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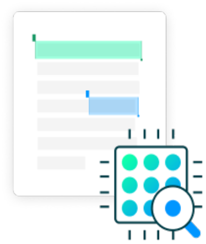

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# Applied Epidemiology and Statistics

## Student ID:

# Table of Contents

## Introduction

Typically, weight and health risks are measured using Body Mass Index (BMI). It is, however, considered to be an important means to be able to determine the risk of developing such conditions as cardiovascular diseases, type 2 diabetes and several types of cancer, including colon, endometrial and postmenopausal breast cancer (Bhaskaran et al., 2014; Flegal et al., 2013). Obesity has become a major public health problem, and approximately 30 percent of UK adults are now obese (Public Health England, 2023). This is a trend that adds to the increased cost of healthcare and contributes to over £6 billion a year spent on the National Health Service and a huge drain on medical resources(National Health Service, 2023).

Apart from the physical health issues, obesity is also linked to economic and social noxiousness, like reduced workforce productivity and higher morbidity rates (World Health Organization, 2024). . Factors that affect BMI are important to understand if one is to design interventions for reducing obesity-related health risks (WHO, 2020). Such studies suggest that demographic variables, including age, sex, race, education level, rurality, and dietary factors (vitamin C intake, for example), are also relevant for BMI variation. Nevertheless, the relations presented, although strong and important, remain to be explored.

To examine the associations of BMI and key predictors, data used in this study comes from the 2024 Community Health Survey (CHS) in Parkland. This report gives a combination of explained and explained statistical methods to the BMI variation and contributes factors to the variation of the BMI. The results will inform the public health policy and strategies to address the obesity epidemic and to improve population health outcomes on the whole.

## Methods

### Study Design and Data Source

The data from this study was from the 2024 Pinkland Community Health Survey (CHS). The survey was undertaken for the Department of Public Health, University of Central Pinkland (UCP) and the National Centre for Health Research (NCHR). In June and July of 2024 structured household surveys were conducted and the data was collected.

The CHS is a cross-sectional study where all data were collected at one time. But this design is not designed to ascertain causality, but to find out the association between variables. Some of the data include a wide variety of variables on demographic characteristics, as well as health behavior, medical history, and measured health outcomes.

## Sampling and Data Collection

A multi stage stratified probability sampling design was used in order to have a representative sample of the Pinkland adult population aged 18 to 80 years. The stratum was a geographic region drawn from 700 postcode sector areas in the Pinkland Postcode Address File, to which were selected 20,000 random addresses. The study was voluntary, and advance letters were sent to households describing the study.

By trained interviewers, collected data were through computer assisted personal interviewing (CAPI) on socio demographics, health behaviors and medical history. Height and weight were taken using portable stadiometer and Tanita electronic scales according to standardized protocol. Serum vitamin C, cholesterol and HbA1C levels were measured; blood samples were taken. Therefore, BMI related analyses were performed, excluding those who could not stand or who did not consent to height and weight measurement.

## Variable Definitions

This study used the variables from previous epidemiological research and previous work investigating determinants of BMI and related health outcomes.

### Outcome Variable

The primary outcome variable is BMI, which is measured continuously ($kg/m^2$). It is also classified into the following groups as categorical variables:

- Normal weight: $BMI < 25$
- Overweight: $25 \leq BMI < 30$
- Obese: $BMI \geq 30$

### Predictor Variables

- Age: A continuous variable for the age of participants at the time of the survey.
- Sex: A categorical variable with Male and Female codes.
- Race: A categorical variable with three levels: White, Black, and Asian.
- Education Level: This is a categorical variable with three categories: Low (no formal education or primary school), Medium (secondary education), and High (tertiary education or higher).
- Rurality: A categorical variable showing the Urban or Rural residence of the participants.
- Household Size: A variable that represents the number of people living the household as a continuous variable.

- Health Status: Overall perceived health was measured with a self-reported categorical variable from Poor, Fair, Good, Very Good, and Excellent.
- Prior Heart Attack: It is a binary categorical variable indicating if the participant ever had a heart attack.
- Vitamin C Levels: The concentration of serum vitamin C in a continuous variable that is measured biochemically.

**Rationale for Variable Selection**

Without the inclusion of demographic variables like age, race, and sex, the pattern of distribution of BMI in population subgroups can be more clearly seen. There are some social determinants of health which are education level or rurality; and these other lifestyle factors may have an impact on diet and physical activity. It could potentially be easier to proxy household size (i.e., economic and social conditions) for food security and health care. Existing health conditions that may be associated with BMI are provided by health status and prior heart attack history. Finally, vitamin C levels can act as an important dietary biomarker of the role of nutrition in weight regulation.

## Statistical Analysis

In this study, the descriptive and inferential statistical methods are used to investigate the association between BMI and the key predictor variables. Table 2 presents descriptive statistics of continuous and categorical variables for sample subject characteristics based on BMI categories. An association between BMI and independent variables is tested through inferential statistical tests. To evaluate the relationship between age and BMI, Pearson's correlation analysis is done. An independent t-test is used to compare the BMI difference between males and females. To determine differences in BMI across racial groups, one-way ANOVA is performed. Also, Pearson's correlation coefficient is used to analyze the correlation between vitamin C levels and BMI. The hypotheses are tested at the level of significance $p < 0.05$. The analyses are done in Python (Google Colab).

