

# Estimation of Resting Metabolic Rate With Simple Linear Regression\*

Subtitle

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Resting metabolic rate (RMR) is a measure of the energy the body requires to maintain basic life functions. People can use RMR to better tailor diet and nutrition plans, but obtaining an accurate measurement requires laboratory-based tests. In this report, we developed a predictive equation using data from 95 observations, ranging from 18 to 65 years old. We used simple linear regression with height as the predictor variable:  $\text{RMR} = -2082.267 + 22.075(\text{height})$  with  $r^2 = 0.469$ . We found height is a moderately accurate predictor of RMR. However, our model explains less of the variation of RMR than more well-established formulas.

## 1 Introduction

Resting metabolic rate (RMR) is the amount of energy the body requires to maintain basic life functions while at rest. In other words, is as the amount of calories one burns at rest. RMR accounts for approximately 60-70% of the total calories burnt daily (Plaza-Florido and Alcantara 2023). Knowing one's RMR can help tailor nutrition and diet plans to individuals' needs.

Accurately measuring RMR requires laboratory testing using gas analysis. By measuring the oxygen consumed and the carbon dioxide expelled while at rest, one can obtain an accurate estimate of RMR. However, due to cost and accessibility, several formula have been developed to estimate RMR. The most widely used, Mifflin-St Jeor Equation, uses, four predictors, weight, height, age, and sex. Although considered the most accurate formula, it still leaves approximately 30% of the variance in RMR unexplained (Mifflin et al. 1990).

The report investigates whether height alone is a good predictor of is height alone a good predictor of resting metabolic rate. We fit a simple linear regression model, with height

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\*Project repository available at: <https://github.com/GrumioEstCoquus/MATH261A-project1>.

as the predictor and resting metabolic rate as the response variable. The fitted model is  $\hat{Y} = -2082.267 \text{ kcal/day} + 22.075 \text{ cm}X$ . On average, RMR increase by 22.075 kcal/day for each additional centimeter of height.

The remainder of this report is structured as follows: Section 2 discusses the data, Section 3 discusses the simple linear regression model, Section 4 discusses the results, and Section 5 discusses the findings, weaknesses, and further questions.

## 2 Data

The data we used in this report comes from the Harvard Dataverse and was used in the study Gender-agnostic Inclusive Estimation for Resting Metabolic Rate. (Navalta 2025). The dataset contains 95 observations, with participant ages ranging from 18 to 65 years. The variables of interest are height and resting metabolic rate Height is measured in centimeters and has a mean of 168.399 cm and a standard deviation of 10.185 cm. Resting metabolic rate is measured in kcal per day with a mean 1635.097 kcal/day and standard deviation 328.428 kcal/day.

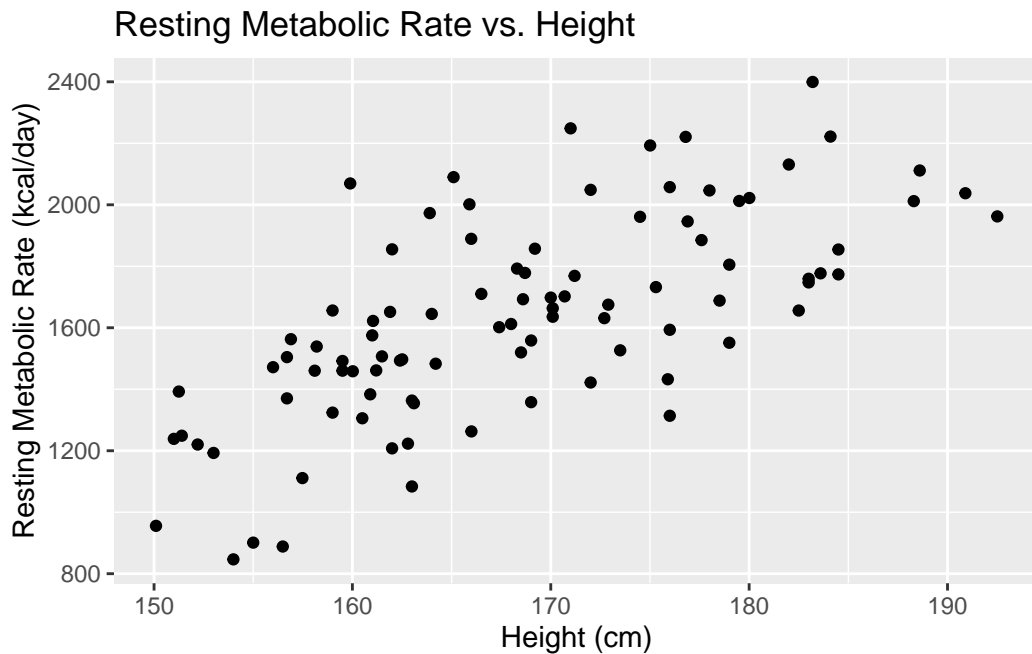


Figure 1: Scatter plot of Resting Metabolic Rate (kcal/day) vs. Height (cm)

A preliminary scatterplot Figure 1 indicated a strong positive linear relationship between height and RMR, suggesting that linear regression would likely be an appropriate model.

