- Milestone5: 12.2 Course Project
- Name: Barath Anandaraman
- Course: DSC630-T301
- Week12: Final Project
- Date: 05/29/2025

Load packages

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
pd.pandas.set_option("display.max_columns", None)
import seaborn as sns
%matplotlib inline
import warnings
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import precision_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
warnings.filterwarnings('ignore')
```

Dataset taken from https://www.hackerearth.com/problem/machine-learning/predict-the-churn-risk-rate-11-fb7a760d/

In [2]:
```
# Load Churn dataset
churn_df = pd.read_csv("churn.csv", index_col=0)
```

Check overview of the dataset

In [3]:
```
churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 36992 entries, 0 to 36991
Data columns (total 23 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   age                           36992 non-null  int64  
 1   gender                        36992 non-null  object 
 2   security_no                   36992 non-null  object 
 3   region_category               31564 non-null  object 
 4   membership_category           36992 non-null  object 
 5   joining_date                  36992 non-null  object 
 6   joined_through_referral       36992 non-null  object 
 7   referral_id                   36992 non-null  object 
 8   preferred_offer_types         36704 non-null  object 
 9   medium_of_operation           36992 non-null  object 
 10  internet_option               36992 non-null  object 
 11  last_visit_time               36992 non-null  object 
 12  days_since_last_login         36992 non-null  int64  
 13  avg_time_spent                36992 non-null  float64
 14  avg_transaction_value         36992 non-null  float64
 15  avg_frequency_login_days      36992 non-null  object 
 16  points_in_wallet              33549 non-null  float64
 17  used_special_discount         36992 non-null  object 
 18  offer_application_preference  36992 non-null  object 
 19  past_complaint                36992 non-null  object 
 20  complaint_status              36992 non-null  object 
 21  feedback                      36992 non-null  object 
 22  churn_risk_score              36992 non-null  int64  
dtypes: float64(3), int64(3), object(17)
memory usage: 6.8+ MB
```

Dataset has 23 columns and 36992 rows

Column explanations

Column	Description
age	Represents the age of a customer
gender	Represents the gender of a customer

Column	Description
security_no	Represents a unique security number that is used to identify a person
region_category	Represents the region that a customer belongs to
membership_category	Represents the category of the membership that a customer is using
joining_date	Represents the date when a customer became a member
joined_through_referral	Represents whether a customer joined using any referral code or ID
referral_id	Represents a referral ID
preferred_offer_types	Represents the type of offer that a customer prefers
medium_of_operation	Represents the medium of operation that a customer uses for transactions
internet_option	Represents the type of internet service a customer uses
last_visit_time	Represents the last time a customer visited the website
days_since_last_login	Represents the no. of days since a customer last logged into the website
avg_time_spent	Represents the average time spent by a customer on the website
avg_transaction_value	Represents the average transaction value of a customer
avg_frequency_login_days	Represents the no. of times a customer has logged in to the website
points_in_wallet	Represents the points awarded to a customer on each transaction
used_special_discount	Represents whether a customer uses special discounts offered
offer_application_preference	Represents whether a customer prefers offers
past_complaint	Represents whether a customer has raised any complaints
complaint_status	Represents whether the complaints raised by a customer was resolved
feedback	Represents the feedback provided by a customer
churn_risk_score	0 or 1 [Customer will Stay or Exit]

Function to check basic issues on the dataset

In [4]:
```
def checkIssues(df):
    """ Check for Issues on the dataframe """
    df_state = []
    columns = df.columns
```

```python
    for i in columns :
        types = df[i].dtypes
        unique_value = df[i].nunique()
        nan_value= df[i].isnull().sum()
        value_count= df[i].isnull().count()
        nan_percentage= round(nan_value/value_count*100,2)
        duplicated= df.duplicated().sum()
        irreg_value = df.apply(lambda x: ((x =='?') | (x == ' ?') | (x =='NA') |
                                          (x =='na') | (x =='xxxxxx')).sum())
        df_state.append ([i , types , unique_value , nan_value, nan_percentage,duplicated,irreg_value ])

    df_state = pd.DataFrame(df_state)
    df_state.columns =['Name of column' , 'Types' ,'Unique_data' , 'NAN value', "NAN_percentage","Duplicated", "Irregul
    print(df_state)
```

In [5]:

```python
# Check for issues visually on the dataset
checkIssues(churn_df)
```

	Name of column	Types	Unique_data	NAN value
0	age	int64	55	0
1	gender	object	3	0
2	security_no	object	36992	0
3	region_category	object	3	5428
4	membership_category	object	6	0
5	joining_date	object	1096	0
6	joined_through_referral	object	3	0
7	referral_id	object	11359	0
8	preferred_offer_types	object	3	288
9	medium_of_operation	object	4	0
10	internet_option	object	3	0
11	last_visit_time	object	30101	0
12	days_since_last_login	int64	27	0
13	avg_time_spent	float64	25961	0
14	avg_transaction_value	float64	36894	0
15	avg_frequency_login_days	object	1654	0
16	points_in_wallet	float64	23699	3443
17	used_special_discount	object	2	0
18	offer_application_preference	object	2	0
19	past_complaint	object	2	0
20	complaint_status	object	5	0
21	feedback	object	9	0
22	churn_risk_score	int64	2	0

\

	NAN_percentage	Duplicated
0	0.00	0
1	0.00	0
2	0.00	0
3	14.67	0
4	0.00	0
5	0.00	0
6	0.00	0
7	0.00	0
8	0.78	0
9	0.00	0
10	0.00	0
11	0.00	0
12	0.00	0
13	0.00	0
14	0.00	0
15	0.00	0
16	9.31	0
17	0.00	0
18	0.00	0

\

```
19            0.00          0
20            0.00          0
21            0.00          0
22            0.00          0

                                            Irregular
0   age                                   0
gender   ...
1   age                                   0
gender   ...
2   age                                   0
gender   ...
3   age                                   0
gender   ...
4   age                                   0
gender   ...
5   age                                   0
gender   ...
6   age                                   0
gender   ...
7   age                                   0
gender   ...
8   age                                   0
gender   ...
9   age                                   0
gender   ...
10  age                                   0
gender   ...
11  age                                   0
gender   ...
12  age                                   0
gender   ...
13  age                                   0
gender   ...
14  age                                   0
gender   ...
15  age                                   0
gender   ...
16  age                                   0
gender   ...
17  age                                   0
gender   ...
18  age                                   0
gender   ...
19  age                                   0
```

```
gender   ...
20  age                              0
gender   ...
21  age                              0
gender   ...
22  age                              0
gender   ...
```

In [6]:

```
# Check the first 5 rows of the data
print(churn_df.head(5))
```

```
   age gender security_no region_category  membership_category joining_date  \
0   18      F     XW0DQ7H         Village  Platinum Membership   2017-08-17   
1   32      F     5K0N3X1            City   Premium Membership   2017-08-28   
2   44      F     1F2TCL3            Town        No Membership   2016-11-11   
3   37      M     VJGJ33N            City        No Membership   2016-10-29   
4   31      F     SVZXCWB            City        No Membership   2017-09-12   

  joined_through_referral referral_id     preferred_offer_types  \
0                      No    xxxxxxxx     Gift Vouchers/Coupons   
1                       ?    CID21329     Gift Vouchers/Coupons   
2                     Yes    CID12313     Gift Vouchers/Coupons   
3                     Yes     CID3793     Gift Vouchers/Coupons   
4                      No    xxxxxxxx  Credit/Debit Card Offers   

  medium_of_operation internet_option last_visit_time  days_since_last_login  \
0                   ?           Wi-Fi        16:08:02                     17   
1             Desktop     Mobile_Data        12:38:13                     16   
2             Desktop           Wi-Fi        22:53:21                     14   
3             Desktop     Mobile_Data        15:57:50                     11   
4          Smartphone     Mobile_Data        15:46:44                     20   

   avg_time_spent  avg_transaction_value avg_frequency_login_days  \
0          300.63               53005.25                     17.0   
1          306.34               12838.38                     10.0   
2          516.16               21027.00                     22.0   
3           53.27               25239.56                      6.0   
4          113.13               24483.66                     16.0   

   points_in_wallet used_special_discount offer_application_preference  \
0            781.75                   Yes                          Yes   
1               NaN                   Yes                           No   
2            500.69                    No                          Yes   
3            567.66                    No                          Yes   
4            663.06                    No                          Yes   

  past_complaint     complaint_status                 feedback  \
0             No       Not Applicable  Products always in Stock   
1            Yes               Solved     Quality Customer Care   
2            Yes  Solved in Follow-up              Poor Website   
3            Yes             Unsolved              Poor Website   
4            Yes               Solved              Poor Website   

