In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import xlrd
```

In [4]:
```
data = pd.read_csv("BankChurners.csv")
```

In [5]:
```
data.sample(10)
```

Out[5]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_ |
|---|---|---|---|---|---|---|
| **8264** | 789151983 | Existing Customer | 43 | F | 4 | Gra |
| **1404** | 710798883 | Existing Customer | 52 | M | 3 | Gra |
| **2005** | 718577958 | Attrited Customer | 39 | M | 2 | Unedu |
| **9212** | 711826983 | Attrited Customer | 47 | F | 3 | Unk |
| **7924** | 780360558 | Existing Customer | 33 | F | 1 | Gra |
| **3746** | 714162033 | Existing Customer | 45 | F | 3 | Post-Gra |
| **8918** | 717382608 | Existing Customer | 59 | M | 1 | Gra |
| **5911** | 709487058 | Existing Customer | 51 | F | 2 | Unk |
| **1426** | 709267308 | Existing Customer | 62 | M | 1 | Gra |
| **1738** | 708623283 | Existing Customer | 35 | M | 2 | Unedu |

10 rows × 23 columns

In [6]:
```
data.columns
```

Out[6]:
```
Index(['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Coun
t_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Coun
t_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2'],
      dtype='object')
```

## Dropped unnecessary coloumns

In [7]:
```
columns_to_drop = ['Naive_Bayes_Classifier_Attrition_Flag_Card_Category_C
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Coun
data = data.drop(columns=columns_to_drop)
```

In [8]:
```
data.head()
```

Out[8]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_Leve |
|---|---|---|---|---|---|---|
| **0** | 768805383 | Existing Customer | 45 | M | 3 | High Schoo |
| **1** | 818770008 | Existing Customer | 49 | F | 5 | Graduat |
| **2** | 713982108 | Existing Customer | 51 | M | 3 | Graduat |
| **3** | 769911858 | Existing Customer | 40 | F | 4 | High Schoo |
| **4** | 709106358 | Existing Customer | 40 | M | 3 | Uneducate |

5 rows × 21 columns

In [9]:
```
data['Attrition_Flag'].value_counts()
```

Out[9]:
```
Attrition_Flag
Existing Customer    8500
Attrited Customer    1627
Name: count, dtype: int64
```

In [10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   CLIENTNUM                 10127 non-null  int64  
 1   Attrition_Flag            10127 non-null  object 
 2   Customer_Age              10127 non-null  int64  
 3   Gender                    10127 non-null  object 
 4   Dependent_count           10127 non-null  int64  
 5   Education_Level           10127 non-null  object 
 6   Marital_Status            10127 non-null  object 
 7   Income_Category           10127 non-null  object 
 8   Card_Category             10127 non-null  object 
 9   Months_on_book            10127 non-null  int64  
 10  Total_Relationship_Count  10127 non-null  int64  
 11  Months_Inactive_12_mon    10127 non-null  int64  
 12  Contacts_Count_12_mon     10127 non-null  int64  
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64  
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64  
 18  Total_Trans_Ct            10127 non-null  int64  
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

In [11]:
```
data1 = data[['Attrition_Flag', 'Avg_Utilization_Ratio']]
data1.head(3)
```

Out[11]:

| | Attrition_Flag | Avg_Utilization_Ratio |
|---|---|---|
| **0** | Existing Customer | 0.061 |
| **1** | Existing Customer | 0.105 |
| **2** | Existing Customer | 0.000 |

In [12]:
```
data1['Attrition_Flag'] = data1['Attrition_Flag'].apply(lambda x: x.split
data1.head(4)
```

```
/var/folders/qr/9x6pfw9d58vf78nhsqtb93mh0000gn/T/ipykernel_819/113016644
3.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data1['Attrition_Flag'] = data1['Attrition_Flag'].apply(lambda x: x.spl
it()[0])
```

Out[12]:

| | Attrition_Flag | Avg_Utilization_Ratio |
|---|---|---|
| **0** | Existing | 0.061 |
| **1** | Existing | 0.105 |
| **2** | Existing | 0.000 |
| **3** | Existing | 0.760 |

In [13]:
```
atr = data1[data1['Attrition_Flag'] == 'Attrited']
atr['Avg_Utilization_Percent'] = atr['Avg_Utilization_Ratio'].apply(lambd
atr = atr.drop('Avg_Utilization_Ratio', axis = 1)
atr.head(4)
```

```
/var/folders/qr/9x6pfw9d58vf78nhsqtb93mh0000gn/T/ipykernel_819/116130579
4.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  atr['Avg_Utilization_Percent'] = atr['Avg_Utilization_Ratio'].apply(lam
bda x: x*100)
```

Out[13]:

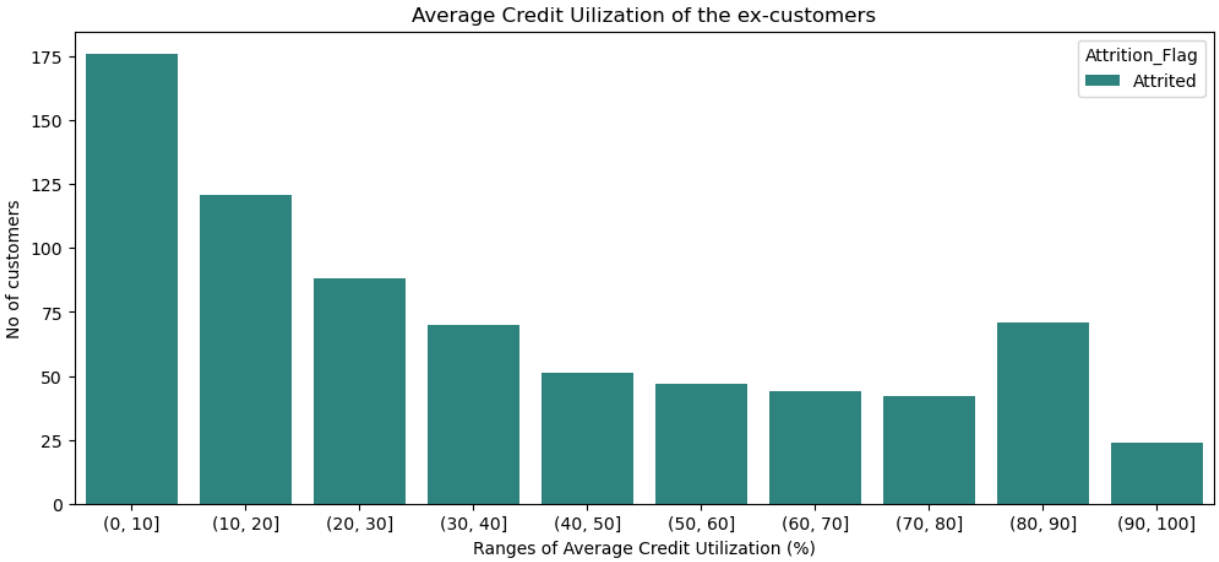
| | Attrition_Flag | Avg_Utilization_Percent |
|---|---|---|
| **21** | Attrited | 0.0 |
| **39** | Attrited | 7.7 |
| **51** | Attrited | 56.2 |
| **54** | Attrited | 0.0 |

In [14]:
```
# Define the bins or ranges
bins = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100]

# Used pd.cut to categorize values into bins
atr['Ratio_Category'] = pd.cut(atr['Avg_Utilization_Percent'], bins=bins)

# Got the count of occurrences in each bin
count_in_ranges = atr['Ratio_Category'].value_counts()

atr.sample(4)
```

Out[14]:

| | Attrition_Flag | Avg_Utilization_Percent | Ratio_Category |
|---|---|---|---|
| **8999** | Attrited | 0.5 | (0.0, 10.0] |
| **8022** | Attrited | 0.0 | NaN |
| **9408** | Attrited | 0.0 | NaN |
| **5155** | Attrited | 0.0 | NaN |

In [15]:
```
plt.figure(figsize=(12, 5))
sns.countplot(x='Ratio_Category', data=atr, hue='Attrition_Flag', palette
plt.title('Average Credit Uilization of the ex-customers')
plt.xlabel('Ranges of Average Credit Utilization (%)')
plt.ylabel('No of customers')
plt.show()
```




- **Inference**

Most ex-customers have used their card **below 10%**.

- Firstly, what we learned from our dataset is the income group of **40-60k USD** is predominant. The lesser the income the lesser becomes the card usage and expense.
- Secondly, the more a person utilizes the card to a higher limit it becomes more difficult to get par with the interest rates.
- Thirdly, there may be reluctancy to use the card from these customers because they wanted to drop the cards.

In [16]:
```
exs = data1[data1['Attrition_Flag'] == 'Existing']
exs['Avg_Utilization_Percent'] = exs['Avg_Utilization_Ratio'].apply(lambd
exs = exs.drop('Avg_Utilization_Ratio', axis = 1)
exs.head(3)
```

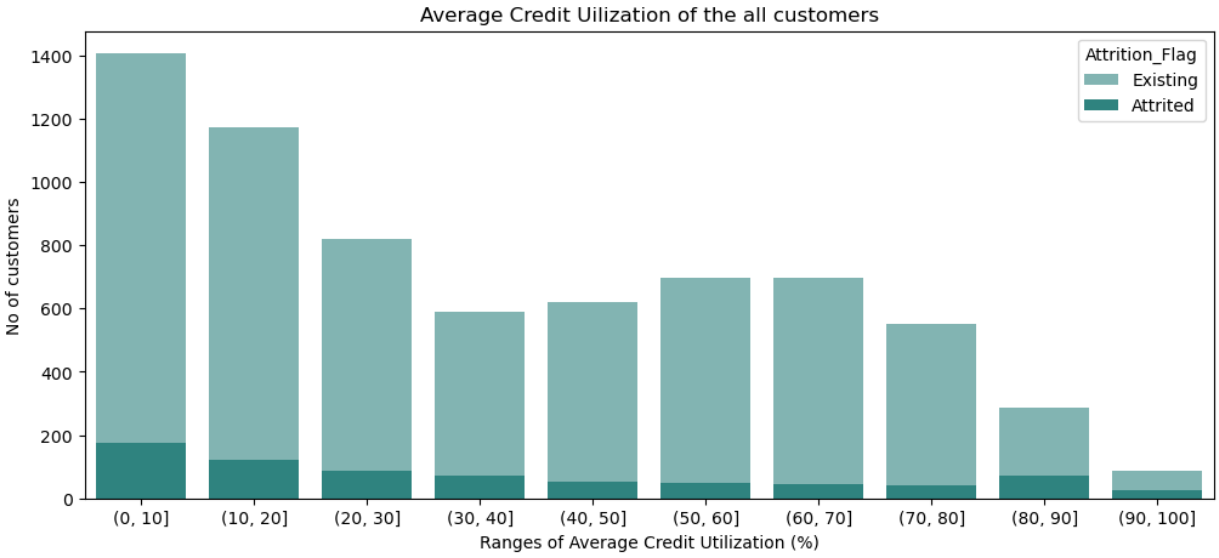
```
/var/folders/qr/9x6pfw9d58vf78nhsqtb93mh0000gn/T/ipykernel_819/178454499
4.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  exs['Avg_Utilization_Percent'] = exs['Avg_Utilization_Ratio'].apply(lam
bda x: x*100)
```

Out[16]:

| | Attrition_Flag | Avg_Utilization_Percent |
|---|---|---|
| **0** | Existing | 6.1 |
| **1** | Existing | 10.5 |
| **2** | Existing | 0.0 |

In [17]:
```
bins = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100] #bins are left closed

# Used pd.cut to categorize values into bins
exs['Ratio_Category'] = pd.cut(exs['Avg_Utilization_Percent'], bins=bins)

# Getting the count of occurrences in each bin
count_in_ranges = exs['Ratio_Category'].value_counts()
```

In [18]:
```
plt.figure(figsize=(12, 5))
sns.countplot(x='Ratio_Category', data=exs, hue='Attrition_Flag', palette
sns.countplot(x='Ratio_Category', data=atr, hue='Attrition_Flag', palette
plt.title('Average Credit Uilization of the all customers')
plt.xlabel('Ranges of Average Credit Utilization (%)')
plt.ylabel('No of customers')
plt.show()
```




- **Inference**

Most customers have used their card **below 10%**. However, there is another rise around **50% - 70%**

- No of attrited or ex-customers are way lesser than the present customers.
- This plot is more influenced by the existing customers. Existing customers have used the cards more than the ex-customer as they wanted to continue using the cards.

# Customers & Card Types

In [19]:
```
data = pd.read_csv("BankChurners.csv")
```

In [20]:
```
data.columns
```

Out[20]:
```
Index(['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Coun
t_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Coun
t_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2'],
      dtype='object')
```

In [21]:
```
card_gen = data[['Gender', 'Card_Category']]
card_gen.head(3)
```

Out[21]:

| | Gender | Card_Category |
|---|---|---|
| **0** | M | Blue |
| **1** | F | Blue |
| **2** | M | Blue |

# Genderwise Distribution of Cards

In [22]:
```
male_cards = card_gen[card_gen['Gender'] == "M"]
male_cards_final = male_cards['Card_Category'].value_counts()
male_cards_final = pd.DataFrame(male_cards_final)
male_cards_final
```

Out[22]:

| | count |
|---|---|
| **Card_Category** | |
| **Blue** | 4335 |
| **Silver** | 345 |
| **Gold** | 78 |
| **Platinum** | 11 |

In [23]:
```
female_cards = card_gen[card_gen['Gender'] == "F"]
female_cards_final = female_cards['Card_Category'].value_counts()
female_cards_final = pd.DataFrame(female_cards_final)
female_cards_final
```

Out[23]:

| Card_Category | count |
|---|---|
| **Blue** | 5101 |
| **Silver** | 210 |
| **Gold** | 38 |
| **Platinum** | 9 |

In [24]:
```
mf_card = pd.merge(female_cards_final, male_cards_final, on = 'Card_Categ
```

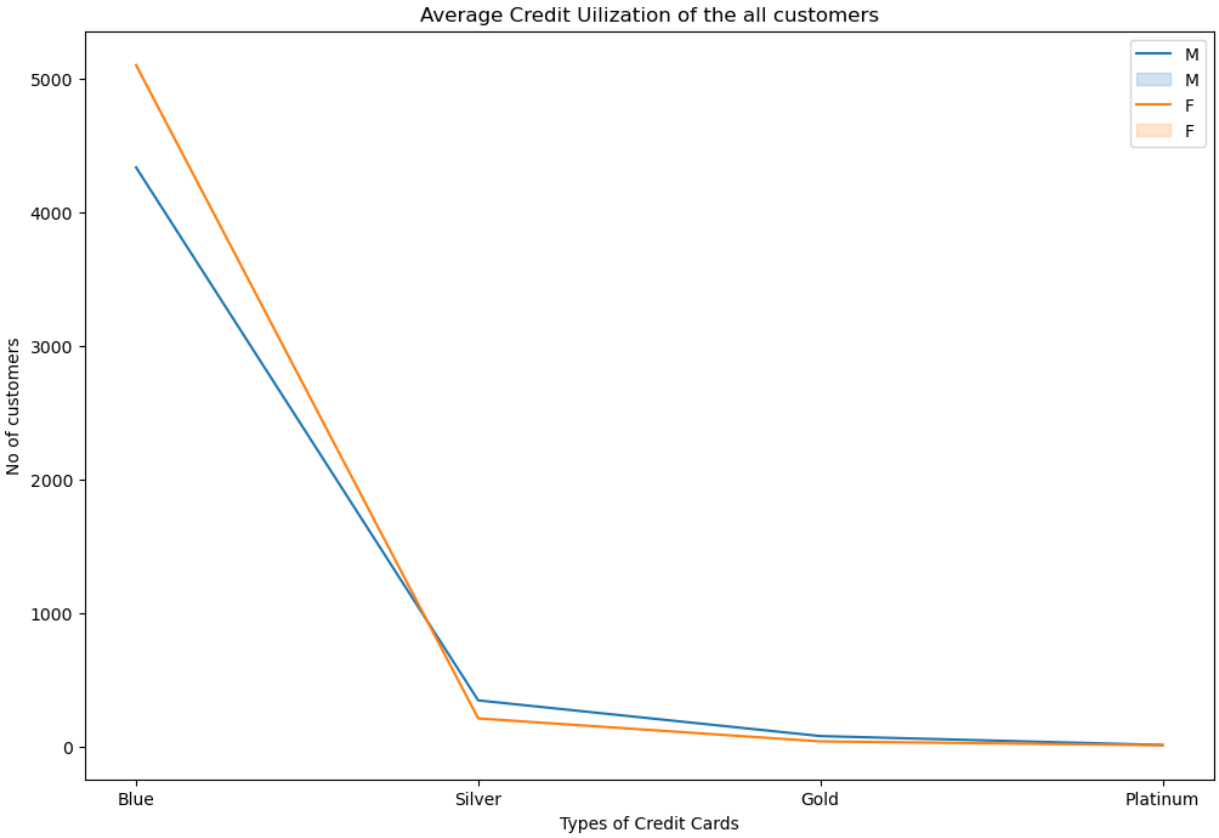
In [25]:
```
mf_card.rename(columns={'count_y': 'Male', 'count_x': 'Female'}, inplace=
```

In [26]:
```
mf_card.reset_index(inplace = True) #very crucial
mf_card
```

Out[26]:

| | Card_Category | Female | Male |
|---|---|---|---|
| **0** | Blue | 5101 | 4335 |
| **1** | Silver | 210 | 345 |
| **2** | Gold | 38 | 78 |
| **3** | Platinum | 9 | 11 |

In [27]:
```
plt.figure(figsize=(12, 8))
sns.lineplot(x='Card_Category', y = 'Male' ,data=mf_card)
sns.lineplot(x='Card_Category', data=mf_card, y = 'Female')
plt.title('Average Credit Uilization of the all customers')
plt.xlabel('Types of Credit Cards')
plt.ylabel('No of customers')
plt.legend('MMFF')
plt.show()
```




- **Inference**

Surprisingly female customers are having more blue cards than male customers.

- Firstly, the less charges of the **blue** cards.
- Secondly, there may have been such cases where husband-wife both use cards, where husband uses higher-tier cards like **Silver, Gold or Platinum**

# Master Dataset

From now on the below dataset is solely used in later cases.

In [28]:
```
e1 = data[['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio']]
```

# Card Type and Age

In [42]:
```
data = pd.read_csv("BankChurners.csv")
```

In [43]:
```
c_age = e1[['Customer_Age', 'Income_Category','Card_Category']]
c_age.sample(3)
```

Out[43]:

| | Customer_Age | Income_Category | Card_Category |
|---|---|---|---|
| **9658** | 41 | $60K-80K$ | Blue |
| **6783** | 50 | Less than $40K | Blue |
| **8741** | 54 | $40K-60K$ | Blue |

In [44]:
```
bins1 = [0, 20, 30, 40, 50, 60, 70, 80] #bins are left closed right open
c_age['Customer_Age_Classes'] = pd.cut(c_age['Customer_Age'], bins=bins1)
c_age.sample(4)
```

