Estimating Body Fat Percentage*

Abdomen as the Strongest Predictor With Contributions From Wrist, Height, and Age For Affordable Health Monitoring

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This study uses a multi-linear regression model to estimate body fat percentage based on circumference measurements. Abdominal size was the strongest predictor, followed by wrist size, height, and age, which showed minimal contributions. These results demonstrate that accessible methods can effectively estimate body fat, offering methods suitable for non-clinical settings. This approach is important for identifying and managing health risks associated with extremely low or high body fat levels in a practical and affordable way.

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*Code and data are available at: https://github.com/kiwindyy/Body-Fat

1 Introduction

Monitoring body fat is important because of the major role it plays in overall health. Current methods, like DXA scans and underwater weighing, are very reliable but often expensive, difficult to access, or only available in specialized facilities. More affordable methods, like body circumference measuring, can provide reasonable estimates of body fat (Tinsley 2023). A lack of easy and reliable ways to measure body fat can lead to missed chances to detect health risks. Excess body fat is strongly linked to conditions such as heart disease, type 2 diabetes, high blood pressure, and even certain cancers. It can also increase strain on the joints, leading to issues like osteoarthritis, and contribute to breathing problems like sleep apnea (Diabetes, Digestive, and Diseases 2023). Extremely low body fat can interfere with key body functions, affecting hormone levels, immune health, and even heart rhythm. For example, not enough body fat can lead to irregular heartbeats, extreme fatigue, and reproductive issues (Fetters 2023). Without proper tools to measure and manage body fat, individuals may unknowingly face these risks, making it important to research methods that are both reliable and affordable.

This study examines the reliability of using circumference measurements to estimate body fat. Starting with a dataset containing many measurements, we used backward selection to identify the most relevant variables impacting body fat. The four variables are: Age, Height, Abdomen, and Wrist circumference. After making sure these variables did not display collinearity, we tested the linear regression assumptions to confirm the model's validity. The selected variables were analyzed in a multiple linear regression model and individually in simple linear regression plots against body fat. This approach gives a clear understanding of how each variable relates to body fat. Finally, we evaluated the coefficients in the multiple regression model to make sure they aligned logically with the model, supporting its reliability.

The study found that different body measurements had different effects on body fat percentage. Abdominal size had the strongest influence, with larger measurements strongly linked to higher body fat. Wrist size and height were associated with lower body fat, meaning that people with bigger wrists or greater height tend to have less fat overall. Age played a smaller role, with older individuals showing a slight tendency to have more body fat, but the effect was weaker than the other factors. Together, these measurements offered a practical way to estimate body fat, with abdominal size standing out as the most important factor.

The remainder of this paper is structured as follows: Section 2 explains the dataset source, how it was collected, and describes the variables used. Section 3 outlines the multi-linear regression setup and the rationale for its use. Section 4 presents the regression outcomes, showing how the predictors explain body fat percentage. Section 5 interprets the findings, notes limitations, and suggests improvements. Section A & Section B & Section C contain supporting data information. Section D explores survey, sampling, and observational data methods, including measurement techniques, simulations.

1.1 Estimand

The estimand of this study is body fat percentage, which we aim to estimate based on measurements from The Data And Story Library (Ricard n.d.). Body fat percentage is an important health metric that cannot be measured directly for every individual, especially outside of specialized settings. To address this, we used a multi-linear regression model, combining predictors such as age, height, abdomen, and wrist circumference to estimate body fat. By analyzing these variables, this study seeks to understand their effects on body fat. The model not only provides a framework for estimation making sure our approach is both structured and practical.

2 Data

This study uses the statistical programming language R (R Core Team 2024) and the packages: tidyverse (Wickham et al. 2019), Arrow (Richardson et al. 2024), MASS (Venables and Ripley 2002), GGally (Schloerke et al. 2024), gridExtra (Auguie 2017), Knitr (Xie 2024), kableExtra (Zhu 2024), Car (Fox and Weisberg 2019), TestThat (Wickham 2011), dplyr (Wickham et al. 2023), readr (Wickham, Hester, and Bryan 2024), tidyr (Wickham, Vaughan, and Girlich 2024). The data used in this study is obtained from The Data And Story Library (Ricard n.d.).

2.1 Measurement

The dataset used in this study, sourced from The Data And Story Library (Ricard n.d.), contains measurements on body fat percentage alongside various physical metrics for 250 male participants. The dataset was collected to analyze body fat as an important health measure, providing variables such as age, weight, height, and circumferences of specific body parts. These measurements were obtained through direct assessments to ensure accuracy and uniform input into the dataset. The dataset allows researchers to consider accessible ways to estimate body fat without relying on costly or specialized methods.

Before analysis, the raw dataset was cleaned to standardize and prepare the data for use. Since the original dataset included measurements in both inches and centimeters, all measurements were converted into centimeters to ensure uniformity. Additionally, measurements in pounds were converted to kilograms. Table 1 & Table 2 & Table 3 show the first 8 observations of the cleaned data. Additional cleaning steps included removing duplicates, addressing outliers, and removing missing observations to improve dataset's usability. This cleaned data makes sure that the variables in the study are accurate and consistent. For reference, the original dataset before cleaning (first 10 observation) is provided in Table 6 & Table 7 in Section A, showing the changes made during this process.

Table 1: Cleaned Data of Body Fat Variables Part 1

Density (g/cm³)	Pct.BF (%)	Age (years)	Weight (kg)	Height (cm)
1.0708	12.3	23	69.96	172.08
1.0853	6.1	22	78.58	183.51
1.0414	25.3	22	69.85	168.27
1.0751	10.4	26	83.80	183.51
1.0340	28.7	24	83.57	180.97
1.0502	20.9	24	95.36	189.86
1.0549	19.2	26	82.10	177.16
1.0704	12.4	25	79.83	184.15

Table 2: Cleaned Data of Body Fat Variables Part 2

Neck (cm)	Chest (cm)	Abdomen (cm)	Waist (cm)	Hip (cm)
36.2	93.1	85.2	85.2	94.5
38.5	93.6	83.0	83.0	98.7
34.0	95.8	87.9	87.9	99.2
37.4	101.8	86.4	86.4	101.2
34.4	97.3	100.0	100.0	101.9
39.0	104.5	94.4	94.4	107.8
36.4	105.1	90.7	90.7	100.3
37.8	99.6	88.5	88.5	97.1

Table 3: Cleaned Data of Body Fat Variables Part 3

Thigh (cm)	Knee (cm)	Ankle (cm)	Bicep (cm)	Forearm (cm)	Wrist (cm)
59.0	37.3	21.9	32.0	27.4	17.1
58.7	37.3	23.4	30.5	28.9	18.2
59.6	38.9	24.0	28.8	25.2	16.6
60.1	37.3	22.8	32.4	29.4	18.2
63.2	42.2	24.0	32.2	27.7	17.7
66.0	42.0	25.6	35.7	30.6	18.8
58.4	38.3	22.9	31.9	27.8	17.7
60.0	39.4	23.2	30.5	29.0	18.8

2.2 Outcome variables

The dependent variable in this study is percent body fat, which represents the proportion of an individual's total body mass that is composed of fat. This variable is a continuous measure and serves as the target outcome we aim to estimate using predictor variables. Percent body fat is an important indicator of health, as both excessive and extremely low levels can lead to various medical issues. In our analysis, understanding the distribution of this variable is essential for ensuring that it aligns with the assumptions required for linear regression modeling.

