In [1]:
```python
import pandas as pd
import numpy as np
from numpy import nan, NaN,NAN
from matplotlib import pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from scipy import stats
```

In [2]:
```python
aerofit=pd.read_csv("aerofit_treadmill.txt")
```

In [3]:
```python
df=aerofit.copy()
df
```

Out[3]:

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

In [4]:
```
df.shape
```

Out[4]:
```
(180, 9)
```

In [5]:
```
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
```

In [6]:
```
df.describe()
```

Out[6]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
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

Observation-No missing values present .

To Identify Unique Values in the data

In [7]:
```
df["Product"].value_counts()
```

Out[7]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [8]:
```
df["Education"].value_counts()
```

Out[8]:
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

In [9]:
```
df["MaritalStatus"].value_counts()
```

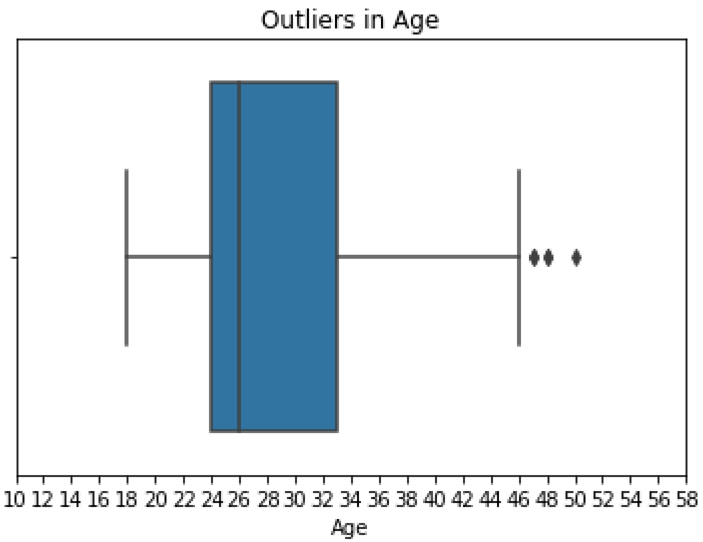
Out[9]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

In [10]:
```python
df["Fitness"].value_counts()
```

Out[10]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

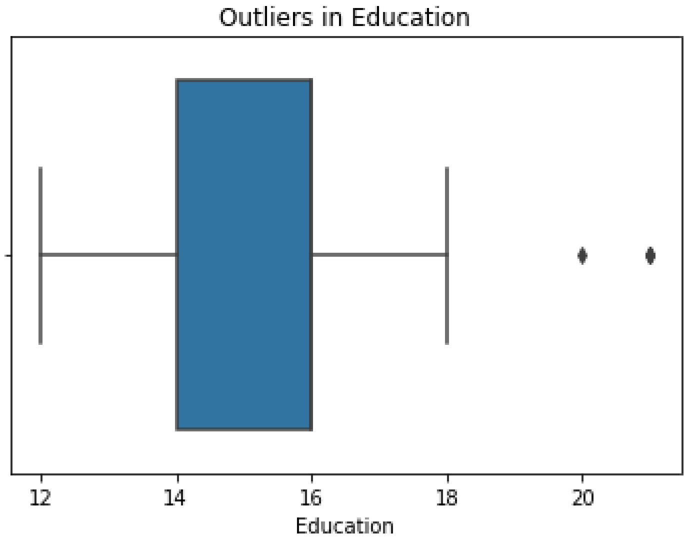
Outlier Detection

In [11]:
```python
sns.boxplot(df["Age"])
plt.xticks(np.arange(10,60,2))
plt.title("Outliers in Age")
#plt.grid()
plt.show()
```



Observation-Age above 46 years are outliers

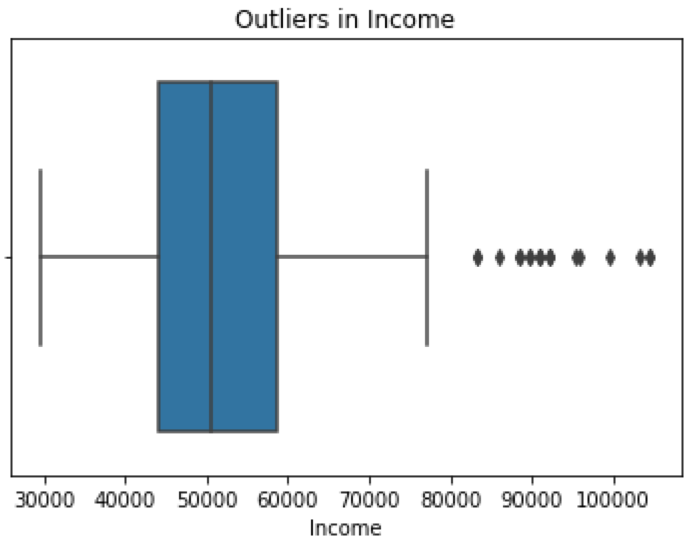
In [12]:
```
sns.boxplot(df["Education"])
plt.title("Outliers in Education")
#plt.grid()
plt.show()
```



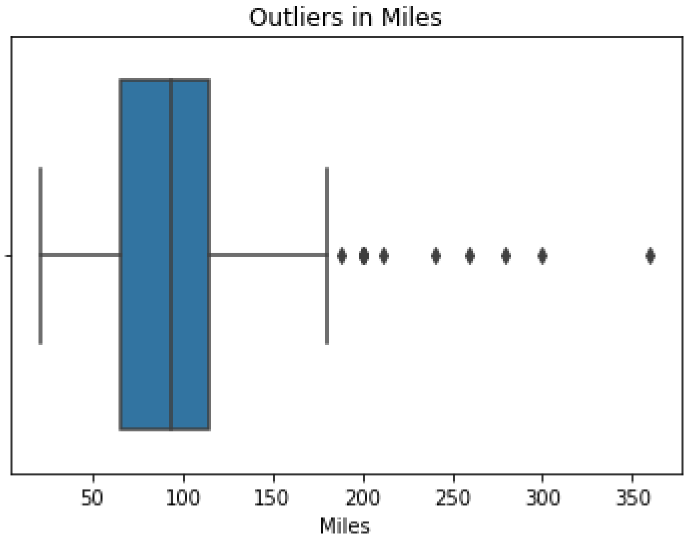
Observation-Education above 18 years are outliers