   churn_risk_score  
0                 0  
1                 0  
```

```
2                    1
3                    1
4                    1
```

Summary based on dataset analysis

1. Dataset has no duplicates

2. NA values are in columns region_category, preferred_offer_types, points_in_wallet

3. Gender column has 3 unique values and needs to be checked

4. avg_frequency_login_days should be numeric, but is currently object, needs to be checked

5. security_no, referral_id can be removed

6. churn_risk_score is the target variable

Correct data in avg_frequency_login_days

Convert avg_frequency_login_days to numeric format

In [7]:
```
churn_df['avg_frequency_login_days'] = pd.to_numeric(churn_df['avg_frequency_login_days'], errors='coerce')
```

In [8]:
```
churn_df['avg_frequency_login_days'] = churn_df['avg_frequency_login_days'].astype('float64')
```

Drop columns not needed for the modeling process

In [9]:
```
churn_df.drop(['security_no','referral_id'],axis=1,inplace=True)
```

In [10]:
```
# Check the new shape of dataset
churn_df.shape
```

Out[10]:
```
(36992, 21)
```

Dataset now has 36,992 rows and 21 columns

In [11]:
```
# Check values of gender column
churn_df['gender'].value_counts()
```

Out[11]:
```
gender
F          18490
M          18443
Unknown       59
Name: count, dtype: int64
```

59 rows have value 'Unknown' in gender

In [12]:
```
# separate numeric and categorical columns
numeric_cols = churn_df.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = churn_df.select_dtypes(include=['object','category', 'bool']).columns.tolist()
```

In [13]:
```
#Print Numeric columns
numeric_cols
```

Out[13]:
```
['age',
 'days_since_last_login',
 'avg_time_spent',
 'avg_transaction_value',
 'avg_frequency_login_days',
 'points_in_wallet',
 'churn_risk_score']
```

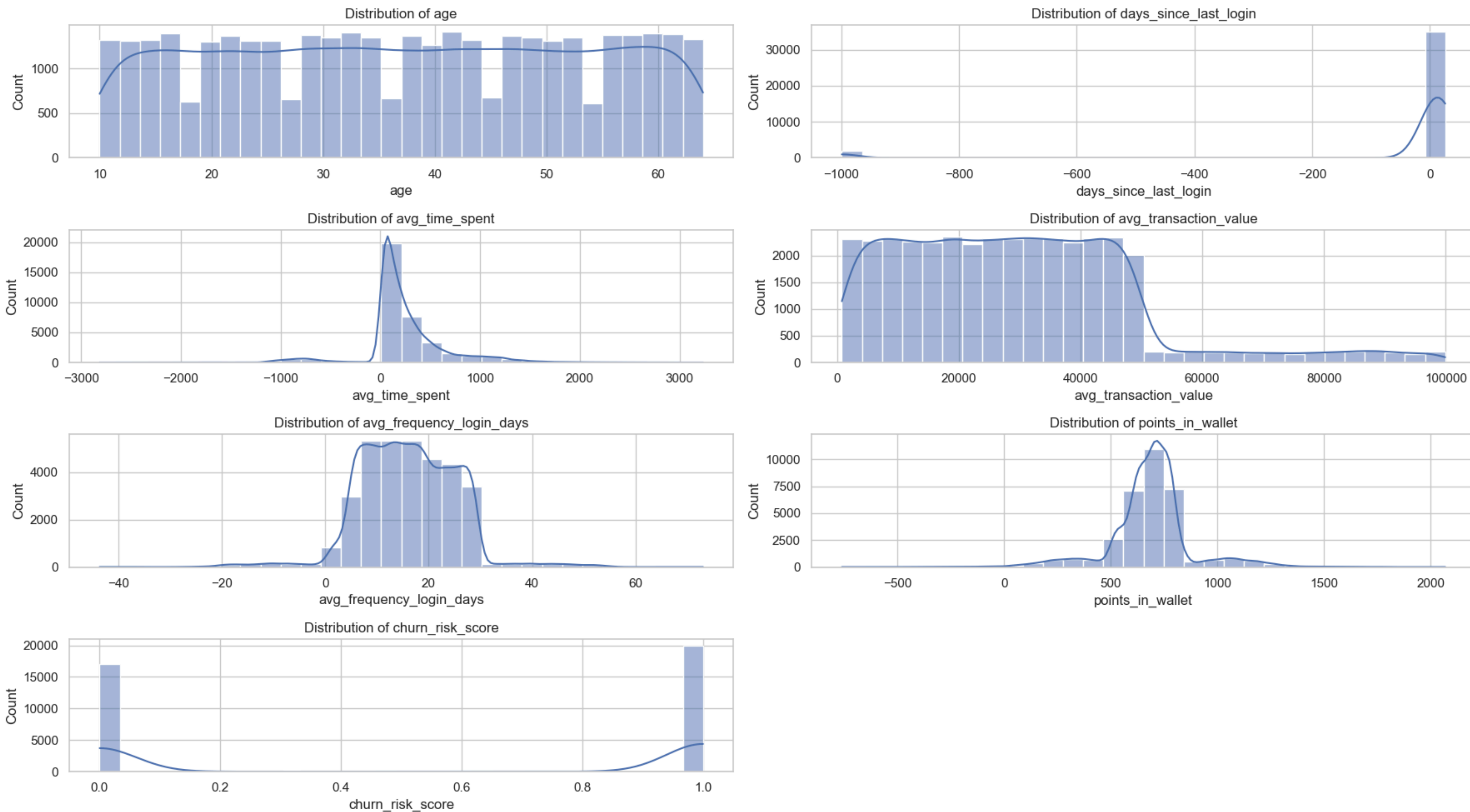
In [14]:
```
# Print Categorical columns
categorical_cols
```

Out[14]:
```
['gender',
 'region_category',
 'membership_category',
 'joining_date',
 'joined_through_referral',
 'preferred_offer_types',
 'medium_of_operation',
 'internet_option',
 'last_visit_time',
 'used_special_discount',
 'offer_application_preference',
 'past_complaint',
 'complaint_status',
 'feedback']
```

Check Numeric distributions using histograms

In [15]:
```python
# Set seaborn style
sns.set(style="whitegrid")
```

In [16]:
```python
# Create numeric distributions
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(18,10))
axes = axes.flatten()

# Plot histograms
numeric_cols_clean = [col for col in numeric_cols if col !='Unnamed: 0']
for i, col in enumerate(numeric_cols_clean):
    sns.histplot(churn_df[col].dropna(), kde=True, ax=axes[i], bins=30)
    axes[i].set_title(f'Distribution of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Count')
# Remove remaining axes
for i in range(7, len(axes)):
    fig.delaxes(axes[i])
plt.tight_layout()
plt.show()
```

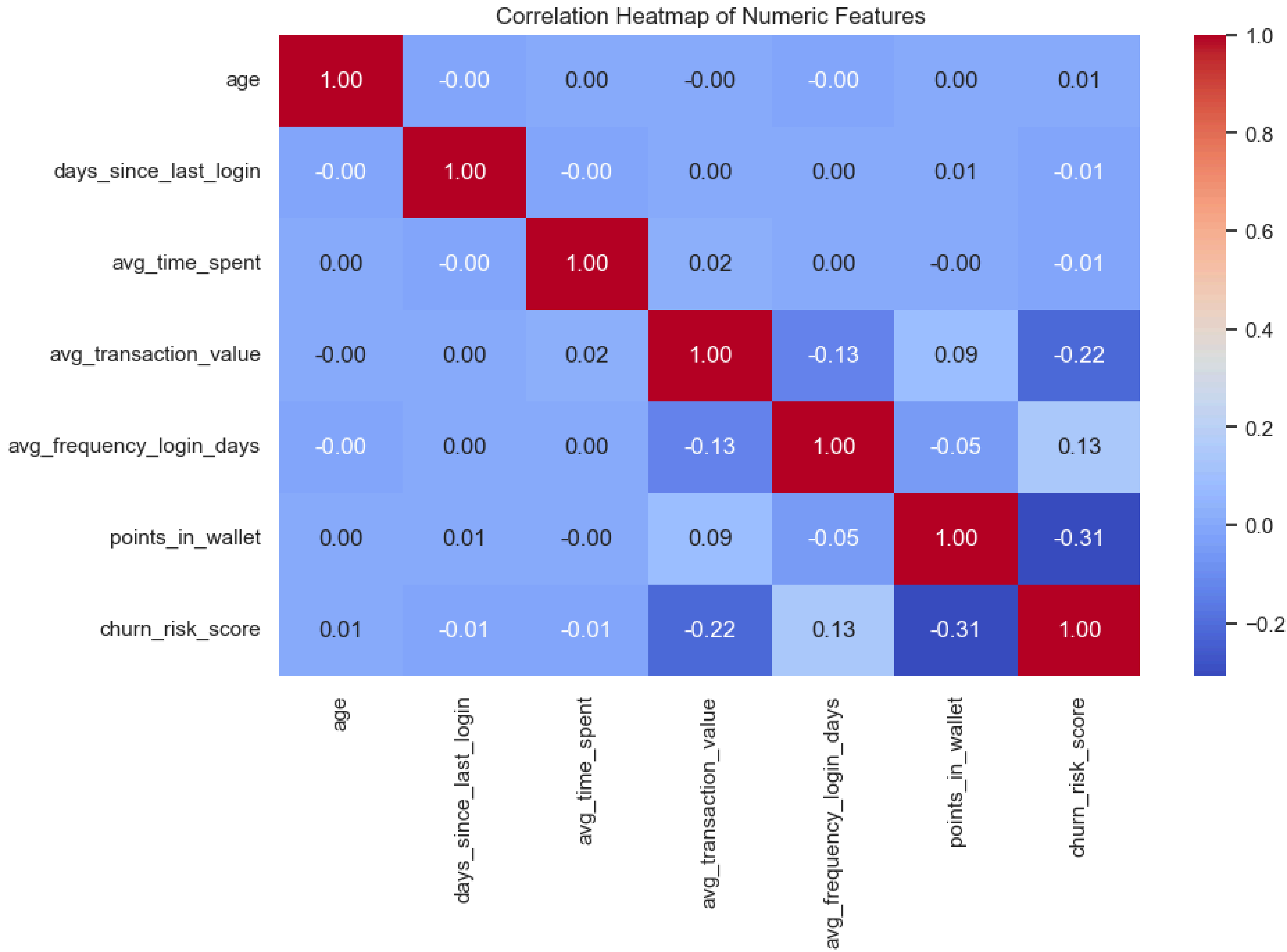


Summary based on histograms

1. age, has even for 10 years, but more data is concentrated from 20-50 years
2. days_since_last_login, heavily right skewed, indicating most users have logged in recently
3. avg_time_spent right skewed, but has negative values
4. avg_transaction_value, right skewed with possible outliers
5. avg_frequency_login_days also has negative values
6. points_in_wallet bell shaped with some outliers
7. churn_risk_score, appears to be discrete and can be used as target variable

Lets check the correlation

In [17]:
```
# Correlation matrix
plt.figure(figsize=(10,6))
corr_matrix = churn_df[numeric_cols_clean].corr()
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```