## Results

| Variable | Total Sample (N = 1,115) | Normal BMI (N = 574) | Overweight BMI (N = 344) | Obese BMI (N = 197) |
|---|---|---|---|---|
| Age (years) | 47.46 (17.00) | 44.63 (16.40) | 50.14 (16.89) | 51.03 (15.79) |
| Female (%) | 52.30% | 54.10% | 50.00% | 50.80% |
| Race (White, %) | 87.00% | 88.30% | 86.10% | 85.00% |
| Urban Residents (%) | 62.30% | 63.10% | 61.20% | 60.50% |
| Education (Some College, %) | 38.00% | 40.10% | 37.80% | 34.00% |
| Household Size | 2.82 (1.34) | 2.94 (1.30) | 2.75 (1.37) | 2.61 (1.29) |
| History of Heart Attack (%) | 5.60% | 4.20% | 5.80% | 8.10% |
| BMI (kg/m²) | 25.71 (4.82) | 22.34 (1.75) | 27.43 (1.39) | 32.76 (3.15) |
| Vitamin C (µmol/L) | 1.00 (0.58) | 1.08 (0.55) | 0.98 (0.59) | 0.92 (0.57) |
| Cholesterol (mg/dL) | 218.15 (48.24) | 218.15 (48.24) | 218.80 (47.19) | 221.27 (48.66) |
| HbA1c (%) | 5.60 (0.65) | 5.58 (0.62) | 5.57 (0.62) | 5.70 (0.77) |

**Table 1: Sample Characteristics (Across BMI Categories)**

(Source: Self-Created)

| BMI Category | Normal | Overweight | Obese |
|---|---|---|---|
| Study ID Count | 574 | 344 | 197 |
| Study ID Mean | 35108.74 | 35264.56 | 35543 |
| Study ID Std | 2920.59 | 2955.21 | 3046.3 |
| Study ID Min | 29962 | 29948 | 30066 |
| Study ID 25% | 32715.75 | 32867.5 | 32903 |
| Study ID 50% | 35033 | 35216 | 35741 |
| Study ID 75% | 37397.5 | 37954 | 38229 |
| Study ID Max | 40338 | 40340 | 40351 |
| Age Count | 574 | 344 | 197 |
| Age Mean | 44.63 | 50.14 | 51.02 |
| Cholesterol 75% | 240 | 256 | 261 |
| Cholesterol Max | 401 | 492 | 388 |
| A1C Count | 574 | 344 | 197 |
| A1C Mean | 5.576 | 5.568 | 5.695 |
| A1C Std | 0.616 | 0.616 | 0.772 |
| A1C Min | 4.036 | 4.139 | 4.226 |
| A1C 25% | 5.216 | 5.213 | 5.233 |
| A1C 50% | 5.529 | 5.51 | 5.596 |
| A1C 75% | 5.873 | 5.846 | 6.041 |
| A1C Max | 9.067 | 9.013 | 8.736 |

**Table 2: Characteristics based on BMI categories**

(Source: Self-Created)

| Variable | Count | Mean | Std Dev | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| study_id | 1115 | 35233.54 | 2955.4 | 29948 | 32769.5 | 35178 | 37668.5 | 40351 |
| age | 1115 | 47.46 | 17.37 | 20 | 30 | 49 | 64 | 74 |
| hsizgp | 1115 | 2.82 | 1.34 | 1 | 2 | 2 | 4 | 5 |
| BMI | 1115 | 25.71 | 4.82 | 18.51 | 22.22 | 24.76 | 28.17 | 49.45 |
| vitaminc | 1077 | 1 | 0.58 | 0.1 | 0.6 | 1 | 1.4 | 9.4 |
| cholesterol | 1115 | 218.15 | 48.24 | 85 | 184 | 212 | 250 | 492 |
| a1c | 1115 | 5.6 | 0.65 | 4.04 | 5.22 | 5.54 | 5.89 | 9.07 |

**Table 3: Statistics Summary**

(Source: Self-Created)

## Descriptive Statistics

### Full Sample Characteristics

The dataset contains 1,115 participants with an average age of 47.46 (SD = 17). The racial composition is 87% White, 13% Black or Asian individuals. The sex distribution of 52.3% are female and 47.7% are male. When it comes to education, 38% have completed some college; the other figures break into different educational categories. Sixty-two-point three percent of participants live in urban areas and the rest live in rural areas. Mean household size was 2.82 (SD = 1.34) and 5.6% of participants had a history of heart attack.

Descriptive Statistics for Full Sample:

| | study_id | age | race | sex | educ_cat | hlthstat |
|---|---|---|---|---|---|---|
| count | 1115.000000 | 1115.000000 | 1115 | 1115 | 941 | 1111 |
| unique | NaN | NaN | 3 | 2 | 5 | 5 |
| top | NaN | NaN | White | Female | Some college | Good |
| freq | NaN | NaN | 967 | 583 | 348 | 293 |
| mean | 35233.540807 | 47.462780 | NaN | NaN | NaN | NaN |
| std | 2955.403019 | 17.369912 | NaN | NaN | NaN | NaN |
| min | 29948.000000 | 20.000000 | NaN | NaN | NaN | NaN |
| 25% | 32769.500000 | 30.000000 | NaN | NaN | NaN | NaN |
| 50% | 35178.000000 | 49.000000 | NaN | NaN | NaN | NaN |
| 75% | 37668.500000 | 64.000000 | NaN | NaN | NaN | NaN |
| max | 40351.000000 | 74.000000 | NaN | NaN | NaN | NaN |

