aerofit_case_study

January 12, 2024

1 Aerofit Case Study

Analyzing the given Aerofit Treadmill dataset, I'd like to explicitly answer the following questions:

1. Import the dataset and do usual data analysis.

   Find the data type of all columns.

   Find the number of rows and columns in the given dataset.

   Check for the missing values.

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2. Univariate Analysis and Outliers detection.

   Continuous variables.

   Find the outliers for every continuous variable in the dataset.

   Remove/clip the data between the 5 percentile and 95 percentile.

   Categorical variables.

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3. Check the effect of features on the product purchased (Bivariate analysis).

   Find if there is any relationship between the categorical variables and the output variable in the data.

   Find if there is any relationship between the continuous variables and the output variable in the data.

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4. Representing the Probability.

   Find the marginal probability (what percent of customers have purchased KP281, KP481, or KP781).

   Find the probability that the customer buys a product based on each column.

   Find the conditional probability that an event occurs given that another event has occurred.

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5. Multivariate Analysis.

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6. Check the correlation among different factors.

   Find the correlation between the given features in the table.

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7. Customer profiling and recommendation.

   Make customer profilings for each and every product.

   Write a detailed recommendation from the analysis that you have done.

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
# get the dataset (csv file) from the link

!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
↪original/aerofit_treadmill.csv
```

```
--2024-01-11 23:26:52--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/125/original/aerofit_treadmill.csv
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
18.238.59.71, 18.238.59.132, 18.238.59.211, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|18.238.59.71|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 7279 (7.1K) [text/plain]
Saving to: 'aerofit_treadmill.csv'

aerofit_treadmill.c 100%[===================>]   7.11K  --.-KB/s    in 0s

2024-01-11 23:26:53 (220 MB/s) - 'aerofit_treadmill.csv' saved [7279/7279]
```

2 General Analysis

[3]:
```
df = pd.read_csv("aerofit_treadmill.csv")
df.shape
```

[3]: (180, 9)

Insights/Conclusion: Dataset has 180 rows and 9 columns.

[4]:
```
df.head()
```

[4]:

	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

[5]:
```
df.columns
```

[5]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

[6]:
```
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
```

Insights/Conclusion:

- String Datatypes: `Product`, `Gender` and `MaritalStatus` columns store categorical data.
- Integer Datatypes: `Age`, `Education`, `Usage`, `Fitness`, `Income` and `Miles` columns hold numerical values.

[7]:
```
df.isna().sum()
```

[7]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
```

```
Miles              0
dtype: int64
```

Insights/Conclusion: The dataset is complete, containing no null or missing values across all columns.

