Diyala Journal of Medicine

ORIGINAL RESEARCH
Published: 25 October 2025
DOI: 10.26505/djm.v29i1.1415

Interplay Between Biometric Profiles, Biomarkers, Body Fat, and Bone Health: A Statistical and Machine Learning Approach

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Received: 19 April 2025
Accepted: 24 August 2025
Published: 25 October 2025

Abstract

Background: Obesity and metabolic disorders are increasingly prevalent public health concerns. Excess adiposity, particularly visceral fat, is associated with metabolic dysfunction, whereas regional fat depots, such as gynoid fat, may confer protective benefits on skeletal integrity.

Objectives: This study aimed to examine the intricate relationship between biometric profiles, biochemical markers, body fat distribution, and bone health.

Patients and Methods: Data were obtained from the National Health and Nutrition Examination Survey (NHANES), including adult participants with complete measurements on body composition (total, visceral, and subcutaneous fat; BMI; waist circumference), biochemical markers (lipid profiles, fasting glucose, insulin, hormonal regulators), and bone health metrics (bone mineral density and content via DXA). Correlation and multivariate regression analyses were conducted to identify predictors among demographic, biometric, and biochemical variables. Machine learning techniques, specifically Random Forest Regression, were employed to enhance predictive modeling of fat indices and bone health outcomes.

Results: BMI and waist circumference emerged as robust predictors of total and visceral fat, with significant gender and age disparities noted. Women exhibited higher total and subcutaneous fat, whereas men demonstrated increased visceral fat. Biochemical markers, notably insulin and glucose, correlated strongly with adiposity indices. Furthermore, bone health was positively associated with BMI and specific biomarkers (testosterone, Creatinine phosphokinase (CPK) and negatively associated with Sex Hormone-Binding Globulin (SHBG) and Alkaline Phosphatases (ALP). Moderate to high predictive accuracy was observed for the machine learning models, confirming the supporting role of predictive analytics in understanding these relationships.

Conclusion: The combination of anthropometric measures, biochemical markers, fat and bone density, and machine learning offers a comprehensive understanding of their correlation. Such insights can inform the design of targeted clinical decision-making strategies and highlight the feasibility of using simple, non-invasive measurements to assess metabolic and skeletal risks.

Keywords: biometric profile, bone health, body fat, machine learning approach.

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Introduction

Metabolic health and obesity are emerging as major healthcare challenges, mainly due to the role of body fat distribution in contributing to associated health risks.

Metabolic health and obesity are becoming major health care problems, which are linked to the distribution of body fat that contributes to associated risks. Metabolic disorders, cardiovascular disease, and impaired bone health are related to fat accumulation, particularly visceral adiposity. To determine individuals at risk for these disorders and provide further preventive actions, we must understand the interplay between body fat distribution, bone integrity, and biochemical markers; the way our bodies store fat is becoming a central issue in healthcare, linking obesity to significant health dangers. Health complications like metabolic syndromes, heart conditions, and even weakened bones are increasingly tied to where fat accumulates, with fat around the organs—known as visceral adiposity—being particularly problematic. To effectively prevent these conditions, it's essential that we gain a deeper insight into how body fat location, bone strength, and various blood markers are all interconnected (1).

These relationships are as intricate as those between fat distribution and bone health. For example, while increased body weight is traditionally seen as protective for bone density due to mechanical loading, excessive adiposity, particularly visceral fat, is increasingly recognized as a potential negative factor in bone metabolism. This is caused by the damaging effects of inflammatory cytokines, hormonal shifts, and metabolic disturbances resulting from fat overload. The negative influence of visceral fat on the skeleton goes down to the cellular level, disrupting the delicate balance between bone creation and breakdown. Fat cells are not inert; they produce hormones like leptin and adiponectin. While leptin can sometimes support bone formation, in states of obesity, the body can become leptin-resistant, nullifying any benefits. At the same time, the chronic inflammation driven by excess visceral fat directly encourages the cells that dissolve bone (osteoclasts) while hindering the cells that build new bone (osteoblasts). This creates an environment where the skeleton is constantly being weakened from within, even while it's carrying a heavier load (2). Conversely, certain types of regional fat distribution, especially gynoid fat, have been linked to positive effects on bone mass, which also highlights the importance of differentiating various fat depots. Unlike the inflammatory nature of deep abdominal fat, the fat stored on the hips, thighs, and buttocks—known as gynoid fat—has a much healthier metabolic profile. This type of fat depot is more stable and less likely to release inflammatory substances into the bloodstream. Instead, it's better at safely storing fatty acids for the long term. It is known to secrete beneficial hormones like adiponectin, which improves the body's sensitivity to insulin and has anti-inflammatory effects. This creates a systemic environment that is much more conducive to healthy bone maintenance, supporting the activity of bone-building cells (3).

Adiposity and bone health have determinants, with key biomarkers such as lipid profiles, glucose metabolism indicators, and hormonal regulators serving as biochemical markers. Fat storage patterns resulting from insulin resistance, dyslipidemia, and hormonal imbalances, along with their impact on bone mineralization changes, warrant concern. This underscores the need for a highly integrated approach to bone health; Beyond their role in cardiovascular risk, specific components of a person's lipid profile have a direct and damaging effect on the bone's internal

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environment. When levels of triglycerides and "bad" LDL cholesterol are high, fatty acids can accumulate within the bone marrow. This lipotoxicity is directly poisonous to the bone-building osteoblast cells and creates a shift in the bone marrow's cellular development. It encourages stem cells to become fat cells (adipocytes) rather than bone cells, effectively "crowding out" the machinery needed for skeletal repair. This results in a bone structure that is not only less dense but is also filled with inflammatory fat tissue, weakening it from the inside out (4,5). The relationship among these factors can be explored more deeply using advanced statistical techniques, such as regression analysis and machine learning models, which will aid in risk stratification and predictive modeling.

This study aims to investigate the relationship between the distribution of body fat, biomarkers, body measurements, and metrics of bone health (density and content) using correlation, regression, and machine learning analysis methods. It aims to explore the crucial relationships between adiposity and bone health, which may aid in developing clinical evaluation and customized treatment strategies using data from the National Health and Nutrition Examination Survey (NHANES) (if any) data set.

