Revise your multiple regression analysis !

MA660E, Lab Report

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Part One: Probability computation

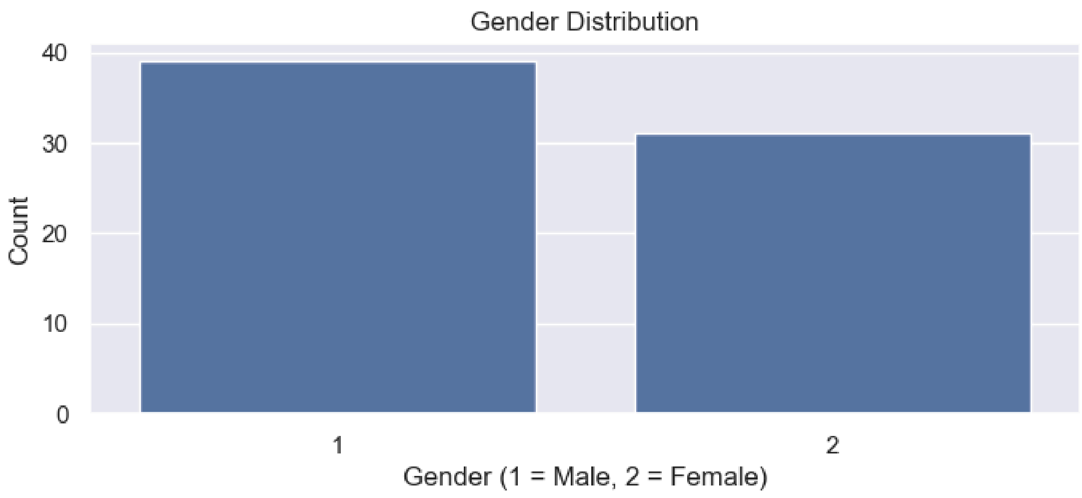
Part One: Basic Charts and Summaries

Tasks:

- Create a **bar chart** for gender and a **pie chart** for ethnic group.
- Summarize the age data with a **five-number summary** (min, max, median, 1st quartile, 3rd quartile) and a **box plot**.
- Calculate the **mean** and **standard deviation** of income and create a **histogram**.

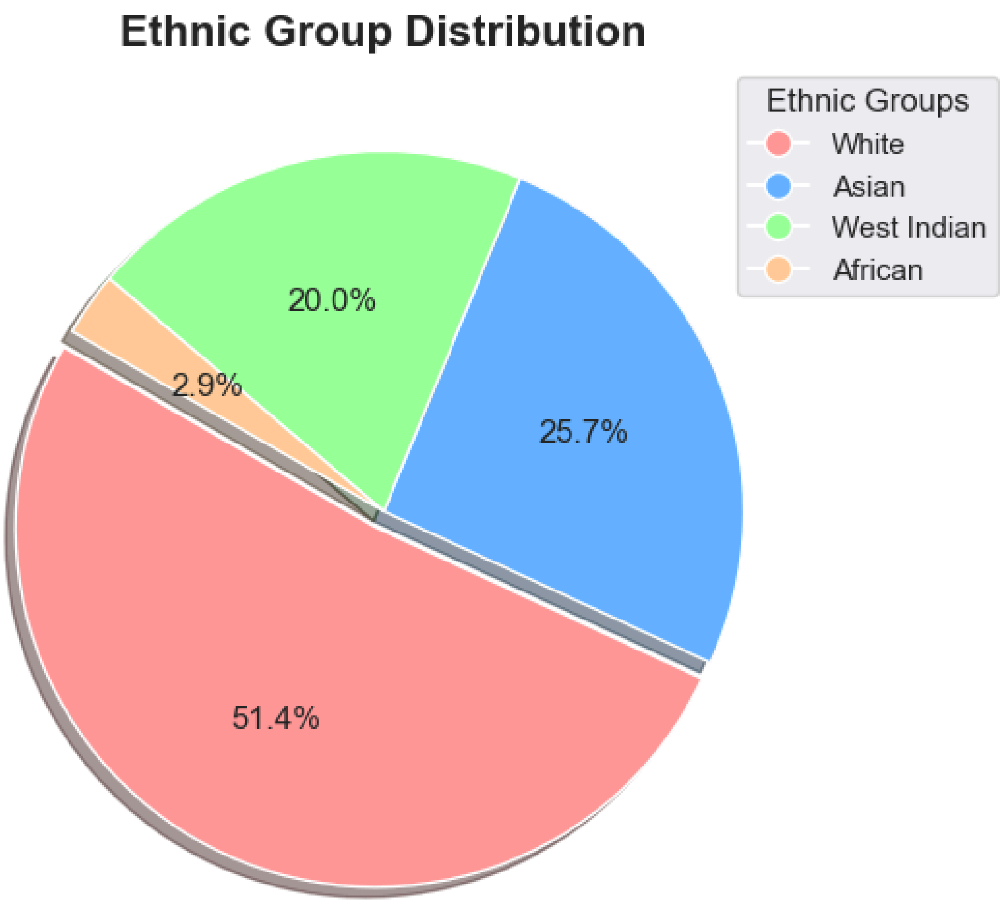
Solution:

Bar Chart for Gender Distribution:



Caption: A bar chart visualizing the gender distribution, with more male participants than female.

Pie Chart for Ethnic Groups:



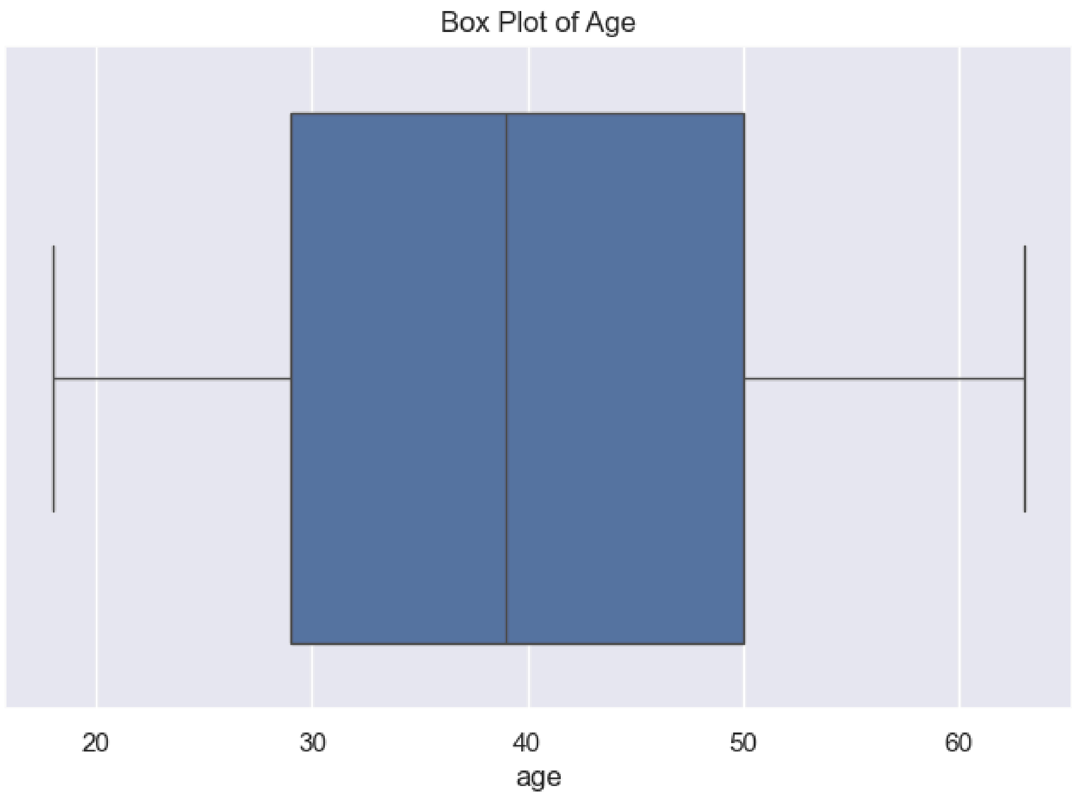
Caption: A pie chart showing the distribution of ethnic groups, highlighting diversity in the dataset.