### 3 Methods

We used a simple linear regression model in this report. The general model is follows:  $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$ .  $Y_i$  are observed responses. In this case the observed RMRs.  $\beta_0$  is the intercept; it represents the average response value when the predictor is 0. In this case, it contains little meaning, since the predictor variable is strictly positive.  $\beta_1$  is the slope of the line of best fit. It represents the average increase in resting metabolic rates for a one centimeter increase in height.  $X_i$  are the observed predictor values. In this case, these are the heights. The  $\varepsilon_i$  are the error terms and represents the variability in  $Y$  not explained by a linear function of  $X$ .

There are several assumptions for simple linear regression. One is that the relationship between the response and predictor must be linear. Meaning,  $E[Y_i] = \beta_0 + \beta_1 X_i$  is correct. The others relate to the  $\varepsilon_i$ . The  $\varepsilon_i$  must be independently and identically distributed normal with constant variance ( $\varepsilon_i \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$ ). If the above assumptions are true, we can use hypothesis testing to test the model estimates. The null hypotheses are  $\beta_0 = 0$  and  $\beta_1 = 0$ . We fit the simple linear regression model using the `lm()` function in R (R Core Team 2024).

### 4 Results

The fitted model is:  $\hat{Y}_i = -2082.267 + 22.075 X_i$

The estimated intercept parameter is  $b_0 = -2082.267$ . This represents the average RMR for a person with height of 0cm. Since height is strictly positive, the intercept does not contain much meaning.

The estimated slope parameter is  $b_1 = 22.075$ . This means that for each one centimeter increase in height the resting metabolic rate increase on average by 22.075.

This simple linear regression has an R-squared of 0.469. This means the model explains around 46.9% of the variation of RMR.

To test the assumptions of linearity, constant variance and independence, we plot the residuals ( $\hat{Y}_i - Y_i$ ) vs the fitted values (Figure 2).

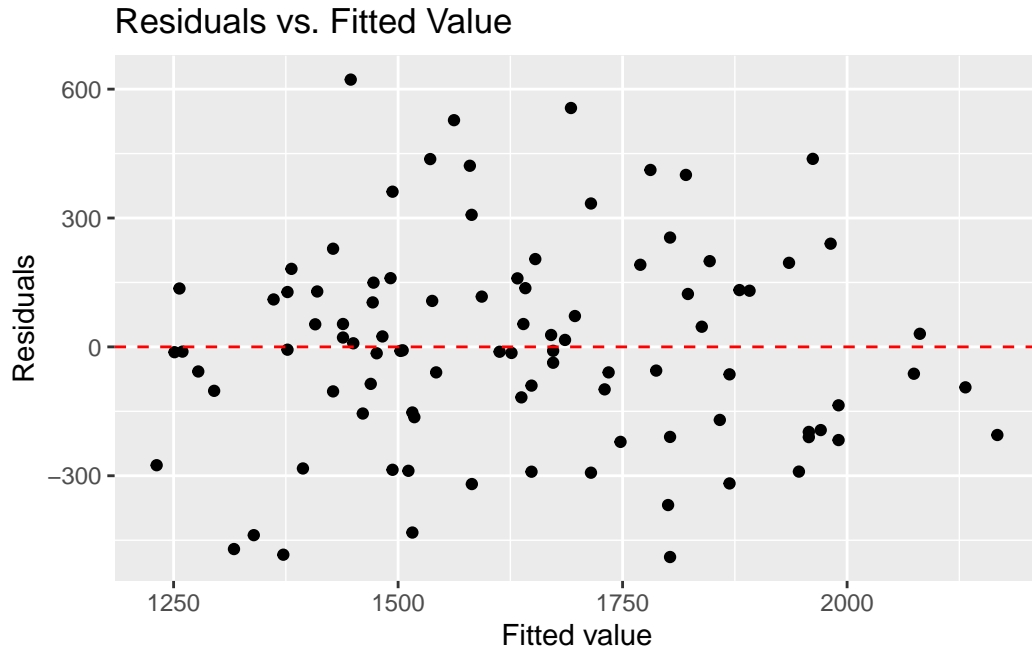


Figure 2: Residuals (y-axis) vs fitted values (x-axis) for a simple linear regression model with resting metabolic rate (kcal/day) as the response and height (cm) as the predictor

Figure 2 shows the residuals evenly distributed vertically, with no clear patterns and no systematic change in variance. While there are a few oddities with extreme points, these are likely due to a lack of data rather than assumption violations. Based on Figure 2, the assumptions of independence, constant variance, and linearity seem satisfied.

