

Effect of Physical Fitness on Body Mass Index through Artificial Intelligence in South Chinese College Students from 2013 to 2025

Xi Jin

Louisiana State University in Shreveport

Zhonghui Wang

Louisiana State University in Shreveport

Xin Zhao

Nanshan People's Hospital

Yang Wen

Shenzhen University

Chunbo Qin

bonnieq@szu.edu.cn

Shenzhen University

Research Article

Keywords: physical fitness, BMI, college students, AI

Posted Date: July 20th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10216470/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at BMC Public Health on August 26th, 2026. See the published version at <https://doi.org/10.1186/s12889-026-29148-5>.

Abstract

Purpose

This study investigated the effect of physical fitness on BMI and evaluated the predictive performance of fitness indicators using artificial intelligence (AI). Methods: A total of 83,664 first-year college students (43,734 males and 39,930 females) from Shenzhen University, China, were included (2013–2025). Fitness assessments included vital capacity, standing long jump, sit-and-reach, 50 m sprint, long-distance running (800 m in females, 1,000 m in males), and pull-ups (males) or sit-ups (females). Four supervised machine learning algorithms (Logistic Regression, Decision Tree, Random Forest, and XGBoost) were developed and compared for BMI prediction. XGBoost achieved the highest predictive performance and was subsequently used to assess feature importance, including analyses stratified by gender. Results: The model showed good predictive accuracy (75% in males, 83% in females), indicating a strong association between fitness and BMI. Pull-ups were the most important predictor in males, while vital capacity and long-distance running showed strong predictive effects in both genders. Conclusions: Physical fitness is closely associated with BMI, and AI models can effectively predict BMI using routine fitness data. These findings support the use of fitness assessments as practical tools for screening and promoting weight management among young adults.

Introduction

Economic development and social progress have driven substantial transformations in modern lifestyles. Among young adults - particularly college students - there has been a notable increase in screen time and a growing tendency toward physical inactivity. A multinational survey conducted across 24 universities in 23 countries reported that approximately 41% of college students are physically inactive (Pengpid et al., 2015). Physical inactivity is widely recognized as a major contributor to elevated body mass index (BMI), which in turn leads to overweight and obesity. In China, data from 2017 indicate that the prevalence of overweight and obesity among college students was 9.5%, with higher rates observed in males (13.5%) compared to females (6.1%) (Jiang et al., 2018). Moreover, increased BMI is associated with a greater risk of chronic diseases, including cardiovascular disease, which may ultimately reduce life expectancy (Khan et al., 2018). Therefore, it is crucial for college students to establish a healthy lifestyle. This is particularly important for first-year students, who are undergoing a critical transitional phase from adolescence to adulthood.

Physical capacity can be effectively assessed through standardized physical fitness tests. In China, systematic physical fitness testing can be traced back to the 1950s, when assessments were designed to evaluate students’ aerobic fitness, muscular strength and endurance, flexibility, power, as well as basic life and sport-related skills. Over more than half a century of development and refinement, the focus of these assessments has gradually shifted from skill-related fitness to health-related fitness, reflecting an increased emphasis on public health and disease prevention. Contemporary physical fitness tests comprise multiple components, including body composition (BMI), pulmonary function (vital capacity), cardiovascular endurance (short- and long-distance running), muscular strength and endurance (pull-up or sit-up), flexibility (sit-and-reach), and explosive power (standing-long-jump). To better understand and promote physical fitness among Chinese college students, participation in these tests is mandatory. Test results are integrated into academic evaluation systems and are often linked to grade point average, scholarship eligibility, and other academic honors (Dong et al., 2023; X. Liu et al., 2017). Furthermore, physical fitness testing serves as an effective tool for assessing college students’ fitness levels, as well as for promoting physical activity and the adoption of healthy lifestyle behaviors.

In recent years, physical fitness among Chinese college students has shown a general decline (Dong et al., 2023), accompanied by a concurrent increase in the prevalence of obesity (Jiang et al., 2018). It is reasonable to hypothesize that higher BMI is associated with poorer physical fitness performance, as excess body fat imposes additional mechanical and metabolic demands, thereby increasing energy expenditure (Ding & Jiang, 2020). Several studies have supported this assumption, demonstrating negative associations between BMI and various components of physical fitness (Qin et al., 2022; Yin et al., 2025). However, inconsistent findings have been reported regarding the relationships between BMI and certain fitness indicators, such as vital capacity (X. Chen et al., 2020a; Karmacharya et al., 2019) and flexibility (Gite et al., 2021a). Meanwhile, with the rapid advancement of artificial intelligence (AI), the application of AI in health area offers new opportunities to more precisely characterize the relationship between BMI and physical performance. Therefore, the present study aims to investigate the effect of physical fitness test outcomes on BMI among Chinese college students using AI-based analytical approaches.

Methods

All participants were first-year undergraduate students enrolled at Shenzhen University, China, between 2013 and 2025. Most participants were from southern regions of China and thus are considered broadly representative of college students from southern China. After excluding cases with extreme values or missing data, the final analytic sample included 43,734 males (52%) and 39,930 females (48%). Sample size of each enrolled year was listed in Table 1. All participants provided written informed consent prior to participation, and the study was approved by the Institutional Review Board of Shenzhen University (PN-202300025).