Patients and Methods

Study design and data source: The study was conducted using data from the National Health and Nutrition Examination Survey (NHANES), which is a nationwide, cross-sectional survey program sponsored by the U.S. Centers for Disease Control and Prevention (CDC). NHANES collects data across multiple U.S. locations, representing the non-institutionalized U.S. civilian population. The analysis was performed on a cohort of approximately 8,000 adults aged 18 years and older, selected from the NHANES dataset (2017-2018 cycle), with complete data on body fat indices, biometric markers, biochemical markers, and bone health parameters. The study period spanned from 2013 to 2016, based on data from two consecutive NHANES cycles (2013–2014 and 2015–2016). This study utilizes publicly accessible information from the National Health and Nutrition Examination Survey (NHANES), a cross-sectional survey sponsored by the Centers for Disease Control and Prevention (CDC) under the American Government. NHANES collects comprehensive data for the entire nation, encompassing health information such as demographics, biometrics, biochemistry, body composition, and other data gathered through interviews, physical assessments, and laboratory investigations.

Study population: The study sample comprises all adult respondents aged 18 years and older who have complete information on body fat indices, biometric, lipid, and metabolic markers, as well as bone health parameters. Exclusion criteria included individuals with missing data for key variables, those with diagnosed metabolic or skeletal disorders that could confound the results, and pregnant women.

Variables and measurements body fat distribution and biometric measures: Total fat mass, measured in grams, was determined using Dual-Energy X-ray Absorptiometry (DXA), a validated imaging method that provides precise assessments of body composition (6). Visceral fat mass, also in grams, was calculated through proprietary DXA-based algorithms specifically designed to estimate fat within the abdominal cavity (7). Subcutaneous fat mass, similarly measured in grams, was estimated using DXA's regional fat segmentation capabilities, which distinguish it from visceral fat (6). The android fat percentage indicates fat accumulation in the abdominal region and is obtained through regional analysis of DXA scans (8). In contrast, the gynoid fat

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percentage reflects fat distribution in the hips and thighs (9). Total body fat percentage was calculated as the ratio of total fat mass to total body weight (8). Body Mass Index (BMI), expressed in kg/m², was derived from directly measured body weight and height (9,10). Waist circumference was measured in centimeters at the level of the iliac crest using a standardized tape measure protocol (11). Age was self-reported by participants, and gender was recorded as male or female (9).

Biochemical markers: Lipid profile assessments included total cholesterol and triglyceride levels, both measured in milligrams per deciliter (mg/dL) using standardized enzymatic assays (12). Metabolic biomarkers included fasting glucose and fasting insulin, measured in milligrams per deciliter (mg/dL) and micro-units per milliliter (µU/mL), respectively (12). Additional biomarkers relevant to metabolic and hormonal status were analyzed through blood samples. These included alkaline phosphatase (ALP) (13,14) and creatine phosphokinase (CPK) (15,16), reported in units per liter (U/L), as well as phosphorus (mg/dL), which plays a role in bone mineralization (17). Vitamin D levels were assessed as serum 25-hydroxyvitamin D [25(OH)D], measured in nanograms per milliliter (ng/mL), serving as an indicator of vitamin D status (18). Sex hormones were also quantified: estradiol (19), testosterone (20), and sex hormone-binding globulin (SHBG) (21, 22), which were reported in appropriate standardized units.

Bone health metrics: Bone health was evaluated using two primary DXA-derived indicators. Bone Mineral Density (BMD), expressed in grams per square centimeter (g/cm²), represents the concentration of mineral content in bone and is a widely used metric for assessing osteoporosis and fracture risk (23, 24, 20). Bone Mineral Content (BMC), measured in grams, reflects the total amount of mineral present in the scanned bone area, complementing BMD in characterizing overall bone strength (17,18,25). Additional associations with bone metabolism include the influence of obesity (23), testosterone (20), SHBG (22), and biochemical markers such as ALP (13) and CPK (15, 16).

Statistical Analysis

To examine the relationships among fat distribution, biometric characteristics, and biochemical markers, Spearman's rank correlation analysis was employed in R (2). This non-parametric method was chosen to capture both linear and non-linear associations between variables that may not follow normal distributions, including fat indices, metabolic biomarkers, and anthropometric measures.

Multivariate linear regression models were constructed to further evaluate the predictive capacity of demographic, biometric, and biochemical variables on outcomes such as fat indices, bone health parameters, and lipid metabolism indicators. These models accounted for potential confounding variables, including age and gender, to isolate the independent effects of the predictors. The goal was to identify key determinants of body composition and bone status within a multifactorial framework.

In addition to classical statistical methods, machine learning approaches were employed to enhance prediction accuracy and uncover complex, non-linear relationships. Random Forest Regression models (3) were developed using the Scikit-learn library in Python (v1.0.2) (1) to predict total fat mass using age, BMI, and waist circumference; visceral fat mass using cholesterol, triglycerides, glucose, and insulin; and bone mineral density and content using a range of metabolic and hormonal biomarkers. Model performance was evaluated using standard metrics: the coefficient of

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determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE), providing insight into both accuracy and model robustness.

All statistical analyses and data preprocessing were conducted using R version 4.1.2 (2) and Python version 3.8. Machine learning models were implemented using the Scikit-learn library (1). The NHANES dataset was accessed, cleaned, and manipulated using Pandas (4) and NumPy (5). Visualization of the analytical results, including correlations, model performance, and feature importance, was performed using Matplotlib (24) and Seaborn (25), allowing for precise and interpretable graphical representation of findings**.**

Results

Biometric variables and fat indices: The relationship between biometric variables and fat indices revealed consistent patterns across both correlation and regression analyses (Table 1, Figure 1). BMI and waist circumference emerged as the strongest predictors of fat accumulation, with Spearman's correlation coefficients exceeding 0.8 when compared to total fat. Gender-based differences were pronounced: women exhibited significantly higher total and subcutaneous fat, while men showed greater visceral fat accumulation. Age was positively associated with visceral fat but showed a slight negative association with total fat percentage. Regression models (Table 2) supported these findings; total fat was highly predictable (R^2 = 0.923) using BMI and waist circumference, with women having approximately 5.7 kg fatter than men. Total percent fat was also well explained (R^2 = 0.784), with a clear gender gap (β = 11.61%, $p < 0.001$). Visceral fat was most strongly associated with waist circumference and age (R^2 = 0.677), and men had significantly higher values. The Random Forest model predicting total fat using age, BMI, and waist circumference yielded robust performance (R^2 = 0.85, RMSE = 4.5 kg, MAE = 3.5 kg) (Table 3), highlighting the dominant role of anthropometric predictors. However, the inclusion of biochemical markers could further improve model accuracy. The feature importance from this model is shown in Figure 2.