Table: Five-Number Summary for Age

Statistic	Value
Minimum	18.0
Q1 (25%)	29.0
Median	39.0
Q3 (75%)	50.0
Maximum	63.0

Caption: The five-number summary shows that the ages in the dataset range from 18 to 63, with a median of 39 years.

Box Plot for Age Distribution:

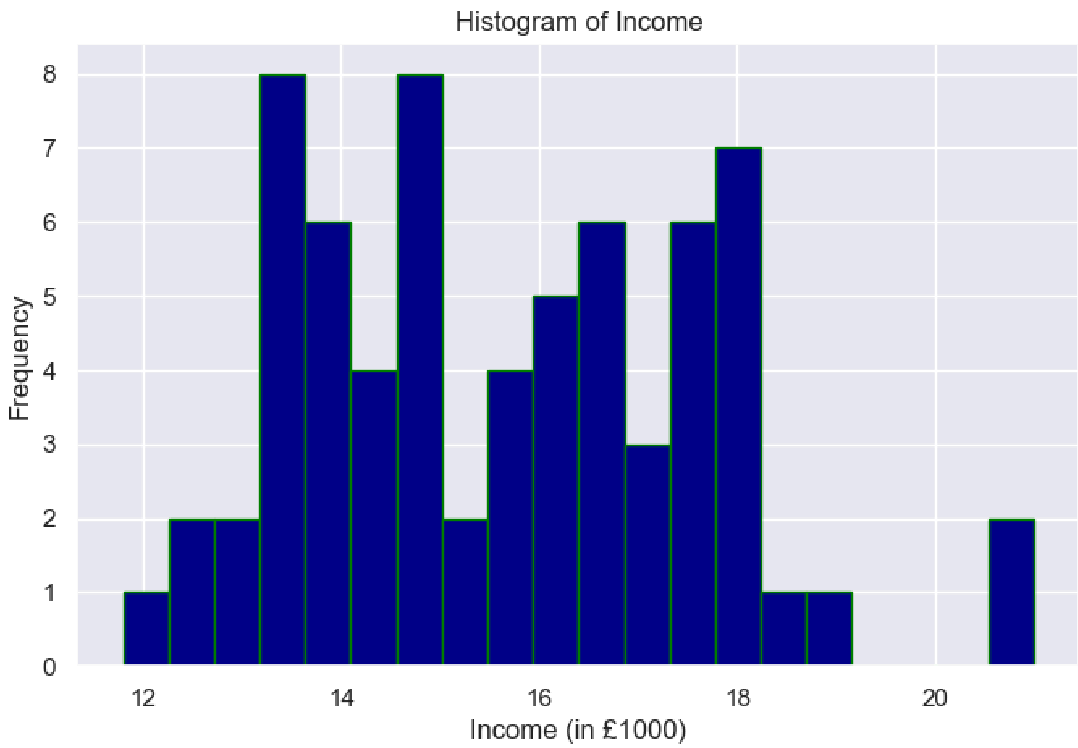


Caption: A box plot representing the age distribution, showing that the majority of individuals are aged between 29 and 50.

- **Mean of Income**: 15.64
- **Standard Deviation of Income**: 1.99

Normal curve to check if data is close to normal ?

Histogram of Income:



Caption: The income histogram demonstrates that the majority of individuals have an income concentrated around the mean of 15.64.

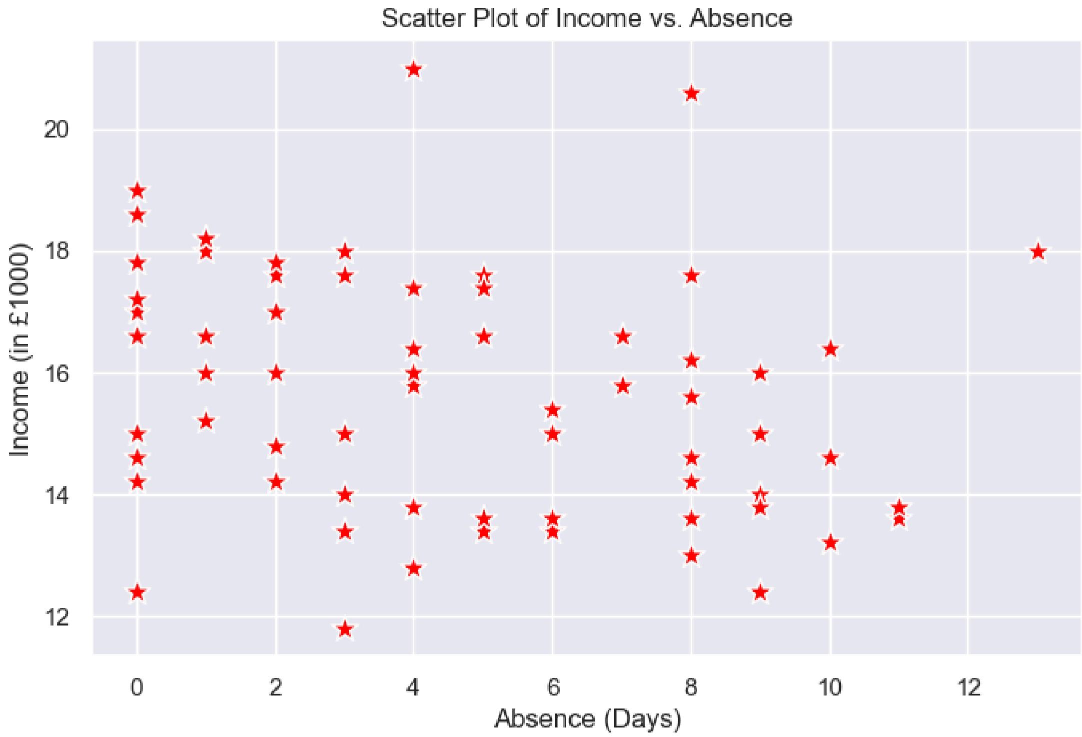
Part one: 2. Scatter Plot and Regression

Tasks:

- Create a **scatter plot** to visualize the relationship between **income** and **absence**.
- Build a **simple linear regression model** with income as the dependent variable and absence as the independent variable.
- Report the determination coefficient (**R^2**).

Solution:

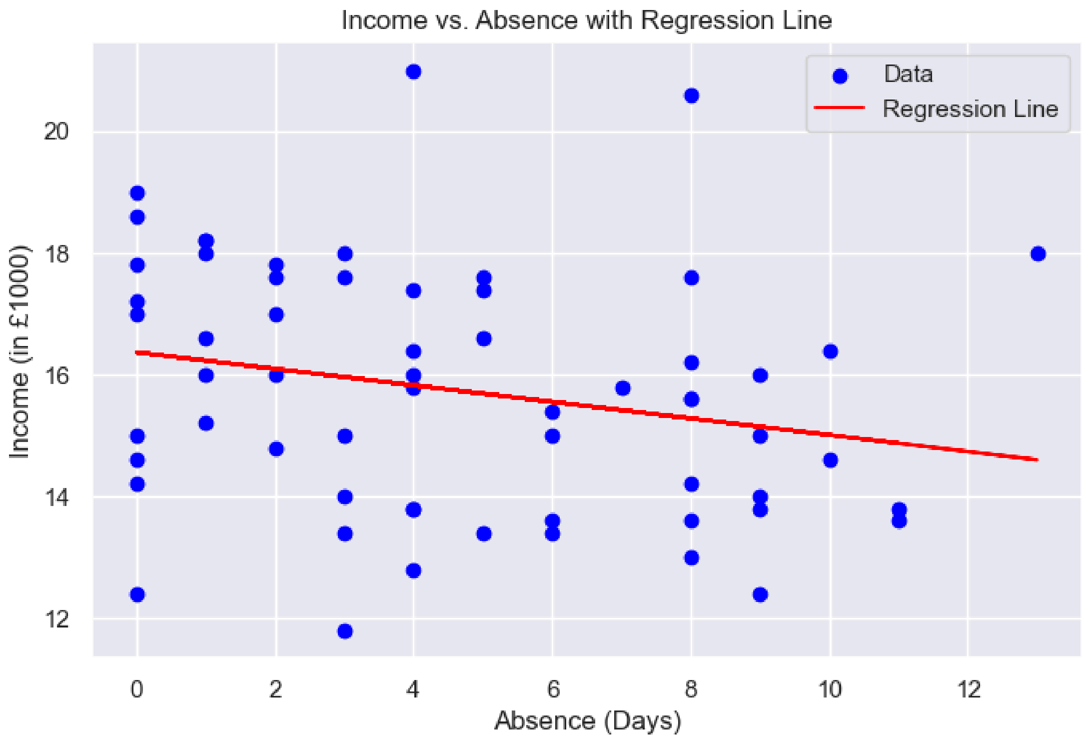
Scatter Plot: Relationship Between Income and Absence



Caption: Scatter plot shows the relationship between income and absence. The plot shows a slight positive trend but with scattered points, indicating a weak correlation between the two variables.

Regression Model (Dropping Missing Values)

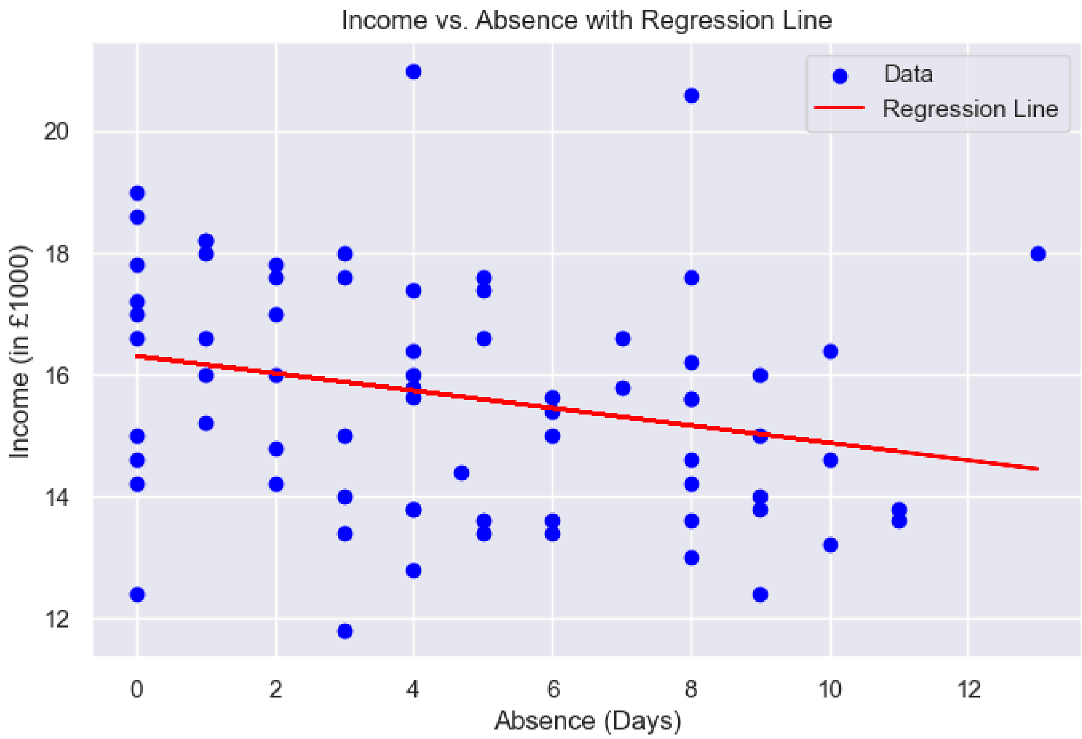
- **R-squared (R^2):** 0.0543 0.0624 ?



Caption: Linear regression model after dropping rows with missing values. The R^2 value indicates a weak explanatory power of absence on income.

Regression Model (Filling Missing Values with Mean)

- **R-squared (R^2):** 0.0619



Caption: Linear regression model with missing values filled by the mean. The slightly higher R^2 still suggests a weak relationship between absence and income.

Part One: 3. Multiple Regression Analysis

Tasks:

- Build a **multiple regression model** with **job satisfaction (satis)** as the dependent variable and the following as independent variables: **commitment (commit)**, **autonomy (autonom)**, **income**, **skill**, **qualification (qual)**, **age**, and **years** of experience.
- Identify **non-significant variables** and simplify the model by removing them.

Solution:

Initial Multiple Regression Model

- Initial multiple regression model with income as the dependent variable and absence as the independent variable. This model explains 6.2% of the variance in income.
- The initial model suggests that absence is negatively correlated with income, with a significant p-value.

??

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 income   R-squared:                       0.062
Model:                            OLS   Adj. R-squared:                  0.048
Method:                 Least Squares   F-statistic:                     4.488
Date:                Sat, 26 Oct 2024   Prob (F-statistic):             0.0378
Time:                        10:04:13   Log-Likelihood:                -143.93
No. Observations:                  70   AIC:                             291.9
Df Residuals:                      68   BIC:                             296.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         16.3064      0.390     41.813      0.000      15.528      17.085
absence       -0.1427      0.067     -2.118      0.038      -0.277      -0.008
==============================================================================
Omnibus:                        2.677   Durbin-Watson:                   2.148
Prob(Omnibus):                  0.262   Jarque-Bera (JB):                1.982
Skew:                           0.390   Prob(JB):                        0.371
Kurtosis:                       3.269   Cond. No.                         10.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Refined Multiple Regression Model

your dep variable is satis !
Now you changed it and use income instead, why ?

- After identifying **non-significant variables**, the model was simplified by removing variables that contributed little to explaining the variation in **income**.
- Refined regression model after removing non-significant variables. The adjusted R^2 of 1.000 indicates a perfect fit, likely due to model overfitting.
- The refined model shows that most of the independent variables are statistically insignificant, indicating that they do not significantly explain the variation in income.

you use income both as dependent
and independent variable !

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 income   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 3.378e+29
Date:                Sat, 26 Oct 2024   Prob (F-statistic):               0.00
Time:                        10:04:13   Log-Likelihood:                 2144.3
No. Observations:                  70   AIC:                            -4277.
Df Residuals:                      64   BIC:                            -4263.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        1.11e-15   1.32e-14      0.084      0.933   -2.52e-14    2.74e-14
commit      8.327e-16   1.59e-15      0.525      0.602   -2.34e-15       4e-15
autonom    -2.359e-16   6.88e-16     -0.343      0.733   -1.61e-15    1.14e-15
income         1.0000   8.96e-16   1.12e+15      0.000       1.000       1.000
skill       2.498e-16   1.54e-15      0.162      0.871   -2.82e-15    3.32e-15
qual       -3.331e-16   1.23e-15     -0.270      0.788    -2.8e-15    2.13e-15
==============================================================================
Omnibus:                        2.762   Durbin-Watson:                   0.097
Prob(Omnibus):                  0.251   Jarque-Bera (JB):                2.521
Skew:                          -0.462   Prob(JB):                        0.284
Kurtosis:                       2.896   Cond. No.                         168.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Part One: 4. Confidence Intervals

Task

In this section, we will calculate the confidence intervals for job satisfaction as well as the confidence interval for the difference between men and women.