3 Univariate Analysis

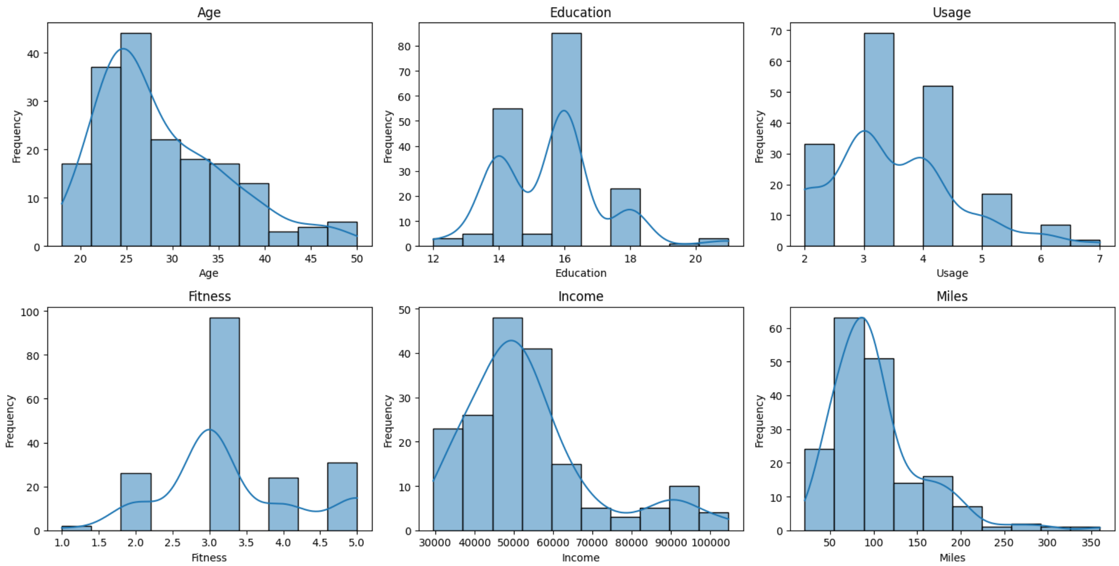
3.1 Continuous variables

[8]:
```python
df.describe()
```

[8]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

[9]:
```python
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Create subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 8))

# Flatten the axes for easier iteration
axes = axes.flatten()

# Plot histograms for each continuous variable
for i, var in enumerate(continuous_vars):
    sns.histplot(df[var], ax=axes[i], bins=10, kde=True)
    axes[i].set_title(var)
    axes[i].set_xlabel(var)
    axes[i].set_ylabel('Frequency')
```

```
# Adjust layout
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



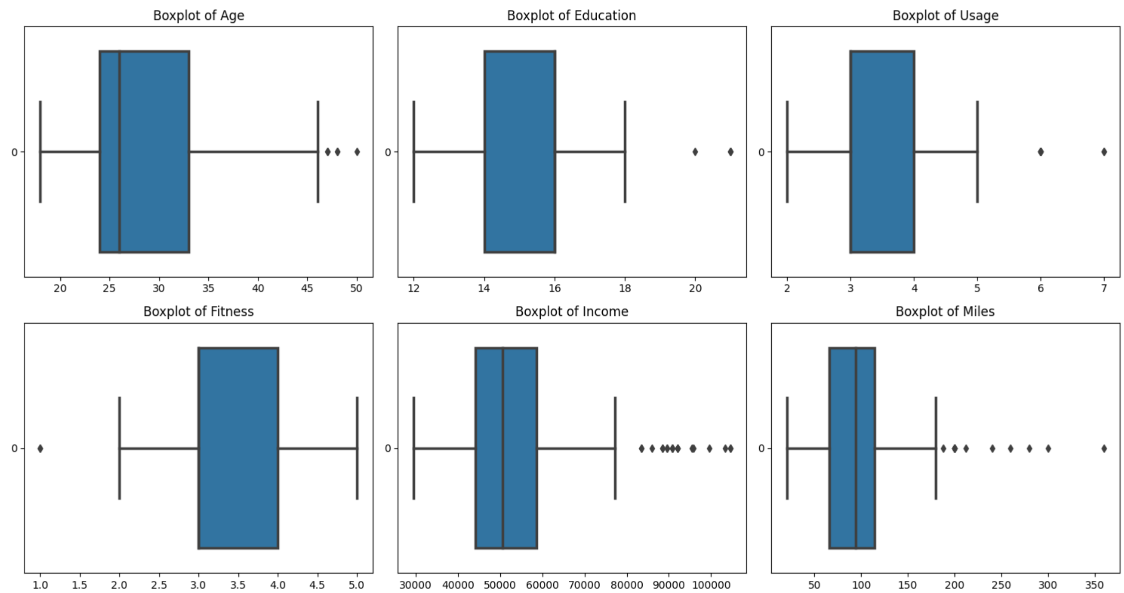
Insights/Conclusion:

- The dataset includes individuals aged 18-50, with an average age of 28.79 years. The majority are below 33 years old.
- Education levels range from 12 to 21, with the majority at 16 years.
- Usage values range from 2 to 7, with the 25th and 75th percentiles at 3 and 4.
- Most individuals have moderate fitness.
- Income ranges from $29,562 to $104,581, with the 25th and 75th percentiles at $44,058.75 and $58,668, respectively.

3.2 Outliers detection using box plot

[10]:
```
# Selecting continuous variables for outlier detection
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Creating subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 8))

# Iterating through each variable and plotting boxplots in subplots
for idx, var in enumerate(continuous_vars):
    row = idx // 3  # Calculate row index
    col = idx % 3   # Calculate column index
```

```
    sns.boxplot(data=df[var], ax=axes[row, col], orient='h', linewidth=2.5)
    axes[row, col].set_title(f'Boxplot of {var}')

# Adjusting layout and displaying the plots
plt.tight_layout()
plt.show()
```

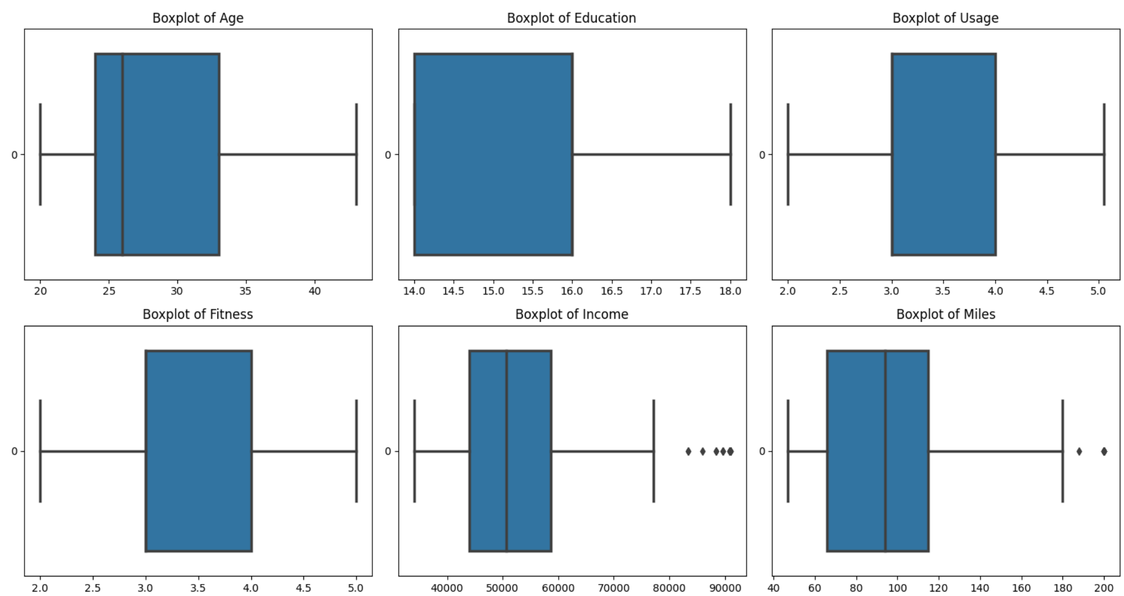


Insights/Conclusion:

- `Education`, `Usage`, `Fitness`: Show minimal outliers, indicating a relatively stable distribution within expected ranges.
- `Age`: Contains a moderate number of outliers, suggesting some deviation from the typical range.
- `Income`, `Miles`: Exhibit a substantial number of outliers, signifying significant deviations from the expected distribution.

[11]:
```
# Selecting continuous variables for clipping
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Clipping data between 5th and 95th percentiles for each variable
for var in continuous_vars:
    lower_bound = np.percentile(df[var], 5)  # Calculate the 5th percentile
    upper_bound = np.percentile(df[var], 95)  # Calculate the 95th percentile

    # Clip the data between the calculated percentiles
    df[var] = np.clip(df[var], lower_bound, upper_bound)
```

[12]:
```python
# Selecting continuous variables for outlier detection
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Creating subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 8))

# Iterating through each variable and plotting boxplots in subplots
for idx, var in enumerate(continuous_vars):
    row = idx // 3  # Calculate row index
    col = idx % 3   # Calculate column index

    sns.boxplot(data=df[var], ax=axes[row, col], orient='h', linewidth=2.5)
    axes[row, col].set_title(f'Boxplot of {var}')

