

Classification of Body Fat based on Physical Measurements and Body Composition*

A comparative analysis of methods of classifying body fat

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BMI values fail to acknowledge the different body composition across both sexes. Using the Waist-Hip-Ratio is more accurate at estimating body fat levels using simple methods at home. This paper compares how this model performs against actual body composition such as isolated fat mass. Using this method makes self-identification of obesity more accessible and preventive measures can be taken earlier.

1 Introduction

BMI is a common indicator for general health but it has its limitations. It does not take into consideration the actual body composition of an individual and other important factors such as sex and age. In its initial design, BMI was designed using only male subjects and thus cannot be applied to females. Due to its inability to capture body composition, a lot of false positives and false negatives are produced. Through this paper, I would like to compare how using the Waist-to-Hip Ratio (WHR) serves as a more accurate way of estimating your body fat levels at home. The inspiration for using the WHR stems from fat accumulation patterns and distribution of fat vertically. This also helps us further differentiate between closer classifications of BMI such as Underweight and Normal Categories and Overweight and Obese Categories. BMI is notorious for classifications. A popular example of this would be body builders being classified as Overweight according to BMI despite having lower levels for body fat and being at a lower risk of obesity health risks. On the other hand, taller people are often excused as false negatives and are failed to be recognized as having higher body fat levels due to their height. The table Table 1 below includes the BMI categories as endorsed by the Government of Canada.

*Code and data are available at: <https://github.com/aamishi/ImprovedBodyFatClassification>

Table 1: BMI vs. Fat Mass by BMI Category

Table 1: BMI Categories as per the Government of Canada Guidelines

| Category | BMI Range |
|-------------------|----------------|
| Underweight | Below 18.5 |
| Normal weight | 18.5–24.9 |
| Overweight | 25.0–29.9 |
| Obese - Class I | 30.0–34.9 |
| Obese - Class II | 35.0–39.9 |
| Obese - Class III | 40.0 and above |

The second prong of this paper is finding the relation between age, height and weight against actual body fat that is separate from a person’s total body weight. This serves as a comparison between the classification of body fat levels based on physical measurements versus more anabolic storage of fat. Actual body fat is estimated using several methods such as skinfold calipers or DEXA {} scans. Both of these methods require professionals to record and experts to decipher. It is unusual for common folk to opt for these methods without medication intervention or expert domain knowledge such as athletic coaches.

Through this paper, I analyse how common factors such as sex, height and weight compare against WHR and Body Scan classifications and how important are the main predictors for the respective models. I employ two multilevel logistical regression models to categorize people based primarily on the WHR and Body Fat Percentages. The paper follows a two pronged approach using two different data sets that estimate the classification in two separate ways. I then compare their accuracy against their respective data set.

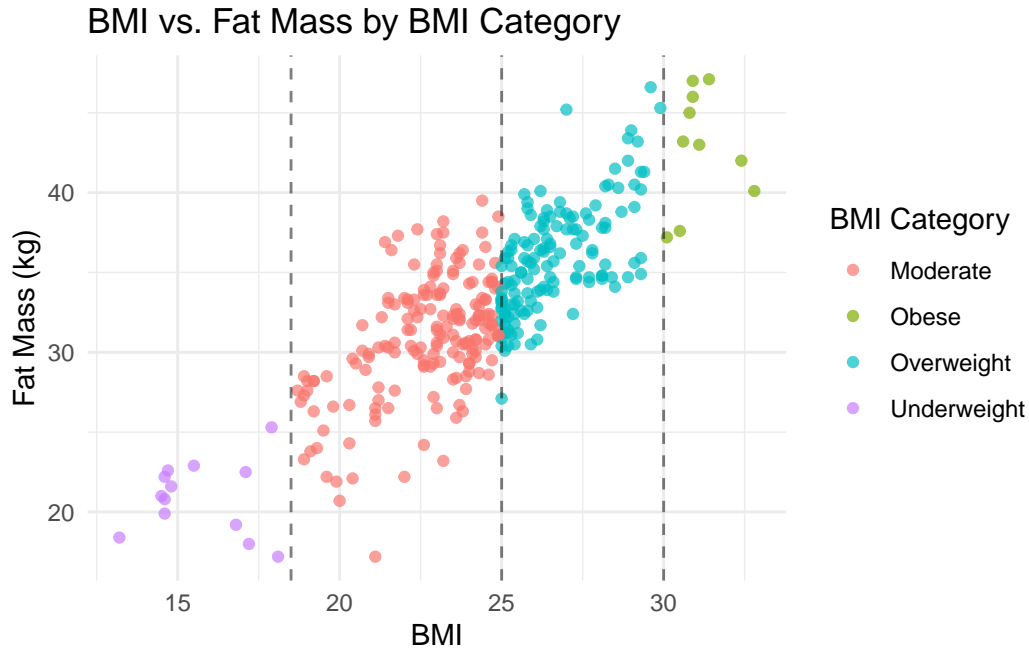
It is a known fact that BMI generalizes several body types based only on height and weight considerations. However, through the work of this paper, it can be noted that High and Extreme levels of body fat are completely disregarded through WHR calculations. Both data sets and models show an increasing trend in body fat levels as weight increases. The model on measurements data predicts a smooth increase of body fat as a person’s weight increases. However, the model based on body compositions predicts a steeper increase in body fat as a person’s weight increases. This fact is more obvious when data is faceted by sex.

This paper uses the R Programming Language {R Core Team (2023)}, to simulate, download, clean and test the data, and create the model. More information on packages and specific methods is included later in the paper. This paper is structured as follows: The Data Section (**paper-data-section?**) introduces the data sets, their variables and how they were tailored to obtain the needed information. The Model section discusses in greater detail the structure of both models and what information they convey. The results and analysis of the models and discussed in the Results section. Lastly, the Discussion section discusses real-life implications from the findings of this paper, limitations faced and next steps.

2 Data Section [#paper-data-section]

This paper uses R (R Core Team 2023), and the `tidyverse` (Wickham et al. 2019), `janitor` (Firke 2023), `ggplot` (`citeggplot?`), `arrow` (`citearrow?`), `dplyr` (Wickham et al. 2023) packages throughout the analysis to clean both data sets and create visualizations. `nnet` (Ripley 2023) is employed to fit and apply the models.

The primary motivator of this paper was the diverse body compositions that were classified under the same BMI category. The graph `?@tbl-bmi-cats-bf` shows the diverse values of Body Fat Percentages classified in the same BMI category.