```
/var/folders/qr/9x6pfw9d58vf78nhsqtb93mh0000gn/T/ipykernel_1824/112471542
3.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  c_age['Customer_Age_Classes'] = pd.cut(c_age['Customer_Age'], bins=bins
1)
```

Out[44]:

| | Customer_Age | Income_Category | Card_Category | Customer_Age_Classes |
|---|---|---|---|---|
| **4070** | 42 | Unknown | Blue | (40, 50] |
| **5726** | 42 | $60K-80K$ | Blue | (40, 50] |
| **3669** | 50 | $60K-80K$ | Blue | (40, 50] |
| **6500** | 42 | Less than $40K | Blue | (40, 50] |

# No of Customers in each Age Group

In [45]:
```
age_count_in_ranges = c_age['Customer_Age_Classes'].value_counts()
age_count_in_ranges.reset_index()
```

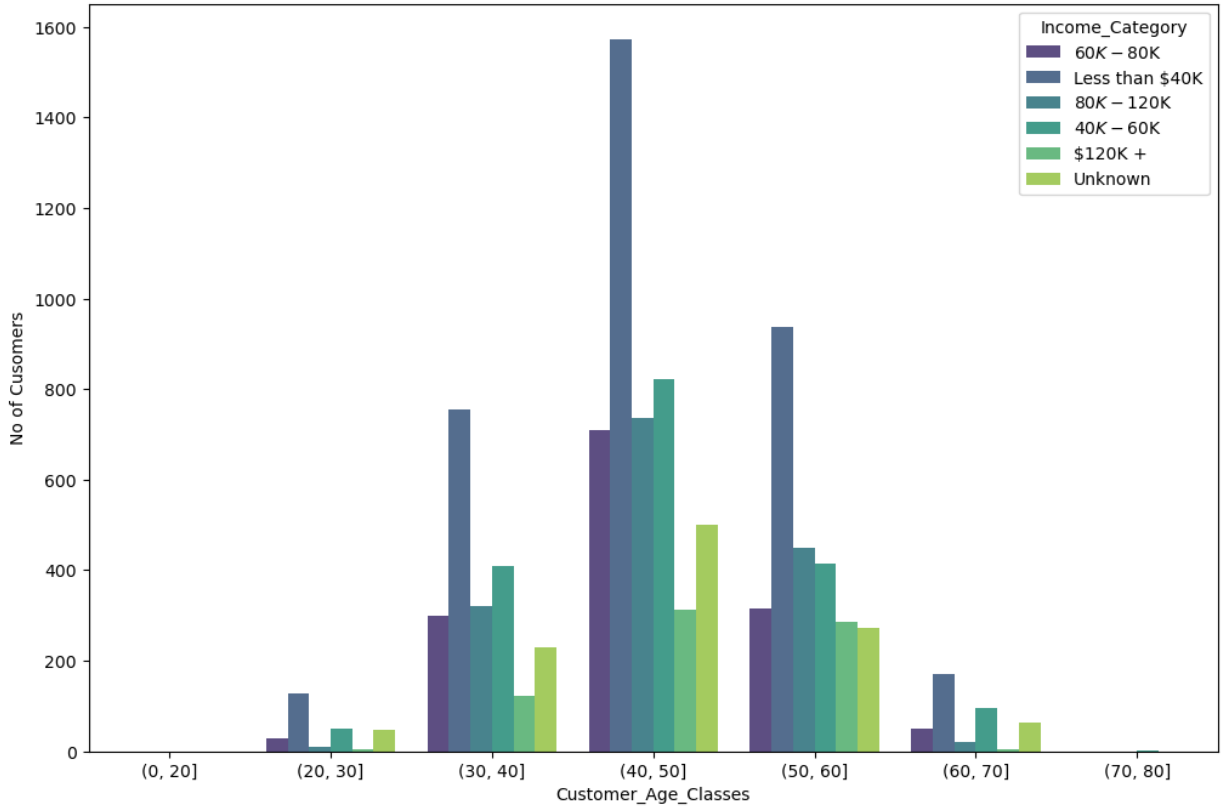
Out[45]:

| | Customer_Age_Classes | count |
|---|---|---|
| **0** | (40, 50] | 4652 |
| **1** | (50, 60] | 2673 |
| **2** | (30, 40] | 2132 |
| **3** | (60, 70] | 404 |
| **4** | (20, 30] | 265 |
| **5** | (70, 80] | 1 |
| **6** | (0, 20] | 0 |

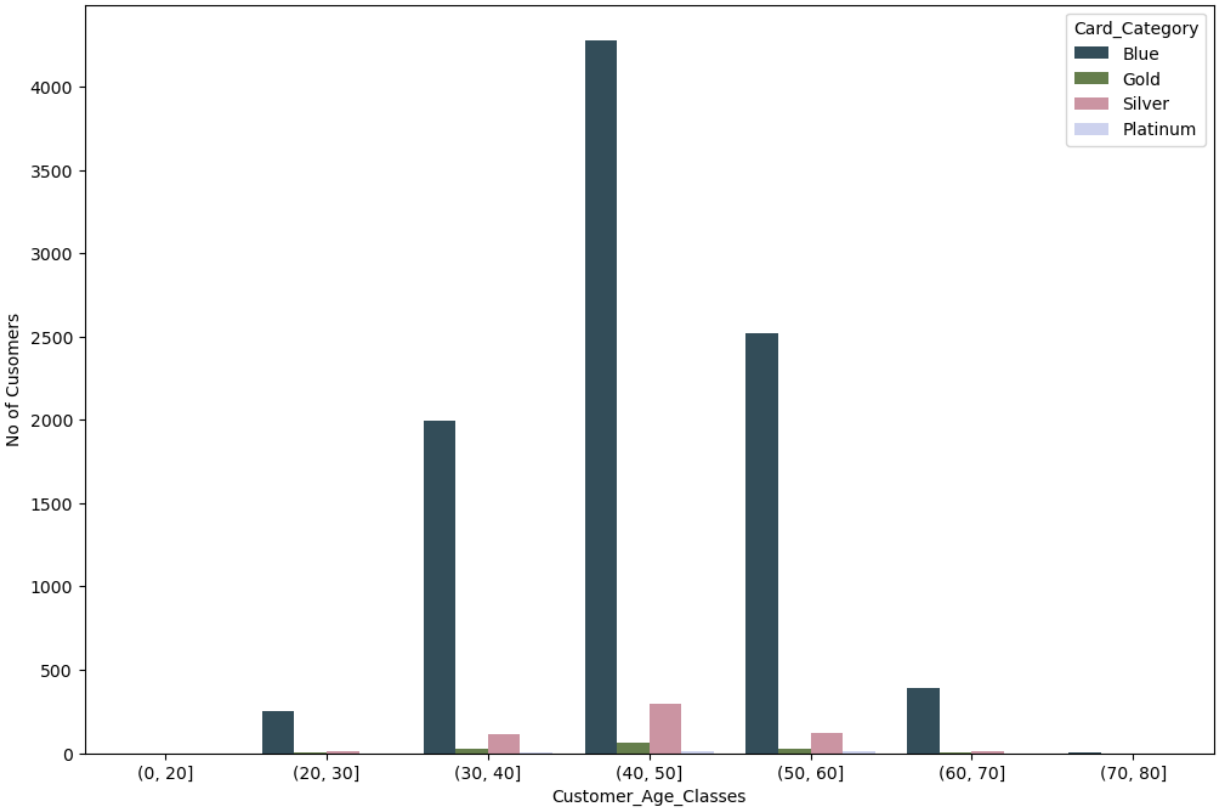
- **Inference**

In almost each age group the customers with annual income between **60000** USD and **80000** USD are dominant, followed by group of annual income less than **40000** USD

In [46]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Customer_Age_Classes',data=c_age, palette = 'viridis', h
plt.ylabel('No of Cusomers');
```




In [47]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='Customer_Age_Classes',data=c_age, palette = 'cubehelix',
plt.ylabel('No of Cusomers');
```




- **Inference**

In almost each age group the customers with **Blue** Cards are dominant, followed by **Silver, Gold & Platinum.** This is due to the service charges, annual charges etc. being lesser than the rest of the cards.

# Marital Status vs Credit Limit

In [48]:
```
main_coloumns = data[['Marital_Status', 'Total_Revolving_Bal', 'Avg_Open_
main_coloumns.sample(4)
```

Out[48]:

| | Marital_Status | Total_Revolving_Bal | Avg_Open_To_Buy | Credit_Limit |
|---|---|---|---|---|
| **362** | Single | 2274 | 32242.0 | 34516.0 |
| **4474** | Married | 916 | 4995.0 | 5911.0 |
| **112** | Divorced | 1674 | 1589.0 | 3263.0 |
| **9873** | Single | 1642 | 32874.0 | 34516.0 |

In [49]:
```
grouped_data = main_coloumns.groupby(['Marital_Status']).mean()
grouped_data.apply(lambda x: round(x, 2))
```

Out[49]:

| Marital_Status | Total_Revolving_Bal | Avg_Open_To_Buy | Credit_Limit |
|---|---|---|---|
| **Divorced** | 1155.98 | 8202.58 | 9358.57 |
| **Married** | 1197.16 | 6879.50 | 8076.66 |
| **Single** | 1124.24 | 7875.44 | 8999.68 |
| **Unknown** | 1157.75 | 8287.53 | 9445.28 |

In [50]:
```
grouped_data.reset_index(inplace = True)
grouped_data
```

Out[50]:

| | Marital_Status | Total_Revolving_Bal | Avg_Open_To_Buy | Credit_Limit |
|---|---|---|---|---|
| **0** | Divorced | 1155.981283 | 8202.583824 | 9358.565107 |
| **1** | Married | 1197.163644 | 6879.498250 | 8076.661895 |
| **2** | Single | 1124.241441 | 7875.443317 | 8999.684758 |
| **3** | Unknown | 1157.748999 | 8287.534179 | 9445.283178 |

In [51]:
```
data = pd.read_csv("BankChurners.csv")
data.sample(4)
```

Out[51]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_ |
|---|---|---|---|---|---|---|
| **7948** | 714424533 | Attrited Customer | 41 | F | 4 | Gra |
| **9288** | 717781608 | Existing Customer | 52 | F | 3 | Gra |
| **9348** | 709934808 | Existing Customer | 59 | M | 1 | Unk |
| **4467** | 708916083 | Attrited Customer | 49 | F | 0 | Doc |

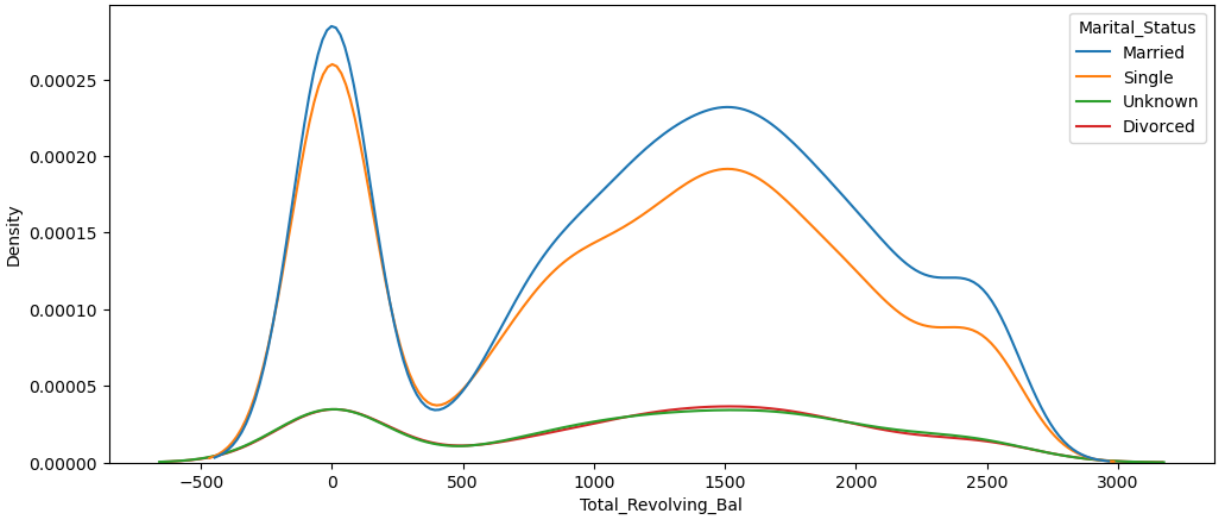
4 rows × 23 columns

In [52]:
```
e1 = data[['Customer_Age','Gender',"Dependent_count", "Attrition_Flag" ,'
           'Marital_Status', 'Total_Revolving_Bal', 'Avg_Open_To_Buy','Cr
           'Avg_Utilization_Ratio', 'Total_Trans_Amt' ,"Total_Trans_Ct",'
       'Contacts_Count_12_mon']]
e1.sample(4)
```

Out[52]:

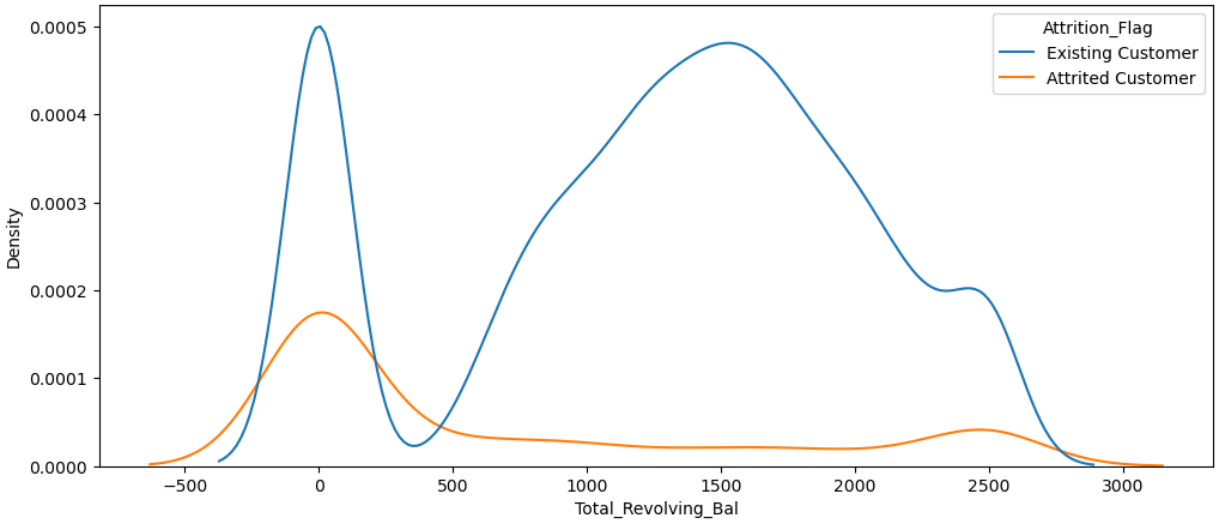
| | Customer_Age | Gender | Dependent_count | Attrition_Flag | Education_Level | Card_C |
|---|---|---|---|---|---|---|
| **4537** | 48 | F | 3 | Attrited Customer | Graduate | |
| **2584** | 54 | M | 1 | Existing Customer | College | |
| **9896** | 44 | F | 1 | Existing Customer | High School | |
| **1276** | 26 | F | 0 | Existing Customer | Graduate | |

In [53]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Total_Revolving_Bal', hue = 'Marital_Status'
```



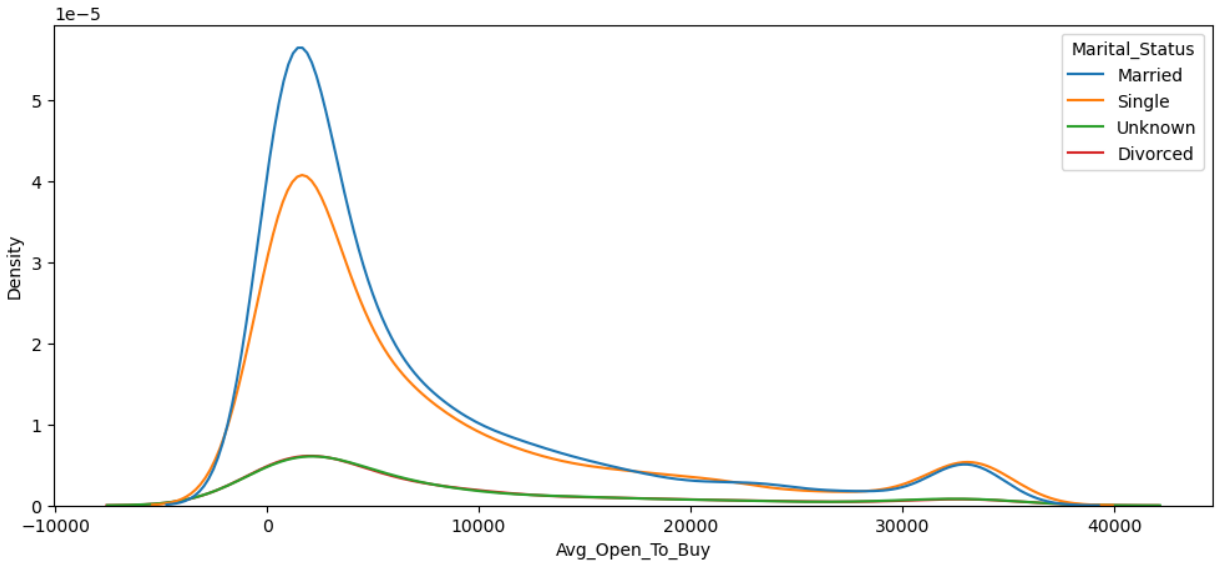

- **Inference:**
  - Married people are dominant.
  - The whole population seemingly has due amount between **1000 - 2500 USD**

In [54]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Total_Revolving_Bal', hue = 'Attrition_Flag')
```



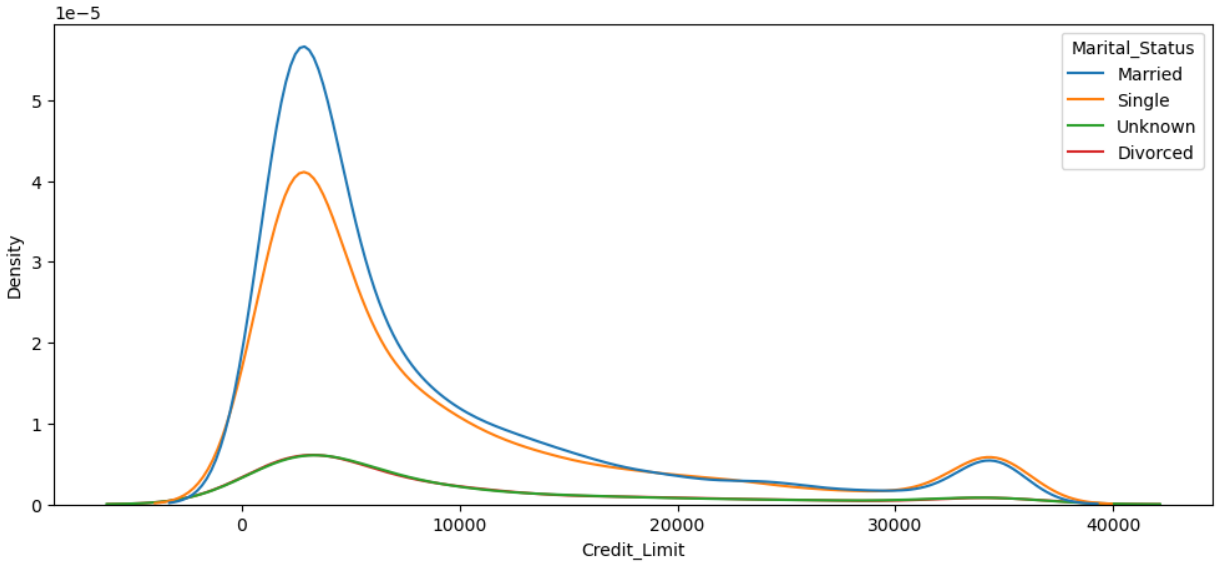

- **Inference:**
  - **Existing** customers are dominant.
  - The whole population seemingly has due amount between **1000 - 2500 USD**

In [55]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Avg_Open_To_Buy', hue = 'Marital_Status');
```