Table 1
Sample size in each enrolled year (n = 83,664)

Male	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Total
	2,367	2,819	2,902	2,762	3,319	2,858	4,056	4,154	3,790	3,564	3,637	3,489	4,017	43,734
Female	2,641	2,914	2,669	2,704	3,260	2,963	3,466	3,378	3,180	3,112	3,236	3,084	3,323	39,930

Body mass index (BMI) was calculated as body mass (kilogram) divided by the square of height (m²). As all participants were college students, the sample comprised young adults. In accordance with the guidelines issued by the Ministry of Education of China, BMI was classified into four categories: underweight

(< 17.8 for males and < 17.1 for females), normal weight (17.9–23.9 for both genders), overweight (24.0–27.9 for both genders), and obesity (≥ 28.0 for both genders).

Physical Fitness Tests

Physical fitness data were collected on the campus of Shenzhen University by qualified physical education specialists who had received standardized training. Participation in the physical fitness tests was mandatory for all students in normal health without restrictions on physical activity. The testing protocols followed the Chinese National Student Physical Fitness Standards, which are issued and endorsed by the Ministry of Education of the People's Republic of China. The test battery included vital capacity (VC), standing long jump (SLJ), sit-and-reach (SR), 50-meter sprint (50 m), 800-meter (800 m) run only for females, 1,000-meter (1,000 m) run only for males, pull-ups (PU) only for males, and sit-ups (SU) only for females. Due to differences in the physical fitness tests administered to males and females, all statistical analyses were conducted separately by gender.

Vital capacity (VC) Participants first inhaled deeply and then exhaled maximally into a sterile mouthpiece, and the highest recorded lung volume (mL) from repeated trials was used for analysis.

Standing long jump (SLJ) Participants jumped forward from a standing position with both feet simultaneously, and the horizontal distance from the take-off line to the nearest landing point was recorded, with the best performance retained.

Sit-and-reach (SR) Participants sat with legs extended and reached forward along a measuring scale as far as possible, and the maximum distance achieved was recorded.

50-meter sprint (50 m) Participants started from a standing position and sprinted to the finish line on command, and the time taken to complete the distance was recorded using a stopwatch.

800-meter run (800 m) for females and **1,000-meter run (1,000 m)** for males Participants ran the prescribed distance on a track following a start signal, and completion time was recorded, with shorter times indicating better performance.

Pull-ups (PU) for males Participants performed repetitions on a horizontal bar, raising the body until the chin passed above the bar, with only correctly executed repetitions counted.

Sit-ups (SU) for females Participants performed repeated trunk flexions from a supine position with knees bent, and the number of correct repetitions completed within the test period was recorded.

Artificial Intelligence-Based Data Analysis

Recent advances in artificial intelligence have enabled researchers to identify complex nonlinear relationships among multiple physiological variables that cannot be adequately captured using conventional statistical techniques. Traditional statistical models, such as linear regression, generally assume linear relationships between predictor variables and outcomes and often require independence among predictors. However, physical fitness components - including muscular strength, pulmonary function, flexibility, explosive power, sprint performance, and endurance - are highly correlated and may interact in complex nonlinear ways when predicting BMI. Machine learning algorithms overcome these limitations by automatically learning nonlinear decision boundaries and high-order interactions directly from the data without requiring explicit assumptions regarding the underlying distributions (Bishop & Nasrabadi, 2006; Hastie et al., 2009).

To comprehensively evaluate the predictive capability of routine physical fitness assessments, four representative supervised machine learning algorithms were implemented in this study: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost). These algorithms represent four fundamentally different machine learning paradigms, including linear statistical learning, nonlinear recursive partitioning, bagging ensemble learning, and gradient boosting ensemble learning, respectively. Comparing multiple algorithms rather than relying on a single model provides a more objective assessment of predictive performance and enables the identification of the most appropriate model for BMI prediction.

The predictor variables included six routinely collected physical fitness indicators: vital capacity, standing long jump, sit-and-reach, 50-meter sprint, 1000-meter run for males or 800-meter run for females, and pull-ups for males or sit-ups for females. BMI category served as the prediction target. Because different physical fitness tests were administered to male and female students, all machine learning analyses were performed independently for each gender.

Data Preprocessing

Data preprocessing was performed before model development to improve data quality and ensure robust model performance. First, duplicated participant records were removed so that each student contributed only one observation to the dataset. Records containing missing BMI values were excluded because BMI served as the prediction target. For the remaining numerical predictor variables, missing observations were imputed using the arithmetic mean of each feature,

$$x_j = \frac{1}{n} \sum_{i=1}^n x_{ij}$$

where x_{ij} represents the value of feature j for participant i , and n denotes the total number of observed samples.

Because the predictor variables were measured using different physical units, including milliliters (vital capacity), centimeters (standing long jump), seconds (running tests), repetitions (pull-ups and sit-ups), and centimeters (sit-and-reach), all continuous variables were standardized using Z-score normalization,

$$z = \frac{x - \mu}{\sigma}$$

where x denotes the original observation, μ is the feature mean, and σ represents the standard deviation. Standardization prevents variables with larger numerical scales from dominating the optimization process and improves convergence for algorithms such as Logistic Regression.

After preprocessing, the dataset was randomly divided into training (80%) and testing (20%) subsets using stratified sampling to preserve the original BMI category distribution. A fixed random seed (42) was adopted to ensure reproducibility.