Body fat percent is measured in percentage (%). Using the method from … body fat percentage is calculated using the relationship between body density (D) and the densities of lean and fat tissue. The formula for the proportion of fat tissue (B) is:

$$B = \frac{1}{D} \cdot \frac{ab}{a-b} - \frac{b}{a-b}$$

For example: If $a = 1.10 g/cm^3$ (lean tissue density), $b = 0.90 g/cm^3$ (fat tissue density), and $D = 1.0708 g/cm^3$. Once B is found, percent body fat (pct.BF) is calculated as:

$$\text{PctBF} = 100 \cdot B$$

The calculation gives about 12.27% body fat. This method provides a simple way to estimate body fat for regression analysis.

As shown in Figure 1, the histogram of percent body fat has a shape that is close to bell-like, though it is not perfectly symmetrical. The values range between 0 to 47.5. Most individuals in the dataset have body fat levels clustered within a common range, with fewer individuals having much higher or much lower levels. There is a slight tendency for more values to stretch toward higher body fat percentages, creating a small imbalance in the shape of the distribution. The spread of values covers a wide range, reflecting the diversity in body fat levels across the individuals studied. At the extremes, a few outliers stand out - some with very low body fat and others with notably high levels.

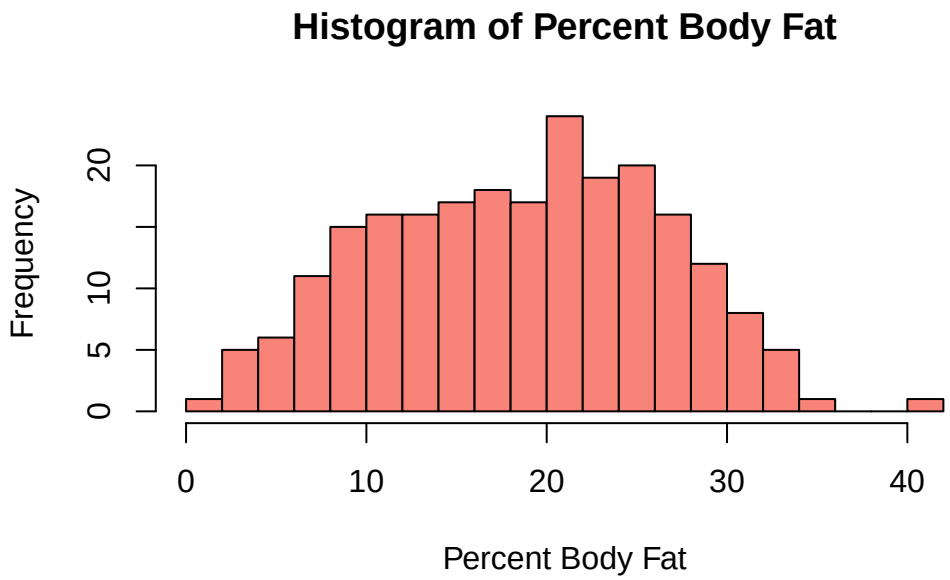

Figure 1: Histogram Distribution of Percent Body Fat

2.3 Predictor variables

The original uncleaned dataset contained the variables below:

- Density: The measure of body density, used as a key variable in estimating body fat percentage. It combines body weight and volume to provide insights into overall composition. It is measured in grams per cm^3 with values ranging from 0.99 to 1.1.
- Age: The age of the individual in years, providing a measure of the person's stage of life, which can influence body composition. It is measured in years with values ranging from 20 to 81.
- Weight: The total body mass of the individual, reflecting the combined weight of bones, muscles, fat, and other tissues. It is measured in pounds (lbs) with values ranging from 118.5-262.75.
- Height: The standing height of the individual, often used alongside weight to calculate proportions and indices. It is measured in inches (in) with values ranging from 64–77.75.
- Neck: The circumference of the neck, offering a measurement of fat and muscle distribution in the upper body. It is measured in centimeters (cm) with values ranging from 31.1-43.9.
- Chest: The circumference of the chest, reflecting the size and structure of the upper torso, including muscle and fat. It is measured in centimeters (cm) with values ranging from 79.3-128.3.
- Abdomen: The circumference around the abdomen, a key indicator of central fat distribution and a significant predictor of body fat percentage. It is measured in centimeters (cm) with values ranging from 69.4-126.2.

- Waist: The measurement around the waist, often used with hip circumference to assess body shape and fat distribution. It is measured in centimeters (cm) with values ranging from 27.3-49.6.
- Hip: The circumference of the hips, providing a measure of lower-body proportions and often paired with waist circumference to calculate ratios. It is measured in centimeters (cm) with values ranging from 85.0-125.6.
- Thigh: The circumference of the thigh, measured to understand muscle and fat distribution in the upper leg. It is measured in centimeters (cm) with values ranging from 47.2-74.4.
- Knee: The circumference of the knee, offering additional detail about lower-body structure and proportions. It is measured in centimeters (cm) with values ranging from 33.5-46.0.
- Ankle: The measurement around the ankle, reflecting skeletal and soft tissue composition in the lower leg. It is measured in centimeters (cm) with values ranging from 20.2-27.0.
- Bicep: The circumference of the bicep, measured with the arm flexed, highlighting upper-arm muscle and fat distribution. It is measured in centimeters (cm) with values ranging from 25.6-39.1.
- Forearm: The circumference of the forearm, providing information about the composition of the lower arm. It is measured in centimeters (cm) with values ranging from 24.6-33.8.
- Wrist: The circumference of the wrist, a useful proxy for skeletal size and overall body frame. It is measured in centimeters (cm) with values ranging from 15.8-21.4.

This study focuses on only four variables. To find the most important ones, backward selection was used to identify the four variables that provided the best model fit, measured by the lowest Akaike Information Criterion (AIC). For this method to work, all variables needed to meet the linear regression assumptions. As discussed in Section B, the analysis showed that all 15 variables meet these assumptions when tested against body fat percentage (Pct.BF). With these conditions met, the study proceeds using AIC to keep the model simple while still explaining the data well.

Backward selection starts with all the variables and gradually removes those that contribute the least to predicting body fat percentage, based on AIC. The process begins with a full model using all variables (excluding Density, as it is directly used to calculate body fat percentage) and continues until only four variables remain. The four variables selected are: **Age, Height, Abdomen, and Wrist**, as seen in Figure 2. They were chosen because they explain differences in body fat percentage well while keeping the model easy to interpret. For a more detailed explanation of this process, see Section C or the script documented in scripts/05-exploratory_data_analysis.R.

x
Age
Height
Abdomen
Wrist

Figure 2: AIC Optimizing Best 4 Variables

The histograms of Age, Height, Abdomen, and Wrist shown in Figure 3 explain their role in predicting body fat. Most participants are between 30 and 60 years old, with fewer older individuals, making the sample mainly middle-aged. Height is evenly spread and follows a balanced shape, making it a reliable variable for the analysis. Abdomen size is mostly within a common range, with a few larger measurements that could influence the results due to their link to higher body fat. Wrist size has less variation but is consistent and still important because of its connection to lower body fat. Overall, these variables work well for modeling body fat, although the uneven spread of Age might need adjustments for better results.

