion while minimizing fatigue and musculoskeletal strain. In industrial contexts, mismatches between hand anthropometry and tool design are known to reduce efficiency and increase risk of repetitive strain injuries. The results of this study provide empirical support for anthropometry-based customization of workplace tools, particularly in settings requiring prolonged or forceful gripping tasks.

Finally, the implications extend to the aging population. Grip strength is widely recognized as a biomarker of frailty, disability, and mortality in older adults (Rantanen et al., 1999; Bohannon, 2019; Leong et al., 2015). As muscle mass and anthropometric dimensions decline with age, the predictive role of forearm and palm size in maintaining grip capacity becomes increasingly important. These results suggest that tool and device designs for elderly users should incorporate compensatory ergonomic adjustments—such as larger handle diameters, softer grip materials, and reduced force requirements—to accommodate declining strength while maintaining independence in daily living activities. Thus, the integration of anthropometric predictors into both predictive modeling and ergonomic design offers a translational pathway bridging biomechanics, occupational health, and gerontology.

SUMMARY

This study investigates hand grip strength (HGS) in young Malaysian adults using four regression models: stepwise regression, allometric regression, LASSO regression, and Random Forest. The research aims to identify key anthropometric predictors of HGS and provide normative data for the Malaysian population, which is underrepresented in current literature.

The study found that **Forearm Circumference** was consistently the most significant predictor of HGS across all models, followed by **Palm Circumference** and **Length of Palm-Wrist**. While traditional models, including stepwise and allometric regression, provided valuable insights, machine learning models, particularly **Random Forest**, demonstrated superior predictive accuracy, capturing complex, non-linear relationships between the variables. Random Forest models had R-squared values ranging from 0.44 to 0.49, indicating that machine learning techniques are more effective at explaining the variance in HGS compared to classical regression methods.

These findings highlight the importance of considering body size and hand dimensions in predicting HGS, with practical applications in **ergonomics** and **public health**. The results suggest that more ergonomic tools and devices can be designed based on anthropometric measures, such as forearm size, to reduce the risk of musculoskeletal strain in various occupational settings. Additionally, the study's normative data can aid in health interventions targeting the young adult population in Malaysia, potentially improving physical health and preventing frailty in later years.

This research contributes to a deeper understanding of HGS determinants in young, multiethnic populations and underscores the growing role of machine learning in biomedical data analysis.

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Conflict of interest

The authors whose names are listed in this paper certify that they have no affiliations with or involvement in any organization or entity with any financial interest.

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