# Adjusting layout and displaying the plots
plt.tight_layout()
plt.show()
```



Insights/Conclusion:

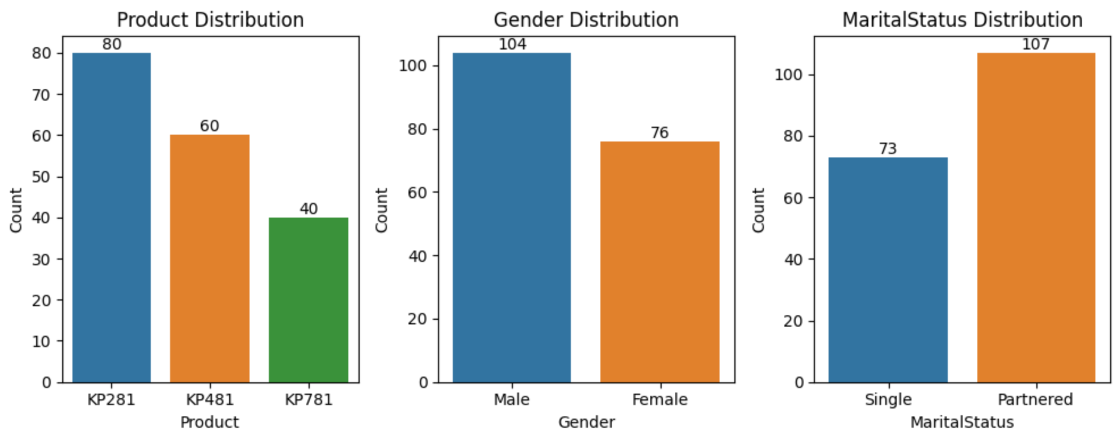
- `Age`, `Education`, `Usage`, `Fitness`: Outliers have been successfully clipped, ensuring a more normalized distribution within expected ranges.
- `Income`, `Miles`: Although some outliers were clipped, these variables still contain remaining outliers, suggesting persistent deviations beyond the 5th and 95th percentiles.

3.3 Categorical variables

[13]:
```python
df[['Product', 'Gender', 'MaritalStatus']].apply(lambda x: x.value_counts()).T.
↪stack()
```

[13]:
```
Product        KP281        80.0
               KP481        60.0
               KP781        40.0
Gender         Female       76.0
               Male        104.0
MaritalStatus  Partnered   107.0
               Single       73.0
dtype: float64
```

[14]:
```python
categorical_vars = ['Product', 'Gender','MaritalStatus']

# Create subplots for count plots of categorical variables
fig, axes = plt.subplots(nrows=1, ncols=len(categorical_vars), figsize=(10, 4))

for i, var in enumerate(categorical_vars):
    ax=sns.countplot(x=var,data=df, ax=axes[i])
    ax.bar_label(ax.containers[0], fontsize=10)
    axes[i].set_title(f'{var} Distribution')
    axes[i].set_xlabel(var)
    axes[i].set_ylabel('Count')

plt.tight_layout()
plt.show()
```



Insights/Conclusion:

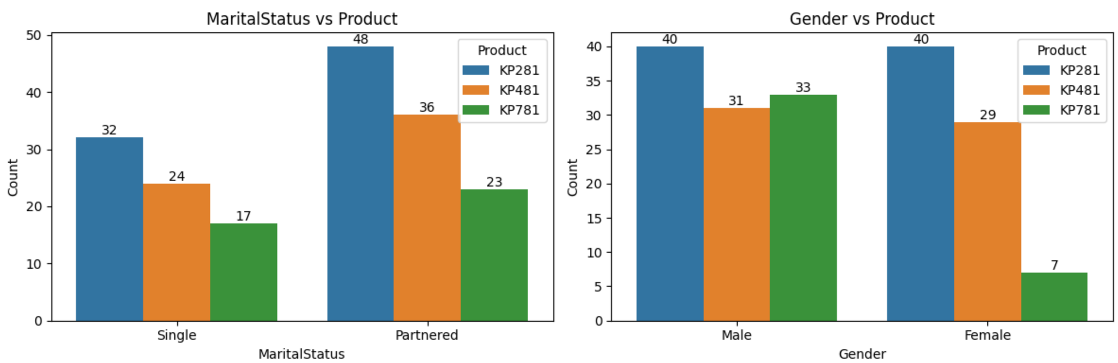
- KP281: Most popular (80 units) due to affordability ($1,500).

- KP481: Attracts mid-level runners ($1,750) with 60 units.
- KP781: Lower (40 units) due to higher cost ($2,500) and specialized features.
- Males are more likely to purchase product as compared to females, with a ratio of around 4:3.
- A Partnered customer is more likely to purchase the product.

4 Bivariate Analysis

4.1 Categorical variables vs Product

[15]:
```
# Categorical variables: MaritalStatus, Gender
categorical_vars = ['MaritalStatus', 'Gender']

