In [1]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

SQL Server Data Extraction

In [3]:

```python
pip install sqlalchemy pyodbc pandas
```

```
Requirement already satisfied: sqlalchemy in c:\users\user\anaconda3\lib\site-packag
es (2.0.34)
Requirement already satisfied: pyodbc in c:\users\user\anaconda3\lib\site-packages
(5.1.0)
Requirement already satisfied: pandas in c:\users\user\anaconda3\lib\site-packages
(2.2.2)
Requirement already satisfied: typing-extensions>=4.6.0 in c:\users\user\anaconda3\l
ib\site-packages (from sqlalchemy) (4.11.0)
Requirement already satisfied: greenlet!=0.4.17 in c:\users\user\anaconda3\lib\site-
packages (from sqlalchemy) (3.2.3)
Requirement already satisfied: numpy>=1.26.0 in c:\users\user\anaconda3\lib\site-pac
kages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\user\anaconda3\lib
\site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\user\anaconda3\lib\site-pack
ages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\user\anaconda3\lib\site-pa
ckages (from pandas) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\user\anaconda3\lib\site-packages
(from python-dateutil>=2.8.2->pandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [4]:

```python
from sqlalchemy import create_engine
import pandas as pd

server = 'LAPTOP-174FML7C\\SQLEXPRESS'
database = 'INSTANT'

engine = create_engine(f"mssql+pyodbc://@{server}/{database}?trusted_connection=yes

tables = ['users_data', 'transactions_data', 'cards_data']

dfs = {}

for table in tables:
    dfs[table] = pd.read_sql_table(table, engine)

engine.dispose()
```

Loading SQL Server Tables into Pandas DataFrames

In [6]:
```
users_df = dfs['users_data']
transactions_df = dfs['transactions_data']
cards_df = dfs['cards_data']
```

In [7]:
```
users_df.head()
```

Out[7]:

	id	current_age	retirement_age	birth_year	birth_month	gender	address	latitude
0	0	33	69	1986	3	Male	858 Plum Avenue	43.590000
1	1	43	74	1976	4	Female	113 Burns Lane	30.440001
2	2	48	64	1971	8	Male	6035 Forest Avenue	40.840000
3	3	49	65	1970	12	Male	840 Elm Avenue	33.889999
4	4	54	72	1965	3	Female	6016 Little Creek Boulevard	47.610001

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

Out[8]:

	id	date	client_id	card_id	amount	use_chip	merchant_id	merchant_city
0	7475327	2010-01-01 00:01:00	1556	2972	$-77.00	Swipe Transaction	59935	Beulah
1	7475328	2010-01-01 00:02:00	561	4575	$14.57	Swipe Transaction	67570	Bettendorf
2	7475329	2010-01-01 00:02:00	1129	102	$80.00	Swipe Transaction	27092	Vista
3	7475331	2010-01-01 00:05:00	430	2860	$200.00	Swipe Transaction	27092	Crown Point
4	7475332	2010-01-01 00:06:00	848	3915	$46.41	Swipe Transaction	13051	Harwood

In [9]:
```
cards_df.head()
```

Out[9]:

	id	client_id	card_brand	card_type	card_number	expires	cvv	has_chip	num_ca
0	0	1362	Amex	Credit	393314135668401	04/2024	866	True	
1	1	550	Mastercard	Credit	5278231764792292	06/2024	396	True	
2	2	556	Mastercard	Debit	5889825928297675	09/2021	422	True	
3	3	1937	Visa	Credit	4289888672554714	04/2020	736	True	
4	4	1981	Mastercard	Debit	5433366978583845	03/2024	530	True	

Load MCC Codes JSON & Merge into Transactions

In [11]:

```python
import json
import pandas as pd

# Load MCC codes JSON
with open('data/Finance/mcc_codes.json', 'r') as f:
    mcc_dict = json.load(f)

# Map MCC descriptions
transactions_df['mcc_description'] = transactions_df['mcc'].map(mcc_dict)

transactions_df.to_csv("transactions_with_mcc.csv", index=False)
transactions_df.head()
```

Out[11]:

	id	date	client_id	card_id	amount	use_chip	merchant_id	merchant_city
0	7475327	2010-01-01 00:01:00	1556	2972	$-77.00	Swipe Transaction	59935	Beulah
1	7475328	2010-01-01 00:02:00	561	4575	$14.57	Swipe Transaction	67570	Bettendorf
2	7475329	2010-01-01 00:02:00	1129	102	$80.00	Swipe Transaction	27092	Vista
3	7475331	2010-01-01 00:05:00	430	2860	$200.00	Swipe Transaction	27092	Crown Point
4	7475332	2010-01-01 00:06:00	848	3915	$46.41	Swipe Transaction	13051	Harwood

Load fraud labels JSON & Merge into Transactions

In [13]:

```python
with open('data/Finance/train_fraud_labels.json', 'r') as f:
    data = json.load(f)
```

```python
# Extract the "target" dictionary
fraud_dict = data["target"]

# Convert to DataFrame
fraud_df = pd.DataFrame(list(fraud_dict.items()), columns=['id', 'fraud_label'])

# Convert id to int and add numeric fraud flag
fraud_df['id'] = fraud_df['id'].astype(int)

# Save to CSV
fraud_df.to_csv("fraud_labels.csv", index=False)

# Merge with transactions data on 'id'
transactions_df = transactions_df.merge(fraud_df, on='id', how='left')
transactions_df.head()
```

Out[13]:

	id	date	client_id	card_id	amount	use_chip	merchant_id	merchant_city
0	7475327	2010-01-01 00:01:00	1556	2972	$-77.00	Swipe Transaction	59935	Beulah
1	7475328	2010-01-01 00:02:00	561	4575	$14.57	Swipe Transaction	67570	Bettendorf
2	7475329	2010-01-01 00:02:00	1129	102	$80.00	Swipe Transaction	27092	Vista
3	7475331	2010-01-01 00:05:00	430	2860	$200.00	Swipe Transaction	27092	Crown Point
4	7475332	2010-01-01 00:06:00	848	3915	$46.41	Swipe Transaction	13051	Harwood

Data Overview

In [15]:

```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

1. Users Data

In [17]:

```python
# Structure Overview
users_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 2000 non-null   int64  
 1   current_age        2000 non-null   int64  
 2   retirement_age     2000 non-null   int64  
 3   birth_year         2000 non-null   int64  
 4   birth_month        2000 non-null   int64  
 5   gender             2000 non-null   object 
 6   address            2000 non-null   object 
 7   latitude           2000 non-null   float64
 8   longitude          2000 non-null   float64
 9   per_capita_income  2000 non-null   float64
 10  yearly_income      2000 non-null   float64
 11  total_debt         2000 non-null   float64
 12  credit_score       2000 non-null   int64  
 13  num_credit_cards   2000 non-null   int64  
dtypes: float64(5), int64(7), object(2)
memory usage: 218.9+ KB
```

In [18]:

```python
# Descriptive Statistics
users_df.describe()
```

Out[18]:

	id	current_age	retirement_age	birth_year	birth_month	latitude	
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2
mean	999.500000	45.391500	66.237500	1973.803000	6.439000	37.389225	
std	577.494589	18.414092	3.628867	18.421234	3.565338	5.114324	
min	0.000000	18.000000	50.000000	1918.000000	1.000000	20.879999	-
25%	499.750000	30.000000	65.000000	1961.000000	3.000000	33.837501	
50%	999.500000	44.000000	66.000000	1975.000000	7.000000	38.250000	
75%	1499.250000	58.000000	68.000000	1989.000000	10.000000	41.200001	
max	1999.000000	101.000000	79.000000	2002.000000	12.000000	61.200001	

In [19]:

```python
# Check Null Values
users_df.isna().sum()
```

Out[19]:
```
id                   0
current_age          0
retirement_age       0
birth_year           0
birth_month          0
gender               0
address              0
latitude             0
longitude            0
per_capita_income    0
yearly_income        0
total_debt           0
credit_score         0
num_credit_cards     0
dtype: int64
```

In [20]:
```
# Check Duplicates
users_df.duplicated().sum()
```

Out[20]:
```
0
```

In [21]:
```
# Summary of Object columns
object_cols = users_df.select_dtypes(include='object')

summary = pd.DataFrame({
    'Unique Count': object_cols.nunique(),
    'Sample Values': object_cols.apply(lambda col: col.dropna().unique()[:5])
}).sort_values(by='Unique Count')

summary
```

Out[21]:

	Unique Count	Sample Values
gender	2	[Male, Female]
address	1999	[858 Plum Avenue, 113 Burns Lane, 6035 Forest ...

2. Transactions Data

In [23]:
```
transactions_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5111652 entries, 0 to 5111651
Data columns (total 14 columns):
 #   Column           Dtype 
---  ------           ----- 
 0   id               int64 
 1   date             object
 2   client_id        int64 
 3   card_id          int64 
 4   amount           object
 5   use_chip         object
 6   merchant_id      object
 7   merchant_city    object
 8   merchant_state   object
 9   zip              object
 10  mcc              object
 11  errors           object
 12  mcc_description  object
 13  fraud_label      object
dtypes: int64(3), object(11)
memory usage: 546.0+ MB
```

In [24]:
```
transactions_df.describe()
```

Out[24]:

	id	client_id	card_id
count	5.111652e+06	5.111652e+06	5.111652e+06
mean	9.014990e+06	1.029610e+03	3.417125e+03
std	8.930758e+05	5.828530e+02	1.677423e+03
min	7.475327e+06	0.000000e+00	0.000000e+00
25%	8.240244e+06	5.140000e+02	2.284000e+03
50%	9.011440e+06	1.075000e+03	3.477000e+03
75%	9.788667e+06	1.534000e+03	4.781000e+03
max	1.056662e+07	1.998000e+03	6.065000e+03

In [25]:
```
transactions_df.isnull().sum()
```

Out[25]:
```
id                        0
date                      0
client_id                 0
card_id                   0
amount                    0
use_chip                  0
merchant_id               0
merchant_city             0
merchant_state            0
zip                       0
mcc                       0
errors                    0
mcc_description           0
fraud_label         1689666
dtype: int64
```

In [26]:
```
transactions_df.duplicated().sum()
```

Out[26]:
```
2555826
```

In [27]:
```
transactions_df['errors'].unique()
```

Out[27]:
```
array(['', 'Technical Glitch', 'Bad Expiration', 'Bad Card Number',
       'Insufficient Balance', 'Bad PIN', 'Bad CVV', 'Bad Zipcode',
       '"Bad PIN,Insufficient Balance"',
       '"Insufficient Balance,Technical Glitch"',
       '"Bad Card Number,Insufficient Balance"',
       '"Bad PIN,Technical Glitch"', '"Bad Expiration,Technical Glitch"',
       '"Bad Card Number,Bad Expiration"',
       '"Bad Expiration,Insufficient Balance"',
       '"Bad Card Number,Bad CVV"', '"Bad Expiration,Bad CVV"',
       '"Bad CVV,Technical Glitch"', '"Bad CVV,Insufficient Balance"',
       '"Bad Card Number,Technical Glitch"',
       '"Bad Zipcode,Insufficient Balance"'], dtype=object)
```

In [28]:
```
# Count empty strings
empty_count = (transactions_df['errors'] == '').sum()
print("Empty strings:", empty_count)

# Count whitespace-only values
space_count = (transactions_df['errors'].str.strip() == '').sum()
print("Whitespace only:", space_count)

# Count 'NULL' strings
null_str_count = (transactions_df['errors'] == 'NULL').sum()
print("NULL strings:", null_str_count)
```

```
Empty strings: 5030982
Whitespace only: 5030982
NULL strings: 0
```

In [29]:
```
# Summary of Object columns
object_cols = transactions_df.select_dtypes(include='object')

summary = pd.DataFrame({
    'Unique Count': object_cols.nunique(),
```

```
    'Sample Values': object_cols.apply(lambda col: col.dropna().unique()[:5])
}).sort_values(by='Unique Count')

summary
```

Out[29]:

	Unique Count	Sample Values
use_chip	2	[Swipe Transaction, Online Transaction]
fraud_label	2	[No, Yes]
errors	21	[, Technical Glitch, Bad Expiration, Bad Card ...
mcc_description	108	[Miscellaneous Food Stores, Department Stores,...
mcc	109	[5499, 5311, 4829, 5813, 5942]
merchant_state	143	[ND, IA, CA, IN, MD]
merchant_city	8915	[Beulah, Bettendorf, Vista, Crown Point, Harwood]
zip	17597	[58523.0, 52722.0, 92084.0, 46307.0, 20776.0]
merchant_id	37381	[59935, 67570, 27092, 13051, 20519]
amount	46604	[−77.00,14.57, 80.00,200.00, $46.41]
date	835782	[2010-01-01 00:01:00, 2010-01-01 00:02:00, 201...

