Aerofit Business Case Study

Problem Statement

AeroFit sells different types of treadmills, but not every treadmill is suitable for every customer. The company wants to understand what kind of customers prefer which type of treadmill (for example, based on age, income, or usage). By learning these customer characteristics, AeroFit can recommend the right treadmill to new buyers, which will improve customer satisfaction and help the company increase sales.

Goal of the Analysis

The aim of this analysis is to uncover key customer segments by developing customer profiles for each AeroFit treadmill product using descriptive analytics. This will involve:

- Constructing two-way contingency tables to explore the relationship between
- customer attributes (e.g, age, gender, income) and product choice.
- Calculating marginal and conditional probabilities to identify trends and insights.
- Visualizing data to better understand customer behavior and preferences for each product.
- Generating actionable insights to guide AeroFit's marketing, product strategies, and customer targeting.

Loading data

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df=pd.read_csv('aerofit_treadmill.csv')
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

Next steps: Generate code with df | View recommended plots | New interactive sheet

Shape

```
df.shape
```

```
(180, 9)
```

Data type of features

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

The dataset contains 9 columns with mixed type of categorical and numeric. Categorical columns include Product, Gender and Material Status while Age, Education, Usage, Fitness, Income and Miles are numerical columns.

Checking Duplictaes

```
print(df.duplicated())
```

```
0      False
1      False
2      False
3      False
4      False
       ...
175    False
176    False
177    False
178    False
179    False
Length: 180, dtype: bool
```

There is no duplicates in the dataset.

Statistical Summary

```
df.describe().round(2)
```

	Age	Education	Usage	Fitness	Income	Miles
count	180.00	180.00	180.00	180.00	180.00	180.00
mean	28.79	15.57	3.46	3.31	53719.58	103.19
std	6.94	1.62	1.08	0.96	16506.68	51.86
min	18.00	12.00	2.00	1.00	29562.00	21.00
25%	24.00	14.00	3.00	3.00	44058.75	66.00
50%	26.00	16.00	3.00	3.00	50596.50	94.00
75%	33.00	16.00	4.00	4.00	58668.00	114.75
max	50.00	21.00	7.00	5.00	104581.00	360.00

Observations

- The dataset contains 180 records.
- Minimum age is 18 and maximum is 50. Mean age is 28. First Quartile(Q1) is 24, the median is 26 and the third Quartile is(Q3) is 33 indicating that there are 25% and 50% and 75% of people younger than the respective ages.
- The average number of education year is approximately 15. 50% people have completed 16 years of education (bachelors degree). Standard deviation is 1.6. the value is neither close nor wide from the mean value so moderate spread.
- The minimum treadmill usage is 2 days and the maximum is 7 days. This indicates that people use the treadmill between 2 to 7 times in a week with an average of 3 times.
- The annual income falls between USD 29562 and USD 104581 with an average salary of USD 53197.
- People expects to walk/run between 21 and 360 miles per week with an average of 103 miles. However the range is quite broad, the upper value 360 miles per week represents extreme or outlier in the dataset.

Checking Missing Values

```
print(df.isna().sum())
```

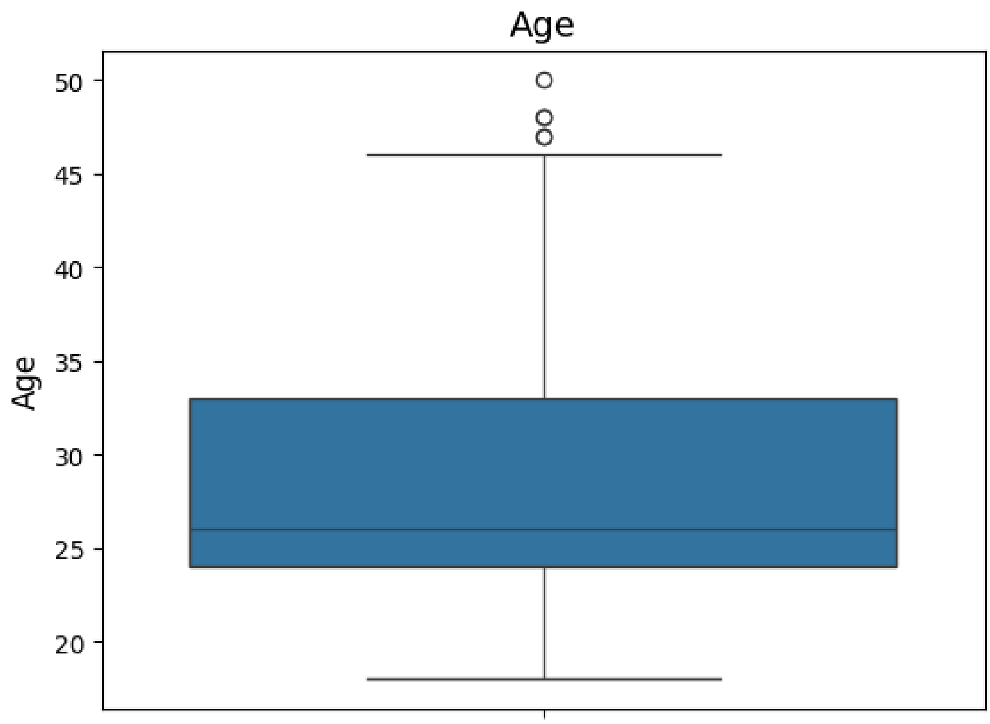
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

There is no missing values in the dataset.

Outliers check

Outliers in Age

```
sns.boxplot(df['Age'])
plt.title("Age",fontsize=14)
plt.ylabel('Age',fontsize=12)
plt.show()
```




```
Q1=df['Age'].quantile(0.25)
Q2=df['Age'].median()
Q3=df['Age'].quantile(0.75)
IQR=Q3-Q1
lower_whisker=Q1-(1.5*IQR)
upper_whisker=Q3+(1.5*IQR)
print(f"Age\n Lower_Whisker : {lower_whisker:.0f}\n Quantile_1 : {Q1:.0f}\n Quantile_2 : {Q2:.0f}\n (
```

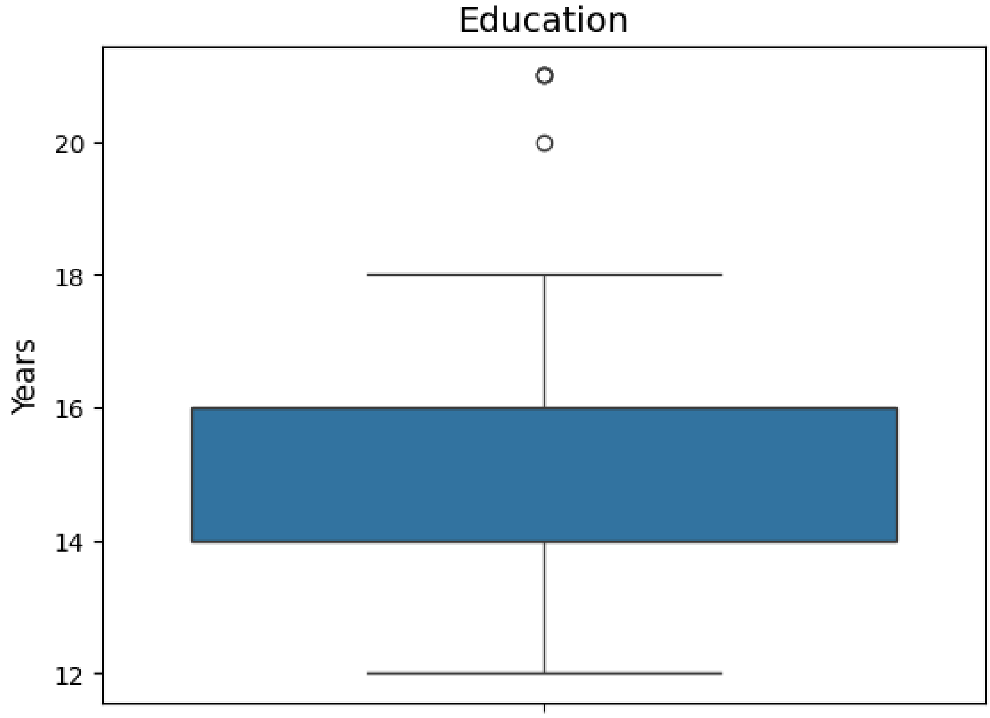
```
Age
 Lower_Whisker : 10
 Quantile_1 : 24
 Quantile_2 : 26
 Quanitile_3 : 33
 IQR : 9
 Upper_Whisker : 46
```

Age column contain only few outliers. Age greater than 46 ans less than 10 are consider as outliers.according to IQR method 50% data falls between age 24 and 33.

