BMC Musculoskeletal Disorders

RESEARCH Open Access

Grip and pinch strength prediction models based on hand anthropometric parameters: an analytic cross-sectional study

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Abstract

Background Hand grip strength (HGS) and pinch strength are important clinical measures for assessing the hand and overall health.

Objective The aim of the present study is to predict HGS and pinch strength based on 1 hand anthropometry, and (2) body anthropometric parameters using machine learning.

Methods A Secondary analysis was conducted on 542 participant aged 30–60 years from the Persian Organizational Cohort study in Mashhad University of Medical Sciences. Artificial Neural Network (ANN) were fitted as prediction model. The dataset was divided into two sets: a training set, which comprised 70% of the data, and a test set, which comprised 30% of the data. Various combinations of the hand anthropometric, demographic, and body anthropometric parameters were used to determine the most accurate model.

Results The optimal HGS model, using the input of gender, body mass, and hand anthropometric parameters of length (both total length and palm), maximum width, maximum breadth, and hand shape index, achieved nearly equal accuracy to the model that incorporated all variables (RMSE = 5.23, Adjusted R^2 = 0.67). As for pinch strength, gender, hand length (both total length and palm), maximum width, maximum breadth, hand shape index, hand span, and middle finger length came closest to the model incorporating all variables (RMSE = 1.20, Adjusted R^2 = 0.52).

Conclusion This ANN model showed that hand anthropometric parameters of total length, palm length, maximum width, maximum breadth, and the hand shape index, emerge as optimal predictors for both HGS and HPS. Body anthropometric factors (e.g., body mass) play roles as predictors for HGS, whereas their influence on pinch strength appears to be less pronounced.

Level of evidence Level III (Diagnosis).

Trial registration Not applicable.

Keywords Anthropometry, Body measures, Neural network model, Hand grip strength, Pinch strength

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Introduction

Handgrip strength (HGS) is defined as the maximum amount of static forceful voluntary flexion of all fingers [1]. Handgrip strength (HGS) is a measure of the strength of the carpal flexor muscles. Every additional hour of light physical activity was associated to a 6-kg increase in HGS among men, but not women [2]. High sedentary time was identified as a cause of sarcopenia due to physical inactivity [2]. Studies suggest that physical well-being and muscle strength, as indicated by HGS, can enhance the quality of life in older adults [3, 4]. Recently, it has also been used as a tool to evaluate and monitor physical characteristics in subjects with certain pathologies [5].

HGS has been shown to be associated with various anthropometric measures, bio impedance parameters such as fat mass and skeletal mass, as well as physical activity levels, among other factors [6]. In grip sports, like rock climbing, basketball and handball, a notable positive correlation has been observed between handgrip strength and a majority of hand anthropometric dimensions [7–9]. These findings hold significant potential for the identification of athletic talent in sports that heavily rely on grip strength [10]. Furthermore, human grip strength plays a pivotal role in the operation of equipment within manufacturing and processing industries, underscoring the importance of assessing and quantifying grip strength to evaluate worker performance [11].

Several studies have been conducted to investigate the relationship between anthropometric measurements and HGS [12–15]. These studies have explored correlations between hand dimensions and maximum grip strength, as well as the influence of variables like grip span and hand dimensions on an individual's maximum grip strength [16]. Predictive models for grip strength have also been developed, encompassing estimates for grip strength, maximum pinch strength, grip strength endurance, and various models for grip strength prediction [17–21]. Notably, a deficiency in data pertaining to hand anthropometrics and grip strength within the Iranian population has led to the design of hand tools in Iran being primarily based on anthropometric data from exporting countries [22]. According to this study, there is significant variation in anthropometric measurements across different ethnicities, including the Iranian population, which is correlated with differences in grip and pinch strength [23]. Compared to other nationalities, Iranian men and women had wider hands with shorter fingers. These differences in hand measurements between the Iranian population and other nationalities [22, 24], underscores the necessity of generating comprehensive data on grip and pinch strength in conjunction with hand anthropometric parameters to support the design of ergonomically sound tools for the Iranian people.

The aim of the present study is to predict HGS and pinch strength based on (1) hand anthropometry, including hand volumes, lengths, and ratios, and (2) body anthropometric parameters using machine learning. We hypothesize that hand anthropometric parameters may serve as indirect predictors of hand strength.

Methods

Study setting and ethics

This study is an analytical cross sectional study in the context of Cohort study at (removed due to blinding), and uses the data gathered in (details omitted for blinding reasons) (POCM), (details omitted for blinding reasons) for 542 personnel who underwent 3D hand scan. The study protocol has received approval from the Iranian MOHME's ethics committee and the institutional review board of the (institution and code are removed for blinding reasons), and adheres to the criteria outlined in the Helsinki declaration. Prior to the study, all participants provide their informed consent, and they were free to decide at any time whether to continue participating or not.

Participants

We evaluate here the 542 employees who underwent hand scan and grip strength measurement in the (removed due to blinding). Patients enrollment process and study design are reported here [25] in details.