In [30]:

```
transactions_df['mcc_description'].isna().sum()
```

Out[30]: 0

3. Cards Data

In [32]:

```
cards_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6146 entries, 0 to 6145
Data columns (total 13 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     6146 non-null   int64  
 1   client_id              6146 non-null   int64  
 2   card_brand             6146 non-null   object 
 3   card_type              6146 non-null   object 
 4   card_number            6146 non-null   int64  
 5   expires                6146 non-null   object 
 6   cvv                    6146 non-null   int64  
 7   has_chip               6146 non-null   bool   
 8   num_cards_issued       6146 non-null   int64  
 9   credit_limit           6146 non-null   float64
 10  acct_open_date         6146 non-null   object 
 11  year_pin_last_changed  6146 non-null   int64  
 12  card_on_dark_web       6146 non-null   object 
dtypes: bool(1), float64(1), int64(6), object(5)
memory usage: 582.3+ KB
```

In [33]:
```python
cards_df.describe()
```

Out[33]:

	id	client_id	card_number	cvv	num_cards_issued	credit_li
count	6146.000000	6146.000000	6.146000e+03	6146.000000	6146.000000	6146.0000
mean	3072.500000	994.939636	4.820426e+15	506.220794	1.503091	14347.493
std	1774.341709	578.614626	1.328582e+15	289.431123	0.519191	12014.463
min	0.000000	0.000000	3.001055e+14	0.000000	1.000000	0.0000
25%	1536.250000	492.250000	4.486365e+15	257.000000	1.000000	7042.7500
50%	3072.500000	992.000000	5.108957e+15	516.500000	1.000000	12592.5000
75%	4608.750000	1495.000000	5.585237e+15	756.000000	2.000000	19156.5000
max	6145.000000	1999.000000	6.997197e+15	999.000000	3.000000	151223.0000

In [34]:
```python
cards_df.isna().sum()
```

Out[34]:
```
id                       0
client_id                0
card_brand               0
card_type                0
card_number              0
expires                  0
cvv                      0
has_chip                 0
num_cards_issued         0
credit_limit             0
acct_open_date           0
year_pin_last_changed    0
card_on_dark_web         0
dtype: int64
```

In [35]:
```
cards_df.duplicated().sum()
```

Out[35]:
```
0
```

In [36]:
```
# Summary of Object columns
object_cols = cards_df.select_dtypes(include='object')

summary = pd.DataFrame({
    'Unique Count': object_cols.nunique(),
    'Sample Values': object_cols.apply(lambda col: col.dropna().unique()[:5])
}).sort_values(by='Unique Count')

summary
```

Out[36]:

	Unique Count	Sample Values
card_on_dark_web	1	[No]
card_type	3	[Credit, Debit, Debit (Prepaid)]
card_brand	4	[Amex, Mastercard, Visa, Discover]
expires	259	[04/2024, 06/2024, 09/2021, 04/2020, 03/2024]
acct_open_date	303	[01/1991, 01/1994, 01/1995, 01/1997, 01/1998]

Data Cleaning

1. Users Data

In [39]:
```
users_df.drop(['birth_year', 'birth_month', 'address'], axis=1, inplace=True)
```

2. Transactions Data

In [41]:
```
# Drop Duplicates
transactions_df.drop_duplicates(inplace=True)
```

In [42]:
```python
# Date from Object to Date/time
transactions_df['date'] = pd.to_datetime(transactions_df['date'], format='%Y-%m-%d
```

In [43]:
```python
# Amount Column from Object into Float
transactions_df['amount'] = transactions_df['amount'].str.replace('$', '', regex=Fa
transactions_df['amount'] = pd.to_numeric(transactions_df['amount'], errors='coerce
```

In [44]:
```python
# Errors: Replace empty strings with NaN
transactions_df['errors'] = transactions_df['errors'].replace('', np.nan)
```

In [45]:
```python
# Errors: Remove quotes and strip spaces
transactions_df['errors'] = transactions_df['errors'].str.replace('"', '', regex=Fa
transactions_df['errors'].value_counts(dropna=False)
```

Out[45]:
```
errors
NaN                                         2515491
Insufficient Balance                          25158
Bad PIN                                        6210
Technical Glitch                               5000
Bad Card Number                                1384
Bad CVV                                        1116
Bad Expiration                                 1065
Bad Zipcode                                     214
Bad PIN,Insufficient Balance                     64
Insufficient Balance,Technical Glitch            50
Bad Card Number,Insufficient Balance             19
Bad PIN,Technical Glitch                         12
Bad CVV,Insufficient Balance                      9
Bad Card Number,Bad CVV                           8
Bad Expiration,Technical Glitch                   5
Bad Card Number,Bad Expiration                    5
Bad Expiration,Insufficient Balance               5
Bad Card Number,Technical Glitch                  4
Bad Expiration,Bad CVV                            3
Bad CVV,Technical Glitch                          2
Bad Zipcode,Insufficient Balance                  2
Name: count, dtype: int64
```

In [46]:
```python
error_map = {
    'Bad PIN': 'Authentication Error',
    'Bad CVV': 'Authentication Error',
    'Bad Card Number': 'Card Info Error',
    'Bad Expiration': 'Card Info Error',
    'Bad Zipcode': 'Card Info Error',
    'Insufficient Balance': 'Balance Error',
    'Technical Glitch': 'System Error',
    '': 'No Error'
}
```

In [47]:
```python
# Convert everything to string first
transactions_df['errors'] = transactions_df['errors'].astype(str)

# Remove quotes and extra spaces
transactions_df['errors'] = transactions_df['errors'].str.replace('"', '').str.stri
```

```
# Replace empty strings or 'nan' with 'No Error'
transactions_df['errors'] = transactions_df['errors'].replace(['', 'nan'], 'No Erro

# Split multiple errors into list
transactions_df['errors_list'] = transactions_df['errors'].str.split(',')
transactions_df['errors_list'] = transactions_df['errors_list'].apply(lambda x: [e.
```

In [48]:
```
# Explode so each error has its own row
errors_exploded = transactions_df.explode('errors_list')

# Map to broad category
errors_exploded['error_category'] = errors_exploded['errors_list'].map(error_map)
```

In [49]:
```
transactions_df['errors_list'].value_counts()
```

Out[49]:
```
errors_list
[No Error]                                   2515491
[Insufficient Balance]                         25158
[Bad PIN]                                       6210
[Technical Glitch]                              5000
[Bad Card Number]                               1384
[Bad CVV]                                       1116
[Bad Expiration]                                1065
[Bad Zipcode]                                    214
[Bad PIN, Insufficient Balance]                   64
[Insufficient Balance, Technical Glitch]          50
[Bad Card Number, Insufficient Balance]           19
[Bad PIN, Technical Glitch]                       12
[Bad CVV, Insufficient Balance]                    9
[Bad Card Number, Bad CVV]                         8
[Bad Expiration, Technical Glitch]                 5
[Bad Card Number, Bad Expiration]                  5
[Bad Expiration, Insufficient Balance]             5
[Bad Card Number, Technical Glitch]                4
[Bad Expiration, Bad CVV]                          3
[Bad CVV, Technical Glitch]                        2
[Bad Zipcode, Insufficient Balance]                2
Name: count, dtype: int64
```

In [50]:
```
transactions_df['merchant_id'] = pd.to_numeric(transactions_df['merchant_id'], erro
```

In [51]:
```
# cleaning the mcc description column
broad_category_map = {
    # Food & Beverage
    'Food & Beverage': [
        'Miscellaneous Food Stores', 'Grocery Stores, Supermarkets',
        'Fast Food Restaurants', 'Eating Places and Restaurants',
        'Drinking Places (Alcoholic Beverages)',
        'Package Stores, Beer, Wine, Liquor'
    ],
    # Transportation
    'Transportation': [
        'Tolls and Bridge Fees', 'Taxicabs and Limousines', 'Bus Lines',
        'Passenger Railways', 'Railroad Passenger Transport', 'Motor Freight Carrie
```

```python
        'Airlines', 'Cruise Lines', 'Local and Suburban Commuter Transportation', '
    ],
    # Retail Stores
    'Retail Stores': [
        'Department Stores', 'Book Stores', 'Electronics Stores', 'Discount Stores'
        'Wholesale Clubs', 'Family Clothing Stores', 'Shoe Stores', 'Leather Goods'
        'Sporting Goods Stores', 'Household Appliance Stores', "Women's Ready-To-We
        'Furniture, Home Furnishings, and Equipment Stores', 'Cosmetic Stores',
        'Gift, Card, Novelty Stores', 'Industrial Equipment and Supplies'
    ],
    # Professional Services
    'Professional Services': [
        'Legal Services and Attorneys', 'Accounting, Auditing, and Bookkeeping Serv
        'Tax Preparation Services', 'Insurance Sales, Underwriting', 'Detective Age
    ],
    # Health & Medical
    'Health & Medical': [
        'Doctors, Physicians', 'Dentists and Orthodontists', 'Hospitals', 'Podiatri
        'Optometrists, Optical Goods and Eyeglasses', 'Chiropractors', 'Medical Ser
    ],
    # Utilities & Telecom
    'Utilities & Telecom': [
        'Utilities - Electric, Gas, Water, Sanitary', 'Telecommunication Services',
        'Cable, Satellite, and Other Pay Television Services', 'Computer Network Se
    ],
    # Entertainment
    'Entertainment': [
        'Motion Picture Theaters', 'Amusement Parks, Carnivals, Circuses',
        'Betting (including Lottery Tickets, Casinos)', 'Recreational Sports, Clubs
        'Athletic Fields, Commercial Sports', 'Theatrical Producers', 'Music Stores
    ]
}

# Function to map mcc_description to broad category
def map_broad_category(x):
    for broad_cat, cat_list in broad_category_map.items():
        if x in cat_list:
            return broad_cat
    return 'Other'  # default if not found

# Overwrite your existing mcc_description column
transactions_df['mcc_description'] = transactions_df['mcc_description'].apply(map_b

# Check results
print(transactions_df['mcc_description'].value_counts())
```

```
mcc_description
Food & Beverage          949513
Other                    832221
Retail Stores            328001
Transportation           256525
Utilities & Telecom      102399
Entertainment             50238
Health & Medical          21445
Professional Services     15484
Name: count, dtype: int64
```

In [52]:
```
transactions_df['fraud_label'] = transactions_df['fraud_label'].fillna('No')
```

3. Cards Data

In [54]:
```
cards_df.drop(['card_on_dark_web', 'cvv', 'card_number'], axis=1, inplace=True)
```

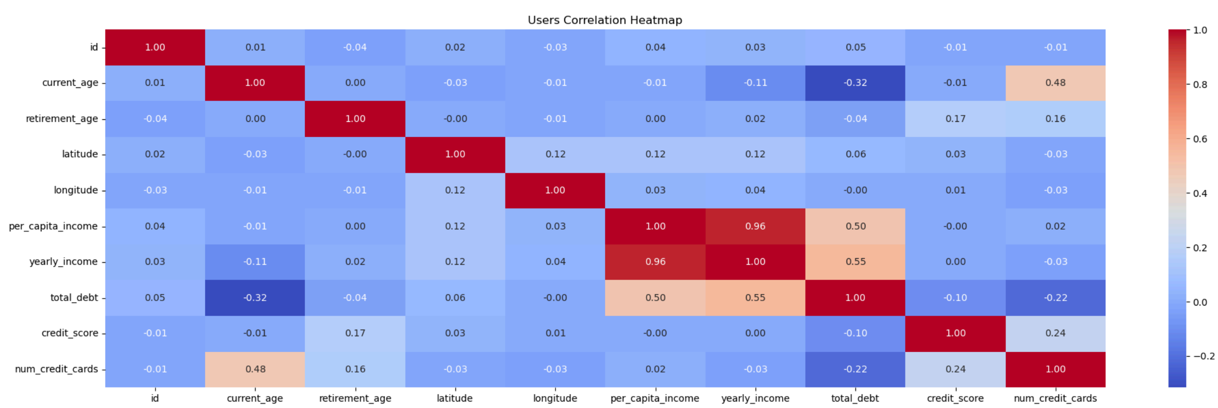
In [55]:
```
# From object to Date/Time
cards_df['expires'] = pd.to_datetime(cards_df['expires'], format='%m/%Y', errors='c
```