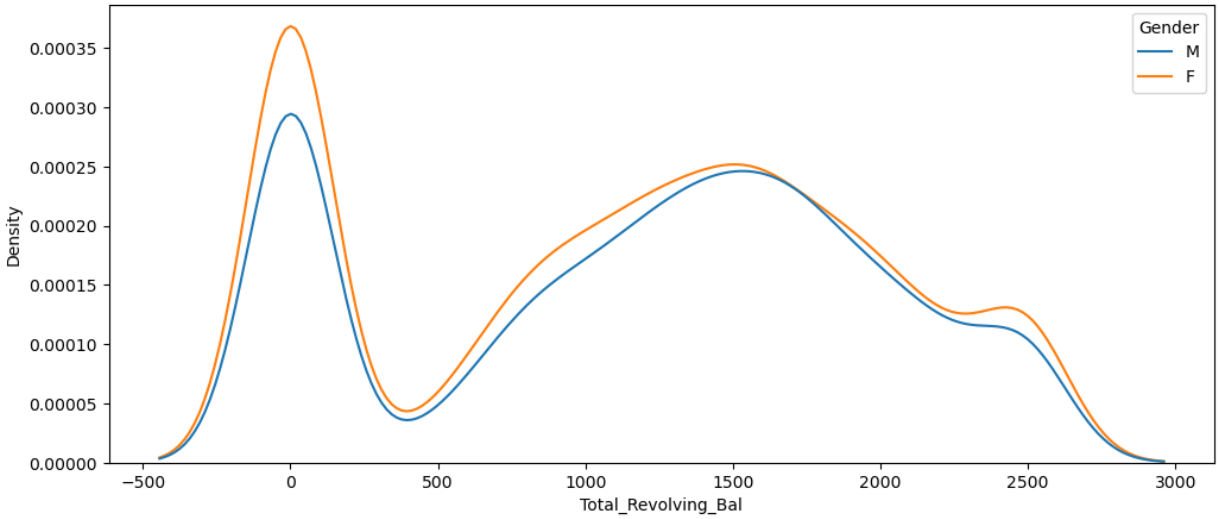

- **Inference:**
  - A lot of **Married** customers have used their card to the limit.

In [56]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Credit_Limit', hue = 'Marital_Status' );
```



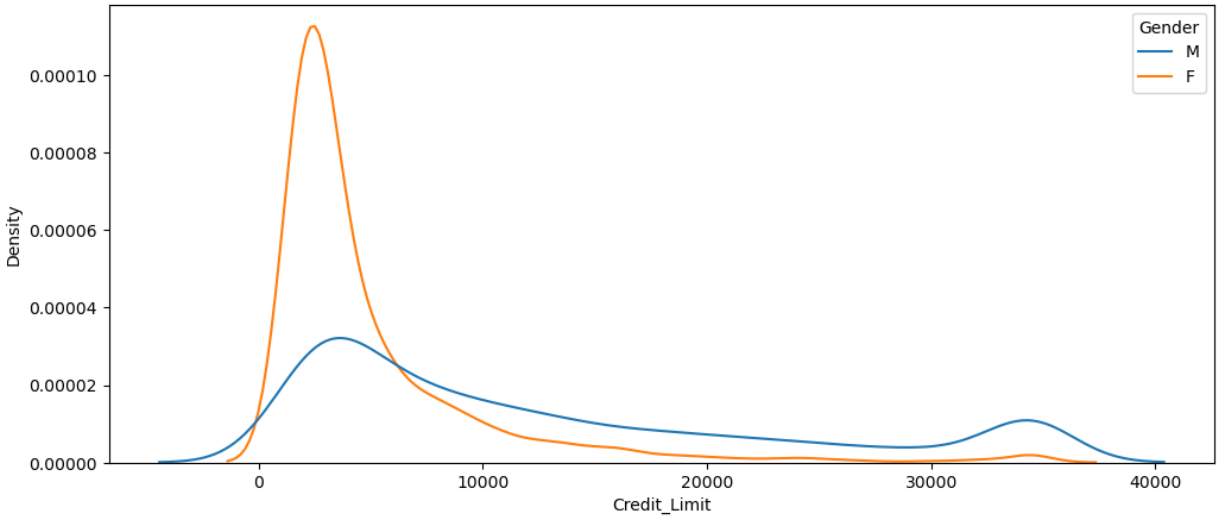

- **Inference:**
  - A lot of **Married** customers have credit limit below **10000 USD**.

In [57]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Total_Revolving_Bal', hue = 'Gender' );
```



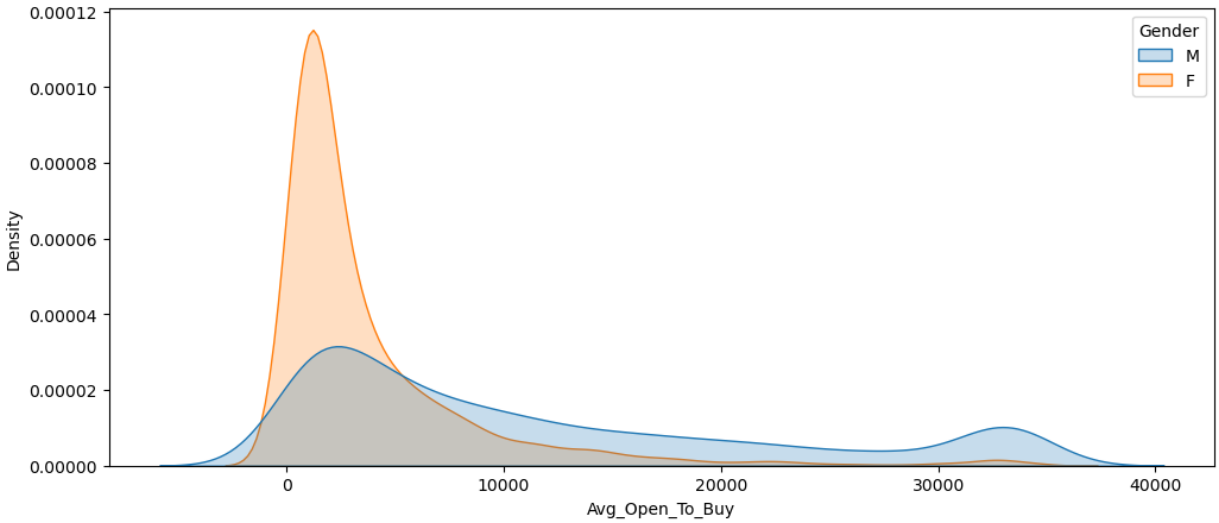

- **Inference:**
  - A lot of male customers have due balance between **1000 - 2000 USD**.

In [58]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Credit_Limit', hue = 'Gender' );
```



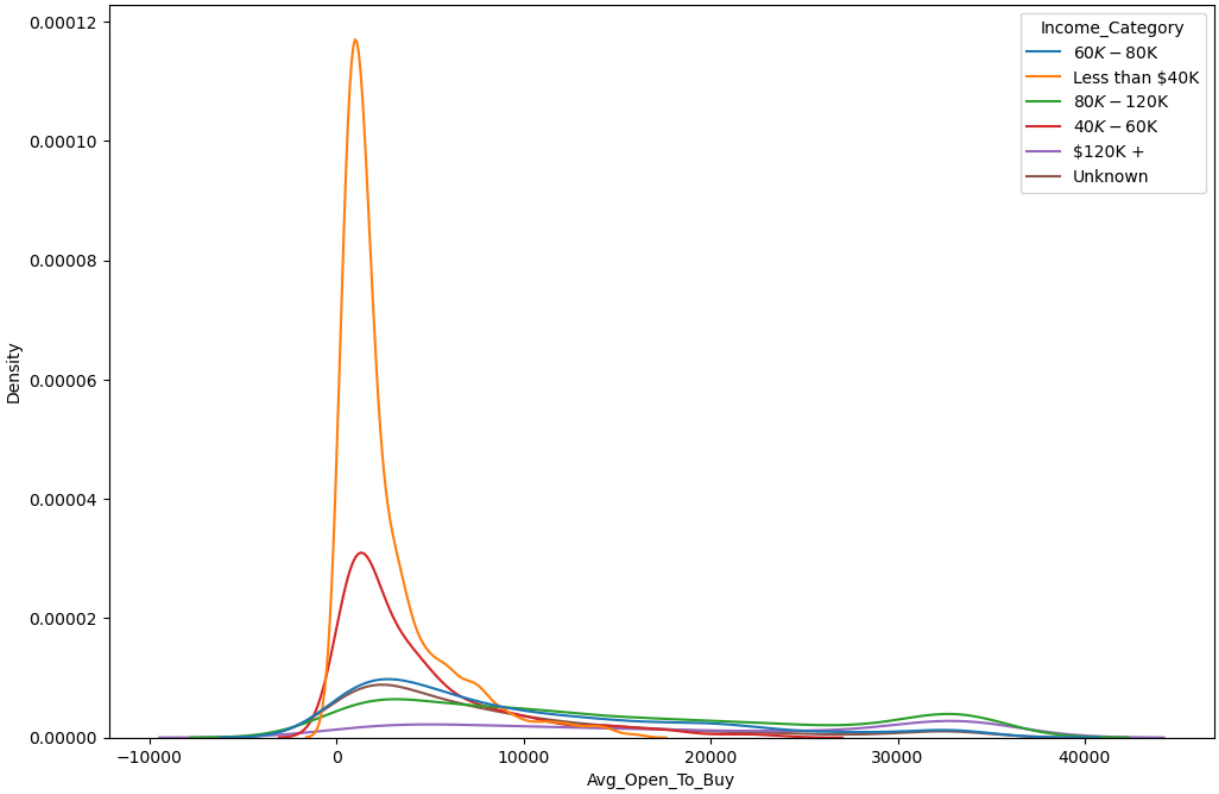

- **Inference:**
  - A lot of **Female** customers have credit limit below **10000 USD**.
  - But male customers have their credit limits distributed between the whole range.

In [59]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Avg_Open_To_Buy', hue = 'Gender', fill = True
```




- **Inference:**
  - A lot of **Female** customers have open balance below **10000 USD**.
    - This may happen due to most of them already have low credit limit. A slight usage also will decrease the open balance.
  - But male customers have their credit limits distributed between the whole range.

In [60]:
```
plt.figure(figsize = (12,8))
sns.kdeplot(data = e1, x = 'Avg_Open_To_Buy', hue = 'Income_Category' );
```

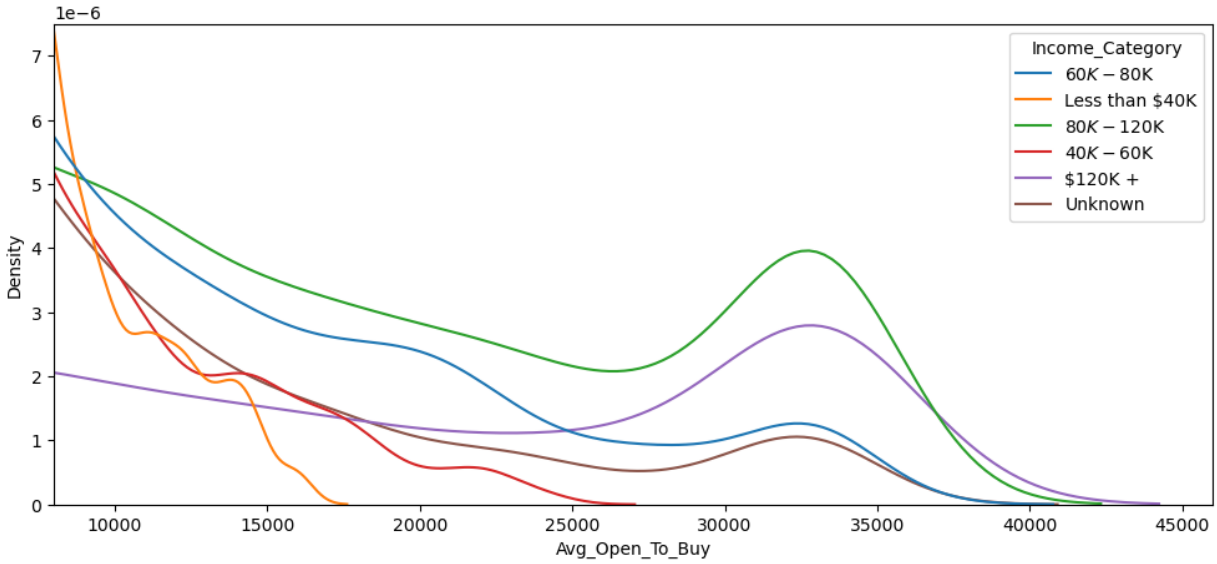



- **Inference:**

Here are a lot of details in this plot.

- Customers with **less than 40000 USD** annual income are centered around opening balance **0 - 5000 USD.**
    - Reason is they mostly have blue cards with **less credit limit** and eventually lower opening balance due to usage.
- Customers with **40000 - 60000 USD** annual income are also centered around opening balance **0 - 5000 USD.** Though they are less in number than the people with less than **40000 USD annual income**
- But there is also a spike in the right-most part with higher opening balance and premium tier cards. As probability or proportion of such users are relatively less, the below graph is rescaled to focus on that part.

In [67]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Avg_Open_To_Buy', hue = 'Income_Category' )
plt.xlim(8000, 46000)
plt.ylim(0, 0.0000075);
```

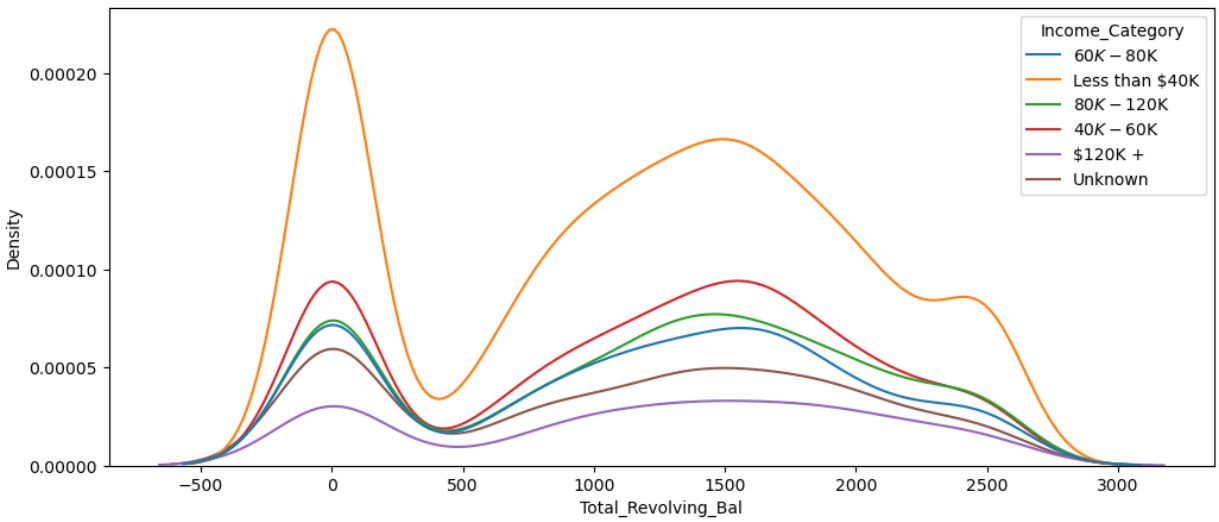



- **Inference:**

The magnified part shows the plot where the average opening balance is more than **8000 USD**

- The income group of **less than 60k USD** did not have opening balance beyond approx **25k USD**.
- This part is mostly pre-shadowed by users from higher income groups with a lot of opening balance or unutilized amount.

In [62]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Total_Revolving_Bal', hue = 'Income_Category'
```

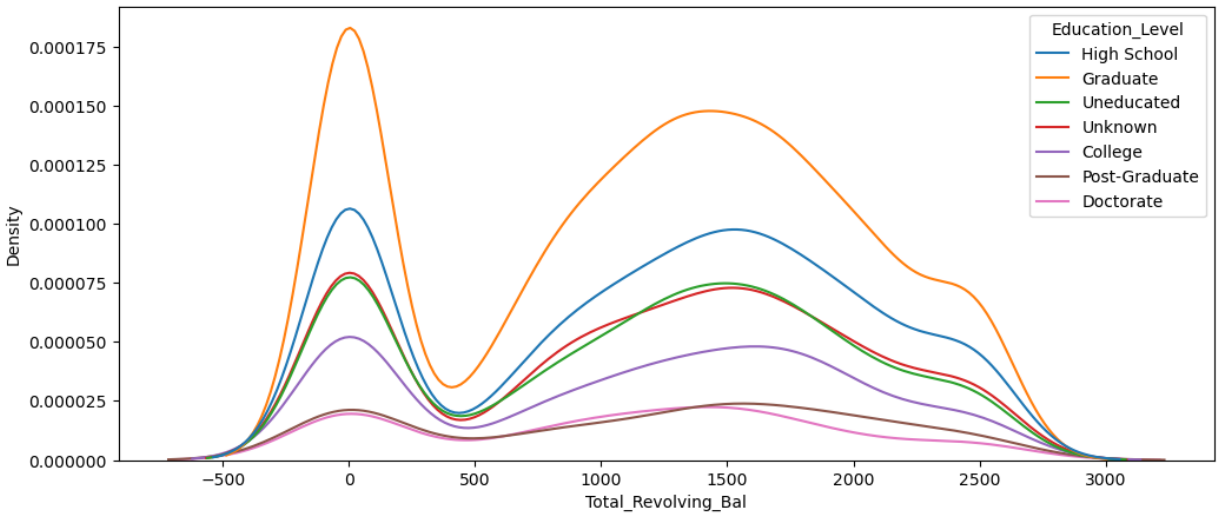


- **Inference:**

The whole plot is bimodal

- The income group of **less than 60k USD** did not have opening balance beyond approx **25k USD**.
- This part is mostly pre-shadowed by users from higher income groups with a lot of opening balance or unutilized amount.