Summary based on correlation

1. avg_frequency_login_days shows mild positive correlation with churn risk

2. points_in_wallet and avg_transaction_value shows negative correlation

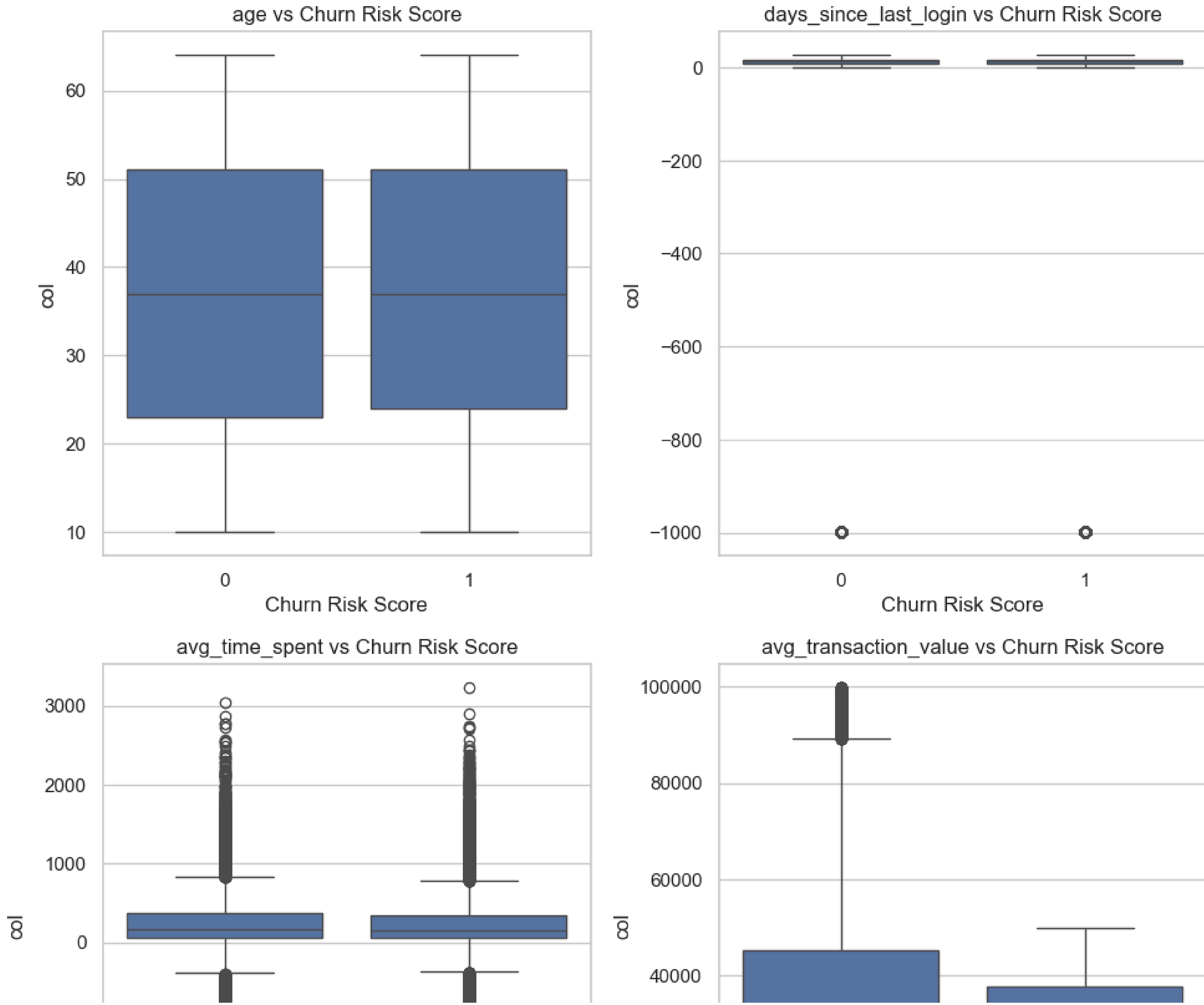
3. age, days_since_last_login, avg_time_spent have weak correlation

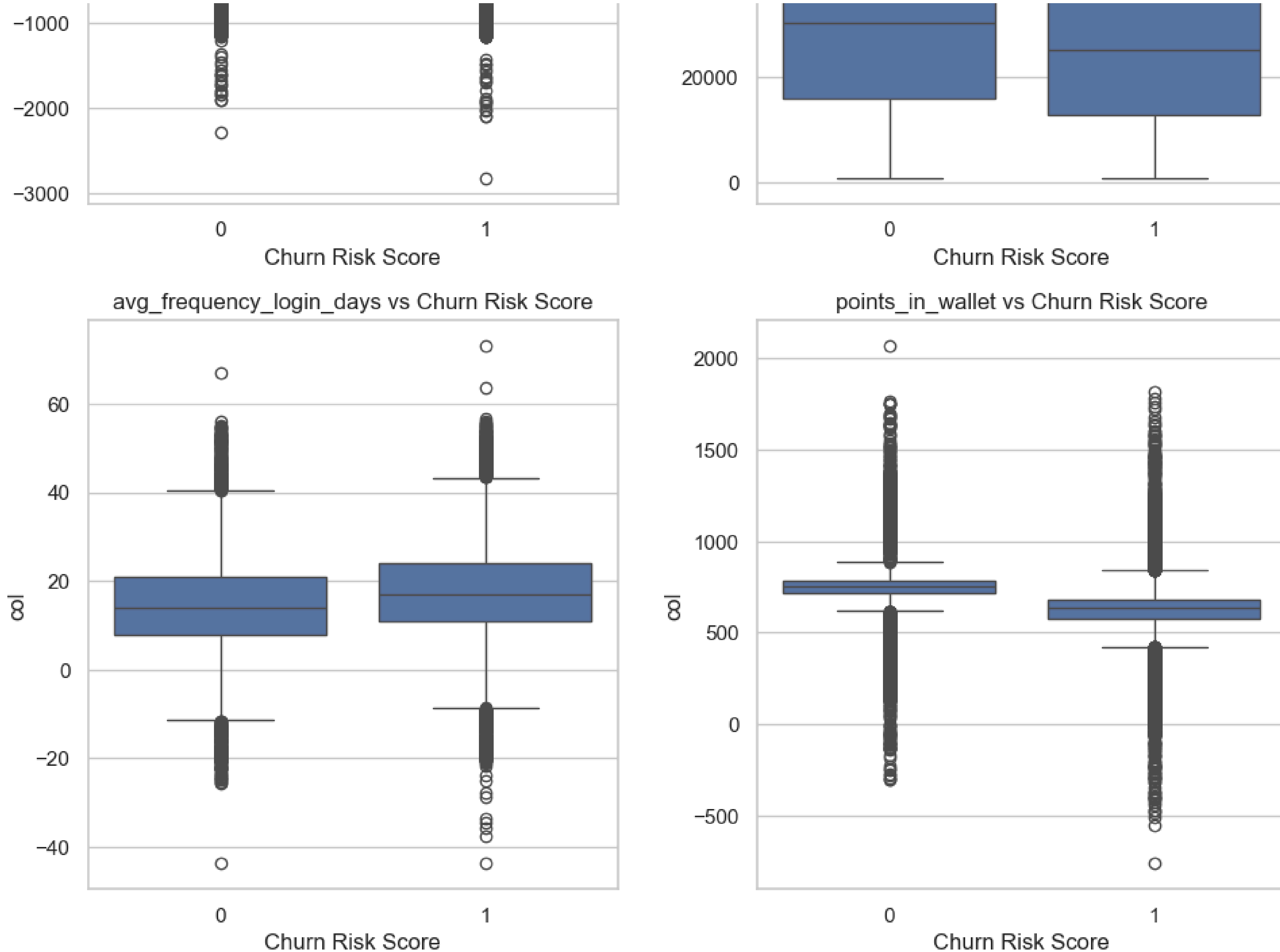
---

Perform box plots

In [18]:

```
# Box plot of numeric features grouped by churn risk score
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(10,20))
axes = axes.flatten()
for i, col in enumerate(numeric_cols_clean):
    sns.boxplot(x='churn_risk_score', y=col, data=churn_df, ax=axes[i])
    axes[i].set_title(f'{col} vs Churn Risk Score')
    axes[i].set_xlabel('Churn Risk Score')
    axes[i].set_ylabel('col')
# Remove remaining axes
for i in range(6, len(axes)):
    fig.delaxes(axes[i])
plt.tight_layout()
plt.show()
```


age vs Churn Risk Score
days_since_last_login vs Churn Risk Score
avg_time_spent vs Churn Risk Score
avg_transaction_value vs Churn Risk Score
col
Churn Risk Score
0
1
60
50
40
30
20
10
0
−200
−400
−600
−800
−1000
3000
2000
1000
100000
80000
60000
40000



