

Is BMI Alone a Good Predictor of Systolic Blood Pressure?*

Susan Peck

December 11, 2025

1 Abstract

This analysis evaluates whether body mass index (BMI) alone is an adequate predictor of systolic blood pressure (SBP) using data from the 2017–2018 National Health and Nutrition Examination Survey (NHANES). Several linear regression models were developed, including a simple model with BMI as the sole predictor, a model incorporating a quadratic BMI term, a robust regression using the Huber loss function, and a full multivariate model that included age, gender, height, weight, waist circumference, and smoking status. Results show that while BMI is statistically associated with systolic blood pressure, it explains only a small proportion of the overall variation. The full model substantially improves predictive accuracy, with age emerging as the strongest predictor and BMI becoming non-significant once other variables are included. Model comparisons using root mean squared error (RMSE) indicated that the full model performed best on both the validation and test datasets. These findings suggest that BMI should not be relied upon as a sole indicator of individual-level blood pressure risk and that multivariate approaches incorporating additional factors provide more meaningful predictive value.

2 Introduction

Body Mass Index (BMI) is a simple calculated metric based on dividing weight by height squared. Major public health organizations like the World Health Organization (WHO) (World Health Organization 2000) and the Centers for Disease Control (CDC) (National Institutes of Health 1998) use BMI threshold values to report general population level statistics of how many people are overweight, underweight, and obese. BMI is simple and standardized making it easy

*Project repository available at: <https://github.com/susanpeck/MATH261A-project-2-multiple-regression>

to calculate and compare between populations. BMI is also used to track population trends over time and general correlations in a population between BMI and disease levels. However, BMI is only so useful at the individual level. In clinical practice, BMI is sometimes used to deny or delay medical treatment like surgery until the patient has lost weight (American Society for Metabolic and Bariatric Surgery (ASMBS) 2022).

BMI is used as a screening tool and is not a direct measure of body fat (Romero-Corral et al. 2008). BMI cannot determine how much body fat or muscle a person has, or where the fat is located. A very muscular person could be classified as overweight or even obese based solely on their BMI value. Abdominal fat is probably a better indicator of risk of heart disease than overall weight (Ross et al. 2020; Ashwell and Hsieh 2012). In addition, BMI does not account for differences in health due to age or sex and should probably not be used as a sole diagnostic criterion (Romero-Corral et al. 2008; Tomiyama et al. 2018).

This paper will look at systolic blood pressure (SBP) data from the National Health and Nutrition Examination Survey (NHANES) conducted by the CDC’s National Center for Health Statistics (NCHS) (Johnson et al. 2013). Using this data (see Section 3) we will test whether BMI alone adequately predicts SBP, and whether multivariate models substantially improve prediction. The analysis will look at a simple linear regression for a single predictor BMI, a model that uses a log transform on the response variable, robust regression with a Huber loss function, a quadratic model, and a full model with seven predictors (see Section 4). The models will be evaluated individually and then compared using training, validation, and test data split from the sample and root mean squared error in the Section 5 section. Limitations of the data and analysis, as well as future directions are in Section 6.

3 Data

This analysis uses data from the 2017-2018 cycle of the National Health and Nutrition Examination Survey (NHANES), conducted by the CDC’s National Center for Health Statistics (NCHS). NHANES is a national survey that assesses the health and nutritional status of adults and children in the United States through interviews, physical examinations, and laboratory tests. The analysis will use body mass index (BMI), age, gender, height, weight, waist circumference and smoking status as predictor variables for average systolic blood pressure. Listed below are details for how the data were collected.

Average Systolic Blood Pressure (avg_systolic): For 2017–2018 NHANES, blood pressure was measured using an automatic oscillometric device. The person had their arm circumference measured to pick the correct blood pressure cuff size, then was seated quietly for 5 minutes. Three blood pressure readings were taken 60 seconds apart, and a fourth reading was taken if necessary (“Blood Pressure Procedures Manual” 2018; Health Statistics (NCHS) 2020). It is recommended to average the readings (Pickering et al. 2005) so this analysis requires a minimum of two valid readings.

Body Mass Index (BMXBMI): BMI (kg/m^2) was calculated as weight in kilograms divided by height in meters squared, rounded to one decimal place.