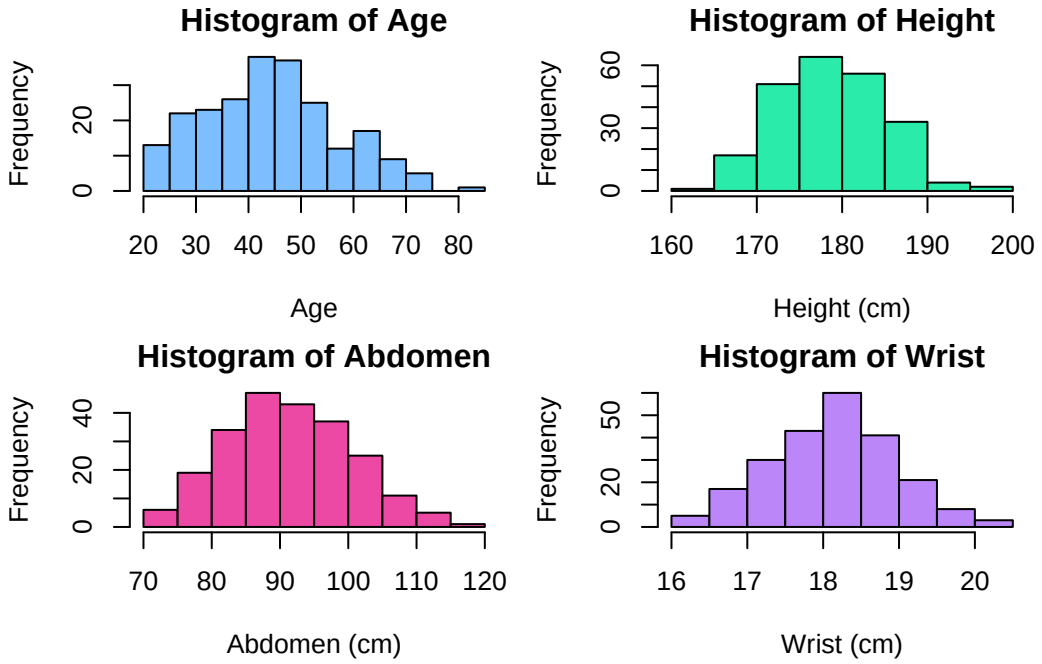

Figure 3: Histogram Distributions of Age, Height, Abdomen, Wrist

The pairwise plot, Figure 4, shows how Age, Height, Abdomen, and Wrist are related to each other. Abdomen and Wrist have the strongest relationship in all the selected variables - as they have a rough linear shape in the pairwise plot. Larger abdominal circumferences

are generally linked to larger wrists, showing overall body size. Age has a weak connection to Abdomen. Older individuals tend to have slightly larger abdominal sizes. However, Age shows no clear relationship with Height or Wrist. Height has small links to both Abdomen and Wrist. Taller individuals tend to have slightly smaller abdominal sizes and larger wrists. Abdomen and Wrist are the most important variables for predicting body fat. Height and Age provide smaller, additional contributions. The lack of strong correlations between these variables means they work well together in a regression model.

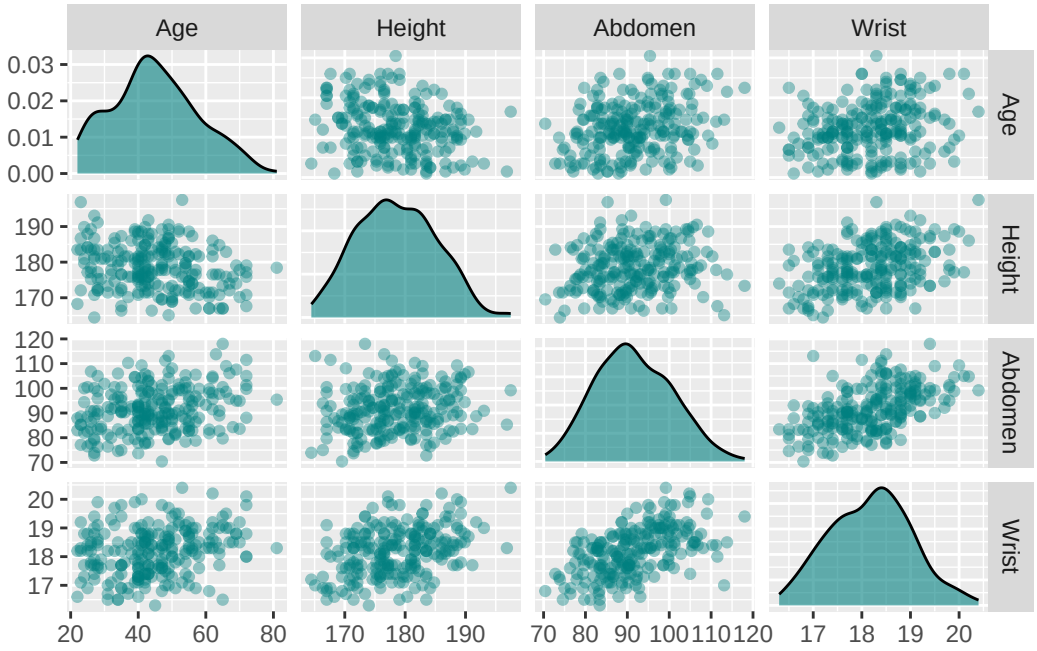

Figure 4: Pairwise Plot Compairing the Relationship Between Age, Heigh, Abdomen, Wrist

The variance inflation factor (VIF) is used to check if the predictors in a regression model are too closely related, a problem called multicollinearity. VIF shows how much a predictor's contribution is influenced by its relationship with other variables. A VIF of 1 means no overlap, while values over 5 or 10 might cause issues and need fixing.

Figure 5 shows the VIF values for Age, Height, Abdomen, and Wrist are all below 2 - meaning there is very little overlap between them. Wrist has the highest value (1.724), but this is still low, meaning it is only slightly related to other variables. The scatterplots showed some small relationships between variables, and the VIF confirms that these are not strong enough to cause problems. This means each variable adds its own useful information to the model.

	x
Age	1.266260
Height	1.346920
Abdomen	1.450437
Wrist	1.695736

Figure 5: VIF Values of Age, Height, Abdomen, Wrist

3 Model

The goal of our model is to estimate body fat percentage using four predictors: Age, Height, Abdomen, and Wrist circumference. This helps us understand how each variable affects body fat while making sure the model gives accurate estimates.

3.1 Model set-up

Define y_i as the body fat percentage for the i-th individual. The predictors in the model are:

- x_{1i}: Age, representing the individual's age in years.
- x_{2i}: Height, measured in centimeters.
- x_{3i}: Abdomen, the abdominal circumference in centimeters.
- x_{4i}: Wrist, the wrist circumference in centimeters.

The model is expressed as:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \epsilon_i$$

where β_0 is the intercept, $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients for each predictor, and ϵ_i represents the error term, assumed to be normally distributed with mean 0. Diagnostic plots and residual checks were performed to assess whether the model passed linear regression assumptions

3.1.1 Model justification

Linear regression has four key assumptions to ensure the model works well. Linearity means the relationship between the predictors and the outcome should be straight, so the model captures the correct pattern. Constance variance means the residuals should have the same spread across all predictor variables. Normality requires the errors to follow a normal distribution. Independence ensures the errors are not related to each other, avoiding bias. Checking these assumptions helps make sure the model is accurate and trustworthy.