3 Data

3.1 Overview

3.1.0.1 General Statement

The data used in this paper comes from two distinct sources, each serving a specific purpose:

2. Body Composition Dataset

This dataset, referred to as the Body Composition dataset for the purposes of this paper,

was collected for estimating a new body fat measurement technique by Isaac Kuzmar et al. (Kuzmar and Zalabata 2020). It is used to calculate fat percentages based on actual body composition and serves as a comparison for the model’s predictions.

3. BodyM Dataset

This dataset, obtained from Amazon Web Services (AWS) (Amazon Web Services 2023), is used as training data for the model to predict body fat categories. It includes silhouettes of real test subjects to capture accurate body compositions. These silhouettes were collected to support the estimation of bodily measurements using Machine Learning techniques. However, the silhouettes are not used in this paper.

The BodyM Dataset, referred to as the Body Measurements dataset throughout this paper, was collected by Ruiz et al. (Ruiz et al. 2022) with a focus on underrepresented body types in the estimation of fat and its subsequent health risks. The primary data captured in this collection consists of the front and lateral silhouettes of approximately [2000] test subjects. These silhouettes were then converted into black-and-white images for use in their augmentation model. The dataset includes X male and Y female subjects, aged A to B. The body measurements in this dataset were generated using their Adversarial Body Simulator (ABS), which was specifically designed to capture underrepresented body types. The S3 package (**reference?**) included three datasets: Training, Test A, and Test B. For the purposes of this paper, only the Training dataset is used. The visual images of the test subjects were photographed and 3D-scanned by lab technicians.

3.1.0.2 The variables of my use:

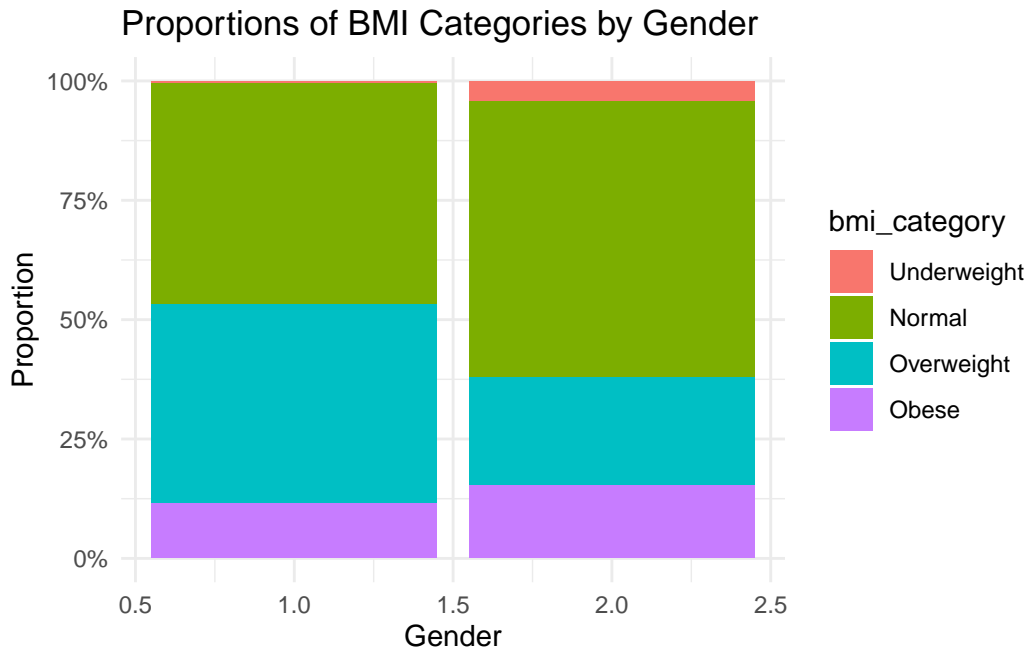
For this paper, the BodyM Dataset is used to estimate the category of body fat that a person carries. To effectively differentiate between the various body types, the model takes into account measurements that could indicate actual body compositions. Gender, height, and weight are used as basic predictors for the model. However, according to (**reference?**, WHO), the waist-to-hip ratio (WHR) is a more accurate predictor of body fat levels. Based on (**reference?**), the two sexes exhibit different tendencies for excess body fat accumulation, also known as adipose fat. In males, excess fat tends to accumulate in the abdominal region, whereas in females, fat is more commonly stored in the hips. This ratio is indicative of fat distribution, and a higher WHR can be a precursor indicator of obesity (**reference?**).

To better account for body composition in relation to height, a new variable called height-to-hip ratio (`height_hip_ratio`) was introduced. As noted by (**reference?**), two individuals with the same WHR could differ in their fat category depending on height. For instance, a taller person with a higher WHR may face a lower risk of developing cardiovascular issues than a shorter person with the same WHR (**reference?**).

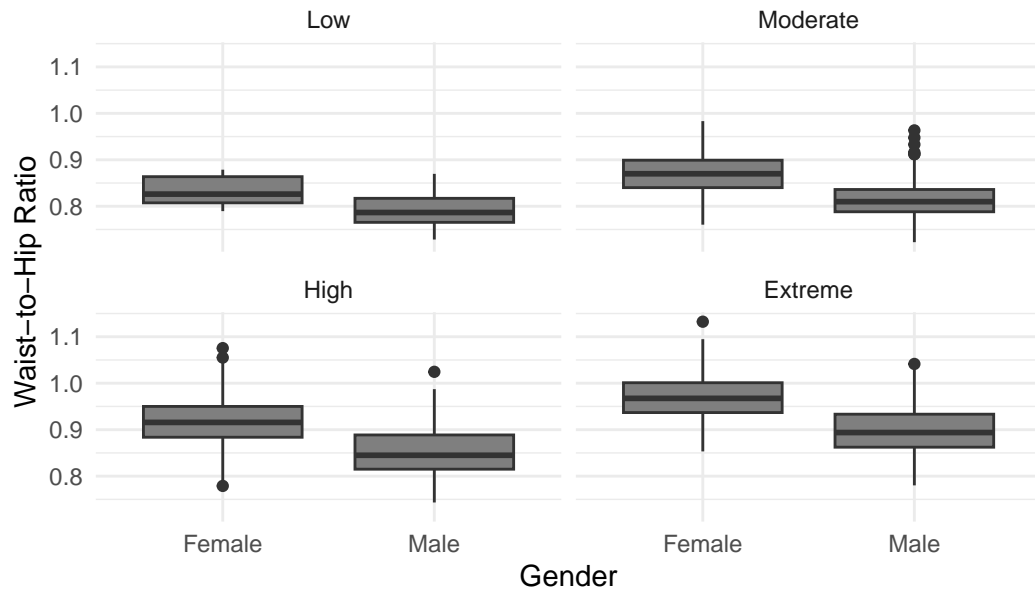
Finally, to enhance the model’s quality, ankle and wrist circumference measurements were also included. These measurements are particularly important for determining boundary values for fat classification (**reference?**).