In [69]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Total_Revolving_Bal', hue = 'Education_Level'
```

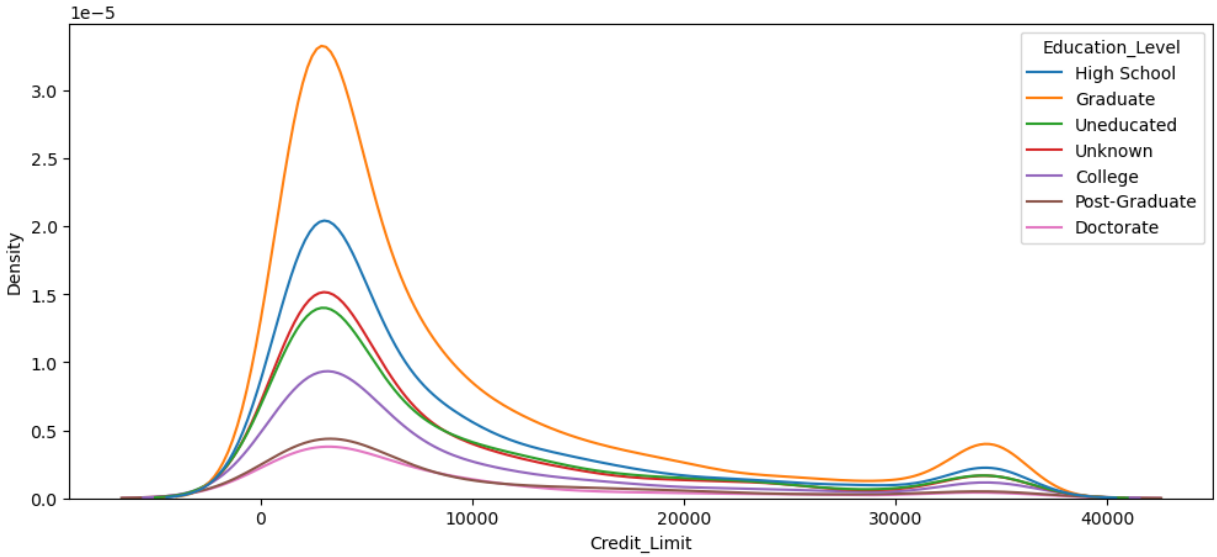



- **Inference:**

The whole plot is seemingly bimodal

- Graduates are more dominant here followed by **High School** qualified, **uneducated people** etc and have due balances around **1000 - 2000 USD**

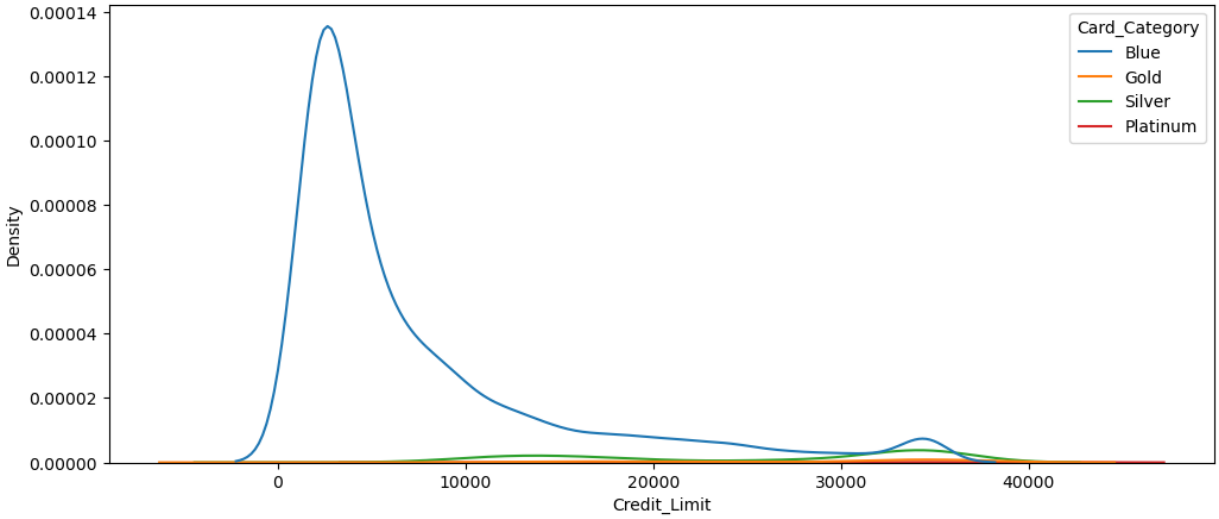
In [99]:
```
e1['Dependent_count'].apply(lambda x: str(x))
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Credit_Limit', hue = 'Education_Level' );
```




- **Inference:**

- Graduates are more dominant here followed by **High School** qualified, **uneducated people**.
- The modal credit limit is close to **5000 USD**

In [95]:
```
plt.figure(figsize = (12,5))
sns.kdeplot(data = e1, x = 'Credit_Limit', hue = 'Card_Category' );
```

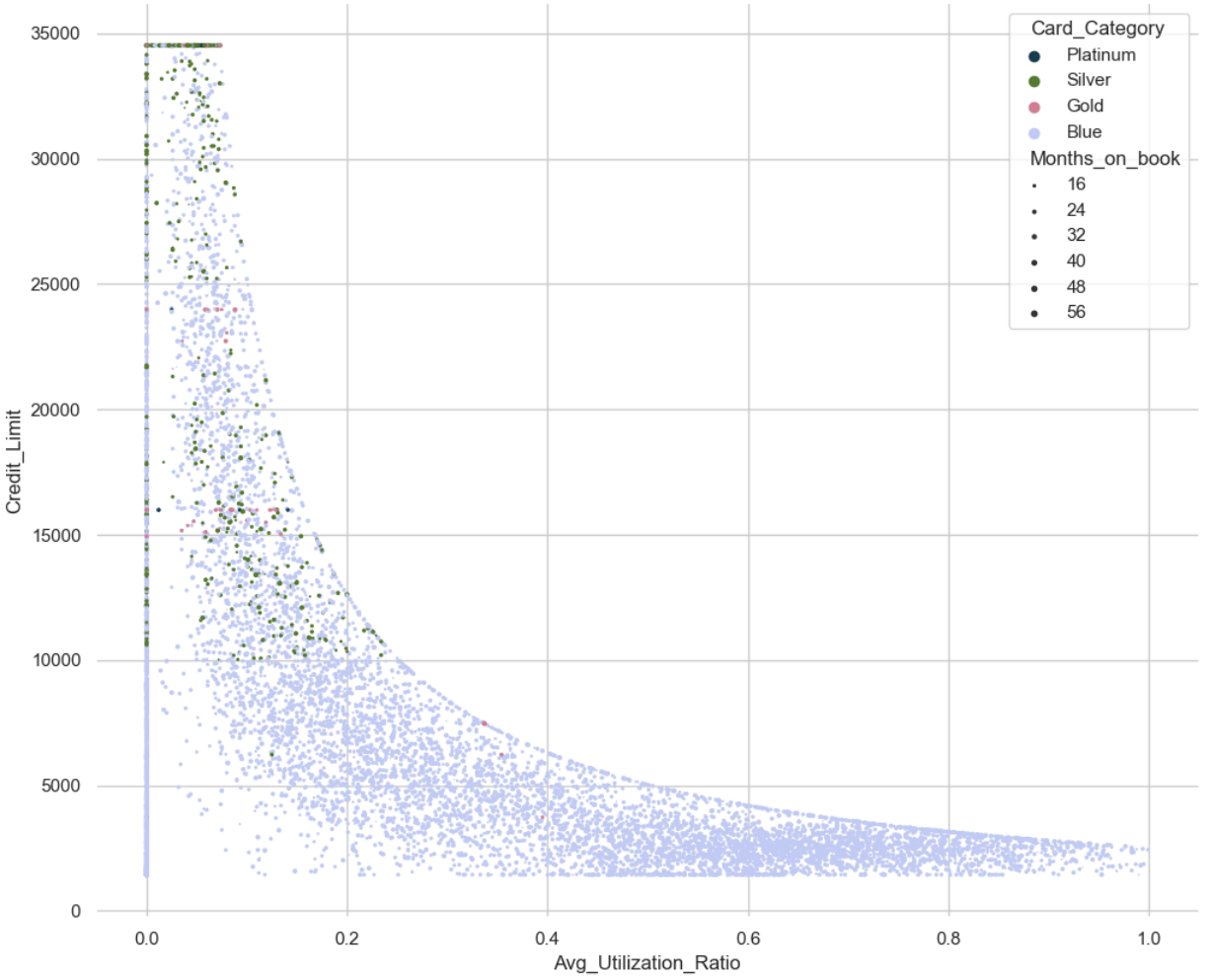



- **Inference:**

- **Blue** cards are heavily dominant here with credit limit below **10000 USD**

In [115…

```
f, ax = plt.subplots(figsize=(12, 10))
sns.despine(f, left=True, bottom=True)
card_ranking = ["Blue", "Gold", "Silver", "Platinum"][::-1]
sns.scatterplot(x="Avg_Utilization_Ratio", y="Credit_Limit",
                hue="Card_Category", size="Months_on_book",
                palette="cubehelix",
                hue_order=card_ranking,
                sizes=(1, 10), linewidth=0,
                data=e1, ax=ax);
```



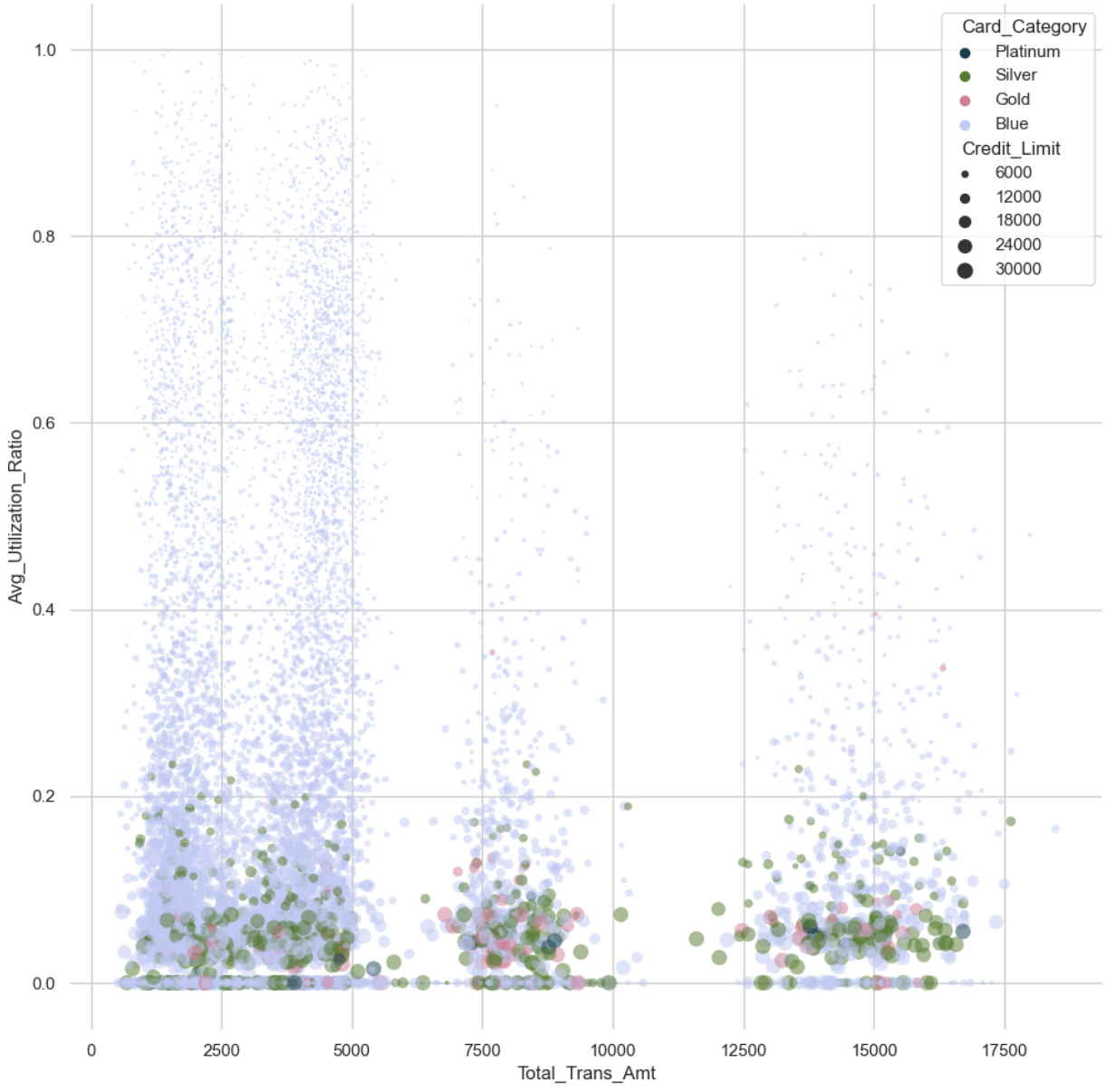

- **Inference:**
- Here the key takeaway from the shape of the graph is that, there is a relationship between **Average_Utilisation_Ratio, Total Revolving Balanc and Credit Limit**.

$$AUR = TRB/CL$$

- So, the credit limit is **inversely proportionate** with Average Utilisation Ratio
- Majority is the blue card holder.
- Other than the blue cards, mostly all of the other type of cards are less than **20%** exhausted.

In [116…