Logistic Regression

Logistic Regression was selected as the baseline statistical learning algorithm because of its simplicity, computational efficiency, and excellent interpretability. Logistic Regression estimates the posterior probability of each BMI category using the SoftMax function,

$$P(y = k | x) = \frac{e^{\beta_k^T x}}{\sum_{j=1}^K e^{\beta_j^T x}}$$

where x represents the feature vector, K denotes the number of BMI categories, and β represents the regression coefficients learned during model training.

Although Logistic Regression assumes approximately linear relationships between predictors and outcomes, it provides an important benchmark for evaluating whether more sophisticated nonlinear models offer substantial performance improvements (Bishop & Nasrabadi, 2006).

Decision Tree

Decision Tree is a nonlinear classification algorithm that recursively partitions the feature space into increasingly homogeneous subsets. At each internal node, the algorithm selects the predictor that minimizes node impurity according to the Gini Index,

$$G = 1 - \sum_{i=1}^K p_i^2$$

where p_i denotes the proportion of observations belonging to BMI category i .

Decision Trees provide highly interpretable decision rules and naturally model nonlinear interactions without requiring feature scaling or distributional assumptions. However, single decision trees are susceptible to overfitting and high prediction variance (Breiman et al., 1993).

Random Forest

Random Forest addresses the instability of single Decision Trees by constructing a large ensemble of bootstrap-sampled decision trees. During training, each tree is generated using a random subset of both observations and predictor variables. Final classification is obtained through majority voting,

$$\hat{y} = \text{mode}(T_1, T_2, \dots, T_n)$$

where T_i denotes the prediction produced by the i^{th} decision tree.

Random Forest generally improves predictive accuracy while substantially reducing overfitting through bootstrap aggregation (bagging) (Breiman, 2001).

XGBoost

XGBoost is an advanced gradient boosting algorithm that sequentially constructs decision trees by minimizing a regularized objective function,

$$Obj = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where $L(\cdot)$ denotes the classification loss function, f_k represents each regression tree, and $\Omega(\cdot)$ is a regularization term controlling model complexity.

Unlike conventional boosting methods, XGBoost employs second-order Taylor expansion, gradient optimization, shrinkage, tree pruning, column subsampling, and both L1 and L2 regularization to improve predictive performance while reducing overfitting (T. Chen & Guestrin, 2016). Because physical fitness variables exhibit complex nonlinear interactions, XGBoost was expected to outperform traditional statistical models.

Model Training Strategy

All machine learning algorithms were implemented using Python (version 3.x), Scikit-learn, and the XGBoost library. Model development followed a standardized workflow to ensure fair comparison among algorithms. Each model was trained using identical training and testing datasets, identical preprocessing procedures, and identical evaluation metrics.

To further reduce potential model bias and improve generalizability, hyperparameters were selected according to widely accepted recommendations in the machine learning literature. For Random Forest and XGBoost, ensemble size, tree depth, and learning rate were optimized to balance predictive accuracy and model complexity while minimizing overfitting.

Cross-Validation

In addition to the independent testing dataset, five-fold stratified cross-validation was performed during model development. The training dataset was randomly divided into five equally sized subsets while preserving the class distribution. During each iteration, four subsets were used for model training, and the remaining subset was used for validation. The average performance across the five folds was calculated as the final cross-validation score. This procedure provides a more reliable estimate of model generalizability and reduces performance fluctuations resulting from a single train-test split.

Model Evaluation

Model performance was evaluated using Accuracy, Precision, Recall, and weighted F1-score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN} \quad F_1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The model achieving the highest weighted F1-score and overall classification accuracy was considered the optimal predictor.

Feature Importance Analysis

To identify the physical fitness variables contributing most strongly to BMI prediction, feature importance analysis was performed using the trained tree-based models. For XGBoost, feature importance was quantified using the cumulative reduction in the objective function (Gain) contributed by each predictor across all decision trees.

$$Importance_j = \frac{\sum Gain_j}{\sum_{k=1}^p Gain_k}$$

where $Gain_j$ denotes the total reduction in classification loss contributed by predictor j , and p represents the total number of predictors.

Variables with larger importance scores contributed more substantially to BMI prediction and were interpreted as having stronger associations with body composition.

Why XGBoost Was Selected

Rather than assuming XGBoost to be the optimal algorithm, all four machine learning models were first trained and evaluated using identical datasets and preprocessing procedures. The predictive performances of Logistic Regression, Decision Tree, Random Forest, and XGBoost were compared using Accuracy, Precision, Recall, and weighted F1-score. XGBoost consistently achieved the highest predictive performance across both male and female datasets. Consequently, XGBoost was selected as the final model for feature importance analysis and biological interpretation.

Results

As shown in Tables 2 and 3, the mean BMI for both genders fell within the normal range. A higher proportion of females were classified as normal weight compared with males (83.84% vs. 69.37%). In addition, the prevalence of overweight and obesity was lower among females than among males. Detailed results for each physical fitness test are presented in Table 3.