In [56]:
```
# From object to Date/Time
cards_df['acct_open_date'] = pd.to_datetime(cards_df['acct_open_date'], format='%m/
```

EDA (Exploratory Data Analysis)

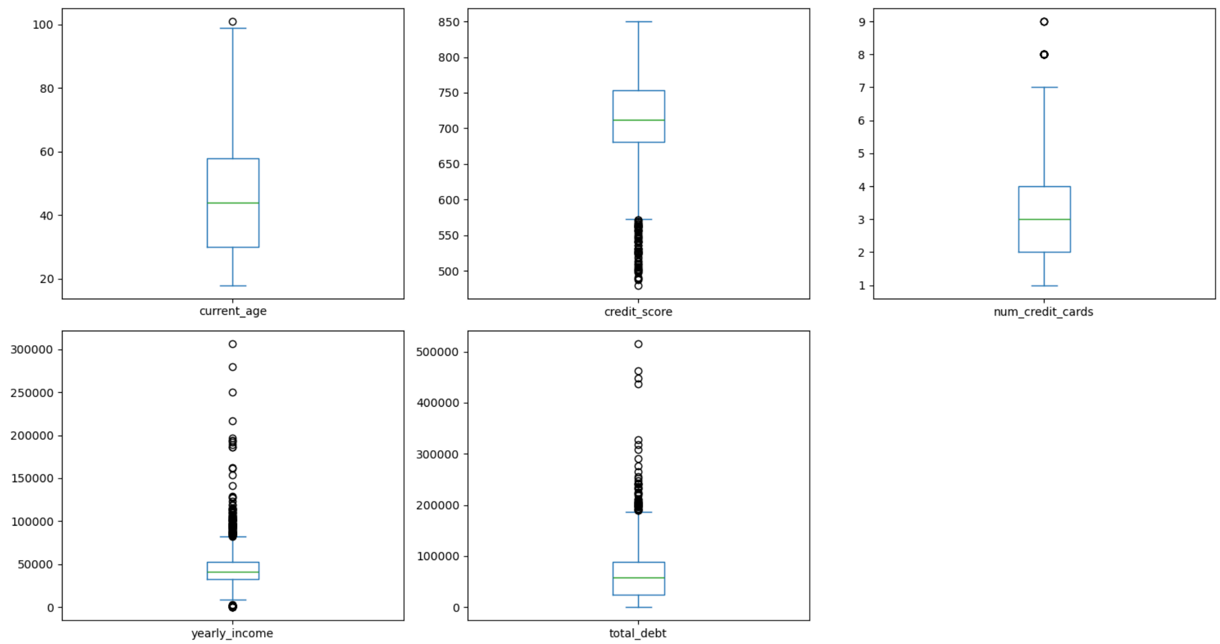
Users Data

In [59]:
```
# Users Heatmap of correlation
num_df = users_df.select_dtypes(include='number')
corr = num_df.corr()
plt.figure(figsize=(20, 6))
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Users Correlation Heatmap')
plt.tight_layout()
plt.show()
```



Box Plots

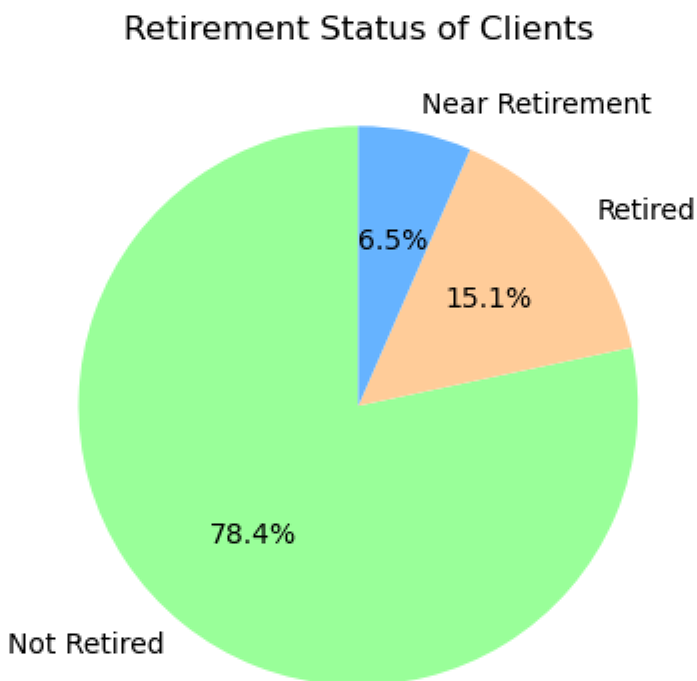
In [61]:
```
cols = ['current_age','credit_score','num_credit_cards','yearly_income','total_debt
users_df[cols].plot(kind='box', subplots=True, layout=(2,3), figsize=(15,8), sharex
plt.tight_layout()
plt.show()
```



Retirement Readiness & Targeting

Identify customers near retirement to market financial planning products.

In [63]:
```python
# Years left until retirement
users_df['years_to_retire'] = users_df['retirement_age'] - users_df['current_age']

# Classify Retirement
def classify_retirement(row):
    if row['current_age'] >= row['retirement_age']:
        return 'Retired'
    elif row['years_to_retire'] <= 5:
        return 'Near Retirement'
    else:
        return 'Not Retired'

users_df['retirement_status'] = users_df.apply(classify_retirement, axis=1)

# Plot
plt.figure(figsize=(4,4))
users_df['retirement_status'].value_counts().plot.pie(
    autopct='%1.1f%%',
    colors=['#99ff99','#ffcc99','#66b3ff'], startangle=90)

plt.title('Retirement Status of Clients')
plt.ylabel('')
plt.tight_layout()
plt.show()
```



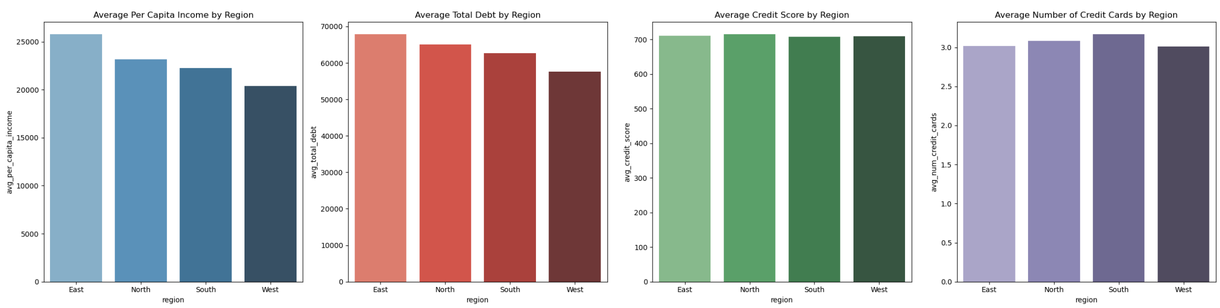
Regional Analysis Using Latitude & Longitude

Identify profitable or risky geographic areas.

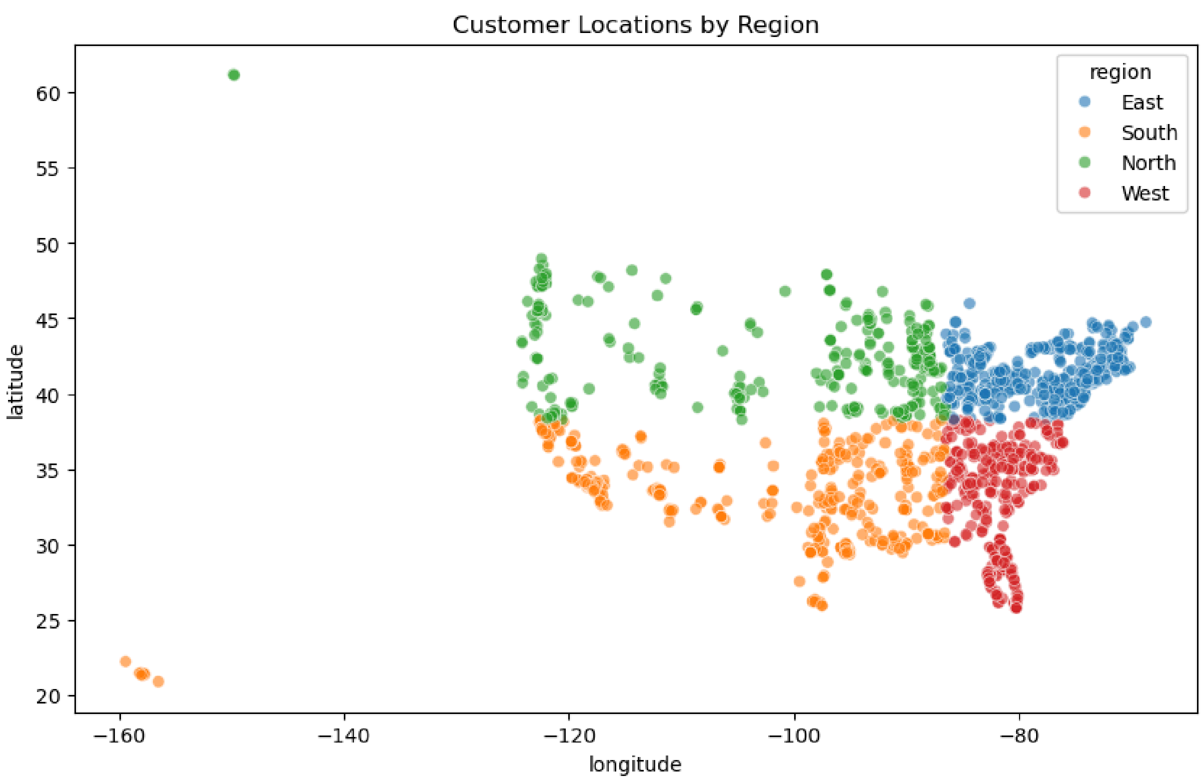
In [65]:
```
# Simple quadrant segmentation
users_df['region'] = users_df.apply(
    lambda row:
    'North' if row['latitude'] >= users_df['latitude'].median() and row['longitude'
    'South' if row['latitude'] < users_df['latitude'].median() and row['longitude']
    'East' if row['latitude'] >= users_df['latitude'].median() and row['longitude']
    'West',
    axis=1
)
```