The residual plot, shown in Figure 6, helps assess both the linearity and independence assumptions in the linear regression model. There is no strong curve or trend in the residuals, confirming that the linearity assumption holds well. The residuals are randomly scattered around the red horizontal line at zero, with no noticeable patterns or clustering, indicating that the model correctly captures the relationships between the predictors and the dependent variable. This randomness also suggests that the residuals are independent, as they are not systematically related to each other or to the fitted values. Together, these results confirm that the model satisfies both the linearity and independence assumptions, providing a solid basis for interpreting the results.

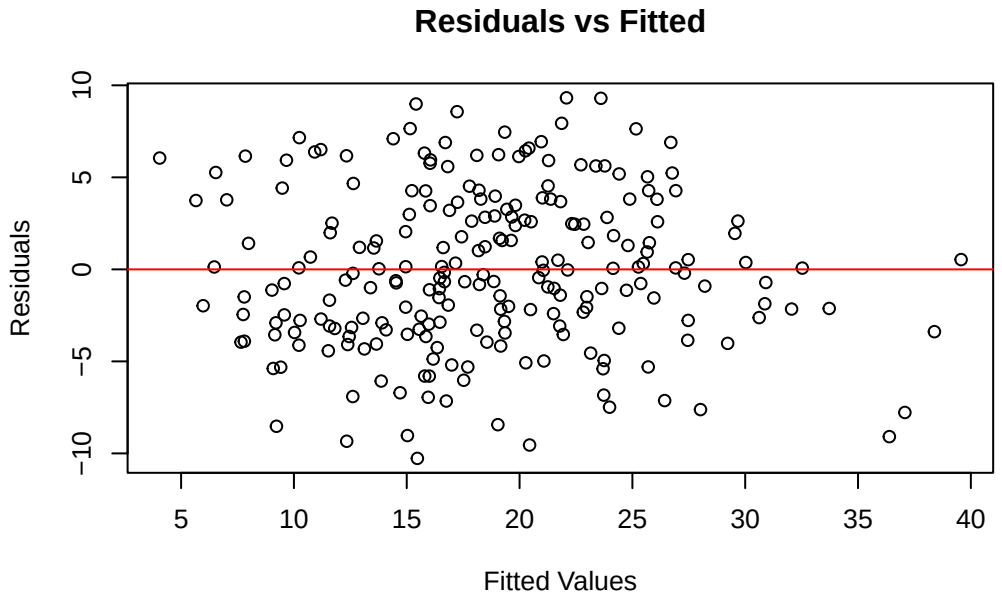

Figure 6: Residual Plot Verifying the Linearity Assumption

The Scale-Location plot, Figure 7, is used to assess the assumption of constant variance in a linear regression model. The standardized residuals are plotted against the fitted values, with the red line representing the trend. For the assumption of constant variance to hold, the points should be scattered randomly around the red line without forming a pattern or a funnel shape. In this plot, the points seem to be spread out evenly across the predicted values, with no clear signs of the spread getting bigger or smaller. This means the errors have a consistent variance confirming the linear regression assumption.

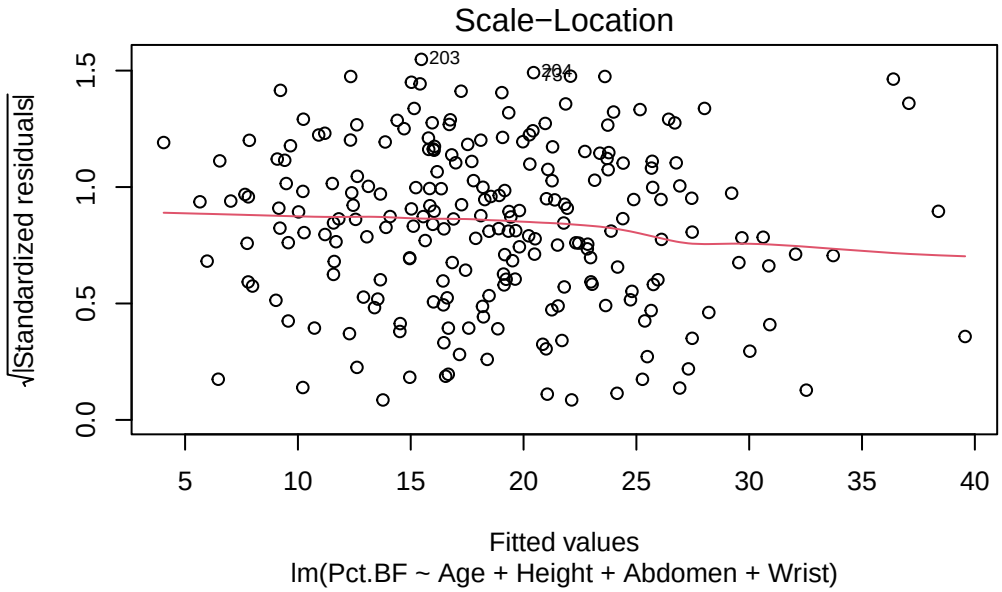

Figure 7: Scale Location Verifying Constance Variance Assumption

The Normal Q-Q plot, Figure 8 checks if the residuals (errors) in the model follow a normal distribution. If the errors are normal, the points should stay close to the red line. Here, most points are close to the line, meaning the errors are roughly normal. At the ends, some points are farther from the line, which might mean there are some extreme values or outliers. Overall, the errors seem mostly normal satisfying the linear regression assumption.

We expect larger body measurements to be linked to higher body fat percentages. Specifically, people with bigger abdominal or wrist circumferences are likely to have more body fat. Abdomen size often shows how much fat is stored in the center of the body, which contributes a lot to total body fat. Wrist circumference, while less variable, can reflect overall body size and fat distribution. In contrast, we expect taller individuals to have less body fat because taller people usually have leaner body compositions.

We also expect older individuals to have slightly more body fat. As people age, changes in metabolism and lifestyle can lead to gradual increases in fat. By using these variables in a multi-linear regression model, we can measure how each one affects body fat percentage. For example, the model will estimate how much body fat percentage increases when abdomen size grows by one unit, while keeping the other variables unchanged. This helps us understand the role of each measurement in predicting body fat.