Height (BMXHT): Standing height was measured in centimeters to the nearest 0.1 cm. Participants stood without shoes with heels together.

Weight (BMXWT): Body weight was measured in kilograms to the nearest 0.1 kg using a calibrated digital scale. Participants removed shoes, heavy clothing, and items from pockets before measurement.

Waist Circumference (BMXWAIST): Waist circumference was measured in centimeters to the nearest 0.1 cm at the iliac crest. Participants stood with feet shoulder-width apart and arms at their sides, with the measurement taken at the end of a normal exhalation.

Gender (RIAGENDR): Sex was self-reported during the household interview as male or female. For analysis, this was coded as a binary variable (0 = Female, 1 = Male).

Age (RIDAGEYR): Age in years was collected via household interview and verified with government-issued documents when possible. Age is top-coded at 80 years in NHANES 2017-2018, meaning all participants 80 years and older are recorded as age 80. For this analysis, only participants aged 18-79 were included.

Current Smoking Status (SMQ020, SMQ040): Smoking status was assessed during the household interview. Participants were first asked if they had smoked at least 100 cigarettes in their lifetime (SMQ020). Those who answered “yes” were then asked if they currently smoke cigarettes every day, some days, or not at all (SMQ040). Current smokers were defined as those who reported smoking either every day or some days (binary: 0 = No, 1 = Yes).

For each observation, NHANES records comment codes when measurements could not be obtained or when specific conditions affected the measurement. Observations were excluded where comment codes indicated measurement issues or participant refusal.

After applying age restrictions (18-79 years), filtering for data quality based on measurement comment codes, and removing observations with missing values, the final dataset contained 4,610 participants. This sample was randomly split into training (70%), validation (15%), and test (15%) sets for model development and evaluation.

4 Methods

This paper analyzes a series of increasingly complex models to evaluate whether BMI alone adequately predicts systolic blood pressure. For most models, Y_i represents the response variable, the average systolic blood pressure (mmHg), for participant i .

Baseline Model: The starting point is a simple linear regression model with BMI as the only predictor to determine if BMI is a good predictor of systolic blood pressure. This was determined by BMI being used as a screening tool for tests and procedures in healthcare.

Simple linear regression with BMI

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

X_i represents the predictor variable, body mass index (kg/m²).

Quadratic Model: Visual inspection of residual plots from the baseline model suggested potential non-linearity as well as prior research (Sun et al. 2010) has indicated that the relationship between BMI and cardiovascular outcomes may not be linear across the entire BMI range.

Polynomial regression with BMI and BMI²

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i$$

X_i represents BMI and X_i^2 represents BMI squared.

Log Transform Model: Initial diagnostic plots revealed right-skewed residuals and heteroscedasticity (non-constant variance). A log transformation of the response variable is a standard approach to address these violations of model assumptions.

Use a log function to transform the response variable.

$$\log(Y_i) = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Huber Loss Robust Regression Q-Q plots revealed the possible presence of influential observations. Robust regression using Huber's loss function provides estimates that are less sensitive to outliers.

$$\rho(u) = \begin{cases} \frac{1}{2}u^2 & \text{if } |u| \leq c \\ c(|u| - \frac{1}{2}c) & \text{if } |u| > c \end{cases}$$

where u is the residual and $c = 1.345$ is the default tuning constant used by `rlm()` function (Venables and Ripley 2002).

Full Model: To assess whether additional clinically relevant predictors improve upon BMI alone, height, weight, waist circumference, age, gender, and smoking status were included. These variables were selected based on established cardiovascular risk factors, simple and easy to obtain data for future data, and availability in the NHANES data.

Multiple linear regression with all predictors

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + \beta_6 X_{i6} + \beta_7 X_{i7} + \varepsilon_i$$

where the predictors are Height (cm), Weight (kg), BMI (kg/m²), Waist circumference (cm), Gender (binary: 0=Female, 1=Male), Age (years), and Current smoking status (binary: 0=No, 1=Yes).

Parameter Interpretation

β_0 is the y-intercept of the model. For the baseline model, this represents the expected mean systolic blood pressure for an individual with a BMI of 0 kg/m². The intercept does not have a practical interpretation since 0 is not in the range of possible BMI values for any person.