Table 2
Description of BMI in males and females

Underweight	Males (n = 43,734)	Females (n = 39,930)
	Number (percentage)	Number (percentage)
	4,061 (9.29%)	2,777 (6.96%)
Normal weight	30,330 (69.37%)	33,471 (83.84%)
Overweight	6,986 (15.98%)	2,953 (7.40%)
Obese	2,344 (5.36%)	720 (1.80%)

Table 3
Descriptive statistics for sample size

Age (years)	Male (n = 43,734)	Female (n = 39,930)
	Mean $\pm$ SD	Mean $\pm$ SD
	19.16 $\pm$ 1.26	19.09 $\pm$ 1.19
BMI (kg/m ²)	21.63 $\pm$ 3.57	20.40 $\pm$ 2.88
Vital capacity (milliliters)	4037.09 $\pm$ 912.36	2719.38 $\pm$ 648.36
Standing long jump (centimeters)	201.39 $\pm$ 53.57	147.63 $\pm$ 43.11
Sit-and-reach (centimeters)	11.93 $\pm$ 7.68	16.02 $\pm$ 7.12
50-m running (seconds)	7.73 $\pm$ 0.81	9.61 $\pm$ 0.91
800-m running (seconds)	None	265.82 $\pm$ 43.99
1,000-m running (seconds)	263.39 $\pm$ 41.48	None
Pull-ups (times)	7.08 $\pm$ 5.47	None
Sit-ups (times)	None	32.79 $\pm$ 9.29
SD: standard deviation		

AI-Based BMI Prediction

To identify the most suitable AI algorithm for predicting BMI categories from routine physical fitness measurements, four supervised machine learning models, including Logistic Regression, Decision Tree, Random Forest, and eXtreme Gradient Boosting, were developed and evaluated separately for male and female students. Model performance was assessed using Accuracy, Precision, Recall, and weighted F1-score on an independent testing dataset.

Model Performance Comparison

For the male dataset, XGBoost achieved the highest overall predictive performance with an accuracy of 75.33%, a weighted precision of 68.11%, a weighted recall of 75.33%, and a weighted F1-score of 68.92%. Random Forest demonstrated comparable performance, with an accuracy of 74.93% and a weighted F1-score of 68.65%, whereas Logistic Regression achieved an accuracy of 74.67% and a weighted F1-score of 66.46%. Decision Tree produced the lowest predictive performance among the four algorithms, with an accuracy of 61.80% and a weighted F1-score of 62.41%. These results indicate that ensemble learning methods consistently outperformed the single-tree classifier, with XGBoost providing the highest overall classification performance for male participants.

For the female dataset, all three advanced machine learning algorithms (Logistic Regression, Random Forest, and XGBoost) achieved comparable predictive performance with classification accuracies above 83%. XGBoost obtained a weighted F1-score of 75.82%, slightly higher than Logistic Regression (75.71%) and Random Forest (75.69%), while Decision Tree again produced substantially lower performance, with an accuracy of 69.38% and a weighted F1-score of 70.60%. Although Logistic Regression achieved a marginally higher overall accuracy (83.23%) than XGBoost (83.12%), XGBoost provided the highest weighted F1-score and weighted precision, indicating better balanced classification performance across BMI categories. Therefore, XGBoost was selected as the final predictive model for subsequent feature importance analysis.

Feature Importance Analysis

Feature importance analysis was subsequently performed using the optimized XGBoost model to quantify the relative contribution of each physical fitness indicator to BMI prediction (Figs. 1 and 2).

Among male students, pull-up performance was by far the most influential predictor, accounting for 45.27% of the total feature importance, followed by vital capacity, 1000-m running time, standing long jump, sit-and-reach, and 50-m sprint. The markedly higher importance assigned to pull-up performance suggests that upper-body muscular strength and endurance provide the greatest contribution to BMI prediction among male college students.

Among female students, the relative contributions of individual physical fitness variables were more evenly distributed. Vital capacity was identified as the most important predictor, followed by 800-m running performance, standing long jump, 50-m sprint, sit-and-reach, and sit-ups. Unlike the male model, no single physical fitness indicator overwhelmingly dominated the prediction process, suggesting that BMI prediction among female students depends on a more balanced contribution from multiple physiological fitness components.

Classification Performance

The XGBoost classifier achieved an overall classification accuracy of 75.33% for males and 83.12% for females. However, the classification reports revealed that prediction performance varied across BMI categories. Most normal-weight participants were correctly classified, whereas lower recall values were observed for underweight, overweight, and obese groups. This imbalance is likely attributable to the substantially larger proportion of normal-weight students in the study population, resulting in class imbalance during model training. Similar reductions in minority-class performance have been reported in previous machine learning studies involving population health datasets (He & Garcia, 2009; Krawczyk, 2016).

Discussion

Physical fitness tests serve not only as indicators of overall physiological health but also as important predictors of chronic conditions, including obesity. In the present study, mandatory physical fitness assessments required for Chinese college students were utilized to examine the associations between specific fitness components and BMI using AI - based analytical approaches. The XGBoost model demonstrated high predictive accuracy for BMI (75% in males and 83% in females), underscoring the relevance of these six fitness measures in reflecting overall health status. These findings offer valuable evidence for practitioners and policymakers to develop targeted interventions aimed at improving public health among young adults.

Among the six physical fitness components, pull-up - an indicator of upper-body muscular strength and endurance - emerged as the strongest contributor to BMI in males, accounting for almost half of the predictive importance (45%). This finding is consistent with previous research demonstrating a close relationship between pull-up performance and body weight (Nikolaidis & Zisimatos, 2014). The pull-up is a typical weight-bearing exercise in which individuals support and lift their entire body mass by grasping a horizontal bar and pulling upward until the chin passes the bar. During this movement, participants must overcome gravitational resistance using upper-limb musculature. On one hand, greater upper-body strength facilitates a higher number of completed repetitions; on the other hand, a higher BMI, often associated with increased body fat, imposes additional load, thereby impairing performance in this weight-bearing task. Additionally, the participants in this study were general college students rather than trained athletes, and successful pull-up performance requires not only strength but also specific technique and practice. Limited experience with this movement may therefore further influence performance outcomes.