Outlier check in Education

```
sns.boxplot(df['Education'])
plt.title("Education",fontsize=14)
plt.ylabel('Years',fontsize=12)
plt.show()
```

```
plt.show()
```



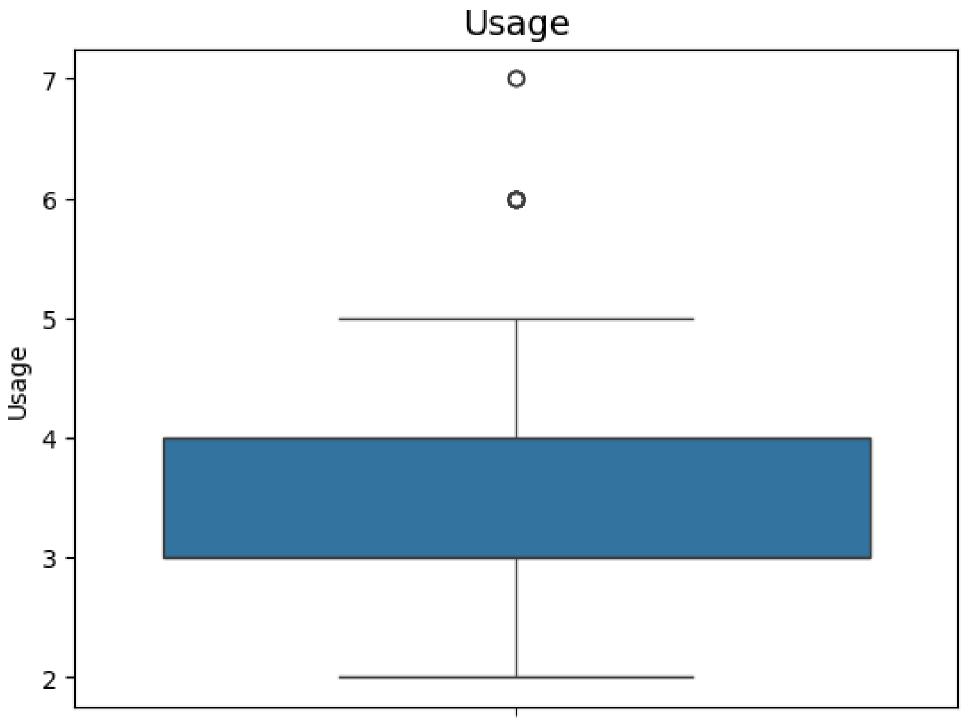

```
Q1=df['Education'].quantile(0.25)
Q2=df['Education'].median()
Q3=df['Education'].quantile(0.75)
IQR=Q3-Q1
lower_whisker=Q1-(1.5*IQR)
upper_whisker=Q3+(1.5*IQR)
print(f"Education\n Lower_Whisker : {lower_whisker:.0f}\n Quantile_1 : {Q1:.0f}\n Quantile_2 : {Q2:.
```

```
Education
 Lower_Whisker : 11
 Quantile_1 : 14
 Quantile_2 : 16
 Quanitile_3 : 16
 IQR : 2
 Upper_Whisker : 19
```

The Education column contains 2 outliers. Education years above 19 are considered outliers.

Outliers check in Usage

```
sns.boxplot(df['Usage'])
plt.title("Usage",fontsize=14)
plt.show()
```



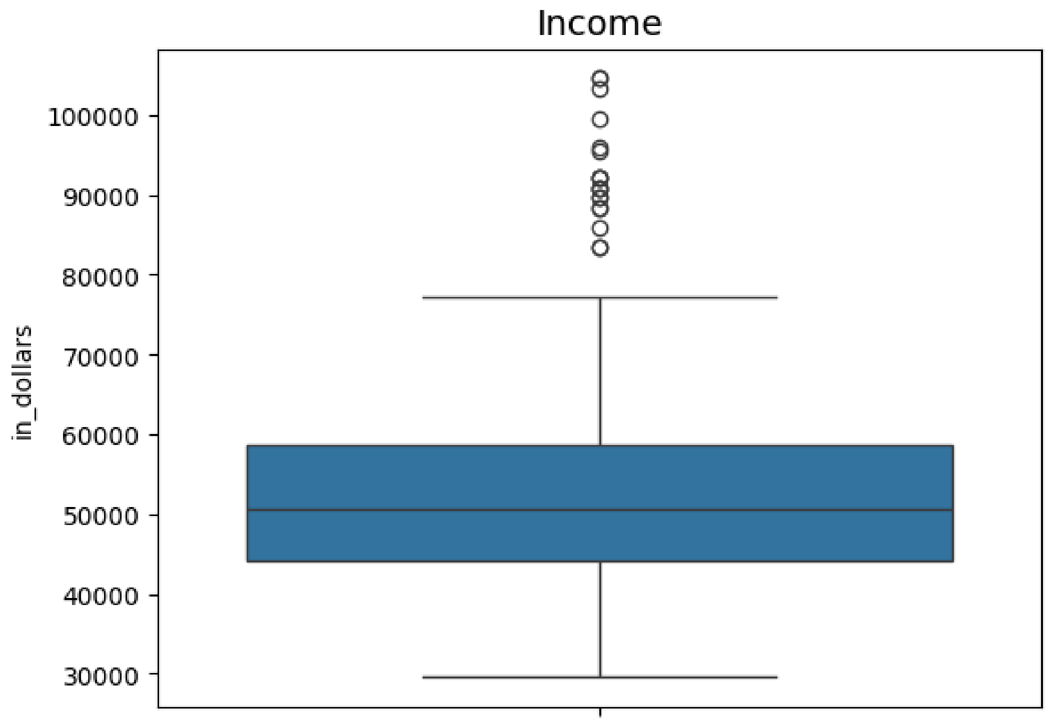

```
Q1=df['Usage'].quantile(0.25)
Q2=df['Usage'].median()
Q3=df['Usage'].quantile(0.75)
IQR=Q3-Q1
lower_whisker=Q1-(1.5*IQR)
upper_whisker=Q3+(1.5*IQR)
print(f"Usage\n Lower_Whisker : {lower_whisker:.0f}\n Quantile_1 : {Q1:.0f}\n Quantile_2 : {Q2:.0f}\n
```

```
Usage
 Lower_Whisker : 2
 Quantile_1 : 3
 Quantile_2 : 3
 Quanitile_3 : 4
 IQR : 1
 Upper_Whisker : 6
```

The data points with values of 6 and 7 are consider as outliers, but treadmil Usage depends on individual preference. However, treadmill usage depends on individual preference and is common among people who use the treadmill every day of the week.

Outlier detection in income

```
sns.boxplot(df['Income'])
plt.title("Income",fontsize=14)
plt.ylabel('in_dollars')
plt.show()
```



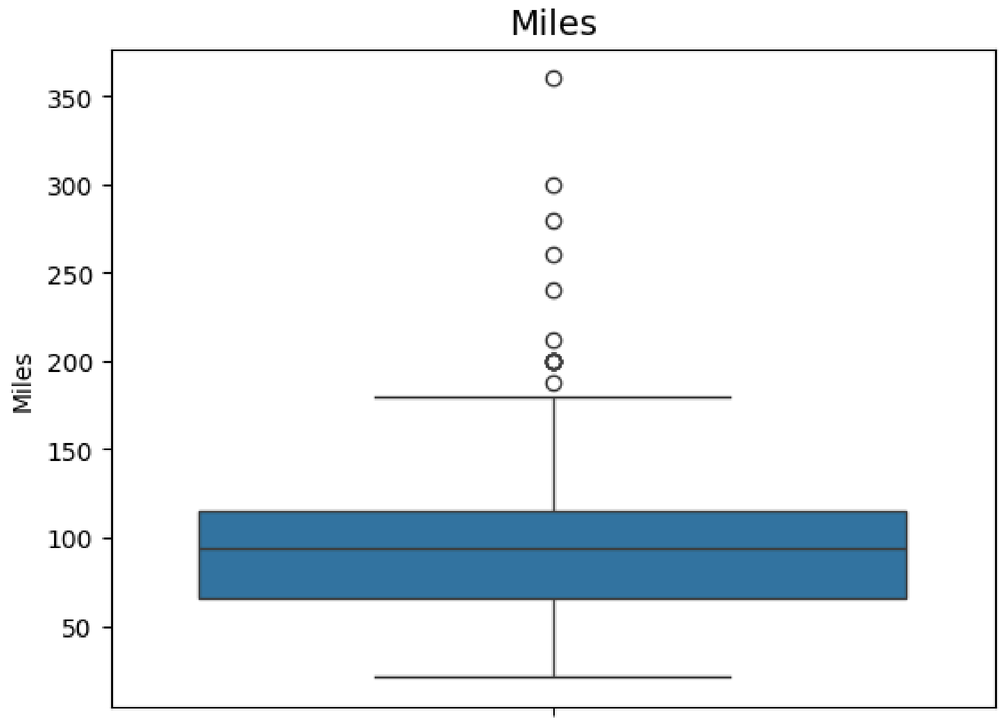

```
Q1=df['Income'].quantile(0.25)
Q2=df['Income'].median()
Q3=df['Income'].quantile(0.75)
IQR=Q3-Q1
#finding whisker
lower_whisker=Q1-(1.5*IQR)
upper_whisker=Q3+(1.5*IQR)
print(f"Income(USD)\n Lower_Whisker : {lower_whisker}\n Quantile_1 : {Q1}\n Quantile_2 : {Q2}\n Quan
```

```
Income(USD)
 Lower_Whisker : 22144.875
 Quantile_1 : 44058.75
 Quantile_2 : 50596.5
 Quantile_3 : 58668.0
 IQR : 14609.25
 Upper_Whisker : 80581.875
```