3.1.0.3 The estimand for the models

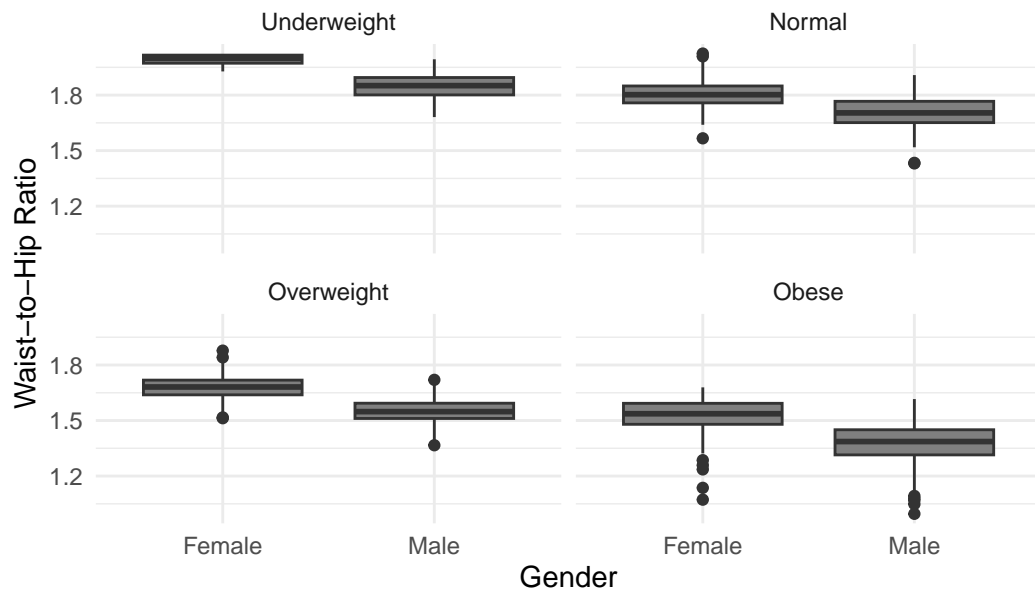
Both models employ `fat_percentage_category` as their independent variable or estimand. The reason for choosing a category over an actual value was the difference in predictors across the two models. Both models use different predictors to estimate `fat_percentage_category` so in order to produce useful comparisons against common predictors such as sex, height and weight, I used a categorical variable.



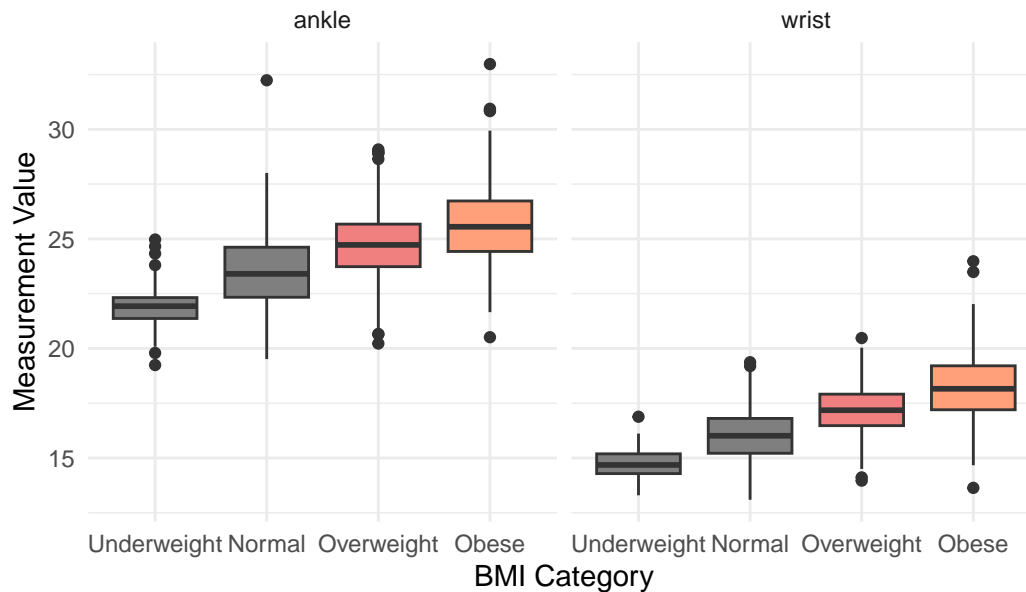
Distribution of Waist-to-Hip Ratio by Gender



Distribution of Waist-to-Hip Ratio by Gender



Comparison of Ankle and Wrist Measurements for Overweight :



3.1.0.4 graph what i will be using in my model

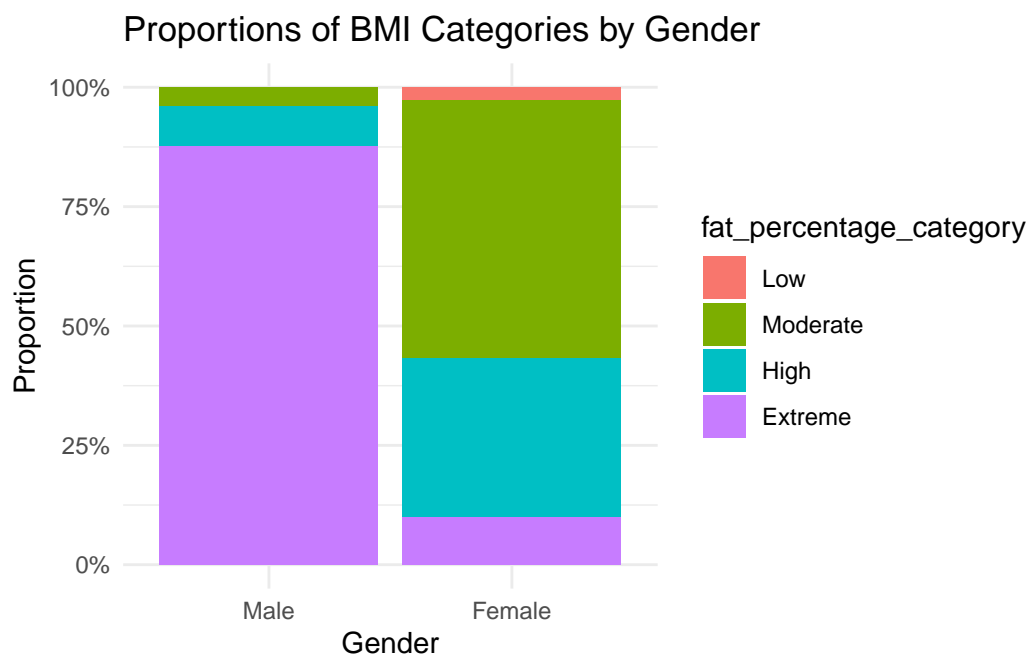
3.1.1 Body Composition Data - Isaac Kuzmar Et Al.