β_1 is the slope coefficient. In the baseline model, the slope represents how much systolic blood pressure is expected to change, on average, for a one unit (kg/m²) increase in BMI. In the quadratic model, β_1 represents the linear effect of BMI while β_2 captures the quadratic (non-linear) relationship. In the full model, each β_j represents the expected change in systolic blood pressure for a one unit increase in predictor j , holding all other predictors constant.

ε_i are the error terms.

Model Assumptions

The models assume a linear relationship between Y and X. If the actual relationship between Y and X is not a linear one, then the model could be a bad fit for the data, to the extreme of not being useful at all, or possibly just have some bias and predictive values are off.

The model also assumes that the error terms are independent, have a constant variance for all levels of the predictor variable X, the mean of the error terms is zero, and the error terms are normally distributed. If these assumptions are not true then the values and confidence intervals can be misleading. For this dataset the sample size is large enough that the normality assumption is less important.

The analysis was done mostly using R programming (R Core Team 2025) and built in function, `lm()`, to fit the linear model and calculate estimated slope and intercept values. The `summary()` function takes the fitted model and provides a p-value for each of the estimates and a R^2 value.

If the relationship between systolic blood pressure and the predictors is not appropriately captured by the model structure, predictions may be biased. If the error assumptions are violated, standard errors, confidence intervals, and p-values may be misleading. However, with the large sample size, the normality assumption is less critical.

Statistical Analysis

The analysis was conducted using R programming (R Core Team 2025). Linear models were fit using the `lm()` function, and model summaries including coefficient estimates, standard errors, and p-values were obtained using the `summary()` function.

For each model, we test the null hypothesis $H_0 : \beta_j = 0$ against the alternative $H_a : \beta_j \neq 0$ for each predictor. A p-value less than 0.05 provides evidence to reject the null hypothesis, suggesting a statistically significant relationship between the predictor and systolic blood pressure.

Model Evaluation

Model performance is evaluated initially using the coefficient of determination, R^2 , which represents the proportion of variance in systolic blood pressure explained by the model:

$$R^2 = \frac{SSR}{SSTO}$$

where SSR is the regression sum of squares and SSTO is the total sum of squares. R^2 ranges from 0 to 1, with higher values indicating better model fit. An adjusted R^2 is used to account for the number of predictors in the third model, and root mean squared error (RMSE) on the validation set to assess predictive performance.

The cleaned data ($n = 4610$) were randomly split into training (70%), validation (15%), and test (15%) sets. Models were fit on the training data, compared using the validation set, and final performance was evaluated on the test set. The comparison metric was RMSE.

Root mean squared error (RMSE) was calculated as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where y_i is the observed systolic blood pressure, \hat{y}_i is the predicted value, and n is the number of observations in the validation set. RMSE represents the average prediction error in the original units (mmHg), with lower values indicating better predictive accuracy.

5 Results

The analysis began with a simple linear regression model to evaluate the relationship between just BMI and systolic blood pressure for the NHANES 2017-2018 cycle data. This baseline model was compared to a simple polynomial model. Some studies have suggested that a linear relationship may not be the most appropriate when BMI is a predictor (Sun et al. 2010) so second model with BMI^2 was chosen to see if there would be significant improvement. And the full model includes other predictors including age, sex, gender, current smoking status, and waist circumference to see if it can better capture the variation in systolic blood pressure. All the models were fit with the training dataset, approximately 70% of the total sample.

The simple linear regression model with BMI as the predictor has an intercept of 111.424 representing the predicted systolic blood pressure for an individual with a BMI of zero. As mentioned in the Section 4, this value doesn't have a real medical meaning since no one can have a BMI of zero. The model has a slope of 0.454 which is the expected change in systolic blood pressure in mm Hg associated with a one-unit increase in BMI (kg/m^2). The R^2 value ($R^2 = 0.03$) suggests that the model explains about 3% of the variation in systolic blood

pressure . And a very small p-value of $2.9706997 \times 10^{-23}$ means that there does seem to be a significant relationship between BMI and systolic blood pressure.

In Figure 1 a scatterplot of systolic blood pressure versus body mass index is shown for the training data with a linear regression model fit. Visually the data matches the results of the linear regression. There does appear to be a positive association between BMI and SBP, but there is a lot of other variation that is not explained. Most of the data points are between 20 and 40 for BMI, and under 160 mmHg for blood pressure. However there are still a lot of points outside those ranges and very few that could possibly be identified as outliers on their own.