In [66]:
```
# Group by region to compute averages
region_summary = users_df.groupby('region').agg({
    'per_capita_income': 'mean',
    'total_debt': 'mean',
    'credit_score': 'mean',
    'num_credit_cards': 'mean'
}).reset_index()

region_summary.rename(columns={
    'per_capita_income': 'avg_per_capita_income',
    'total_debt': 'avg_total_debt',
    'credit_score': 'avg_credit_score',
    'num_credit_cards': 'avg_num_credit_cards'
}, inplace=True)

# Create 1 row × 4 columns of subplots
fig, axes = plt.subplots(1, 4, figsize=(24, 6))  # wider figure
```

```python
sns.barplot(x='region', y='avg_per_capita_income', data=region_summary, ax=axes[0],
axes[0].set_title('Average Per Capita Income by Region')

sns.barplot(x='region', y='avg_total_debt', data=region_summary, ax=axes[1], palett
axes[1].set_title('Average Total Debt by Region')

sns.barplot(x='region', y='avg_credit_score', data=region_summary, ax=axes[2], pale
axes[2].set_title('Average Credit Score by Region')

sns.barplot(x='region', y='avg_num_credit_cards', data=region_summary, ax=axes[3],
axes[3].set_title('Average Number of Credit Cards by Region')

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



In [67]:
```python
# scatter map
plt.figure(figsize=(10,6))
sns.scatterplot(x='longitude', y='latitude', hue='region', data=users_df, alpha=0.6
plt.title('Customer Locations by Region')
plt.show()
```

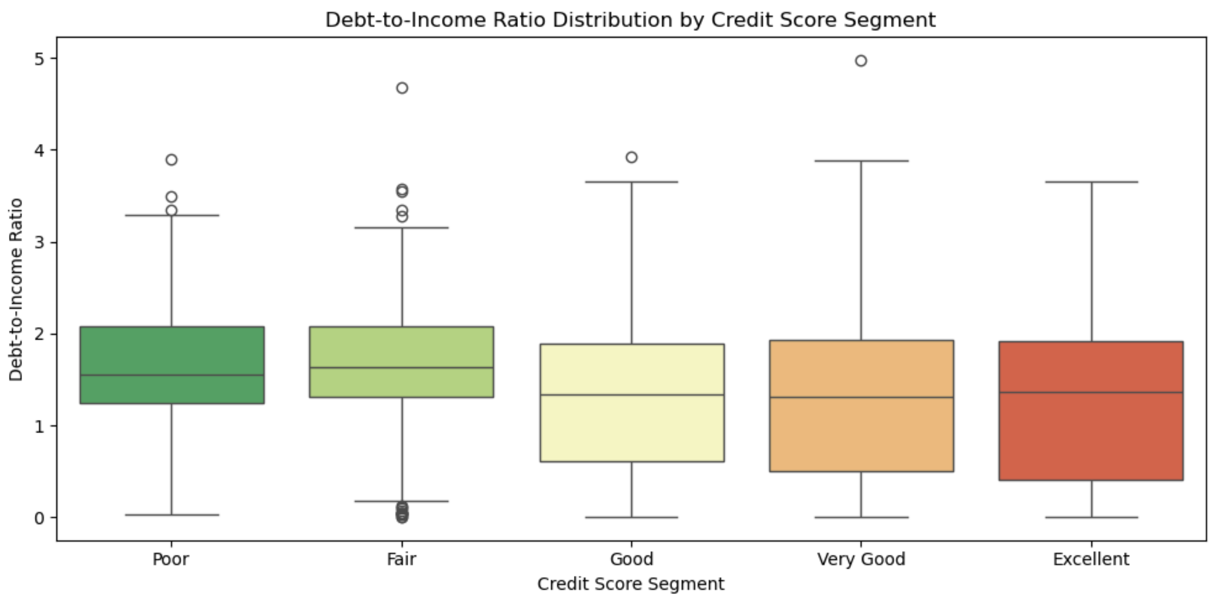


Credit Risk Profiling

Detect high-risk customers for credit products or limit increases.

In [69]:
```
users_df['debt_to_income_ratio'] = users_df['total_debt'] / users_df['yearly_income

# Segment customers
risk_segments = pd.cut(users_df['credit_score'],
                       bins=[300,580,670,740,800,850],
                       labels=['Poor','Fair','Good','Very Good','Excellent'])

users_df['credit_segment'] = risk_segments
```

In [70]:
```
risk_order = ['Poor','Fair','Good','Very Good','Excellent']

plt.figure(figsize=(10,5))
sns.boxplot(
    x='credit_segment', y='debt_to_income_ratio',
    data=users_df, order=risk_order, palette='RdYlGn_r')

plt.title('Debt-to-Income Ratio Distribution by Credit Score Segment')
plt.xlabel('Credit Score Segment')
plt.ylabel('Debt-to-Income Ratio')
plt.tight_layout()
plt.show()
```

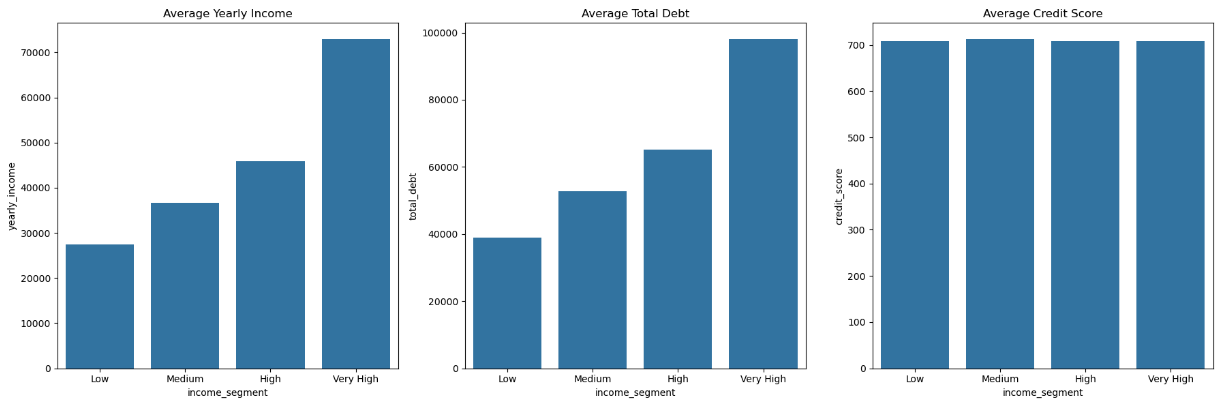


Income Segmentation

Design premium products for high earners and budget solutions for low earners.

In [72]:
```
# Segment by per_capita_income
income_segments = pd.qcut(users_df['per_capita_income'], q=4, labels=['Low','Medium
users_df['income_segment'] = income_segments

income_summary = users_df.groupby('income_segment')[['yearly_income','total_debt','

fig, axes = plt.subplots(1,3, figsize=(18,6))

sns.barplot(x='income_segment', y='yearly_income', data=income_summary, ax=axes[0])
```

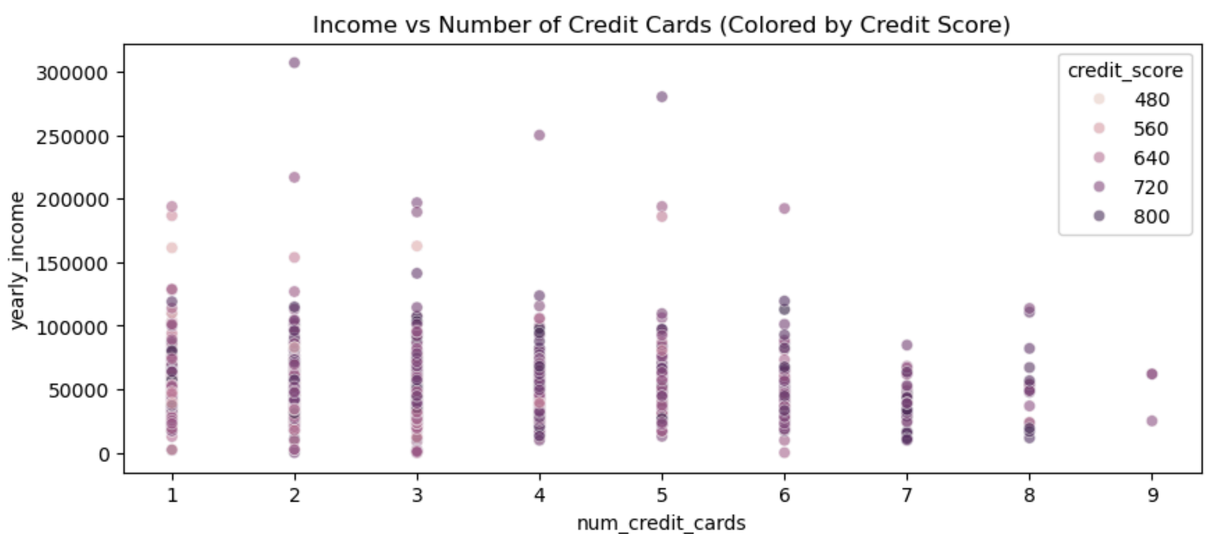
```python
axes[0].set_title('Average Yearly Income')

sns.barplot(x='income_segment', y='total_debt', data=income_summary, ax=axes[1])
axes[1].set_title('Average Total Debt')

sns.barplot(x='income_segment', y='credit_score', data=income_summary, ax=axes[2])
axes[2].set_title('Average Credit Score')

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



Number of Credit Cards vs Income vs Credit Score

Shows which clients have high spending capacity but low credit scores

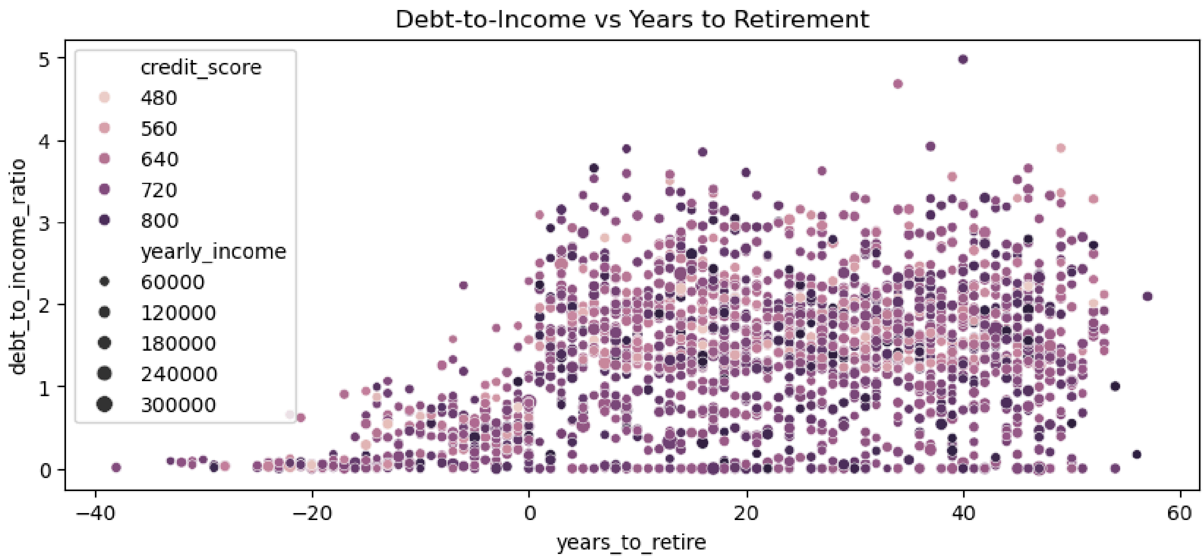
In [74]:
```python
plt.figure(figsize=(10,4))
sns.scatterplot(x='num_credit_cards', y='yearly_income',
                hue='credit_score', data=users_df, alpha=0.6)
plt.title('Income vs Number of Credit Cards (Colored by Credit Score)')
plt.show()
```



Debt-to-Income Ratio vs. Credit Score & Retirement Age

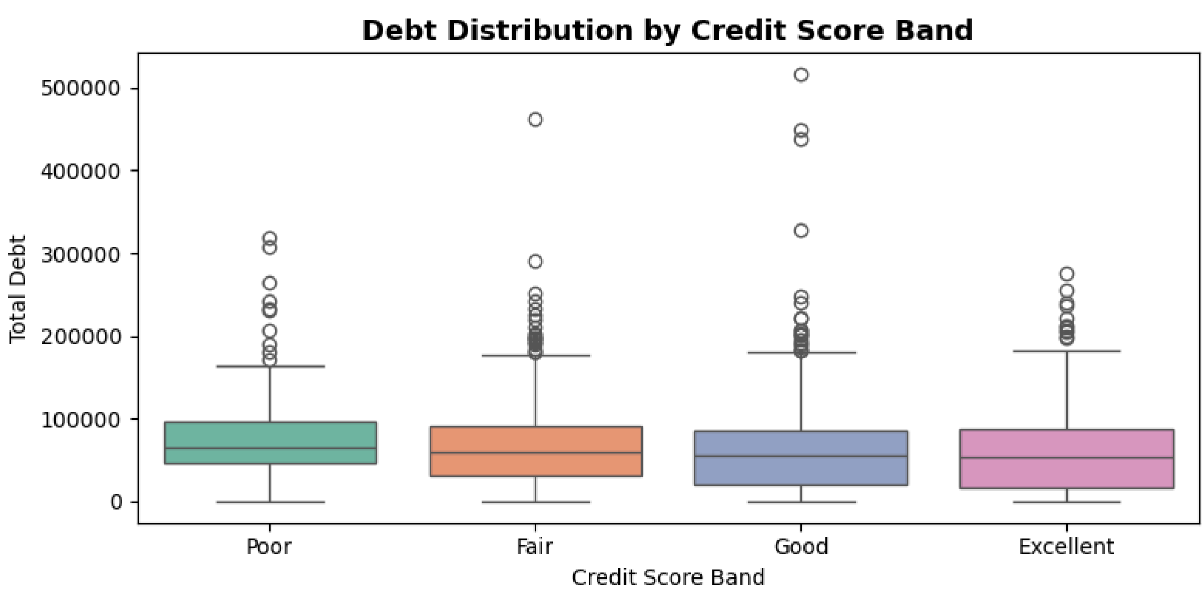
Shows whether people nearing retirement are financially stressed (high debt but low credit score).