Summary based on Box plots

1. avg_transaction_value tend to decrease as churn risk increases

2. avg_frequency_login_days tend to increase as churn risk increases

3. points_in_wallet tend to decrease as churn risk increases

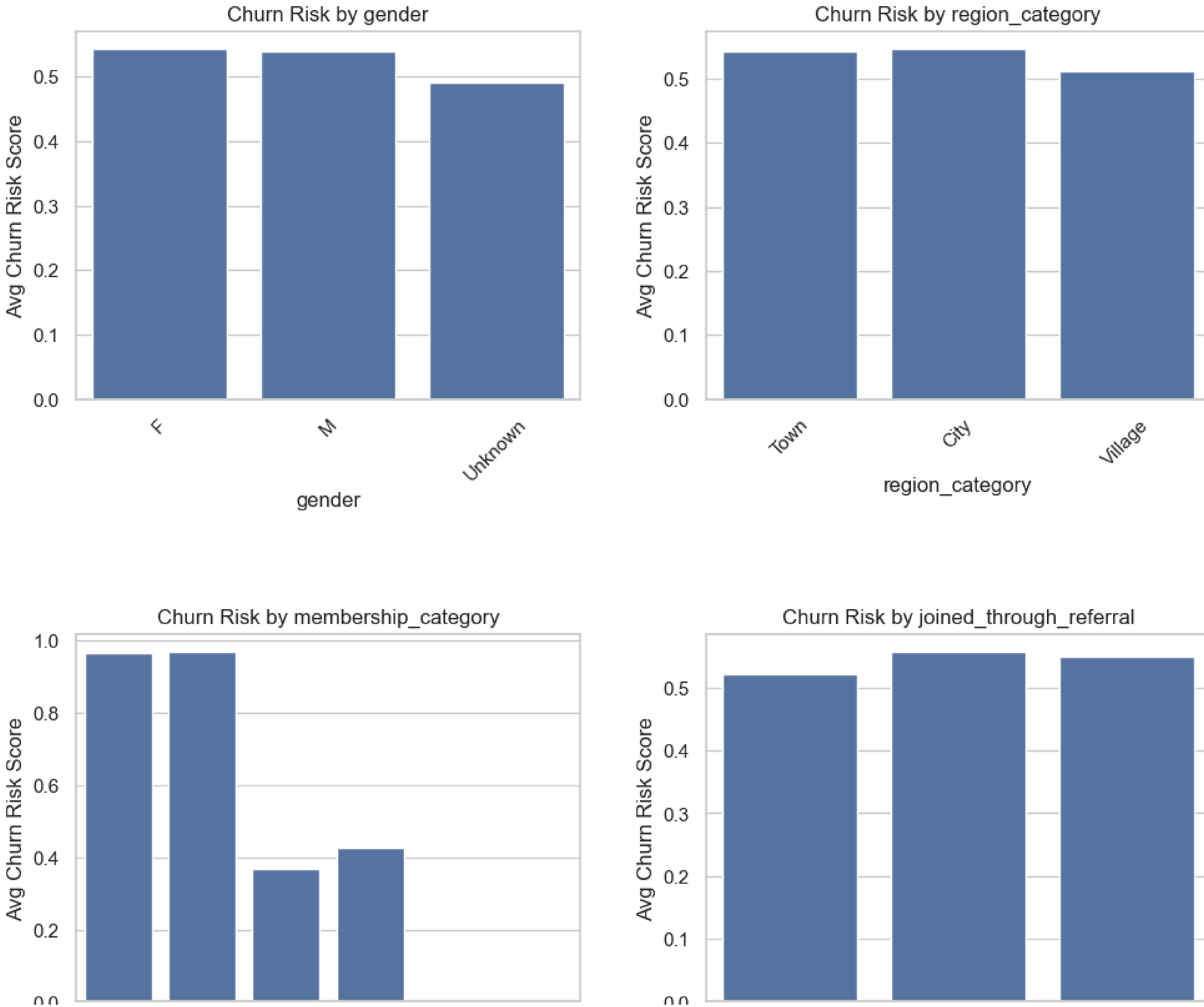
Important categorical features are gender, region_category, membership_category,

joined_through_referral,medium_of_operation, internet_option

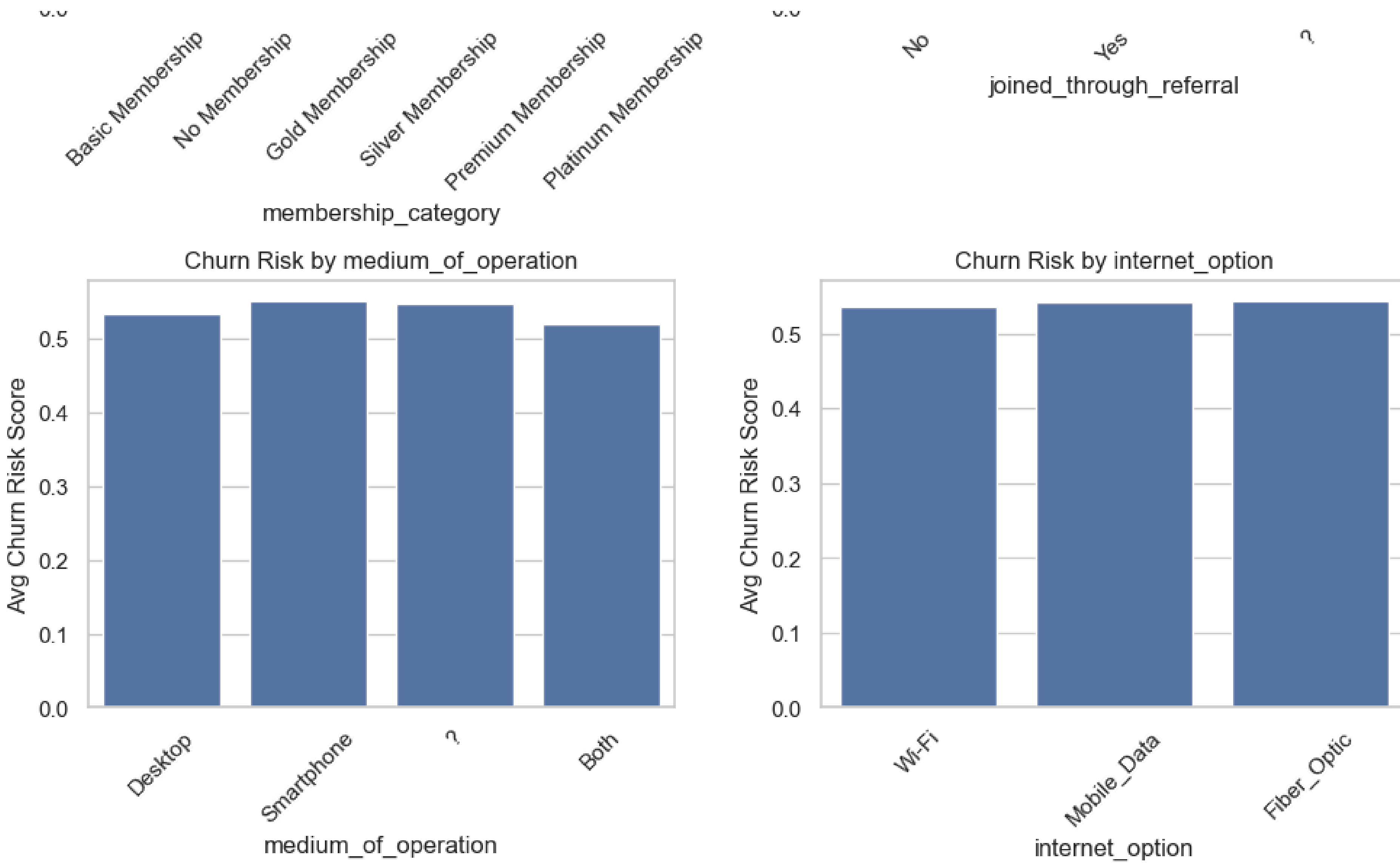
In [19]:
```
selected_cat_cols = ['gender', 'region_category', 'membership_category',
'joined_through_referral', 'medium_of_operation', 'internet_option']
```

Bar plot for categorical columns

In [20]:
```
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(10,18))
axes = axes.flatten()
for i,col in enumerate(selected_cat_cols):
    sns.barplot(x=col, y='churn_risk_score', data=churn_df,
                ax=axes[i], ci=None, order=churn_df[col].value_counts().index)
    axes[i].set_title(f'Churn Risk by {col}')
    axes[i].set_ylabel('Avg Churn Risk Score')
    axes[i].tick_params(axis='x', rotation=45)
# Remove remaining axes
for i in range(6, len(axes)):
    fig.delaxes(axes[i])
plt.tight_layout()
plt.show()
```



Churn Risk by gender
Avg Churn Risk Score
0.0
0.1
0.2
0.3
0.4
0.5
F
M
Unknown
gender
Churn Risk by region_category
Avg Churn Risk Score
0.0
0.1
0.2
0.3
0.4
0.5
Town
City
Village
region_category
Churn Risk by membership_category
Avg Churn Risk Score
0.2
0.4
0.6
0.8
1.0
Churn Risk by joined_through_referral
Avg Churn Risk Score
0.1
0.2
0.3
0.4
0.5



Summary of box plots

1. membership_category: Customers with No Membership show higher churn risk on average