Boxplot clearly indicating that income column contains more outliers. According to the IQR method incomes greater than 80581 considered as outliers. The median salary is 50596. 50% of data falls between 44058.75 and 58668.

Outlier detection in Miles

```
sns.boxplot(df['Miles'])
plt.title("Miles",fontsize=14)
plt.show()
```




```
Q1=df['Miles'].quantile(0.25)
Q2=df['Miles'].median()
Q3=df['Miles'].quantile(0.75)
IQR=Q3-Q1
lower_whisker=Q1-(1.5*IQR)
upper_whisker=Q3+(1.5*IQR)
print(f"Miles\n Lower_Whisker : {lower_whisker:.0f}\n Quantile_1 : {Q1:.0f}\n Quantile_2 : {Q2:.0f}\
```

```
Miles
 Lower_Whisker : -7
 Quantile_1 : 66
 Quantile_2 : 94
 Quantile_3 : 115
 IQR : 49
 Upper_Whisker : 188
```

Boxplot clearly shows that there are more outliers in the Miles column. According to IQR method miles greater than 188 are consider as outliers.

Outlier Analysis

Age: There are no unrealistic values (e.g., ages above 100 or negative ages). Therefore, no removal was necessary.

Income: Variations in income are expected due to differences in education level and profession. Even extreme values represent valid customers and were retained.

Miles & Usage per Week: These reflect individual lifestyle and fitness habits. While some customers use the treadmill for short walks, others run hundreds of miles. Such variations are genuine and not data errors.

- Based on this assessment, no values were removed, as they represent meaningful differences in customer behavior rather than outliers.

Non-Graphical Analysis

Analyzing Product Frequency

```
df['Product'].unique()
```

```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

```
df['Product'].value_counts(normalize=True).mul(100).round(2)
```

Product	proportion
KP281	44.44
KP481	33.33
KP781	22.22

dtype: float64

There are three unique products. KP281 is the most frequent product.

Gender Count

```
df['Gender'].value_counts(normalize=True).mul(100).round(2)
```

Gender	proportion
Male	57.78
Female	42.22

dtype: float64

The proportion of male accounts is slightly higher than female accounts.

Education Frequency

```
df['Education'].unique()
```

```
array([14, 15, 12, 13, 16, 18, 20, 21])
```

```
df['Education'].value_counts(normalize=True).mul(100).round(2)
```

Education	proportion
16	47.22
14	30.56
18	12.78
15	2.78
13	2.78
12	1.67
21	1.67
20	0.56

dtype: float64

- The dataset contains 8 categories of education. people have atleast 12 years of education and maximum 21 years of education.
- Customers with 16 years of education are the most common in this dataset, accounting for 47% of the total.

MaritalStatus Count

```
df['MaritalStatus'].value_counts(normalize=True).mul(100).round(2)
```

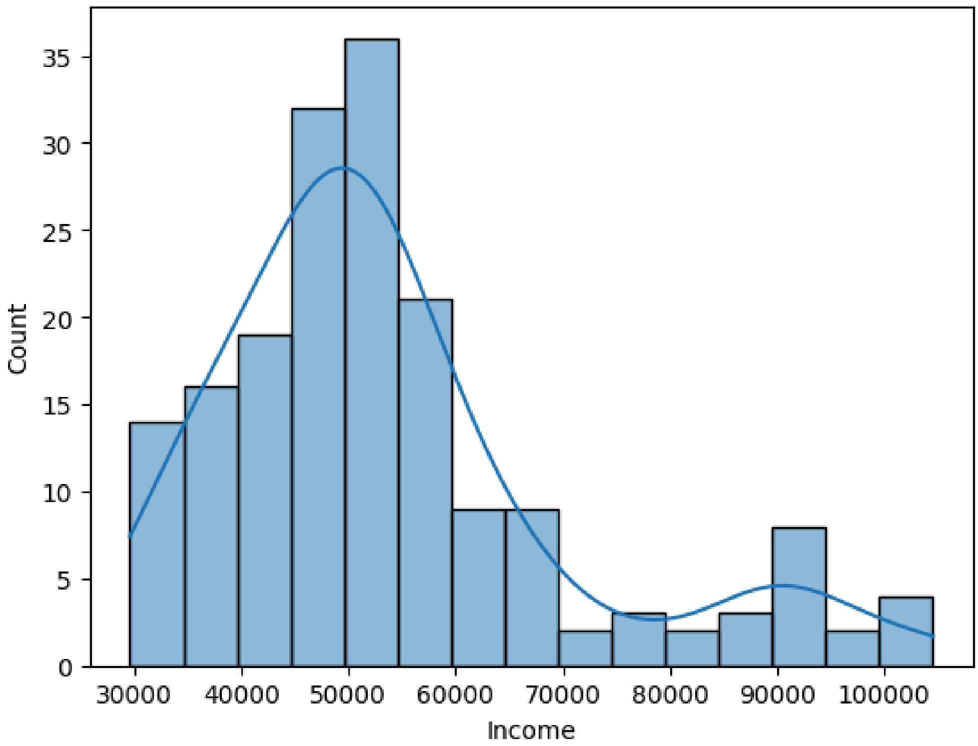
MaritalStatus	proportion
Partnered	59.44
Single	40.56

dtype: float64

Customers with a partner account for a higher proportion compared to singles.

Univariate Analysis

```
sns.histplot(df['Income'],kde=True)
plt.show()
```

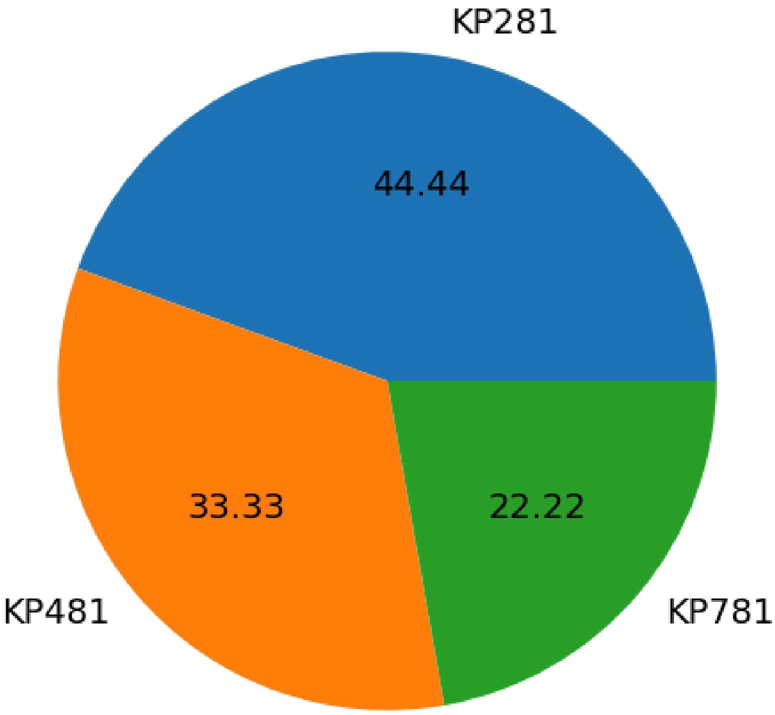


Insights

- The income distribution is slightly right-skewed.
- The majority of customers fall within the middle-income bracket (50000K–60000K), while only a few earn above 80,000.

Product Distribution