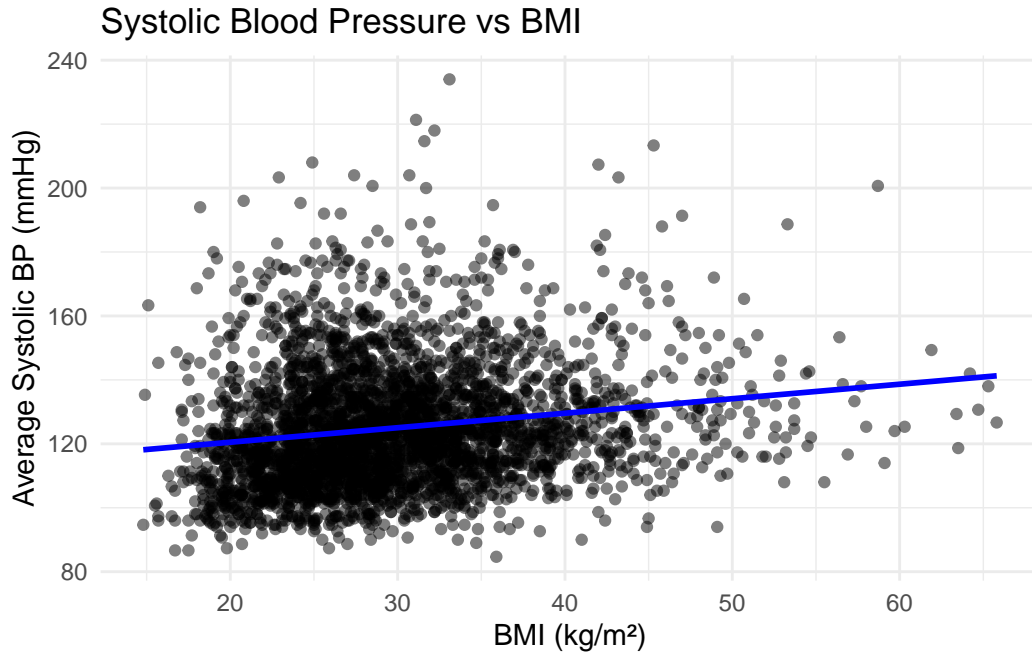


Figure 1: Scatterplot of Systolic Blood Pressure vs BMI

The residual versus fitted plot in Figure 2 resembles the original scatterplot and might have a non-linear trend appearing as a reflected quadratic. The similarity to the original scatterplot makes sense since not a lot of the variation was explained by the model. The possible non-linear trend in the residuals will be investigated with a quadratic model as the second model in this analysis. The residual plot also shows more clearly that the data does not appear to have a constant variance. Specifically, SRP values above average tend to be more spread out than SRP values below the average.

A QQ plot of the residuals in Figure 3 shows where some of the model assumptions about normality might not be met. For values near the mean, the assumption the model seems to meet the assumptions of normality. However the tails are both deviating from the $y=x$ line. Two possible ways to investigate. The first is to try a log transform of the response variable,