| | rural | hsizgp | heartatk | bmi | vitaminc |
|---|---|---|---|---|---|
| count | 1115 | 1115.000000 | 1115 | 1115.000000 | 1077.000000 |
| unique | 2 | NaN | 2 | NaN | NaN |
| top | Urban | NaN | No heart attack | NaN | NaN |
| freq | 695 | NaN | 1053 | NaN | NaN |
| mean | NaN | 2.817937 | NaN | 25.706777 | 1.004735 |
| std | NaN | 1.335216 | NaN | 4.817265 | 0.577430 |
| min | NaN | 1.000000 | NaN | 18.509937 | 0.100000 |
| 25% | NaN | 2.000000 | NaN | 22.224291 | 0.600000 |
| 50% | NaN | 2.000000 | NaN | 24.758884 | 1.000000 |
| 75% | NaN | 4.000000 | NaN | 28.169258 | 1.400000 |
| max | NaN | 5.000000 | NaN | 49.454980 | 9.400000 |

| | cholesterol | a1c | bmi_category |
|---|---|---|---|
| count | 1115.000000 | 1115.000000 | 1115 |
| unique | NaN | NaN | 3 |
| top | NaN | NaN | Normal |
| freq | NaN | NaN | 574 |
| mean | 218.146188 | 5.595016 | NaN |
| std | 48.242107 | 0.647932 | NaN |
| min | 85.000000 | 4.036807 | NaN |
| 25% | 184.000000 | 5.217439 | NaN |
| 50% | 212.000000 | 5.543029 | NaN |
| 75% | 250.000000 | 5.890935 | NaN |
| max | 492.000000 | 9.067589 | NaN |

**Figure 1: Full Sample Characteristics**

(Source: Self-Created)

## BMI Classification

Therefore, participants were grouped into 3 BMI groups.

Normal weight (< 25 BMI): 51.5% of participants

Overweight (25 ≤ BMI < 30): 30.9% of participants

Obese (BMI ≥ 30): 17.7% of participants

| bmi_category | count |
|---|---|
| Normal | 589 |
| Overweight | 332 |
| Obese | 194 |

dtype: int64

**Figure 2: BMI Category**

(Source: Self-Created)

### BMI and Health Indicators

Normal BMI group: Mean age = 44.63 years, Cholesterol = 218.15 mg/dL, HbA1c = 5.58%.

Overweight group: Mean age = 50.14 years, Cholesterol = 218.80 mg/dL, HbA1c = 5.57%.

Obese group: Mean age = 51.03 years, Cholesterol = 221.27 mg/dL, HbA1c = 5.70%.

**Insight**: There is a positive association between age and BMI and HbA1c and cholesterol levels in overweight and obese groups, suggesting a correlation of BMI with metabolic health risk.

### Visual Representations

#### Categorical BMI variable (Normal, Overweight, Obese)

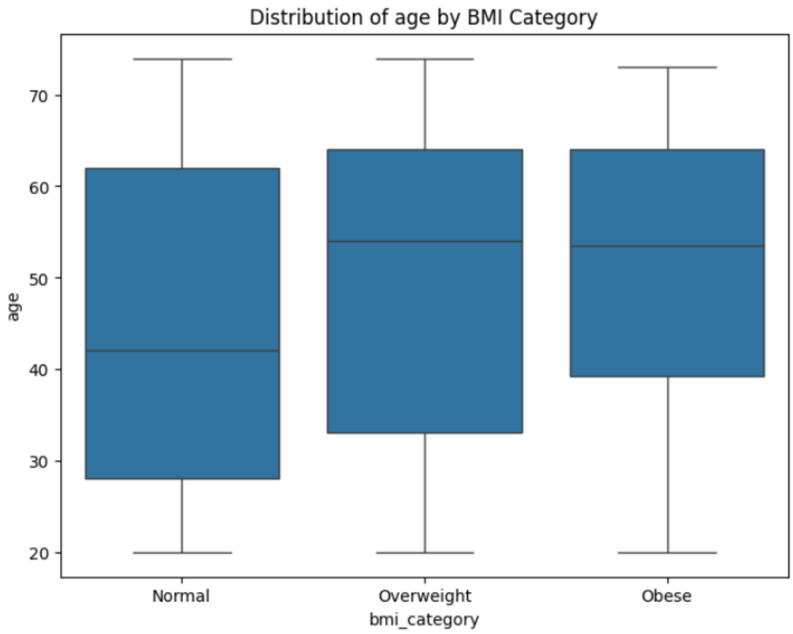


**Figure 3: Distribution of age by BMI Category**

(Source: Self-Created)