Sample size

All the participants who consented and reserved a date through the scheduling system were included in this cohort study. The study encompassed multiple sections for various clinical departments, including internal medicine, nutrition, psychiatry, and cardiovascular medicine, among others. While most sections were mandatory for all participants, three sections were randomly assigned, including orthopedic surgery. Meaning that among each three individuals who enrolled, one person was randomly selected and invited to undergo evaluation in the Orthopedics room. For this study, data collected between 2017 and 2019 in the orthopedics section were utilized. Exclusion criteria were poor hand scan quality, and individuals with insufficient data. Finally, a total of 543 people included in the analysis (Fig.1).

Variables

Demographic information (gender and age), anthropometric parameters (stature, body mass, body mass index and waist circumference) and hand dimensions (hand width and length, ratio of hand width to length, wrist circumference, palm length, maximum breadth, maximum diameter, hand spam and middle, index and ring fingers

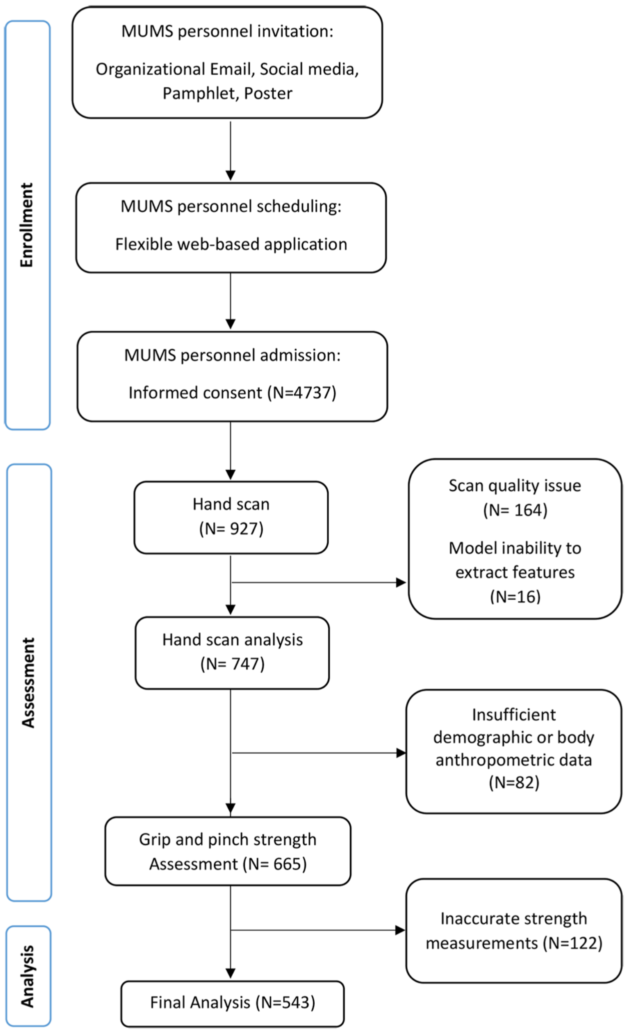

Fig. 1 Population enrollment flowchart

length) were measured as predictor variables. The outcomes of interest were grip and pinch strength.

Three-dimensional (3D) scans and image processing

To obtain a 3D scan of the hand in a neutral position, patients were asked to place their right hand palm down on a flat surface. The fingers were to be slightly spread, but kept relaxed, without excessive tension or bending. The wrist was positioned so that it aligned with the forearm in a neutral, straight posture. The hand needed to remain still during the scan, which was conducted using a scanner equipped with six 3D cameras (PT-3DScan, PAYATECH, Iran, Fig. 2A). Image processing were conducted using Python programming language, and point clouds were applied to recreate 3D images, and calculate the anthropometric indices automatically. Pre-processing was done in two steps to improve the quality of the 3D meshes. The first step involves repairing the meshes, and the second step involves examining the mesh quality and removing outliers. In general, there are two types of algorithms used for mesh repair: surface-based algorithms and volume-based algorithms. In this study, the meshes were repaired using the Python "Pymeshfix" library, which is a powerful tool for repairing 3D meshes, with the volume-based method [26]. Using the "Trimesh" library, we obtained 3D projections in two dimension. The morphologic procedure including "Dulation" and "Erosion" was performed to project mesh points on a 2D surface. As can be seen in Fig. 2C-left, the points in the 3D mesh image on the z=0 plane are not continuous. To solve this problem, dilation and erosion methods, which are morphological operations, are used. In the dilation operation, the value of each pixel is changed to the highest value in the neighboring pixels, which causes filling the gaps between the pixels. Then, using the erosion technique, the value of each pixel changed to the smallest value of the neighboring pixels, which causes the excess thin lines to be removed and only the original shape which gaps remain filled (Fig. 2C-right).

We defined key points for 2D images. Applying the 2D corresponding key points in 3D images, hand 3D anthropometric parameters like volume and circumference were measured (Fig. 2D).

In our methodology for extracting feature points from a 3D mesh by projecting it onto a 2D image and subsequently transforming the points back to the 3D mesh, we propose that the error introduced by this process is negligible. This is based on the following considerations:

Selection of Common Reference Points: We identified two reference points that are easily recognizable in both the 2D image and the 3D mesh:

- The top of the middle finger, corresponding to the bottommost pixel in the 2D image.
- The top of the thumb, corresponding to the rightmost pixel in the 2D image.

Ease of Identification: These reference points were chosen because they can be clearly and unambiguously identified in both the 2D and 3D representations. Locating the bottommost and rightmost pixels is straightforward and reliable, ensuring high accuracy in identifying these points.