In contrast, sit-ups - used to assess muscular strength and endurance in females - showed a relatively modest contribution to BMI prediction (13%). Sit-up primarily targets abdominal musculature rather than total body mass movement. Although previous studies have reported negative associations between sit-up performance and measures of regional adiposity (e.g., abdominal and subscapular skinfolds) (Esco et al., 2008), the overall contribution of sit-up to BMI prediction appears limited. This may also be explained by the fact that the majority of female participants in the present study fell within the normal BMI range, thereby reducing variability and attenuating the association between sit-up performance and BMI.

Vital capacity, an indicator of pulmonary function, represents the maximum volume of air that can be exhaled following a maximal inhalation. Although some studies have reported no significant association between VC and BMI (Karmacharya et al., 2019; P. Liu et al., 2017), the present findings indicate that lung capacity makes a substantial important contribution to BMI prediction models in both males and females. The relationship between VC and BMI appears to be complex and potentially bidirectional. The positive association is explained that a higher body mass may increase oxygen demand, which could be offset by greater lung capacity (X. Chen et al., 2020b; Song et al., 2023; Sun et al., 2022; Wang et al., 2020). Alternatively, excess adiposity - particularly fat accumulation in the thoracic and abdominal regions - may impair respiratory function by increasing airway resistance, restricting the movement of respiratory muscles, limiting diaphragmatic excursion and rib cage expansion, and leading obesity-related inflammation (Karmacharya et al., 2019; Li et al., 2022; Sinha et al., 2021). Overall, these findings highlight the multifaceted association between pulmonary function and body composition, emphasizing the importance of considering both physiological demand and mechanical constraints when interpreting the relationship between VC and BMI.

Cardiorespiratory endurance in college students is commonly assessed through both short-distance (50 m sprint) and long-distance running tests (800 m for females and 1,000 m for males). In the present study, long-distance running exhibited a greater contribution to BMI compared with short-distance sprinting. This difference may be attributed to the metabolic demands of the activities, as long-distance running primarily relies on the aerobic energy system, which is more closely influenced by body composition. An inverse relationship between BMI and running performance was observed (Ding & Jiang, 2020; Nikolaidis & Zisimatos, 2014), indicating that excess body weight is associated with diminished speed- and endurance-related performance (Nikolaidis et al., 2015; Wang et al., 2020). Increased body fat contributes to greater mechanical load during locomotion and elevates heat production, thereby increasing energy expenditure and reducing aerobic efficiency during prolonged exercise (Thuany et al., 2023). Consequently, individuals with higher BMI require more time to complete long-distance running tests, reflecting poorer performance.

In contrast, the 50 m sprint emphasizes speed, agility, and explosive muscular strength, which are less dependent on aerobic capacity. In elite athletic populations, sprinters often exhibit higher BMI values attributable to greater muscle mass required for rapid energy output over short durations (Sedeaud et al., 2014). However, the participants in this study were non-athlete college students, and higher BMI in this population is more likely associated with excess adiposity rather than increased muscle mass. As a result, the 50 m sprint demonstrated a relatively weaker association with BMI, particularly among males, where it contributed the least among all six physical fitness tests.

Compared with upper-body muscular strength exercises such as pull-ups, the standing long jump primarily reflects lower-limb explosive strength and power, and has been identified as a predictor of sarcopenic obesity (Sylejmani et al., 2024). During the jumping movement, the muscles of the lower body must overcome the individual's body weight to propel the entire body forward. A significant negative relationship exists between BMI and standing long jump performance (Nikolaidis et al., 2015; Sun et al., 2022), as greater body weight imposes a mechanical constraint that reduces forward distance (Ding & Jiang, 2020). However, the contribution of muscular strength in the trunk and upper limbs has often been overlooked. Arm swing and recoil play a crucial role in transferring velocity and optimizing the projection angle of the body's center of gravity, thereby facilitating forward motion of the trunk and lower limbs. In addition, trunk muscle stabilization enhances the efficient generation and transmission of force and power in the limbs (Nakai et al., 2024). Although standing long jump performance is sensitive to body weight, appropriate jumping techniques can mitigate this limitation and contribute to improved performance.

In physical fitness assessments, body flexibility is evaluated using the sit-and-reach test, which is influenced by factors such as adequate warm-up, joint extensibility, and muscle viscosity (Gite et al., 2021b). As a result, no consistent association between BMI and flexibility has been established (Ding & Jiang, 2020). A study of Chinese male college freshmen reported that individuals in the overweight group performed better on the sit-and-reach test than those in the underweight group (Sun et al., 2022), suggesting that excess adiposity may not hinder performance in this activity (Deforche et al., 2003; Guo et al.,

2022). In contrast, research conducted among Taiwanese women found a negative relationship between body fat percentage and sit-and-reach performance (Chiang et al., 2022). These inconsistent findings may be explained by sex-related differences in fat distribution, with variations in fat deposition patterns between males and females potentially influencing flexibility outcomes.