In [76]:
```
plt.figure(figsize=(10,4))
sns.scatterplot(x='years_to_retire', y='debt_to_income_ratio', hue='credit_score',
plt.title('Debt-to-Income vs Years to Retirement')
plt.show()
```



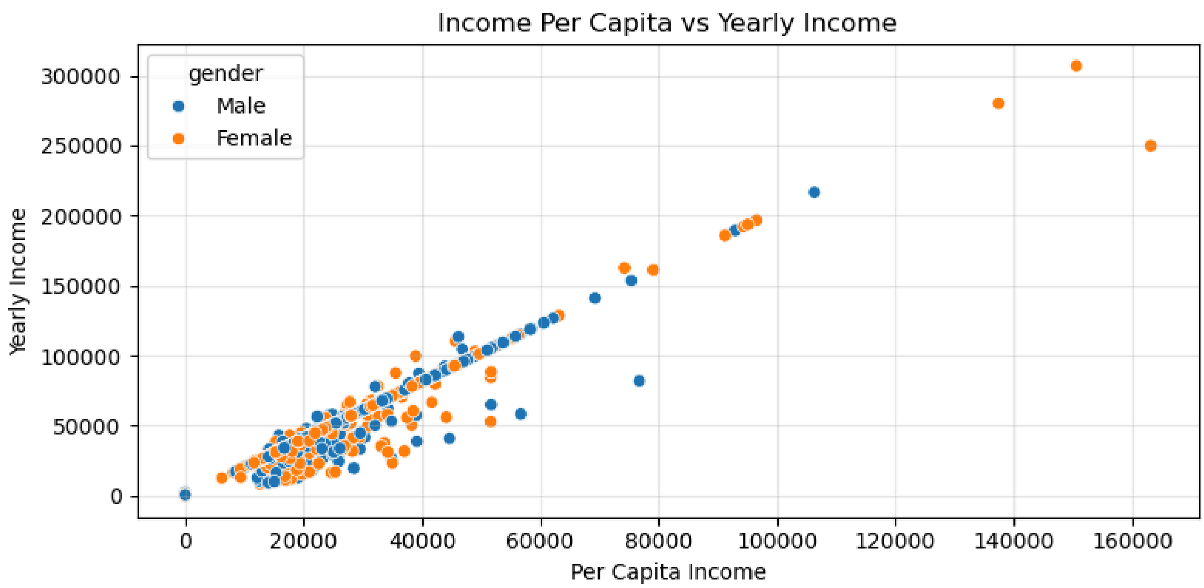
Debt by Credit Score Bands

In [78]:
```
bins = [0,600,700,750,850]
labels = ['Poor','Fair','Good','Excellent']
users_df['score_band'] = pd.cut(users_df['credit_score'], bins=bins, labels=labels)

plt.figure(figsize=(8,4))
sns.boxplot(x='score_band', y='total_debt', data=users_df, palette='Set2')
plt.title('Debt Distribution by Credit Score Band', fontsize=13, weight='bold')
plt.xlabel('Credit Score Band'); plt.ylabel('Total Debt')
plt.tight_layout()
plt.show()
```



PCI vs Yearly Income Scatter

In [80]:
```
# PCI vs Yearly Income Scatter
plt.figure(figsize=(8,4))
sns.scatterplot(x='per_capita_income', y='yearly_income', data=users_df, hue='gende
plt.title('Income Per Capita vs Yearly Income')
plt.xlabel('Per Capita Income')
plt.ylabel('Yearly Income')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```



In [81]:
```
# Age Group
bins = [17, 24, 34, 44, 54, 64, 120]
labels = ['18-24', '25-34', '35-44', '45-54', '55-64', '65+']

users_df['age_group'] = pd.cut(users_df['current_age'], bins=bins, labels=labels)
```

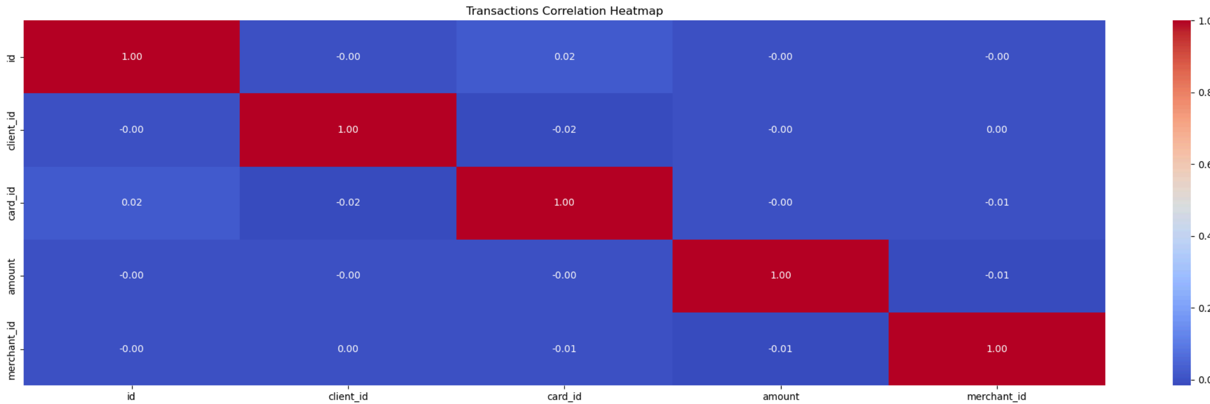
In [82]:
```
# Income Group
bins = [0, 30000, 60000, 100000, 200000, users_df['yearly_income'].max()]
labels = ['Low', 'Lower-Middle', 'Upper-Middle', 'High', 'Very High']

users_df['income_group'] = pd.cut(users_df['yearly_income'], bins=bins, labels=labe
```

Transactions Data

Heatmap of correlation

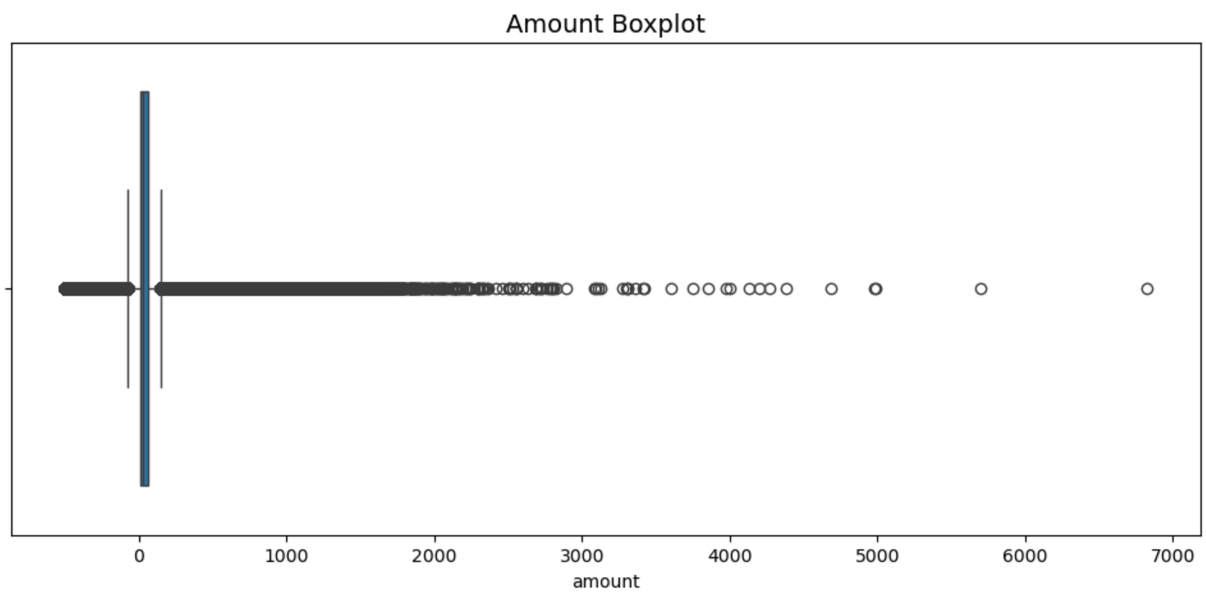
In [85]:
```
num_df = transactions_df.select_dtypes(include='number')
corr = num_df.corr()
plt.figure(figsize=(20, 6))
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Transactions Correlation Heatmap')
```

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



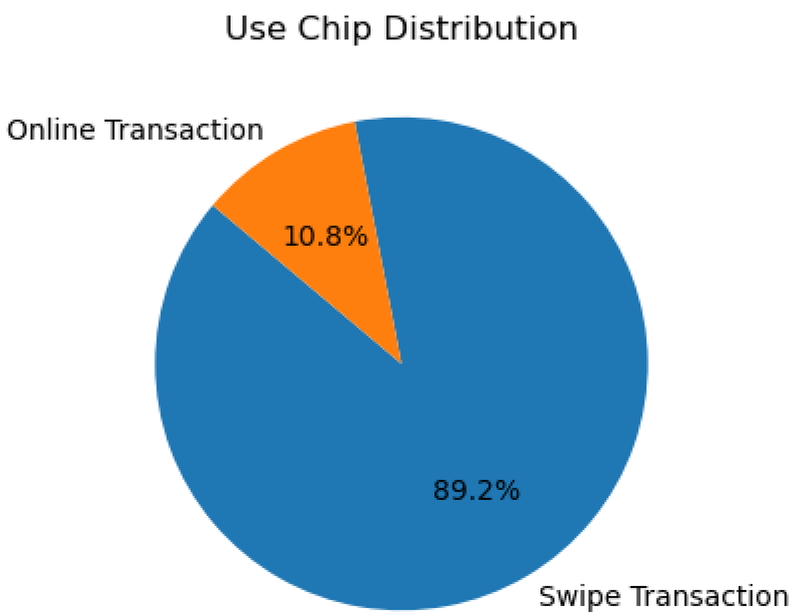
Box Plot Transactions Amount

In [87]:
```
plt.figure(figsize=(12,5))
sns.boxplot(x=transactions_df['amount'])
plt.title('Amount Boxplot', fontsize=14)
plt.show()
```



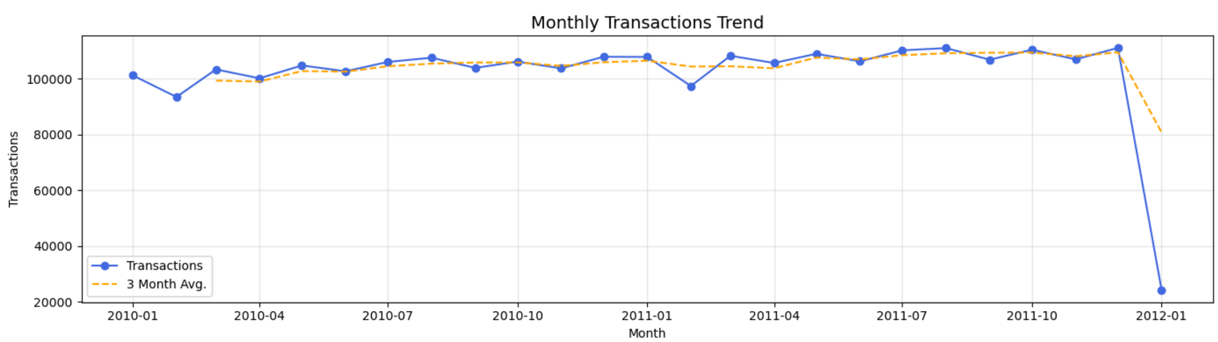
Use Chip Distribution

In [89]:
```
use_chip_counts = transactions_df['use_chip'].value_counts()
plt.figure(figsize=(4,4))
plt.pie(use_chip_counts, labels=use_chip_counts.index, autopct='%1.1f%%', startangl
plt.title('Use Chip Distribution')
plt.show()
```



Trend Analysis

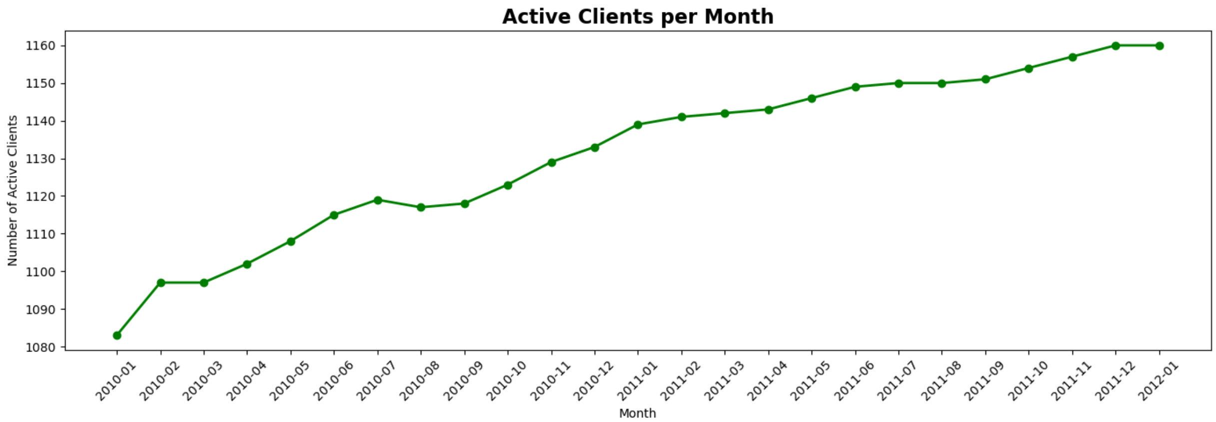
In [91]:
```
transactions_df['month'] = transactions_df['date'].dt.to_period('M').dt.to_timestam
monthly = transactions_df.groupby('month').size()