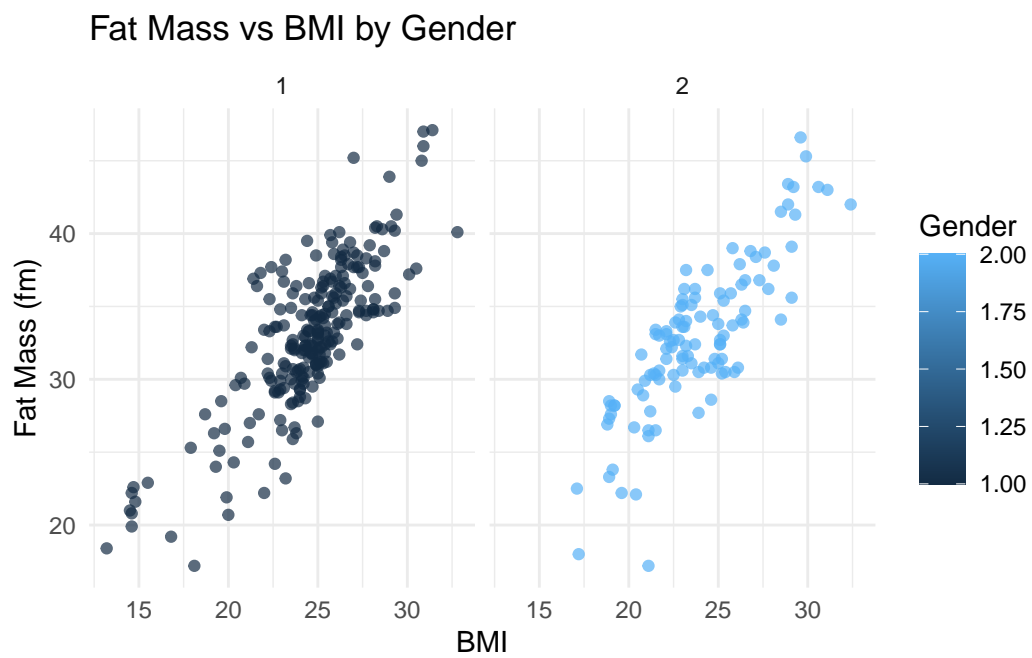
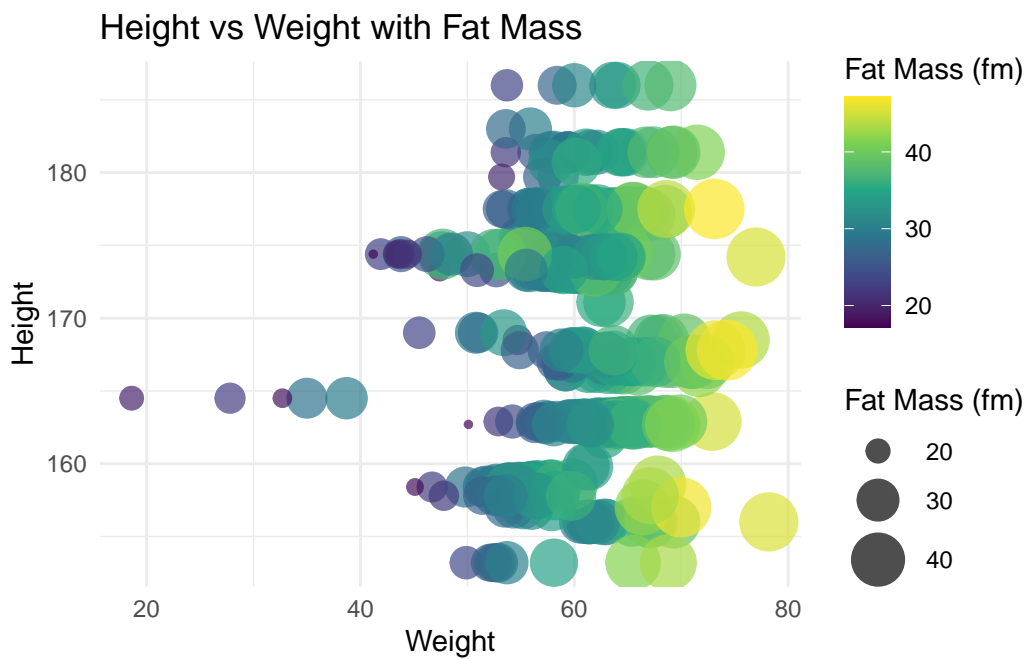
3.1.2 Data Overview

The dataset compiles the body measurements of subjects aged, 18 and 60, and specifically with a desire to lose weight and improve body image. The participants resided in Barranquilla, Colombia and consisted of 234 males and 111 females. Medical exclusions were made while recruiting the subjects, such as pregnant women or people with medical pacemakers. The bodily measurements such as fat mass in kilograms and fat free mas in kilograms were determined using the Tanita MC-780 [reference] body composition analyzer.

