```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv('aerofit_treadmill.csv')
df.head(5)
                                                                                          臣
         Product Age Gender Education MaritalStatus Usage Fitness Income Miles
          KP281
                         Male
                                      14
                                                                      4
                                                                          29562
                   18
                                                  Single
                                                                                    112
                                                                                          ıl.
      1
          KP281
                   19
                         Male
                                      15
                                                  Single
                                                             2
                                                                      3
                                                                          31836
                                                                                     75
      2
          KP281
                   19 Female
                                      14
                                               Partnered
                                                                      3
                                                                          30699
                                                                                    66
      3
          KP281
                   19
                         Male
                                      12
                                                  Single
                                                             3
                                                                      3
                                                                          32973
                                                                                     85
          ₩D201
                                               Dartnarad
df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):

200	COTO ( COCOT	- co_u	
#	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

df.shape

(180, 9)

df.describe()

	Age	Education	Usage	Fitness	Income	Miles	$\blacksquare$
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000	ıl.
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444	
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605	
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000	
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000	
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000	
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000	
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000	

Age: The age of customers ranges from around 18 to 50 years, indicating a diverse age group among customers.

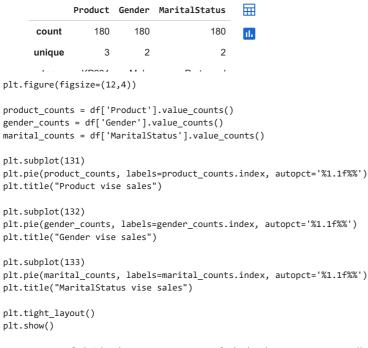
**Education**: Education years range from 12 to 21 years. This suggests that customers have varying levels of education, which may influence their preferences and choices.

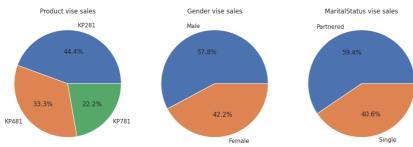
**Income**: Annual income varies significantly, with a range from approximately 29,562 to 104,561. This wide income range implies that AeroFit caters to customers with different income levels.

Fitness: Mean of fitness(3.3) indicates that customers having good fitness level.

Miles: Customers expect to walk/run different average miles per week, with the range covering 21 to approximately 360 miles.

df.describe(include='object')





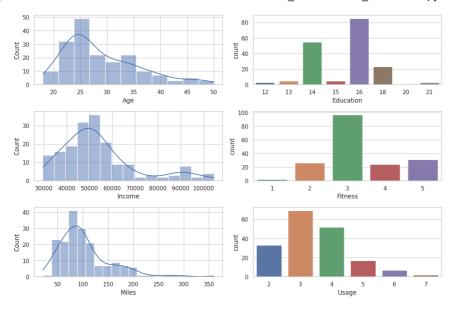
KP281, is the most popular choice among customers, followed by the mid-level KP481 and the advanced KP781.

Nearly 58% of the customers who purchase AeroFit's treadmills are male.

Approximately 59% of customers who buy AeroFit's products are partnered.