High Resolution of 2D Image: In our projection method, every millimeter in the 3D scan was represented by 4 pixels in the 2D image. This high pixel density provides a detailed and accurate 2D representation of the 3D mesh, significantly reducing projection and backprojection errors.

Finding Reference Points in 3D Mesh: The 3D mesh is represented as a list of 3D coordinates. To identify the reference points:

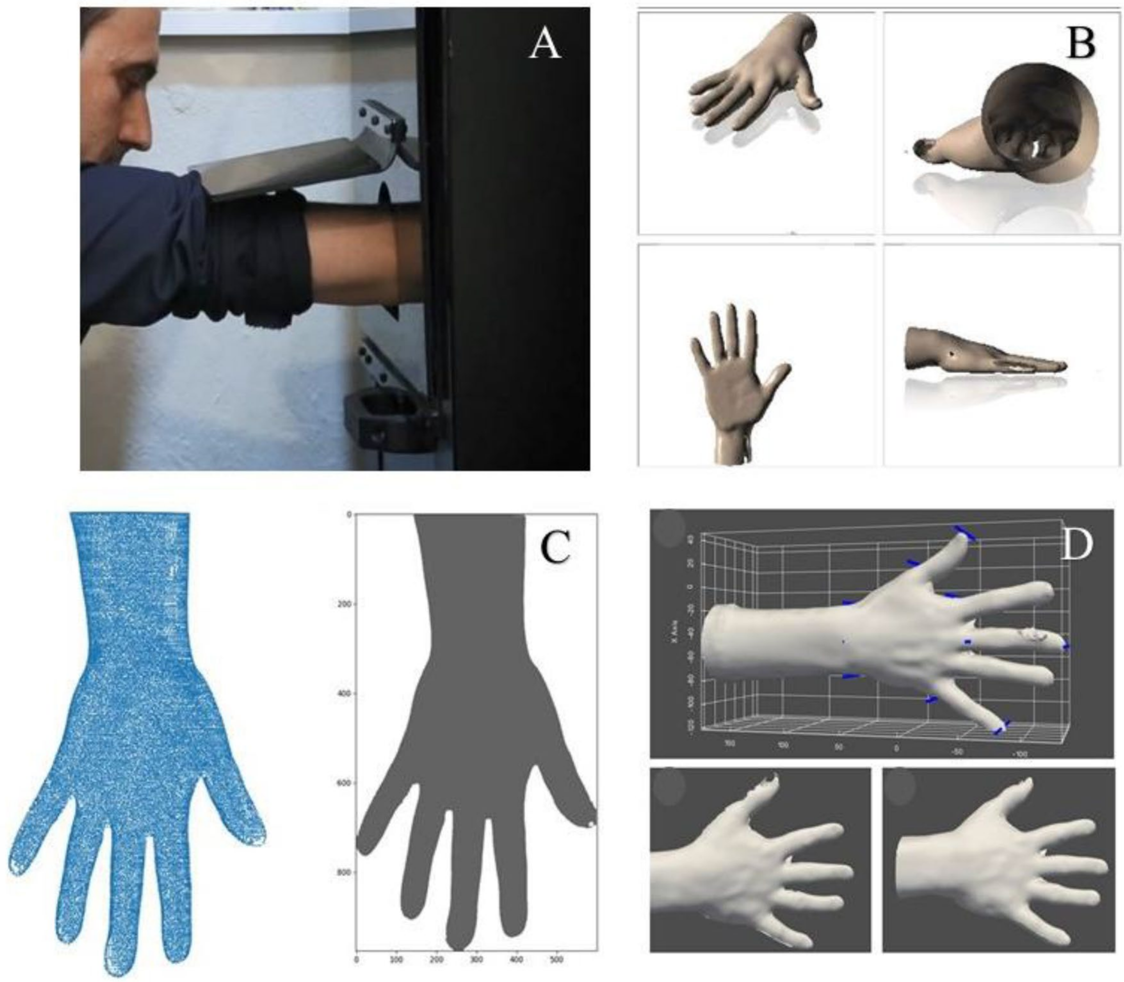

Fig. 2 The limb position in scanner (**A**) and the hand scan output (**B**). The mesh projection points before repair (**C**-left) and the integrated image after repair (**C**-right). The 2D corresponding key points in the 3D images (**D**-above); the 3D image before repair (**D**-left below); the 3D image after repair (**D**-right-below)