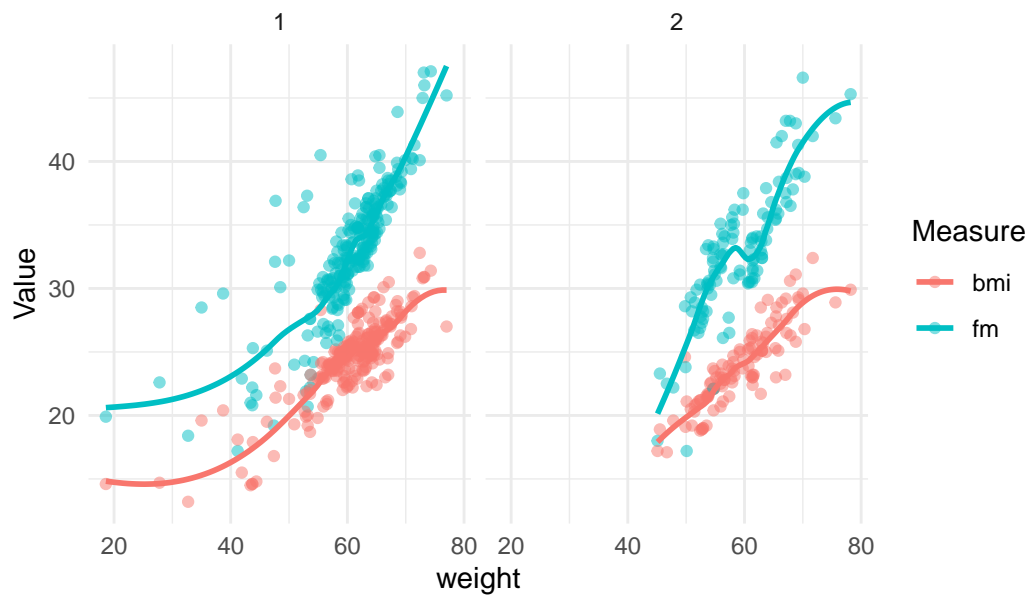
3.1.3 The variables of my use:

The main variables that I considered fat mass percentage fm. This variable is obtained by dividing the fat mass in kilogram by the total weight in kilograms. The fat mass percentage is considered the main predictor for fat mass categories. As the body composition is more accuarate at measuring the actual amount of excess fat a person carries and can differentiate it from other weights such as fat free muscle mass [reference the variable] ##### graph what i will be using in my model





Smoothed Trends of FM and BMI by Age



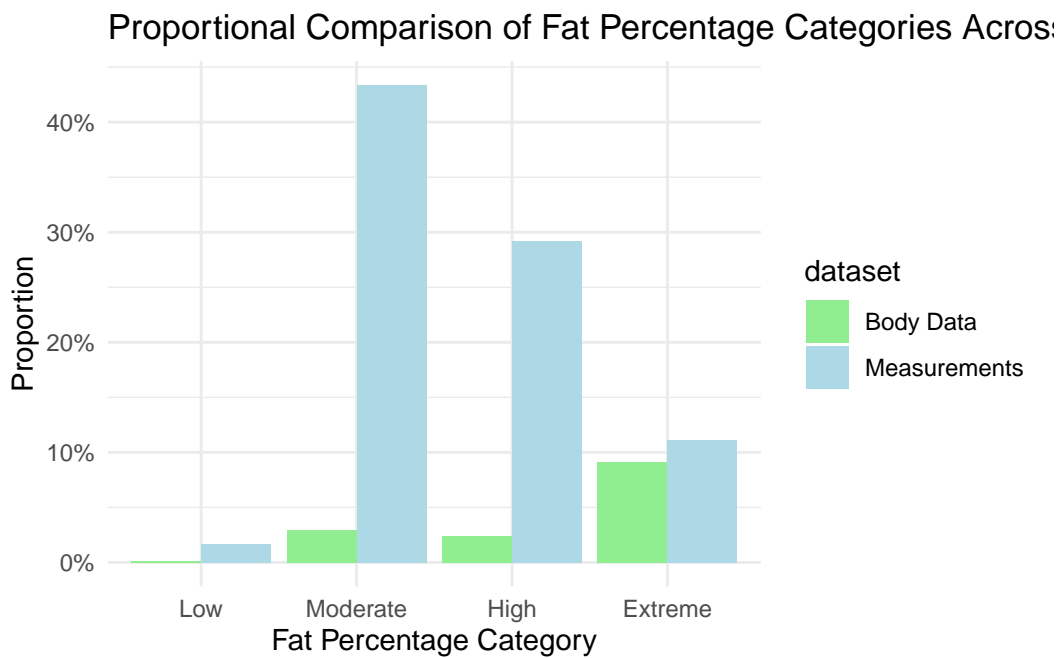
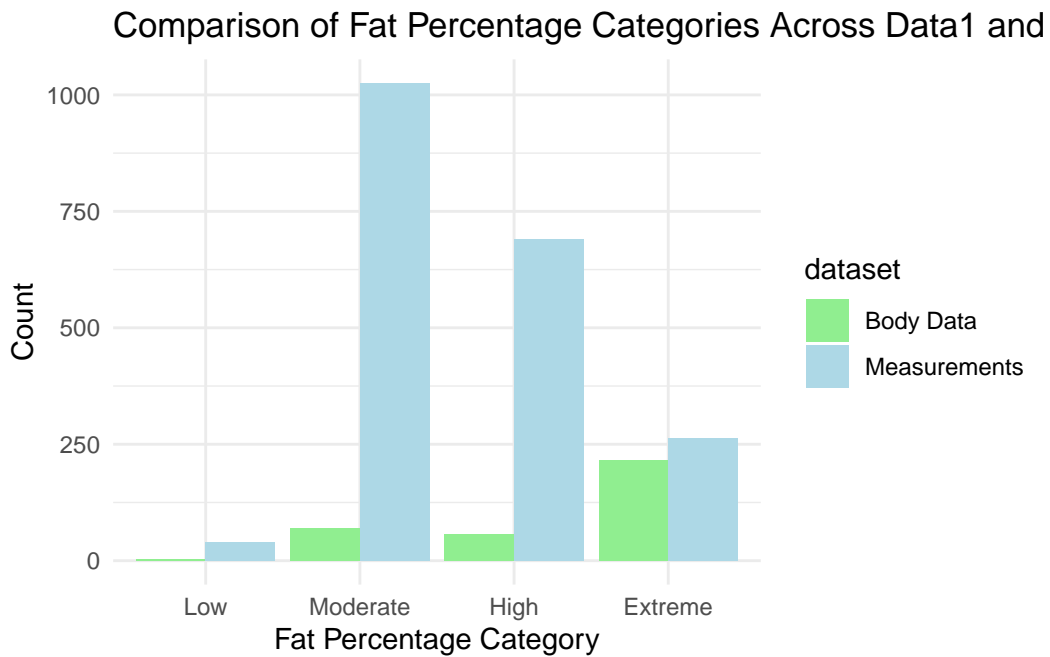
- talk about the crowding for men

3.2 what original BMI and WHR fail to capture

3.3 How are these data sets important are how they relate to each other

3.3.0.1 desitination

3.3.0.2 well as any relationships between the variables.