Biochemical markers and fat indices:

In examining the influence of biochemical markers on fat indices, correlations revealed modest but significant relationships (Figure 3). Total cholesterol showed weak-to-moderate associations with total and subcutaneous fat, while triglycerides correlated moderately with android, gynoid, and total fat. Glucose demonstrated similar correlations, particularly with android and visceral fat. Insulin was the strongest biochemical predictor, showing moderate-to-strong correlations ($\rho \approx 0.5–0.6$) across all fat measures. Regression models (Table 4) confirmed insulin's dominant role, especially in predicting total fat (R^2 = 0.196) and visceral fat (R^2 = 0.281), with glucose contributing as a secondary predictor. Total percent fat was more weakly explained by biomarkers alone (R^2 = 0.095). In machine learning models predicting visceral fat using cholesterol, triglycerides, glucose, and insulin, the model achieved limited performance (R^2 = 0.33) (Table 3), reinforcing that lipid and glucose metabolism markers, while important, are insufficient as standalone predictors of fat accumulation, likely due to missing physiological or genetic variables.

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Table 1. Correlation between biometric variables and fat indices (spearman's ρ).

Fat Index	Age	Gender (M=0, F=1)	BMI	Waist Circumference
Total Fat (g)	-0.18	0.62	0.85	0.83
Visceral Fat (g)	0.42	-0.51	0.65	0.77
Subcutaneous Fat (g)	-0.05	0.59	0.79	0.76
Android Fat (%)	0.21	0.10	0.68	0.72
Gynoid Fat (%)	-0.12	0.48	0.63	0.54

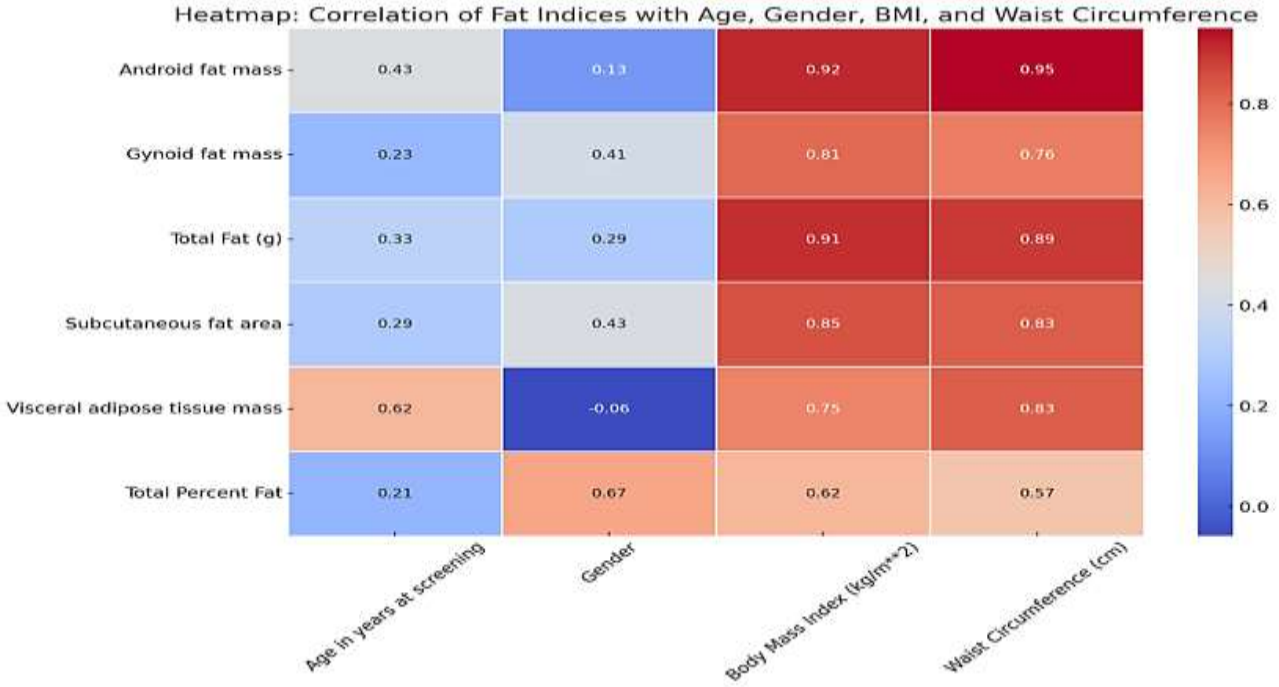

Figure 1. Correlation of fat indices with age, gender, bmi, and waist circumference.

Table 2. Regression results for predicting fat indices.

Dependent Variable	Predictor	β (Coefficient)	p-value	R^2
Total Fat (g)	BMI	841.64	< 0.001	0.923
	Waist Circumference	328.41	< 0.001	
	Gender (F)	5726.02	< 0.001	
Total Fat (%)	Waist Circumference	0.25	< 0.001	0.784
	BMI	0.16	< 0.001	
	Age	-0.027	< 0.001	
	Gender (F)	11.61	< 0.001	
Visceral Fat (g)	Age	6.59	< 0.001	0.677
	Waist Circumference	11.01	< 0.001	
	Gender (F)	-28.79	< 0.001	

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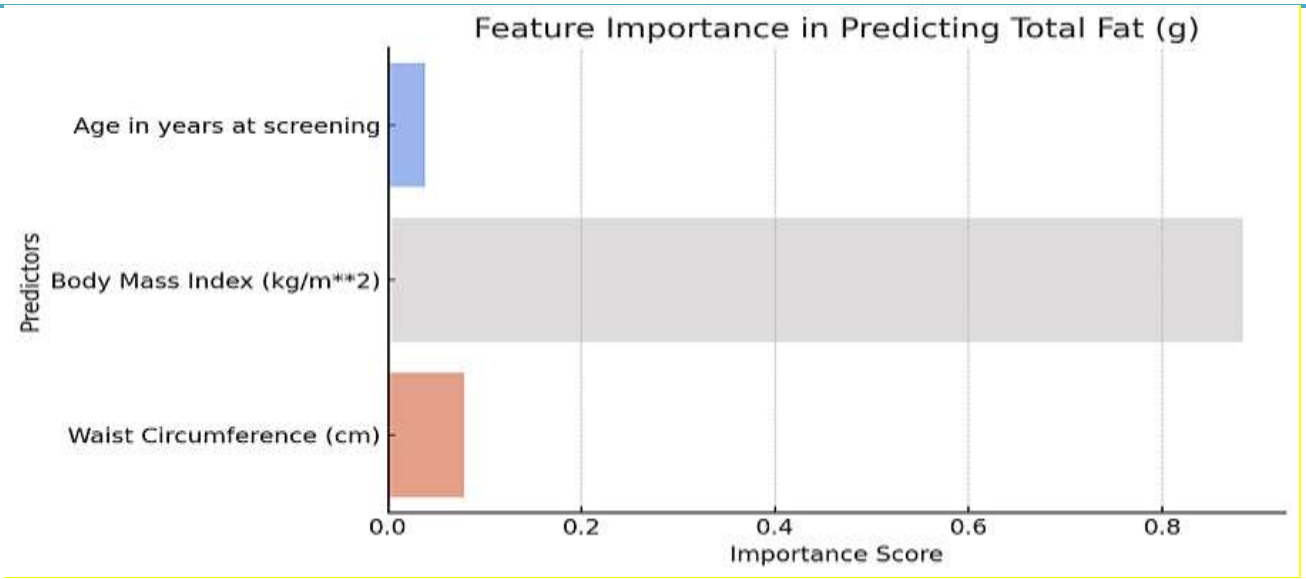

Figure 2. Feature importance in predicting total fat (g).