```
f, ax1 = plt.subplots(figsize=(12, 12))
sns.despine(f, left=True, bottom=True)
card_ranking = ["Blue", "Gold", "Silver", "Platinum"][::-1]
sns.scatterplot(x="Total_Trans_Amt", y="Avg_Utilization_Ratio",
                hue="Card_Category", size="Credit_Limit", alpha = 0.5,
                palette="cubehelix",
                hue_order=card_ranking,
                sizes=(1, 100), linewidth=0,
                data=e1,ax=ax1);
```



- **Inference:**

- There is a clear division of the Total Transaction Amounts of the customers. **Under 5k USD, 7.5k - 10k USD, 12k - 17k USD**

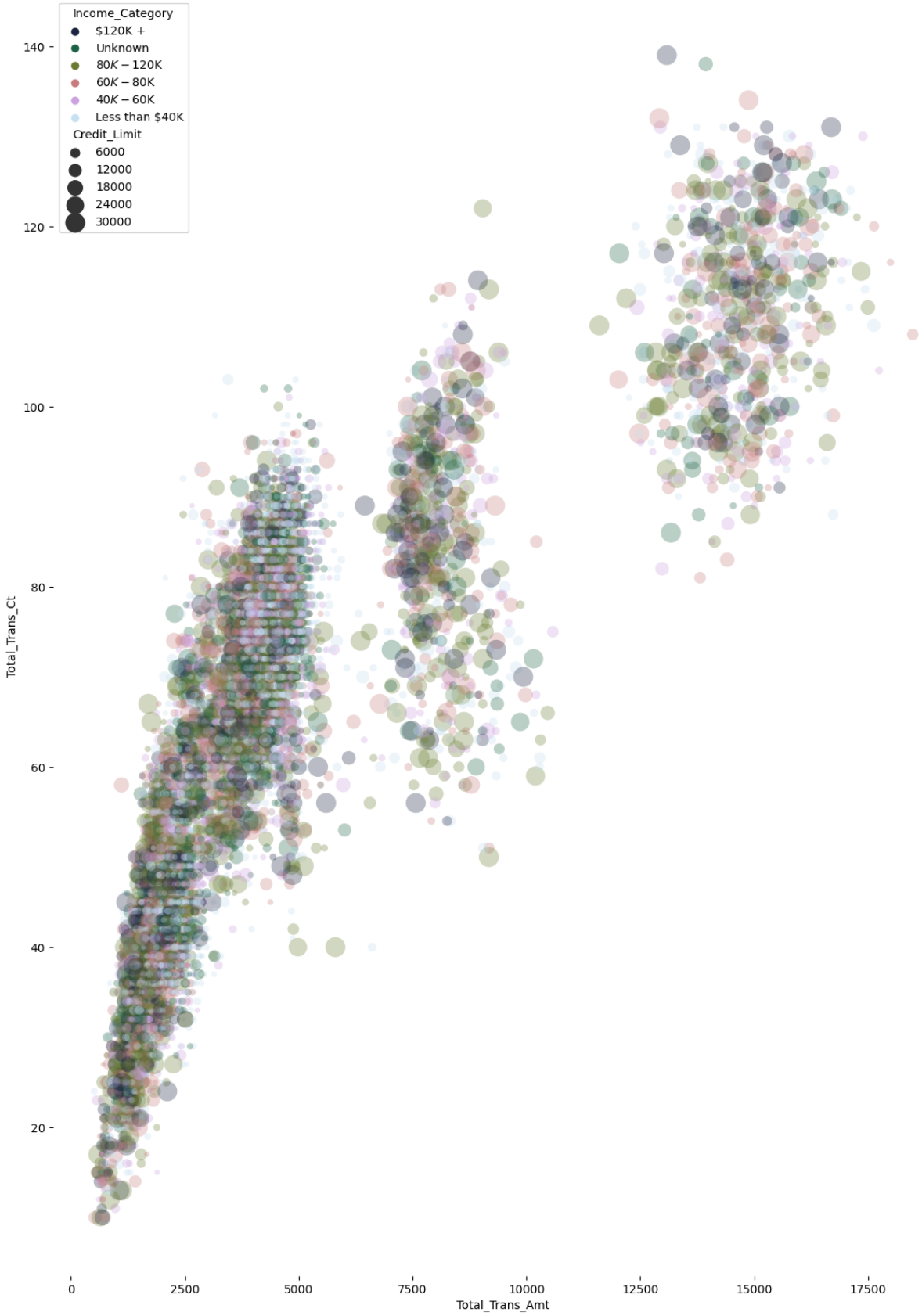
- **Under 5k USD**

  - **Blue cards** are heavily congested and are also utilized to the limit. Here Blue Cards under credit limit of **6k USD** are mostly utilized over **30%** . Even there are a lot of observations with over **80%** utilization.
  - **Silver, Gold and Platinum Cards** are utilized under **25%** with credit limit mostly over **8k USD.**
- **Between 7.5k - 10k USD**

  - **Blue card** concentration is low but credit limit is higher than before. Still there are a lot of observations with low credit limit but higher transaction amount. That can be explained by the fact that, users with low limit blue card exhaust or utilize their card multiple times and by repay it to gain the limit again.
  - **Silver & Gold Cards** are roughly utilized under **20%** with credit limit mostly over **8k USD**.
  - **Platinum Cards** are utilized under **15%** with credit limit mostly over **12k USD**.
- **Over 12.5k USD**

  - **Blue Card** concentration is lowest here. Here Blue Cards under credit limit of **6k USD** are utilized over **40%**
  - **Silver & Gold Cards** are roughly utilized under **20%** with even higher credit limits.
  - **Platinum Cards** are utilized under **15%** with credit limit mostly over **12k USD**.

In [37]:
```
f, ax2 = plt.subplots(figsize=(14, 20))
sns.despine(f, left=True, bottom=True)
income_ranking = ["Less than $40K", "$40K - $60K","$60K - $80K", "$80K -
sns.scatterplot(x="Total_Trans_Amt", y="Total_Trans_Ct",
                hue="Income_Category", size="Credit_Limit",
                palette="cubehelix",
                hue_order=income_ranking,
                sizes=(20, 300), linewidth=0, alpha = 0.3,
                data=e1, ax=ax2);
```


Income_Category
$120K +
Unknown
80K − 120K
60K − 80K
40K − 60K
Less than $40K
Credit_Limit
6000
12000
18000
24000
30000
Total_Trans_Ct
Total_Trans_Amt
140
120
100
80
60
40
20
0
2500
5000
7500
10000
12500
15000
17500

- **Inference:**
- There is a clear division of the Total Transaction Amounts of the customers -- **Under 5k, 7.5k - 12k** & **12.5k - 17k USD**
- **Under 5k USD**
  - Density of people under this amount of usage is very high. So most of the customers from every income group has total annual transaction **below 5k USD**. But this region is populated by people with less than **40k USD** annual income and credit limit of **6k USD**. Number of transactions here are roughly between **10 - 100** times.
- **Between 7.5k - 10k USD**
  - Here all the income groups accept less than **40k USD** are persistent. This region is dominated by people with income of more than **60k USD** and credit limit over **6k USD**. Number of transactions here are roughly between **55 - 120** times.
- **Between 12.5k - 17k USD**
  - This region is dominated by people with income of more than **80k USD** and credit limit over **10k USD**. Number of transactions here are roughly between **80 - 140** times.

# Income Distribution

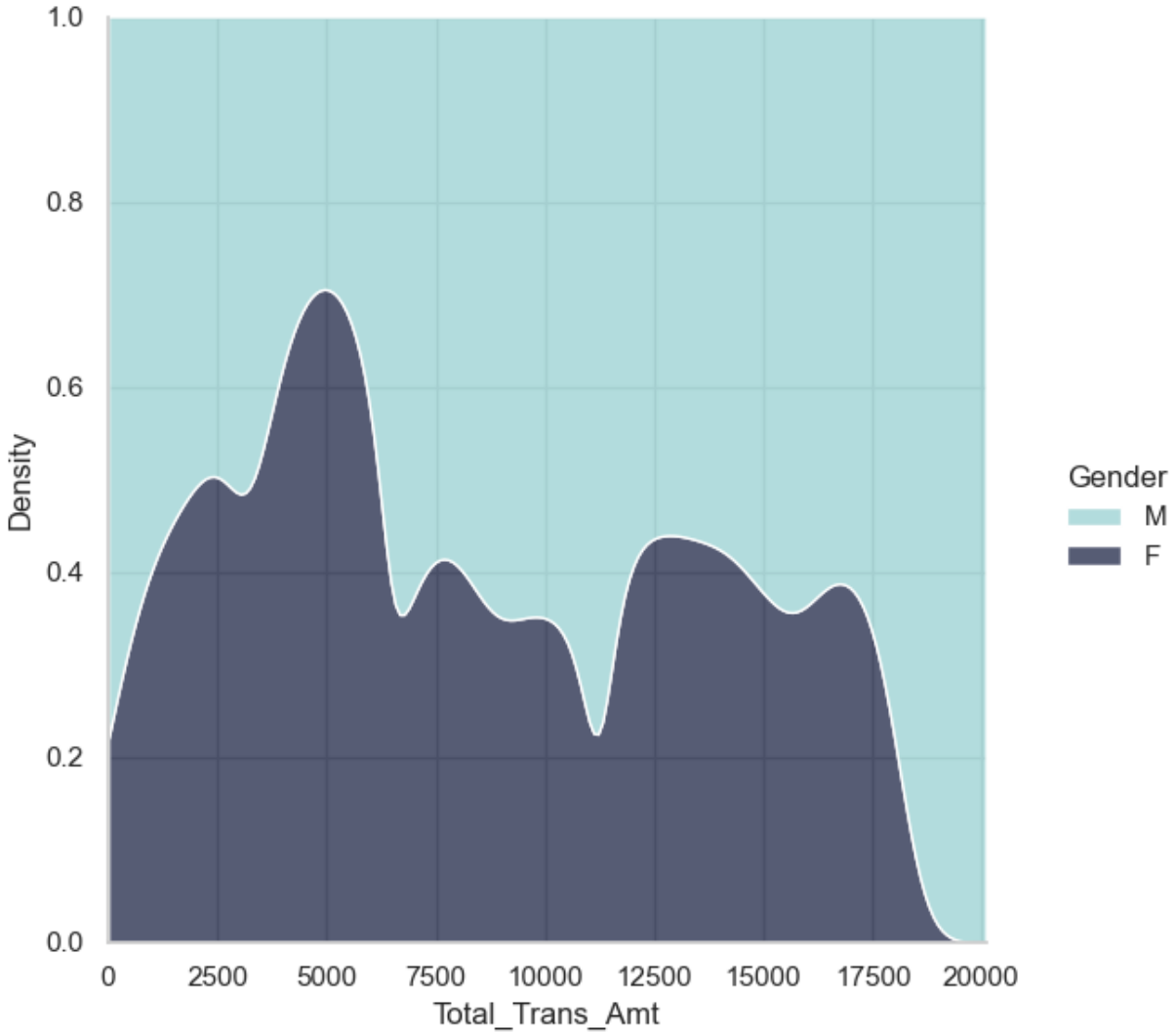
In [107…
```
e1['Income_Category'].value_counts()
```

Out[107]:
```
Income_Category
Less than $40K    3561
$40K - $60K       1790
$80K - $120K      1535
$60K - $80K       1402
Unknown           1112
$120K +            727
Name: count, dtype: int64
```

# Gender-wise Expense

In [39]:
```
sns.set_theme(style="whitegrid")
plt.figure(figsize = (20,5))
sns.displot(
    data=e1,
    x="Total_Trans_Amt", hue="Gender",
    kind="kde", height=6,
    multiple="fill", clip=(0, None),
    palette="ch:rot=-.25,hue=1,light=.75");
```

```
/Users/sayantabiswas/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
<Figure size 2000x500 with 0 Axes>
```



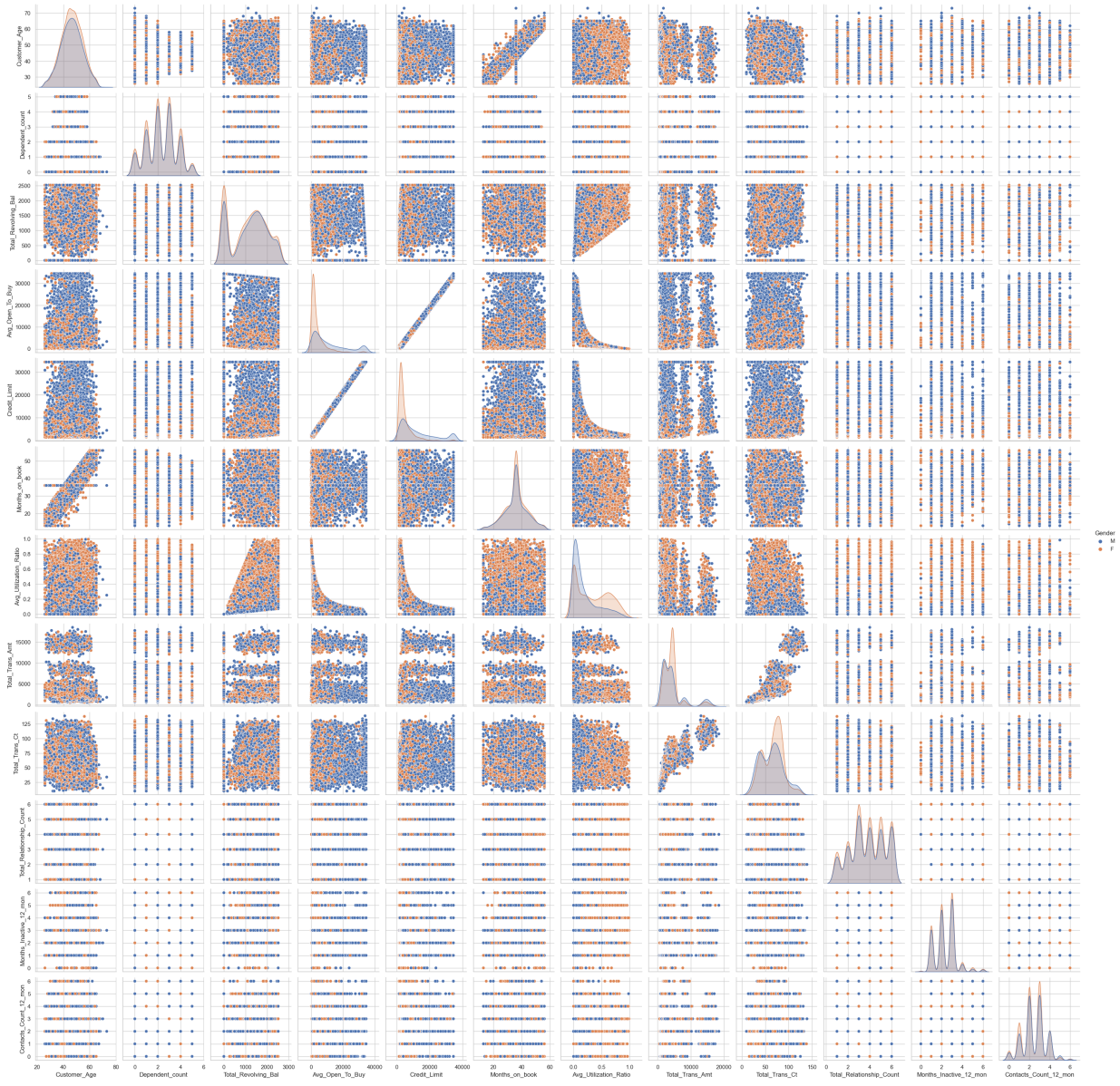

- This plot here shows that no of male customers are more than female customers and most of them spent between **2.5k - 7.5k** in a year.

In [109…
```
plt.figure(figsize = (20,20))
sns.pairplot(data = e1, hue = "Gender");
```

```
/Users/sayantabiswas/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[109]: <seaborn.axisgrid.PairGrid at 0x29ddf2fd0>

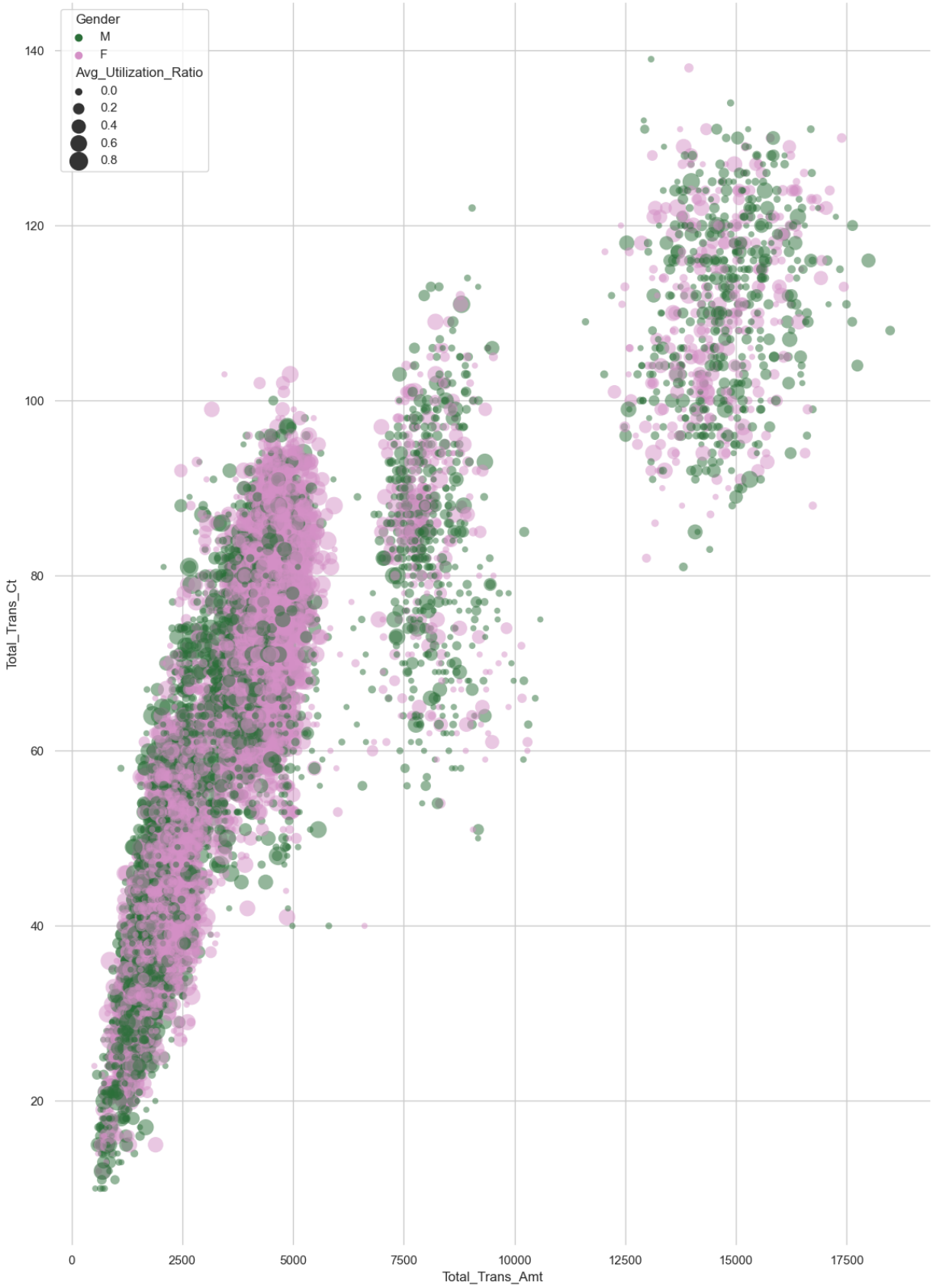
<Figure size 2000x2000 with 0 Axes>




# Female and Male Customers (Total Transaction amount vs No of Transactions)

In [40]:
```
f, ax3 = plt.subplots(figsize=(14, 20))
sns.despine(f, left=True, bottom=True)
gender_ranking = ["M", "F"]#[::-1]
sns.scatterplot(x="Total_Trans_Amt", y="Total_Trans_Ct",
                hue="Gender", size="Avg_Utilization_Ratio",
                palette="cubehelix",
                hue_order=gender_ranking,
                sizes=(30,300), linewidth=0, alpha = 0.5,  #adjusting siz
                data=e1, ax=ax3)
# Set x-axis limits
#ax3.set_xlim(10500, 18000)
```

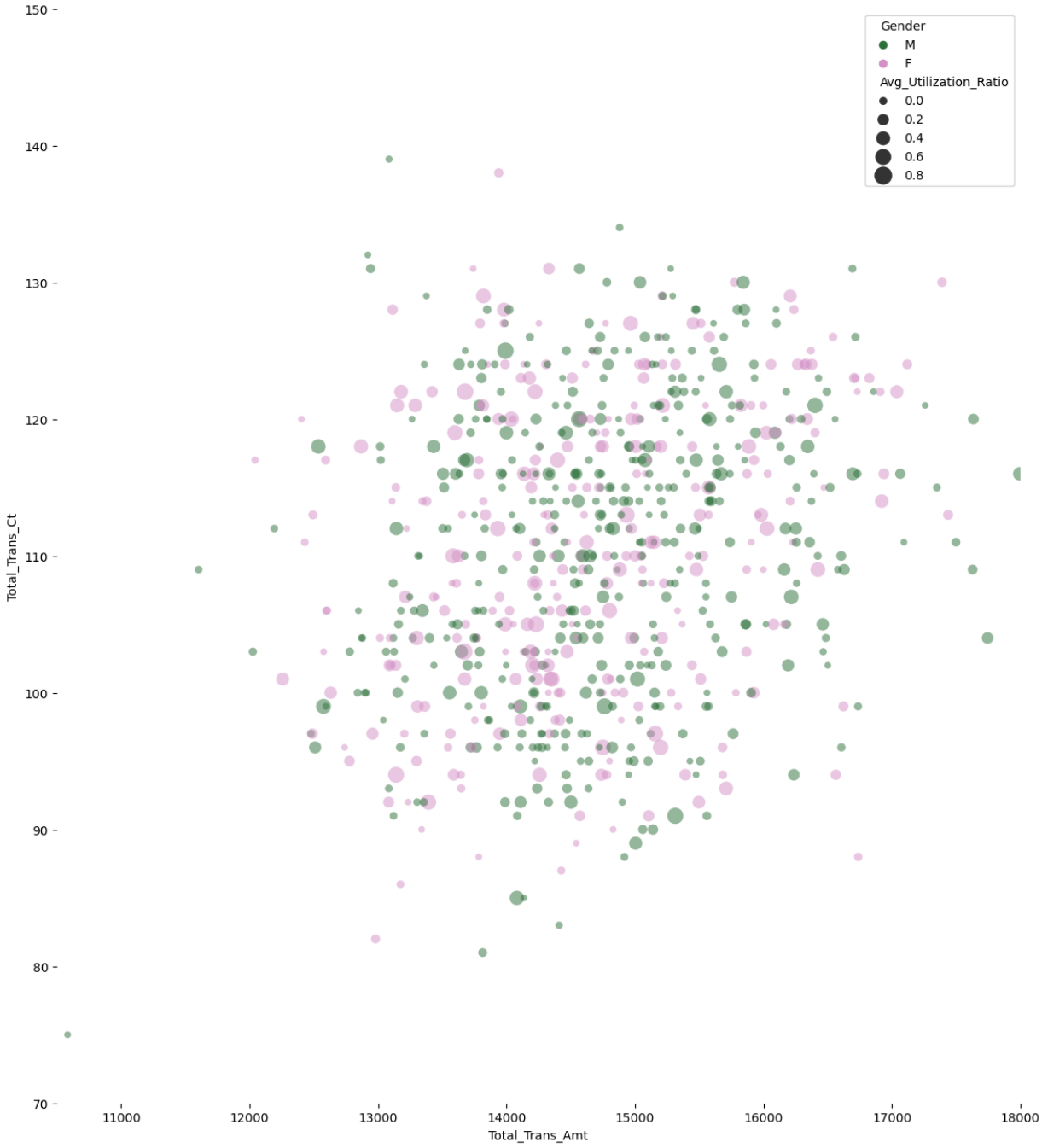
Out[40]:
```
<Axes: xlabel='Total_Trans_Amt', ylabel='Total_Trans_Ct'>
```


Gender
M
F
Avg_Utilization_Ratio
0.0
0.2
0.4
0.6
0.8
Total_Trans_Ct
140
120
100
80
60
40
20
0
2500
5000
7500
10000
12500
15000
17500
Total_Trans_Amt

- **Inference:**
- There is a clear division of the Total Transaction Amounts of the customers -- **Under 6k, 7.5k - 12k** & **12.5k - 17k USD**
- **Under 6k USD**
  - Most of the female customers spent under **6k USD** and utilised their cards mostly over **60%**. This region is dominated by female customers in terms of density. Number of transactions here are roughly between **10 - 100** times.
- **Between 7.5k - 10k USD**
  - Here, male customers are prominent. Utilization of cards here is less than **30%**. Number of transactions here are roughly between **60 - 110** times.
- **Between 12.5k - 17k USD**
  - Here both male and female customers are present with card utilization under **20%**. Number of transactions here are roughly between **85 - 135** times.