# Create subplots for count plots of categorical variables against the output␣
↪variable
fig, axes = plt.subplots(nrows=1, ncols=len(categorical_vars), figsize=(12, 4))

for i, var in enumerate(categorical_vars):
    ax=sns.countplot(x=var, hue='Product', data=df, ax=axes[i])
    # Add count labels for all containers (bars)
    for container in ax.containers:
        ax.bar_label(container, fontsize=10, fmt='%d')
    axes[i].set_title(f'{var} vs Product')
    axes[i].set_xlabel(var)
    axes[i].set_ylabel('Count')
    axes[i].legend(title='Product', loc='upper right')

plt.tight_layout()
plt.show()
```



Insights/Conclusion:

- The majority of both partnered and single individuals opt for KP281, followed by KP481, while KP781 has a comparatively lower distribution in both groups.

- Both genders prefer KP281, while there's a notable difference in the choice of KP781, with more males opting for it compared to females. KP481 shows a relatively balanced distribution between genders.

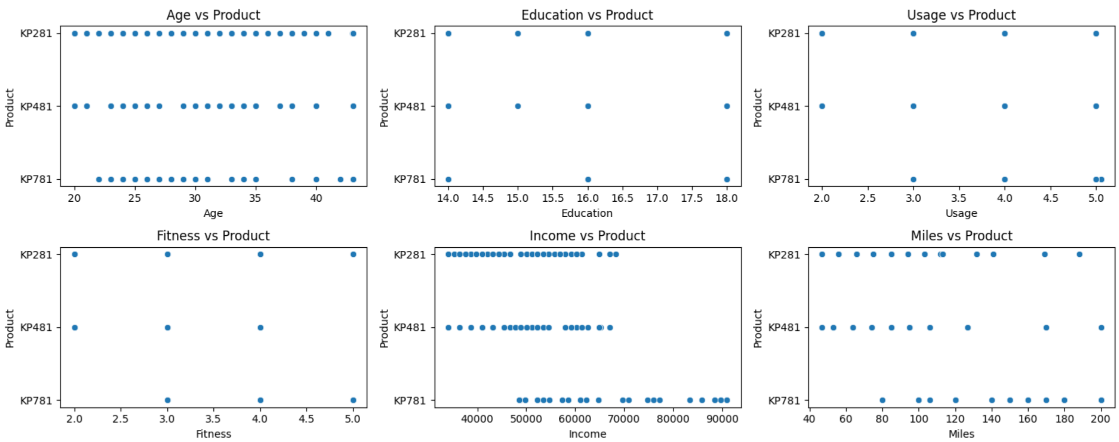
4.2 Continuous variables vs Product

[16]:
```
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

for var in continuous_vars:
  df_new = df.groupby('Product')[var].describe().reset_index()
  print(f"Product wise {var} description")
  print(df_new,end="\n\n")
```

```
Product wise Age description
  Product  count       mean       std   min    25%   50%    75%    max
0   KP281   80.0  28.427500  6.678313  20.0  23.00  26.0  33.00  43.05
1   KP481   60.0  28.801667  6.327830  20.0  24.00  26.0  33.25  43.05
2   KP781   40.0  28.828750  6.296182  22.0  24.75  27.0  30.25  43.05

Product wise Education description
  Product  count       mean       std   min   25%   50%   75%   max
0   KP281   80.0  15.125000  1.071790  14.0  14.0  16.0  16.0  18.0
1   KP481   60.0  15.183333  1.112208  14.0  14.0  16.0  16.0  18.0
2   KP781   40.0  17.050000  1.197219  14.0  16.0  18.0  18.0  18.0

Product wise Usage description
  Product  count      mean       std  min  25%  50%   75%   max
0   KP281   80.0  3.087500  0.782624  2.0  3.0  3.0  4.00  5.00
1   KP481   60.0  3.066667  0.799717  2.0  3.0  3.0  3.25  5.00
2   KP781   40.0  4.511250  0.565401  3.0  4.0  5.0  5.00  5.05

Product wise Fitness description
  Product  count      mean       std  min  25%  50%  75%  max
0   KP281   80.0  2.975000  0.635948  2.0  3.0  3.0  3.0  5.0
1   KP481   60.0  2.916667  0.590652  2.0  3.0  3.0  3.0  4.0
2   KP781   40.0  4.625000  0.667467  3.0  4.0  5.0  5.0  5.0

Product wise Income description
  Product  count         mean           std       min       25%      50%  \
0   KP281   80.0  46584.31125   8813.246103  34053.15  38658.00  46617.0
1   KP481   60.0  49046.60750   8517.583361  34053.15  44911.50  49459.5
2   KP781   40.0  73908.28125  16572.164368  48556.00  58204.75  76568.5

       75%       max
0  53439.0  68220.00
1  53439.0  67083.00
2  90886.0  90948.25
```

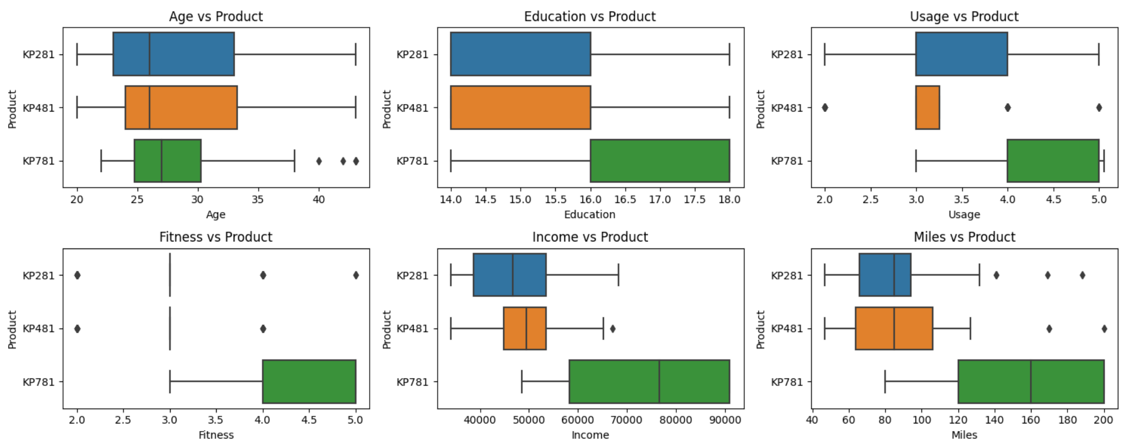
```
Product wise Miles description
  Product  count     mean        std   min    25%    50%    75%    max
0   KP281   80.0   83.125  28.391198  47.0   66.0   85.0   94.0  188.0
1   KP481   60.0   88.500  31.322543  47.0   64.0   85.0  106.0  200.0
2   KP781   40.0  155.900  39.073763  80.0  120.0  160.0  200.0  200.0
```

[17]:
```python
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Create a subplot grid for scatter plots of continuous variables against
 ↪'Product'
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 6))