In [13]:

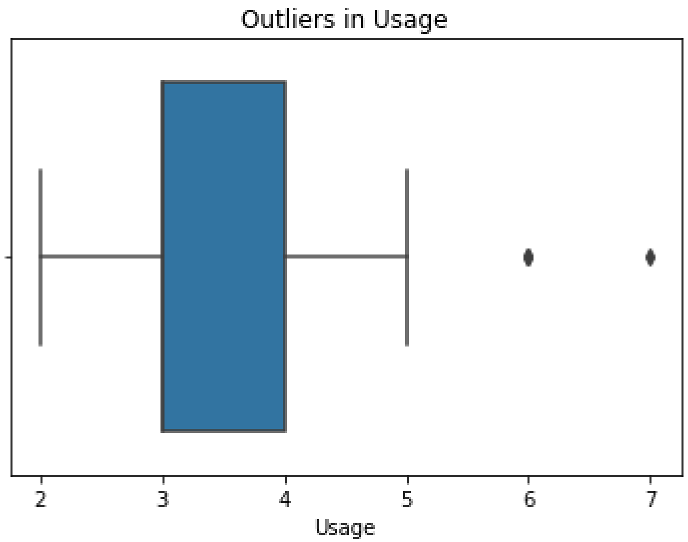
```
sns.boxplot(df["Income"])
plt.title("Outliers in Income")
#plt.grid()
plt.show()
```



In [14]:
```
sns.boxplot(df["Miles"])
plt.title("Outliers in Miles")
#plt.grid()
plt.show()
```

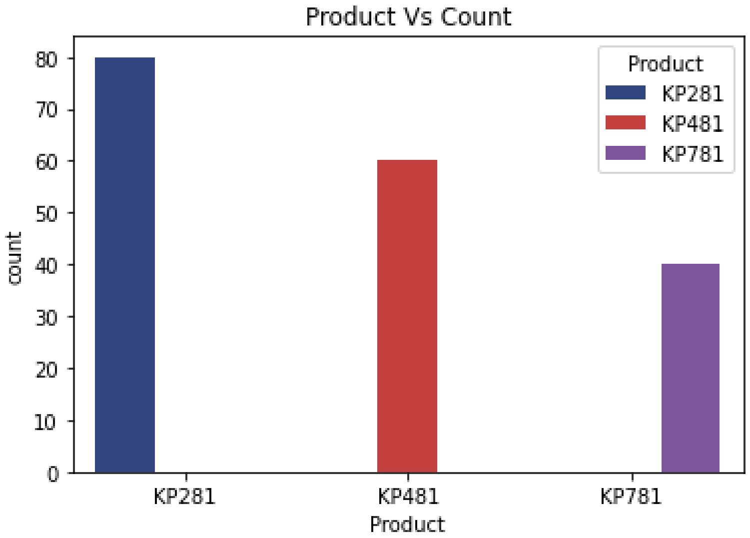


In [15]:
```
sns.boxplot(df["Usage"])
plt.title("Outliers in Usage")
#plt.grid()
plt.show()
```



Observation-There are more outliers in Income and Miles as compared to other data variables

In [16]:
```
colors = ["#243E8D", "#DB2A27","#7D49A8"]
sns.set_palette(sns.color_palette(colors))
sns.countplot(x="Product",data=df,hue="Product")
plt.title("Product Vs Count")
plt.show()
```



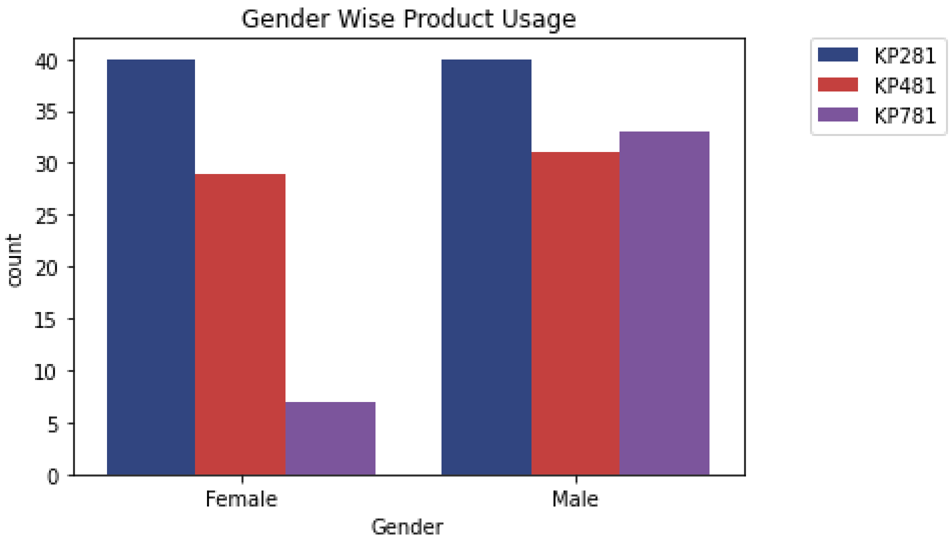
Observation -The most selled is the base model ie,KP281 and the least selled is the high end model ie,KP781

