## **Analysis**

```
* Out of 576 active players, 84% were male and 14% were female.

* The main age demographic are players aged 20-24 (44.79%). Secondary and tertiary groups fell between 15-19 (18.60%) and 25-29 (13.4%), respectively.

* The most popular item was "Oathbreaker, Last Hope of the Breaking Storm"
```

### **Player Count**

```
In [1]: # Dependencies and Setup
import pandas as pd
import numpy as np

# File to Load
pymoli_df = "Resources/purchase_data.csv"

# Read Purchasing File and store into Pandas data frame
purchase_data = pd.read_csv(pymoli_df)
```

```
In [3]: player_count = purchase_data["SN"].nunique()
    total_df = pd.DataFrame({"Total Players": [player_count]})
    total_df
```

#### Out[3]:

```
Total Players

0 576
```

# **Purchasing Analysis (Total)**

```
In [18]: item_count = purchase_data["Item ID"].nunique()
    average_price = round(purchase_data["Price"].mean(),2)
    purchase_count = purchase_data["Purchase ID"].nunique()
    total_revenue = purchase_data["Price"].sum()

purchase_summary_df = pd.DataFrame({
        "Number of Unique Items": [item_count],
        "Average Price": [average_price],
        "Number of Purchases": [purchase_count],
        "Total Revenue": [total_revenue]

})

purchase_summary_df
```

#### Out[18]:

	Number of Unique Items	Average Price	Number of Purchases	Total Revenue
0	183	3.05	780	2379.77

### **Gender Demographics**

#### Out[7]:

	Total Count	Percentage of Players
Male	484	84.03%
Female	81	14.06%
Other / Non-Disclosed	11	1.91%

### **Purchasing Analysis (Gender)**

```
In [26]: grouped_gender_df = purchase_data.groupby(['Gender'])

gender_purchase_count = grouped_gender_df["Price"].count()
purchase_price_avg = round(grouped_gender_df["Price"].mean(),2)
purchase_total_avg = grouped_gender_df["Price"].sum()
avg_purchase_pp = purchase_total_avg/gender_count_total

purchase_analysis_gender = pd.DataFrame({"Purchase Count": gender_purcha "Average Purchase Price": purch "Total Purchase Value": purchase "Avg Total Purchase Per Person"

})

purchase_analysis_gender
```

#### Out[26]:

	Purchase Count	Average Purchase Price	Total Purchase Value	Avg Total Purchase Per Person
Gender				
Female	113	\$3.20	\$361.94	\$4.47
Male	652	\$3.02	\$1,967.64	\$4.07
Other / Non-	15	\$3.35	\$50.19	\$4.56

### **Age Demographics**

```
In [21]: bins = [0, 9.90, 14.90, 19.90, 24.90, 29.90,
                 34.90, 39.90, 9991
         group_labels = ["< 10", "10-14", "15-19", "20-24", "25-29", "30-34",
                         "35-39", "40+"]
         pd.cut(purchase data["Age"], bins, labels=group labels)
         purchase data["Age Group"] = pd.cut(purchase data["Age"], bins, labels=g
         age df = purchase data.groupby("Age Group")
         total age count = age df["Age"].count()
         clean age count = purchase data[['SN', 'Gender', 'Age', 'Age Group']].drop
         clean age df = clean age count.drop duplicates()
         clean age df2 = clean age df.groupby("Age Group")
         clean total age count = clean age df2["Age"].count()
         age percentage = clean age df2["Age"].count()/player count *100
         age_demographic_df = pd.DataFrame({"Total Count": clean_total_age_count,
                                              "Percentage of Players": age percent
         age demographic df
```

#### Out[21]:

#### **Total Count Percentage of Players**

Age Group		
< 10	17	2.95%
10-14	22	3.82%
15-19	107	18.58%
20-24	258	44.79%
25-29	77	13.37%
30-34	52	9.03%
35-39	31	5.38%
40+	12	2.08%

# **Purchasing Analysis (Age)**

```
bins = [0, 9.90, 14.90, 19.90, 24.90, 29.90,
In [25]:
                 34.90, 39.90, 9991
         group_labels = ["< 10", "10-14", "15-19", "20-24", "25-29", "30-34",
                         "35-39", "40+"]
         pd.cut(purchase data["Age"], bins, labels=group labels)
         age purchase df = purchase data.groupby("Age Group")
         age_purchase_count = age_purchase_df["Item ID"].count()
         age avgpurchase = age purchase df["Price"].mean()
         total purchase value = age purchase df["Price"].sum()
         avg purchase pp = total purchase value/clean total age count
         purchase analysis age df = pd.DataFrame({"Purchase Count":age purchase c
                                                   age avgpurchase.map("${:,.2f}".
                                                   "Total Purchase Value": total p
                                                   "Avg Total Purchase Per Person"
                                              })
         purchase analysis age df
```

#### Out[25]:

	Purchase Count	Average Purchase Price	Total Purchase Value	Avg Total Purchase Per Person
Age Group				
< 10	23	\$3.35	\$77.13	\$4.54
10-14	28	\$2.96	\$82.78	\$3.76
15-19	136	\$3.04	\$412.89	\$3.86
20-24	365	\$3.05	\$1,114.06	\$4.32
25-29	101	\$2.90	\$293.00	\$3.81
30-34	73	\$2.93	\$214.00	\$4.12
35-39	41	\$3.60	\$147.67	\$4.76
40+	13	\$2.94	\$38.24	\$3.19

### **Top Spenders**

#### Out[12]:

Purchase Count		Average Purchase Price	Total Purchase Value
SN			
Lisosia93	5	\$3.79	\$18.96
Iral74	4	\$3.40	\$13.62
Idastidru52	4	\$3.86	\$15.45
Asur53	3	\$2.48	\$7.44
Inguron55	3	\$3.70	\$11.11

# **Most Popular Items**

#### Out[13]:

		Purchase Count	Item Price	Total Purchase Value
Item ID	Item Name			
178	Oathbreaker, Last Hope of the Breaking Storm	12	4.23	\$50.76
145	Fiery Glass Crusader	9	4.58	\$41.22
108	Extraction, Quickblade Of Trembling Hands	9	3.53	\$31.77
82	Nirvana	9	4.90	\$44.10
19	Pursuit, Cudgel of Necromancy	8	1.02	\$8.16

### **Most Profitable Items**

In [20]: sorted\_profitable\_df = sorted\_popular\_df.sort\_values(by=['Total Purchase sorted\_profitable\_df.head()

#### Out[20]:

		<b>Purchase Count</b>	Item Price	Total Purchase Value
Item ID	Item Name			
63	Stormfury Mace	2	4.99	\$9.98
29	Chaos, Ender of the End	5	1.98	\$9.90
173	Stormfury Longsword	2	4.93	\$9.86
1	Crucifer	3	3.26	\$9.78
38	The Void, Vengeance of Dark Magic	4	2.37	\$9.48