Table 3. Machine learning model performance summary.

Outcome	Model	R^2	RMSE	MAE
Total Fat (g)	Random Forest	0.85	4.5 kg	3.5 kg
Visceral Fat (g)	Random Forest	0.33	229.1 g	171.1 g
Bone Density (g/cm²)	Random Forest	0.24	0.105 g/cm²	0.084 g/cm²
Bone Content (g)	Random Forest	0.36	379.42 g	302.95 g

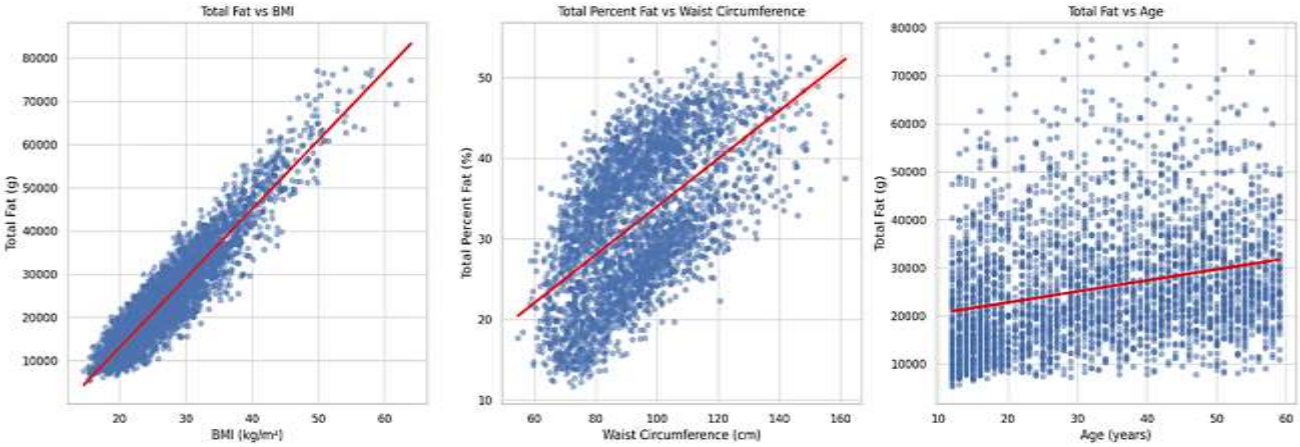

Figure 3. Regression of biomarkers with fat indices.

Table 4. Machine learning model performance summary.

Dependent Variable	Predictor	B	p-value	R^2
Total Fat (g)	Insulin	318	<0.001	0.196
	Glucose	48.8	<0.001	
Total Fat (%)	Insulin	0.165	<0.001	0.095
Visceral Fat (g)	Insulin	4.74	<0.001	0.281
	Glucose	1.99	<0.001	

Bone health and biometric characteristics: The association between bone health and biometric characteristics revealed both intuitive and novel findings (Figure 4, Figure 5). Age, BMI, and waist circumference were all positively associated with bone density and bone content, though gender differences were notable, with women displaying significantly lower values in

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both metrics. Regression analysis (Table 5). Showed that BMI and age positively predicted bone mineral density (BMD), whereas waist circumference had a small but negative association (R^2 = 0.131). For bone mineral content (BMC), BMI, age, and waist circumference were all positive predictors, explaining a larger portion of variance (R^2 = 0.338). Machine learning models showed moderate predictive power for bone density (R^2 = 0.17) and stronger performance for bone content (R^2 = 0.37) (Table 3), suggesting anthropometric data are more effective at capturing skeletal mass rather than bone mineral quality.

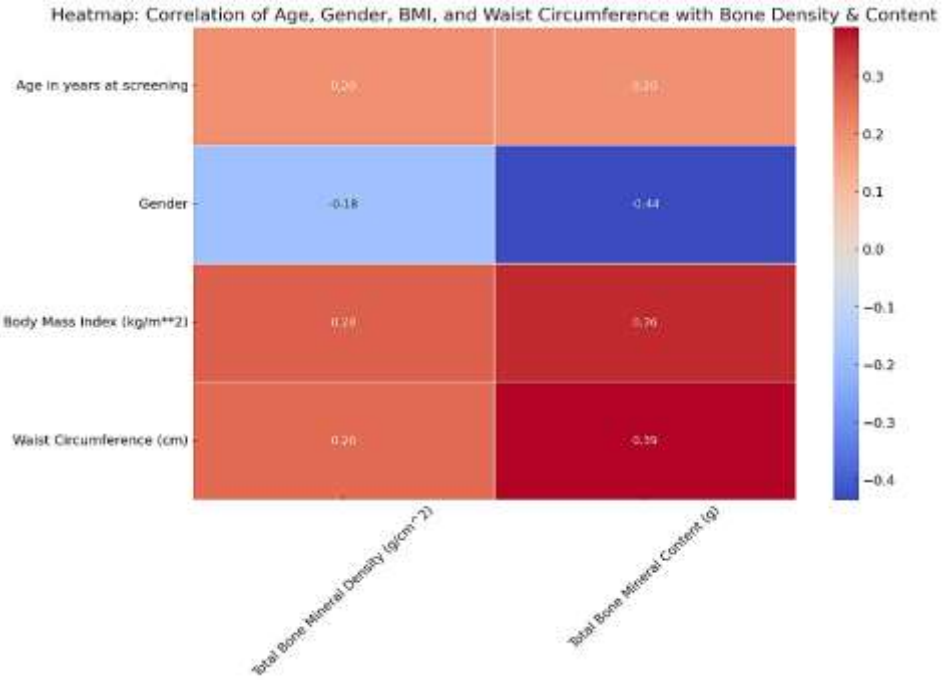

Figure 4. Correlation of bone health markers with Age, Gender, BMI, and Waist Circumference.