In [17]:
```
pr_gen=df.groupby(["Product","Gender"])["Product"].count().to_frame()
pr_gen.rename(columns={"Product":"count"},inplace=True)
pr_gen.reset_index(inplace=True)
pr_gen
```

Out[17]:

	Product	Gender	count
0	KP281	Female	40
1	KP281	Male	40
2	KP481	Female	29
3	KP481	Male	31
4	KP781	Female	7
5	KP781	Male	33

In [18]:
```
colors = ["#243E8D", "#DB2A27","#7D49A8"]
sns.set_palette(sns.color_palette(colors))
sns.barplot(x="Gender",y="count",data=pr_gen,hue="Product")
plt.title("Gender Wise Product Usage")
plt.legend(bbox_to_anchor=(1.1 ,1), loc='upper left', borderaxespad=0)
plt.show()
```



Observation-Males preffered the high end model KP781 more.The other two models seems to be equily liked by both the genders,but this can be better decided by the probabilty plots done under the head Customer Profiling.

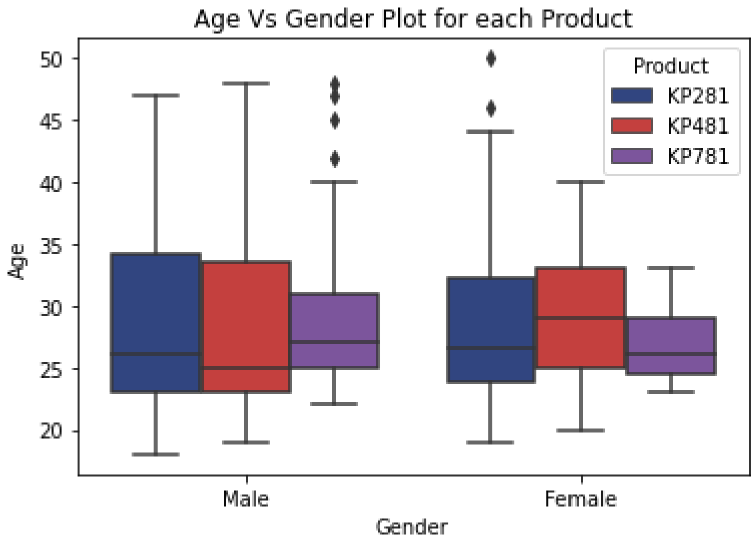
In [19]:
```
pr_gen_age=df.groupby(["Product","Gender","Age"])["Product"].count().to_frame()
pr_gen_age.rename(columns={"Product":"count"},inplace=True)
pr_gen_age.reset_index(inplace=True)
pr_gen_age
```

Out[19]:

	Product	Gender	Age	count
0	KP281	Female	19	1
1	KP281	Female	20	1
2	KP281	Female	21	2
3	KP281	Female	22	3
4	KP281	Female	23	3
...	...	...	...	...
97	KP781	Male	40	1
98	KP781	Male	42	1
99	KP781	Male	45	1
100	KP781	Male	47	1
101	KP781	Male	48	1

102 rows × 4 columns

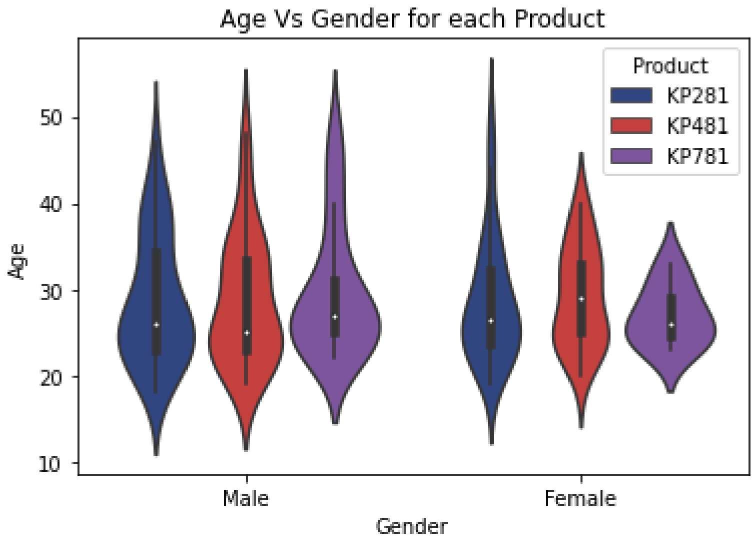
In [20]:
```
colors = ["#243E8D", "#DB2A27","#7D49A8"]
sns.set_palette(sns.color_palette(colors))
sns.boxplot(x="Gender",y="Age",data=df,hue="Product")
plt.title("Age Vs Gender Plot for each Product")
#plt.yticks(np.arange(16,60,2))
plt.show()
```



Observation-The median ages of females using KP481 is higher than males whereas for the other two models the median age of males are higher .Outliers are observed in the plot for the combination of Male-KP781 and Female-KP281.