```
sns.set(style="whitegrid")
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(12,8))
sns.histplot(data=df, x='Age', ax=axes[0, 0], kde=True)
sns.histplot(data=df, x='Income', ax=axes[1, 0], kde=True)
sns.histplot(data=df, x='Miles', ax=axes[2, 0], kde=True)
sns.countplot(data=df, x='Usage', ax=axes[2,1])
sns.countplot(data=df, x='Fitness', ax=axes[1,1])
sns.countplot(data=df, x='Education', ax=axes[0,1])
plt.tight_layout()
plt.show()
```





A substantial 78% of AeroFit's customers fall within the age range of 21-35. This age group shows a strong inclination towards purchasing AeroFit's products.

An impressive 75% of AeroFit's customers report an annual income falling within the range of 30000-60000 dollars

Approximately 75% of AeroFit's customers share a common expectation when it comes to their weekly walking or running goals, with a significant number aiming to cover a range of 40-120 miles.

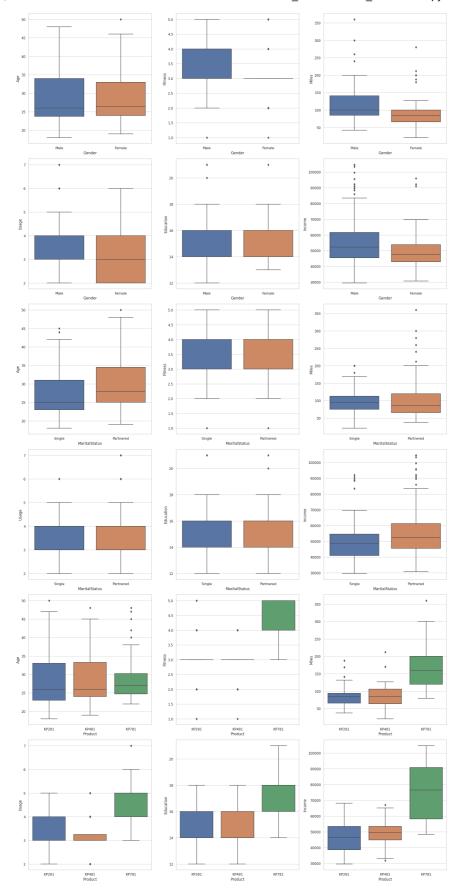
The majority of customers (approximately 75%) who purchase AeroFit's products have a self-rated fitness level of 3, aligning with a moderate fitness level.

Furthermore, these customers typically hold educational qualifications of 14 or 16 years.

Around 39% of AeroFit's customers intend to use the treadmill three times a week, making this the most common usage frequency. Following closely, 4 times a week and 2 times a week are also popular choices.

```
fig, axes = plt.subplots(nrows=6, ncols=3, figsize=(20, 40))
sns.boxplot(data=df, x='Gender', y='Age', ax=axes[0,0])
\verb|sns.boxplot(data=df, x='Gender', y='Fitness', ax=axes[0,1])|\\
sns.boxplot(data=df, x='Gender', y='Miles', ax=axes[0,2])
sns.boxplot(data=df, x='Gender', y='Usage', ax=axes[1,0])
sns.boxplot(data=df, x='Gender', y='Education', ax=axes[1,1])
sns.boxplot(data=df, x='Gender', y='Income', ax=axes[1,2])
sns.boxplot(data=df, x='MaritalStatus', y='Age', ax=axes[2,0])
sns.boxplot(data=df, \ x='MaritalStatus', \ y='Fitness', \ ax=axes[2,1])
sns.boxplot(data=df, x='MaritalStatus', y='Miles', ax=axes[2,2])
sns.boxplot(data=df, \ x='MaritalStatus', \ y='Usage', \ ax=axes[3,0])
sns.boxplot(data=df, \ x='MaritalStatus', \ y='Education', \ ax=axes[3,1])
sns.boxplot(data=df, x='MaritalStatus', y='Income', ax=axes[3,2])
sns.boxplot(data=df, x='Product', y='Fitness', ax=axes[4,1])
sns.boxplot(data=df, \ x='Product', \ y='Miles', \ ax=axes[4,2])
sns.boxplot(data=df, \ x='Product', \ y='Usage', \ ax=axes[5,0])
sns.boxplot(data=df, x='Product', y='Education', ax=axes[5,1])
sns.boxplot(data=df, x='Product', y='Income', ax=axes[5,2])
plt.tight_layout()
plt.show()
```







Age distribution for both genders is fairly similar, with a median age around 25-30. However, there are slightly more older customers (outliers) among males compared to females.

The expected miles to be covered per week are relatively more for male with compared to female.

The income distribution is fairly consistent between genders, with medians indicating similar earning levels. However, there are more high-income outliers among males.

The income and age distribution is fairly consistent between single and partnered customers. Hoever, partnered customers are having slighlty more median with more outliers.

The age distribution varies by product, with KP281 having a younger customer base and KP781 having relatively older customers. KP481 falls in between.

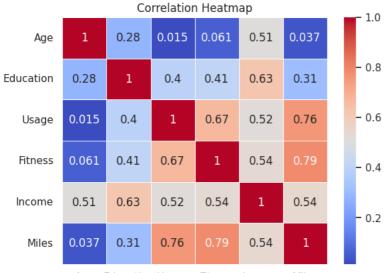
The expected miles to be covered per week vary by product, with KP781 customers having higher mileage expectations, followed by KP481 and KP281.

Income levels vary slightly between products, with KP781 customers having higher median incomes, followed by KP481 and KP281.

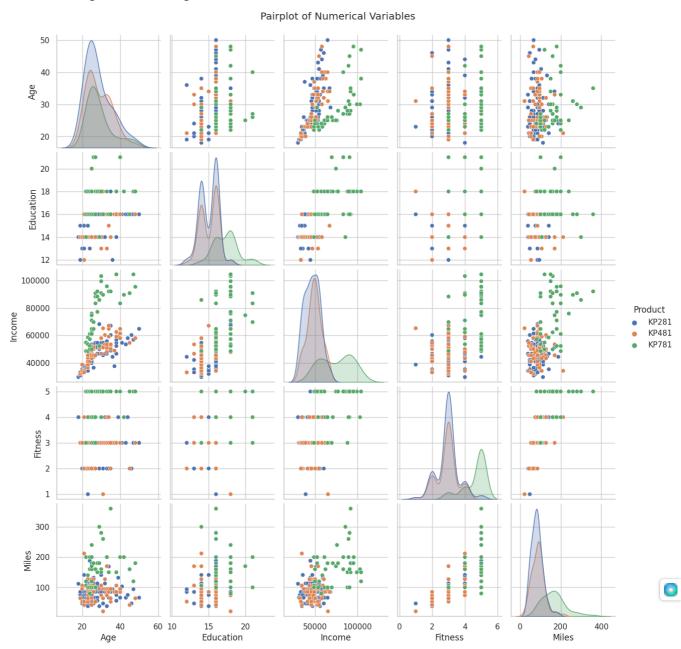
```
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", linewidths=.5)
plt.title("Correlation Heatmap")
plt.show()
sns.pairplot(data=df, vars=['Age', 'Education', 'Income', 'Fitness', 'Miles'], hue='Product')
plt.suptitle("Pairplot of Numerical Variables", y=1.02)
plt.show()
```



<ipython-input-27-6adb63b42bf9>:2: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future ver correlation\_matrix = df.corr()



Age Education Usage Fitness Income Miles



There is a positive correlation between income and education, suggesting that individuals with higher levels of education tend to have higher incomes

Fitness and income also show a positive correlation, suggesting that individuals with higher incomes tend to rate their fitness higher.

There is a moderate positive correlation between income and age, indicating that older customers tend to have higher incomes.

Miles and usage have a positive correlation, suggesting that customers who plan to run or walk more miles per week tend to use the treadmill more frequently.

Miles and fitness have a positive correlation, indicating that customers who expect to cover more miles tend to rate their fitness higher.