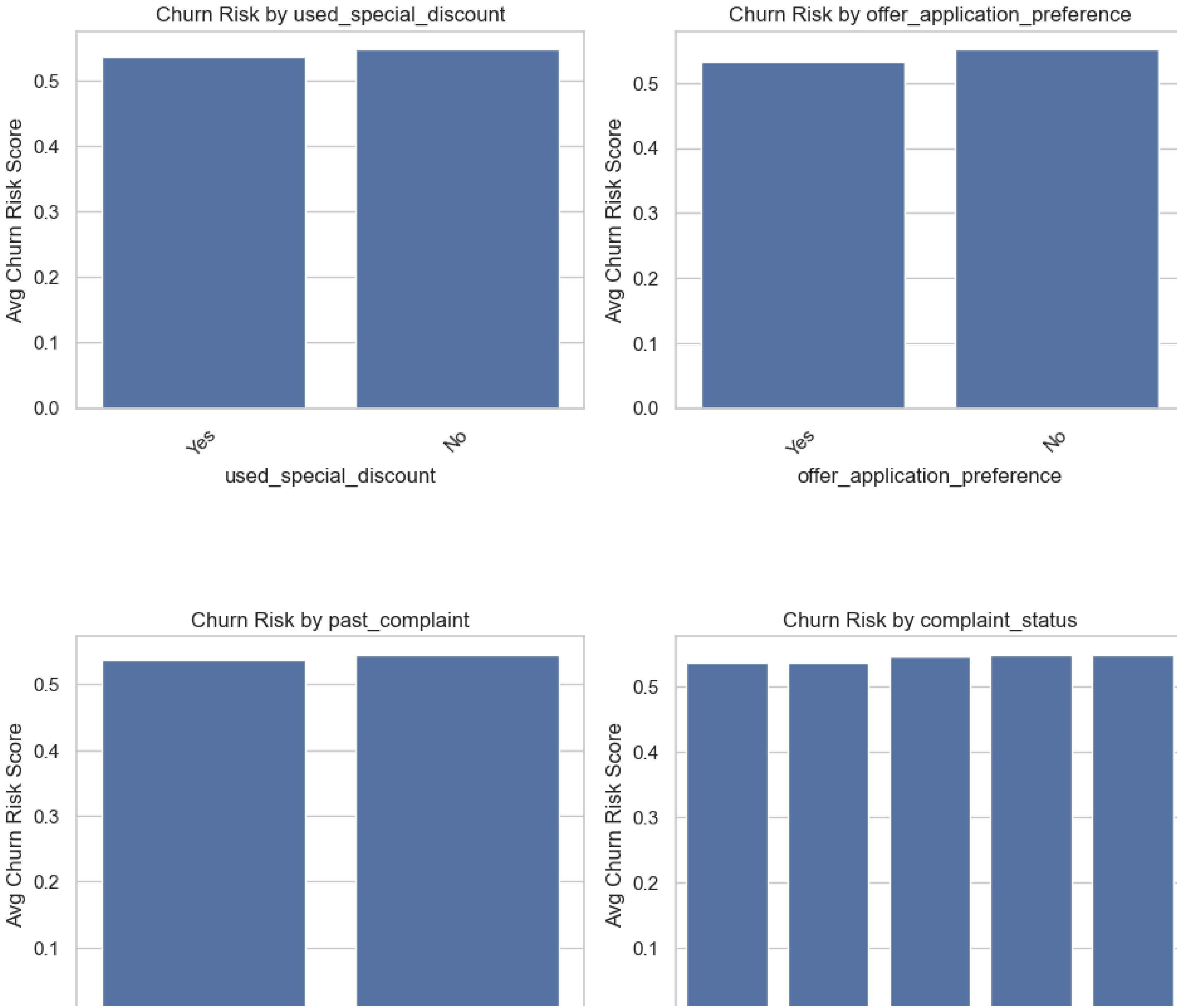
2. joined_through_referral: those who did not join through referral tend to have higher churn

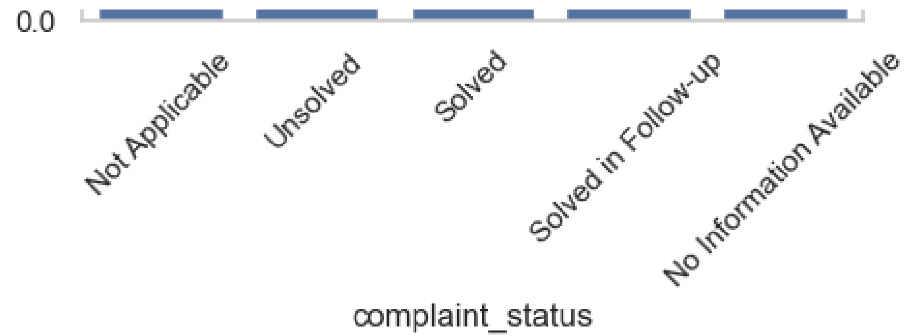
---

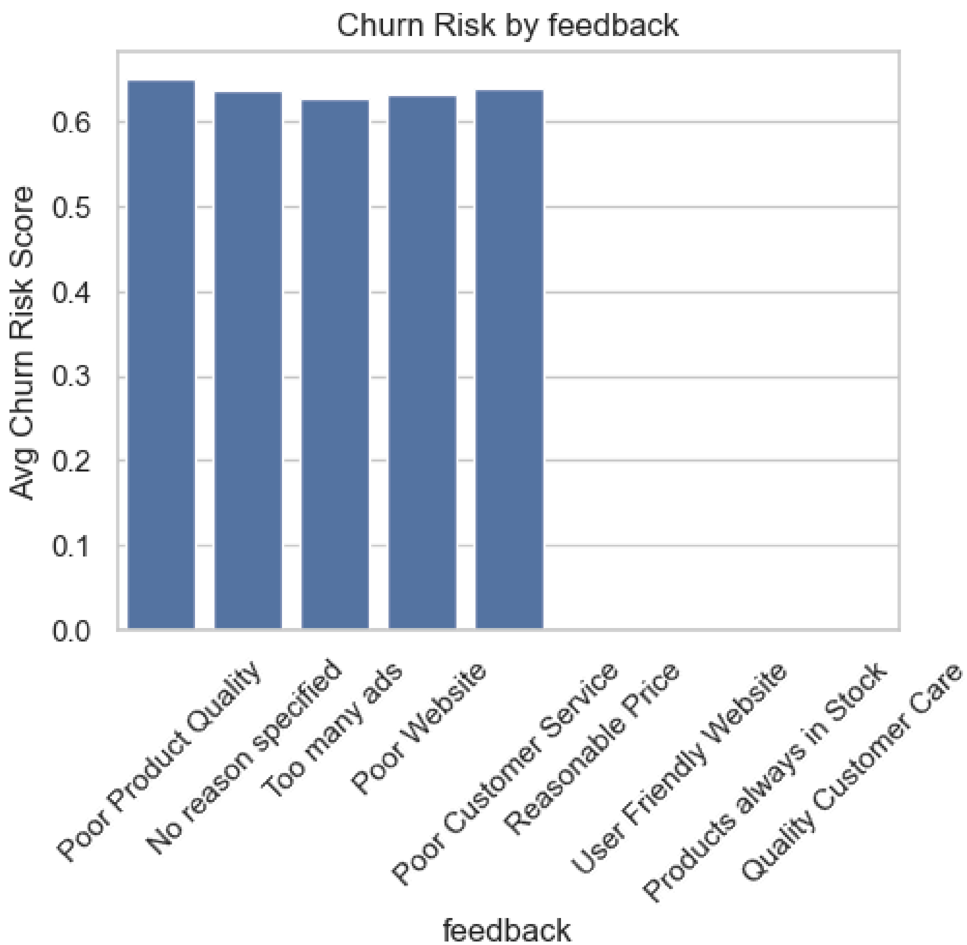
Visualize relationship of other categorical features

In [21]:
```python
selected_features = [
    'used_special_discount', 'offer_application_preference',
    'past_complaint', 'complaint_status', 'feedback'
]
```

In [22]:
```python
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(10,18))
axes = axes.flatten()
for i,col in enumerate(selected_features):
    sns.barplot(x=col, y='churn_risk_score', data=churn_df,
                ax=axes[i], ci=None, order=churn_df[col].value_counts().index)
    axes[i].set_title(f'Churn Risk by {col}')
    axes[i].set_ylabel('Avg Churn Risk Score')
    axes[i].tick_params(axis='x', rotation=45)
# Remove remaining axes
for i in range(5, len(axes)):
    fig.delaxes(axes[i])
plt.tight_layout()
plt.show()
```


Churn Risk by used_special_discount
Avg Churn Risk Score
0.0
0.1
0.2
0.3
0.4
0.5
Yes
No
used_special_discount
Churn Risk by offer_application_preference
Avg Churn Risk Score
0.0
0.1
0.2
0.3
0.4
0.5
Yes
No
offer_application_preference
Churn Risk by past_complaint
Avg Churn Risk Score
0.1
0.2
0.3
0.4
0.5
Churn Risk by complaint_status
Avg Churn Risk Score
0.1
0.2
0.3
0.4
0.5