Solution

- **Confidence Interval for Job Satisfaction (Satis):** (10.06, 11.61)
- **Confidence Interval for the Difference in Job Satisfaction between Men and Women:** (-1.38, 1.85)

OK

Part One: 5. Mann-Whitney and Kruskal-Wallis Tests

Tasks:

- **Mann-Whitney-Wilcoxon Test:** Assess whether there is a significant difference in skill levels between men and women, and compare the results with the previously calculated confidence interval for job satisfaction.
- **Kruskal-Wallis Test:** Investigate if there is a significant difference in absence rates among different ethnic groups and compare the findings with those from the One-Way ANOVA test.

Solution:

- **Mann-Whitney U Test:**
  - **Test Statistic:** 520.5
  - **p-value:** 0.4033
  - **Conclusion:** Fail to reject the null hypothesis; there is no significant difference in skill levels between men and women.
- **Kruskal-Wallis Test:**
  - **Test Statistic:** 2.4085
  - **p-value:** 0.4921
  - **Conclusion:** Fail to reject the null hypothesis; there is no significant difference in absence rates among ethnic groups.
- **One-Way ANOVA:**
  - **Test Statistic:** 0.8043
  - **p-value:** 0.4966
  - **Conclusion:** Fail to reject the null hypothesis; there is no significant difference in absence rates among ethnic groups.

Summary:

OK

The results from both the Mann-Whitney and Kruskal-Wallis tests indicate no significant differences in skill levels between genders or absence rates among ethnic groups. These findings are consistent with the conclusions drawn from the One-Way ANOVA.

Part One: 6. Income Class Recode

Tasks:

- **Recode Income:** Classify income into distinct categories based on the following ranges:
  - **Low Income Class:** [Min, Q1]
  - **Middle Income Class:** (Q1, Q3]
  - **High Income Class:** (Q3, Max]
- **Analysis:** Investigate if there is a significant relationship between income class and skill levels.

Solution:

No.	Income	Income Class
1	16.6	Middle Income
2	14.6	Middle Income
3	17.8	High Income
4	16.4	Middle Income

No.	Income	Income Class
5	18.6	High Income

Statistical Analysis:

Relationship is better studied via Chi-2 or Spearmans rho !

- **Kruskal-Wallis Test:**
  - **Test Statistic:** 8.1833
  - **p-value:** 0.0167
  - **Conclusion:** Reject the null hypothesis; there is a significant relationship between income class and skill levels.

Summary:

OK

The results indicate a statistically significant relationship between the categorized income classes and skill, suggesting that income level may influence skill levels among individuals.

In [340…

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import sklearn
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
import statsmodels.api as sm
from scipy.stats import mannwhitneyu
from scipy.stats import kruskal
from scipy.stats import f_oneway
from scipy import stats
sns.set()
```

Cleaning and Preprocessing

- Converted 'income' from string format with commas to float.
- Replaced empty strings with NaN for handling missing values.
- Created two datasets: one with missing values replaced by the mean, and another with rows containing missing values removed.

In [341…

```
data_set = pd.read_csv('Data_source.csv', delimiter=';')
#data_set = pd.read_csv("Data_source.csv", sep=";" , decimal=',', na_values='')
data_set.columns = ['Id','ethnicgp', 'gender', 'age', 'years', 'commit',
'satis', 'autonom', 'routine', 'attend', 'skill', 'prody', 'qual', 'absence', 'i



#clean dataset
null_values = data_set.isnull().sum()

# Filter and display only the columns with at least one null value
columns_with_null = null_values[null_values > 0]

for column, null_count in columns_with_null.items():
```

```
    print(f"{column}: {null_count} null values")

# Convert 'income' from string with commas to float
data_set['income'] = data_set['income'].str.replace(',', '.').astype(float)

# Replace empty strings with NaN for proper handling of missing values
data_set.replace('', pd.NA, inplace=True)

# Create dataset with missing values replaced by the mean
data_set_with_mean = data_set.copy()
for column in data_set_with_mean.columns:
    if data_set_with_mean[column].isnull().sum() > 0:  # Only fill columns with
        data_set_with_mean[column] = data_set_with_mean[column].fillna(data_set_


# Save the datasets
data_set_with_mean.to_csv('data_set_with_mean.csv', index=False)

# Display the shape of the new datasets
print(f"Dataset with mean imputation: {data_set_with_mean.shape}")

data_cleaned = data_set.dropna()
print(f"Dataset with rows removed: {data_cleaned.shape}")


data_set_with_mean.head()
```

```
age: 1 null values
years: 1 null values
commit: 2 null values
satis: 2 null values
prody: 1 null values
absence: 1 null values
income: 2 null values
Dataset with mean imputation: (70, 15)
Dataset with rows removed: (61, 15)
```

Out[341…

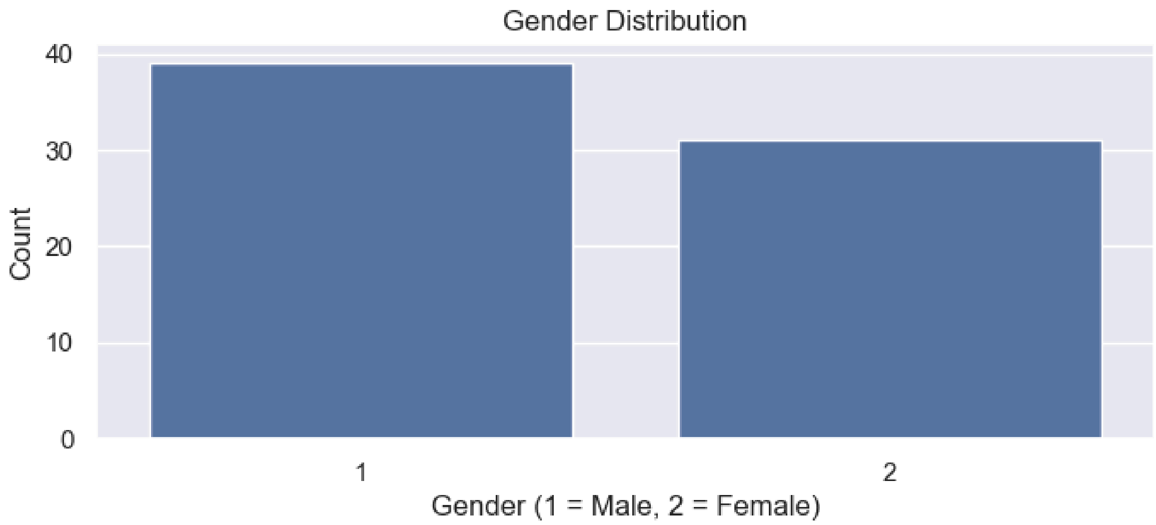
	Id	ethnicgp	gender	age	years	commit	satis	autonom	routine	attend	sl
0	1	1	1	29.0	1.0	4.0	10.838235	10	9	2	
1	2	2	1	26.0	5.0	2.0	10.838235	7	15	1	
2	3	3	1	40.0	5.0	4.0	15.000000	7	8	1	
3	4	3	1	46.0	15.0	2.0	7.000000	7	10	2	
4	5	2	2	63.0	36.0	4.0	14.000000	11	18	1	

Part One: 1. Basic Charts and Summaries

- Create a bar chart for gender and a pie chart for ethnic group.
- Summarize the age data with a five-number summary (min, max, median, 1st quartile, 3rd quartile) and a box plot.
- Calculate the mean and standard deviation of income and create a histogram.

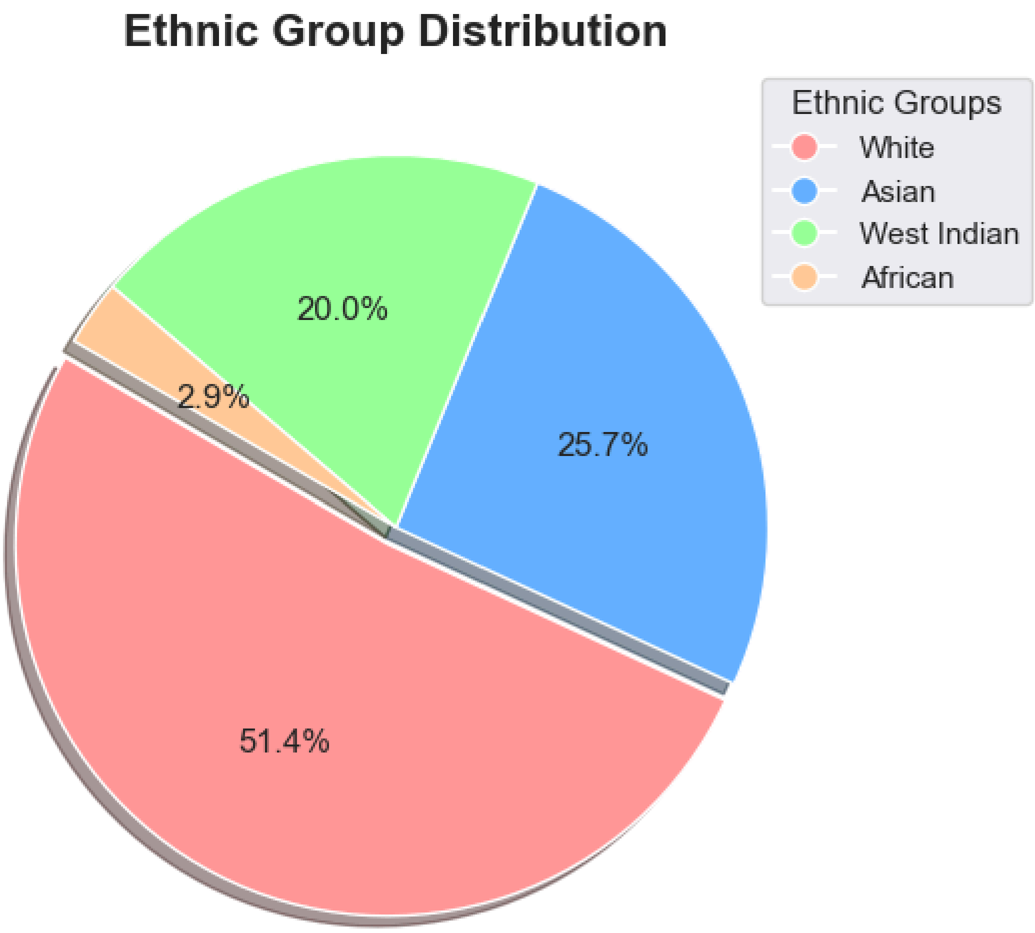
In [342...