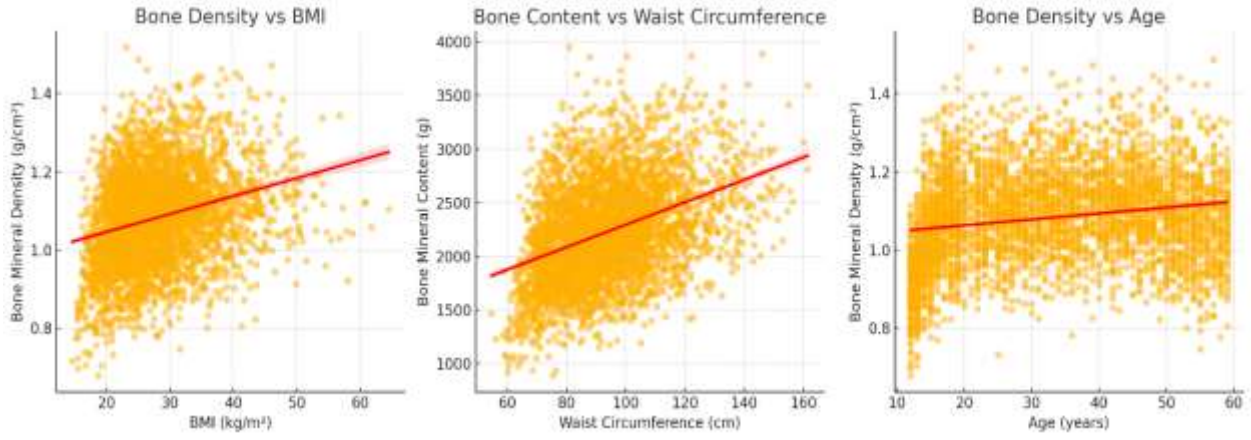

Figure 5. Regression of biometrics with bone health markers.

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Table 5. Biometric predictors of bone health metrics.

Bone Metric	Predictor	B	p-value	R^2
Bone Density	BMI	0.0071	<0.001	0.131
	Age	0.0012	<0.001	
	Waist Circumference	-0.0012	<0.001	
	Gender (F)	-0.0541	<0.001	
Bone Content	BMI	16.75	<0.001	0.338
	Waist Circumference	3.28	0.004	
	Age	2.24	<0.001	
	Gender (F)	-420.27	<0.001	

Hormonal and biochemical contributions to bone health: Further analysis of biochemical markers in relation to bone health highlighted hormonal and metabolic contributions. Testosterone was strongly and positively associated with both BMD and BMC, while SHBG demonstrated an inverse relationship. Muscle-related enzyme CPK also had a positive impact, reinforcing the mechanical linkage between muscle and bone health. In contrast, alkaline phosphatase (ALP) and phosphorus were negatively associated with bone health metrics, suggesting a role in bone turnover or mineral imbalance. Estradiol had a moderate but statistically significant positive effect, supporting its known protective role in bone metabolism. Regression models (Table 6) showed that testosterone, CPK, and estradiol were the strongest positive predictors of bone density (R^2 = 0.242) and bone content (R^2 = 0.358), while ALP, SHBG, and phosphorus were negative contributors. Machine learning models incorporating these biochemical predictors yielded similar results to traditional regression, with R^2 values of 0.24 and 0.36 for BMD and BMC, respectively (Table 6). The feature importance for these models is detailed in Figure 6. Fat Indices and Bone Health Interactions The interaction between fat indices and bone health metrics demonstrated both positive and negative associations (Figure 6, Figure 7). Total fat showed a strong positive correlation with bone content (ρ = 0.21) and a moderate one with BMD (ρ = 0.16), suggesting that higher overall fat mass may support bone maintenance to some extent. Conversely, higher gynoid fat was negatively associated with BMC (ρ = -0.32), while android fat showed a weak negative association with BMD (ρ = -0.04). Total percent fat and subcutaneous fat area were also negatively linked to bone content and density, albeit modestly. Regression analysis indicated that total fat and gynoid fat had positive contributions to BMD, while total percent fat and subcutaneous fat area had minor adverse effects (R^2 = 0.371). BMC was more strongly explained (R^2 = 0.689), with android and gynoid fat being strong positive predictors, though higher overall fat percentage and subcutaneous fat were negatively associated. Machine learning models reflected these patterns, with better performance in predicting bone content (R^2 = 0.65) than bone density (R^2 = 0.31, Table 3), underscoring the complexity of fat-bone interactions (Figure 8, and Figure 9).

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Table 6. Hormonal and biochemical predictors of bone health metrics.

Bone Metric	Predictor	B	p-value	R^2
Bone Density	Testosterone	8.85e-05	<0.001	0.242
	SHBG	-0.0002	<0.001	
	CPK	9.42e-05	<0.001	
	ALP	-0.0007	<0.001	
	Estradiol	0.0021	0.004	
Bone Content	Testosterone	0.6634	<0.001	0.358
	SHBG	-1.6952	<0.001	
	CPK	0.3703	<0.001	
	ALP	-2.4138	<0.001	
	Estradiol	3.2147	0.001	
	Phosphorus	-52.0294	<0.001	
	Vitamin D	0.6459	0.027	