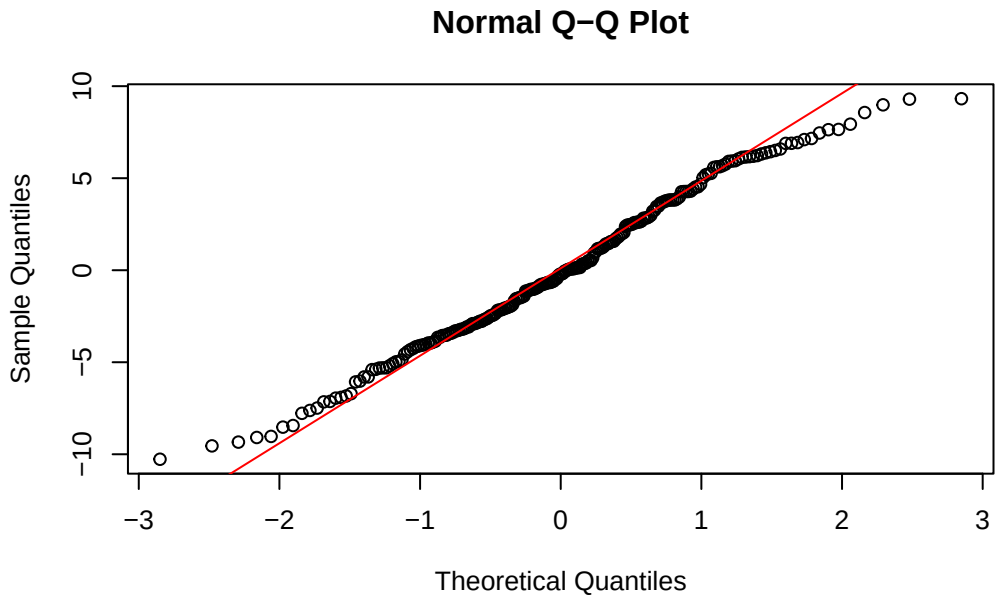

Figure 8: QQ-Plot Verifying the Normality of Errors Assumption

4 Results

The scatterplots from Figure 9 provide an initial look at the relationships between body fat percentage and the variables: Age, Height, Abdomen, and Wrist circumference. It looks at whether trends exist between the dependent variable and the predictors, giving a sense of how each variable may contribute to the model.

- Pct.BF vs Age: There is a slight positive trend, indicating that body fat percentage tends to increase as Age increases. While this relationship is not very strong, it suggests age could have a modest impact on body fat.
- Pct.BF vs Height: The plot shows no clear trend, with a nearly flat line indicating that Height likely has little influence on body fat percentage.
- Pct.BF vs Abdomen: A strong positive relationship is visible, as body fat percentage increases significantly with Abdomen circumference. This suggests Abdomen size is a key predictor of body fat due to its role in central fat storage.
- Pct.BF vs Wrist: A weak negative trend is observed, suggesting that individuals with larger Wrist circumferences tend to have slightly lower body fat percentages.

The regression results are summarized in Table 4, showing the coefficients and pvalues & Table 5, showing the R^2 and standard error. For the code and full model see the script document in: scripts/06-model_data.R. The intercept, which represents the estimated body fat percentage when all predictors are zero, is 2.01. However, this value doesn't have much real-world meaning because variables like height and abdomen size cannot actually be zero.

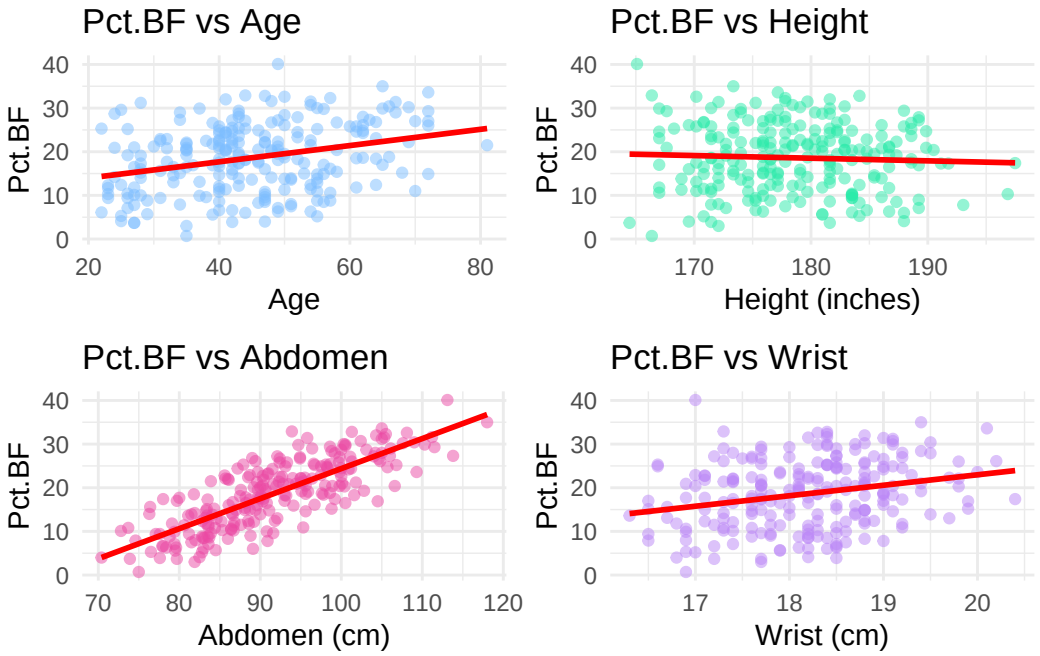

Figure 9: Simple Linear Regression Plots Against Body Fat Percent for Age, Height, Abdomen, Wrist

Among the predictors, Abdomen circumference has the strongest positive effect on body fat percentage. For every 1 cm increase in abdomen size, body fat percentage increases by about 0.78%, while keeping other factors unchanged.

Wrist circumference shows a significant negative relationship with body fat percentage. This means that people with larger wrists tend to have lower body fat percentages. Height also has a small negative effect, indicating that taller individuals are likely to have slightly lower body fat. Age has a weak positive effect, meaning body fat percentage may slightly increase with age, but this result is less certain. The p-value of each variable tells us the likely the data would have occurred. Assuming the alpha significance level is $\alpha = 0.05$ then height, abdomen & wrist would be good predictors for body fat percentage. However, since the p-value of age is 0.08 (greater than 0.05) then it is not necessarily a good predictor for body fat percentage.

The model explains about 70.3% of the variation in body fat percentage, showing it fits the data well. The residual standard error is 4.33, meaning the model's predictions are fairly accurate on average. Overall, Abdomen and Wrist are the most important predictors, with Height and Age playing smaller roles. Abdomen circumference stands out as the strongest factor for estimating body fat percentage.

Table 4: Multi-linear Regression Model Coefficients & P-Values

Variable	Estimate	P.Value
(Intercept)	2.7976254	0.7526650
Age	0.0449137	0.0806241
Height	-0.1235321	0.0168463
Abdomen	0.7809149	0.0000000
Wrist	-1.9621380	0.0000206

Table 5: Multi-linear Regression Model R-squared & RSE

Metric	Value
Residual Standard Error	4.3299071
Multiple R-squared	0.6981541
Adjusted R-squared	0.6927398

4.1 Model Validation

The plot, Figure 10 verifies the reliability of the multi-linear regression model by showing the estimated effects of each predictor and their 90% confidence intervals. It confirms that the model's results are consistent and aligns with key assumptions of linear regression.

- Abdomen: The strong positive coefficient and confidence interval far from zero confirm that Abdomen is a significant predictor of body fat percentage. This shows the model correctly identifies meaningful relationships between predictors and the dependent variable.
- Wrist: The negative coefficient and confidence interval that does not cross zero confirm that the model captures the relationship between Wrist size and lower body fat. While the interval for Wrist is slightly wider, it still supports the model's reliability.
- Height: The negative coefficient with a confidence interval just avoiding zero confirms the model captures a small but reliable relationship between Height and body fat percentage.
- Age: The confidence interval for Age includes zero, confirming the model's result that Age has a weaker and statistically insignificant effect on body fat percentage.