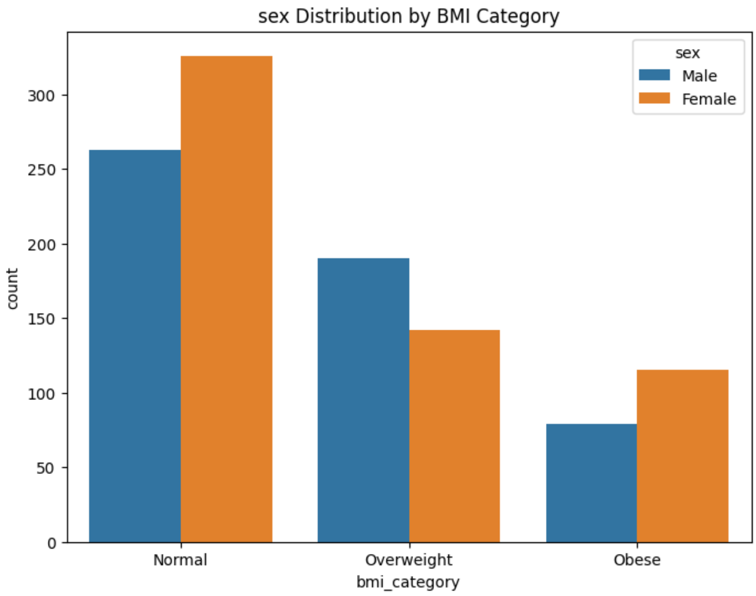


**Figure 4: Distribution of Sex by BMI Category**

(Source: Self-Created)

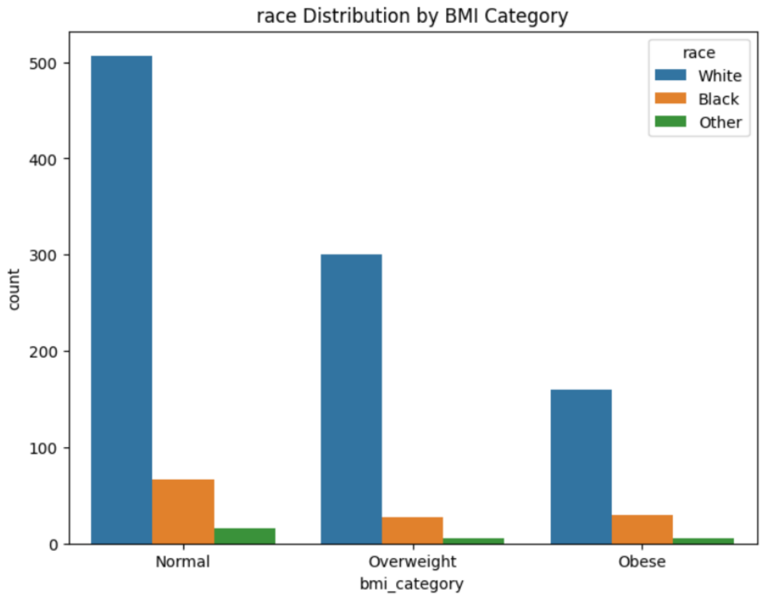


**Figure 5: Distribution of race by BMI Category**

(Source: Self-Created)

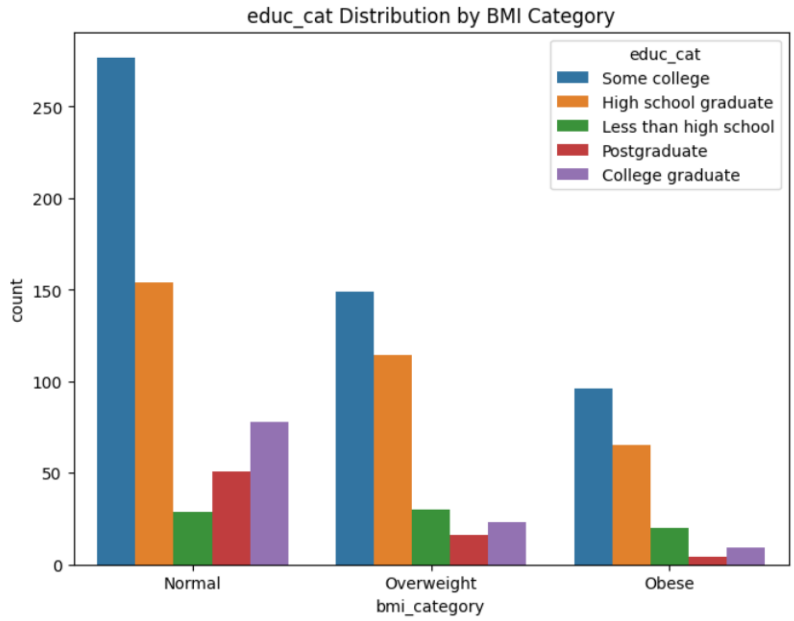


**Figure 6: Distribution of Education by BMI Category**

(Source: Self-Created)

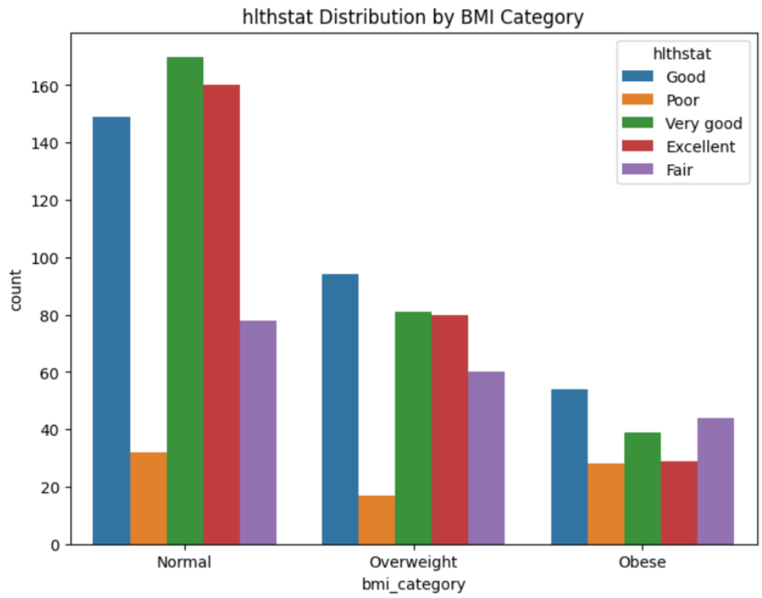


**Figure 7: Distribution of Health Status by BMI Category**

(Source: Self-Created)