# Flatten the 2D subplot array for easy iteration
axes = axes.flatten()

# Plotting scatter plots for each continuous variable against 'Product'
for i, var in enumerate(continuous_vars):
    sns.scatterplot(x=var, y='Product', data=df, ax=axes[i])
    axes[i].set_title(f'{var} vs Product')
    axes[i].set_xlabel(var)
    axes[i].set_ylabel('Product')

plt.tight_layout()
plt.show()
```



[18]:
```python
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Create a subplot grid for box plots of continuous variables against 'Product'
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 6))

# Flatten the 2D subplot array for easy iteration
```

```
axes = axes.flatten()

# Plotting box plots for each continuous variable against 'Product'
for i, var in enumerate(continuous_vars):
    sns.boxplot(x=var, y='Product', data=df, ax=axes[i])
    axes[i].set_title(f'{var} vs Product')
    axes[i].set_xlabel(var)
    axes[i].set_ylabel('Product')

plt.tight_layout()
plt.show()
```



Insights/Conclusion:

`Product vs Age:`

- Customers purchasing KP281 and KP481 have same median ages.
- The age group of 25-30 is associated with a higher chances of purchasing KP781.

`Product vs Education:`

- Customers with education levels greater than 16 are more likely to purchase KP781.
- Those with education levels below 16 have an equal chances of choosing KP281 or KP481.

`Product vs Usage:`

Customers planning to use the treadmill more than four times a week are more likely to purchase KP781, while others are more likely to buy KP281 or KP481.

`Product vs Fitness:`

Higher fitness levels (fitness >= 3) increase the chances of purchasing KP781.

`Product vs Income:`

- Higher income (Income >= $60,000) corresponds to a higher chances of choosing KP781.

- The median income for KP281 and KP481 demonstrates similar central tendencies, with KP481 slightly higher.

Product vs Miles:

Customers expecting to cover more than 120 miles per week are more likely to buy KP781.

5 Probability Computation

5.1 Marginal Probability

[19]:
```python
# Using crosstab()
pd.crosstab(df.Product, columns='count', normalize = True)
```

[19]:
```
col_0       count
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
```

[20]:
```python
# Using value_counts()
df['Product'].value_counts(normalize=True)
```

[20]:
```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

[21]:
```python
df['Gender'].value_counts(normalize=True)
```

[21]:
```
Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
```

[22]:
```python
df['MaritalStatus'].value_counts(normalize=True)
```

[22]:
```
Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64
```

Insights/Conclusion:

Product:

- 44.44% of the customers have purchased KP281 treadmill.
- 33.33% of the customers have purchased KP481 treadmill.
- 22.22% of the customers have purchased KP781 treadmill.

Gender:

57.78% of the customers are Males and 42.22% are Females.

MaritalStatus:

59.44% of the customers are Partnered and rest are Single.

5.2 Conditional Probability

[23]:
```
pd.crosstab(df.Product, df.Gender, normalize = 'columns', margins=True,␣
  ↪margins_name='Total')
```

[23]:
```
Gender     Female      Male     Total
Product
KP281    0.526316  0.384615  0.444444
KP481    0.381579  0.298077  0.333333
KP781    0.092105  0.317308  0.222222
```

Insights/Conclusion:

P(KP281 | Female) = 0.53

P(KP481 | Female) = 0.38

P(KP781 | Female) = 0.09

======================

P(KP281 | Male) = 0.38

P(KP481 | Male) = 0.30

P(KP781 | Male) = 0.31

[24]:
```
pd.crosstab(df.Product, df.MaritalStatus, normalize = 'columns', margins=True,␣
  ↪margins_name='Total')
```

[24]:
```
MaritalStatus  Partnered    Single     Total
Product
KP281           0.448598  0.438356  0.444444
KP481           0.336449  0.328767  0.333333
KP781           0.214953  0.232877  0.222222
```

Insights/Conclusion:

P(KP281 | Partnered) = 0.45

P(KP481 | Partnered) = 0.34

P(KP781 | Partnered) = 0.21

======================

P(KP281 | Single) = 0.43

P(KP481 | Single) = 0.33

P(KP781 | Single) = 0.23

[25]:
```
df.head()
```

[25]:
```
  Product   Age  Gender  Education MaritalStatus  Usage  Fitness    Income  \
0   KP281  20.0    Male         14        Single    3.0        4  34053.15
1   KP281  20.0    Male         15        Single    2.0        3  34053.15
2   KP281  20.0  Female         14     Partnered    4.0        3  34053.15
3   KP281  20.0    Male         14        Single    3.0        3  34053.15
4   KP281  20.0    Male         14     Partnered    4.0        2  35247.00

   Miles
0    112
1     75
2     66
3     85
4     47
```

[26]:
```
# Creating categorical columns for Age, Income and Miles.

age_bins = [0, 10, 20, 30, 40, 50]
df['AgeBin'] = pd.cut(df['Age'], bins = age_bins)

income_bins = [0, 20000, 30000, 40000, 50000, 70000, 100000]
df['IncomeBin'] = pd.cut(df['Income'], bins = income_bins)

miles_bins = [0, 40, 60, 80, 100, 120, 200]
df['MilesBin'] = pd.cut(df['Miles'], bins = miles_bins)
```

[27]:
```
df.head()
```

[27]:
```
  Product   Age  Gender  Education MaritalStatus  Usage  Fitness    Income  \
0   KP281  20.0    Male         14        Single    3.0        4  34053.15
1   KP281  20.0    Male         15        Single    2.0        3  34053.15
2   KP281  20.0  Female         14     Partnered    4.0        3  34053.15
3   KP281  20.0    Male         14        Single    3.0        3  34053.15
4   KP281  20.0    Male         14     Partnered    4.0        2  35247.00

   Miles    AgeBin       IncomeBin    MilesBin
0    112  (10, 20]  (30000, 40000]  (100, 120]
1     75  (10, 20]  (30000, 40000]    (60, 80]
2     66  (10, 20]  (30000, 40000]    (60, 80]
3     85  (10, 20]  (30000, 40000]   (80, 100]
4     47  (10, 20]  (30000, 40000]    (40, 60]
```