Overall, the physical fitness test battery used in China provides a comprehensive evaluation of college students' physiological functions, including cardiorespiratory endurance, muscular strength, explosive power, pulmonary function, and flexibility. To our knowledge, this is the first study to use artificial intelligence techniques to predict BMI based on data from more than 83,000 young adults collected over a 13-year period. The high predictive accuracy of BMI based on these six fitness tests indicates a close association between physical fitness components and body composition. Notably, pull-up performance in males, as well as vital capacity and running performance in both genders, demonstrate particularly well-established relationships with BMI.

In summary, these findings provide important implications for university physical education programs, highlighting the need to enhance awareness of the importance of physical activity and to encourage college students to engage in regular exercise, particularly activities that develop muscular strength and endurance. Such efforts may also facilitate the adoption of healthier lifestyles among young adults. Moreover, these fitness assessments can serve not only as evaluative tools but also as practical indicators for weight management. Enhancing performance in these activities may contribute to effective strategies aimed at reducing the prevalence of obesity in this population.

Limitation

Despite the strengths of this study, several limitations should be acknowledged. First, all participants were recruited from Shenzhen University, located in southern China, and were limited to young adults. Therefore, the findings may not be generalizable to the broader population of college students across China or to other age groups. Additionally, this study employed a cross-sectional design, which identifies associations between physical fitness measures and body mass index but does not establish causal relationships. Future research should adopt longitudinal designs to further examine and confirm the causal links between physical fitness and BMI.

Conclusion

As the first study to apply artificial intelligence techniques to predict body mass index using physical fitness test data from more than 83,000 college students, these findings demonstrate a strong association between physical fitness components and body composition. In particular, pull-up performance in males, as well as vital capacity and running performance in both genders, showed the notable effect on BMI. These results suggest that university health program can utilize simple physical fitness tests as effective screening tools to identify students at risk of unhealthy BMI levels. Furthermore, prioritizing training in muscular strength, endurance, and cardiorespiratory fitness may serve as a practical intervention strategy to support weight management and reduce the prevalence of obesity among young adults.

Declarations

Declaration of Interest Statement

The authors declare no competing financial interests.

Fundings

This study was supported by the Research Project on League Members and Youth Development of Shenzhen University (Grant No. 2025YB11).

Acknowledgement

The authors gratefully acknowledge the financial support provided by the Research Project on League Members and Youth Development of Shenzhen University (Grant No. 2025YB11). The authors also extend sincere thanks to all participants and colleagues whose contributions were invaluable to this research.

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Shenzhen University (PN-202300025). All participants provided written informed consent prior to participation.

Author Contribution

Xi Jin drafted the original manuscript and performed the data analysis. Zhonghui Wang was responsible for the development of the methodology, artificial intelligence modeling, and data computation. Xin Zhao conducted clinical validation and provided expert interpretation of physical fitness indicators. Yang Wen carried out the investigation and organized the raw physical fitness data. Chunbo Qin oversaw project administration, secured funding, and provided

overall supervision, and, as the corresponding author, contributed to manuscript review and editing. All authors have read and approved the final version of the manuscript.

Data Availability

The datasets generated and analyzed during the current study are not publicly available due to privacy and ethical restrictions, as they contain potentially identifying information of individual participants. The data were collected under the approval of the Institutional Review Board of Shenzhen University (PN-202300025), and participants provided informed consent that did not include public data sharing. Data may be made available from the corresponding author upon reasonable request, subject to institutional review board approval and a formal data-sharing agreement that ensures participant confidentiality.