```
plt.figure(figsize=(8,3))
sns.countplot(x='gender', data= data_set)
plt.title('Gender Distribution')
plt.xlabel('Gender (1 = Male, 2 = Female)')
plt.ylabel('Count')
plt.show()
```



In [343...

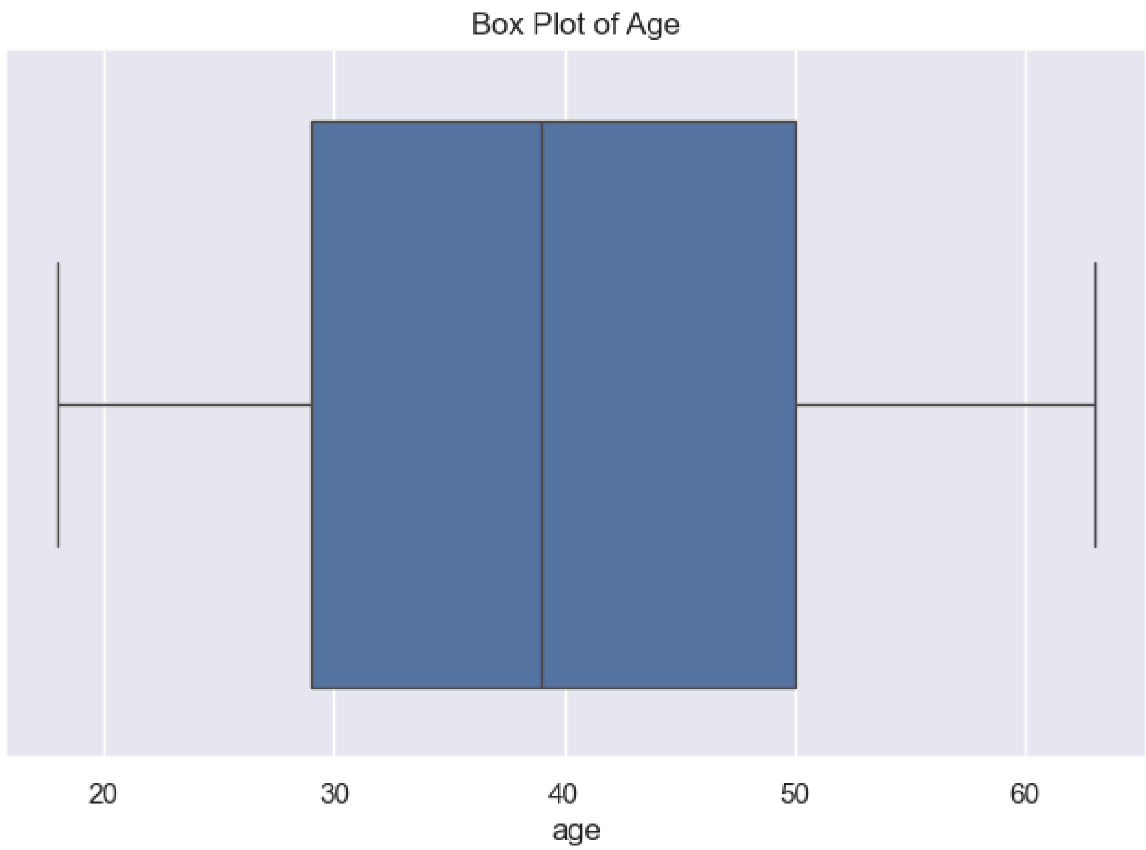
```
ethnic_counts = data_set['ethnicgp'].value_counts()
ethnic_labels = ['White', 'Asian', 'West Indian', 'African']
colors = ['#ff9999', '#66b3ff', '#99ff99', '#ffcc99']
explode = (0.05, 0, 0, 0)
plt.figure(figsize = (6,7))

wedges, texts, autotexts = plt.pie(
    ethnic_counts,
    labels=None,
    autopct='%1.1f%%',
    startangle=150,
    colors=colors,
    explode=explode,
    shadow=True
)

# Step 4: Create a custom legend with stacked labels
# Create a list of handle objects for the legend
handles = []
for i, label in enumerate(ethnic_labels):
    handles.append(plt.Line2D([0], [0], marker='o', color='w', label=label,
                                markerfacecolor=colors[i], markersize=10))

# Add the legend to the plot
plt.legend(handles=handles, title='Ethnic Groups', loc='upper right', bbox_to_an



plt.title('Ethnic Group Distribution', fontsize=16, fontweight='bold')
plt.show()
```



In [344…