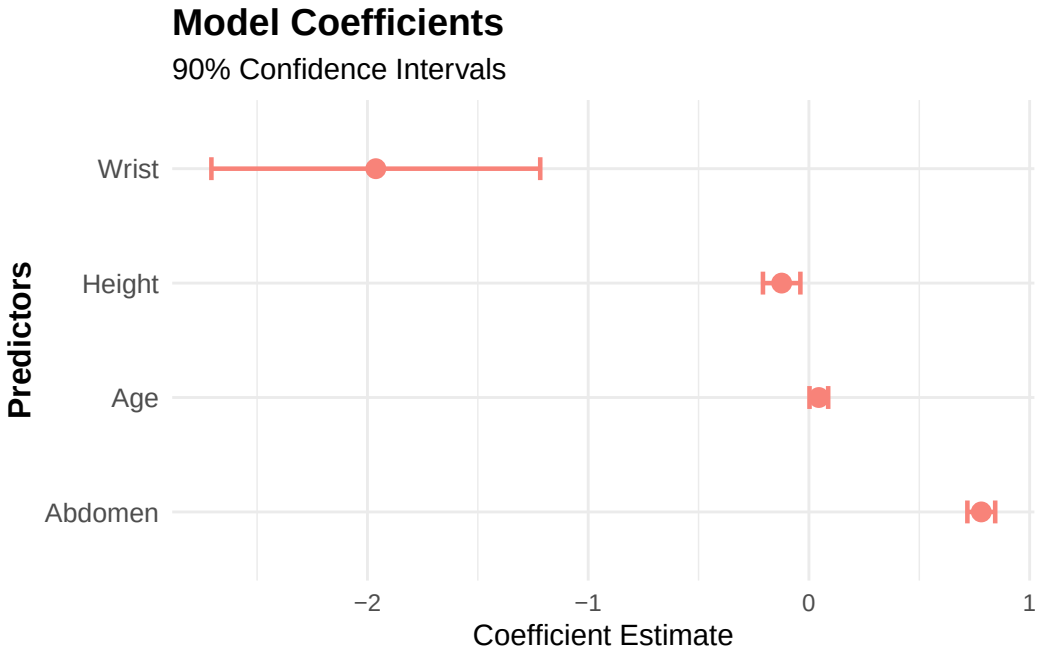

Figure 10: Model Coefficients Confidence Intervals

5 Discussion

5.1 Best Predictor: Abdomen

The regression results confirm that abdomen circumference is the strongest predictor of body fat percentage, with a coefficient of 0.784 and a highly significant p-value (<2e-16). This means that for every 1 cm increase in abdomen size, body fat percentage increases by approximately 0.78%, holding all other variables constant. Abdomen size is directly related to fat accumulation around the central part of the body, which is often linked to overall body fat levels. This finding aligns with the understanding that abdominal fat is a strong indicator of general adiposity and health risks, such as heart disease and metabolic disorders. The importance of abdomen as a predictor highlights its role in practical applications of body fat estimation models, particularly for tracking health outcomes and identifying individuals at risk for fat-related conditions.

5.2 Contributions of Wrist and Height

The results also show meaningful contributions from wrist circumference and height, though their relationships with body fat differ. Wrist circumference has a significant negative coefficient (-1.942, p = 2.38e-05), indicating that individuals with larger wrists tend to have lower

body fat percentages. This could reflect differences in body structure, where a larger wrist size often suggests a higher proportion of bone mass compared to fat mass. Height, on the other hand, has a smaller negative coefficient (-0.123, p = 0.0169), showing that taller individuals generally have slightly lower body fat percentages. This relationship may stem from taller individuals having a larger lean body mass proportion relative to their overall size. These results suggest that, while Abdomen plays the main role, Wrist and Height provide important context in understanding body fat distribution. They highlight the need to consider body structure, not just size, when evaluating fat levels.

5.3 Model Fit and Predictive Strength

The model demonstrates strong predictive ability, with an R^2 value of 0.7033 and an adjusted R^2 of 0.698. This means that approximately 70% of the variation in body fat percentage is explained by the four predictors in the model: Age, Height, Abdomen, and Wrist. The residual standard error of 4.33 indicates that the model's predictions are reasonably close to the actual values, with only a small degree of error. While Abdomen is a primary predictor, and Wrist and Height also contribute, Age appears to be a weaker predictor. Its coefficient (0.046) has a p-value of 0.071, indicating it is not statistically significant at the 5% level. This suggests that while body fat percentage might slightly increase with age, the relationship is not strong enough to rely on for predictive purposes. Including Age adds only marginal value to the model, and its role is less important compared to the other predictors. These results validate the model's usefulness in estimating body fat and emphasize its role in applications such as health monitoring, where accessible and reliable measurement tools are needed.

6 Weaknesses and Next Steps

This paper creates a multi-linear regression model to estimate body fat percentage using four predictors: Age, Height, Abdomen, and Wrist circumference. The dataset includes male participants, and the study ensures the model follows linear regression assumptions. The results show how each predictor contributes to body fat percentage, with Abdomen being the most important factor.

One finding is that abdominal size is a strong predictor of body fat percentage. This supports the idea that fat stored in the abdominal area plays a main role in overall body fat levels. Abdomen circumference serves as a useful and accessible measure for monitoring body fat, making it helpful for health-related purposes.

We also learn that structural factors like wrist size are connected to body fat percentage. Larger wrists are linked to lower body fat, possibly because of a higher proportion of bone mass compared to fat mass. This finding shows the need to consider body structure, not just size, when assessing body fat.

6.0.1 Weaknesses

One issue with this study is that the data only includes men, making it difficult to apply the findings to other groups, such as women or people from different backgrounds. Body fat distribution and its predictors vary by gender and other factors, which limits how useful the model is for the general population. The dataset also focuses mostly on people aged 30 to 60, with very few younger or older individuals. As a result, the model may not work well for teenagers, young adults, or seniors, who might have different patterns of body fat.

Another limitation is the number of predictors used. The model includes Age, Height, Abdomen, and Wrist but leaves out others like weight, hip size, and thigh size, which could improve predictions. These variables were excluded during backward selection to simplify the model, but some of them might still be important. Excluding these predictors could make the model less accurate in explaining body fat differences across individuals.

The residual analysis also showed minor issues. While the model works well overall, there are some outliers and slight deviations from normality in the residuals. These could affect how well the model predicts body fat for people with very high or very low values. Additionally, the residual patterns suggest there might be other predictors not included in the model that could explain some of the remaining variability.

6.0.2 Future Steps

Future research should focus on expanding the dataset to include more diverse groups. Adding data for women and people from different backgrounds would make the model more useful for a wider population. Including people of all ages, especially teenagers and seniors, would help the model predict body fat for everyone, not just middle-aged adults. A more balanced dataset would also make it easier to detect patterns that apply to specific groups.

Researchers should also consider adding more predictors to the model. Including variables like weight, hip size, and thigh size could give a fuller picture of body fat distribution and improve the model's accuracy. Looking at how important each variable is could help decide which ones to add while keeping the model manageable.

Finally, using different methods to model the data could address some of the limitations. For example, machine learning techniques or non-linear models could find patterns that linear regression might miss, especially for outliers. Future studies could also use data collected over time to see how body fat changes as people age and whether the same predictors still apply. This would help create a better understanding of body fat and how it changes throughout life.