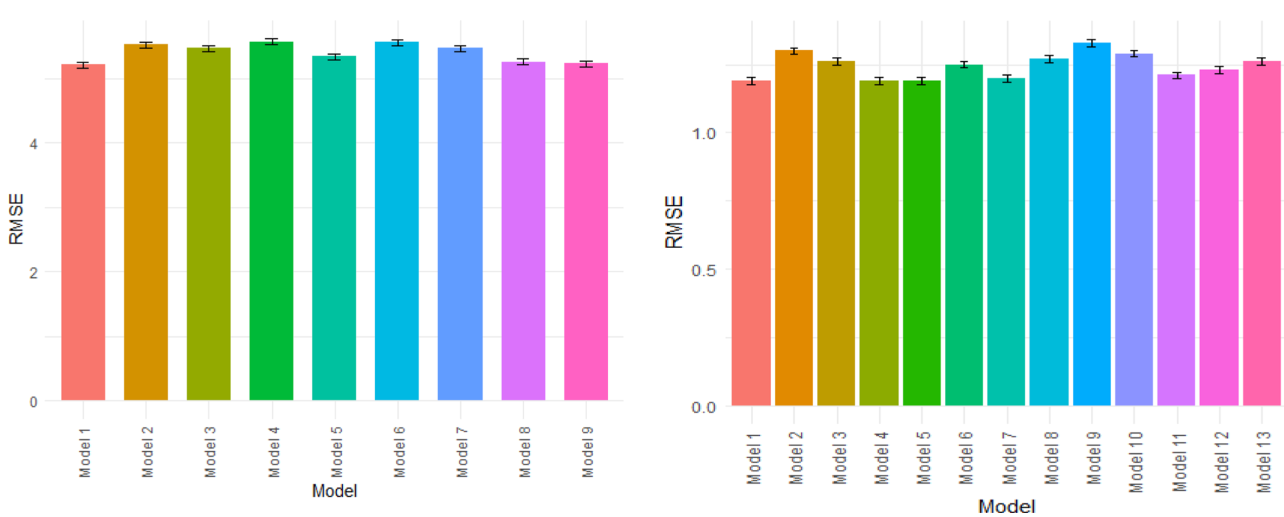

Fig. 3 Root Mean Square (RMSE) for each model of grip (left) and pinch (right) strength by using ANN

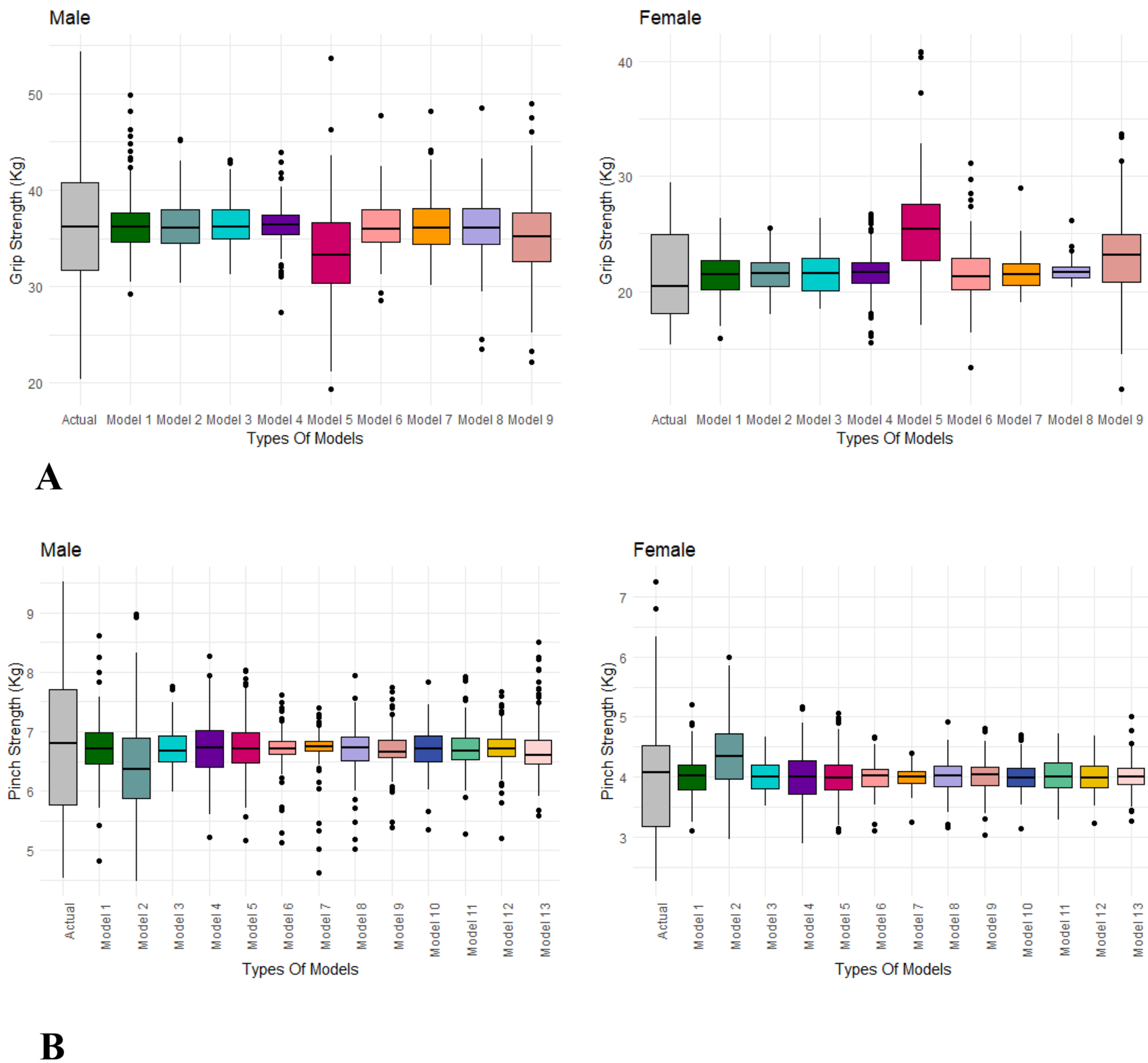

Fig. 4 Comparison of mean actual and predicted grip strength values by gender (**A**) Comparison of mean actual and predicted pinch strength values by gender (**B**)

- For the top of the middle finger, we selected the point with the lowest y-coordinate.
- For the top of the thumb, we selected the point with the highest x-coordinate.