```
age_summary = data_set['age'].describe()[['min', '25%', '50%', '75%', 'max']]
print("Five-Number Summary for Age:")
print(age_summary)

plt.figure(figsize=(8, 5))
sns.boxplot(x='age', data=data_set)
plt.title('Box Plot of Age')
plt.show()
```

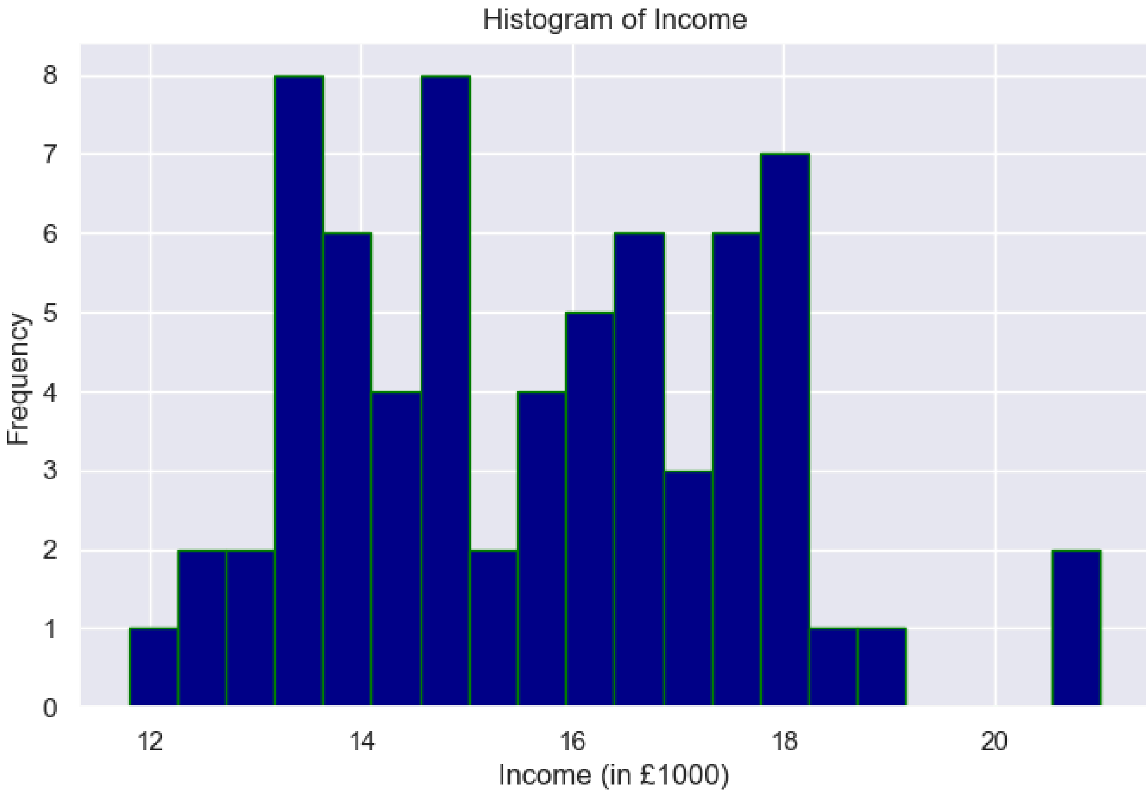
```
Five-Number Summary for Age:
min    18.0
25%    29.0
50%    39.0
75%    50.0
max    63.0
Name: age, dtype: float64
```



In [345…

```
income_mean = data_set['income'].mean()
income_std = data_set['income'].std()

print(f"Mean of Income: {income_mean}")
print(f"Standard Deviation of Income: {income_std}")

# Histogram of income
plt.figure(figsize=(8, 5))
plt.hist(data_set['income'], bins=20, color='darkblue', edgecolor='green')
plt.title('Histogram of Income')
plt.xlabel('Income (in £1000)')
plt.ylabel('Frequency')
plt.show()
```

```
Mean of Income: 15.63823529411765
Standard Deviation of Income: 1.9958935014633157
```

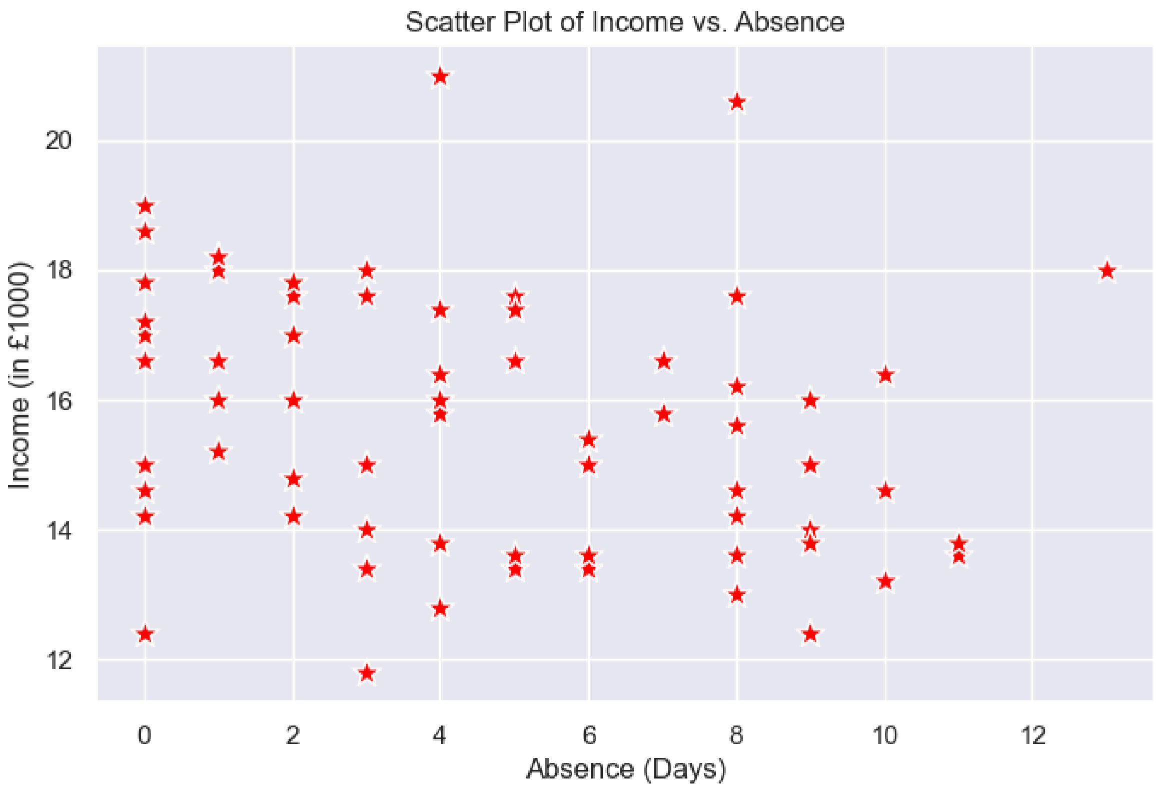


Part One: 2. Scatter Plot and Regression

- Create a scatter plot to visualize the relationship between income and absence.
- Build a simple regression model with income as the dependent variable and absence as the independent variable. Report the determination coefficient (R^2).

In [346…

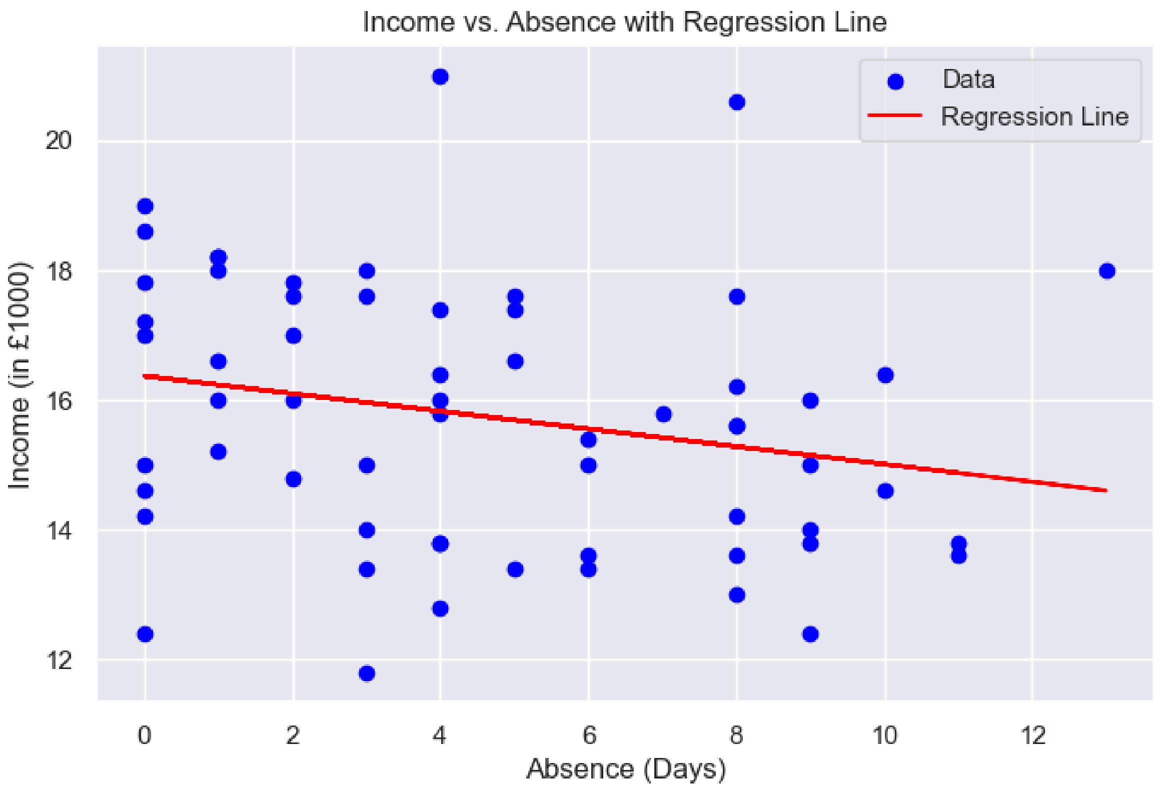
```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='absence', y='income', marker='*', c='red',s=150, data=data_se
plt.title('Scatter Plot of Income vs. Absence')
plt.xlabel('Absence (Days)')
plt.ylabel('Income (in £1000)')
plt.show()
```



In [347…