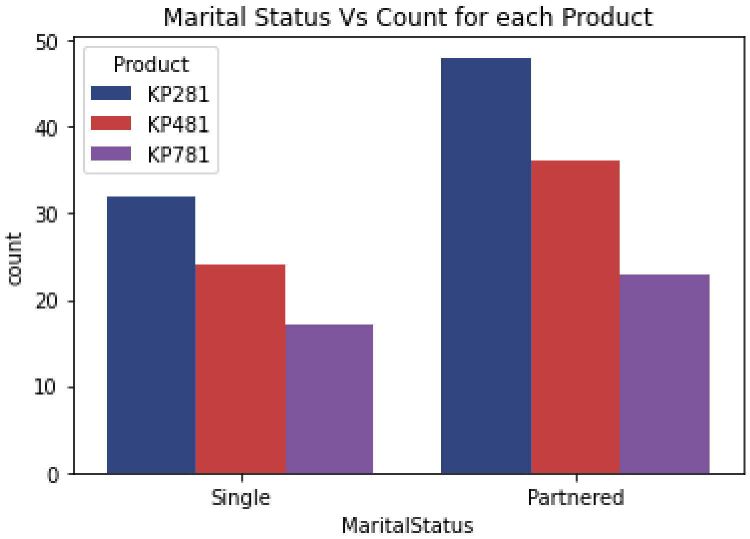
In [21]:
```
colors = ["#243E8D", "#DB2A27","#7D49A8"]
sns.set_palette(sns.color_palette(colors))
sns.violinplot(x="Gender",y="Age",data=df,hue="Product")
plt.title("Age Vs Gender for each Product")

plt.show()
```



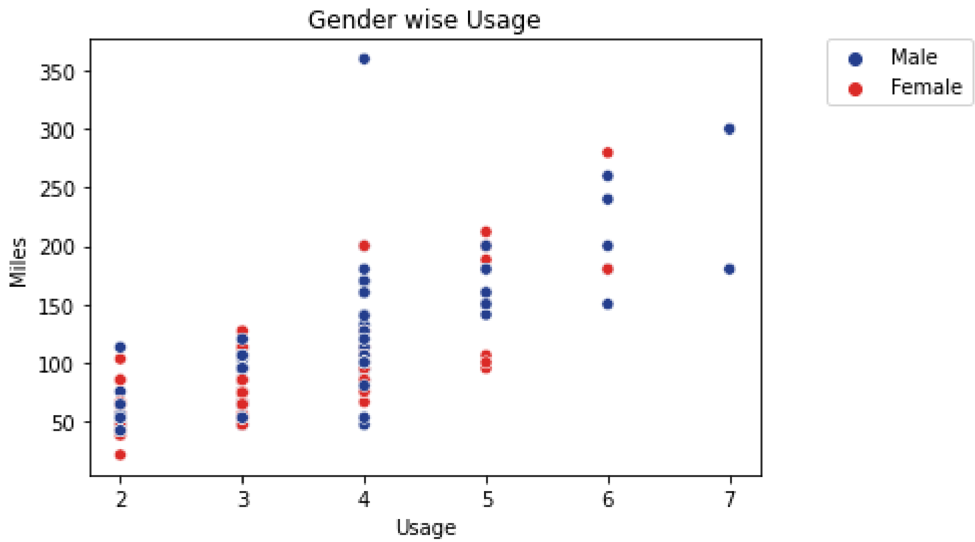
Observation-For KP281and KP481 there are more male users in the age group 20-30 than female users.Whereas for KP781 there are no female users beyond age 35

In [22]:
```
sns.countplot(x="MaritalStatus",data=df,hue="Product")
plt.title("Marital Status Vs Count for each Product")
plt.show()
```



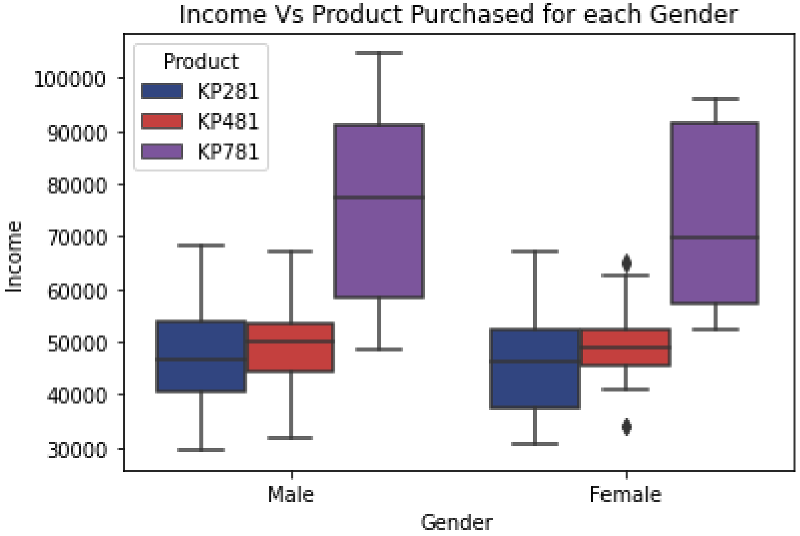
Observation-Across all models,people with marital status as Partnered are using the fitness equipments more

In [23]:
```
sns.scatterplot(x="Usage",y="Miles",data=df,hue="Gender")
plt.title("Gender wise Usage")
plt.legend(bbox_to_anchor=(1.1 ,1), loc='upper left', borderaxespad=0)
#plt.yticks(np.arange(16,60,2))
plt.show()
```



Observation-The miles covered and the usage of the product is higher in males as compared to females

In [24]:
```
sns.boxplot(x="Gender",y="Income",data=df,hue="Product")
plt.title("Income Vs Product Purchased for each Gender")
plt.show()
```



Observation-The people who purchased the high end model KP781 are having higher income compared to the lower variants.Their median income is close to 8000 and 7000 dollars for male and female repectively

Customer Profiling

In [25]:
```
pd.crosstab(index=df["Product"],columns=df["Gender"],margins=True,margins_name="Total")
```

Out[25]:

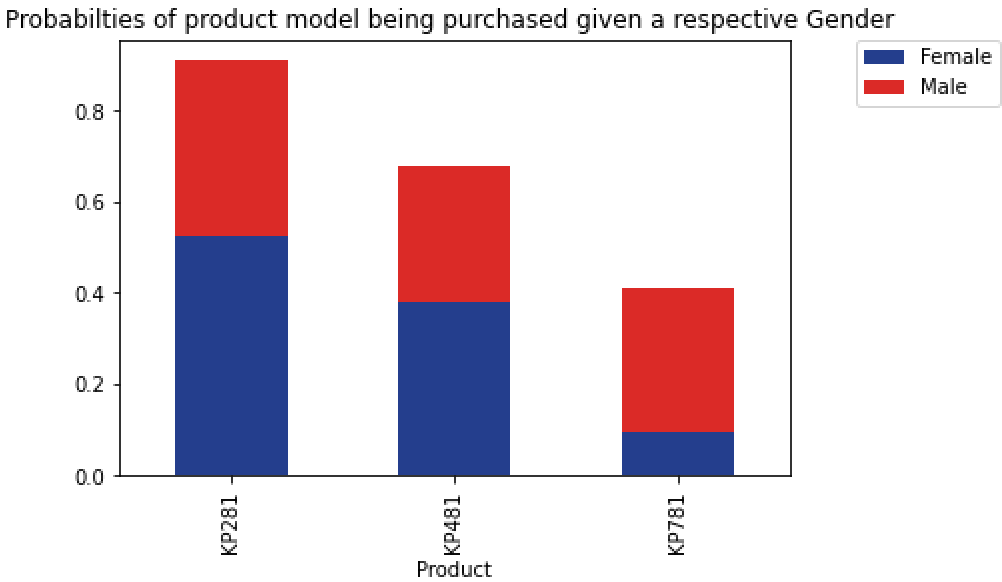
Gender Product	Female	Male	Total
KP281	40	40	80
KP481	29	31	60
KP781	7	33	40
Total	76	104	180

In [26]:
```
pd.crosstab(index=df["Product"],columns=df["Gender"],normalize="columns",margins=True,margins_name="Marginal Probability
```

Out[26]:

Gender Product	Female	Male	Marginal Probability
KP281	0.526316	0.384615	0.444444
KP481	0.381579	0.298077	0.333333
KP781	0.092105	0.317308	0.222222

In [27]:
```
pd.crosstab(index=df["Product"],columns=df["Gender"],normalize="columns").plot.bar(stacked=True)
plt.title("Probabilties of product model being purchased given a respective Gender ")
plt.legend(bbox_to_anchor=(1.1 ,1), loc='upper left', borderaxespad=0)
plt.show()
```



Observation-Females prefered the base and the intermediate models more than Males.Whereas the advanced model is prefered more by males.

In [28]:
```
pd.crosstab(index=df["Product"],columns=df["Fitness"],margins=True,margins_name="Total")
```

Out[28]:

Fitness	1	2	3	4	5	Total
Product						
KP281	1	14	54	9	2	80
KP481	1	12	39	8	0	60
KP781	0	0	4	7	29	40
Total	2	26	97	24	31	180

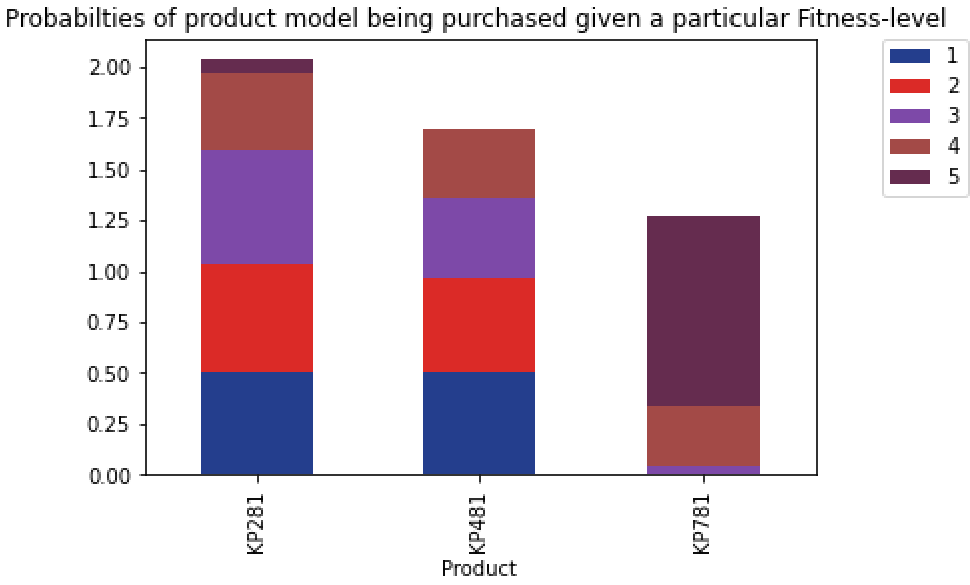
Observation-53% of the sample belonged to Fitness level 3 .17.2% in fitness level 5 and 14% in fitness level 2

In [29]:
```
d=pd.crosstab(index=df["Product"],columns=df["Fitness"],normalize="columns")
d
```

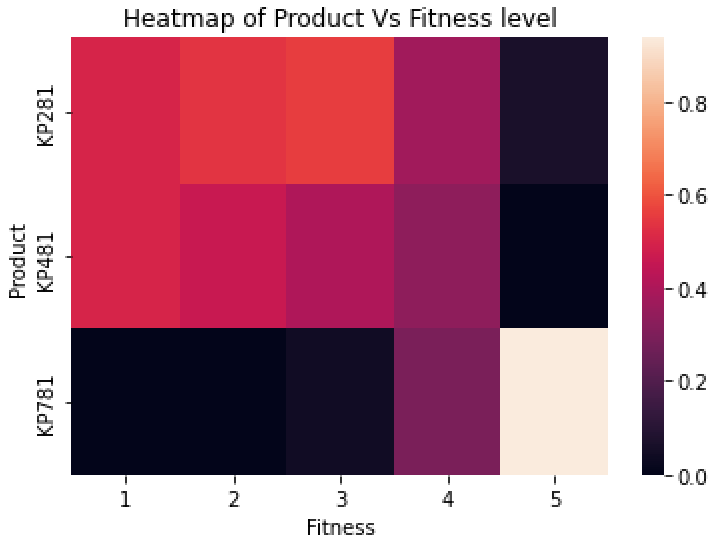
Out[29]:

Fitness	1	2	3	4	5
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

In [30]:
```
colors = ["#243E8D", "#DB2A27","#7D49A8","#A34A47","#652C4F"]
sns.set_palette(sns.color_palette(colors))
pd.crosstab(index=df["Product"],columns=df["Fitness"],normalize="columns").plot.bar(stacked=True)
plt.title("Probabilties of product model being purchased given a particular Fitness-level ")
plt.legend(bbox_to_anchor=(1.1 ,1), loc='upper left', borderaxespad=0)
plt.show()
```



In [31]:
```
sns.heatmap(d)
plt.title("Heatmap of Product Vs Fitness level")
plt.show()
```



Observation-Given fitness level is 5,the probability that advanced model is purchased is 0.93.Given fitness level 4,3 and 2 the popular model is the base model(KP281)

In [32]:
```
df.insert(9,"AgeGroup","")
```

In [33]:
```
idx=df.loc[(df["Age"]>=18)&(df["Age"]<=24)].index
idx
```

Out[33]:
```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,
             13,  14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,
             26,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,  91,
             92,  93,  94,  95,  96, 140, 141, 142, 143, 144, 145, 146, 147,
            148, 149],
           dtype='int64')
```

In [34]:
```
df.loc[idx,["AgeGroup"]]='18-24'
```

In [35]:
```
idx=df.loc[(df["Age"]>=25)&(df["Age"]<=34)].index
idx
```

Out[35]:
```
Int64Index([ 27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,  39,
             40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,  52,
             53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  97,  98,  99,
            100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112,
            113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125,
            126, 127, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160,
            161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172],
           dtype='int64')
```

In [36]:
```
df.loc[idx,["AgeGroup"]]='25-34'
```

In [37]:
```
idx=df.loc[(df["Age"]>=35)&(df["Age"]<=44)].index
idx
```

Out[37]:
```
Int64Index([ 63,  64,  65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,
             76, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 173, 174,
            175, 176],
           dtype='int64')
```

In [38]:
```
df.loc[idx,["AgeGroup"]]='35-44'
```

In [39]:
```
idx=df.loc[(df["Age"]>=45)].index
idx
```
Out[39]:
```
Int64Index([77, 78, 79, 138, 139, 177, 178, 179], dtype='int64')
```
In [40]:
```
df.loc[idx,["AgeGroup"]]='45&above'
```
In [41]:
```
pd.crosstab(index=df["Product"],columns=df["AgeGroup"],margins=True,margins_name="Total")
```
Out[41]:

AgeGroup	18-24	25-34	35-44	45&above	Total
Product					
KP281	27	36	14	3	80
KP481	17	31	10	2	60
KP781	10	23	4	3	40
Total	54	90	28	8	180

In [42]:
```
pd.crosstab(index=df["Product"],columns=df["AgeGroup"],normalize="all",margins=True,margins_name="Total")
```
Out[42]:

AgeGroup	18-24	25-34	35-44	45&above	Total
Product					
KP281	0.150000	0.200000	0.077778	0.016667	0.444444
KP481	0.094444	0.172222	0.055556	0.011111	0.333333
KP781	0.055556	0.127778	0.022222	0.016667	0.222222
Total	0.300000	0.500000	0.155556	0.044444	1.000000

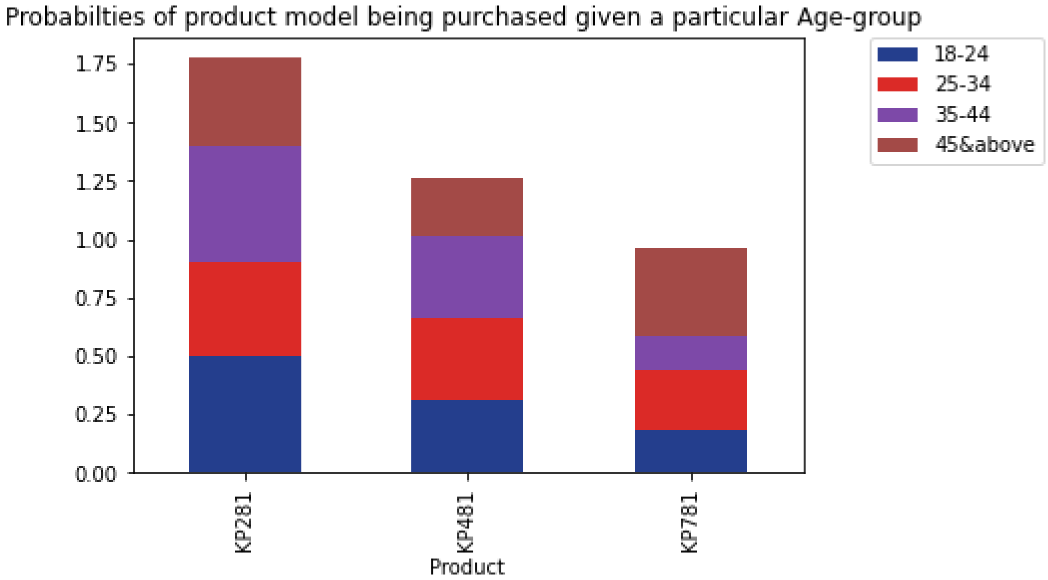
Observation-Young Adults in the age group of 18-24 years(30%) and 25-34 years(50%) are mostly the users of the product.