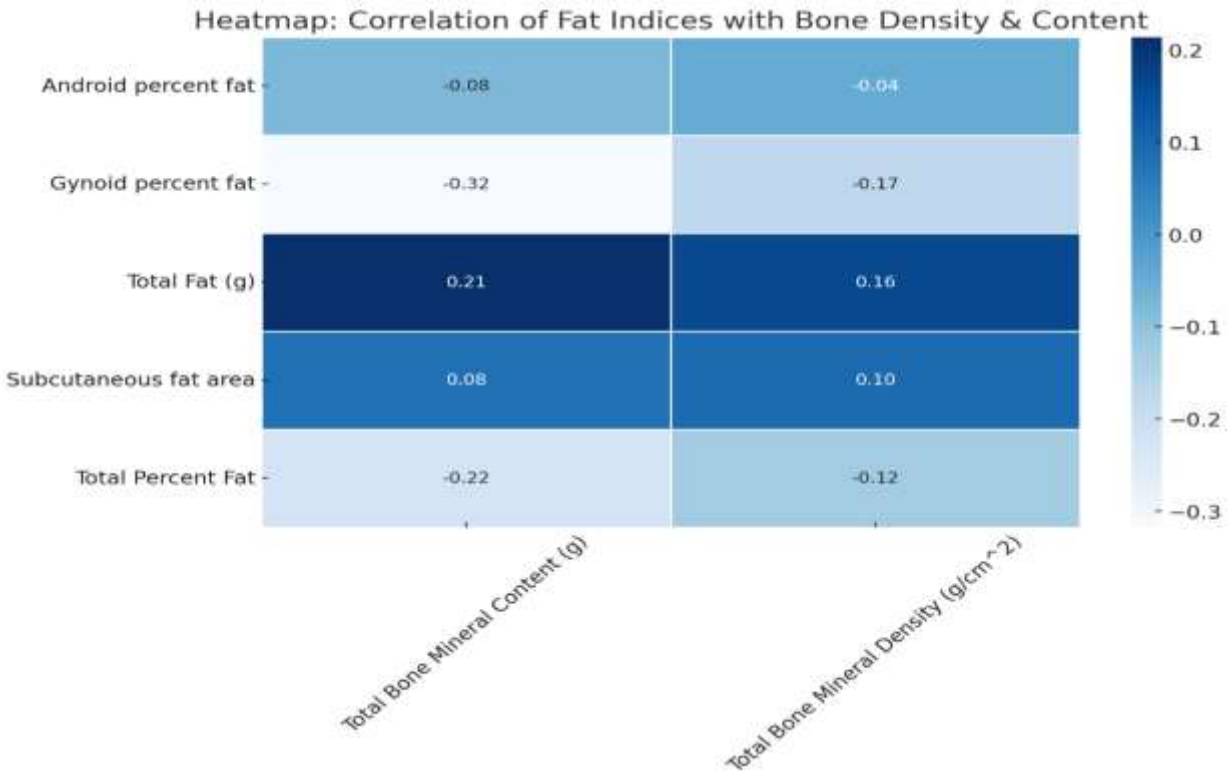

Figure 6. Correlation of bone health markers with fat indices.

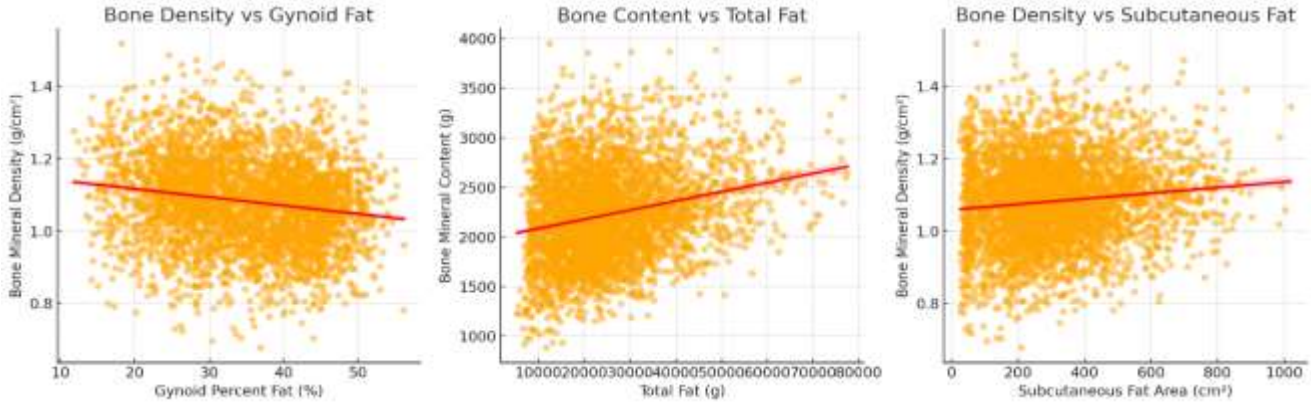

Figure 7. Regression of fat indices with bone health markers.

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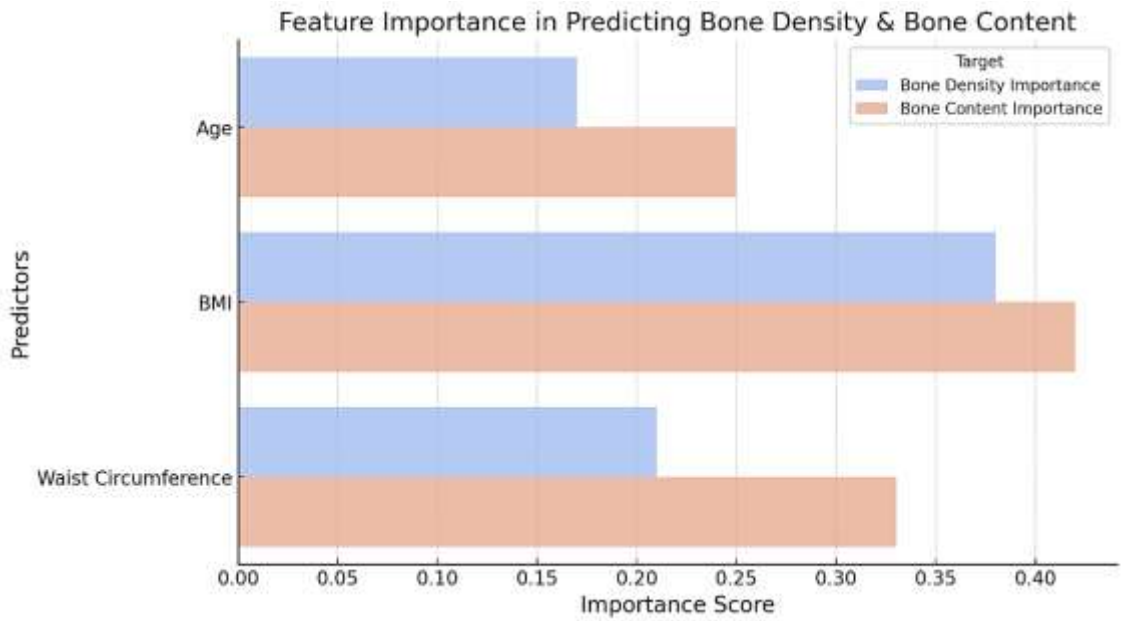

Figure 8. Feature importance in BMD and BMC.

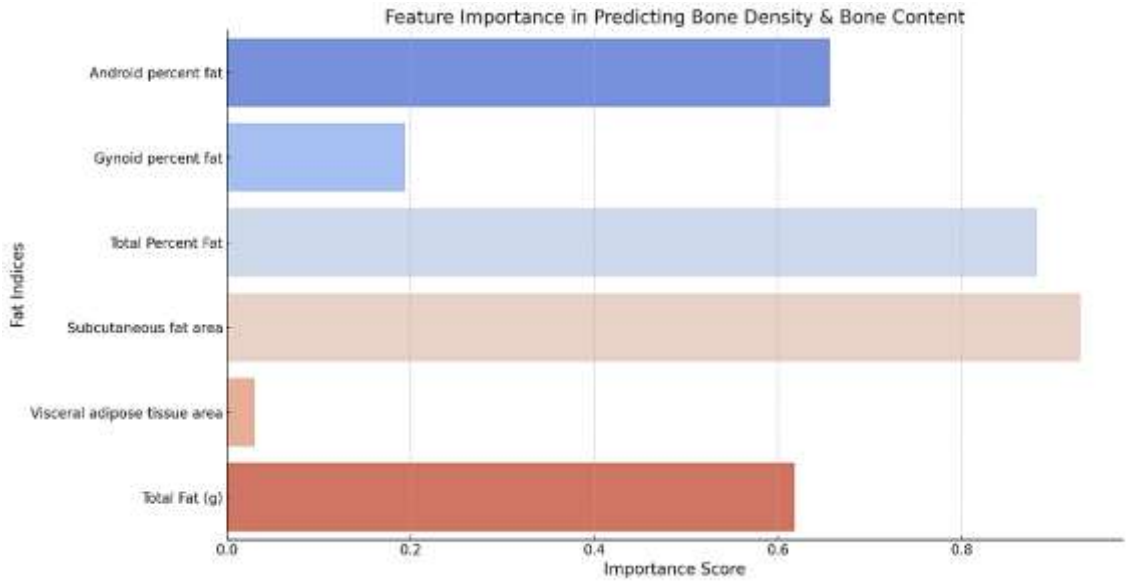

Figure 9. Feature importance in predicting bone density and bone content using fat indices