```
# removed missing values from dataset
X = data_cleaned[['absence']]
y = data_cleaned[['income']]
model = LinearRegression()
model.fit(X, y)

y_pred = model.predict(X)

r2 = r2_score(y, y_pred)
print(f"R-squared: {r2}")

plt.figure(figsize=(8, 5))
plt.scatter(data_cleaned['absence'], data_cleaned['income'], color='blue', label
plt.plot(data_cleaned['absence'], y_pred, color='red', label='Regression Line')
plt.title('Income vs. Absence with Regression Line')
plt.xlabel('Absence (Days)')
plt.ylabel('Income (in £1000)')
plt.legend()
plt.show()
```

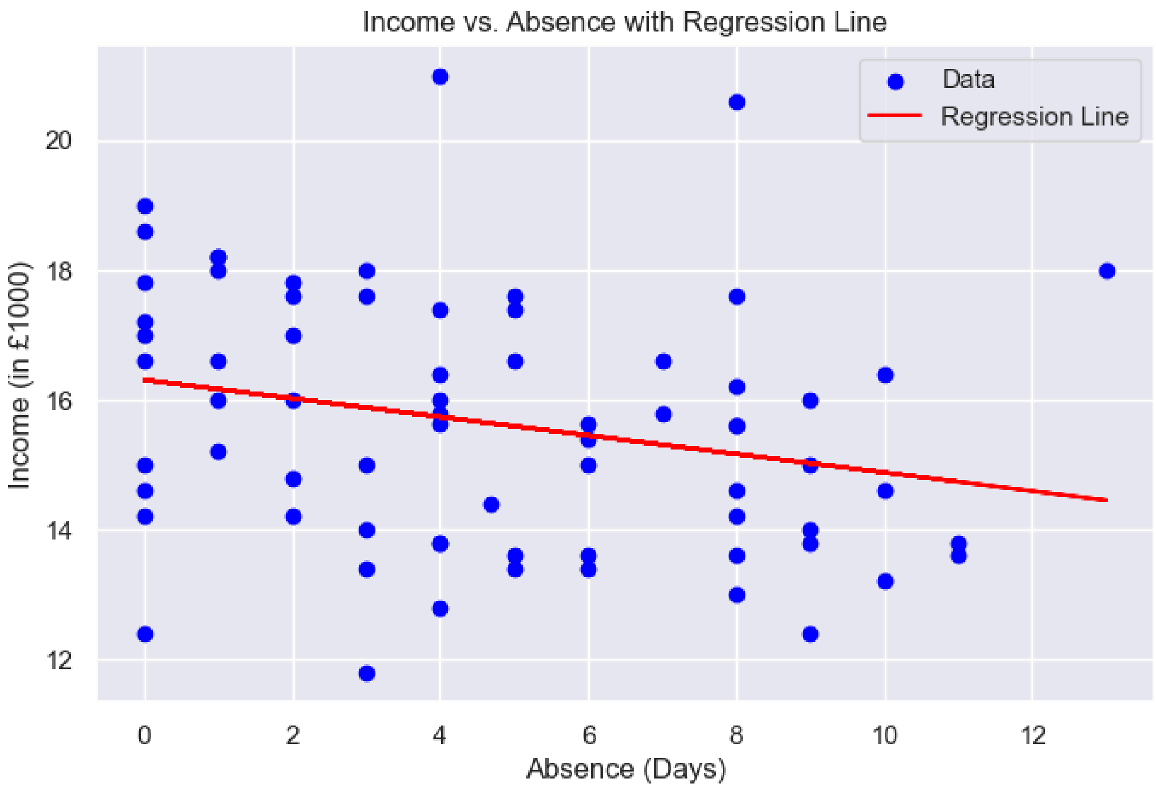
```
R-squared: 0.05433573230072963
```



In [348…

```
# fill missing values
data_set['absence'] = data_set['absence'].fillna(data_set['absence'].mean())
data_set['income'] = data_set['income'].fillna(data_set['income'].mean())

X = data_set[['absence']]
y = data_set[['income']]

model = LinearRegression()
model.fit(X, y)

y_pred = model.predict(X)

r2 = r2_score(y, y_pred)
print(f"R-squared: {r2}")

plt.figure(figsize=(8, 5))
plt.scatter(data_set['absence'], data_set['income'], color='blue', label='Data')
plt.plot(data_set['absence'], y_pred, color='red', label='Regression Line')
plt.title('Income vs. Absence with Regression Line')
plt.xlabel('Absence (Days)')
plt.ylabel('Income (in £1000)')
plt.legend()
plt.show()
```

```
R-squared: 0.061913392866861816
```



Part One: 3. Multiple Regression

- Study a multiple regression model where satis (job satisfaction) is the dependent variable, and the following are independent variables: commit, autonom, income, skill, qual, age, and years.
- Identify non-significant variables and simplify the model by removing them.

In [349…

```
X_multi = data_set_with_mean[['commit', 'autonom', 'income', 'skill', 'qual', 'a
y_multi = data_set_with_mean['satis']

# Fit the multiple regression model
multi_model = LinearRegression()
multi_model.fit(X_multi, y_multi)

# Add a constant to the model (required for statsmodels to include an intercept)
X = sm.add_constant(X)

# Step 5: Fit the multiple regression model
model = sm.OLS(y, X).fit()

# Step 6: View the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 income   R-squared:                       0.062
Model:                            OLS   Adj. R-squared:                  0.048
Method:                 Least Squares   F-statistic:                     4.488
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No. Observations:                  70   AIC:                             291.9
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Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
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------------------------------------------------------------------------------
const         16.3064      0.390     41.813      0.000      15.528      17.085
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Prob(Omnibus):                  0.262   Jarque-Bera (JB):                1.982
Skew:                           0.390   Prob(JB):                        0.371
Kurtosis:                       3.269   Cond. No.                         10.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