plt.figure(figsize=(14,4))
plt.plot(monthly.index, monthly.values, marker='o', color='royalblue', label='Trans
plt.plot(monthly.index, monthly.rolling(3).mean(), color='orange', linestyle='--',
plt.title('Monthly Transactions Trend', fontsize=14)
plt.xlabel('Month'); plt.ylabel('Transactions'); plt.grid(alpha=0.3); plt.legend()
plt.tight_layout(); plt.show()
```



Customer Activity Rate (Active Clients)

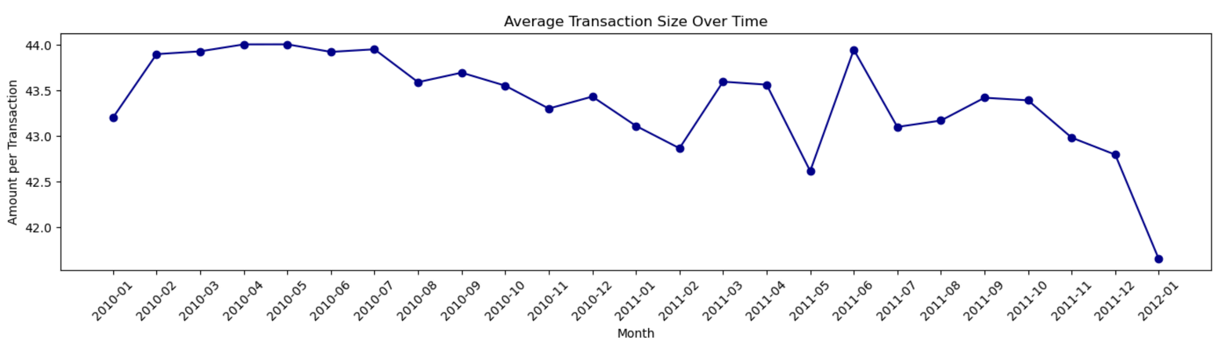
In [93]:
```
transactions_df['month'] = transactions_df['date'].dt.to_period('M')
# Group by month to count unique clients
active_clients = transactions_df.groupby('month')['client_id'].nunique()

# Plot
plt.figure(figsize=(14,5))
plt.plot(active_clients.index.astype(str), active_clients.values,
         marker='o', color='green', linewidth=2)
```

```python
plt.title('Active Clients per Month', fontsize=16, fontweight='bold')
plt.xlabel('Month')
plt.ylabel('Number of Active Clients')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Average Ticket Size (ATS) (average spend per transaction over time)

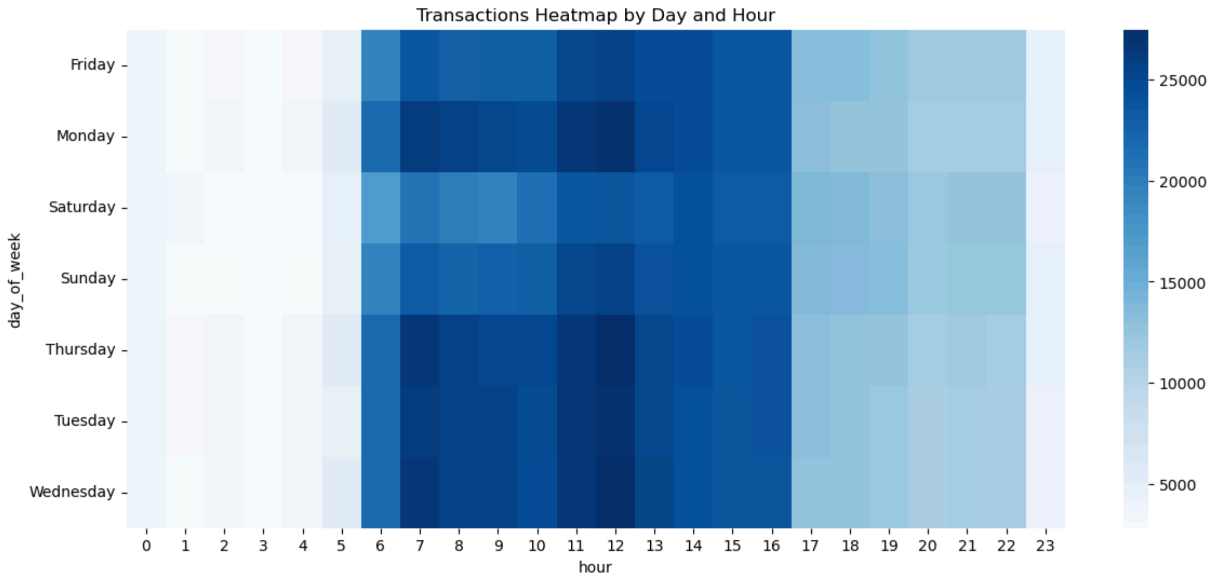
In [96]:
```python
monthly_amount = transactions_df.groupby('month')['amount'].sum()
monthly_count  = transactions_df.groupby('month').size()
ats = monthly_amount / monthly_count

plt.figure(figsize=(14,4))
plt.plot(ats.index.astype(str),
         ats.values, marker='o', color='darkblue')
plt.title('Average Transaction Size Over Time')
plt.ylabel('Amount per Transaction')
plt.xlabel('Month')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Transactions Heatmap by Day and Hour

In [98]:
```python
transactions_df['day_of_week'] = transactions_df['date'].dt.day_name()
transactions_df['hour'] = transactions_df['date'].dt.hour

heatmap_data = transactions_df.groupby(['day_of_week','hour']).size().unstack(fill_
```

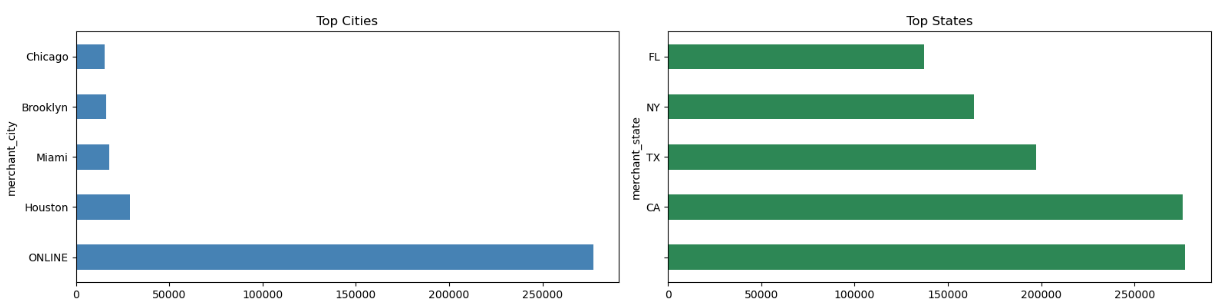
```
plt.figure(figsize=(14,6))
sns.heatmap(heatmap_data, cmap='Blues')
plt.title('Transactions Heatmap by Day and Hour')
plt.show()
```



Top 5 Cities and States

In [100…

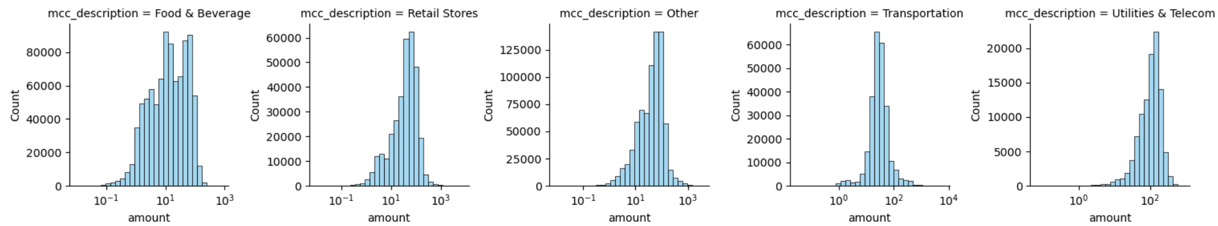
```
fig,ax=plt.subplots(1,2,figsize=(16,4))
transactions_df['merchant_city'].value_counts().head().plot(kind='barh',ax=ax[0],co
transactions_df['merchant_state'].value_counts().head().plot(kind='barh',ax=ax[1],c
plt.tight_layout();plt.show()
```



Amount vs MCC

In [102…

```
top_mcc = transactions_df['mcc_description'].value_counts().head().index.tolist()