Discussion

This study provides a comprehensive analysis of the complex relationships between body fat distribution, demographic and biometric factors, and a broad range of lipid and hormonal biomarkers in influencing bone health. By integrating correlation, regression, and machine learning analyses, the findings reveal critical insights that hold significant clinical and research implications.

The study highlights how specific anthropometric measures, particularly body mass index and waist circumference, are key predictors of both fat accumulation and bone mineral metrics. Measurement of waist circumference is essential to understand central fat accumulation, which is strongly linked to various metabolic problems and complications (2). The remarkable observed associations highlight the importance of these variables as simple, easy-to-apply, and non-invasive

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methods for measuring or mapping body fat dispersal in medical practice. The potential of these measurements suggests a possible replacement or enhancement for more accurate existing radiological or analytical methods for detecting people at risk of metabolic disturbances.

There is an apparent difference in body fat distribution among males & females, with males prone to metabolic syndrome, insulin resistance, and cardiovascular disease because of high visceral fat accumulation. In contrast, females have total and subcutaneous fat in a more obvious distribution (3). These gender differences would highlight the known biological variances in the pattern of fat distribution and necessitate a gender-specific approach to handle such risks (4).

The study indicates that body fat distribution is further influenced by age differences, with a trend toward increased fat accumulation in the belly area, particularly in older individuals, regardless of total fat amounts, consistent with previous observations (5). This distribution will explain the relatively high cardio-metabolic risk in old-age patients. This will highlight the importance of preventive strategies such as directed exercises and dietary adjustments to minimize this non-correctable risk factor.

The results underscore the value of customized (gender & age) specific strategies in handling body fat distributions and bone well-being. For males, controlling visceral fat is vital to minimize associated cardio-metabolic risks through lifestyle interventions such as resistance exercise, dietary changes, or medications according to the guidelines (24). In females, maintaining good bone health is essential, especially for postmenopausal women. This can be achieved through simple screening using dual-energy X-ray absorptiometry (DXA) scans, along with proper instructions on weight-bearing exercises, vitamin D and calcium

prescriptions, or even hormone replacement therapy when necessary (25). A wise gathering and interpretation of anthropometric variables, biomarker readings, and body composition is a fundamental observation from this study to measure related risks and implement designed interventions. The waist circumference measurements should be routinely done in metabolic risk calculations to improve the early recognition of those at risk for cardio-metabolic disorders, given their high association with visceral fat (2).

The association between fat maps and lipid profiles provides further understanding of metabolic health. Glucose and insulin levels are now considered essential predictors of regional fat distribution, with high levels linked to increased total and abdominal fat and insulin resistance. Nevertheless, lipid profiles alone partially explain the uneven fat distributions throughout the body, highlighting the possible effects of other important factors such as genetic issues, chronic inflammation, and lifestyle attitudes (6). The modest prognostic ability of these biomarkers recommends an integrated approach, combining anthropometric and metabolic values for a complete evaluation of health risks related to fat disorders.

Bone metrics are significantly influenced by body mass index, gender, and age, with a high body mass index linked to good bone mineral density and bone mineral constituents. These positive associations may be explained by the intermittent mechanical loading effect of high body weight, which in turn stimulates new bone formation and strengthens skeletal integrity (11). Differences in bone health by gender are remarkable. In general, Women exhibit low bone mineral density and bone mineral content. This may explain the high prevalence of osteoporosis in women, especially after menopause, when there is a sharp decline in estrogen levels (9).

Central obesity seems to hurt bone density despite its good contribution to overall bone content. This

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complex relationship may be better understood when we recognize that the metabolic penalties of central adiposity, such as chronic inflammation and hormonal inequities, can negatively affect bone quality despite the mechanical support provided to bones by high body weight (23).

Hormones have a fundamental effect in maintaining adequate bone health. Testosterone has been recognized to have a positive influence on bone mineral density and bone mineral content (20). This observation repeats the well-documented positive effects of testosterone in maintaining and improving bone and skeletal integrity. On the other hand, Sex hormone-binding globulin is associated with a negative contribution to bone health, possibly due to its effect in reducing the essential anabolic hormones like testosterone and estradiol (21). Evaluation of bone turnover markers also provides insight into the biological mechanisms controlling skeletal health. Creatine phosphokinase, which is a muscle enzyme reflecting muscle function, shows a positive effect on bone health in contrast to alkaline phosphatase, a marker of high bone turnover, which is associated with low bone mineral density; this observation confirmed the previous reports regarding the effects of alkaline phosphatase & creatine phosphokinase on bone health (13,16). Phosphorus level imbalances, caused by excessive intake or other factors, may affect bone mineralization and bone contents, stressing the need for vigilant checking of dietary and metabolic factors in bone health evaluations.

The complex interplay between fat profiles and bone health shows a characteristic association. Regional fat accumulation has divergent influences, with fat depositions in specific areas such as the thighs and hips being linked to higher bone mineral content. In contrast, total body fat and subcutaneous fat show negative contributions. This complexity highlights the need to consider fat distribution

rather than total fat mass alone when evaluating bone health risks. The predictive models established in this topic perform well in approximating bone mineral content over bone mineral density, indicating that bone density is influenced by a broader range of factors beyond adiposity, even though fat indices help predict overall bone mass (26).

Nevertheless, the study has remarkable limitations. It was a cross-sectional study that precludes causal extrapolations, mainly concerning the unanticipated positive relationship between age and bone health, which reverses the traditional trends of age-related bone loss. This incongruity may arise from untested confounders such as the level of physical activity, diet, or survival bias, emphasizing the need for longitudinal research to elucidate these associations. The limited descriptive efficacy of lipid profiles in estimating fat accumulation suggests that other important factors, such as genetics, lifestyle, or inflammation, are absent, which restricts model accuracy. Moreover, the study's dependence on a particular population may limit the generalizability of conclusions, especially the age-bone health relationship, which might be affected by cohort properties. Incorporating other variables such as muscle mass, hormonal variations, or genetic tendencies will enhance the predictive power of machine learning models (27).