```
plt.figure(figsize=(10,6))
df['Product'].value_counts().plot(kind='pie',autopct="%.2f")
plt.ylabel("")
for text in plt.gca().texts:
    text.set_fontsize(14)
plt.show()
```

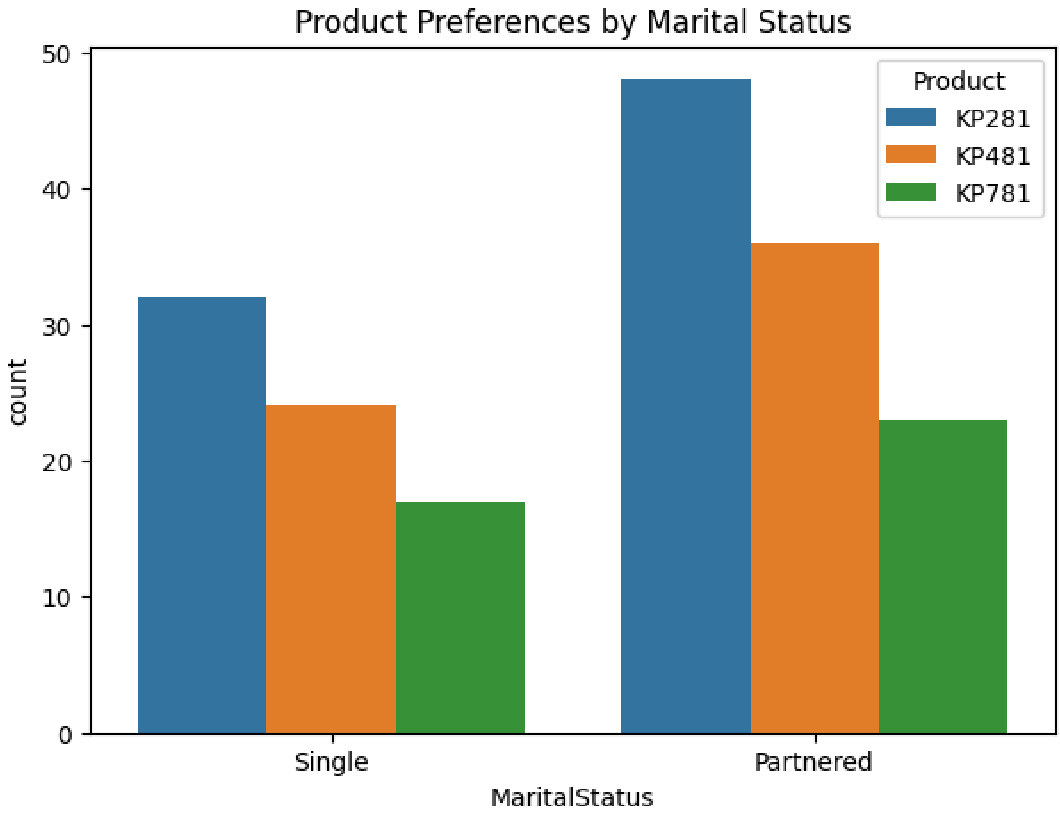


Insights

- The Pie chart shows that product KP281 has the highest percentage share, indicating that it is the most popular or focused product.
- This may be due to its lower price compared to other two products as shown in the product portfolio.

MaritialStatus Prefences

```
plt.figure(figsize=(7,5))
sns.countplot(x='MaritalStatus',hue='Product',data=df)
plt.title("Product Preferences by Marital Status")
plt.show()
```

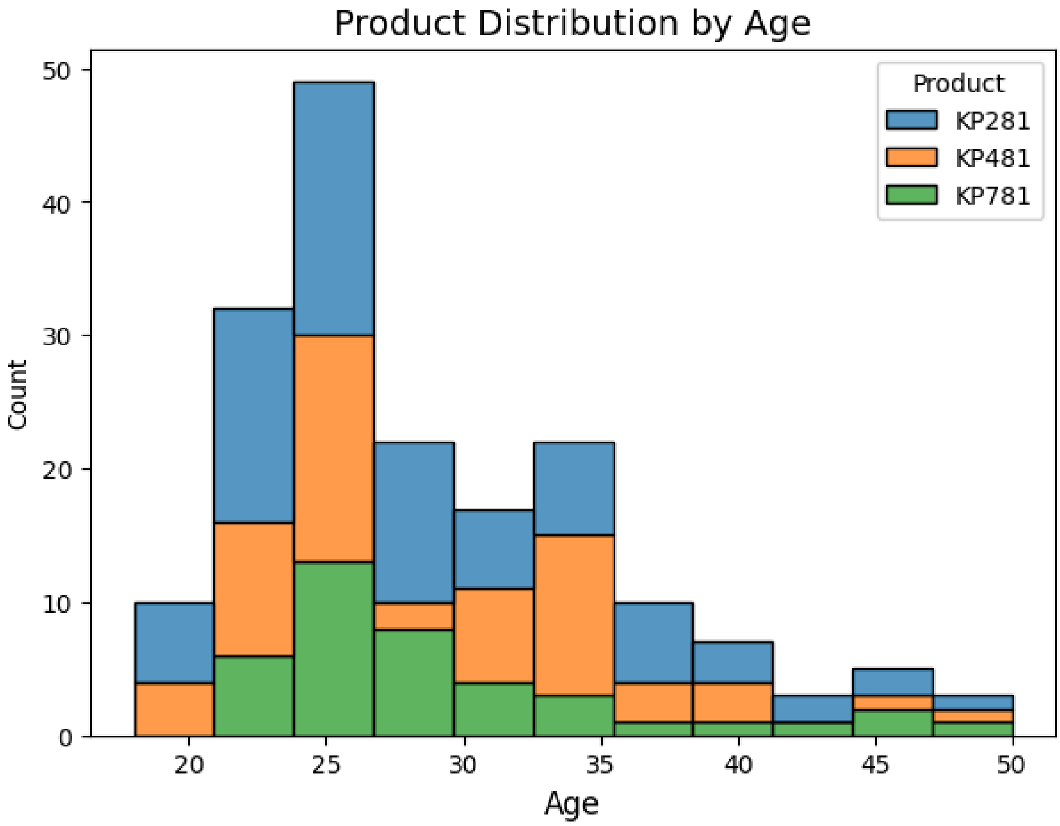


Insights

- Although the partnered group has a higher count, both the groups predominantly use the KP281 product which is an entry level treadmill and offered at a lower price compared to other products.
- KP481, KP781 take second and third positions respectively in both the groups.

Product vs Age