Summary

1. Customers who did not use discounts have slightly higher churn

2. offer_application_preference, those who dont prefer offers churn more

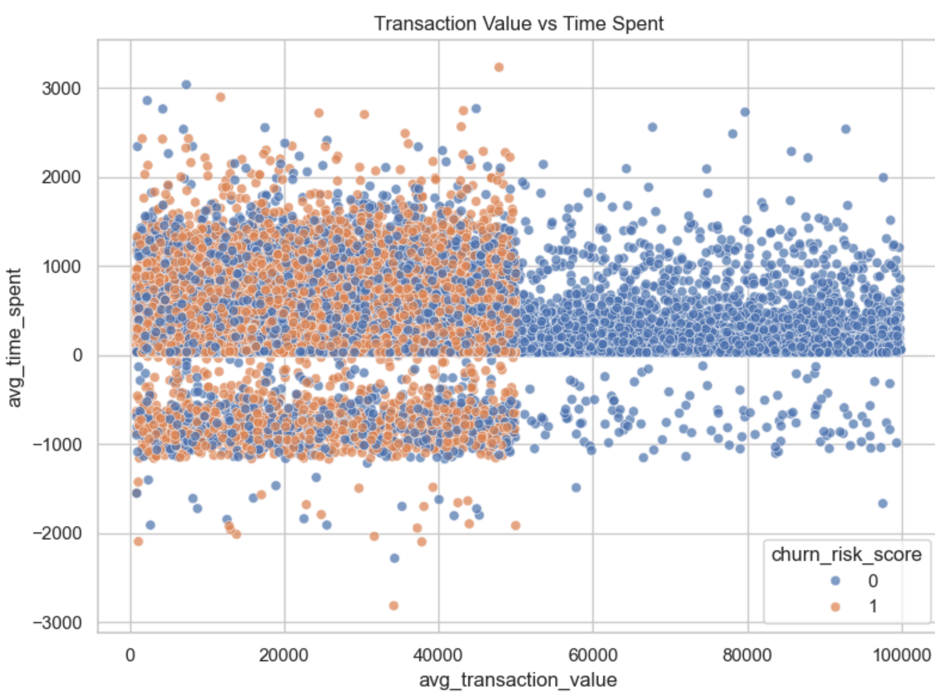
3. Higher complaint history tends to churn more

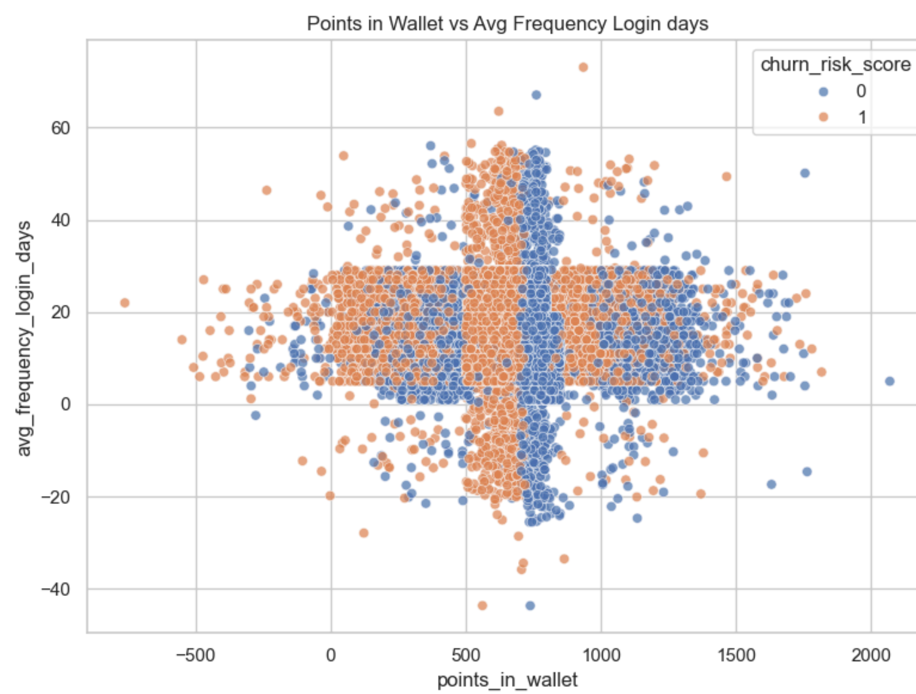
4. Unsolved complaints are strongly associated with churn

5. Negative feedback have higher churn

Explore pair wise relationship

In [23]:
```
fig, axes = plt.subplots(1,2,figsize=(16,6))
sns.scatterplot(
    data=churn_df, x='avg_transaction_value', y='avg_time_spent',
    hue='churn_risk_score', alpha=0.7, ax=axes[0]
)
axes[0].set_title("Transaction Value vs Time Spent")

sns.scatterplot(
    data=churn_df, x='points_in_wallet', y='avg_frequency_login_days',
    hue='churn_risk_score', alpha=0.7, ax=axes[1]
)
axes[1].set_title("Points in Wallet vs Avg Frequency Login days")
plt.tight_layout()
plt.show()
```





Summary Transaction Value vs Time Spent

1. Cluster of low churn scores exists in high spending and high engagement regions

2. Customers with lower spending and less time spent are more likely to have higher churn risk

Summary Points in Wallet vs Avg Frequency Login days

1. Higher churn risk tend to have fewer login days

2. Active users with more wallet points have lower churn risk

---

Top Contributors to churn

1. Points In Wallet - Strong predictor of churn

2. Membership Category - Plays a significant role

3. Average Transaction Value - Tied to engagement impacts churn

4. Feedback - Customer sentiment

5. Average Time Spent - Indicates how active an user is

Milestone 4

In [24]:
```
churn_df_model = churn_df.copy()
```

In [25]:
```
# Convert the 'joining_date' column to datetime objects
churn_df_model['joining_date'] = pd.to_datetime(churn_df_model['joining_date'])
# Extract the year
churn_df_model['join_year'] = churn_df_model['joining_date'].dt.year
```

Perform Feature Engineering

In [26]:
```
# Feature Engineering
churn_df_model['age_group'] = pd.cut(churn_df_model['age'], bins=[0,25,35,45,60],
                                     labels=['<25', '25-35', '45-60','>60'])
churn_df_model['high_spender'] = (churn_df_model['avg_transaction_value'] >
```

```
                                    churn_df_model['avg_transaction_value'].median()).astype(int)
churn_df_model['active_user'] = ((churn_df_model['avg_frequency_login_days'] >
                                    churn_df_model['avg_frequency_login_days'].median()) &
                                   (churn_df_model['avg_time_spent'] > churn_df_model['avg_time_spent'].median()).astype(
                                  )
churn_df_model['wallet_x_transaction'] = churn_df_model['points_in_wallet'] * churn_df_model['avg_transaction_value']
churn_df_model['tenure'] = 2025 - churn_df_model['join_year']
```

Drop unused and non-informative columns

In [27]:
```
drop_cols = ['Unnamed: 0','joining_date', 'last_visit_time', 'join_month']
churn_df_model.drop(columns = drop_cols, inplace=True, errors = 'ignore')
```

In [28]:
```
churn_df_model.dtypes
```

Out[28]:
```
age                              int64
gender                          object
region_category                 object
membership_category             object
joined_through_referral         object
preferred_offer_types           object
medium_of_operation             object
internet_option                 object
days_since_last_login            int64
avg_time_spent                 float64
avg_transaction_value          float64
avg_frequency_login_days       float64
points_in_wallet               float64
used_special_discount           object
offer_application_preference    object
past_complaint                  object
complaint_status                object
feedback                        object
churn_risk_score                 int64
join_year                        int32
age_group                     category
high_spender                     int64
active_user                       bool
wallet_x_transaction           float64
tenure                           int32
dtype: object
```

Get unique values to perform Label Encoding

In [29]:

```
# Get unique values to perform label encoding
print("Gender: ",churn_df_model['gender'].unique())
print("region_category: ",churn_df_model['region_category'].unique())
print("membership_category: ",churn_df_model['membership_category'].unique())
print("joined_through_referral: ",churn_df_model['joined_through_referral'].unique())
print("preferred_offer_types: ",churn_df_model['preferred_offer_types'].unique())
print("medium_of_operation: ",churn_df_model['medium_of_operation'].unique())
print("internet_option: ",churn_df_model['internet_option'].unique())
print("used_special_discount: ",churn_df_model['used_special_discount'].unique())
print("offer_application_preference: ",churn_df_model['offer_application_preference'].unique())
print("past_complaint: ",churn_df_model['past_complaint'].unique())
print("complaint_status: ",churn_df_model['complaint_status'].unique())
print("feedback: ",churn_df_model['feedback'].unique())
print("age_group: ",churn_df_model['age_group'].unique())
```

```
Gender:  ['F' 'M' 'Unknown']
region_category:  ['Village' 'City' 'Town' nan]
membership_category:  ['Platinum Membership' 'Premium Membership' 'No Membership'
 'Gold Membership' 'Silver Membership' 'Basic Membership']
joined_through_referral:  ['No' '?' 'Yes']
preferred_offer_types:  ['Gift Vouchers/Coupons' 'Credit/Debit Card Offers' 'Without Offers' nan]
medium_of_operation:  ['?' 'Desktop' 'Smartphone' 'Both']
internet_option:  ['Wi-Fi' 'Mobile_Data' 'Fiber_Optic']
used_special_discount:  ['Yes' 'No']
offer_application_preference:  ['Yes' 'No']
past_complaint:  ['No' 'Yes']
complaint_status:  ['Not Applicable' 'Solved' 'Solved in Follow-up' 'Unsolved'
 'No Information Available']
feedback:  ['Products always in Stock' 'Quality Customer Care' 'Poor Website'
 'No reason specified' 'Poor Product Quality' 'Poor Customer Service'
 'Too many ads' 'User Friendly Website' 'Reasonable Price']
age_group:  ['<25', '25-35', '45-60', '>60', NaN]
Categories (4, object): ['<25' < '25-35' < '45-60' < '>60']
```