A Raw Data of Body Fat Percentage

A.1 First 8 Variables

Table 6: Raw Data of Body Fat Variables Part 1

V1	V2	V3	V4	V5	V6	V7	V8
Density	Pct.BF	Age	Weight	Height	Neck	Chest	Abdomen
1.0708	12.3	23	154.25	67.75	36.2	93.1	85.2
1.0853	6.1	22	173.25	72.25	38.5	93.6	83
1.0414	25.3	22	154	66.25	34	95.8	87.9
1.0751	10.4	26	184.75	72.25	37.4	101.8	86.4
1.034	28.7	24	184.25	71.25	34.4	97.3	100
1.0502	20.9	24	210.25	74.75	39	104.5	94.4
1.0549	19.2	26	181	69.75	36.4	105.1	90.7
1.0704	12.4	25	176	72.5	37.8	99.6	88.5
1.09	4.1	25	191	74	38.1	100.9	82.5

A.2 Final 8 Variables

Table 7: Raw Data of Body Fat Variables Part 2

V9	V10	V11	V12	V13	V14	V15	V16
Waist	Hip	Thigh	Knee	Ankle	Bicep	Forearm	Wrist
33.543307	94.5	59	37.3	21.9	32	27.4	17.1
32.677165	98.7	58.7	37.3	23.4	30.5	28.9	18.2
34.606299	99.2	59.6	38.9	24	28.8	25.2	16.6
34.015748	101.2	60.1	37.3	22.8	32.4	29.4	18.2
39.370079	101.9	63.2	42.2	24	32.2	27.7	17.7
37.165354	107.8	66	42	25.6	35.7	30.6	18.8
35.708661	100.3	58.4	38.3	22.9	31.9	27.8	17.7
34.842520	97.1	60	39.4	23.2	30.5	29	18.8
32.480315	99.9	62.9	38.3	23.8	35.9	31.1	18.2

B All Variable Linear Regression Assumption

The diagnostic plots confirm that the linear regression assumptions are met for all variables, supporting the model's reliability. The Residuals vs. Fitted plot, Figure 11, shows that the residuals are randomly scattered around the horizontal red line at zero, with no noticeable patterns or curvature. This suggests that the relationship between the predictors and the outcome is properly captured by the linear regression model, satisfying the linearity assumption. Additionally, the absence of clustering or systematic trends indicates that the residuals are not related to one another, meeting the independence assumption.

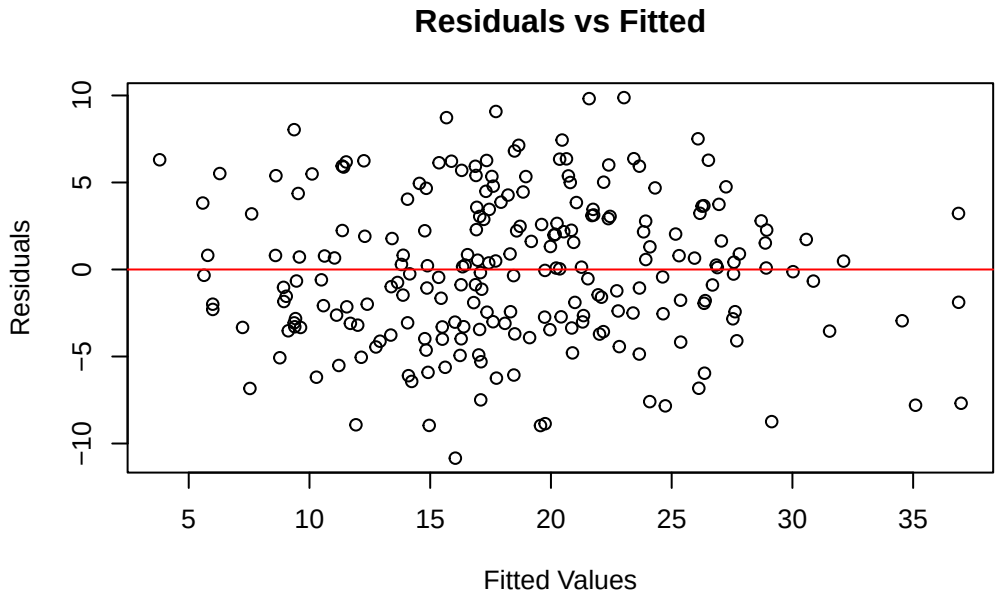

Figure 11: Residual Plot Verifying the Linearity for All Variables

The Scale-Location plot, Figure 12, further supports the model by demonstrating that the residuals are evenly spread across the range of fitted values. The residuals do not show a funnel shape or varying spread, and the red trend line remains fairly flat, confirming that the constant variance assumption (homoscedasticity) holds. This ensures that the model does not suffer from uneven variability, which could affect the results.

Lastly, the Normal Q-Q plot, Figure 13, shows that the residuals closely follow the red diagonal line, meaning they are approximately normally distributed. While there are minor deviations at the ends, they are not significant enough to impact the model's validity. This satisfies the normality assumption, which is necessary for accurate hypothesis testing and confidence intervals in linear regression.

Since the assumptions are satisfied, we can confidently move forward with evaluating the model.