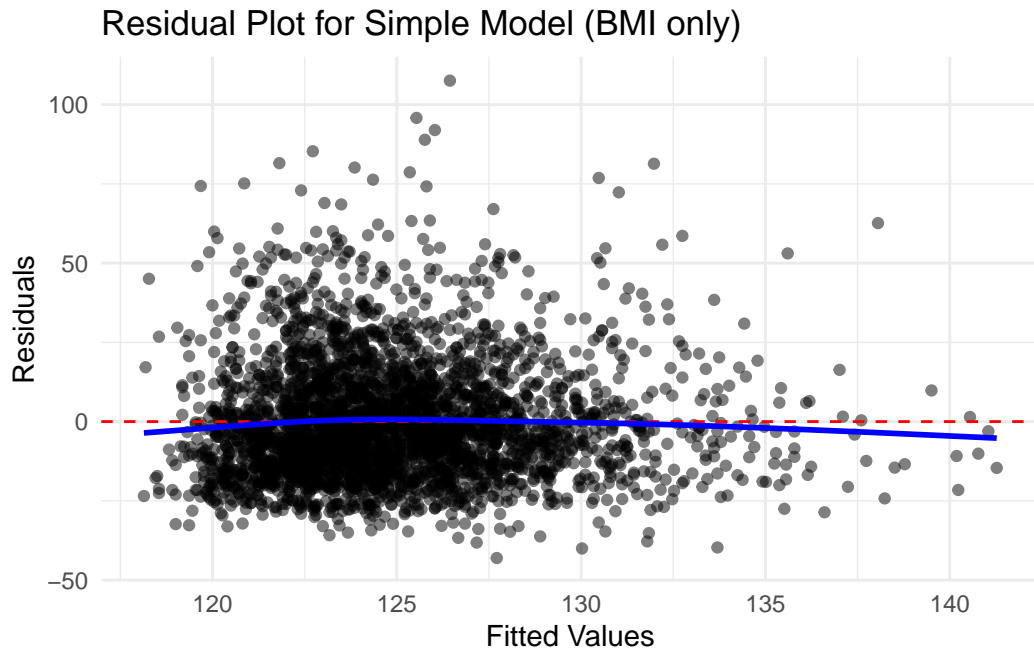


Figure 2: Residual vs Fitted Values for Simple Linear Regression Baseline Model 1

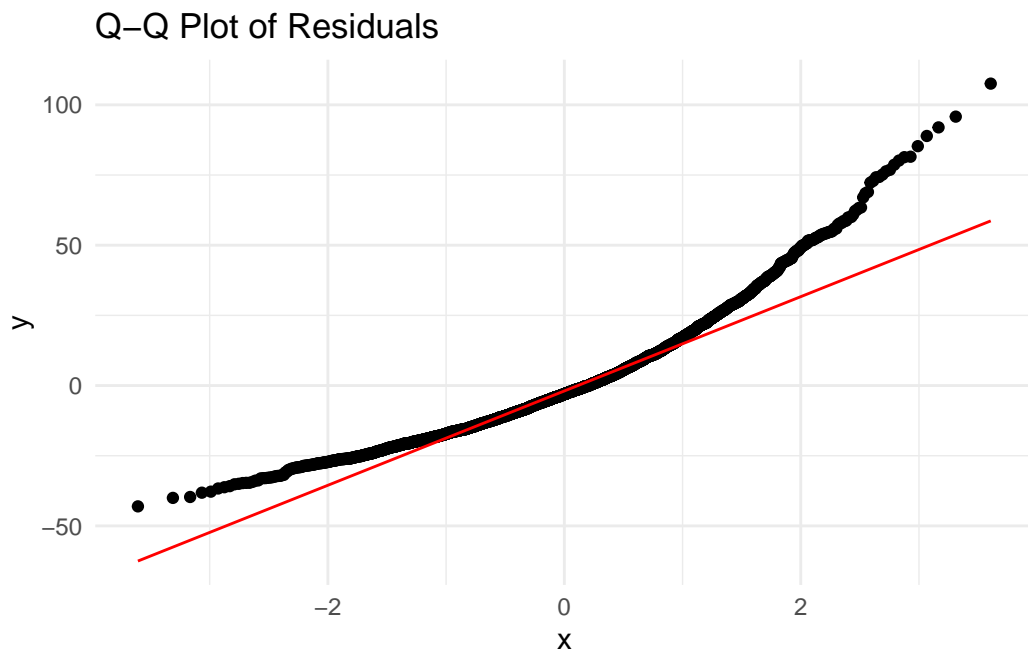


Figure 3: QQ plot for Normality Check

SRP, to see if that will give a better fit with the skewed variance. Another is a robust regression with Huber loss function to try to account for data points far from the mean having a large influence on the model fit.