g = sns.FacetGrid(
    transactions_df[transactions_df['mcc_description'].isin(top_mcc)],
    col='mcc_description', col_wrap=5, height=3, sharex=False, sharey=False
)
g.map(sns.histplot, 'amount', log_scale=True, bins=30, color='skyblue')
plt.tight_layout()
plt.show()
```

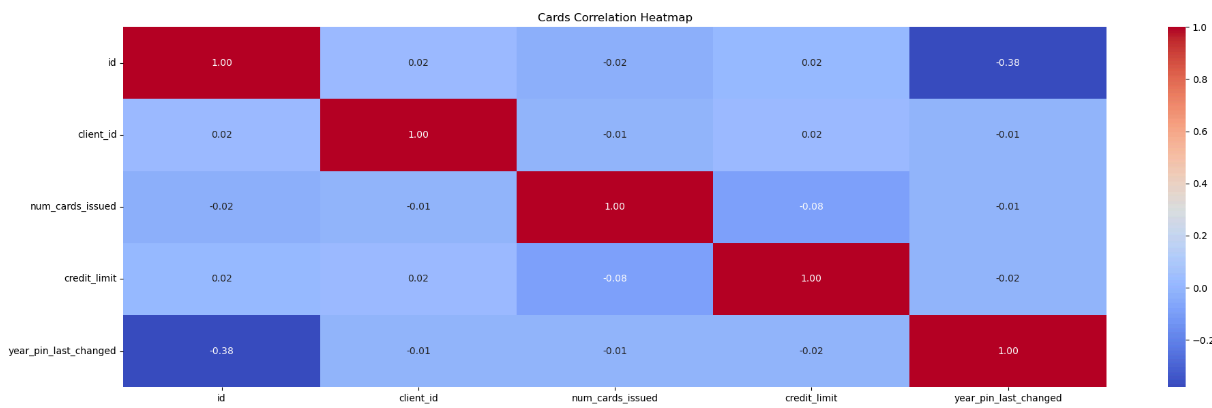


Cards Data

Heatmap of correlation

In [106…

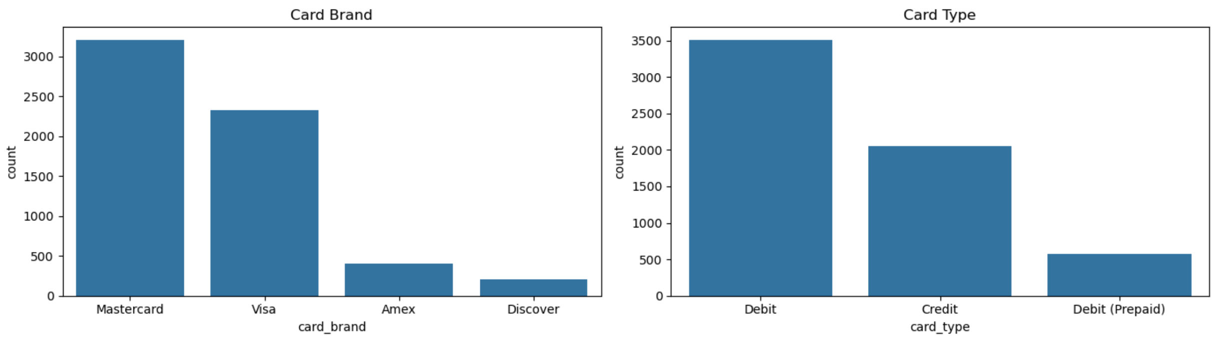
```python
num_df = cards_df.select_dtypes(include='number')
corr = num_df.corr()
plt.figure(figsize=(20, 6))
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Cards Correlation Heatmap')
plt.tight_layout()
plt.show()
```



Card Brand & Type Distribution

In [108…

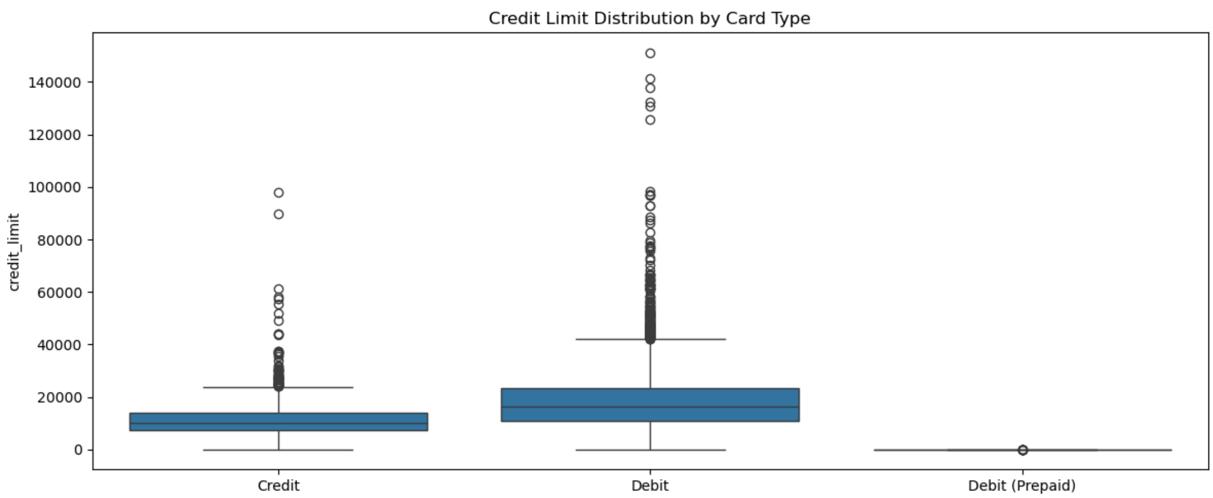
```python
fig,ax=plt.subplots(1,2,figsize=(14,4))
sns.countplot(x='card_brand',data=cards_df,
              order=cards_df['card_brand'].value_counts().index,ax=ax[0])
ax[0].set_title('Card Brand')

sns.countplot(x='card_type',data=cards_df,
              order=cards_df['card_type'].value_counts().index,ax=ax[1])
ax[1].set_title('Card Type')

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



Average Credit Limit by Card Type / Brand

In [111…

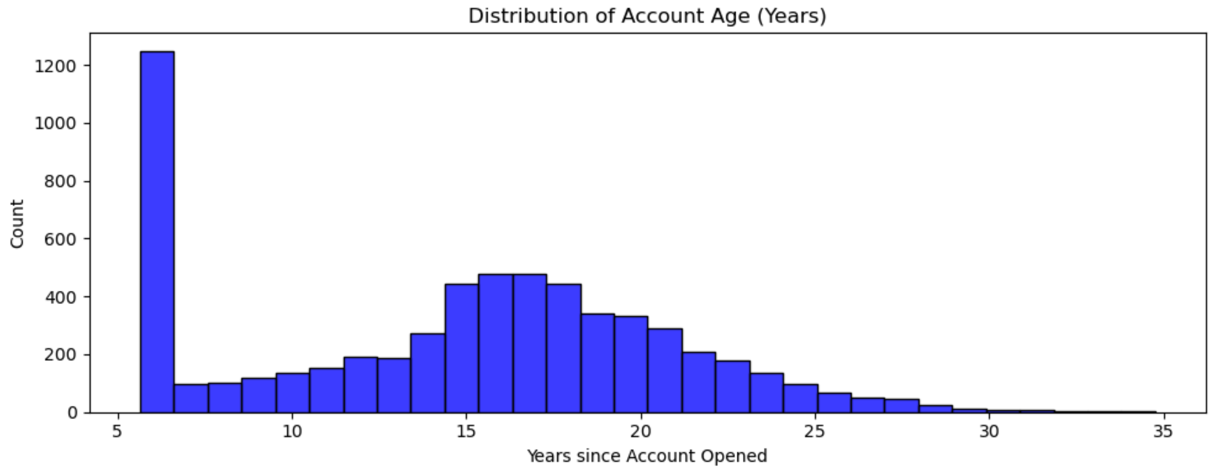
```
plt.figure(figsize=(12,5))
sns.boxplot(x='card_type', y='credit_limit', data=cards_df)
plt.title('Credit Limit Distribution by Card Type')
plt.xlabel('')
plt.tight_layout()
plt.show()
```



Customer Age with the Bank

In [113…

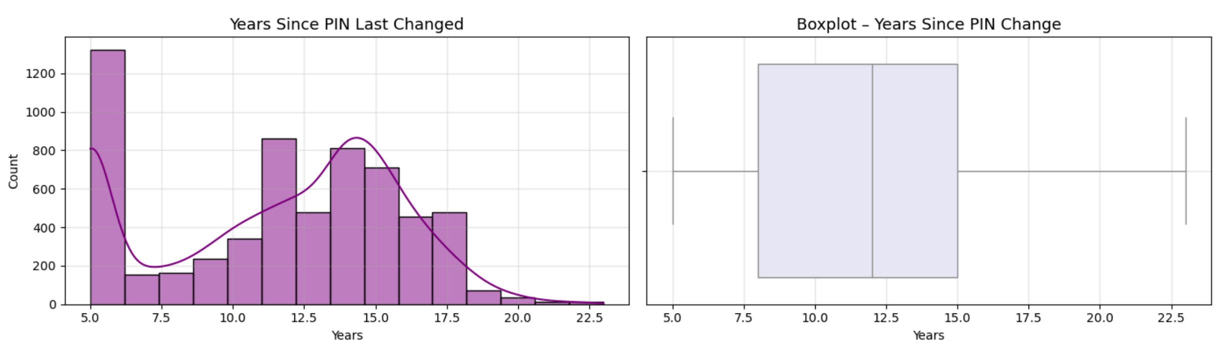
```
cards_df['acct_age_years'] = (pd.Timestamp.today() - cards_df['acct_open_date']).dt

plt.figure(figsize=(10,4))
sns.histplot(cards_df['acct_age_years'], bins=30, color='blue')
plt.title('Distribution of Account Age (Years)')
plt.xlabel('Years since Account Opened')
plt.tight_layout()
plt.show()
```



PIN Security Hygiene (Find customers who haven’t changed their PIN recently)

In [115…

```
recent_year = pd.Timestamp.today().year
cards_df['years_since_pin_change'] = recent_year - cards_df['year_pin_last_changed'

fig, ax = plt.subplots(1,2,figsize=(14,4))

# KDE + histogram
sns.histplot(cards_df['years_since_pin_change'], bins=15, kde=True, color='purple',
ax[0].set_title('Years Since PIN Last Changed', fontsize=13)
ax[0].set_xlabel('Years')
ax[0].grid(alpha=0.3)

# Boxplot for quick outlier view
sns.boxplot(x=cards_df['years_since_pin_change'], color='lavender', ax=ax[1])
ax[1].set_title('Boxplot – Years Since PIN Change', fontsize=13)
ax[1].set_xlabel('Years')
ax[1].grid(alpha=0.3)

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

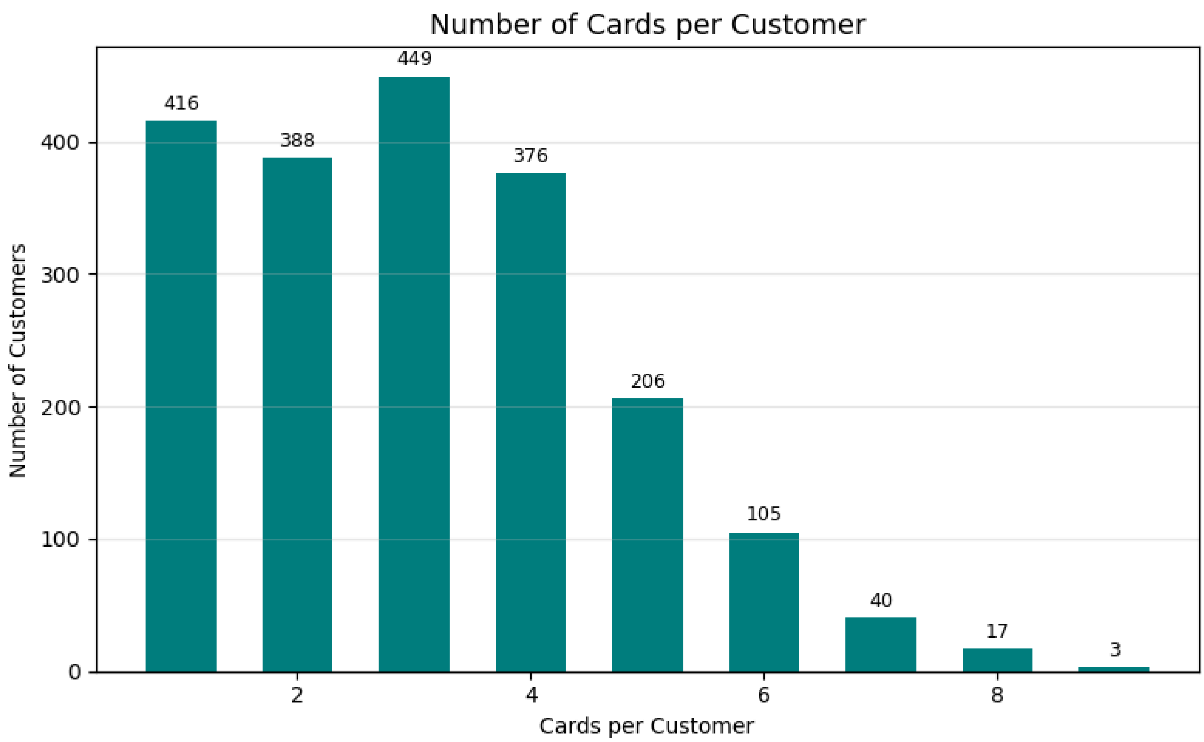


Cards Per Customer

In [117…