To test the assumption of normality, we graph a Quantile-Quantile plot, the sample quantiles vs the theoretical normal quantiles (Figure 3). If the data is normal, the points on the Quantile-Quantile plot will lie on a straight line.

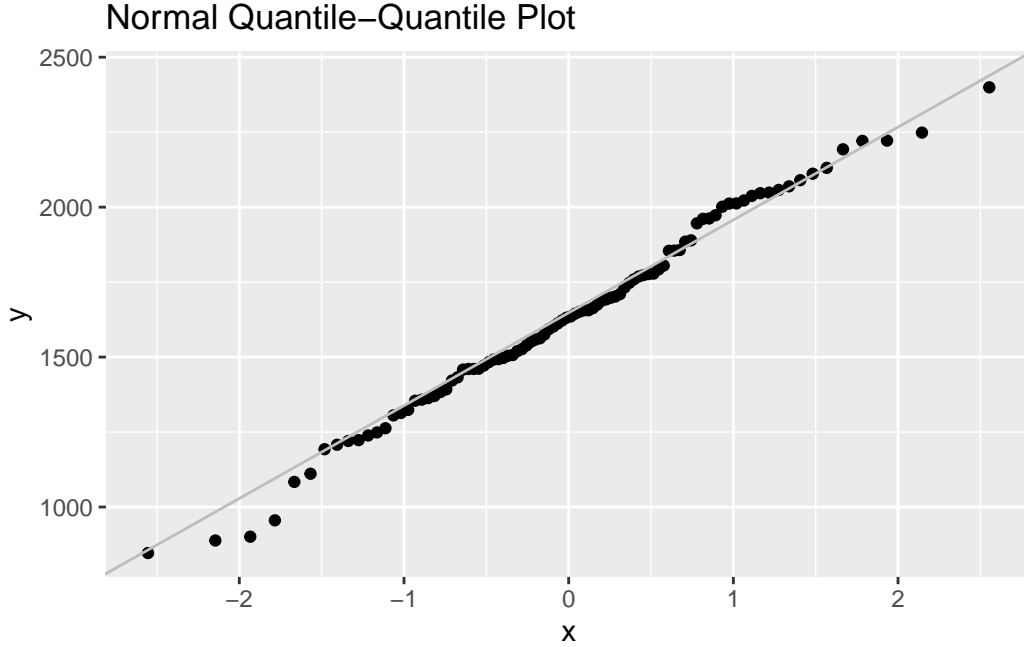


Figure 3: Plot of quantiles of residuals vs the theoritical normal distribution quantiles

Figure 3 shows very little deviations from the straight line, indicating that the assumption of normality of the error terms is also satisfied.

Because the data satisfy the assumptions, we can use hypothesis testing to check the model fit. We conducted a two-sided t-test with null hypothesis  $\beta_1 = 0$  and alternative hypothesis  $\beta_1 \neq 0$ . The associated p-value for  $\beta_1$  is  $2.8057667 \times 10^{-14}$  which is much smaller than the classical significance of  $\alpha = 0.05$ . Hence we reject the null hypothesis. There is evidence to suggest that  $\beta_1 \neq 0$ .

## 5 Discussion

The simple linear regression model indicates that height is a moderately strong predictor of RMR, explaining nearly half of its variation  $R^2 = 0.469$ . Moreover, the result of the hypothesis test indicate that the estimated slope is statistically significant. However, while height alone is a decent predictor, it leaves a lot variation unexplained. The Mifflin-St Jeor Equation is which includes height, weight, age, and gender is more accurate and likely better.

Height may also be a proxy for weight. Taller people on average will weigh more than shorter people. Future research could test whether weight provides a stronger relationship, or use BMI

as a way to standardize height and weight.

A valuable next step would be fitting a multiple linear regression using additional body composition variables as predictors, and could explore if it is necessary for men and women to have separate equations, as in the Mifflin-St Jeor Equation.

## References

- Mifflin, MD, ST St Jeor, LA Hill, BJ Scott, SA Daugherty, and YO Koh. 1990. “A New Predictive Equation for Resting Energy Expenditure in Healthy Individuals.” *The American Journal of Clinical Nutrition* 51 (2): 241–47. <https://doi.org/https://doi.org/10.1093/ajcn/51.2.241>.
- Navalta, James. 2025. “Data for: A Gender-agnostic Inclusive Estimation for Resting Metabolic Rate.” Harvard Dataverse. <https://doi.org/10.7910/DVN/MIOESN>.
- Plaza-Florido, Abel, and Juan M. Alcantara. 2023. “Resting Metabolic Rate of Individuals.” *Metabolites* 13 (8): 926. <https://doi.org/10.3390/metabo13080926>.
- R Core Team. 2024. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.