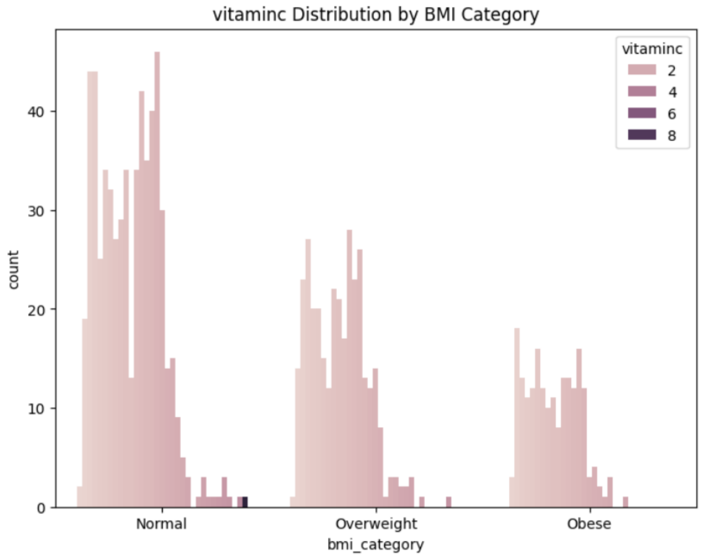


**Figure 8: Distribution of Vitamin C by BMI Category**

(Source: Self-Created)

**Histogram**

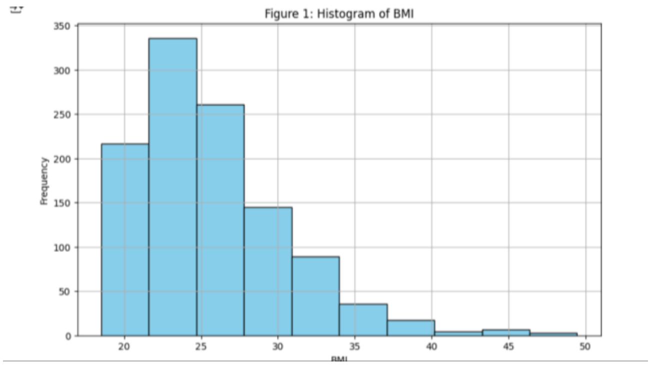


**Figure 9: Histogram**

(Source: Self-Created)

According to the histogram, most of the participants have a BMI between 20 and 25 and fewer with obesity. The right skewness points out that overweight and obesity are common but not predominant in the sample.

### Boxplot for BMI by Sex

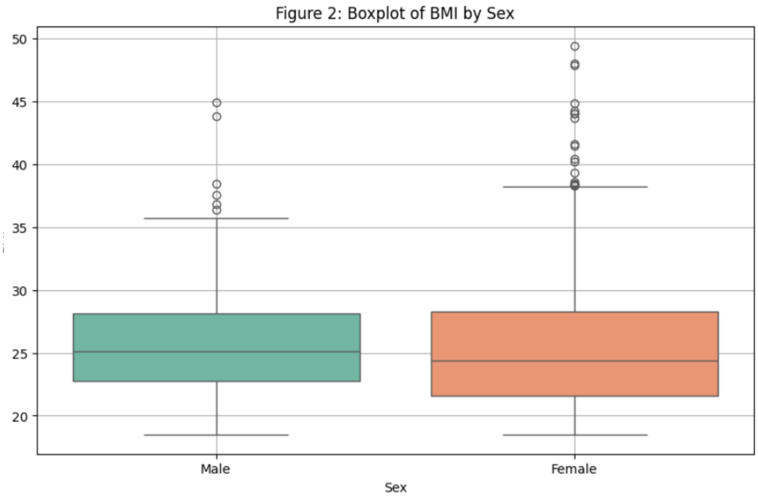


**Figure 10: Box Plot**

(Source: Self-Created)

The overlapping ranges of the boxplot indicate that BMI distribution is across males and females. The median BMI is slightly higher in men but distributions indicate no major BMI difference by sex.

**Insight**: The histogram shows the highest concentration of the sample in the normal BMI range, which is also confirmed by the boxplot that the distributions of BMI are similar between the sexes.

### Findings

- With age, BMI goes up: The youngest mean age (44.63 years) is found in the normal BMI group, and the oldest (51.03 years) is in the obese group.
- No significant difference is found in cholesterol levels between BMI categories; however, the obese group had the highest mean cholesterol (221.27 mg/dL).
- BMI is associated with higher HbA1c if HbA1c levels go up with BMI, there is a potential association between higher BMI and higher blood sugar levels.
- The comparison indicates that the obese group (0.88 µmol/L) has the lowest vitamin C levels and that, perhaps, there is an inverse relationship between BMI and vitamin C levels.