```
# Contingency Table 1: Product vs. Gender
contingency_table1 = pd.crosstab(df['Product'], df['Gender'])
# Contingency Table 2: Product vs. Marital Status
contingency_table2 = pd.crosstab(df['Product'], df['MaritalStatus'])
# Contingency Table 3: Product vs. Usage
contingency_table3 = pd.crosstab(df['Product'], pd.cut(df['Usage'], [0, 2, 4, 7]))
# Contingency Table 4: Product vs. Fitness
contingency_table4 = pd.crosstab(df['Product'], df['Fitness'])
# Calculate conditional probabilities
conditional_probabilities1 = contingency_table1 / contingency_table1.sum(axis=0)
conditional_probabilities2 = contingency_table2 / contingency_table2.sum(axis=0)
conditional_probabilities3 = contingency_table3 / contingency_table3.sum(axis=0)
conditional_probabilities4 = contingency_table4 / contingency_table4.sum(axis=0)
# Calculate marginal probabilities
marginal_probabilities1 = contingency_table1 / contingency_table1.sum().sum()
marginal_probabilities2 = contingency_table2 / contingency_table2.sum().sum()
marginal probabilities3 = contingency table3 / contingency table3.sum().sum()
marginal_probabilities4 = contingency_table4 / contingency_table4.sum().sum()
print("Contingency Table 1: Product vs. Gender")
print(contingency_table1)
print("\nConditional Probabilities for Table 1")
print(conditional probabilities1)
print("\nMarginal Probabilities for Table 1")
print(marginal_probabilities1)

→ Contingency Table 1: Product vs. Gender

     Gender Female Male
     Product
     KP281
                 40
                       40
     KP481
                 29
                       31
     KP781
                        33
     Conditional Probabilities for Table 1
     Gender
               Female
                           Male
     Product
     KP281
              0.526316 0.384615
     KP481
              0.381579 0.298077
     KP781
              0.092105 0.317308
     Marginal Probabilities for Table 1
     Gender
               Female
                           Male
     Product
              0.222222 0.222222
     KP281
              0.161111 0.172222
     KP481
             0.038889 0.183333
     KP781
```

KP281 has a relatively balanced gender distribution, suggesting its broad appeal. KP781 seems to be more popular among male customers, indicating a potential gender-specific appeal.