The regression model with BMI as the predictor and a log transform of the response variable SRP has an intercept of 4.706 representing the expected log of the systolic blood pressure for an individual with a BMI of zero. This means that the expected systolic blood pressure would be e^{b_0} which is 110.596. The model has a slope of 0.004 which is the expected change in the log of systolic blood pressure in mm Hg associated with a one-unit increase in BMI (kg/m²).

$$\log(Y_i) = \beta_0 + \beta_1 X_i + \varepsilon_i$$

$$E[\log(Y_i)] = \beta_0 + \beta_1 X_i$$

To find how much the systolic blood pressure might change due to an increase in BMI of 1 kg/m², we would need to substitute $X_i + 1$ and solve for Y.

$$\log(Y_2) = \beta_0 + \beta_1 (X_i + 1)$$

$$Y_1 = e^{\beta_0 + \beta_1 X_1}$$

$$Y_2 = e^{\beta_0 + \beta_1 (X_1 + 1)}$$

$$Y_2 = e^{\beta_0 + \beta_1 X_1} e^{\beta_1}$$

$$Y_2 = e^{\beta_1} Y_1$$

So the value estimated by the model for β_1 of 0.004 leads to a multiplicative change in the systolic blood pressure value for a unit change in BMI of 1.004. For an increase of 1 BMI it would be expected that the systolic blood pressure is 1.004 times more.

In Figure 4 a QQ plot shows that there is a change from Figure 3 that flattens the tails, but some of the deviation from normal still exists and the log model only explains a similar portion of the variance to the baseline model.

The regression model with BMI as the predictor and a robust regression using the Huber loss function with a tuning parameter of $c = 1.345$ has an intercept of 109.063 representing the expected systolic blood pressure for an individual with a BMI of zero. The model has a slope of 0.473 which is the expected change systolic blood pressure in mm Hg associated with a one-unit increase in BMI (kg/m²).

The regression model with BMI^2 as an added predictor has an intercept of 100.043 representing the predicted systolic blood pressure for an individual with a BMI of zero. The model has an estimated value for β_1 of 1.176 which is the slope when BMI is zero, and an estimated value for β_2 of -0.011. The R^2 value ($R^2 = 0.033$) suggests that the model explains about 3.3% of the variation in systolic blood pressure. The negative coefficient for the term with a degree of 2 matches the residual trend seen in the baseline model. However, the model does not explain much more of the variance than the baseline model.