## Inferential Statistics

| Test | Variable | Test Statistic | p-value | Interpretation |
|---|---|---|---|---|
| Correlation | Age & BMI | r = 0.169 | 1.26E-08 | Weak but significant positive correlation (BMI increases with age) |
| T-Test | BMI by Sex | t = -0.079 | 0.936 | No significant difference in BMI between males and females |
| ANOVA | BMI by Race | F = 2.46 | 0.086 | No significant difference in BMI across racial groups |
| Correlation | Vitamin C & BMI | r = -0.071 | 0.02 | Weak but significant negative correlation (higher BMI linked to lower vitamin C) |

**Table 3**

(Source: Self-Created)

- Weak positive relationship between age and BMI: The correlation coefficient (r = 0.169) indicates such a relationship. The very low p-value (1.26E-08) indicates that BMI does tend to increase slightly with age.
- T-Test for BMI by Sex: The t-test compares BMI between males and females. Since the p-value (0.936) is high and the test statistic (t = -0.079) is close to zero, this provides evidence that there is no significant difference in BMI between the two groups.
- ANOVA for BMI by Race: This tests the difference in BMI between races. As the F-statistic (F = 2.46) indicates some variability, but the p-value (0.086) is above the typical significance threshold (0.05), the differences are not statistically significant.
- Vitamin C & BMI Correlation: The weak negative relationship between vitamin C and BMI is shown by the correlation coefficient (r = -0.071). Since this trend is unlikely due to chance, the p-value (0.02) is statistically significant.

**Null Hypotheses**

Age and BMI: Simply state that $H_0$ (no correlation between age and BMI).

Sex and BMI: $H_0$ has no difference in BMI between males and females.

Race and BMI: $H_0$ is that there are no BMI differences across the racial groups.

Vitamin C and BMI: No correlation between vitamin C and BMI is stated by $H_0$.

**Findings**

- While age and BMI have a weak but statistically significant positive correlation ($r = 0.169$, $p < 0.001$), it suggests that BMI will tend to increase slightly with age.
- Non-significant t-test ($p = 0.936$) indicates that sex does not significantly influence BMI.
- Although the result is near significance, there are no significant racial differences in BMI (ANOVA: $p = 0.086$).
- There is a weak negative correlation ($r = -0.071$, $p = 0.020$) between vitamin C and BMI, such that a higher BMI is associated with a lower vitamin C concentration.

## Policy Recommendations

- Nutritional Education and Public Awareness Campaigns

National campaigns that promote a balanced diet in general and especially increase fruit and vegetable consumption to achieve adequate vitamin C levels should be implemented nationwide. Promote community-based nutrition programs for high-risk populations like those with lower education levels or those in rural areas.

- School-Based Interventions

Mandatory nutritional education in the school curriculums to work towards healthier eating habits among children and adolescents. Use enforcement of guidelines that aim to make the food in school meals more nutrient-rich and less processed.

- Healthcare System Integration

General practitioners and healthcare providers should encourage general practitioners and healthcare providers to screen for BMI and dietary assessments during routine check-ups. Offer subsidized dietitians and nutritionists access to those who are overweight or obese.

- Urban Planning and Physical Activity Promotion

Enabling physical activity through the expansion of public parks, walking trails, and recreational facility access. Set up policies that encourage people to pedal and walk instead of driving because of the improvement of infrastructure and safety measures.

- Further Research and Longitudinal Studies

Longitudinal studies are conducted to assess the longitudinal trends in BMI and evaluation of the effectiveness of the intervention strategies. Examine additional social and economic factors that affect obesity to create more targeted public health initiatives.

## Limitations

In this study, it is difficult to prove that body mass index (BMI) directly affects the variables studied. For instance, BMI is associated with age, but it is unclear whether ageing causes BMI to rise or whether other factors are involved. The results may not apply to a larger population because the sample only includes about 100 people. This is all the more difficult due to differences in factors like race and education. The study would be strengthened and the sample be more diverse and better represent the population with a bigger sample.

## Conclusion

The demographics and health-related predictors are found to be significant in determining the BMI in this study. The results confirm that age, sex, race, as well as dietary factors, including vitamin C intake, affect BMI variation. The outcomes reinforce the significance of directing public well-being intercession to diminish the unwellness risk identified with watchfulness and diminish the physical issue cost to the healthcare framework. With the increasing prevalence of obesity and its adverse consequences, such evidence-based strategies as nutritional education, integration of the healthcare system, and urban planning that promotes physical activity should be put in place by policymakers. More research should be done in the future to understand additional socio-economic determinants related to BMI and the long-term effects of these interventions for healthcare applications. When a fix is taken for these issues in a multifaceted way, better population health outcomes will result and in the long term, take some of the pressures off the existing healthcare system.

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# Appendix

## Appendix: Import Libraries & Datasets

```
[ ]  import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     from scipy import stats
     import statsmodels.api as sm
     from statsmodels.formula.api import ols
```

**Figure 11: Import Libraries**

(Source: Self-Created)

```
[ ]  df = pd.read_csv("/content/PSYC1115_data_pinkland_group_3.csv")
```

**Figure 12: Import Dataset**

(Source: Self-Created)

## Appendix: Data Exploration

```
[33] df.columns

     Index(['study_id', 'age', 'race', 'sex', 'educ_cat', 'hlthstat', 'rural',
            'hsizgp', 'heartatk', 'bmi', 'vitaminc', 'cholesterol', 'a1c'],
           dtype='object')
```