# People with Higher expenditure

In [38]:
```
f, ax4 = plt.subplots(figsize=(14, 16))
sns.despine(f, left=True, bottom=True)
gender_ranking = ["M", "F"]#[::-1]
#vec = list(np.linspace(0, 1, 50)) #to adjust
sns.scatterplot(x="Total_Trans_Amt", y="Total_Trans_Ct",
                hue="Gender", size="Avg_Utilization_Ratio",
                palette="cubehelix",
                hue_order=gender_ranking,
                sizes=(30,220), linewidth=0, alpha = 0.5, #size_order = v
                data=e1, ax=ax4)

# Set x-axis limits
ax4.set_xlim(10500, 18000)
ax4.set_ylim(70,150);
```

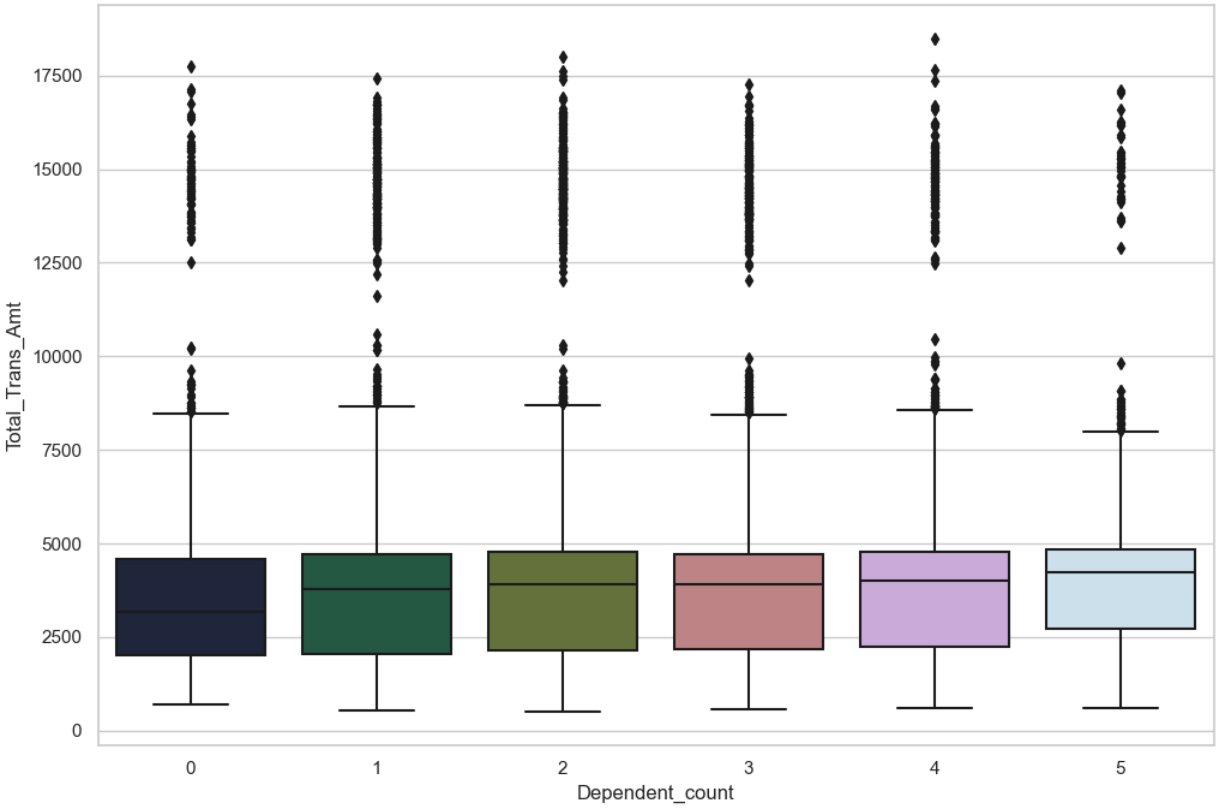



- **Inferences:**

- Here both male and female customers are present with card utilization under **20%**. But still it seems that, female customers have utilized their card more than the male customers. Because, this amount of expenditure is done by premium gold, silver or platinum cards. But we saw earlier that females use mostly blue card. Eventually that much expense with less credit limit pushes up their average card utilization ratio.

# No of Dependent Family Members

In [43]:
```
plt.figure(figsize=(12, 8))
sns.boxplot(x="Dependent_count", y="Total_Trans_Amt", data=e1, palette="c
```

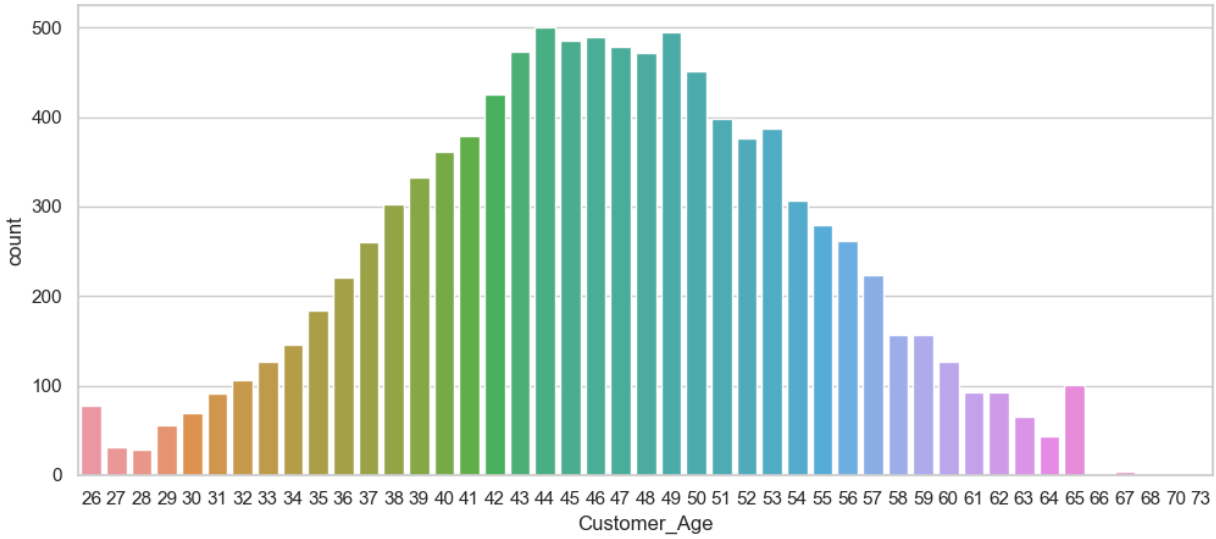



- **Inferences:**
- Here median expenses of families with members **0-5** are distributed as expected as individuals with more dependent family members have more median expenses. The spreads and outliers are also mostly identical.

# Age Distribution

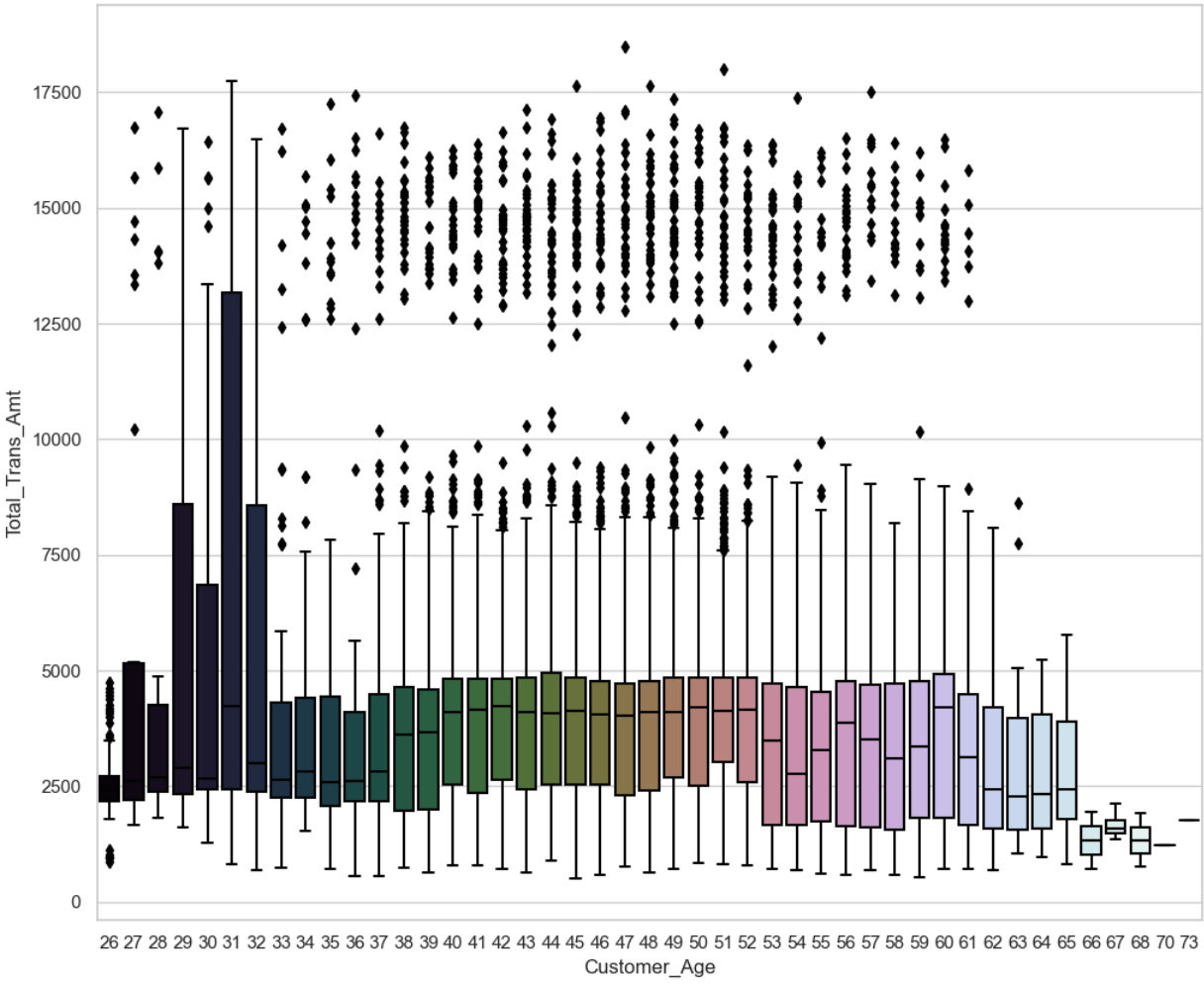
In [52]:
```
age1 = e1['Customer_Age'].value_counts()
age2 = pd.DataFrame(age1)
age2.reset_index(inplace = True)
```

In [56]:
```
plt.figure(figsize = (12,5))
sns.barplot(data = age2, y = 'count', x = 'Customer_Age');
```




- **Inferences**
- Here ages of the customers are normally distributed. It is clear that people from age **30-60** years have the urge to use cards more than any other age group.

In [41]:
```
plt.figure(figsize=(12, 10))
sns.boxplot(x="Customer_Age", y="Total_Trans_Amt", data=e1, palette="cube
```

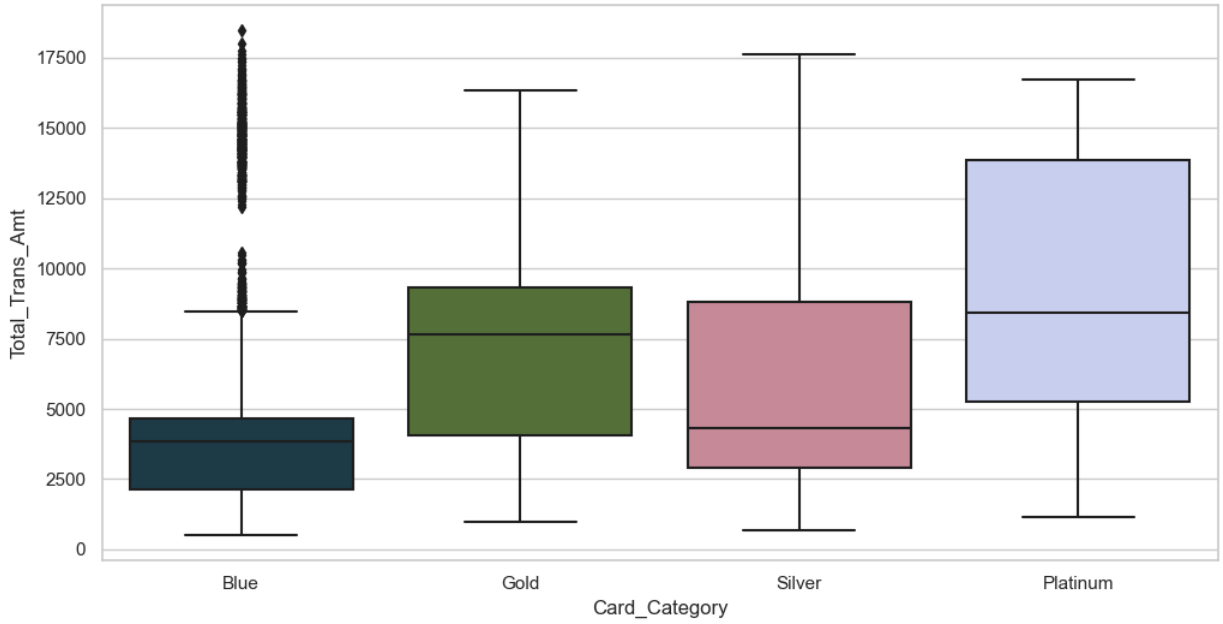


- **Inferences**

- Here ages of the customers are normally distributed. It is clear that people from age **30-60** years have the urge to use cards more than any other age group.

In [154…
```
plt.figure(figsize=(12, 6))
sns.boxplot(x="Card_Category", y="Total_Trans_Amt", data=e1, palette="cub
```

Out[154]:
```
<Axes: xlabel='Card_Category', ylabel='Total_Trans_Amt'>
```

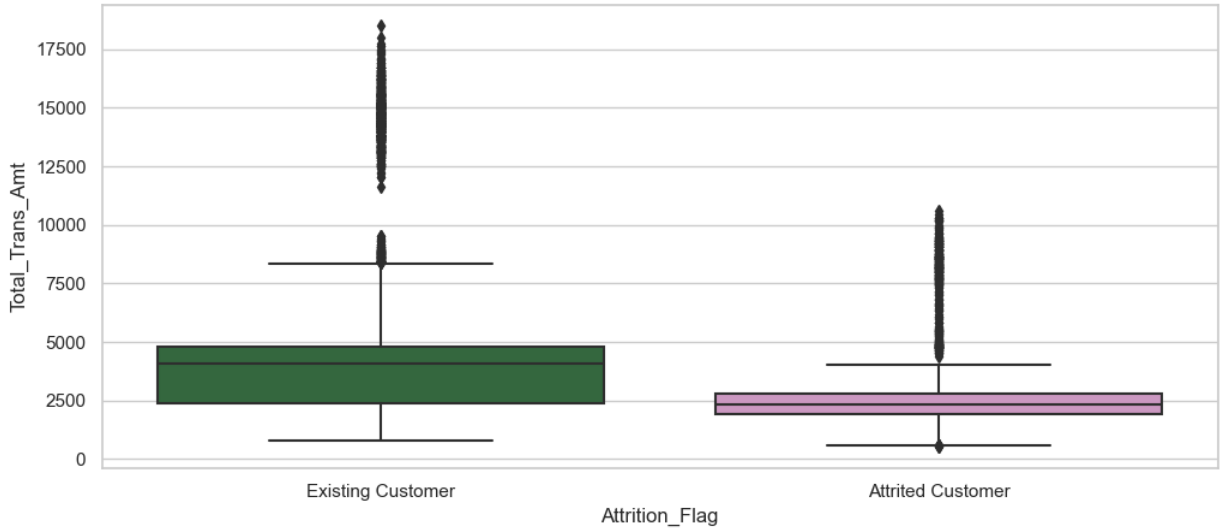



- **Inferences**

- Here the median transaction amount is highest for the platinum card holders and lowest is for blue card.