[28]:
```
pd.crosstab(df.Product, df['AgeBin'], normalize = 'columns')
```

[28]:

AgeBin	(10, 20]	(20, 30]	(30, 40]	(40, 50]
Product				
KP281	0.6	0.445455	0.395833	0.500000
KP481	0.4	0.281818	0.479167	0.166667
KP781	0.0	0.272727	0.125000	0.333333

Insights/Conclusion:

- For 10 to 20 years old people, KP281 is most likely followed by KP481.
- For 20 to 30 years old people, KP281 is most likely followed by KP481 and KP781 with around equal probability.
- For 30 to 40 years old people, KP481 is most likely followed by KP281.
- For 40 to 50 years old people, KP281 is most likely followed by KP781.

[29]:
```
pd.crosstab(df.Product, df['IncomeBin'], normalize = 'columns')
```

[29]:

IncomeBin	(30000, 40000]	(40000, 50000]	(50000, 70000]	(70000, 100000]
Product				
KP281	0.71875	0.490196	0.432432	0.0
KP481	0.28125	0.411765	0.405405	0.0
KP781	0.00000	0.098039	0.162162	1.0

Insights/Conclusion:

- People with a salary above $70000 will definitely purchase KP781, while those with a salary below $30000 are more likely to purchase KP281.
- People having salary between $40000 to $70000 are more likely to purchase KP281 or KP481.

[30]:
```
pd.crosstab(df.Product, df['MilesBin'], normalize = 'columns')
```

[30]:

MilesBin	(40, 60]	(60, 80]	(80, 100]	(100, 120]	(120, 200]
Product					
KP281	0.6	0.666667	0.444444	0.500000	0.142857
KP481	0.4	0.300000	0.425926	0.333333	0.190476
KP781	0.0	0.033333	0.129630	0.166667	0.666667

Insights/Conclusion:

Users running over 120 miles a week are most likely to buy KP781, while rest all are likely to buy KP281 or KP481.

[31]:
```
pd.crosstab(df.Product, df.Usage, normalize = 'columns')
```

[31]:

Usage	2.00	3.00	4.00	5.00	5.05
Product					
KP281	0.575758	0.536232	0.423077	0.117647	0.0
KP481	0.424242	0.449275	0.230769	0.176471	0.0
KP781	0.000000	0.014493	0.346154	0.705882	1.0

Insights/Conclusion:

- Users over 4 times a week are most likely to buy KP781.
- Users twice/thrice a week are most likely to buy KP281 or KP481.
- Users 4 times weekly have nearly equal distribution.

[32]:
```
pd.crosstab(df.Product, df.Fitness, normalize = 'columns')
```

[32]:
```
Fitness         2         3         4         5
Product
KP281    0.535714  0.556701  0.375000  0.064516
KP481    0.464286  0.402062  0.333333  0.000000
KP781    0.000000  0.041237  0.291667  0.935484
```

Insights/Conclusion:

- Users with fitness scale 5 are most likely to buy KP781.
- Users with fitness scale 2/3 are most likely to buy KP281 or KP481.
- Users with fitness scale 4 have nearly equal distribution.

[33]:
```
pd.crosstab(df.Product, df.Education, normalize = 'columns')
```

[33]:
```
Education         14   15        16        18
Product
KP281       0.555556  0.8  0.458824  0.074074
KP481       0.412698  0.2  0.364706  0.074074
KP781       0.031746  0.0  0.176471  0.851852
```

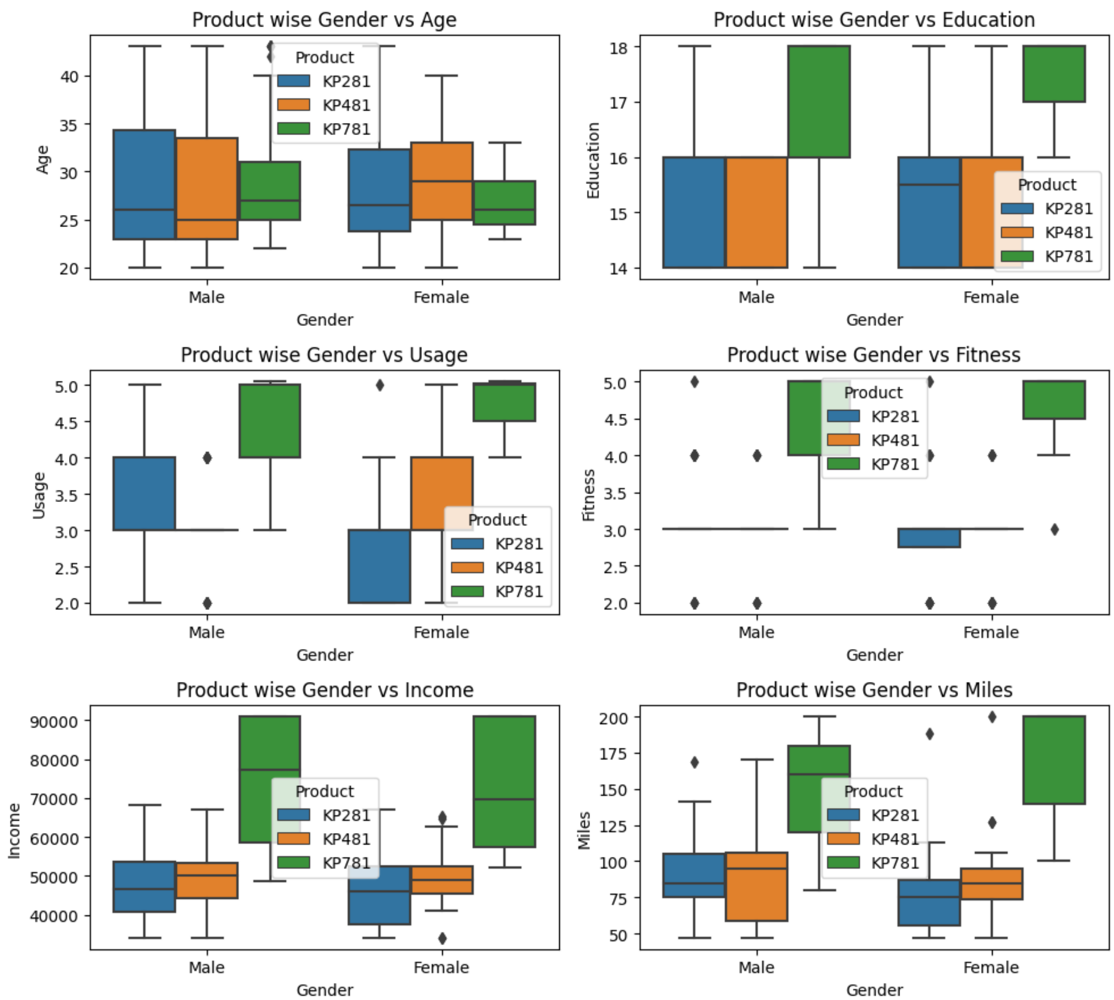
Insights/Conclusion:

Users with education over 16 years are most likely to buy KP781, while rest are likely to buy KP281 or KP481.

6 Multivariate Analysis

[34]:
```
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Create a subplot grid for box plots of 'Gender' against continuous variables
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(10, 9))

# Flatten the 2D subplot array for easy iteration
axes = axes.flatten()

# Plotting box plots for each 'Gender' against continuous variables
for i, var in enumerate(continuous_vars):
    sns.boxplot(data=df, x='Gender', y=var, hue='Product', ax=axes[i])
    axes[i].set_title(f'Product wise Gender vs {var}')
```

```
    axes[i].set_xlabel('Gender')
    axes[i].set_ylabel(var)

plt.tight_layout()
plt.show()
```



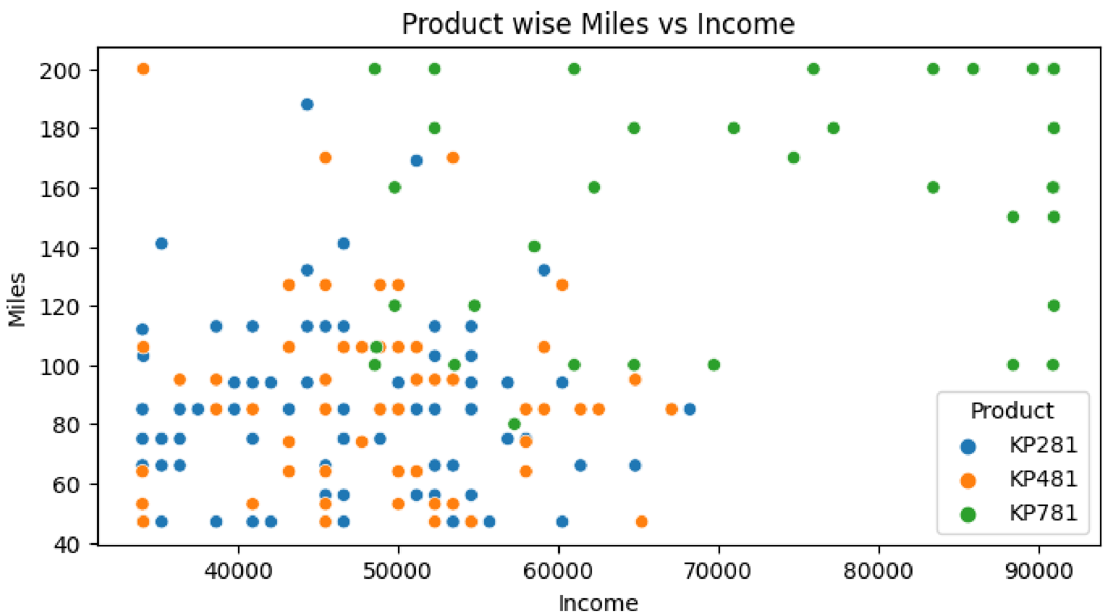
Insights/Conclusion:

- The KP781 product is primarily purchased by individuals under 30 due to health concerns or atheletes. Males beyond 40 buy it for income, while no female over 35 buys it.
- KP481 is primarily purchased by those with good income and around 30 years of age, while KP281 is primarily purchased by those under 27 years old.
- KP781 is a popular product among males with high salaries, while those with lower salaries are more likely to purchase KP281.
- The boxplot shows that fitness enthusiasts and health conscious individuals are purchasing

KP781, regardless of gender.

- KP281 is primarily purchased by females running less miles and looking to stay in shape. Male customers, running less than 100 miles a week, tend to purchase KP281, while those running below 150 miles and above 100 miles will purchase KP481.