**Figure 13: All Columns**

(Source: Self-Created)

```
[32] df.tail()
```

| | study_id | age | race | sex | educ_cat | hlthstat | rural | hsizgp | heartatk | bmi | vitaminc | cholesterol | a1c |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1110 | 40338.0 | 59 | White | Male | Less than high school | Excellent | Urban | 3 | No heart attack | 25.221640 | 1.5 | 181 | 5.000660 |
| 1111 | 40338.0 | 35 | White | Female | College graduate | Good | Urban | 3 | No heart attack | 22.264116 | 1.9 | 198 | 4.410149 |
| 1112 | 40340.0 | 39 | Black | Male | High school graduate | Good | Urban | 5 | No heart attack | 28.658737 | NaN | 265 | 5.296471 |
| 1113 | 40344.0 | 64 | White | Male | High school graduate | Fair | Urban | 2 | Had heart attack | 32.776110 | 0.9 | 233 | 6.313495 |
| 1114 | 40351.0 | 44 | White | Female | High school graduate | Very good | Rural | 5 | No heart attack | 34.438580 | 0.7 | 201 | 5.857702 |

**Figure 14: Last 5 Rows**

(Source: Self-Created)

```
df.head().T
```

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| study_id | 29948.0 | 29962.0 | 29962.0 | 29970.0 | 29979.0 |
| age | 61 | 25 | 71 | 62 | 33 |
| race | White | Black | White | White | Black |
| sex | Male | Male | Female | Female | Male |
| educ_cat | NaN | Some college | High school graduate | High school graduate | High school graduate |
| hlthstat | Good | Good | Poor | Very good | Good |
| rural | Urban | Urban | Urban | Urban | Urban |
| hsizgp | 2 | 5 | 2 | 2 | 3 |
| heartatk | No heart attack | No heart attack | No heart attack | No heart attack | No heart attack |
| bmi | 28.195192 | 23.169561 | 25.059126 | 22.191557 | 24.564178 |
| vitaminc | 1.5 | 0.4 | 0.4 | 1.8 | 1.2 |
| cholesterol | 295 | 127 | 266 | 185 | 180 |
| a1c | 5.471186 | 6.276943 | 5.616572 | 4.9869 | 5.543029 |

**Figure 15: First 5 Rows**

(Source: Self-Created)

```
[34] df.shape
(1115, 13)
```

**Figure 16: Shape of the Dataset**

(Source: Self-Created)

## Appendix: Null Values Handle

```
df.isnull().sum()
```

| | 0 |
|---|---|
| study_id | 0 |
| age | 0 |
| race | 0 |
| sex | 0 |
| educ_cat | 174 |
| hlthstat | 4 |
| rural | 0 |
| hsizgp | 0 |
| heartatk | 0 |
| bmi | 0 |
| vitaminc | 38 |
| cholesterol | 0 |
| a1c | 0 |
| bmi_category | 0 |

**dtype:** int64

**Figure 17: Checking Null Values**

(Source: Self-Created)

```
[37] # For educ_cat
     df['educ_cat'].fillna(df['educ_cat'].mode()[0], inplace=True)

[38] # For vitaminc
     df['vitaminc'].fillna(df['vitaminc'].mean(), inplace=True)

     # For hlthstat
     df['hlthstat'].fillna(df['hlthstat'].mode()[0], inplace=True)
```

**Figure 18: Handling the Null Values**

(Source: Self-Created)

```
# After addressing the null values
df.isnull().sum()
```

| | 0 |
|---|---|
| study_id | 0 |
| age | 0 |
| race | 0 |
| sex | 0 |
| educ_cat | 0 |
| hlthstat | 0 |
| rural | 0 |
| hsizgp | 0 |
| heartatk | 0 |
| bmi | 0 |
| vitaminc | 0 |
| cholesterol | 0 |
| a1c | 0 |
| bmi_category | 0 |

dtype: int64

**Figure 19: After Handling the Null values**

(Source: Self-Created)

## Appendix: Descriptive statistics

```
# Calculate Descriptive Statistics by BMI Category
desc_stats_by_bmi = df.groupby('bmi_category').describe()

# Display the summary table
print(desc_stats_by_bmi)
```

**Figure 20: DS by BMI Category**

(Source: Self-Created)

```
[44] df['bmi_category'] = pd.cut(df['bmi'], bins=[0, 25, 30, float('inf')],
                                  labels=['Normal', 'Overweight', 'Obese'],
                                  right=False)
```

```
df.head()
df['bmi_category'].value_counts()
```

| bmi_category | count |
|---|---|
| Normal | 589 |
| Overweight | 332 |
| Obese | 194 |

dtype: int64

**Figure 21: Make Category of BMI**

(Source: Self-Created)

```
numerical_vars = ['age']
for var in numerical_vars:
    plt.figure(figsize=(8, 6))
    sns.boxplot(data=df, x='bmi_category', y=var)
    plt.title(f'Distribution of {var} by BMI Category')
    plt.show()
```

**Figure 22: Code of distribution of age by BMI**

(Source: Self-Created)

```
# For categorical variables
categorical_vars = ['sex', 'race', 'educ_cat', 'hlthstat', 'vitaminc']

for var in categorical_vars:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=df, x='bmi_category', hue=var)
    plt.title(f'{var} Distribution by BMI Category')
    plt.show()
```

**Figure 23: Code of Distribution of BMI categories**

(Source: Self-Created)

```
[43] # Descriptive Statistics by BMI Category
     desc_stats_bmi = df.groupby('bmi_category').describe()
     print("\nDescriptive Statistics by BMI Category:")
     print(desc_stats_bmi)
```