These coordinates accurately correspond to the reference points identified in the 2D image.

Scaling and Correspondence: Once the reference points are identified, calculating the scale and corresponding points between the 2D and 3D versions becomes straightforward. The precise identification of reference points ensures an accurate scaling factor, thereby maintaining correspondence between the 2D and 3D points.

Error Study with Ground Truth Establishment: To further validate our method, we conducted an error study using a subset of 200 samples. Feature points were manually extracted from these samples, and the results were compared to automatically extracted points from the 2D projections.

The average errors, expressed as proportions of the feature values, are as follows: Finger Length at 0.041740, Hand Length at 0.022957, Hand Span at 0.038949, Hand Width at 0.032955, Index1 at 0.055207, Index Length at 0.102851, Max Breadth at 0.083534, Max Diameter at 0.162818, Palm Length at 0.052384, Ring Length at 0.107444, Volume at 0.030052, Wrist Circumference at 0.048310, and Wrist Ratio at 0.124560.

Measurement of grip and pinch strength

Hand grip strength of both hands was measured, with the order of dominant and non-dominant limbs randomized, using a hydraulic hand dynamometer (Jamar, Jackson, MI, USA), by a trained orthopedic surgery resident (PGY2). Each participant completed the three trial for each hand, and the final estimate of HGS was the highest of all measurement (maximum: 200 Ibs (lbs: libra pondo, meaning a pound by body mass) and minimum: 0 Ibs). Also pinch of both thumbs, measured with Lafayette Hydraulic Pinch Gauge (Lafayette Company, Indiana, USA) in the same way (maximum: 45 Ibs and minimum: 0 Ibs). The participants were seated comfortably on a chair without armrest, with his or her back leaned against the chair; with their shoulders adducted, without any rotation, while their elbows were flexed at a 90-degree angle, and their forearms and wrists maintained a neutral position. Each participant was instructed to sit with their hips and knees also flexed at a 90-degree angle.

Statistical analysis

A comprehensive evaluation of our data distribution was performed. We assessed normality through visual inspection using histograms and statistical tests such as the Kolmogorov–Smirnov test. Additionally, univariate analysis was used to examine the differences in hand strength and anthropometric characteristics between genders. For the prediction of grip and pinch strength, an Artificial Neural Network (ANN), a machine learning technique, was employed.

Table 1 Characteristics of the participants based on gender

Variables	Men	Women	*p*-value
Age	42.52 (7.40)	40.56 (6.11)	< 0.001
Height	173.73 (6.02)	159.66 (10.48)	< 0.001
Weight	79.83 (11.05)	67.74 (9.63)	< 0.001
BMI	26.41 (3.14)	26.37 (3.52)	0.890
Waist circumference	98.66 (7.73)	92.12 (9.50)	< 0.001
Hand volume	339.69 (78.31)	341.51 (76.01)	0.805
Hand shape	51.62 (3.47)	51.01 (3.41)	0.067
Hand length	18.69 (1.17)	17.28 (1.05)	< 0.001
Hand width	9.62 (0.49)	8.79 (0.45)	< 0.001
Palm length	10.71 (1.02)	9.83 (0.84)	< 0.001
Middle finger length	8.03 (0.78)	7.52 (0.65)	< 0.001
Index finger length	6.33 (1.01)	6.00 (0.86)	< 0.001
Ring length finger	7.38 (1.31)	6.77 (1.13)	< 0.001
Max breadth	12.27 (1.32)	10.80 (1.41)	< 0.001
Max diameter	6.36 (0.71)	6.42 (0.66)	0.377
Wrist ratio	0.90 (0.14)	0.93 (0.13)	0.035
Grip dominant	36.45 (6.77)	21.61 (3.50)	< 0.001
Grip non-dominant	32.52 (6.41)	19.40 (3.31)	< 0.001
Pinch dominant	6.69 (1.25)	4.00 (1.00)	< 0.001
Pinch non-dominant	5.76 (1.15)	3.37 (0.88)	< 0.001

Artificial neural networks (ANNs)

ANNs have garnered significant attention as a robust modeling technique for predicting outcomes in various domains. They are particularly adept at modeling complex relationships between input variables and output, capturing non-linear relationships, and handling large datasets. A typical neural network comprises an input layer, one or more hidden layers, and an output layer. In the implementation of the Artificial Neural Network (ANN), the data were divided into two sets: the training set and the test set. The training set was used to train the network by adjusting its weights and biases based on input-output pairs. Subsequently, the test set was utilized to evaluate the performance of the trained network by measuring accuracy or error rate. In the ANN analysis, the dataset was split into training (70%) and test (30%) subsets. To mitigate overfitting, cross-validation was employed for validation purposes. The model was trained for a maximum of 3000 epochs using the 'max_iter' parameter. It consisted of two hidden layers, each with 10 neurons, utilizing the ReLU activation function. For optimization, the 'lbfgs' solver was employed. The best model was selected based on the lowest Root Mean Square Error (RMSE) and the highest value of adjusted R-squared, considering the continuous outcome. Various combinations of variables were explored in order to identify the optimal configuration that yields the most accurate predictions while minimizing error. All analysis was performed using R-4.3.1.