[35]:
```
plt.figure(figsize = (8, 4))
sns.scatterplot(data = df, x = 'Income',y = 'Miles', hue = 'Product')
plt.title(f'Product wise Miles vs Income')
plt.show()
```



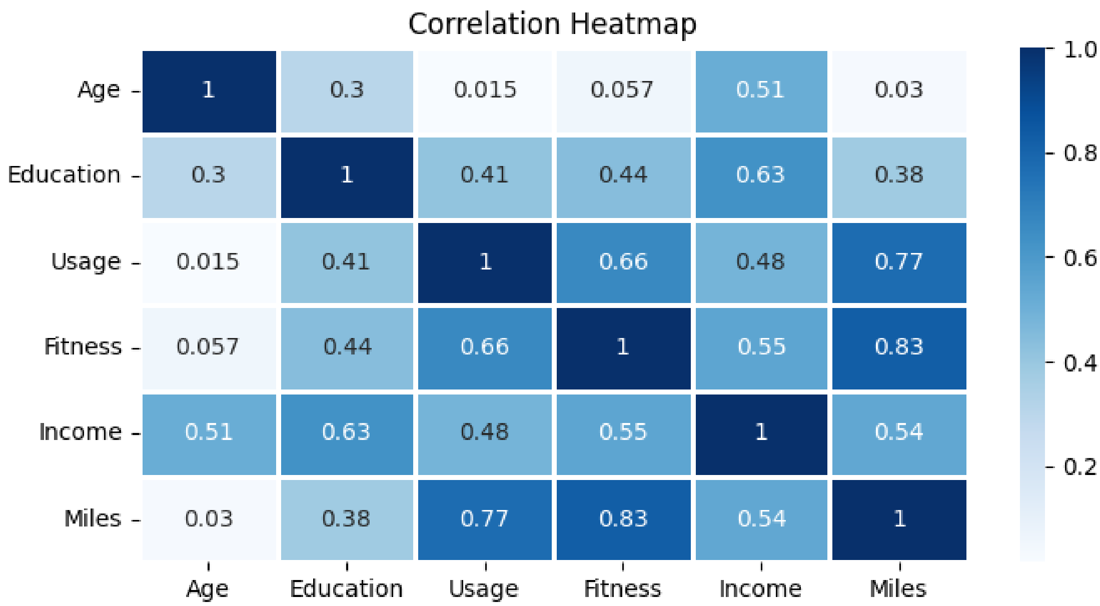
Insights/Conclusion:

KP781 buyers have high incomes and run more miles, while KP281 and KP481 buyers have incomes less than $700,000 and are mostly running for good health.

7 Correlation among different factors

[36]:
```
# Calculate correlation matrix
correlation_matrix = df.corr(numeric_only=True)

# Create a heatmap for the correlation matrix
plt.figure(figsize=(8, 4))
sns.heatmap(correlation_matrix, annot=True,␣
 ↪cmap='Blues',edgecolors='black',linewidths=1)
plt.title('Correlation Heatmap')
```

```
plt.show()
```



Insights/Conclusion:

- Positive correlations exist between age and income (0.51) and education and income (0.63).
- Strong positive correlations between usage and fitness (0.66) and usage and miles (0.77) indicate exercise-related patterns.
- Miles and fitness exhibit a strong positive correlation (0.83).

8 Customer profiling and recommendation

8.1 Customer profiling

KP281:

`Demographics:` Predominantly purchased by individuals under 30.

`Gender:` No distinct gender bias; popular among both males and females.

`Income:` Attracts individuals with incomes below $70,000.

`Education:` No specific education bias; preferred across various education levels.

`Fitness & Health:` Attracts individuals running less than 100 miles per week, focusing on health and moderate fitness.

`Usage:` Customers planning to use the treadmill 2-4 times a week.

KP481:

`Demographics:` Attracts individuals around 30 years old.

`Gender:` No distinct gender bias; balanced distribution between males and females.

`Income:` Appeals to those with moderate to high incomes ($40,000 to $70,000).

`Education:` No specific education bias; preferred across various education levels.

`Fitness & Health:` Preferred by individuals with moderate fitness.

`Usage:` Balanced distribution among customers planning to use the treadmill 2-4 times a week.

KP781:

`Demographics:` Primarily purchased by males, especially those beyond 40.

`Gender:` Skewed towards males; fewer females choose this product.

`Income:` Attracts individuals with higher incomes (above $70,000).

`Education:` More popular among individuals with education levels above 16 years.

`Fitness & Health:` Attracts fitness enthusiasts, individuals running over 120 miles per week.

`Usage:` Preferred by customers planning to use the treadmill more than 4 times a week.

8.2 Recommendations

Product Strategy:

- Focus on promoting KP281 as an affordable and versatile option for a wide age group.
- Emphasize the mid-level running features of KP481 to attract customers in their 30s.
- Position KP781 as a premium product with specialized features, targeting fitness enthusiasts and higher-income individuals.

Income-Based Strategies:

Develop targeted strategies for income groups:

- For high-income individuals (> $70,000), emphasize the advanced features and benefits of KP781.
- For those with lower incomes (< $30,000), highlight the affordability and basic features of KP281.

Educational Marketing:

- Tailor marketing messages to individuals with education levels above 16, focusing on the advanced features of KP781.
- For those with education levels below 16, emphasize the versatility and affordability of KP281 and KP481.

Usage Patterns:

- Consider promoting KP781 to customers planning to use the treadmill more than four times a week, emphasizing its durability and advanced features.
- For customers using the treadmill two to three times a week, highlight the affordability and basic features of KP281 or mid-level features of KP481.

Fitness Enthusiasts:

- Leverage the positive correlation between fitness level and KP781 purchases by targeting fitness enthusiasts.
- Promote KP781 as the choice for individuals seeking an advanced workout experience.

Miles and Usage Correlation:

Capitalize on the strong correlation between miles covered and fitness levels to market KP781 to individuals running over 120 miles per week.

Partnered vs. Single Preferences:

Consider different marketing strategies for partnered and single individuals:

- Partnered individuals tend to prefer KP281, so emphasize its family-friendly features.
- Single individuals show a more balanced preference; highlight the unique features of KP781.

Continuous Monitoring:

Regularly monitor sales data and customer feedback to adapt marketing strategies based on evolving preferences and market trends.

In-Store Experience:

Enhance the in-store experience for customers by providing product demonstrations, allowing them to experience the unique features of KP781.

Diversity in Product Line:

- Consider introducing more products with different price points to cater to a broader audience.
- Conduct market research to identify potential gaps in the product line and consumer preferences.