```
plt.figure(figsize=(7,5))
sns.histplot(data=df, x='Age', hue='Product', multiple="stack")
plt.title("Product Distribution by Age", fontsize=14)
plt.xlabel("Age",fontsize=12)
plt.show()
```



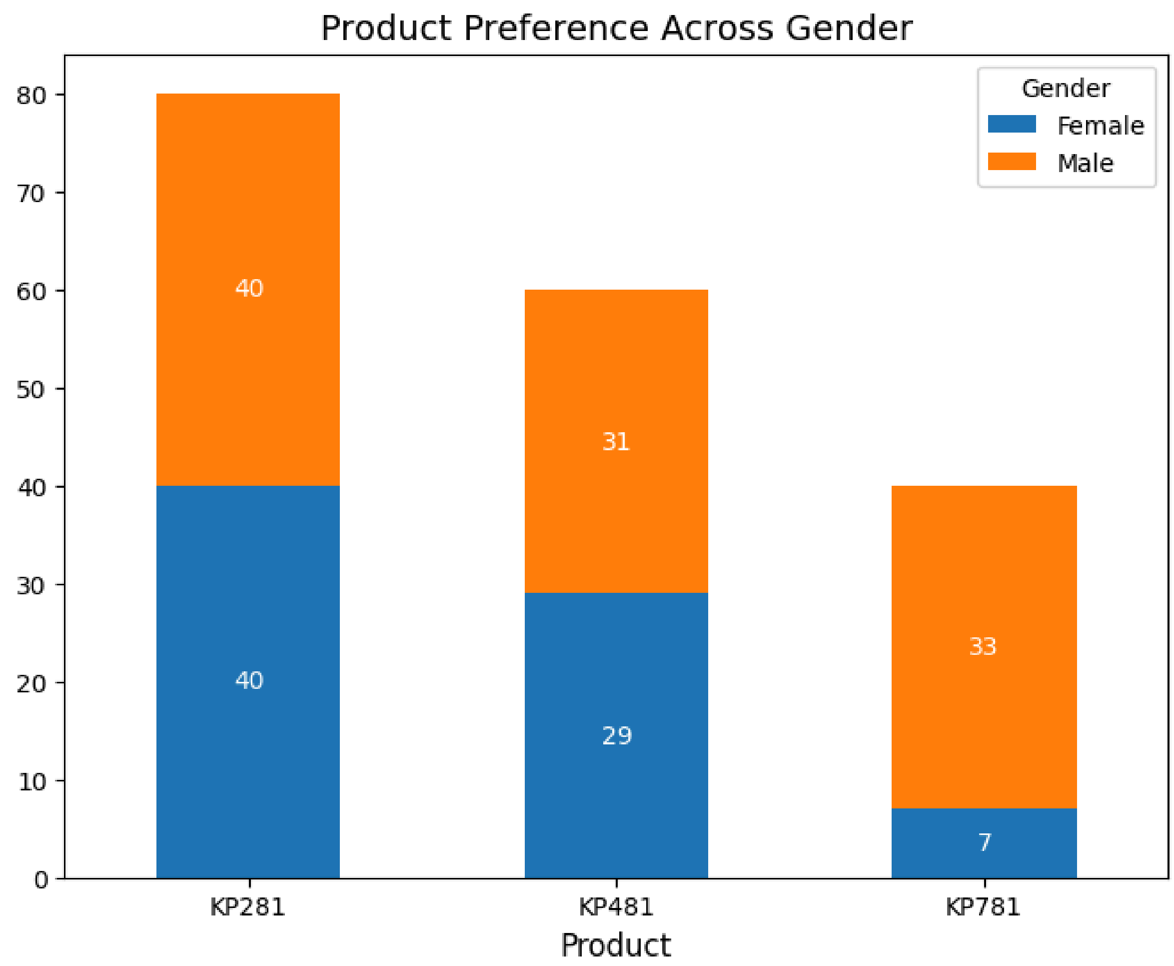
Insights

- Each segment represents the age distribution of the products KP281, KP481 and KP781.
- KP281, KP481 and KP781 preferred by all age gropus, from teens to adults, with the highest number of customers in the 25 year age group.
- Age does not seem to have a significant impact on the preference for any of the products, as all age groups show relatively similar preferences for each product.

Gender Effects on Product

```
gender_df=df.groupby('Product')['Gender'].value_counts().reset_index()
gen_pivot=gender_df.pivot(index='Product',columns='Gender',values='count')

ax=gen_pivot.plot(kind='bar',stacked=True,figsize=(8,6))
plt.title("Product Preference Across Gender",fontsize=14)
plt.xlabel("Product",fontsize=12)
plt.xticks(rotation=0)
for bars in ax.containers:
    ax.bar_label(bars, label_type='center', color='white', fontsize=10)
```

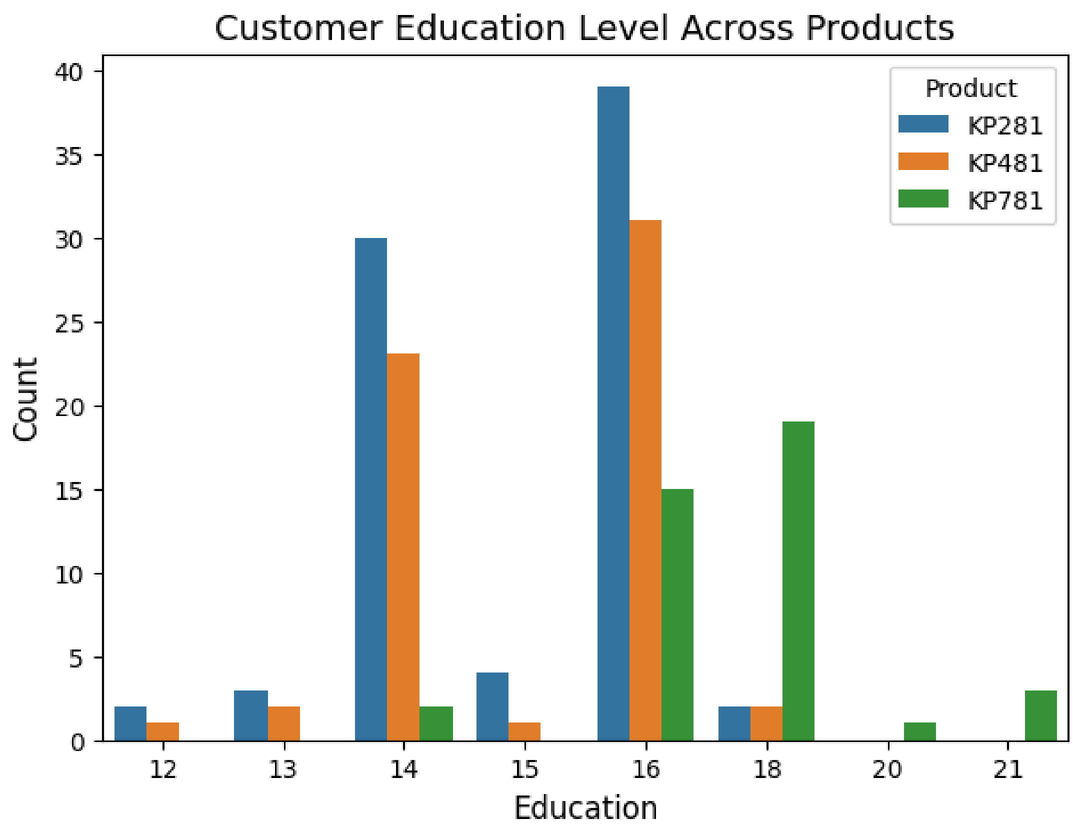


Insights

- KP281 is equally preferred by both male and female, indicating there is no significant gender bias in preference. As it is an entry level treadmill and easy to access, which likely leads to its popularity among both genders, especially in female.
- In Total KP481 has 60 customers. Among them 31 are male and 29 are female. It is showing only a slight difference. This may be because KP481 is sold at a slighly higher price than K9281.
- KP781 has fewer customers compared to the other two products, with 33 male and only 7 female out of 180 people.

Analyzing Customer Preference Based on Education

```
plt.figure(figsize=(7,5))
sns.countplot(x='Education',hue="Product",data=df)
plt.title("Customer Education Level Across Products",fontsize=14)
plt.xlabel("Education",fontsize=12),plt.ylabel("Count",fontsize=12)
plt.show()
```



Insights

- Aerofit has the highest number of customers in the 16 years of education group.
- The countplot shows that customers with 14 and 16 years of education prefer all three products, while other education levels show limited or no preference for some products.
- customers with 18 years or more of education prefers only KP781.

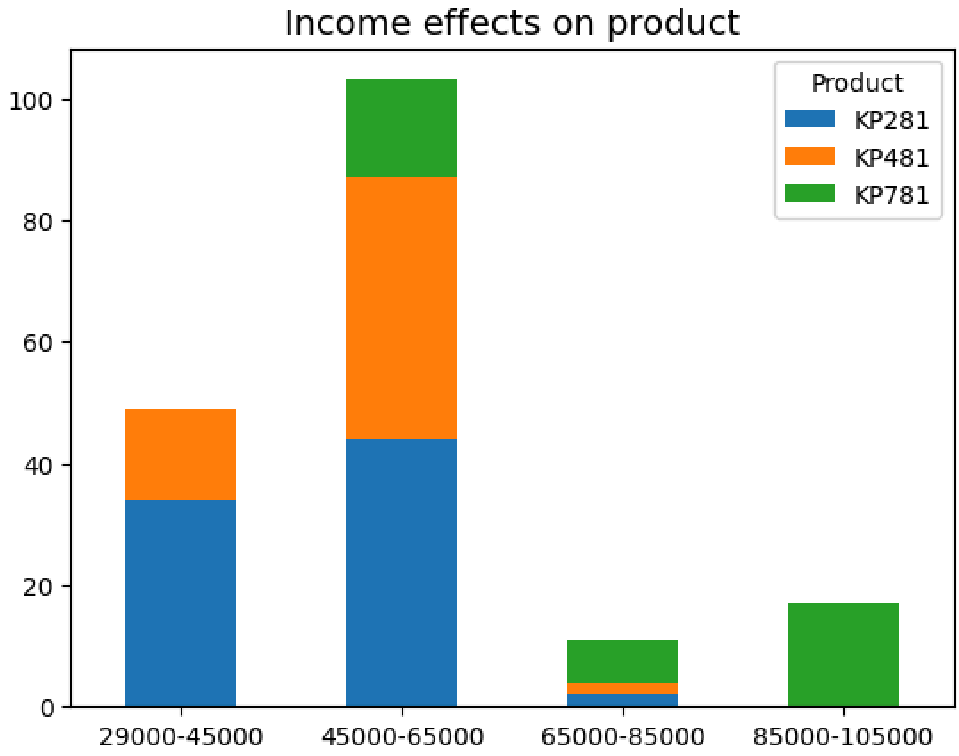
```
aerofit=df.copy()
aerofit.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