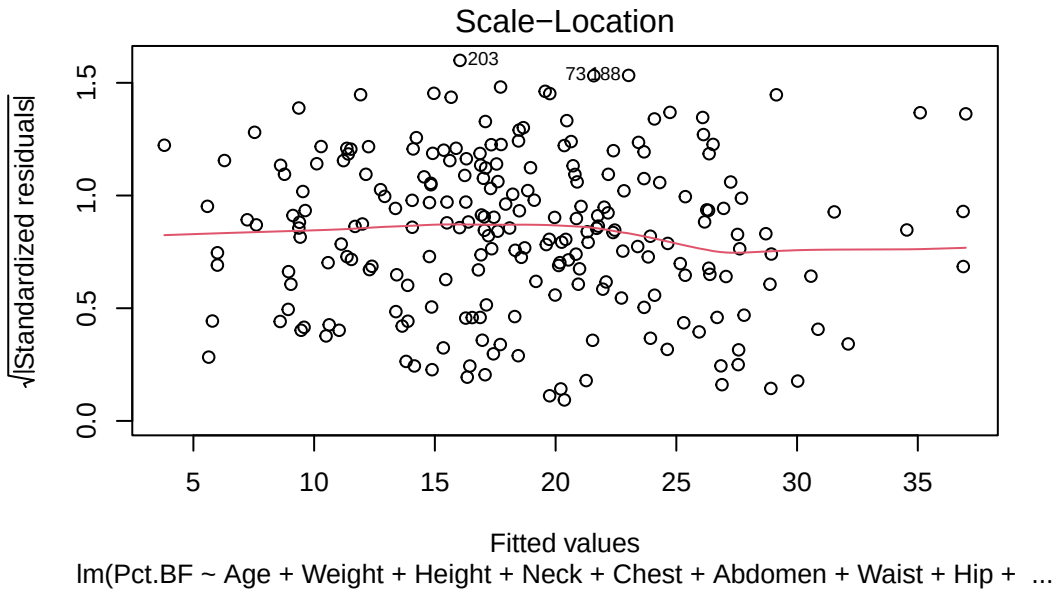

Figure 12: Scale Location Verifying Constance Variance for All Variables

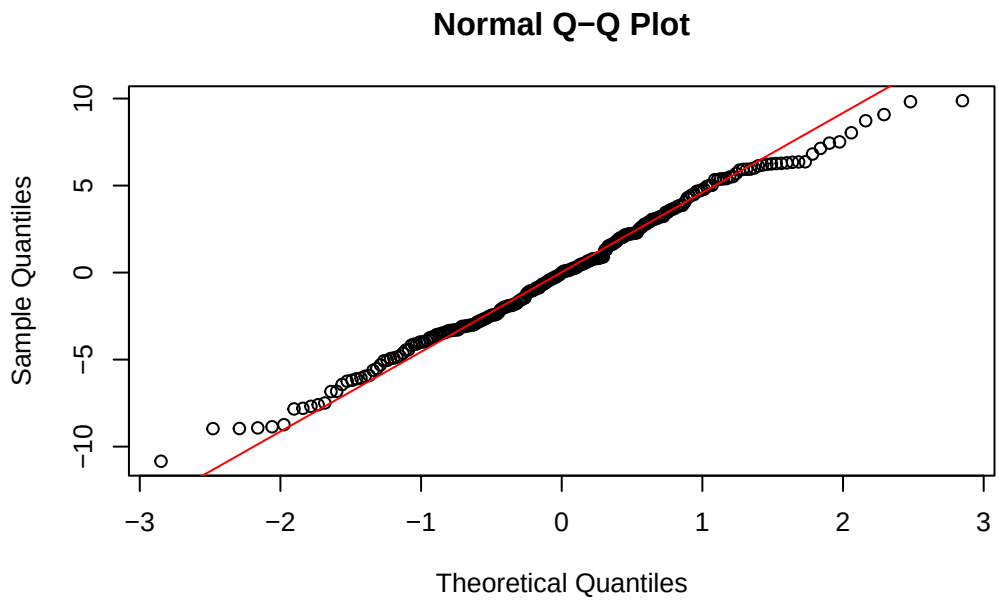

Figure 13: QQ-Plot Verifying the Normality of Errors for All Variables

C AIC Backwards Selection Explained

This script performs backward selection to identify the four variables that best predict body fat percentage (Pct.BF) while minimizing the Akaike Information Criterion (AIC). Here's a breakdown of what each part of the code does:

1. Setup and Data Preparation:
    - The necessary libraries (tidyverse, arrow, MASS, and knitr) are loaded.
    - The dataset is read from a .parquet file, and the Density variable is excluded because it is directly related to body fat percentage.
2. Full Model Creation:
    - A linear regression model (full_model) is fit using all variables in the dataset, excluding Density.
3. Initial Backward Selection with stepAIC:
    - The stepAIC function from the MASS package is used to perform backward selection. This function starts with the full model and removes variables one by one, based on AIC, until no further improvement can be made.
4. Refinement to Four Variables:
    - The code then refines the model further to ensure it includes exactly four variables. It starts with the variables identified by stepAIC and iteratively removes the variable that contributes the least to reducing AIC, recalculating AIC after each removal.
    - This process continues until only four variables remain.
5. Output the Final Variables:
    - The final four variables selected by the backward selection process are displayed in a table using the kable function.

This process is outlined in reference document scripts/05-exploratory_data_analysis.R. The script automates the selection process, making it systematic and reproducible.

D Surveys, sampling, and observational data

D.1 Similar Methodologies From Literature

The study by Potter et al. (2022), Circumference-Based Predictions of Body Fat Revisited, analyzed the use of abdominal circumference measurements to estimate body fat percentage. This method, used by the United States Marine Corps, was compared against dual-energy X-ray absorptiometry, a standard reference, and bioelectrical impedance analysis to evaluate its accuracy. The sample included 609 Marines, consisting of 430 men and 179 women, aged 18–57 years, and the study looked at differences in results by gender and age.

Strengths & Limitations of the Study

The study found that abdominal circumference is a practical predictor of body fat percentage in men, particularly when their body fat percentage is within the range expected for military fitness standards (18–26%) (Potter et al. 2022). The method's simplicity and low cost make it suitable for widespread use in military settings where assessments need to be performed efficiently. By including men and women from different age groups, the study provided a broad view of how the method performs across a variety of individuals who meet Marine Corps fitness standards. The study also addressed the relationship between age and body fat. Older individuals tended to have slightly more fat mass but similar fat-free mass compared to younger participants. This suggests the method is generally consistent across age groups in terms of patterns of underestimation or overestimation.

However, the study also highlighted significant limitations (Potter et al. 2022). The method underestimated body fat percentage in men by an average of 2.6 percent, while it overestimated body fat in women by 2.3 percent for younger participants and 1.3 percent for older participants. These differences were due to variations in fat distribution. Women often store fat in areas not measured by abdominal circumference, such as the hips and thighs, leading to overestimations. For men, especially those with lower body fat, the method struggled to account for intra-abdominal fat, resulting in underestimations. The study also tested bioelectrical impedance analysis, which was more accurate overall but still affected by errors in individuals with extreme body fat percentages and by hydration variability. Both methods were found to lack the precision needed for detailed body composition assessments.

Comparison to This Paper

This paper builds on Potter et al. (2022) work by addressing some of the identified shortcomings. For example, while Potter et al. (2022) focused solely on abdominal circumference, this study incorporates additional variables, such as wrist size and height, into a statistical model. These extra measurements aim to make predictions more accurate, especially for individuals at the lower or higher ends of the body fat range. Additionally, Potter et al. (2022) highlighted that body fat is distributed differently between genders. This study focuses only on middle-aged men. By concentrating on this group, the research aims to provide a method that better captures the specific fat distribution patterns and characteristics of this demographic.

Potter et al. (2022) findings show that while the abdominal circumference method is useful for broad categorization and operational use, it is less effective for individual assessments where greater precision is required. This study builds on that foundation by proposing a refined model that combines multiple variables to improve accuracy. This approach can be applied in both military and civilian settings where body fat estimation needs to be quick, low-cost, and reliable.

D.2 Simulated Survey

To collect data on body fat estimation using circumference measurements, a well-structured survey was designed to gather relevant information from adult participants. The survey starts with an introductory section explaining the purpose of the study, which is to create affordable and practical methods for estimating body fat. It assures participants that their data will be kept confidential and used only for research. The introduction also provides contact details for the lead researcher in case participants have questions.

The survey is divided into three sections. The first section gathers basic demographic details, such as age, gender, and height, to set the context for analysis. These straightforward questions help respondents begin the survey with ease. The second section focuses on circumference measurements, including wrist and abdomen size, measured in centimeters. To ensure consistency, this section includes clear instructions and visual aids, such as diagrams, to guide participants. Responses are collected using dropdown fields for precise numerical entries. The final section includes optional open-ended questions about participants' general health habits, such as diet and physical activity, to provide additional context about their body composition. The survey ends with a thank-you note, acknowledging the participants' time and effort.

A stratified random sampling method was used to ensure the study represents adults from different age groups and body types, which is important for building a reliable predictive model. The target population included adults aged 20 to 70 years. Participants were grouped into age brackets (e.g., 20–30, 31–40) to ensure fair representation. The sampling frame was built using contacts from community health organizations, fitness centers, and social media recruitment. A pilot test with 30 participants helped identify unclear questions and improve measurement instructions.

This methodology uses best practices in survey design by including a mix of question types (e.g., multiple-choice, numerical entries, and open-ended responses) and clear instructions to ensure accurate and consistent data collection. By aligning the survey with the study's goals, the collected data will support the development of effective regression models for estimating body fat. The sampling strategy minimizes bias and enhances the ability to apply the findings broadly.

Link to survey: https://forms.gle/353vGHrE5QcBRGuH7

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