In [57]:
```
plt.figure(figsize=(12, 5))
sns.boxplot(x="Attrition_Flag", y="Total_Trans_Amt", data=e1, palette="cu
```

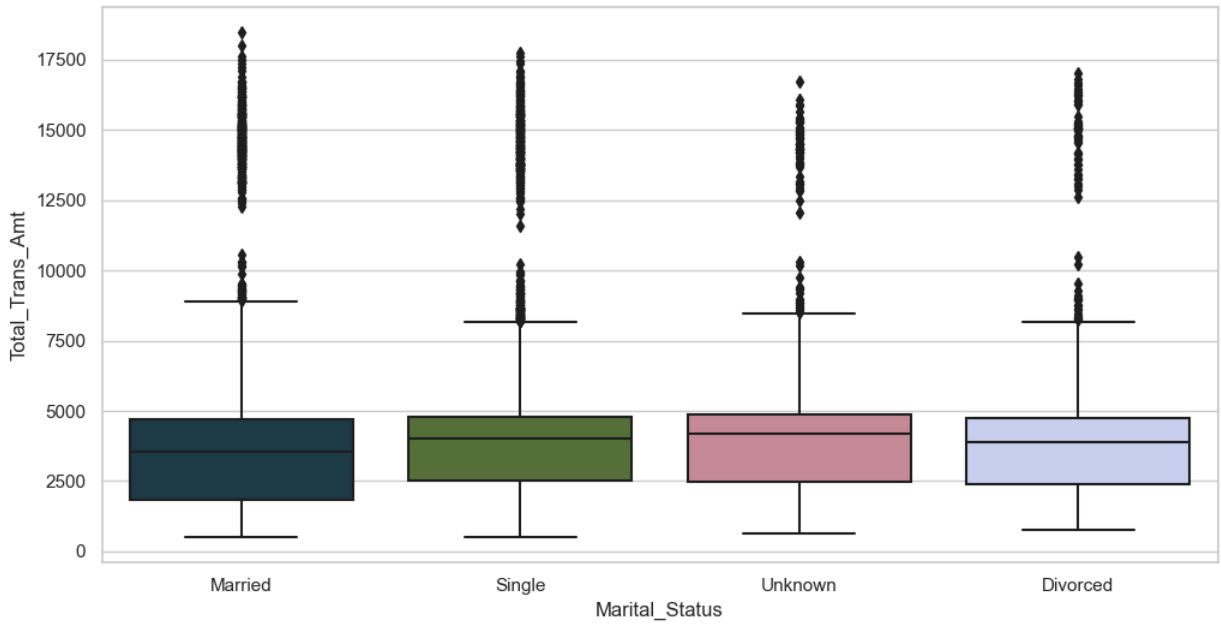
Out[57]:
```
<Axes: xlabel='Attrition_Flag', ylabel='Total_Trans_Amt'>
```




- **Inferences**
- Here the median transaction amount is higher of the existing customers. The IQR for ex-customer is very low that means they mostly transacted for around **2500 USD**

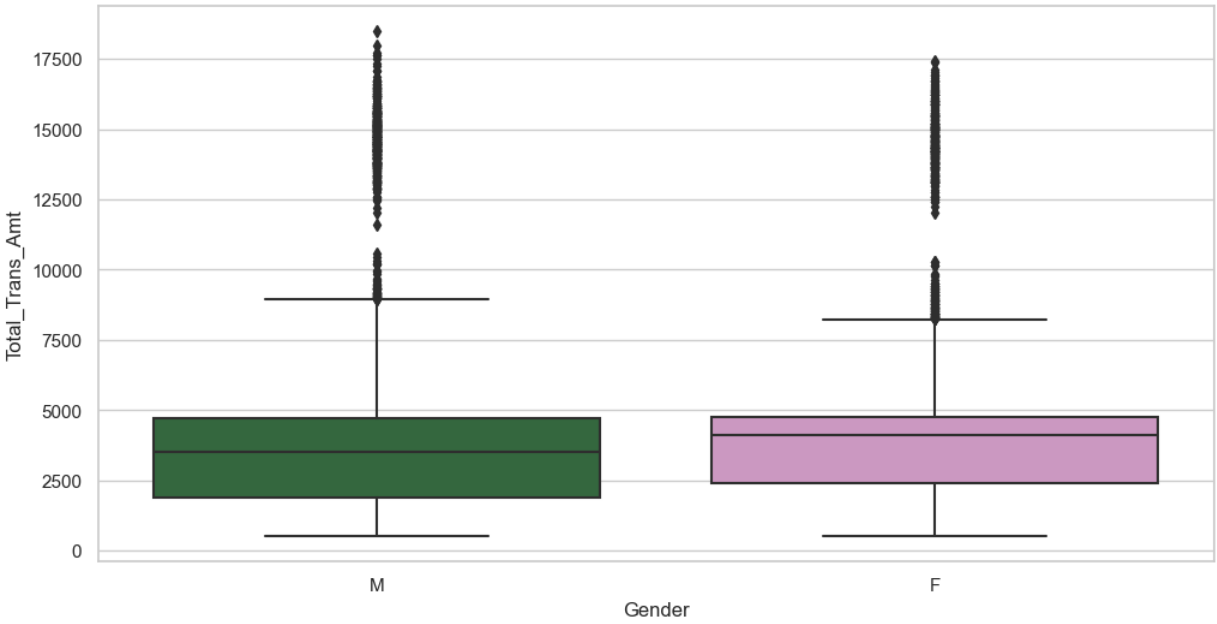
In [159…
```
plt.figure(figsize=(12, 6))
sns.boxplot(x="Marital_Status", y="Total_Trans_Amt", data=e1, palette="cu
```

Out[159]:
```
<Axes: xlabel='Marital_Status', ylabel='Total_Trans_Amt'>
```



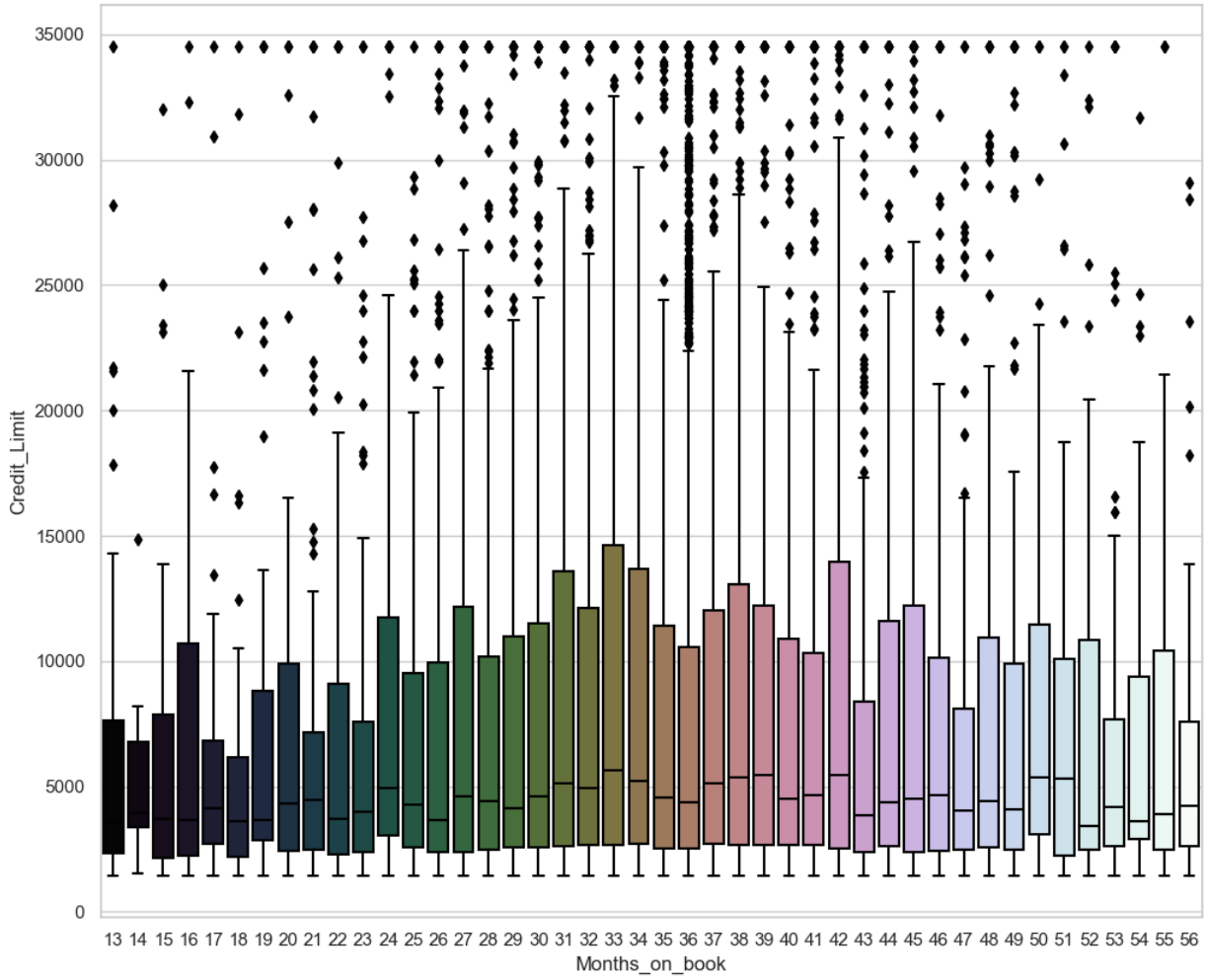

In [161…
```
plt.figure(figsize=(12, 6))
sns.boxplot(x="Gender", y="Total_Trans_Amt", data=e1, palette="cubehelix"
```

Out[161]:
```
<Axes: xlabel='Gender', ylabel='Total_Trans_Amt'>
```




- **Inferences**
- Here the median transaction amount is higher of the existing customers. The IQR for ex-customer is very low that means they mostly transacted for around **2500 USD**

In [59]:
```
plt.figure(figsize=(12, 10))
sns.boxplot(x="Months_on_book", y="Credit_Limit", data=e1, palette="cubeh
```


Credit_Limit
Months_on_book
0
5000
10000
15000
20000
25000
30000
35000
13 14 15 16 17 18 19 20 21 22 23 24 25 26 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

In [60]:
```
e1
```

Out[60]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_ |
|---|---|---|---|---|---|---|
| **0** | 768805383 | Existing Customer | 45 | M | 3 | High S |
| **1** | 818770008 | Existing Customer | 49 | F | 5 | Gra |
| **2** | 713982108 | Existing Customer | 51 | M | 3 | Gra |
| **3** | 769911858 | Existing Customer | 40 | F | 4 | High S |
| **4** | 709106358 | Existing Customer | 40 | M | 3 | Unedu |
| **...** | ... | ... | ... | ... | ... | |
| **10122** | 772366833 | Existing Customer | 50 | M | 2 | Gra |
| **10123** | 710638233 | Attrited Customer | 41 | M | 2 | Un |
| **10124** | 716506083 | Attrited Customer | 44 | F | 1 | High S |
| **10125** | 717406983 | Attrited Customer | 30 | M | 2 | Gra |
| **10126** | 714337233 | Attrited Customer | 43 | F | 2 | Gra |

10127 rows × 22 columns

# Genderwise Income Category vs Total transaction count

In [61]:
```
e1['Average_Amt_Per_Tran'] = e1['Total_Trans_Amt']/e1['Total_Trans_Ct']
e1
```

```
/var/folders/qr/9x6pfw9d58vf78nhsqtb93mh0000gn/T/ipykernel_819/2441558379.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  e1['Average_Amt_Per_Tran'] = e1['Total_Trans_Amt']/e1['Total_Trans_Ct']
```

Out[61]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_ |
|---|---|---|---|---|---|---|
| **0** | 768805383 | Existing Customer | 45 | M | 3 | High S |
| **1** | 818770008 | Existing Customer | 49 | F | 5 | Gra |
| **2** | 713982108 | Existing Customer | 51 | M | 3 | Gra |
| **3** | 769911858 | Existing Customer | 40 | F | 4 | High S |
| **4** | 709106358 | Existing Customer | 40 | M | 3 | Unedu |
| **...** | ... | ... | ... | ... | ... | |
| **10122** | 772366833 | Existing Customer | 50 | M | 2 | Gra |
| **10123** | 710638233 | Attrited Customer | 41 | M | 2 | Un |
| **10124** | 716506083 | Attrited Customer | 44 | F | 1 | High S |
| **10125** | 717406983 | Attrited Customer | 30 | M | 2 | Gra |
| **10126** | 714337233 | Attrited Customer | 43 | F | 2 | Gra |

10127 rows × 22 columns

## Creating a new column

In [62]:
```
in_trnc =  e1[['Gender', "Income_Category", "Total_Trans_Ct","Average_Amt
in_trnc1 = in_trnc.groupby(['Gender','Income_Category']).describe()
```

In [63]:
```
df=in_trnc
df
```

Out[63]:

| | Gender | Income_Category | Total_Trans_Ct | Average_Amt_Per_Tran |
|---|---|---|---|---|
| **0** | M | $60K-80K$ | 42 | 27.238095 |
| **1** | F | Less than $40K | 33 | 39.121212 |
| **2** | M | $80K-120K$ | 20 | 94.350000 |
| **3** | F | Less than $40K | 20 | 58.550000 |
| **4** | M | $60K-80K$ | 28 | 29.142857 |
| **...** | ... | ... | ... | ... |
| **10122** | M | $40K-60K$ | 117 | 132.273504 |
| **10123** | M | $40K-60K$ | 69 | 127.014493 |
| **10124** | F | Less than $40K | 60 | 171.516667 |
| **10125** | M | $40K-60K$ | 62 | 135.403226 |
| **10126** | F | Less than $40K | 61 | 168.754098 |

10127 rows × 4 columns

In [64]:
```
male = df[df['Gender'] == 'M']
quart = male.groupby(['Gender', 'Income_Category']).describe()
```

In [65]:
```
quart
```

Out[65]:

| | | Total_Trans_Ct | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | count | mean | std | min | 25% | 50% | 75% | max |
| **Gender** | **Income_Category** | | | | | | | | |
| **M** | **$120K +** | 727.0 | 63.704264 | 25.750910 | 10.0 | 43.00 | 64.0 | 81.00 | 139.0 |
| | **$40K-60K** | 776.0 | 63.412371 | 25.262903 | 11.0 | 42.00 | 64.0 | 79.00 | 131.0 |
| | **$60K-80K** | 1402.0 | 63.247504 | 24.911737 | 10.0 | 42.00 | 65.0 | 79.00 | 134.0 |
| | **$80K-120K** | 1535.0 | 62.696417 | 24.838914 | 10.0 | 41.00 | 63.0 | 79.00 | 127.0 |
| | **Less than $40K** | 277.0 | 64.054152 | 26.073210 | 13.0 | 43.00 | 65.0 | 80.00 | 128.0 |
| | **Unknown** | 52.0 | 60.230769 | 21.411574 | 24.0 | 42.75 | 59.5 | 72.75 | 127.0 |

In [66]:
```
quart1 = male.groupby(['Gender', 'Income_Category']).describe()['Average_
up_male =quart1['75%']
```

In [67]:
```
up_male_75 = pd.DataFrame(up_male)
up_male_75.reset_index(inplace = True)
up_male_75
```

Out[67]:

| | Gender | Income_Category | 75% |
|---|---|---|---|
| **0** | M | $120K + | 69.474638 |
| **1** | M | $40K - 60K$ | 69.422403 |
| **2** | M | $60K - 80K$ | 65.472783 |
| **3** | M | $80K - 120K$ | 67.899314 |
| **4** | M | Less than $40K | 66.014925 |
| **5** | M | Unknown | 60.083807 |

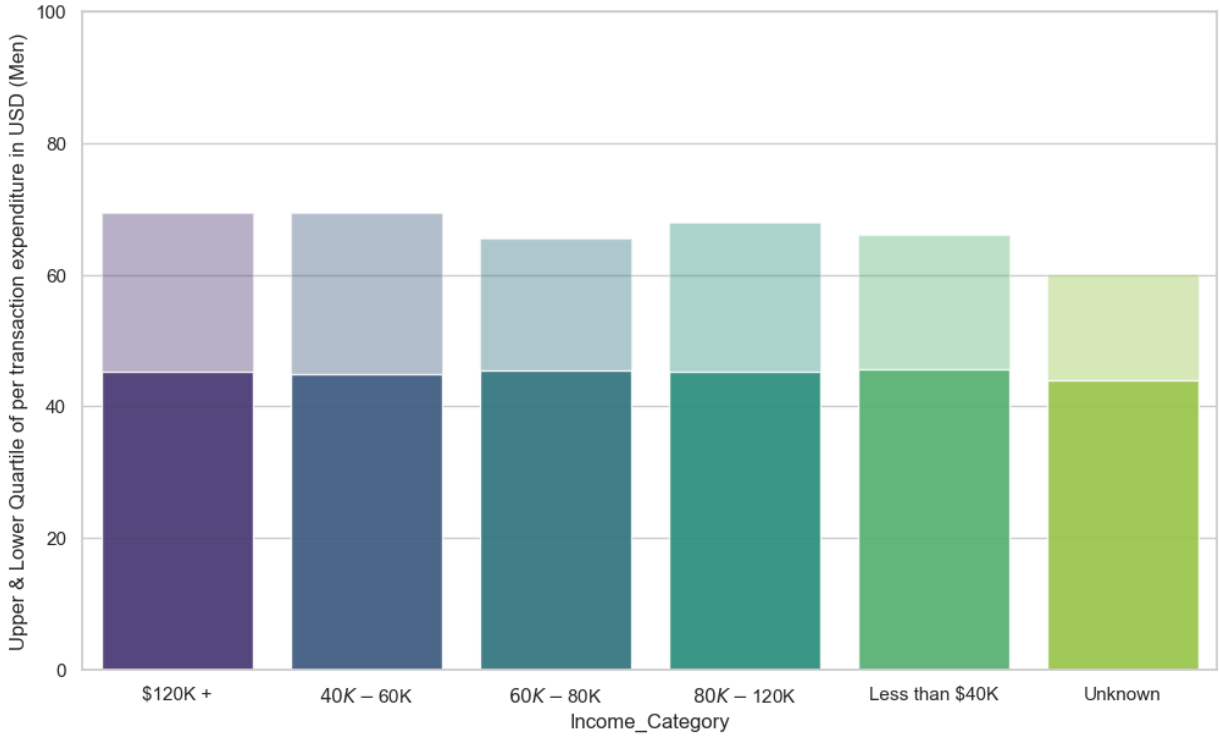
In [68]:
```
quart2 = male.groupby(['Gender', 'Income_Category']).describe()['Average_
low_male =quart1['25%']
low_male_25 = pd.DataFrame(low_male)
low_male_25.reset_index(inplace = True)
```

In [69]:
```
low_male_25
```

Out[69]:

| | Gender | Income_Category | 25% |
|---|---|---|---|
| **0** | M | $120K + | 45.342330 |
| **1** | M | $40K - 60K$ | 44.932495 |
| **2** | M | $60K - 80K$ | 45.437899 |
| **3** | M | $80K - 120K$ | 45.219374 |
| **4** | M | Less than $40K | 45.611111 |
| **5** | M | Unknown | 43.884159 |

In [70]:
```
plt.figure(figsize = (12,7))
sns.barplot(data = up_male_75, y = '75%',
            x = 'Income_Category', palette = 'viridis', alpha = 0.4)
sns.barplot(data = low_male_25, y = '25%',
            x = 'Income_Category', palette = 'viridis', alpha = 0.9)
plt.ylim(0,100)
plt.ylabel('Upper & Lower Quartile of per transaction expenditure in USD
```




Here the IQR is also visible.