Analysis on Income

```
bin_value=[29000,45000,65000,85000,105000]
label_value=['29000-45000','45000-65000','65000-85000','85000-105000']
aerofit['Income_Group']=pd.cut(df['Income'],bins=bin_value,labels=label_value)
income_df=aerofit.groupby(['Income_Group','Product'],observed=False).size().unstack(fill_value=0)
ax=income_df.plot(kind='bar',stacked=True)
plt.title("Income effects on product",fontsize=14)
```

```
plt.xlabel(""),plt.xticks(rotation=0)
plt.show()
```

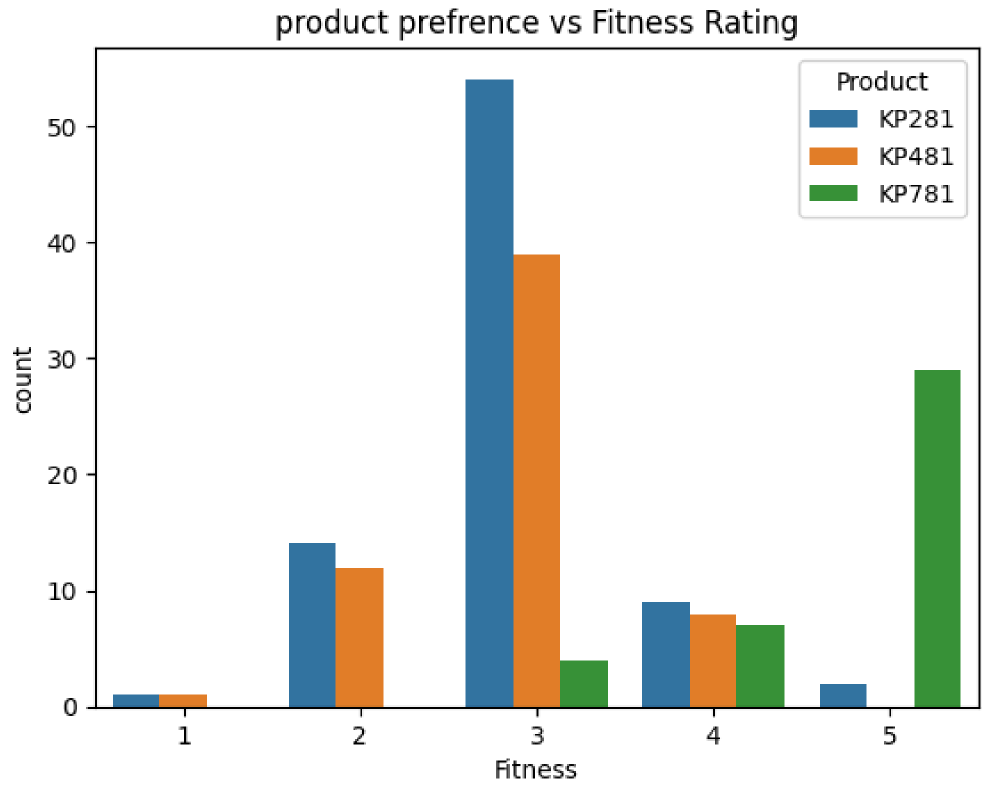


Insights

KP281 is highly preferred by the low income group, while KP781 is preferred by both low and medium income customers. Both products are purchased by customers with an average salary ranging from USD 40,000 to USD 46,000. KP781 is primarily preferred by customers with an income above USD 60,000.

Fitness Rating and Its Impact on Product Choice

```
sns.countplot(x='Fitness',hue='Product',data=df)
plt.title("product prefrence vs Fitness Rating",fontsize=12)
plt.show()
```

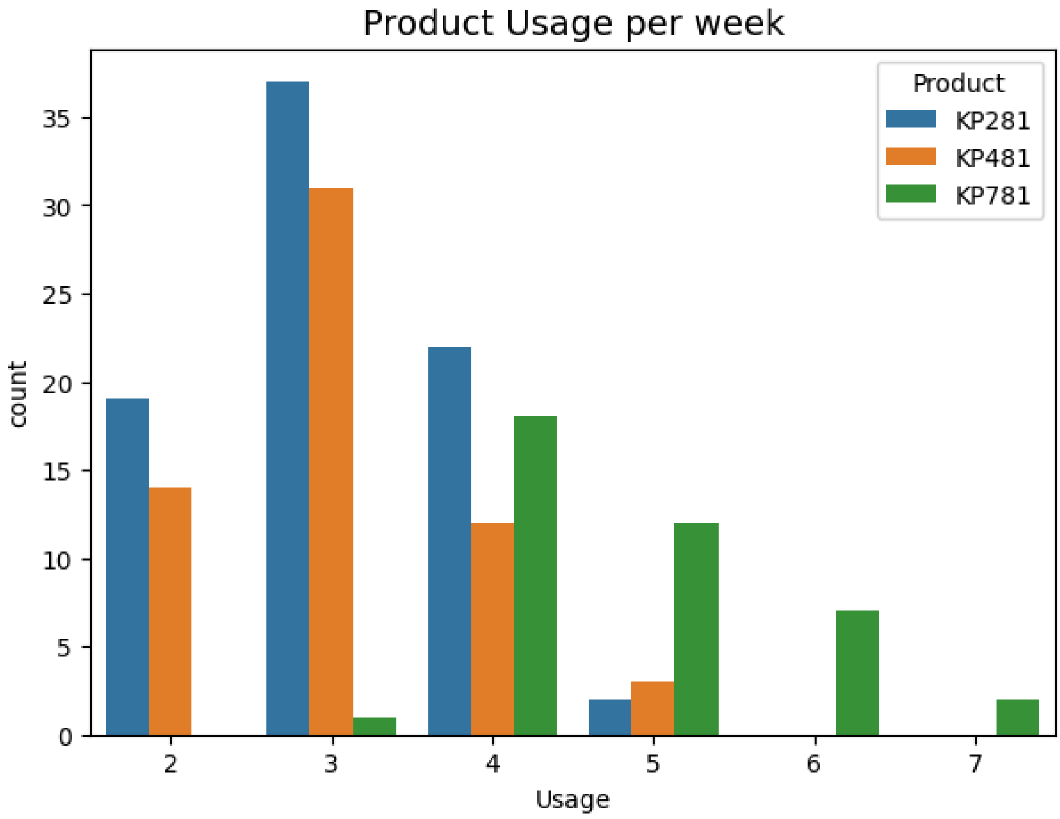


Insights

- KP281 and KP481 have the higest ratings in fitness scale 3, it indicating that majority of customers using these products are moderately fit.
- KP781 is has the highest rating in fitness scale 5, suggesting that it is primarily used by customers who are extremely fit.