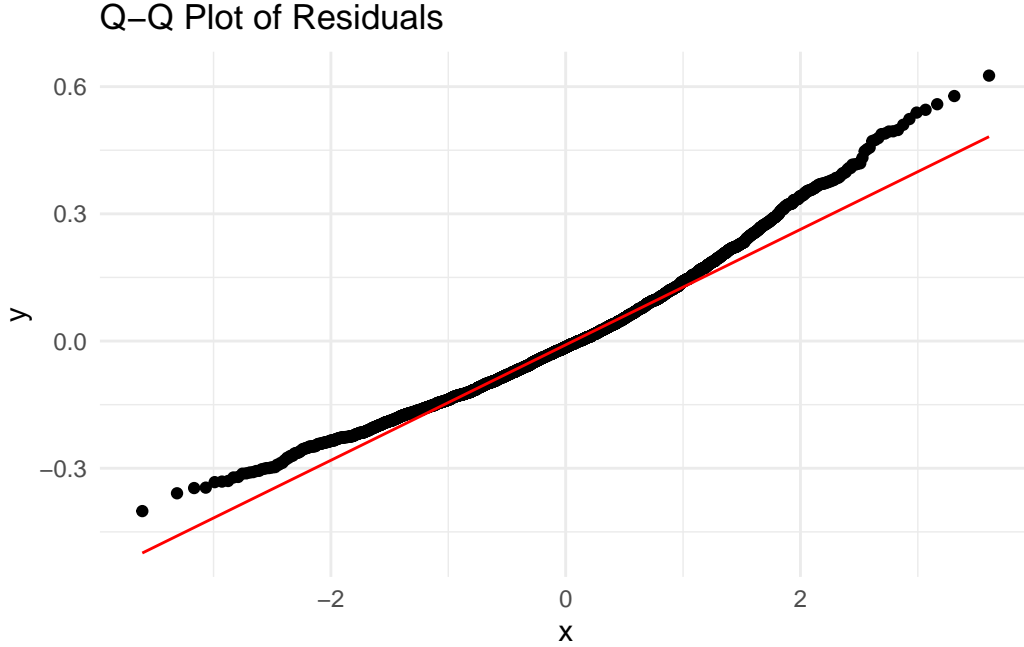


Figure 4: Q-Q Plot for Log Regression Baseline Model

The full linear regression model suggests that age is highly significant, height, weight, and gender are significant, currently smoking is borderline significant, and BMI and waist circumference are not significant. The full model explains about 23.471% of the variation in average systolic blood pressure. Holding all other predictors constant, age seemed to be the strongest predictor, with an estimated coefficient of 0.493 mmHg for every additional year in age ($p = 1.0527142 \times 10^{-122}$). Gender was also statistically significant, with males having 2.466 mmHg higher systolic blood pressure on average ($p = 0.0026068$). Height and weight showed small but statistically significant associations, with coefficients of -0.3 ($p = 0.0199822$) and 0.273 ($p = 0.0288057$), respectively. BMI (-0.341, $p = 0.3163257$) and waist circumference (-0.008, $p = 0.8845457$) were not statistically significant. Smoking status had a marginal association, contributing 1.406 mmHg on average ($p = 0.0629904$).

The models that have been fitted to the training data are the simple linear regression baseline model with BMI as the only predictor, a log transform of response variable for the baseline model, a robust regression using a Huber loss function, a quadratic model with BMI only, and a full model. For comparison, only the baseline, the quadratic, and the full model will be used. The log transform and the Huber loss did not have a large enough change in the fit to justify the added complexity in the model.

The models will be compared by using the root mean squared error as defined in Section 4. As shown below in the table, the full model has the smallest RMSE, so it is the chosen model.

| | Model | RMSE |
|---|--------------|----------|
| 1 | Simple (BMI) | 18.91125 |
| 2 | BMI Squared | 18.84777 |
| 3 | Full Model | 16.49457 |

The final RMSE value using the full model and predicting values using the test data is 15.981155.

6 Discussion

This analysis evaluated whether BMI alone adequately predicts systolic blood pressure using NHANES 2017-2018 data, and whether multivariate models substantially improve prediction. The results demonstrate that while BMI shows a statistically significant positive association with systolic blood pressure, it explains only 3% of the variance when used as a sole predictor. BMI alone is insufficient for predicting individual level systolic blood pressure, despite being useful as a population level screening tool. In addition, the residual plots revealed non constant variance and problems with normality, suggesting that other factors probably also influence blood pressure variation. Adding a quadratic BMI term provided minimal improvement and it didn't seem to improve in predictive accuracy.

The full multivariate model improved predictive performance and explained about 23.5% of systolic blood pressure variance. Age seemed to be the strongest predictor and males showed 2.47 mmHg higher systolic blood pressure than females on average. Once height, weight, and waist circumference were included in the model, BMI became non-significant. This might be due in part by some multicollinearity because BMI is calculated directly from height and weight. When other predictors were held constant, systolic blood pressure increased with weight and decreased with height. This is consistent with the calculation for BMI.

These results confirm that BMI should not be used by itself to assess cardiovascular risk at the individual level. A prediction error of approximately 19 mmHg from the baseline model RMSE is a large value. That value would put a person into a different level of hypertension because the difference between 'elevated' and 'stage 1 hypertension' is 10 mmHg.

Even the full multivariate model with seven predictors has only moderate predictive accuracy. This indicates the model is missing important predictors for systolic blood pressure. Possibilities include diet, physical activity, stress, medications, and other health conditions. For the strongest predictor, age, the model suggests that between ages 40 and 70, a person could expect approximately 15 mmHg higher systolic blood pressure, holding other factors constant.

Several limitations should be considered when interpreting these results. First, the analysis restricts the ages to adults between 18-79. This is because the data is top-coded at 80 years in NHANES 2017-2018 for privacy and security reasons. However, this means the findings should not be generalized to those 80 and older. This analysis cannot determine whether

these associations seen in the results are causal or just correlated. The models assume linear relationships between predictors and systolic blood pressure. While the analysis tested a quadratic BMI term, other non-linear relationships or interactions between predictors may exist that were not explored. Finally, the residual plots showed some observations have larger prediction errors than expected under normality. We explored log transformation and robust regression using Huber loss, but neither provided substantial improvement. A more flexible model may be appropriate.

This analysis should further explore predictors such as diet, physical activity and known family history of high blood pressure. It could further explore the possible multicollinearity of height, weight, and BMI, as well as other associated factors like waist measurement. This analysis purposely chose to use easier to obtain values for the predictors, but to truly understand what affects blood pressure, using predictors that show fat versus lean muscle quantities in the body, and how much abdominal fat is present, would probably help explain more of the variance in the data.