In [43]:
```
s=pd.crosstab(index=df["Product"],columns=df["AgeGroup"],normalize="columns")
s
```

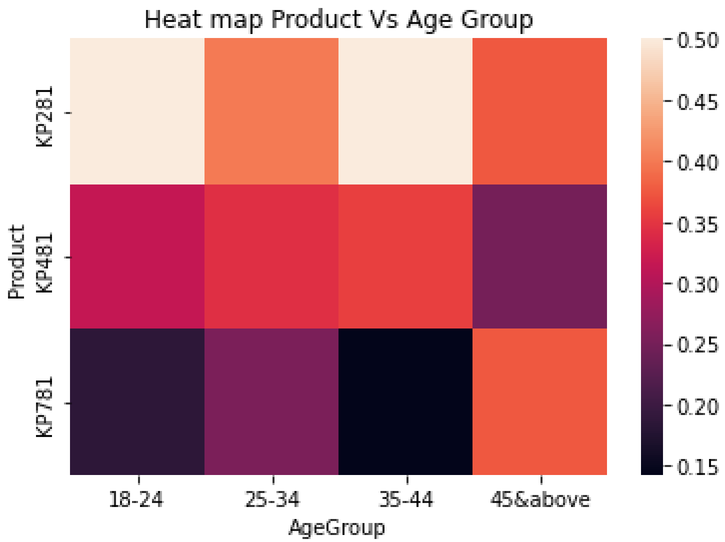
Out[43]:

AgeGroup Product	18-24	25-34	35-44	45&above
KP281	0.500000	0.400000	0.500000	0.375
KP481	0.314815	0.344444	0.357143	0.250
KP781	0.185185	0.255556	0.142857	0.375

In [44]:
```
pd.crosstab(index=df["Product"],columns=df["AgeGroup"],normalize="columns").plot.bar(stacked=True)
plt.title("Probabilties of product model being purchased given a particular Age-group ")
plt.legend(bbox_to_anchor=(1.1 ,1), loc='upper left', borderaxespad=0)
plt.show()
```



In [45]:
```
sns.heatmap(s)
plt.title("Heat map Product Vs Age Group")
plt.show()
```



Observation-The base model are popular within the age groups from 18-24 and 35- 44 years.The Intermediate within age groups between 18 to 44 years with slight variations in their conditional probabilities. The advanced model is popular mostly for age group 25-34 years and 45&above years

In [46]:
```
pd.crosstab(index=df["Product"],columns=[df.AgeGroup,df.MaritalStatus],margins=True)
```

Out[46]:

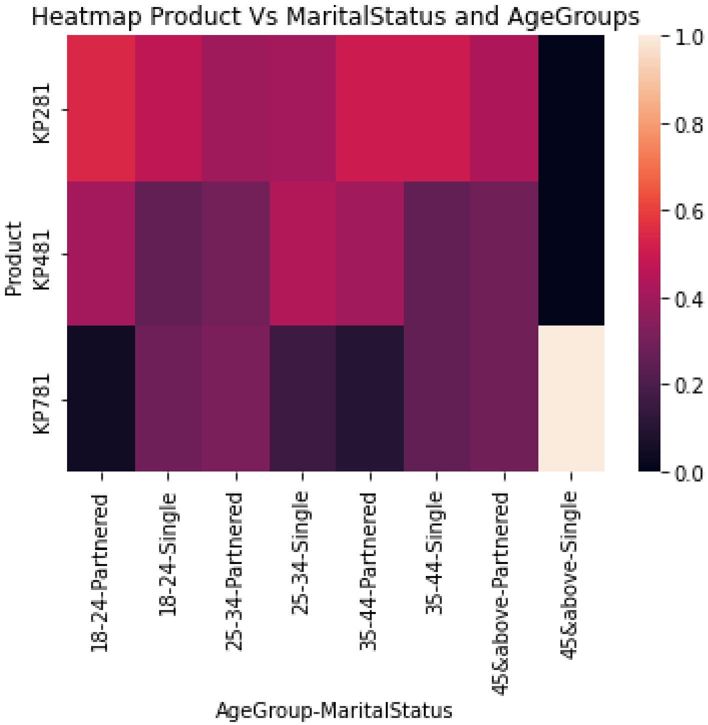
AgeGroup	18-24		25-34		35-44		45&above		All
MaritalStatus	Partnered	Single	Partnered	Single	Partnered	Single	Partnered	Single	
Product									
KP281	12	15	23	13	10	4	3	0	80
KP481	9	8	17	14	8	2	2	0	60
KP781	1	9	18	5	2	2	2	1	40
All	22	32	58	32	20	8	7	1	180

In [47]:
```
k=pd.crosstab(index=df["Product"],columns=[df.AgeGroup,df.MaritalStatus],normalize="columns")
k
```

Out[47]:

AgeGroup	18-24		25-34		35-44		45&above	
MaritalStatus	Partnered	Single	Partnered	Single	Partnered	Single	Partnered	Single
Product								
KP281	0.545455	0.46875	0.396552	0.40625	0.5	0.50	0.428571	0.0
KP481	0.409091	0.25000	0.293103	0.43750	0.4	0.25	0.285714	0.0
KP781	0.045455	0.28125	0.310345	0.15625	0.1	0.25	0.285714	1.0

In [75]:
```
sns.heatmap(k)
plt.title("Heatmap Product Vs MaritalStatus and AgeGroups")
plt.show()
```



Observation-For Partnered age groups base model is prefered more.Whereas for single the preference also depends on the age group they belong to.For instance the people with Marital status as single in the age group of 18-24 years and 35-44 years prefered

the base model more while25-34 years prefered the Intermediate model.For 45&above strong conclusions cannot be drawn since only 4% of the total sample is from this age group.