Product Usage

```
plt.figure(figsize=(7,5))
sns.countplot(x='Usage',hue='Product',data=df)
plt.title("Product Usage per week",fontsize=14)
plt.show()
```

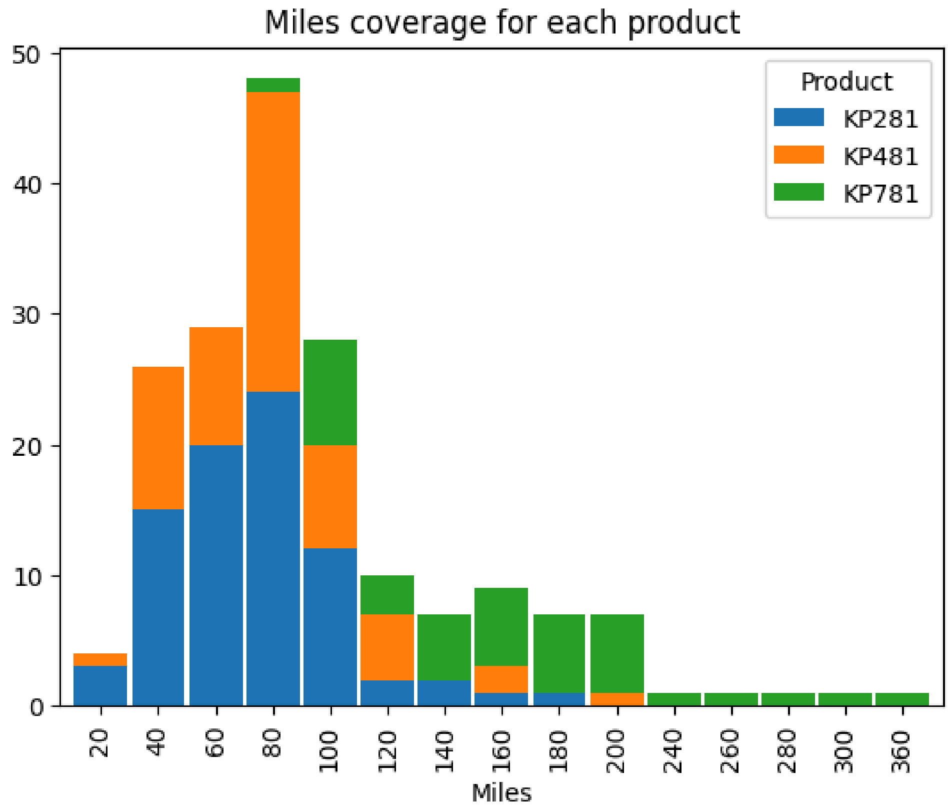


Insights

KP281 and KP481 are used on average 3 times in a week, while KP781 used more than 4 times a week. A few customers use KP781 for all 7 days.

Expected walk/run

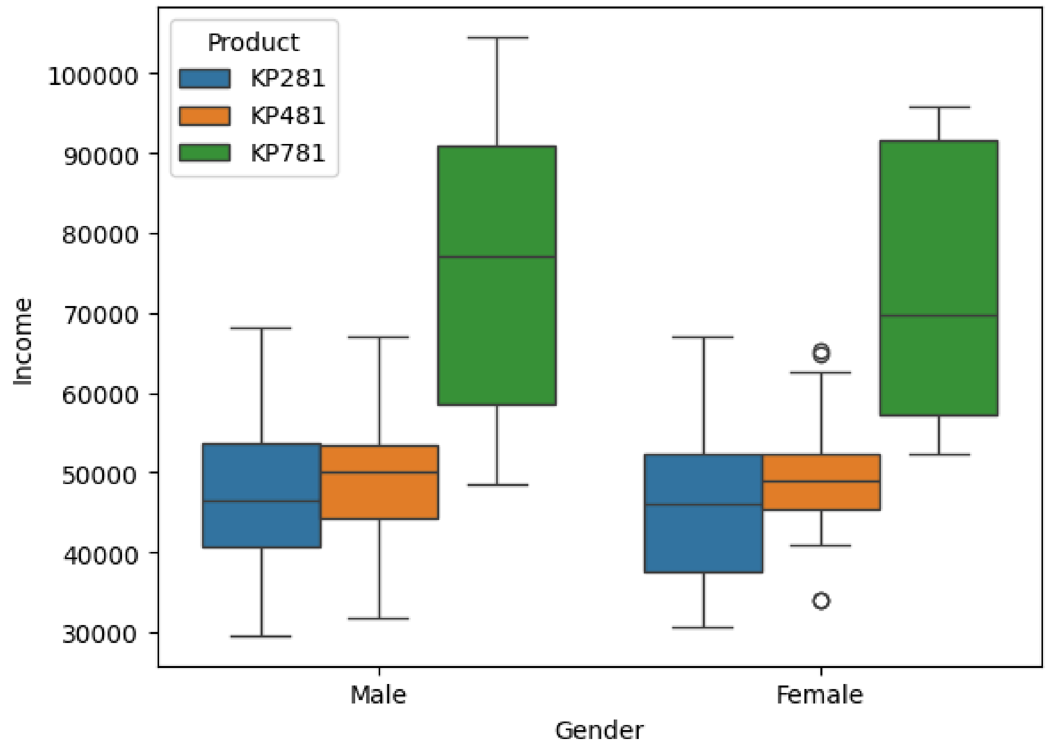
```
aerofit['Miles']=(df['Miles']//20)*20
miles_df=aerofit.groupby(['Miles','Product']).size().unstack(fill_value=0)
miles_df.plot(kind='bar',stacked=True,width=0.93)
plt.title('Miles coverage for each product')
plt.show()
```



Insights

The highest expected walk/run distance for both KP281 and KP481 is between 80 to 85 miles per week, while customers who use KP781 expect to walk/run more than 100 miles, with some walking upto 360 miles per week. Based on all analysis above, customers with higher incomes who purchase the KP781 tend to use it more frequently and walk/run more miles.

```
sns.boxplot(x="Gender",y="Income",hue='Product',data=df)
plt.show()
```

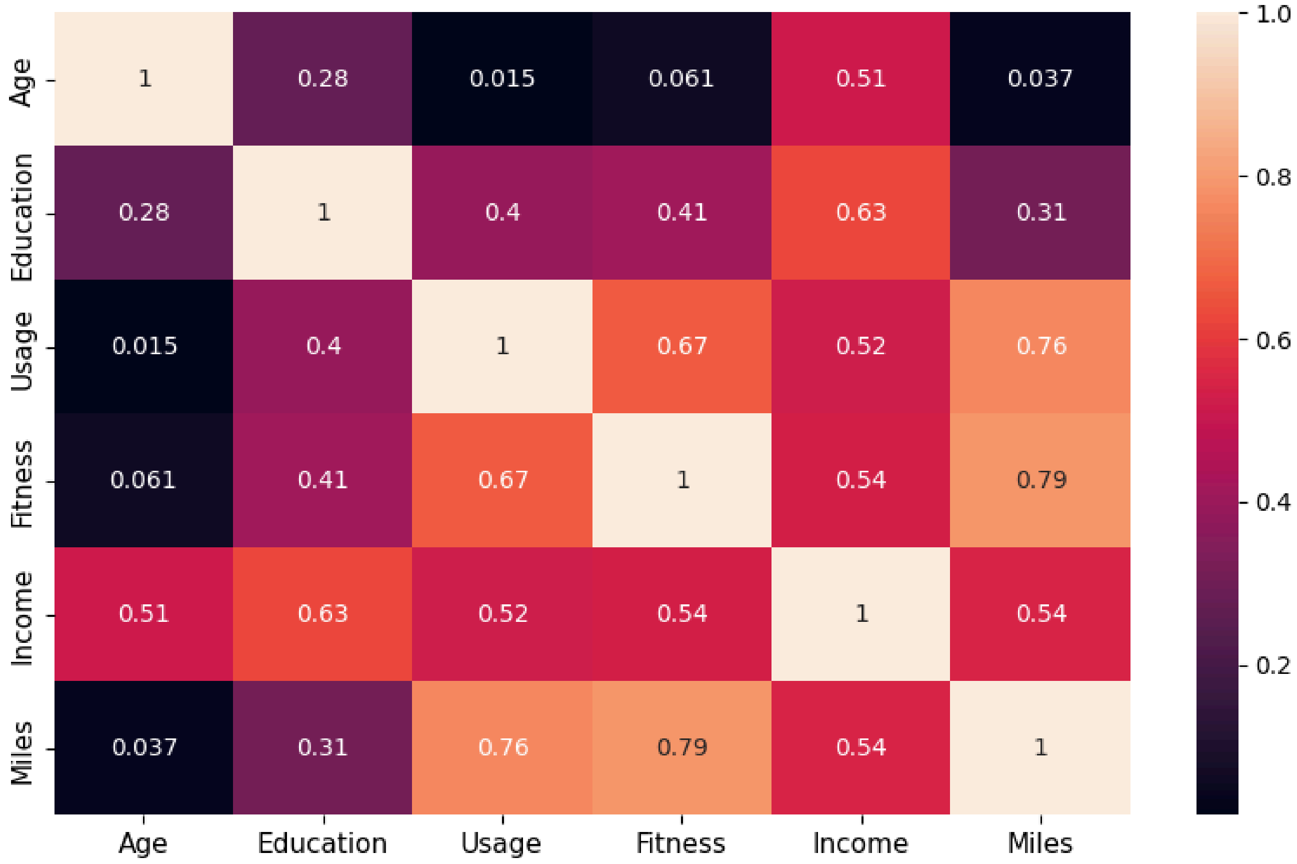


Insights

- KP-281 appeals to lower-income customers (~45,000).
- KP-481 targets middle-income customers (~50,000).
- KP-781 is preferred by high-income customers (>70,000).
- Median preferences are nearly identical for males and females for each product.