Results

Participant characteristics

A total of 543 participants were included in the study, with a mean age of 41.67 years; 43.09% ($n=234$) were women. Detailed characteristics by gender are presented in Table 1. Men had significantly higher mean values for height and weight compared to women ($p<0.001$), while BMI differences were not statistically significant ($p>0.05$). Men also had larger hand dimensions, including hand width, hand length, palm length, middle finger length, index finger length, and ring finger length ($p<0.001$). However, no significant differences were observed in maximum diameter, hand volume, and hand shape ($p>0.05$).

Hand strength

Hand strength was significantly greater in men for both dominant and non-dominant hands ($p<0.001$). The mean grip strength for the dominant hand was 36.45 (6.77) for men and 21.61 (3.50) for women. The mean pinch strength for the dominant hand was 6.69 (1.25) for men and 4.00 (1.00) for women.

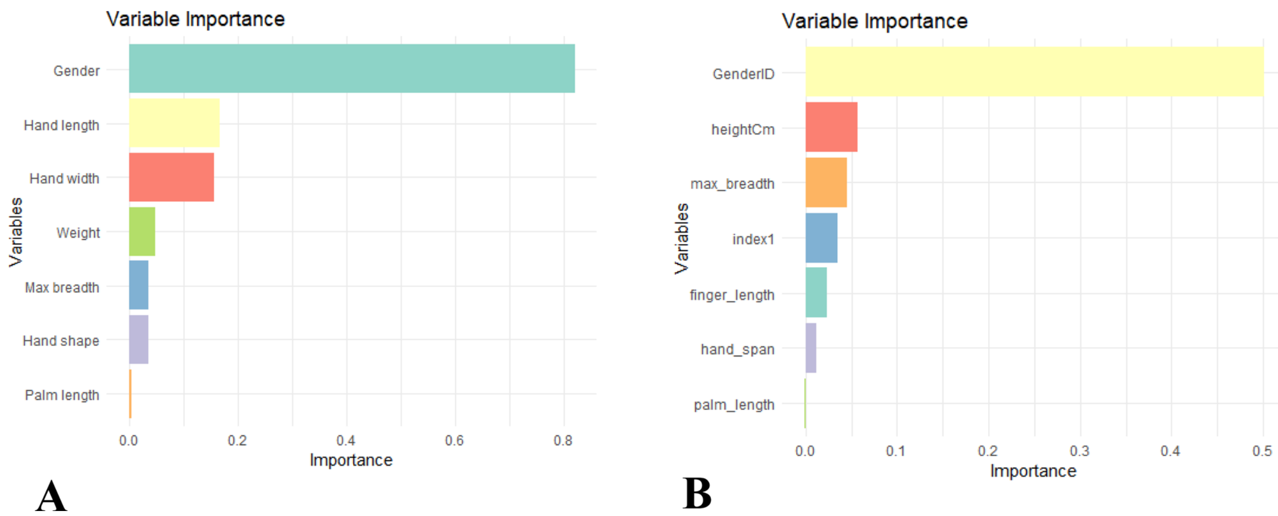

Fig. 5 Key predictors of grips (**A**); key predictors of pinch strength (**B**)

Table 2 Artificial neurall networkk (ANN) results for grip prediction models

Model Details	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**	**Model9**
Inputs									
Gender	*	*	*	*	*	*	*	*	*
Age (year)	*	*		*					
Height (cm)	*	*	*				*	*	
Weight (kg)	*	*	*				*		*
BMI	*	*	*						
Waist Circumference	*	*	*						
Hand volume (cm^3)	*			*	*				
Hand Length (cm)	*			*	*	*	*	*	*
Palm length (cm)	*			*	*	*	*	*	*
Middle finger length (cm)	*			*	*				
Hand Width (cm)	*			*	*	*	*	*	*
Max breadth	*			*	*	*	*	*	*
Hand shape index	*			*	*	*	*	*	*
Index finger length (cm)	*			*	*				
Ring finger length (cm)	*			*	*				
Hand spam (cm)	*			*	*				
Max diameter	*			*	*				
Wrist ratio	*			*	*				
Performance Metrics									
Train-RMSE	**4.98**	5.41	5.04	4.70	5.05	4.92	5.60	5.00	**5.12**
Train-R^2	**0.71**	0.66	0.70	0.74	0.70	0.71	0.63	0.70	**0.69**
Test-RMSE	**5.21**	5.52	5.47	5.57	5.34	5.56	5.47	5.26	**5.23**
Test-R^2	**0.67**	0.63	0.64	0.63	0.65	0.63	0.64	0.66	**0.67**

The neural structures in bold represent the best structures that generated the lowest RMSE

Artificial neural network

The Root Mean Square Error (RMSE) for grip and pinch strength, utilizing various combinations of input parameters (including gender, age, body anthropometric measurements, and hand dimension factors), is presented in Fig. 3.