References

1. Bishop CM, Nasrabadi NM. (2006). *Pattern recognition and machine learning* (Vol. 4). Springer. <https://link.springer.com/in/book/9780387310732>
2. Breiman L. Random Forests. *Mach Learn*. 2001;45(1):5–32. <https://doi.org/10.1023/A:1010933404324>.
3. Breiman L, Friedman JH, Olshen RA, Stone CJ. (1993). Classification and regression trees. Wadsworth, 1984. *Google Scholar*.
4. Chen T, Guestrin C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
5. Chen X, Cui J, Zhang Y, Peng W. The association between BMI and health-related physical fitness among Chinese college students: A cross-sectional study. *BMC Public Health*. 2020a;20(1):444. <https://doi.org/10.1186/s12889-020-08517-8>.
6. Chiang H-H, Lee P-F, Chen Y-T, Lin C-F, Xu S, Lin Y-T, Lin Y-T, Su Y-J, Shia B-C, Changchien W-S. (2022). Low cardiorespiratory fitness, muscular fitness, and flexibility are associated with body fat distribution and obesity risk using bioelectrical impedance in Taiwanese adults. *International Journal of Environmental Research and Public Health*, 19(14), 8858. <https://www.mdpi.com/1660-4601/19/14/8858>
7. Deforche B, Lefevre J, De Bourdeaudhuij I, Hills AP, Duquet W, Bouckaert J. Physical Fitness and Physical Activity in Obese and Nonobese Flemish Youth. *Obes Res*. 2003;11(3):434–41. <https://doi.org/10.1038/oby.2003.59>.
8. Ding C, Jiang Y. (2020). The relationship between body mass index and physical fitness among Chinese university students: Results of a longitudinal study. *Healthcare*, 8(4), 570. <https://www.mdpi.com/2227-9032/8/4/570>
9. Dong X, Huang F, Starratt G, Yang Z. Trend in health-related physical fitness for Chinese male first-year college students: 2013–2019. *Front Public Health*. 2023;11:984511. 10.3389/fpubh.2023.984511/full. <https://www.frontiersin.org/journals/public-health/articles/>.
10. Esco MR, Olson MS, Williford H. Relationship of push-ups and sit-ups tests to selected anthropometric variables and performance results: A multiple regression study. *J Strength Conditioning Res*. 2008;22(6):1862–8. https://journals.lww.com/nsca-jscr/fulltext/2008/11000/Relationship_of_Push_Ups_and_Sit_Ups_Tests_to.21.aspx.
11. Gite AA, Mukkamala N, Parmar L. Relationship between body mass index and flexibility in young adults. *J Pharm Res Int*. 2021a;33(32A):119–26. https://www.researchgate.net/profile/Neha-Mukkamala/publication/352564791_Relationship_between_Body_Mass_Index_and_Flexibility_in_Young_Adults/links/6894555cd3c4ac316e2ebf83/Relationship-between-Body-Mass-Index-and-Flexibility-in-Young-Adults.pdf.
12. Guo MM, Wang XZ, Koh KT. Association between physical activity, sedentary time, and physical fitness of female college students in China. *BMC Women's Health*. 2022;22(1):502. <https://doi.org/10.1186/s12905-022-02108-y>.
13. Hastie T, Tibshirani R, Friedman J. (2009). *The elements of statistical learning*. Springer series in statistics New-York. <https://www.academia.edu/download/31156736/10.1.1.158.8831.pdf>
14. He H, Garcia EA. Learning from imbalanced data. *IEEE Trans Knowl Data Eng*. 2009;21(9):1263–84. <https://ieeexplore.ieee.org/abstract/document/5128907/>.
15. Jiang S, Peng S, Yang T, Cottrell RR, Li L. Overweight and Obesity Among Chinese College Students: An Exploration of Gender as Related to External Environmental Influences. *Am J Men's Health*. 2018;12(4):926–34. <https://doi.org/10.1177/1557988317750990>.
16. Karmacharya P, Shrestha GL, Singh S, Shrestha OK. Relation of waist hip ratio and BMI with the vital capacity. *J Chitwan Med Coll*. 2019;9(3):51–5. <https://nepjol.info/index.php/JCMC/article/view/25783>.
17. Khan SS, Ning H, Wilkins JT, Allen N, Carnethon M, Berry JD, Sweis RN, Lloyd-Jones DM. (2018). Association of body mass index with lifetime risk of cardiovascular disease and compression of morbidity. *JAMA Cardiology*, 3(4), 280–287. https://jamanetwork.com/journals/jamacardiology/articlepdf/2673289/jamacardiology_Khan_2018_oi_180002.pdf?link_time=2020-02-07_01:45:04.305568
18. Krawczyk B. Learning from imbalanced data: Open challenges and future directions. *Progress Artif Intell*. 2016;5(4):221–32. <https://doi.org/10.1007/s13748-016-0094-0>.
19. Li B, Sun L, Yu Y, Xin H, Zhang H, Liu J, Zhang Z. (2022). Associations between body composition and physical fitness among Chinese medical students: A cross-sectional study. *BMC Public Health*, 22(1), 2041. <https://doi.org/10.1186/s12889-022-14548-0>
20. Liu P, Ye Z, Lu H, Lu J, Huang L, Gong J, Deng Q, Xu L. Association between body mass index (BMI) and vital capacity of college students of Zhuang nationality in China: A cross-section study. *Oncotarget*. 2017;8(46):80923. <https://pmc.ncbi.nlm.nih.gov/articles/PMC5655250/>.
21. Liu X, Keating XD, Shangguan R. Historical Analyses of Fitness Testing of College Students in China. *ICHPER-SD J Res*. 2017;9(1):24–32. <https://eric.ed.gov/?id=EJ1196806>.