Encode Categorical Variables

In [30]:

```
# Encode Categorical variables
label_encoders = {}
for col in churn_df_model.select_dtypes(include=['object', 'category']).columns:
    le= LabelEncoder()
    churn_df_model[col] = churn_df_model[col].astype(str)
    churn_df_model[col] = le.fit_transform(churn_df_model[col])
    label_encoders[col] = le
```

Get unique values after Label Encoding

In [31]:
```
# Get unique values after label encoding
print("Gender: ",churn_df_model['gender'].unique())
print("region_category: ",churn_df_model['region_category'].unique())
print("membership_category: ",churn_df_model['membership_category'].unique())
print("joined_through_referral: ",churn_df_model['joined_through_referral'].unique())
print("preferred_offer_types: ",churn_df_model['preferred_offer_types'].unique())
print("medium_of_operation: ",churn_df_model['medium_of_operation'].unique())
print("internet_option: ",churn_df_model['internet_option'].unique())
print("used_special_discount: ",churn_df_model['used_special_discount'].unique())
print("offer_application_preference: ",churn_df_model['offer_application_preference'].unique())
print("past_complaint: ",churn_df_model['past_complaint'].unique())
print("complaint_status: ",churn_df_model['complaint_status'].unique())
print("feedback: ",churn_df_model['feedback'].unique())
print("age_group: ",churn_df_model['age_group'].unique())
```

```
Gender:  [0 1 2]
region_category:  [2 0 1 3]
membership_category:  [3 4 2 1 5 0]
joined_through_referral:  [1 0 2]
preferred_offer_types:  [1 0 2 3]
medium_of_operation:  [0 2 3 1]
internet_option:  [2 1 0]
used_special_discount:  [1 0]
offer_application_preference:  [1 0]
past_complaint:  [0 1]
complaint_status:  [1 2 3 4 0]
feedback:  [4 5 3 0 2 1 7 8 6]
age_group:  [2 0 1 3 4]
```

Impute missing values of numeric values with mean

In [32]:
```
# Impute missing numeric values
imputer = SimpleImputer(strategy='mean')
churn_df_model[churn_df_model.columns] = imputer.fit_transform(churn_df_model)
```

Split into features (X) and the target variable (y), which is churn_risk_score

In [33]:
```
# Define features and target
X = churn_df_model.drop(columns= ['churn_risk_score'])
y = churn_df_model['churn_risk_score']
```

Train-Test Split with 20% for evaluation, and random_state=42 for reproducibility

In [34]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train Random Forest Model

In [35]:
```
# Train a Random Forest Model
rf = RandomForestClassifier( n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
```

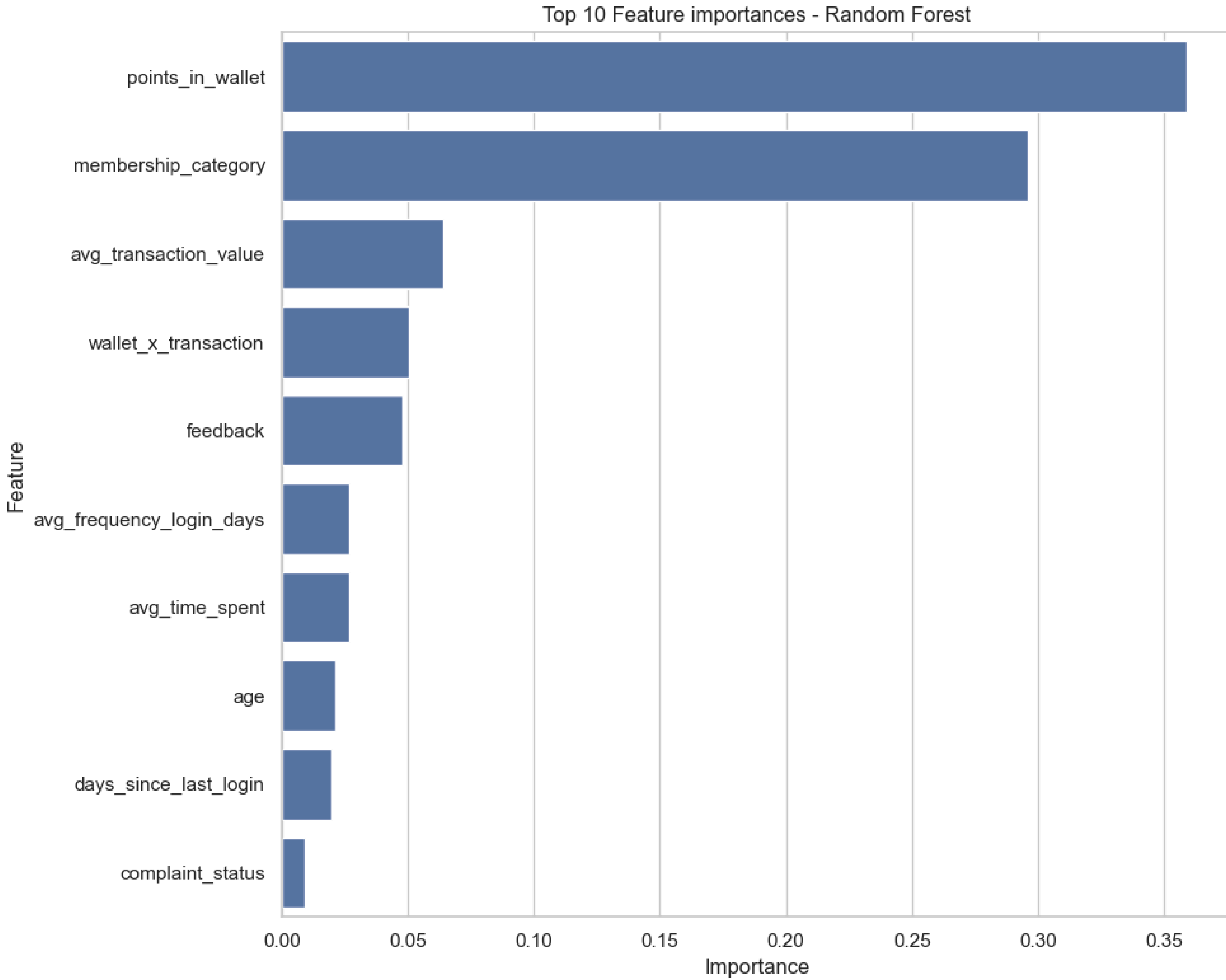
Out[35]:
```
RandomForestClassifier

RandomForestClassifier(random_state=42)
```

Capture Feature Importance based on Random Forest

In [36]:
```
# Feature Importance
importances = rf.feature_importances_
feature_importance_df = pd.DataFrame(
    {
        'Feature': X.columns,
        'Importance': importances
    }
).sort_values(by='Importance', ascending=False)
```

Visualize Top 10 Feature Importance - Random Forest

In [37]:
```
plt.figure(figsize=(10,8))
sns.barplot(data = feature_importance_df.head(10), x= 'Importance', y='Feature')
plt.title('Top 10 Feature importances - Random Forest')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```


Top 10 Feature importances - Random Forest
points_in_wallet
membership_category
avg_transaction_value
wallet_x_transaction
feedback
avg_frequency_login_days
avg_time_spent
age
days_since_last_login
complaint_status
Feature
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Importance

Define 3 models for training and further evaluation

In [38]:
```
# Define models
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42)
}
```

Model training process for Logistic, Decision Tree & Random Forest, including K-Fold cross-validation

In [39]:
```
# K-fold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)
results = []
for name, model in models.items():
    scores = cross_val_score(model, X, y, cv = kf, scoring='f1_weighted')
    results.append({
        'Model': name,
        'F1 Score (mean)': scores.mean(),
        'F1 Score (std)': scores.std()
    })