Correlation Analysis

```
numeric_df=df.select_dtypes(include=['number'])
numeric_df.corr()
plt.figure(figsize=(10,6))
sns.heatmap(numeric_df.corr(),annot=True)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.show()
```



Insights

- There is a week positive correlation (0.28) between Age and Education. There is some relationship between two variables but not strong or highly reliable. we can infer that higher education does not strongly depend on age.
- Correlation between Education and Income is 0.63, indicating a strong positive relationship between the two variables. This suggests that higher levels of education tend have higher income.
- There is a moderate positive correlation between Education and Fitness (0.41). This suggests that higher levels of education may have a positive influence on fitness. But the relationship depends on individual preferences.
- There is a strong positive correlation of 0.67 between Usage and Fitness,suggesting that individuals who use the treadmill more frequently tend to have higher levels of fitness.
- A very strong positive correlation (0.79) between Fitness and Miles suggests that individuals who cover more miles on the threadmill tend to have higher fitness levels.
- Age has a very week positive correlation with both Usage(r=0.015) and Fitness (0.061). This suggests that age has less influence on the treadmill usage and fitness scale.

Marginal Probability

Marginal probability of Male and Female

```
pd.crosstab(index=df['Gender'],columns=df['Product'],margins=True,normalize='columns')
```

Product	KP281	KP481	KP781	All
Gender				
Female	0.5	0.483333	0.175	0.422222
Male	0.5	0.516667	0.825	0.577778

Insights

- The values in the All column represents the mariginal probabilities of female and male customer buying a product.
- The value 0.4222 represents the probability of female customer buying a product.
- 0.577 represents the probability of male customer buying the product.
- It,s inferred that there is **42%** (76/108) chances of female customer buying a product, and **57.7%** (104/180) chances of male customer buying a product.

Marginal probability for MaritalStatus

```
pd.crosstab(index=df['MaritalStatus'],columns=df['Product'],margins=True,normalize='columns')
```

Product	KP281	KP481	KP781	All
MaritalStatus				
Partnered	0.6	0.6	0.575	0.594444
Single	0.4	0.4	0.425	0.405556

Insights

- Marginal Probability:
- For Partnered Customers : 59.44 %.
- for Single Customers : 40.55 %
- The chances of partnered customers buying a product are higher than single customers.

Marginal probability for Fitness

```
pd.crosstab(index=df['Fitness'],columns=df['Product'],margins=True,normalize='columns')
```

Product	KP281	KP481	KP781	All
Fitness				
1	0.0125	0.016667	0.000	0.011111
2	0.1750	0.200000	0.000	0.144444
3	0.6750	0.650000	0.100	0.538889
4	0.1125	0.133333	0.175	0.133333
5	0.0250	0.000000	0.725	0.172222

Insights

- The probability of customers with a fitness scale rating of 3 buying the product is **53.8%,** which is higher compared to customers with a fitness scale rating of 5 **(17,2%).**

Conditional probability

conditional probabilities for Gender

```
pd.crosstab(index=df['Gender'],columns=df['Product'],normalize='index')
```

Product	KP281	KP481	KP781
Gender			
Female	0.526316	0.381579	0.092105
Male	0.384615	0.298077	0.317308

Insights

- Given that the customer is female, the chances of buying **KP281 is 52%,** while the chances of buying **KP781 is 9.2%,** which is significantly lower compared to the other products.
- **Given that customer is male, the probability of buying a KP781 treadmil is 31.7% (33/104)**, here probabilities are fairly close to each other.

Conditional probability for MaritalStatus

```
pd.crosstab(index=df['MaritalStatus'],columns=df['Product'],normalize='index')
```

Product	KP281	KP481	KP781
MaritalStatus			
Partnered	0.448598	0.336449	0.214953
Single	0.438356	0.328767	0.232877

Insights

- Given that customer is partnered, the probability of buying KP281 is 44.8%, KP481 is 33.6% and KP781 is 21.4%.
- The probability of buying KP281 is 43.8%, KP481 is 32.8% and KP781 is 23.2%.
- Both groups show relatively close probabilities.
- The chances to buying KP281 are higher for both partnered and single customers.

Conditional probability for income

```
pd.crosstab(index=aerofit['Income_Group'],columns=aerofit['Product'],normalize='index')
```

Product Income_Group	KP281	KP481	KP781
29000-45000	0.693878	0.306122	0.000000
45000-65000	0.427184	0.417476	0.155340
65000-85000	0.181818	0.181818	0.636364
85000-105000	0.000000	0.000000	1.000000

Insights

- The probability of low income group buying KP281 is **69%**, higher than the probability of buying KP481. Suggesting that customers in the low income group are more likely to purcahse KP281. There is no probability of purchasing KP781 in this group.
- Customers in the medium income group are equally likely to purchase KP281 and KP481.
- For the high income group the probabilitity of buying KP781 is **63%**, indicating that they are more likely to choose KP781 compared to the other products.

Conditional probabilities for Fitness

```
pd.crosstab(index=df['Fitness'],columns=df['Product'],normalize='index')
```

Product Fitness	KP281	KP481	KP781
1	0.500000	0.500000	0.000000
2	0.538462	0.461538	0.000000
3	0.556701	0.402062	0.041237
4	0.375000	0.333333	0.291667
5	0.064516	0.000000	0.935484

Insights

- Given that customer is moderately fit, the probability of buying **KP281 product is 55.7%.**
- Given that customer is extremely fit, the probability of buying **KP781 is 93.5%,** which is significantly higher compared to other fitness levels, where customers tend to choose KP281 and KP481.
- The probability of customers with a fitness scale rating of 5, choosing KP281 and KP481 are very low.

Customer profiling

KP281

- Age: Preferred by customers across all age groups.
- Gender: Equally preferred by both male and female cutomers.
- Education: Maximum customers are from 16 and 14 years of education.
- MaritalStatus: Partnered customers prefer more than single customers.
- Usage: Used by 4 times in a week, but majority use it 3 times in a week.
- Income (in dollars): Preferred by customers with an income ranging from 29,000 to 65000, but majority of income are around 40000.
- Fitness: Majoritly preferred by customers of fitness level 3.
- Miles: The Highest expected walk/run distance is 85 miles.

KP481

- Age: Preferred across all age groups.
- Gender: Preferred equally by male and female customers, with a slight difference.
- Education: Highly preferred by customers with 14 and 16 years of education.
- MaritalStatus: Preferred by partnered customers than single customers.
- Usage: Used by 2 to 5 times, but majority use 3 times in a week.
- Income: Customers with an average income $49,000 prefer the product.
- Fitness: Highly preferred by customers with fitness level 3 more than those who with fitness levels 2 and 4.
- Miles: Customers expect to walk an average of 86 miles per week prefer this product.

KP781

- Age: Preferred by customers of all the age group.
- Gender: The majority of customers are male.

- Education: Highly preferred by customers with 16 and 18 years of education.
- MaritalStatus: Preferred by partnered customers than single customers.
- Usage: Used by 4 to 7 times a week.
- Income: Preferred by customers with high income, with an average income of around USD 75000 and maximum is above $100000.
- Fitness: Mostly preferred by extremely fit customers.
- Miles: The average expected walk/run distance is 167 miles per week.

Recommendations

- Based on the analysis, age is not a significant factor, so Aerofit can continue focusing on all age groups for all three products.
- Customers with low to medium income prefer both KP281 and KP481. Therefore, Aerofit should continue focussing on customers with an income less than $60000 customers across all gender and maritalstatus.
- Aerofit has higher number of customers for KP281 and KP481 in the low-income group, compared to the high-income users of KP781. Therefore, Aerofit should focus on targeting the high income group including both male and female customers through customized marketing campaigns, Brand ambassador programs, and premium promotions that highlight the KP781's exclusive features aiming to increase its sales among this segment.
- KP281 makes up 44.44% of purchases, which is double that of KP781 (22.22%). There fore Aerofit should consider reducing the price of KP281 even slightly. This strategy could help capture even more customers, particularly in the low income group.
- Since the probability of female customers buying KP781 is only 9.2%, Aerofit should conduct a survey with existing female customers to understand why they prefer other products over KP781. This feedback will help identify areas for improvement and suggest ways to better meet female customers needs.