22. Nakai Y, Usumoto Y, Takeshita Y. (2024). The effects of regional muscle strength and mass on standing long jump performance. *Muscles*, 3(1). <https://www.mdpi.com/2813-0413/3/1/7>
23. Nikolaidis PT, Asadi A, Santos EJ, Calleja-González J, Padulo J, Chtourou H, Zemkova E. Relationship of body mass status with running and jumping performances in young basketball players. *Muscles Ligaments Tendons J.* 2015;5(3):187. <https://pmc.ncbi.nlm.nih.gov/articles/PMC4617219/>.
24. Nikolaidis PT, Zisimatos D. Relationship of body mass index with 1,600 m running, 50 m swimming, and pull-ups performance in army cadets. *Saudi J Sports Med.* 2014;14(2):144–50. https://journals.lww.com/sjsm/fulltext/2014/14020/relationship_of_body_mass_index_with_1,600_m.16.aspx.
25. Pengpid S, Peltzer K, Kassean HK, Tsala Tsala JP, Sychareun V, Müller-Riemenschneider F. Physical inactivity and associated factors among university students in 23 low-, middle- and high-income countries. *Int J Public Health.* 2015;60(5):539–49. <https://doi.org/10.1007/s00038-015-0680-0>.
26. Qin G, Qin Y, Liu B. Association between BMI and health-related physical fitness: A cross-sectional study in Chinese high school students. *Front Public Health.* 2022;10:1047501. 10.3389/fpubh.2022.1047501/full. <https://www.frontiersin.org/journals/public-health/articles/>.
27. Sedeaud A, Marc A, Marck A, Dor F, Schipman J, Dorsey M, Haida A, Berthelot G, Toussaint J-F. BMI, a performance parameter for speed improvement. *PLoS ONE.* 2014;9(2):e90183. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0090183>.
28. Sinha HP, Deep A, Panda SK. Effect of body mass index on vital capacity in young adults-A cross-sectional study. *Natl J Physiol Pharm Pharmacol.* 2021;11(1):84–8. <https://search.proquest.com/openview/07ae6e020da97c1aac4ed2406d83263d/1?pq-origsite=gscholar&cbl=706378>.
29. Song L, Li J, Yu S, Cai Y, He H, Lun J, Zheng L, Ye J. Body Mass Index is Associated with blood pressure and vital capacity in medical students. *Lipids Health Dis.* 2023;22(1):174. <https://doi.org/10.1186/s12944-023-01920-1>.
30. Sun F, He Q, Sun X, Wang J. (2022). The association between body mass index and muscular fitness in Chinese college freshmen. *International Journal of Environmental Research and Public Health*, 19(21), 14060. <https://www.mdpi.com/1660-4601/19/21/14060>
31. Sylejmani B, Maliqi A, Veseli R, Gontarev S, Georgiev G. (2024). Standing-Long-Jump Test Application in Identifying Female Adolescents at Risk of Sarcopenic Obesity. *Int J Morphology*, 42(2). https://www.intjmorphol.com/wp-content/uploads/2024/03/Art_11_422_2024.pdf
32. Thuany M, Hill L, Alvero-Cruz JR, Knechtle B, Gomes TN. The relationship between training volume and bmi in the expression of running performance in runners: A mediation model. *J Sci Sport Exerc.* 2023;5(2):142–8. 10.1007/s42978-022-00172-2&. https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/. casa_token=FIGQ7zVRk-EAAAAA:0R6T2IVU4nDNLzMcJVptSozkDumA0kYWHAOmVLuKBClezBZeonlIFaazy6CnNsviH1IsaHN539JUI.
33. Wang J, Xie Z, Li Y, Song Y, Yan J, Bai W, Zhou T, Qin J. Relationship between health status and physical fitness of college students from south China: An empirical study by data mining approach. *IEEE Access.* 2020;8:67466–73. <https://ieeexplore.ieee.org/abstract/document/9057616/>.
34. Yin S, Jin P, He Q, Zhi Y. Physical Fitness Index and body mass index: A cross-sectional study based on 1.3 million college students. *PLoS ONE.* 2025;20(10):e0335194. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0335194>.

Figures

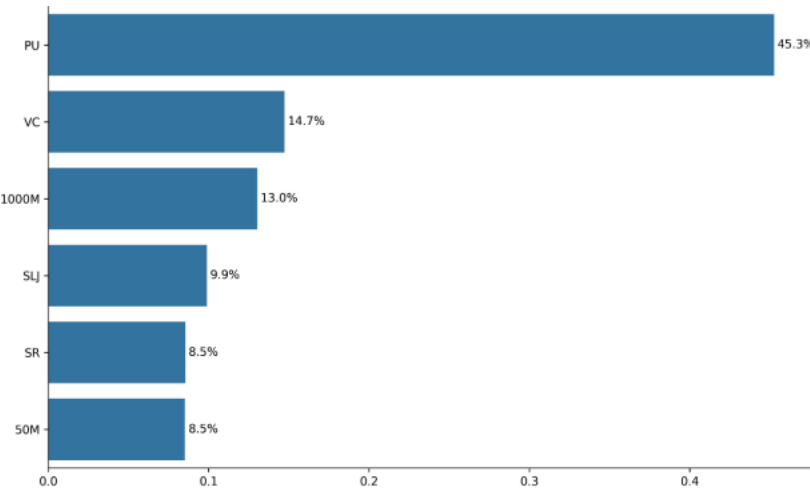


Figure 1
Importance of each physical fitness test on BMI in males

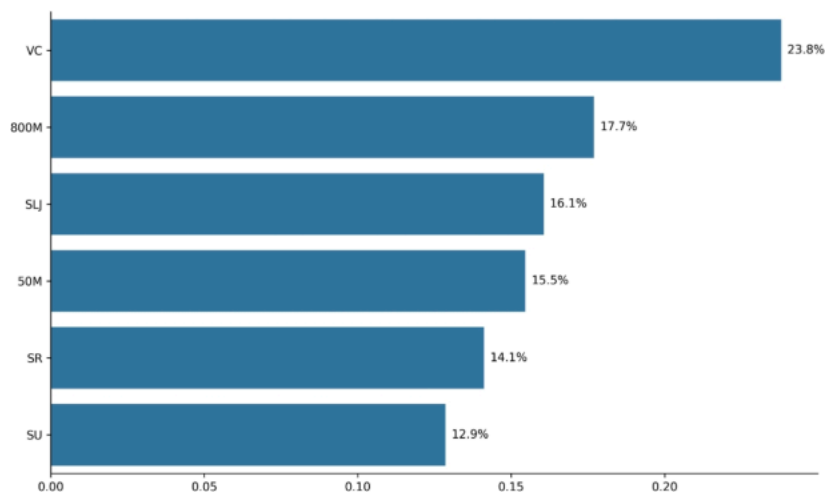


Figure 2

Importance of each physical fitness test on BMI in females