Overview text

3.4 Measurement

Some paragraphs about how we go from a phenomena in the world to an entry in the dataset.

4 Model

I aimed to provide a categorization of body fat levels in an individual based on simple measurements. By using measurements such as height, weight, waist-to-hip ratio (WHR), and ankle and wrist circumference, I sought to capture a person's body composition as accurately as possible. I expected a positive relationship between excess body fat levels and WHR. Additionally, height is an important factor to consider in capturing fat distribution—specifically, a shorter person with a high WHR would be at a higher risk of obesity-related diseases.

Men are more likely to accumulate fat in the abdominal region, while women tend to store fat in the hip area. To capture natural body shapes and leanness, I also considered other factors that influence body composition, such as height-hip ratio that would capture the distribution of fat . ## Model General Overview:

This paper uses 2 models to model the two datasets. The first model, the Body Measurements Model, would be used to predict fat percentage categories using the measurements of person's body that can be obtained using a measuring tape. The second model, the Body Composition Model, is also designed to access the relation between different bodily compositions such as total body weight, excess fat weight, lean muscle mass in kilograms.

I used the packages `lme4` to do `glmer`. Both models employ Multilevel Regression `glmer` as the Fat Percentage Category has multiple categories including: essential, athlete, normal, high.

4.0.1 Model 1:

In this model, the dependent variable is `fat_percentage_category`. The model is set up as follows

$$\log \left(\frac{P(y = j)}{P(y = \text{ref})} \right) = \beta_{0j} + \beta_{1j} \cdot \text{height} + \beta_{2j} \cdot \text{gender} + \beta_{3j} \cdot \text{waist_hip_ratio} + \beta_{4j} \cdot \text{height_hip_ratio} \quad (1)$$

Where: - (y) is the **fat percentage category**. The categories include low, moderate, high, and extreme. These equate low, moderate, high and extreme levels of body fat. - ($P(y = j)$) is the probability that the fat percentage falls into category (j). - ($P(y = \text{ref})$) is the reference category. - ($\{\beta_{0j}\}, \{\beta_{1j}\}, \dots$) are the coefficients to be estimated for each category (j).

4.0.2 Model Justification

It is incredibly challenging to differentiate the body composition of a person based solely on their total weight, height and weight only. However, to increase the [goodness] of the classification, this model uses the waist_to_hip ratio, which is especially an important indicator for fat accumulation across both genders. The model also uses height_hip_ratio to account for different body types. [this sentence might go in the data section] As height is an important factor to evaluate the collection of fat in the body (how tf do you spell it) placed on a person's body, this is an important factor to consider. However, using height simply does not effectively communicate how a person's body is composed latitudinally. So I chose to employ the height_hip_ratio ratio to provide more classification between body types. Additional features such as ankle and wrist are used to further differentiate between the categories.

4.0.3 Assumptions and limitations

Assumptions: - this model assumes that there is an obvious difference in body measurements and fat storing capacities in males and females, hence gender is an important predictor and also affects the proxy values of fat percentage owing to the calculation based on WHR.

Limitations:

- The dataset does not include the age of the participants. While a general age range is provided, such as 18-X years old, different age groups could differ in how they are categorised.
- This model would not be able to differentiate between age groups and hence would work poorly if this information is included.
-

4.0.4 Model validation

4.0.5 Model 2:

The model fits a multinomial logistic regression model to predict the fat percentage category (`fat_percentage_category`) based on the following predictors:

- `height` (a continuous variable representing the individual's height),
- `gender` (a categorical variable representing the individual's gender),
- `fm` (a continuous variable representing fat mass or a related measure).

The model is defined as follows:

$$P(Y = k | X_1, X_2, X_3) = \frac{e^{\beta_{0k} + \beta_{1k}X_1 + \beta_{2k}X_2 + \beta_{3k}X_3}}{1 + \sum_{m=1}^{K-1} e^{\beta_{0m} + \beta_{1m}X_1 + \beta_{2m}X_2 + \beta_{3m}X_3}} \quad (2)$$

Where:

- ($P(Y = k | X_1, X_2, X_3)$) is the probability of observing the (k)-th category of **fat_percentage_category** given the values of **height** (X_1), **gender** (X_2), and **fm** (X_3).
- ($\{\beta_{0k}\}, \{\beta_{1k}\}, \{\beta_{2k}\}, \{\beta_{3k}\}$) are the estimated coefficients for each category (k) of the outcome variable, where the reference category is typically set to 0.
- (K) is the total number of categories in the dependent variable **fat_percentage_category**.

This model allows us to assess the relationship between the categorical outcome (**fat_percentage_category**) and the continuous and categorical predictors (**height**, **gender**, **fm**), estimating the probabilities for each category of fat percentage based on the input predictors.

4.0.6 Model Justification

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Assumptions: - this model assumes that there is an obvious difference in body measurements and fat storing capacities in males and females, hence gender is an important predictor and also affects the proxy values of fat percentage owing to the calculation based on WHR.

Limitations:

- The dataset does not include the age of the participants. while a general age range is provided, such as 18-X years old, different age groups could differ in how they are categorised.
- This model would not be able to differentiate between age groups and hence would work poorly if this information is included.
- This model is also built on data that was generated by the ABS [] simulator so it may be inherently working with an error.

4.0.8 Model validation:

Model out-of-sample testing:

The dataset provided by BodyM already had a training and testing split. I used the Test A to test the accuracy of the model. As the method of collection was similar to the training data, the potential errors in the model could only arise from the fact that it is unseen data.

More elaborate explanation, tables and figures can be found at [\[\]](#).

RSME: I also computed the RSME to evaluate the model's performance as a lower RSME indicates accuracy in predicted vs actual fat percentage categories.