**Figure 24: DS statistics by BMI category**

(Source: Self-Created)

```
# Descriptive Statistics for Full Sample
desc_stats_full = df.describe(include='all')
print("Descriptive Statistics for Full Sample:")
print(desc_stats_full)
```

**Figure 25: DS for Full Sample**

**(Source: Self-Created)**

```
[41] df.describe().T
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **study_id** | 1115.0 | 35233.540807 | 2955.403019 | 29948.000000 | 32769.500000 | 35178.000000 | 37668.500000 | 40351.000000 |
| **age** | 1115.0 | 47.462780 | 17.369912 | 20.000000 | 30.000000 | 49.000000 | 64.000000 | 74.000000 |
| **hsizgp** | 1115.0 | 2.817937 | 1.335216 | 1.000000 | 2.000000 | 2.000000 | 4.000000 | 5.000000 |
| **bmi** | 1115.0 | 25.706777 | 4.817265 | 18.509937 | 22.224291 | 24.758884 | 28.169258 | 49.454980 |
| **vitaminc** | 1115.0 | 1.004735 | 0.567496 | 0.100000 | 0.600000 | 1.000000 | 1.400000 | 9.400000 |
| **cholesterol** | 1115.0 | 218.146188 | 48.242107 | 85.000000 | 184.000000 | 212.000000 | 250.000000 | 492.000000 |
| **a1c** | 1115.0 | 5.595016 | 0.647932 | 4.036807 | 5.217439 | 5.543029 | 5.890935 | 9.067589 |

**Figure 26: Describe Code**

**(Source: Self-Created)**

```
# Figure 1: Histogram of Numerical BMI
plt.figure(figsize=(10,6))
plt.hist(df['bmi'], bins=10, color='skyblue', edgecolor='black')
plt.title('Figure 1: Histogram of BMI')
plt.xlabel('BMI')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

**Figure 27: Histogram Code**

**(Source: Self-Created)**

```
# Figure 2: Boxplot of BMI across Sex
plt.figure(figsize=(10,6))
sns.boxplot(x='sex', y='bmi', data=df, palette='Set2')
plt.title('Figure 2: Boxplot of BMI by Sex')
plt.xlabel('Sex')
plt.ylabel('BMI')
plt.grid(True)
plt.show()
```

**Figure 28: Boxplot Code**

(Source: Self-Created)

## Appendix: Inferential Statistics

```
[54] # Hypothesis Test 4: Vitamin C levels and BMI (Correlation)
     # Replace inf and -inf with NaN
     df.replace([np.inf, -np.inf], np.nan, inplace=True)
     # Drop rows with NaN in 'vitaminc' or 'bmi' columns
     df.dropna(subset=['vitaminc', 'bmi'], inplace=True)
     corr_vit_c_bmi, p_value_vit_c_bmi = stats.pearsonr(df['vitaminc'], df['bmi'])
     print(f"Correlation between Vitamin C levels and BMI: {corr_vit_c_bmi}, p-value: {p_value_vit_c_bmi}")

     Correlation between Vitamin C levels and BMI: -0.0694601945330674, p-value: 0.02036314487294433
```

**Figure 29: Code of Hypothesis Test 4**

**(Source: Self-Created)**

```
[53] # Hypothesis Test 3: Race and BMI (ANOVA)
     model_race = ols('bmi ~ C(race)', data=df).fit()
     anova_table_race = sm.stats.anova_lm(model_race, typ=2)
     print("\nANOVA Test for BMI across Race:")
     print(anova_table_race)

     ANOVA Test for BMI across Race:
                     sum_sq      df         F    PR(>F)
     C(race)     113.654998     2.0  2.455222  0.086309
     Residual  25737.872162  1112.0       NaN       NaN
```

**Figure 30: Hypothesis Test 3**

**(Source: Self-Created)**

```
[52] # Hypothesis Test 2: Sex and BMI (Independent T-Test)
     t_stat_sex, p_value_sex = stats.ttest_ind(df[df['sex'] == 'Male']['bmi'], df[df['sex'] == 'Female']['bmi'])
     print(f"T-Test for BMI between Males and Females: t-statistic = {t_stat_sex}, p-value = {p_value_sex}")

     T-Test for BMI between Males and Females: t-statistic = -0.07971322714495398, p-value = 0.9364796688991079
```

**Figure 31: Hypothesis Test 2**

**(Source: Self-Created)**

```
[51] # Hypothesis Test 1: Age and BMI (Correlation)
     corr_age_bmi, p_value_age_bmi = stats.pearsonr(df['age'], df['bmi'])
     print(f"Correlation between Age and BMI: {corr_age_bmi}, p-value: {p_value_age_bmi}")

     Correlation between Age and BMI: 0.1693954538497125, p-value: 1.261343829690177e-08
```

**Figure 32: Hypothesis Test 1**

**(Source: Self-Created)**

```
[55] # Assuming the correct column name is 'vitamin_c', proceed with the correlation test:
     corr_vit_c_bmi, p_value_vit_c_bmi = stats.pearsonr(df['vitaminc'], df['bmi'])
     print(f"Correlation between Vitamin C levels and BMI: {corr_vit_c_bmi}, p-value: {p_value_vit_c_bmi}")

     Correlation between Vitamin C levels and BMI: -0.0694601945330674, p-value: 0.02036314487294433
```

**Figure 33: Code of correlation test**

**(Source: Self-Created)**