To interpret these results practically, physicians should integrate body mass index measurements with waist circumference in routine evaluations to address possible metabolic risks. DXA scans should be utilized for bone health proactive screening, especially in high-risk groups, including middle-aged women, postmenopausal women, and those with high total or subcutaneous fat, alongside lifestyle assessments. Consideration of testosterone replacement therapy with careful supervision should be discussed in patients with low bone mass after

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Published: 25 October 2025
DOI: 10.26505/djm.v29i1.1415

checking and monitoring testosterone levels. Measuring fasting insulin and glucose levels to identify possible abnormal metabolic functions is also recommended. Future studies should embrace longitudinal strategies to establish causality and consider factors such as genetic issues, chronic inflammation, and lifestyle to improve predictive models. These understandings recommend a multidimensional, evidence-based methodology, balancing integrated evaluations and customized interventions to enhance conclusions on metabolic and skeletal health (28).

Conclusion

This study highlights the complex interplay between body composition, metabolic biomarkers, and bone health. Waist circumference and BMI are strong, non-invasive predictors of both fat distribution and skeletal metrics, with apparent variations by age and gender. Hormonal and biochemical markers, particularly insulin, testosterone, SHBG, and CPK, significantly influence adiposity and bone outcomes. Machine learning models show moderate predictive accuracy, suggesting room for enhancement through the inclusion of additional factors such as muscle mass and genetics. These findings support a comprehensive, individualized approach to assessing metabolic and bone health, emphasizing the utility of simple clinical measures in guiding risk stratification and intervention strategies. It was recommended that routine Measurement of Waist Circumference and BMI should be integrated into clinical assessments to estimate fat distribution and associated risks. In addition, hormonal Evaluations, including testosterone and SHBG, should be considered in bone health assessments, especially in aging men and women with low bone mass.

Source of funding: No source of funding.

Ethical clearance: This study utilized data from the National Health and Nutrition Examination Survey (NHANES), which is publicly available and fully de-identified in accordance with the Health Insurance. Portability and Accountability Act (HIPAA) Privacy Rule. As such, the analysis of this secondary data does not constitute human subjects research and does not require additional Institutional Review Board (IRB) approval. All NHANES study protocols were reviewed and approved by the National Center for Health Statistics (NCHS) Research Ethics Review Board under Protocol #2011-17, and written informed consent was obtained from all participants before data collection. The study adheres to the ethical standards outlined in the Declaration of Helsinki and complies with U.S. federal regulations governing research using publicly available datasets.

Conflict of interest: None.

Use of Artificial Intelligence: The authors declare that they did not use generative artificial intelligence for creating or preparing the manuscript.

Acknowledgments: The authors would like to express their deep thanks to all those who aided in the completion of this work, especially our families and colleagues, for their continuous encouragement and understanding during the period of this study.

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Diyala Journal of Medicine

ORIGINAL RESEARCH
Published: 25 October 2025
DOI: 10.26505/djm.v29i1.1415

التفاعل بين الملامح الحيوية والعلامات الحيوية ونسبة الدهون في الجسم وصحة العظام: نهج احصائي وتعلّم الي

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الملخص

الخلفية: : السمنة واضطرابات التمثيل الغذائي هي مخاوف صحية عامة منتشرة بشكل متزايد. ترتبط السمنة الزائدة ، وخاصة الدهون الحشوية ، بخلل التمثيل الغذائي ، في حين أن مستودعات الدهون الإقليمية مثل الدهون الجينويد قد تمنح فوائد وقائية على سلامة الهيكل العظمي

الأهداف: هدفت هذا الدراسة إلى دراسة العلاقة المعقدة بين الملامح الحيوية والعلامات الكيميائية الحيوية وتوزيع الدهون في الجسم وصحة العظام.

المواد والطرق: تم الحصول على البيانات من المسح الوطني لفحص الصحة والتغذية (**NHANES**) ، بما في ذلك المشاركين البالغين الذين لديهم قياسات كاملة لتكوين الجسم (الدهون الكلية ، الحشوية ، وتحت الجلد. مؤشر كتله الجسم; محيط الخصر) ، والعلامات الكيميائية الحيوية (ملامح الدهون ، والجلوكوز الصائم ، والأنسولين ، والمنظمين الهرمونيين) ، ومقاييس صحة العظام (كثافة المعادن في العظام ومحتواها عبر **DXA**). تم إجراء تحليلات الارتباط والانحدار متعدد المتغيرات لتحديد المتنبئين بين المتغيرات الديموغرافية والقياسية الحيوية والكيميائية الحيوية. تم استخدام تقنيات التعلم الآلي ، وتحديدا الانحدار العشوائي، لتعزيز النمذجة التنبؤية لمؤشرات الدهون ونتائج صحة العظام.

النتائج: ظهر مؤشر كتلة الجسم ومحيط الخصر كتنبؤات قوية للدهون الكلية والحشوية ، مع ملاحظة تفاوتات كبيرة بين الجنسين والعمر. أظهرت النساء دهونا إجمالية وتحت الجلد أعلى ، بينما أظهر الرجال زيادة في الدهون الحشوية. ترتبط العلامات الكيميائية الحيوية ، ولا سيما الأنسولين والجلوكوز ، ارتباطا وثيقا بمؤشرات السمنة. علاوة على ذلك ، ارتبطت صحة العظام بشكل إيجابي بمؤشر كتلة الجسم والمؤشرات الحيوية المحددة (التستوستيرون ، CPK) وبشكل سلبي مع SHBG و ALP. لوحظت دقة تنبؤية متوسطة إلى عالية لنماذج التعلم الآلي ، مما يؤكد المساهمة الداعمة للتحليلات التنبؤية في فهم هذه العلاقات.

الاستنتاج: يقدم الجمع بين المقاييس الأنثروبومترية والعلامات الكيميائية الحيوية والدهون والعظام مع التعلم الآلي شرحا شاملا لارتباطها وارتباطها. يمكن لمثل هذه الأفكار أن توجه تصميم استراتيجيات محددة لاتخاذ القرار السريري والتأكيد على جدوى استخدام قياسات بسيطة غير جراحية لتقييم مخاطر التمثيل الغذائي والهيكل العظمي.

الكلمات المفتاحية: الملف الحيوي، صحة الهيكل العظمي، نسبة الدهون في الجسم، منهج التعلم الآلي.

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تاريخ الاستلام: ١٩ نيسان ٢٠٢٥

تاريخ القبول: ٢٤ أب ٢٠٢٥

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