Grip strength

Table 2 shows the details of the ANN process. Among the input features considered in the ANN model, gender emerged as a significant predictor. To assess the role of age, Models 2 and 3 were developed. However, the results indicated that the inclusion of age led to an increase in RMSE. This trend was consistent when examining the impact of age on grip prediction based on hand dimensions. The best-performing model, with the highest adjusted R-Score and the lowest RMSE, is Model 1, encompassing all the body and hand anthropometric variables for HGS prediction. Consequently, age was excluded from the models to enhance the neural network's performance. Models 6, 7, and 8 represent combinations of the most critical demographic, anthropometric, and hand dimension factors for predicting HGS. Model 9 exhibited mean and standard deviation values for HGS that were highly comparable to the original data and closely aligned with the results of Model 1, despite including only the most influential predictor variables for HGS. The distributions of all predicted values for all models are illustrated in Fig. 4A. In light of these findings, it can be concluded that hand dimensions, including total length, palm length, maximum width, maximum breadth, and the hand shape index (calculated as hand width multiplied by 100 divided by hand length), in conjunction with gender and body mass, are the optimal predictors for grip strength (Table 2). Key predictors of grip strength are illustrated in Fig. 5A.

Pinch strength

As reported in Table 3, the RMSE values for Models 1, 4, and 5 are identical, all equating to 1.19. Similar to grip strength, gender was a significant factor in the ANN modeling of pinch strength, and according to Models 2–5, it remained unaffected by age. Notably, Model 7 demonstrated mean and SD values for pinch strength that closely approximated the original data, aligning closely with the results of Models 2–5 (Fig. 4B). Model 7 underscores that hand length (both total and palm length), maximum width, maximum breadth, hand shape index (calculated as hand width multiplied by 100 divided by hand length), hand span, and middle finger length are the most influential predictors among hand dimension factors. The ANN suggests that hand pinch strength is primarily influenced by hand dimensions, distinguishing it from hand grip strength (Table 3). Key predictors of pinch strength are illustrated in Fig. 5B.

Discussion

The present study predicted hand grip and pinch strength by considering a variety of hand anthropometric parameters, as well as demographic and body anthropometry of the general population, using ANNs. The present study's ANN model demonstrated that hand anthropometric parameters—specifically total length, palm length, maximum width, maximum breadth, and the hand shape index—are the best predictors for both HGS and HPS. While body anthropometric factors, such as body mass, significantly predict HGS, their impact on pinch strength is less significant. Previous studies, indicated that ANN models outperform regression models in accurately predicting grip and pinch strength with smaller RMSEs [17, 27–29].

In a study conducted by Gómez-Campos, it was observed that the relationship between age and hand strength is not linear, as evidenced by the use of nonlinear (cubic) regression analysis models [30]. In another study by Taha Z., which examined Malaysian industrial workers (included 146 participants; age between 18 and 42) using ANN, it was found that the most accurate prediction of grip strength for women involved a combination of age, body mass, wrist circumference, hand length, palm length, and hand breadth. However, in the case of male workers in heavy industries, age did not significantly influence grip strength [17]. Our research revealed that age had a detrimental impact on the performance of ANN, leading to an increase in the RMSE. The findings presented in Carmeli, E.'s study, which demonstrated that hand function diminishes with age in both men and women, especially after reaching the age of 65 [31]. Therefore, as our study's participants fell within the limited age range of 30 to 60 years, this discrepancy in results may be attributed to the less variations in age range, in our study.

Furthermore, our investigation identified maximum hand width and the hand shape index as pivotal predictors of grip strength. These findings supplement the established factors considered in prior studies and highlight their relevance in the context of grip strength analysis.

In a study involving 33 Taiwanese individuals aged 20–40 years conducted by Sung et al., the authors compared stepwise regression and ANN models to investigate the determinants of grip and pinch strength. Their analysis revealed that gender, fingertip to root digit 5 (little finger length), body mass, and maximum hand breadth were identified as the most influential factors for pinch strength [27]. Notably, our study suggested that pinch strength may be predominantly influenced by hand dimensions rather than general body anthropometric characteristics, such as body mass. In a manner consistent with Sung, P.C.'s study, which focused on the comparison of multiple regression and ANN models, our research concentrated on the identification of critical variables with non-linear relationships, primarily using ANN. Notably, our study emphasized the significance of recognizing variables that exhibit non-linear relationships with hand strength. It is worth noting that in Sung, P.C.'s study, the identification of such important non-linear variables may not have been the primary focus.

In comparison to other nationalities, Iranian men and women were found to have wider hands with shorter fingers [22, 24]. Two studies on the Iranian population, consistent with our findings, identified palm width as the best predictor of hand grip strength (HGS) in both