```
cards_per_client = cards_df.groupby('client_id')['num_cards_issued'].count()
cards_count = cards_per_client.value_counts().sort_index()

fig, ax = plt.subplots(figsize=(8,5))
```

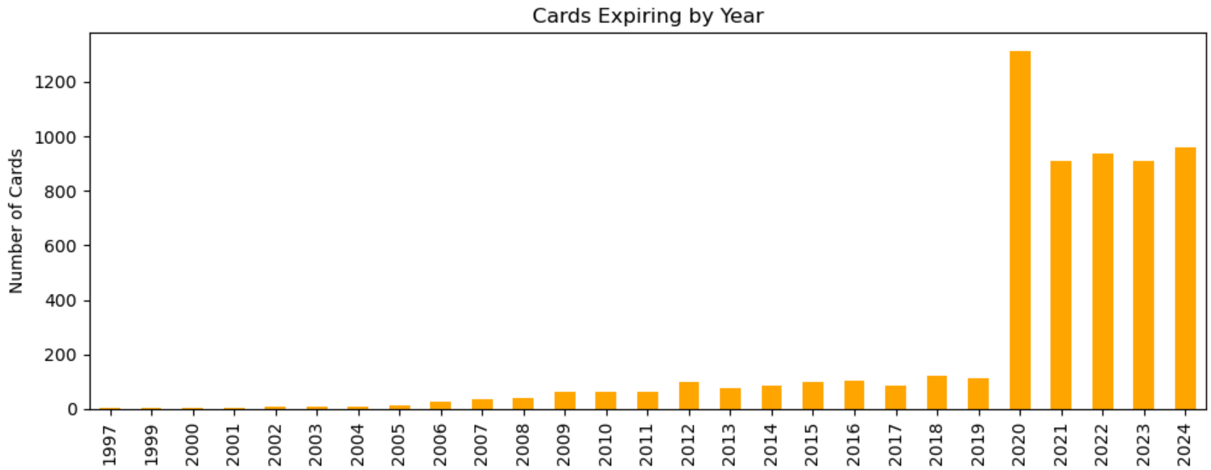
```python
bars = ax.bar(cards_count.index, cards_count.values, color='teal', width=0.6)
ax.set_title('Number of Cards per Customer', fontsize=13)
ax.set_xlabel('Cards per Customer')
ax.set_ylabel('Number of Customers')
ax.grid(axis='y', alpha=0.3)

for bar in bars:
    ax.text(bar.get_x() + bar.get_width()/2, bar.get_height()+5,
            f"{bar.get_height()}", ha='center', va='bottom', fontsize=9)

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



Expiring Cards

In [119…

```python
cards_df['expires_year'] = cards_df['expires'].dt.year
expiring = cards_df['expires_year'].value_counts().sort_index()

expiring.plot(kind='bar', figsize=(10,4), color='orange')
plt.title('Cards Expiring by Year')
plt.xlabel(''); plt.ylabel('Number of Cards')
plt.tight_layout()
plt.show()
```



Fraud Analysis

In [121…

```
fraud_rate = transactions_df['fraud_label'].value_counts(normalize=True) * 100
print(fraud_rate)
```

```
fraud_label
No     99.897215
Yes     0.102785
Name: proportion, dtype: float64
```

Fraud by Transaction Amount

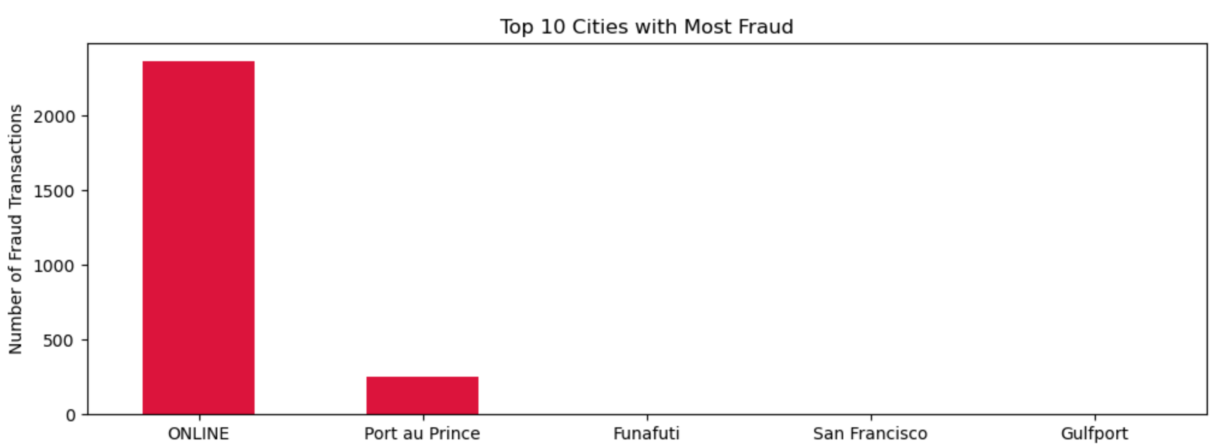
In [123…

```
plt.figure(figsize=(10,6))
sns.boxplot(x='fraud_label', y='amount', data=transactions_df[transactions_df['amou
plt.title('Transaction Amounts by Fraud Label')
plt.xlabel('Fraud Label')
plt.ylabel('Transaction Amount')
plt.show()
```

Fraud by Merchant City / State

In [125…

```
fraud_by_city = transactions_df[transactions_df['fraud_label']=='Yes']['merchant_ci

plt.figure(figsize=(12,4))
fraud_by_city.plot(kind='bar', color='crimson')
plt.title('Top 10 Cities with Most Fraud')
plt.xlabel('')
plt.ylabel('Number of Fraud Transactions')
plt.xticks(rotation=0)
plt.show()
```

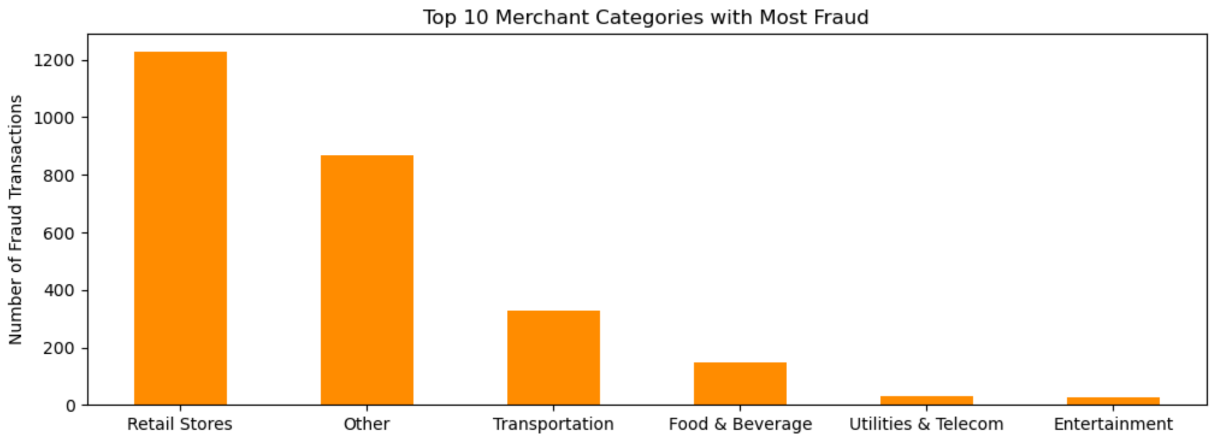


Fraud by Merchant Category (MCC)

In [127…

```
fraud_by_mcc = transactions_df[transactions_df['fraud_label']=='Yes']['mcc_descript

plt.figure(figsize=(12,4))
```

```
fraud_by_mcc.plot(kind='bar', color='darkorange')
plt.title('Top 10 Merchant Categories with Most Fraud')
plt.xlabel('')
plt.ylabel('Number of Fraud Transactions')
plt.xticks(rotation=0)
plt.show()
```



Fraud Amount Loss Estimation

In [129…

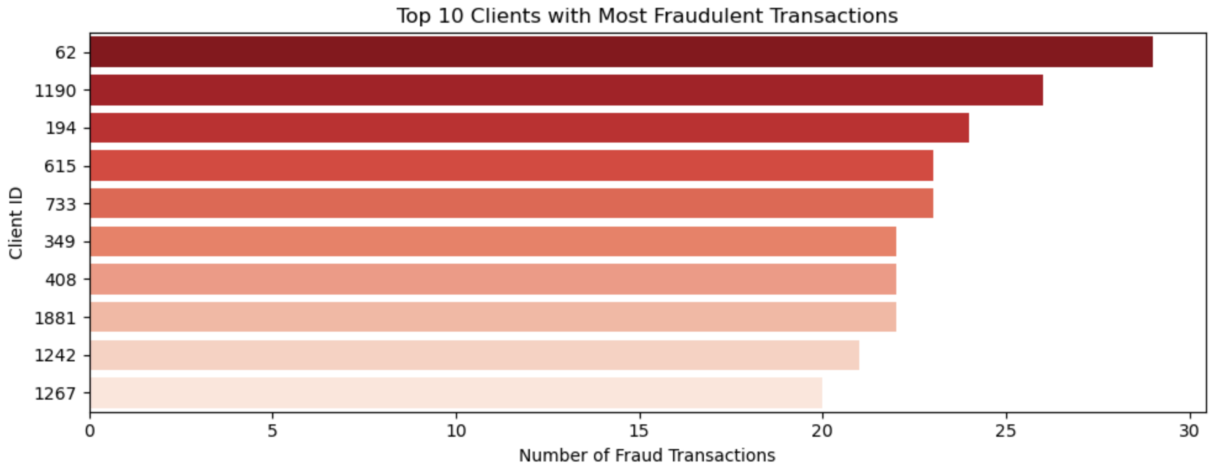
```
fraud_loss = transactions_df.loc[transactions_df['fraud_label']=='Yes','amount'].su
total_loss = transactions_df['amount'].sum()

print(f"💰 Total Fraud Loss: ${fraud_loss:,.2f}")
print(f"⚠️ Fraud Loss Percentage: {fraud_loss/total_loss*100:.2f}%")
```

```
💰 Total Fraud Loss: $313,545.28
⚠️ Fraud Loss Percentage: 0.28%
```

Top 10 Clients Involved in Fraud (by count)

In [131…

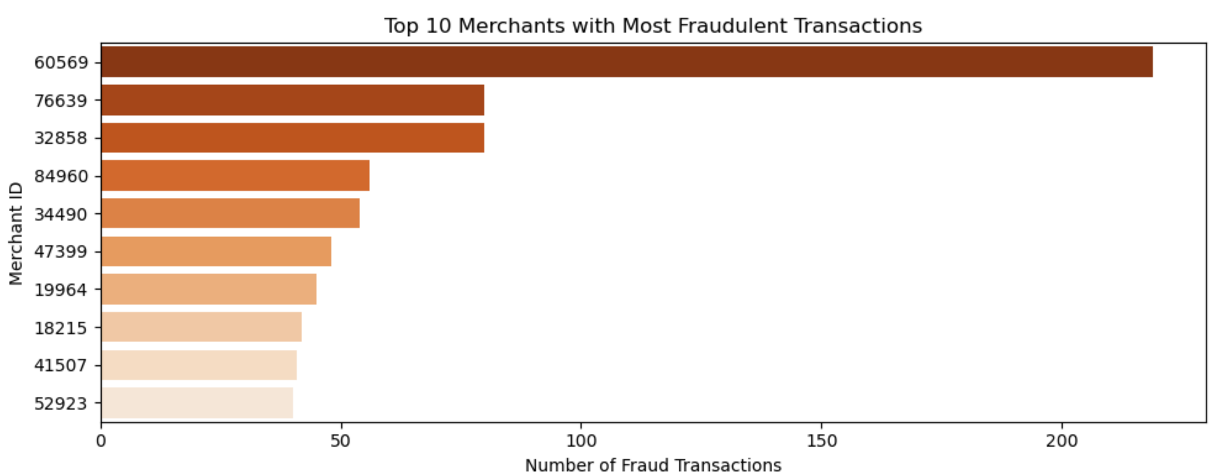
```
fraud_clients = (transactions_df[transactions_df['fraud_label'] == 'Yes']['client_i

plt.figure(figsize=(10,4))
sns.barplot(
    x=fraud_clients.values,
    y=fraud_clients.index.astype(str),
    palette='Reds_r'
)
plt.title('Top 10 Clients with Most Fraudulent Transactions')
plt.xlabel('Number of Fraud Transactions')
plt.ylabel('Client ID')
plt.tight_layout()
plt.show()
```



Top 10 Merchants Involved in Fraud (by count)

In [133…

```
fraud_merchants = (transactions_df[transactions_df['fraud_label'] == 'Yes']['mercha

plt.figure(figsize=(10,4))
sns.barplot(
    x=fraud_merchants.values,
    y=fraud_merchants.index.astype(str),
    palette='Oranges_r'
)
plt.title('Top 10 Merchants with Most Fraudulent Transactions')
plt.xlabel('Number of Fraud Transactions')
plt.ylabel('Merchant ID')
plt.tight_layout()
plt.show()
```



In [134…

```
# Download the files
users_df.to_csv('users_df.csv', index=False)
transactions_df.to_csv('transactions_df.csv', index=False)
cards_df.to_csv('cards_df.csv', index=False)
```