5 Results

Our results are summarized in Table 2 and Table 3. Our model's results and interpretation:

Table 2: TODO

Table 2: Summary of Measurements Model

| | (Intercept) | height | gender | waist_hip_ratio | height_hip_ratio |
|----------|-------------|-----------|-----------|-----------------|------------------|
| Moderate | 34.34511 | 0.1632657 | -2.997520 | 18.21029 | -37.45804 |
| High | 60.03388 | 0.3063854 | -5.101766 | 34.97975 | -74.26296 |
| Extreme | 78.18906 | 0.4569892 | -6.262725 | 54.36190 | -113.34181 |

From the table {} we can see that the intercepts are very low and negative. The probability of the model making a classification is very unlikely with the category with the highest probability being high. As our data is composed of people with a desire to improve body image, this makes sense, as the people with higher fat percentages are more likely to participate in such a study. `waist_hip_ratio` has a negative correlation with the levels of the fat percentage category prediction. High `waist_hip_ratios` are associated with higher body fat percentage. So the lower a person's `waist_hip_ratio` is, the less likely the model classifies them in the `high` category. On the other hand, `height_hip_ratio` has a positive relation with the classification levels. `height_hip_ratio` takes into a consideration the overall mass (and fat) distribution of a person vertically. So if a person has a more evenly distributed composition, they would have a higher `height_hip_ratio` ratio with a higher chance of being classified in a lower fat category. Despite the model having very few subjects that were underweight, the classification between Underweight and Normal BMI values has improved with more diverse factors. It is likely that Normal BMI categories are also being correctly identified with lower fat levels. There is a negative correlation with the heights of the subjects suggesting that taller people are less likely to be classified with higher levels of fat. Detailed interpretation of this fact is

later discussed in the Results Section {}.

Table 3: TODO

Table 3: Summary of Body Mass Model

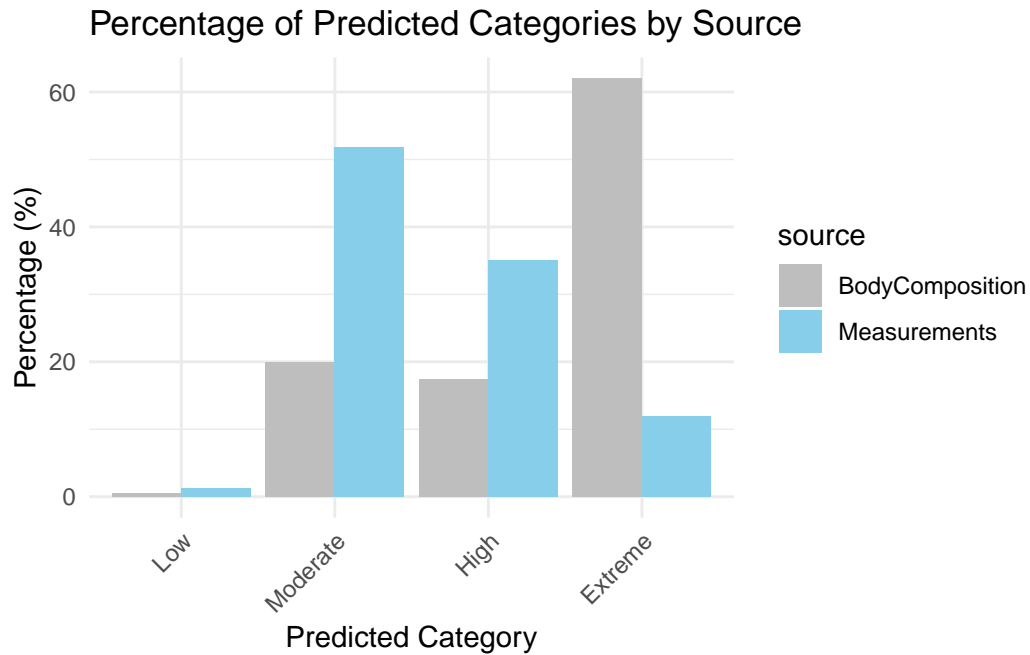
| | (Intercept) | height | gender | fm |
|----------|-------------|------------|-----------|----------|
| Moderate | -15.87179 | 0.1811493 | -27.88642 | 1.946447 |
| High | -12.83259 | 0.0020248 | -63.42437 | 4.850373 |
| Extreme | -14.02425 | -0.1279283 | -85.85319 | 6.537356 |

The negative intercepts indicate that in the absence of any predictors, the model has very low estimates for the body fat classifications. However, the model is most likely to classify a person in the **High** category owing to the distribution of the dataset. The positive intercept for a **Normal** classification mean that the taller a person is, the more likely they are to be classified as **Normal**. As this model is directly based on the actual body composition of a person, the increasing levels of fat percentage indicated by **fm** show that the higher percentage of fat that a person has, the more likely they would be higher in the classification levels.

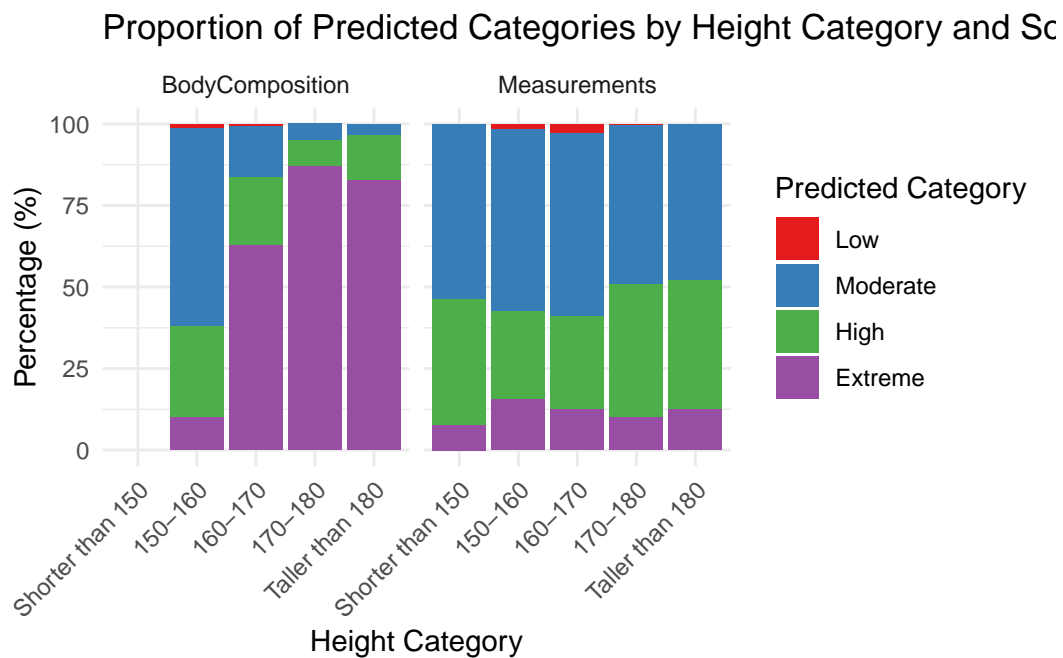
5.1 Predictions based body circumferences overgeneralize the population