```
KP781
                          23
                                  17
    Conditional Probabilities for Table 2
     MaritalStatus Partnered
                                Single
     Product
     KP281
                    0.448598 0.438356
     KP481
                    0.336449 0.328767
     KP781
                    0.214953 0.232877
     Marginal Probabilities for Table 2
    MaritalStatus Partnered
                                Single
    Product
     KP281
                    0.266667 0.177778
     KP481
                     0.200000 0.133333
     KP781
                     0.127778 0.094444
print("\nContingency Table 3: Product vs. Usage")
print(contingency_table3)
print("\nConditional Probabilities for Table 3")
print(conditional_probabilities3)
print("\nMarginal Probabilities for Table 3")
print(marginal_probabilities3)
     Contingency Table 3: Product vs. Usage
     Usage
              (0, 2] (2, 4] (4, 7]
     Product
                 19
                         59
     KP281
                                  2
     KP481
                 14
                         43
                                  3
     KP781
                  0
                         19
                                  21
    Conditional Probabilities for Table 3
               (0, 2] (2, 4]
    Usage
     Product
              0.575758 0.487603 0.076923
     KP281
     KP481
              0.424242 0.355372 0.115385
              0.000000 0.157025 0.807692
     KP781
    Marginal Probabilities for Table 3
     Usage
                (0, 2]
                         (2, 4]
                                    (4, 7]
     Product
     KP281
              0.105556 0.327778 0.011111
     KP481
              0.077778 0.238889
                                 0.016667
              0.000000 0.105556 0.116667
```

KP281 and KP481 are used most frequently in the "2-4 times a week" usage category. KP781 is used primarily by customers who use the treadmill "4-7 times a week."

```
print(contingency_table4)
print("\nConditional Probabilities for Table 4")
print(conditional probabilities4)
print("\nMarginal Probabilities for Table 4")
print(marginal_probabilities4)
     Contingency Table 4: Product vs. Fitness
     Fitness 1
                 2
                    3 4
     KP281
             1
               14 54 9
                            2
     KP481
             1 12 39 8
     KP781
    Conditional Probabilities for Table 4
    Fitness
               1
                         2
                                  3
     Product
     KP281
             0.5 0.538462 0.556701 0.375000 0.064516
     KP481
             0.5 0.461538 0.402062 0.333333 0.000000
     KP781
             0.0 0.000000 0.041237 0.291667
                                               0.935484
    Marginal Probabilities for Table 4
                                        3
    Fitness
                    1
     Product
     KP281
             0.005556 0.077778 0.300000 0.050000 0.011111
     KP481
             0.005556
                       0.066667
                                0.216667
                                          0.044444
                                                    0.000000
     KP781
                                          0.038889
             0.000000 0.000000 0.022222
                                                    0.161111
```

print("\nContingency Table 4: Product vs. Fitness")



The majority of customers using all products have a fitness level of 3, indicating that fitness level 3 is the most common among customers.

KP781 stands out with a significant number of customers having a fitness level of 5, suggesting that this product may appeal to more fitness enthusiasts.

## **Recommendations for AeroFit**

- Given that "KP281" is the top-selling product, consider promoting it more prominently.
- · It is evident that "KP781" attracts customers with a fitness level of 5, consider promoting it to fitness enthusiasts.
- With almost 59% of customers being partnered, consider marketing strategies that target couples or promote the idea of sharing fitness goals with a partner.
- As nearly 75% of customers fall within the income range of 30,000to60,000, offer financing options, discounts, or special packages that cater to customers within this income bracket.
- Since around 75% of customers expect to cover 40-120 miles per week, provide training plans, tracking apps, or support to help them achieve their mileage goals.
- Since 39% of customers plan to use the treadmill 3 times a week, consider offering special promotions, maintenance plans, or reminders to encourage consistent usage.
- With most customers having a fitness rating of 3, consider creating fitness programs or classes for this specific fitness level, catering to their needs and helping them progress.