# Upper Quartile & Lower Quartile Expense (per income group)(Female)

In [71]:
```
fem = df[df['Gender'] == 'F']
qu3 = fem.groupby(['Gender', 'Income_Category']).describe()['Average_Amt_
qu3
```

Out[71]:

| | | count | mean | std | min | 25% | 5( |
|---|---|---|---|---|---|---|---|
| **Gender** | **Income_Category** | | | | | | |
| **F** | $40K – 60K$ | 1014.0 | 61.163852 | 22.369084 | 26.836066 | 49.829025 | 56.7675 |
| | **Less than $40K** | 3284.0 | 61.687834 | 23.250600 | 21.250000 | 49.328947 | 56.6666 |
| | **Unknown** | 1060.0 | 61.293798 | 22.778924 | 26.789474 | 49.717865 | 56.500 |

In [72]:
```
low_f =qu3['25%']
low_f_25 = pd.DataFrame(low_f)
low_f_25.reset_index(inplace = True)
low_f_25
```

Out[72]:

| | Gender | Income_Category | 25% |
|---|---|---|---|
| **0** | F | $40K – 60K$ | 49.829025 |
| **1** | F | Less than $40K | 49.328947 |
| **2** | F | Unknown | 49.717865 |

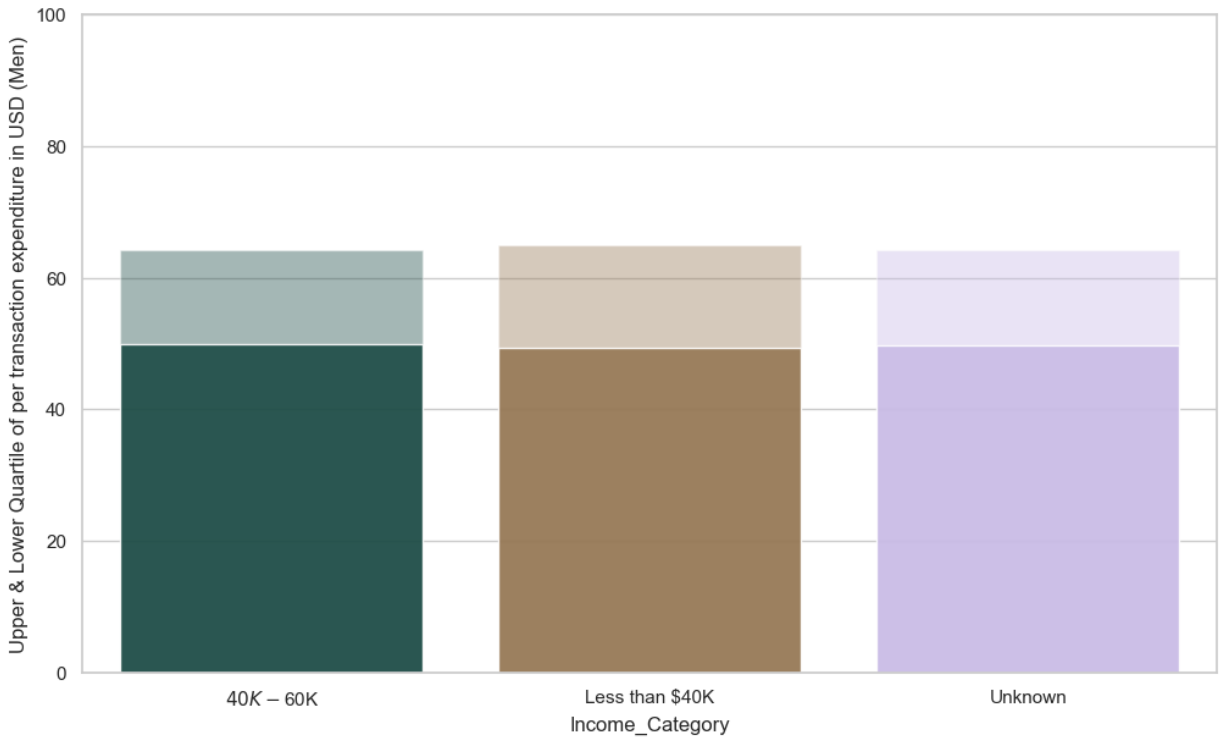
In [73]:
```
high_f =qu3['75%']
high_f_75 = pd.DataFrame(high_f)
high_f_75.reset_index(inplace = True)
high_f_75
```

Out[73]:

| | Gender | Income_Category | 75% |
|---|---|---|---|
| **0** | F | $40K – 60K | 64.279503 |
| **1** | F | Less than $40K | 64.990854 |
| **2** | F | Unknown | 64.177229 |

In [74]:
```
plt.figure(figsize = (12,7))
sns.barplot(data = high_f_75, y = '75%',
            x = 'Income_Category', palette = 'cubehelix', alpha = 0.4)
sns.barplot(data = low_f_25, y = '25%',
            x = 'Income_Category', palette = 'cubehelix', alpha = 0.9)
plt.ylabel('Upper & Lower Quartile of per transaction expenditure in USD
plt.ylim(0,100)
```

Out[74]:
```
(0.0, 100.0)
```




# Median Expense per transaction (Male vs Female)

In [75]:
```
quart2 = male.groupby(['Gender', 'Income_Category']).describe()['Average_
median_male =quart1['50%']
med_m = pd.DataFrame(median_male)
med_m.reset_index(inplace = True)
med_m
```

Out[75]:

| | Gender | Income_Category | 50% |
|---|---|---|---|
| **0** | M | $120K + | 54.175676 |
| **1** | M | $40K – 60K | 53.547065 |
| **2** | M | $60K – 80K | 54.985798 |
| **3** | M | $80K – 120K | 54.600000 |
| **4** | M | Less than $40K | 53.923077 |
| **5** | M | Unknown | 52.226343 |

Here we have to drop unnecessary rows like the income groups "80$K$– 120K, 60$K$– 80K and more than $120K" as there are no females with this income in the dataset.

In [76]:
```
med_m1 = med_m.iloc[1:6]
med_m2 = med_m1.drop(3)
med_m3 = med_m2.drop(2)
med_m3
```

Out[76]:

| | Gender | Income_Category | 50% |
|---|---|---|---|
| **1** | M | $40K – 60K | 53.547065 |
| **4** | M | Less than $40K | 53.923077 |
| **5** | M | Unknown | 52.226343 |

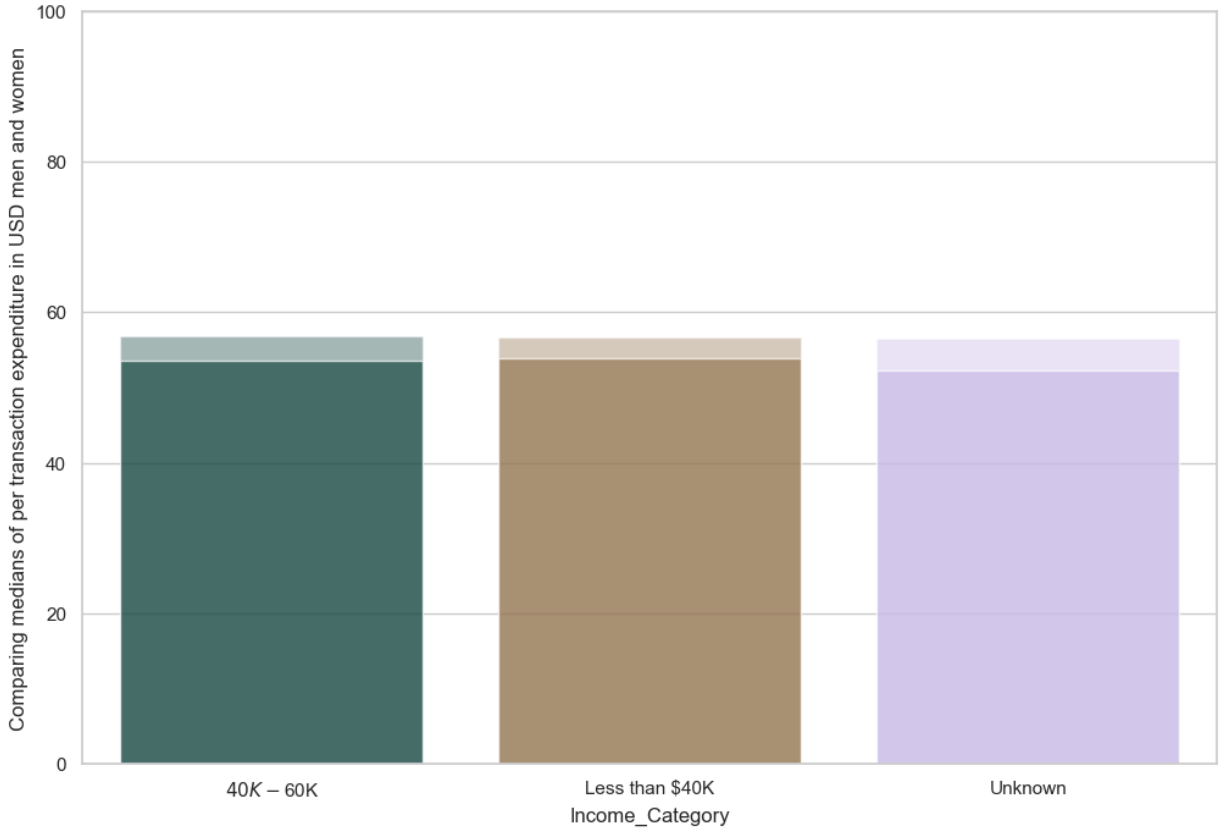
In [77]:
```
qu3 = fem.groupby(['Gender', 'Income_Category']).describe()['Average_Amt_
median_female =qu3['50%']
med_f = pd.DataFrame(median_female)
med_f.reset_index(inplace = True)
med_f
```

Out[77]:

| | Gender | Income_Category | 50% |
|---|---|---|---|
| **0** | F | $40K – 60K | 56.767578 |
| **1** | F | Less than $40K | 56.666667 |
| **2** | F | Unknown | 56.500145 |

In [78]:
```
plt.figure(figsize = (12,8))
sns.barplot(data = med_f, y = '50%',
            x = 'Income_Category', palette = 'cubehelix', alpha = 0.4)
sns.barplot(data = med_m3, y = '50%',
            x = 'Income_Category', palette = 'cubehelix', alpha = 0.7)
plt.ylabel('Comparing medians of per transaction expenditure in USD men a
plt.ylim(0,100)
```

Out[78]:
```
(0.0, 100.0)
```




Surprisingly, the median expense per transaction of females here shows up to be greater than that of the males

# Per Month Transactions and Amounts

Here we will try to find the coloumn with the

In [79]:
```
e1['Months_Active'] = e1['Months_Inactive_12_mon'].apply(lambda x: (12-x)
```

In [80]:
```
e1['Tran_per_month'] = e1['Total_Trans_Ct']/e1['Months_Active']
```

In [81]:
```
e1['Expense_Per_Active_Month'] = e1['Total_Trans_Amt']/e1['Months_Active'
```

In [82]:
```
e1.head(3)
```

Out[82]:

| | CLIENTNUM | Attrition_Flag | Customer_Age | Gender | Dependent_count | Education_Leve |
|---|---|---|---|---|---|---|
| **0** | 768805383 | Existing Customer | 45 | M | 3 | High Schoo |
| **1** | 818770008 | Existing Customer | 49 | F | 5 | Graduat |
| **2** | 713982108 | Existing Customer | 51 | M | 3 | Graduat |

3 rows × 25 columns

# Expense per Active Month (Card Type)

In [83]:
```
e1.columns
```

Out[83]:
```
Index(['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio',
       'Average_Amt_Per_Tran', 'Months_Active', 'Tran_per_month',
       'Expense_Per_Active_Month'],
      dtype='object')
```

In [84]:
```
card_month = e1[['Card_Category', 'Expense_Per_Active_Month']]
```

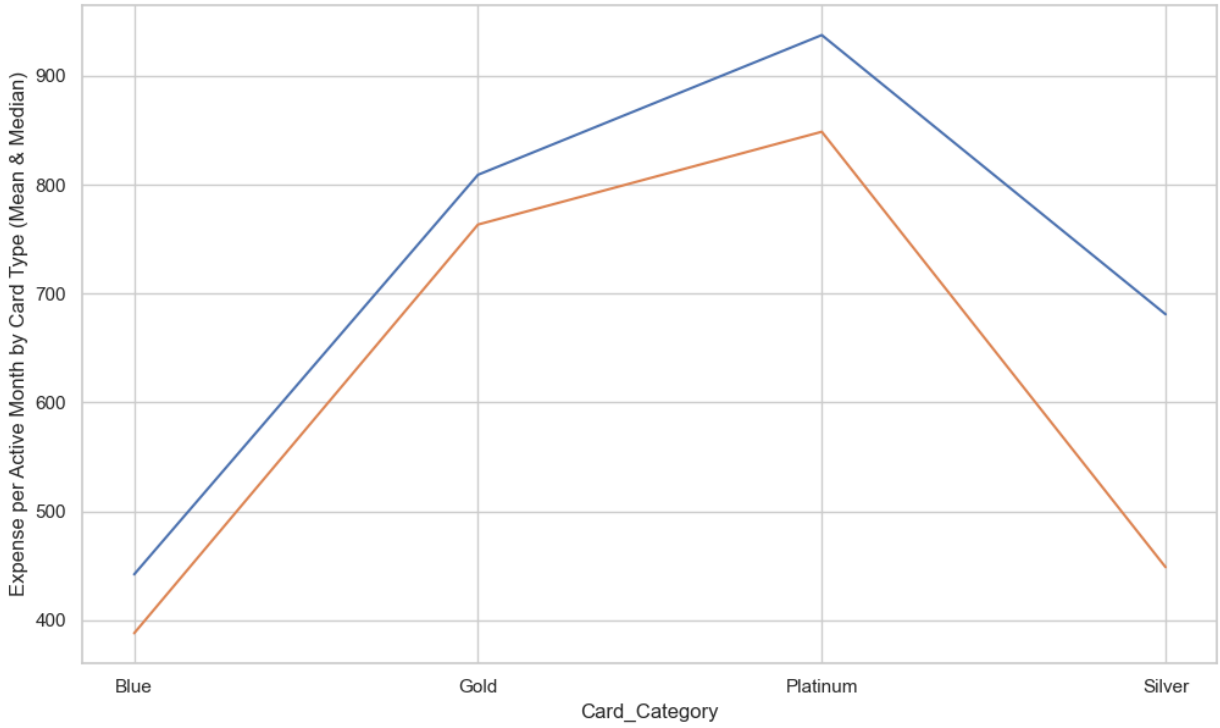
In [85]:
```
cm1 = card_month.groupby(['Card_Category']).median()
cm2 = card_month.groupby(['Card_Category']).mean()
cm = pd.merge(cm1, cm2, on = 'Card_Category', how = 'outer')
cm.columns = ['Expense_Per_Active_Month_Median', 'Expense_Per_Active_Mont
cm.reset_index(inplace = True)
cm
```

Out[85]:

| | Card_Category | Expense_Per_Active_Month_Median | Expense_Per_Active_Month_Mean |
|---|---|---|---|
| **0** | Blue | 387.894444 | 441.957175 |
| **1** | Gold | 763.350000 | 809.077049 |
| **2** | Platinum | 848.622222 | 937.438068 |
| **3** | Silver | 448.555556 | 680.904958 |

In [86]:
```
plt.figure(figsize = (12,7))
sns.lineplot(data = cm, x = 'Card_Category', y = 'Expense_Per_Active_Mont
sns.lineplot(data = cm, x = 'Card_Category', y = 'Expense_Per_Active_Mont
plt.ylabel('Expense per Active Month by Card Type (Mean & Median)')
```

Out[86]:
```
Text(0, 0.5, 'Expense per Active Month by Card Type (Mean & Median)')
```




# Expense Per Active Month (Attrited vs Existing)

In [87]:
```
attr_month = e1[['Attrition_Flag', 'Expense_Per_Active_Month']]
```

In [88]:
```
attr_month.sample(3)
```

Out[88]:

| | Attrition_Flag | Expense_Per_Active_Month |
|---|---|---|
| **8414** | Existing Customer | 492.600000 |
| **5235** | Existing Customer | 448.090909 |
| **8437** | Existing Customer | 556.777778 |

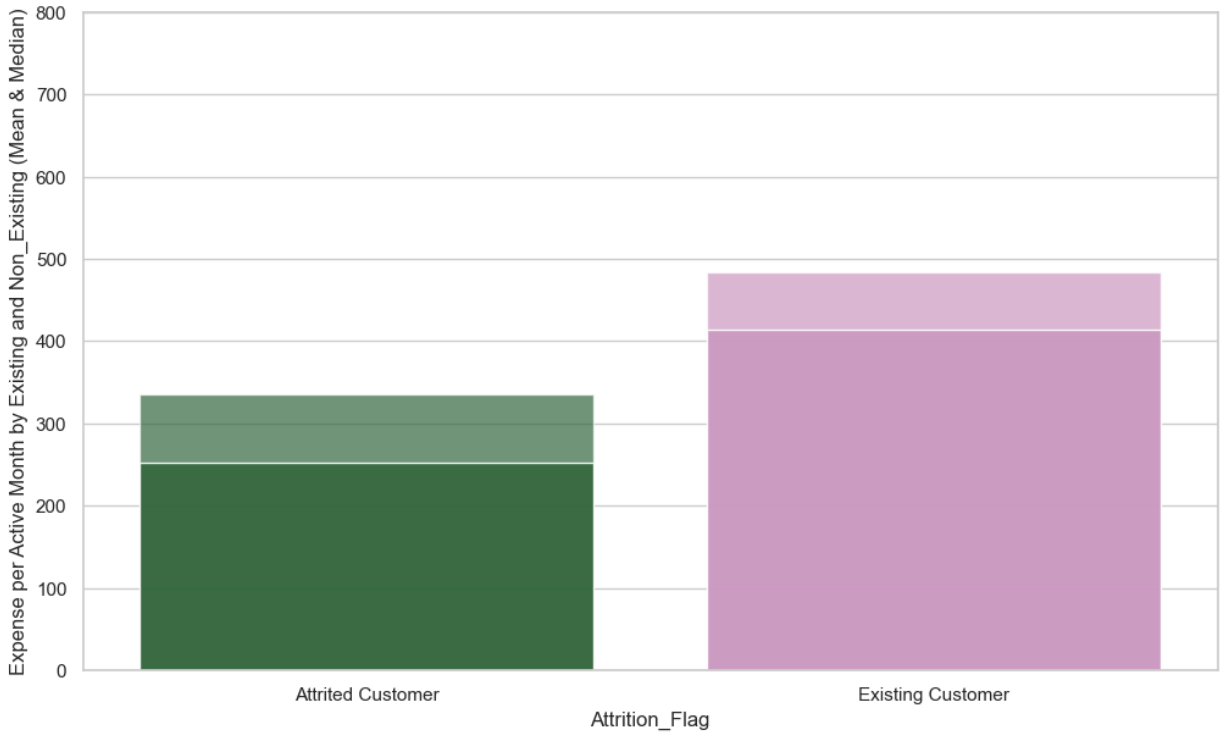
In [89]:
```
att1 = attr_month.groupby('Attrition_Flag').median()
att2 = attr_month.groupby('Attrition_Flag').mean()
att = pd.merge(att1, att2, on = 'Attrition_Flag', how = 'outer')
att.columns = ['Expense_Per_Active_Month_Median', 'Expense_Per_Active_Mon
att.reset_index(inplace = True)
att
```

Out[89]:

| | Attrition_Flag | Expense_Per_Active_Month_Median | Expense_Per_Active_Month_Mean |
|---|---|---|---|
| **0** | Attrited Customer | 252.444444 | 335.263166 |
| **1** | Existing Customer | 414.472222 | 484.157492 |

In [90]:
```
plt.figure(figsize = (12,7))
sns.barplot(data = att, x = 'Attrition_Flag', y = 'Expense_Per_Active_Mon
            palette = 'cubehelix')
sns.barplot(data = att, x = 'Attrition_Flag', y = 'Expense_Per_Active_Mon
            alpha = 0.9)
plt.ylabel('Expense per Active Month by Existing and Non_Existing (Mean &
plt.ylim(0,800)
```

Out[90]:
```
(0.0, 800.0)
```




In [ ]:

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