From the above prediction density chart by each model per fat percentage category, we see that the Measurements model has higher peaks at the each classification. This suggests that more people are being classified into a similar category only based on their physical traits such as height and Waist-to-Hip ratio. The peaks of each category from the Body Composition is accurate in identifying the major classification. However, the distribution not being as concentrated as from the Measurements model suggest that the diversification of different body types is being identified properly.

```
# A tibble: 8 x 3
# Groups:   source [2]
  source      predicted_category percentage
  <chr>      <fct>                <dbl>
1 BodyComposition Low                0.580
2 BodyComposition Moderate          20
3 BodyComposition High             17.4
4 BodyComposition Extreme          62.0
5 Measurements Low                1.24
6 Measurements Moderate          51.8
7 Measurements High              35.1
8 Measurements Extreme          11.9
```

5.2 The Body Composition Model has diverse classification for different heights groups

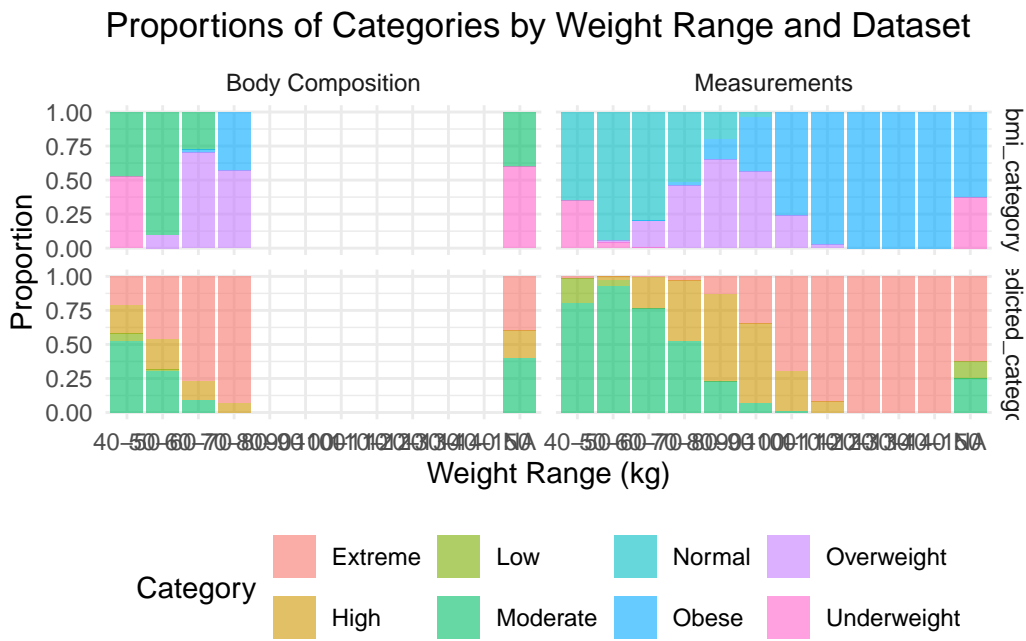


The primary shortfall of the BMI categories was that it failed to differentiate the body types

based on other factors such as where the fat was collected. From the above graph, we can see that across different heights, the Measurements Model is pretty consistent with providing similar proportions for different fat categories. This suggest that it was group people on too broad categories that did not necessarily capture the right effect of height of body compostion. Specifically, BMI fails to recognize the vertical spread of fat accumulation and so taller people get naturally classified as having lower fat levels. However, the body composition model, has a better ability a higher percentage of people actually have a higher classification of high and extreme body fat across all height groups.

5.3 Differentiating between different levels of Obesity.

5.4 What BMI fails to capture



6 Discussion

6.1 Obesity Risk Identification

This paper's main goal was to compare how accurate are body measurements to estimate fat percentage at home. Other ways of estimating a person's body fat include scans like DEXA {source}. These scans are expensive and inaccessible. Most people turn to measuring BMI's to estimate their general level of health. The Government of Cananda also advices that adults use BMI to estimate their health []. As seen in this paper, this inherently flawed as BMI fails to

capture the composition of a body. However, even the introduction of simple measurement like Waist-to-Hip ratio, shows that there is a general improvement in differentiating fat levels. The Waist-to-Hip ratio is especially important between the two sexes as fat accumulation pattern differs, which is not even considered in the BMI formula. Additionally, as a higher proportion of people are classified as Normal using BMI, without failing to recognise that having a high level of fat despite having a lower BMI is still dangerous as it could potentially prevent them from seeking early care against illnesses like insulin resistance. Insulin resistance occurs when there is a body fat percentage of $\{ \}$. By popularising a more accurate system, we could urge people to take earlier preventive care.

6.2 Second discussion point

Please don't use these as sub-heading labels - change them to be what your point actually is.

6.3 Second discussion point

6.4 Third discussion point

6.5 Weaknesses and next steps

- the BodyM dataset does not include age. An older person has lower metabolism \square and a higher chance of collecting fat on their abdomen.

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

we compare the posterior with the prior. This shows...

```
C {r} # modelplot(political_preferences, conf_level = 0.9)
+ #   labs(x = "90 per cent credibility interval") #
```

References

- Amazon Web Services. 2023. “AWS Bodym.” <https://registry.opendata.aws/bodym/>.
- Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. <https://github.com/sfirke/janitor>.
- Kuzmar, Isaac, and Zalabata. 2020. “DATASET FOR NEW BODY FAT MEASUREMENT.” <https://doi.org/10.6084/m9.figshare.12982223.v2>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Ripley, B. 2023. *Nnet: Feed-Forward Neural Networks and Multinomial Log-Linear Models*. <https://CRAN.R-project.org/package=nnet>.
- Ruiz, Nataniel, Miriam Bellver Bueno, Timo Bolkart, Ambuj Arora, Ming Lin, Javier Romero, and Raja Bala. 2022. “Human Body Measurement Estimation with Adversarial Augmentation.” In *International Conference on 3D Vision 2022*. <https://www.amazon.science/publications/human-body-measurement-estimation-with-adversarial-augmentation>.
- Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Golemund, et al. 2019. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.
- Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2023. *Dplyr: A Grammar of Data Manipulation*. <https://CRAN.R-project.org/package=dplyr>.