In [350…

```python
X_simplified = data_set_with_mean[['commit', 'autonom', 'income', 'skill', 'qual

# Add a constant to the simplified model
X_simplified = sm.add_constant(X_simplified)

# Step 8: Refit the simplified model
model_simplified = sm.OLS(y, X_simplified).fit()

# Step 9: View the summary of the simplified model
print(model_simplified.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 income   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 3.378e+29
Date:                Sat, 26 Oct 2024   Prob (F-statistic):               0.00
Time:                        23:30:47   Log-Likelihood:                 2144.3
No. Observations:                  70   AIC:                            -4277.
Df Residuals:                      64   BIC:                            -4263.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        1.11e-15   1.32e-14      0.084      0.933   -2.52e-14    2.74e-14
commit      8.327e-16   1.59e-15      0.525      0.602   -2.34e-15       4e-15
autonom    -2.359e-16   6.88e-16     -0.343      0.733   -1.61e-15    1.14e-15
income         1.0000   8.96e-16   1.12e+15      0.000       1.000       1.000
skill       2.498e-16   1.54e-15      0.162      0.871   -2.82e-15    3.32e-15
qual       -3.331e-16   1.23e-15     -0.270      0.788    -2.8e-15    2.13e-15
==============================================================================
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Kurtosis:                       2.896   Cond. No.                         168.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Part One: 4. Confidence Intervals

- Calculate the confidence interval for job satisfaction and the confidence interval for the difference between men and women.

In [351…

```
mean_satis = data_set_with_mean['satis'].mean()
std_satis = data_set_with_mean['satis'].std()
n_satis = len(data_set_with_mean['satis'])
#print(f"Mean of satis: {mean_satis}, Standard Deviation of satis: {std_satis},
# Calculate standard error
se_satis = std_satis / np.sqrt(n_satis)

# Calculate 95% confidence interval
ci_satis = stats.t.interval(0.95, df=n_satis-1, loc=mean_satis, scale=se_satis)
ci_satis_clean = tuple(map(float, ci_satis))
print(f"Confidence Interval for Job Satisfaction (satis): {ci_satis_clean}")

satis_men = data_set_with_mean[data_set_with_mean['gender'] == 1]['satis']
satis_women = data_set[data_set_with_mean['gender'] == 2]['satis']

mean_men = satis_men.mean()
mean_women = satis_women.mean()

std_men = satis_men.std()
std_women = satis_women.std()

n_men = len(satis_men)
```

```
n_women = len(satis_women)

# Standard error of the difference
se_diff = np.sqrt((std_men**2 / n_men) + (std_women**2 / n_women))

# Mean difference
mean_diff = mean_men - mean_women

# 95% confidence interval for the difference in means
ci_diff = stats.t.interval(0.95, df=min(n_men, n_women)-1, loc=mean_diff, scale=
ci_diff_clean = tuple(map(float, ci_diff))
print(f"Confidence Interval for the Difference in Job Satisfaction between Men a
```

```
Confidence Interval for Job Satisfaction (satis): (10.062020962148376, 11.6144496
26086921)
Confidence Interval for the Difference in Job Satisfaction between Men and Women:
(-1.3849796796368963, 1.8464694864777484)
```

Part One: 5.Mann-Whitney and Kruskal-Wallis Tests

- Use the Mann-Whitney-Wilcoxon test to check if there is a significant difference in skill levels between men and women. Compare the results with the confidence interval.
- Use the Kruskal-Wallis test to determine if there is a significant difference in absence among ethnic groups. Compare this with results from One-Way ANOVA.

In [352…

```
##Mann-Whitney-Wilcoxon Test
# Split data into two groups based on gender
men_skills = data_cleaned[data_cleaned['gender'] == 1]['skill']
women_skills = data_cleaned[data_cleaned['gender'] == 2]['skill']

# Perform Mann-Whitney U test
stat, p_value = mannwhitneyu(men_skills, women_skills)

# Display the results
print(f"Mann-Whitney U Test Statistic: {stat}, p-value: {p_value}")

if p_value < 0.05:
    print("Reject the null hypothesis: There is a significant difference in skil
else:
    print("Fail to reject the null hypothesis: There is no significant differenc
```

```
Mann-Whitney U Test Statistic: 520.5, p-value: 0.4032893852621183
Fail to reject the null hypothesis: There is no significant difference in skill l
evels between men and women.
```

In [353…

```
## Kruskal-Wallis Test

# Split data by ethnic groups
ethnic_groups = [data_cleaned[data_cleaned['ethnicgp'] == i]['absence'] for i in

# Perform Kruskal-Wallis H test
stat, p_value = kruskal(*ethnic_groups)

print(f"Kruskal-Wallis Test Statistic: {stat}, p-value: {p_value}")
```

```python
if p_value < 0.05:
    print("Reject the null hypothesis: There is a significant difference in abse
else:
    print("Fail to reject the null hypothesis: There is no significant differenc
```

```
Kruskal-Wallis Test Statistic: 2.4084534950343763, p-value: 0.49206294724690613
Fail to reject the null hypothesis: There is no significant difference in absence
among ethnic groups.
```

In [354…

```python
anova_stat, anova_p_value = f_oneway(*ethnic_groups)

# Display the results
print(f"One-Way ANOVA Test Statistic: {anova_stat}, p-value: {anova_p_value}")

if anova_p_value < 0.05:
    print("Reject the null hypothesis: There is a significant difference in abse
else:
    print("Fail to reject the null hypothesis: There is no significant differenc
```

```
One-Way ANOVA Test Statistic: 0.8043403320870688, p-value: 0.4966477589834961
Fail to reject the null hypothesis: There is no significant difference in absence
among ethnic groups.
```

Part one: 6. Income Class Recode

- Recode income into income classes using the following ranges:
- Low income class: [Min, Q1]
- Middle income class: (Q1, Q3]
- High income class: (Q3, Max]
- Investigate if there is a significant relationship between income class and skill.

In [355…

```python
Q1 = data_cleaned['income'].quantile(0.25)
Q3 = data_cleaned['income'].quantile(0.75)
min_income = data_cleaned['income'].min()
max_income = data_cleaned['income'].max()

# Recode the income into classes
def income_class(row):
    if row['income'] <= Q1:
        return 'Low Income'
    elif Q1 < row['income'] <= Q3:
        return 'Middle Income'
    else:
        return 'High Income'

data_set['income_class'] = data_set.apply(income_class, axis=1)

# Display the first few rows to check the recoding
print(data_set[['income', 'income_class']].head())
```

```
   income   income_class
0    16.6  Middle Income
1    14.6  Middle Income
2    17.8    High Income
3    16.4  Middle Income
4    18.6    High Income
```

In [356…

```
data_cleaned = data_set[['income_class', 'skill']].dropna()

# Split the data based on income class
low_income_skills = data_cleaned[data_cleaned['income_class'] == 'Low Income']['
middle_income_skills = data_cleaned[data_cleaned['income_class'] == 'Middle Inco
high_income_skills = data_cleaned[data_cleaned['income_class'] == 'High Income']

# Perform the Kruskal-Wallis test
stat, p_value = kruskal(low_income_skills, middle_income_skills, high_income_ski

# Display the results
print(f"Kruskal-Wallis Test Statistic: {stat}, p-value: {p_value}")

if p_value < 0.05:
    print("Reject the null hypothesis: There is a significant relationship betwe
else:
    print("Fail to reject the null hypothesis: There is no significant relations
```

```
Kruskal-Wallis Test Statistic: 8.1833181642631, p-value: 0.016711484820370597
Reject the null hypothesis: There is a significant relationship between income cl
ass and skill.
```