Table 3 Artificial neural network results (ANN) for pinch prediction models

Model Details	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12	Model13
Inputs													
Gender	*	*	*	*	*	*	*	*	*	*	*	*	*
Age (year)	*	*		*		*		*		*		*	
Height (cm)	*	*	*							*	*	*	*
Weight (kg)	*	*	*										
BMI	*	*	*										
Waist circumference	*	*	*										
Hand volume (cm^3)	*			*	*								
Hand length (cm)	*			*	*	*	*			*	*		
Palm length (cm)	*			*	*	*	*	*	*	*	*	*	*
Middle finger length (cm)	*			*	*	*	*	*	*	*	*	*	*
Hand width (cm)	*			*	*	*	*			*	*		
Max breath	*			*	*	*	*	*	*	*	*	*	*
Shape index	*			*	*	*	*	*	*	*	*	*	*
Index finger length (cm)	*			*	*								
Ring finger length (cm)	*			*	*								
Hand span (cm)	*			*	*	*	*	*	*	*	*	*	*
Max diameter	*			*	*								
Wrist ratio	*			*	*								
Performance Metrics													
Train-RMSE	**1.19**	1.30	1.26	**1.19**	**1.19**	1.25	**1.20**	1.27	1.33	1.29	1.21	1.23	1.26
Train-R^2	**0.52**	0.44	0.47	**0.53**	**0.52**	0.48	**0.52**	0.46	0.41	0.45	0.51	0.50	0.47
Test-RMSE	**1.19**	1.30	1.26	**1.19**	**1.19**	1.25	**1.20**	1.27	1.33	1.29	1.21	1.23	1.26
Test-R^2	**0.52**	0.44	0.47	**0.53**	**0.52**	0.48	**0.52**	0.46	0.41	0.45	0.51	0.50	0.47

The neural structures in bold represent the best structures that generated the lowest RMSE genders [32, 33]. This may be due to the presence of strong, bulky muscles and a larger hand skeleton, which enable a better grip on manual tools. Additionally, hand length and hand span showed a significant positive correlation with grip strength in both males and females [33]. Similar results were reported in studies by Wu et al. [34] and Nicolay and Walker [20], where hand length was strongly correlated with grip strength. The variation in HGS across different ethnic groups and nations [23] can also be linked to nutritional factors. This association has been observed particularly in athletes, where a sufficient intake of protein and phosphorus, essential for bone development and muscle growth in the arms, plays a key role [35].

Our study was population-based, meaning that it included individuals from different occupations and with different characteristics. When compared to the studies by Sung, P.C. and Taha Z., our results may be more representative of the general population. Another study conducted by Hwang, J tested various combinations of demographic, anthropometric, and upper extremity and lower body postures to determine the most predictive model using regression and artificial neural networks (ANN). The study collected maximal grip strength data from 164 young adults. The results demonstrated that a combination of all variables (gender, age, body mass, stature, hand width and length, lower body posture, upper arm posture, and forearm posture) are the most important factors for predicting hand grip strength [29]. Our results align with the findings of this study, indicating that grip strength prediction depends not only on hand dimensions but also on body anthropometrics and posture-related variables. When considered together, these factors can lead to more accurate grip strength prediction.

ANN can be influenced by the size of the sample used. Larger sample sizes tend to result in better ANN performance. One of the strengths of our study was that we used a larger sample size than previous studies [17, 27–29]. However, to obtain more consistent results, it would be preferable to conduct the study with an even larger sample size [36, 37]. Despite the application of ANN to identify optimal models and the promising results obtained, Figs. 4 and 5 illustrate that certain participants exhibited a notable variability in their ability to exert maximum hand strength. This variability among a few extreme data patterns has the potential to influence the learning process of ANN significantly. To enhance the performance of ANN, it becomes imperative to compile a more extensive dataset that encompasses a sufficient number of observations representing extreme data characteristics. Moreover, it is worth considering that the input variables utilized in this study may not encompass the entirety of factors associated with hand strength. For instance, individual muscle strength and other personal characteristics, such as physical activity levels, may serve as additional variables to augment the model's predictive capacity. Additionally, our study focused on participants aged between 30 and 60. Given the influence of aging on hand strength, it is advisable that future research extends its scope to include older age groups. This would allow for a more comprehensive understanding of the dynamics of hand strength across the lifespan.

Conclusion

The ANN model showed that hand anthropometric parameters of total length, palm length, maximum width, maximum breadth, and the hand shape index, emerge as optimal predictors for both HGS and HPS. Body anthropometric factors (e.g., body mass) play roles as predictors for HGS, whereas their influence on pinch strength appears to be less pronounced.

Acknowledgements

We appreciate the assistance with the submission from Shahryar Hashemi. We also thank PERSIAN cohort study in Mashhad University of Medical Science.

Author contributions

MS: Methodology, Investigation, Statistical Analysis, Proofreading. MD: Investigation, Manuscript Writing, Proofreading. MR: Methodology, Statistical Analysis, Investigation. PS: Methodology, Investigation. MS: Methodology, Statistical Analysis, Proofreading. JKM: Proofreading, Manuscript Editing. AM: Conceptualization, Methodology, Supervision, Proofreading.

Funding

This work was supported as a research project financed by the Research Council of Mashhad University of Medical Sciences (research project number 4001209).

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. Correspondence and requests for materials should be addressed to MoradiAL@mums.ac.ir, almor0012@gmail.com.

Declarations

Ethics approval

This study is performed in accordance with the ethical standards in the 1964 Declaration of Helsinki. The study protocol has received approval from the institutional review board of Mashhad University of Medical Sciences (MUMS) with the Approval ID: IR.MUMS.MEDICAL.REC.1401.130.

Informed consent

Patients were provided with and signed written informed consents prior to recruitment.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Statement of the location

Present study was performed in Orthopaedics Research Center, Ghaem hospital, Mashhad University of Medical Sciences (MUMS).

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Received: 19 April 2024 / Accepted: 1 October 2024
Published online: 12 October 2024

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