Another type of analysis would be to try and figure out if there is a time delay between predictors like BMI and developing a condition. If certain health indicators actually do cause conditions or noncontagious disease, then to actually analyze the results appropriately we would need to factor in the delay from the onset of the health indicator to the condition being present.

In conclusion, these findings reinforce that BMI is best suited as a population-level screening tool rather than a diagnostic criterion for individual cardiovascular risk assessment.

References

- American Society for Metabolic and Bariatric Surgery (ASMBS). 2022. “Clinical Practice Guidelines for the Perioperative Support of Patients with Obesity.”
- Ashwell, M., and S. D. Hsieh. 2012. “Six Reasons Why the Waist-to-Height Ratio Is a Rapid and Effective Global Indicator for Health Risks of Obesity and How Its Use Could Simplify the International Public Health Message on Obesity.” *International Journal of Food Sciences and Nutrition* 63 (3): 226–30. <https://doi.org/10.3109/09637486.2011.635659>.
- “Blood Pressure Procedures Manual.” 2018. National Center for Health Statistics (NCHS), Centers for Disease Control; Prevention. https://wwwn.cdc.gov/nchs/data/nhanes/2017-2018/manuals/BP_Procedures_Manual_2017.pdf.
- Health Statistics (NCHS), National Center for. 2020. “Blood Pressure (Oscillometric) Data Documentation, Codebook, and Frequencies: NHANES 2017–2018.” https://wwwn.cdc.gov/Nchs/Nhanes/2017-2018/BPXO_J.htm.
- Johnson, Clifford L., Ryma Paulose-Ram, Cynthia Ogden, et al. 2013. “National Health and Nutrition Examination Survey: Analytic Guidelines, 1999–2010.” *Vital and Health Statistics* 2 (161). https://www.cdc.gov/nchs/data/series/sr_02/sr02_161.pdf.
- National Institutes of Health. 1998. “Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults.” *Obesity Research* 6: 51S–209S.
- Pickering, Thomas G., John E. Hall, Lawrence J. Appel, Bonita E. Falkner, John W. Graves, Martha N. Hill, Daniel W. Jones, Theodore Kurtz, Sheldon G. Sheps, and Edward J. Roccella. 2005. “Recommendations for Blood Pressure Measurement in Humans and Experimental Animals: Part 1: Blood Pressure Measurement in Humans.” *Hypertension* 45 (1): 142–61. <https://doi.org/10.1161/01.HYP.0000150859.47929.8e>.
- R Core Team. 2025. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Romero-Corral, A., V. K. Somers, J. Sierra-Johnson, Y. Korenfeld, S. Boarin, J. Korinek, M. D. Jensen, and F. Lopez-Jimenez. 2008. “Accuracy of Body Mass Index in Diagnosing Obesity in the Adult General Population.” *International Journal of Obesity* 32: 959–66. <https://doi.org/10.1038/ijo.2008.11>.
- Ross, Robert, Ian J. Neeland, Shuichi Yamashita, et al. 2020. “Waist Circumference as a Vital Sign in Clinical Practice: A Consensus Statement.” *Obesity* 28 (3): 454–63. <https://doi.org/10.1002/oby.22755>.
- Sun, Qi, Rob M. van Dam, Donna Spiegelman, et al. 2010. “Comparison of Dual-Energy x-Ray Absorptiometry and BMI in Predicting Cardiometabolic Risk Factors.” *The American Journal of Clinical Nutrition* 91 (2): 443–50. <https://doi.org/10.3945/ajcn.2009.28090>.
- Tomiyama, A. Janet, Deborah Carr, Ellen M. Granberg, et al. 2018. “How and Why Weight Stigma Drives the Obesity ‘Epidemic’ and Harms Health.” *BMC Medicine* 16 (1): 123. <https://doi.org/10.1186/s12916-018-1116-5>.
- Venables, William N., and Brian D. Ripley. 2002. *Modern Applied Statistics with s*. Fourth. New York: Springer. <https://www.stats.ox.ac.uk/pub/MASS4/>.
- World Health Organization. 2000. “Obesity: Preventing and Managing the Global Epidemic.

Report of a WHO Consultation.” World Health Organization.