In [52]:
```
df.insert(10,"IncomeGroup","")
```

In [56]:
```
idx=df.loc[(df["Income"]>25000)&(df["Age"]<=45000)].index
df.loc[idx,["IncomeGroup"]]='25001-45000'
```

In [57]:
```
idx=df.loc[(df["Income"]>45000)&(df["Age"]<=65000)].index
df.loc[idx,["IncomeGroup"]]='45001-65000'
```

In [58]:
```
idx=df.loc[(df["Income"]>65000)&(df["Age"]<=85000)].index
df.loc[idx,["IncomeGroup"]]='65001-85000'
```

In [60]:
```
idx=df.loc[(df["Income"]>85000)].index
df.loc[idx,["IncomeGroup"]]='85001&above'
```

In [61]:
```
df
```

Out[61]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	AgeGroup	IncomeGroup
0	KP281	18	Male	14	Single	3	4	29562	112	18-24	25001-45000
1	KP281	19	Male	15	Single	2	3	31836	75	18-24	25001-45000
2	KP281	19	Female	14	Partnered	4	3	30699	66	18-24	25001-45000
3	KP281	19	Male	12	Single	3	3	32973	85	18-24	25001-45000
4	KP281	20	Male	13	Partnered	4	2	35247	47	18-24	25001-45000
...	...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	35-44	65001-85000
176	KP781	42	Male	18	Single	5	4	89641	200	35-44	85001&above
177	KP781	45	Male	16	Single	5	5	90886	160	45&above	85001&above
178	KP781	47	Male	18	Partnered	4	5	104581	120	45&above	85001&above
179	KP781	48	Male	18	Partnered	4	5	95508	180	45&above	85001&above

180 rows × 11 columns

In [63]:
```
pd.crosstab(index=df["Product"],columns=df["IncomeGroup"],margins=True)
```

Out[63]:

IncomeGroup	25001-45000	45001-65000	65001-85000	85001&above	All
Product					
KP281	34	44	2	0	80
KP481	15	43	2	0	60
KP781	0	16	7	17	40
All	49	103	11	17	180

Observation-People with income less than 65000 dollars preffered the base in intermediate models more.Whereas people with income higher that than this prefered the Advance model .

In [64]:
```
pd.crosstab(index=df["Product"],columns=df["Education"],margins=True)
```

Out[64]:

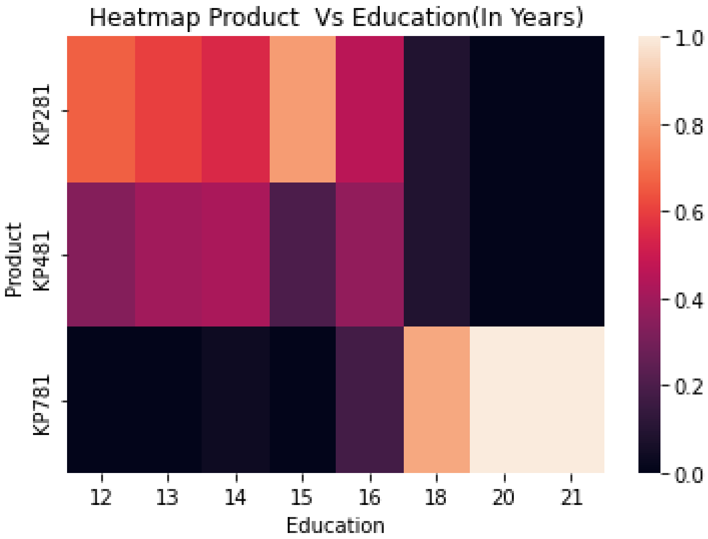
Education	12	13	14	15	16	18	20	21	All
Product									
KP281	2	3	30	4	39	2	0	0	80
KP481	1	2	23	1	31	2	0	0	60
KP781	0	0	2	0	15	19	1	3	40
All	3	5	55	5	85	23	1	3	180

In [67]:
```
s=pd.crosstab(index=df["Product"],columns=df["Education"],normalize='columns')
s
```

Out[67]:

Education	12	13	14	15	16	18	20	21
Product								
KP281	0.666667	0.6	0.545455	0.8	0.458824	0.086957	0.0	0.0
KP481	0.333333	0.4	0.418182	0.2	0.364706	0.086957	0.0	0.0
KP781	0.000000	0.0	0.036364	0.0	0.176471	0.826087	1.0	1.0

In [70]:
```
sns.heatmap(s)
plt.title("Heatmap Product  Vs Education(In Years)")
plt.show()
```



Observation-There is a clear distinction in the preference of model ie,People with upto 15years of education prefer Base model more over the other models.A person with higher years of education say (18 years)prefers the advance model more.Since education above 18years are outliers in the sample strong conclusions cannot be made for them .

Recommendation

44% of the sample prefered the entry level treadmill KP281,followed by the mid-level .The advanced model is having least preference(22%).So its likely to have more KP281 models which could sell more than the other models

53% of the sample belonged to Fitness level 3 followed by Fitness level 5 and 2 .Hence more emphasis must be given to their preferences.The Probability plots reveal that probability of choosing the basemodel given that the person is in Fitness level 3 is 0.556 and that he/she choose the intermediate model is 0.4.Thus once again the base model is prefered more.

The probability plots also shows that people with fitness level 5,uses the advanced model ie,KP781.Its probability is 0.93.Hence the sales of this model can be increased among people who are very fit.

People with Higher income (>65000 dollars)prefered the Advanced model more whereas people with lower income prefered the base and intermediate models.Hence sales of the repective models can be increased based on customer Income

The people with Marital status as single in the age group of 18-24 years and 35-44 years prefered the base model more while25-34 years prefered the Intermediate model.For 45&above strong conclusions cannot be drawn since only 4% of the total sample is from this age group and they are also outliers

People with Marital status as Partnered prefered the Base model hence the sales of KP281 can be increased in the partnered age groups