results
```

Out[39]:
```
[{'Model': 'Logistic Regression',
  'F1 Score (mean)': np.float64(0.6918363161459112),
  'F1 Score (std)': np.float64(0.005037445734782721)},
 {'Model': 'Decision Tree',
  'F1 Score (mean)': np.float64(0.9074570138886596),
  'F1 Score (std)': np.float64(0.0022508884770795915)},
 {'Model': 'Random Forest',
  'F1 Score (mean)': np.float64(0.9294175363680359),
  'F1 Score (std)': np.float64(0.0025392840740118693)}]
```

Fit each models based on training data set

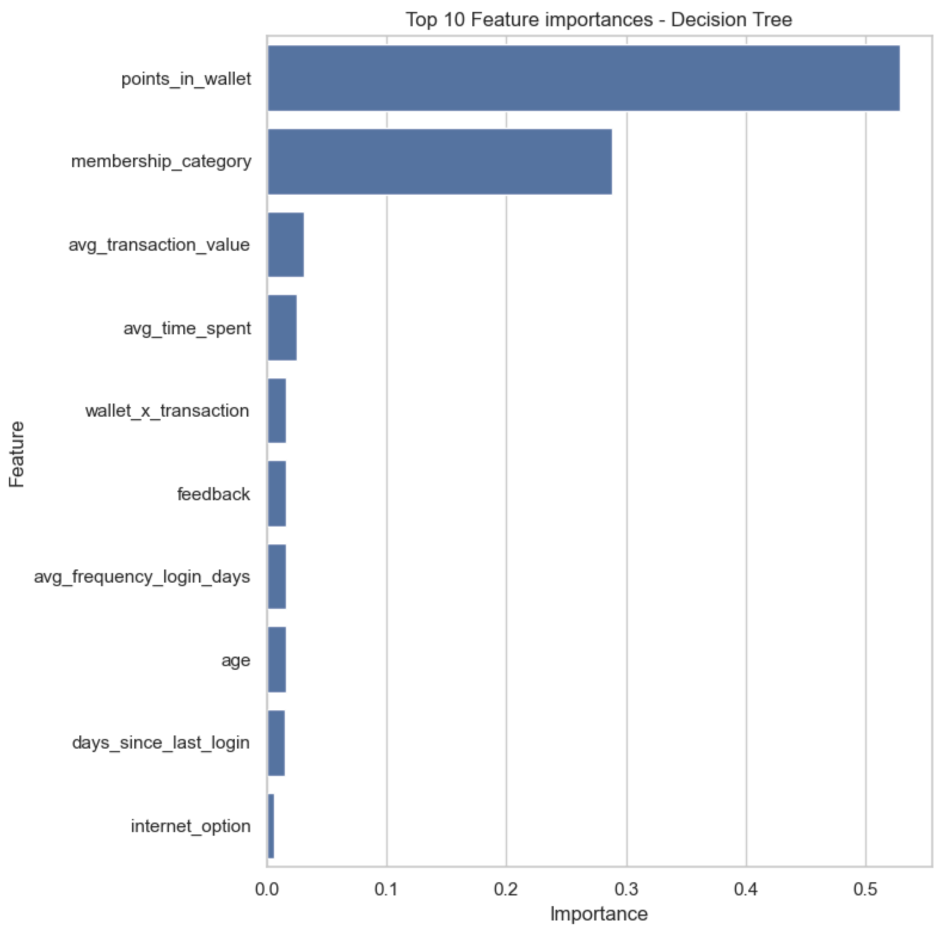
In [40]:
```
# Train models on training set
trained_models = {
    name: model.fit(X_train, y_train) for name, model in models.items()
}
```

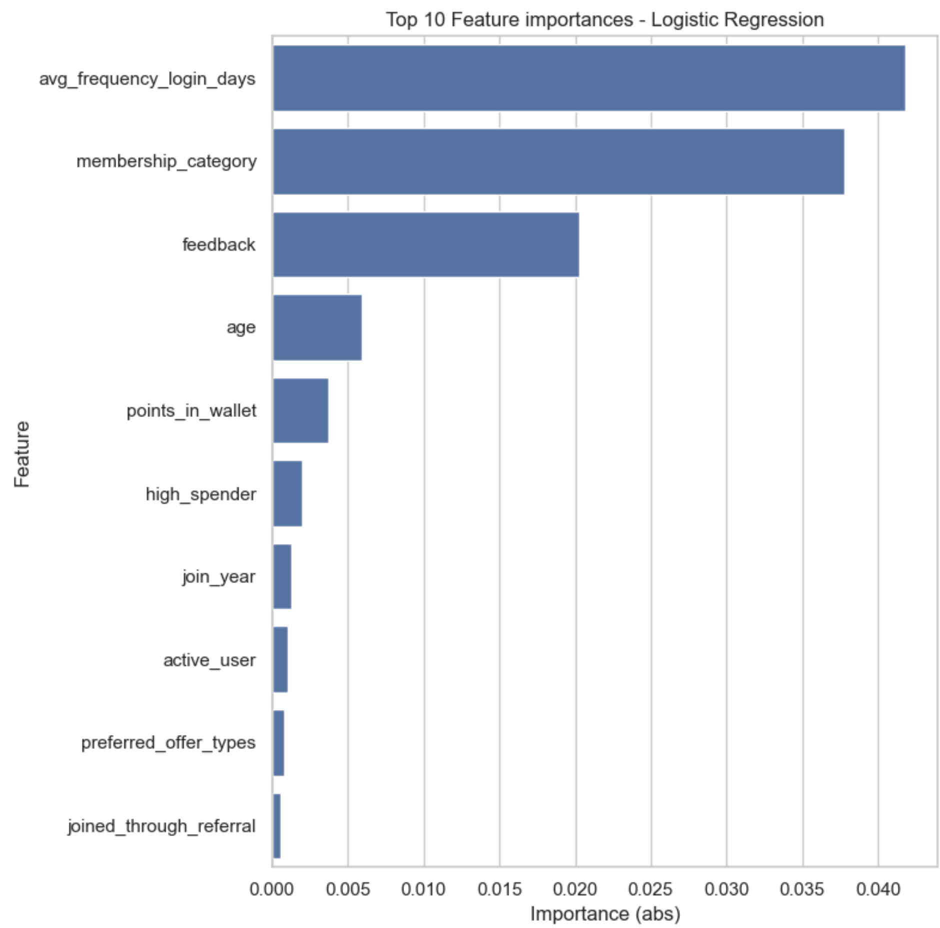
Visualize Top 10 Feature Importance - Decision Tree & Logistic Regression

In [41]:
```python
# Decision Tree Feature importance
dt_importances = trained_models['Decision Tree'].feature_importances_
dt_importances_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': dt_importances
}).sort_values(by = 'Importance', ascending=False)
```

In [42]:
```python
# Logistic Regression Feature importance (based on coefficient magnitude)
lr_coeffs = trained_models['Logistic Regression'].coef_[0]
lr_importances_df = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': lr_coeffs,
    'Importance (abs)': np.abs(lr_coeffs)
}).sort_values(by = 'Importance (abs)', ascending=False)
```

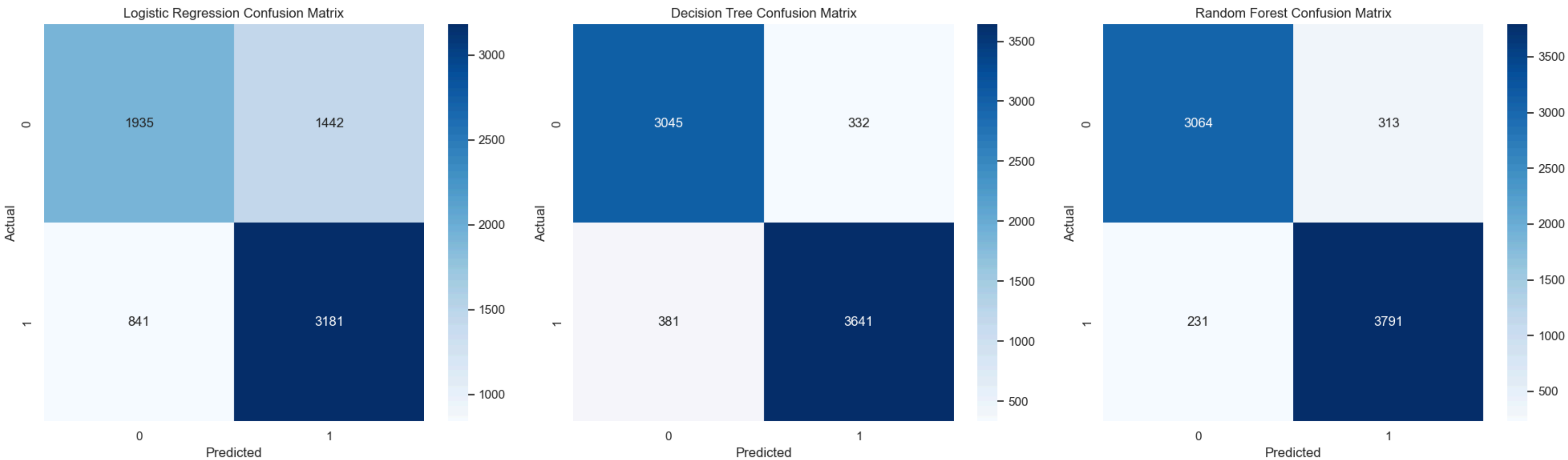
In [49]:
```python
# Plot Feature Importance
fig, axs = plt.subplots(1,2, figsize=(16,8))
sns.barplot(data = dt_importances_df.head(10),x= 'Importance', y='Feature', ax=axs[0])
axs[0].set_title('Top 10 Feature importances - Decision Tree')
sns.barplot(data = lr_importances_df.head(10),x= 'Importance (abs)', y='Feature', ax=axs[1])
axs[1].set_title('Top 10 Feature importances - Logistic Regression')
plt.tight_layout()
plt.show()
```





Confusion matrix for the trained models

In [44]:
```
# Plot confusion matrices
fig, axes = plt.subplots(1,3, figsize=(20,6))
for ax, (name,model) in zip(axes,trained_models.items()):
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", ax=ax)
    ax.set_title(f'{name} Confusion Matrix')
    ax.set_xlabel('Predicted')
    ax.set_ylabel('Actual')
plt.tight_layout()
plt.show()
```



Evaluate the trained models using various classification metrics.

In [45]:
```python
# Evaluate classification metrices
metrics = []
for name, model in trained_models.items():
    y_pred = model.predict(X_test)
    precision = precision_score(y_test, y_pred, zero_division=0)
    recall = recall_score(y_test, y_pred, zero_division=0)
    f1 = f1_score(y_test, y_pred, zero_division=0)
    auc = roc_auc_score(y_test, model.predict_proba(X_test)[:,1])
    metrics.append({
        'Model': name,
        'Precision': precision,
        'Recall': recall,
        'F1 Score': f1,
        'ROC AUC': auc
    })
```

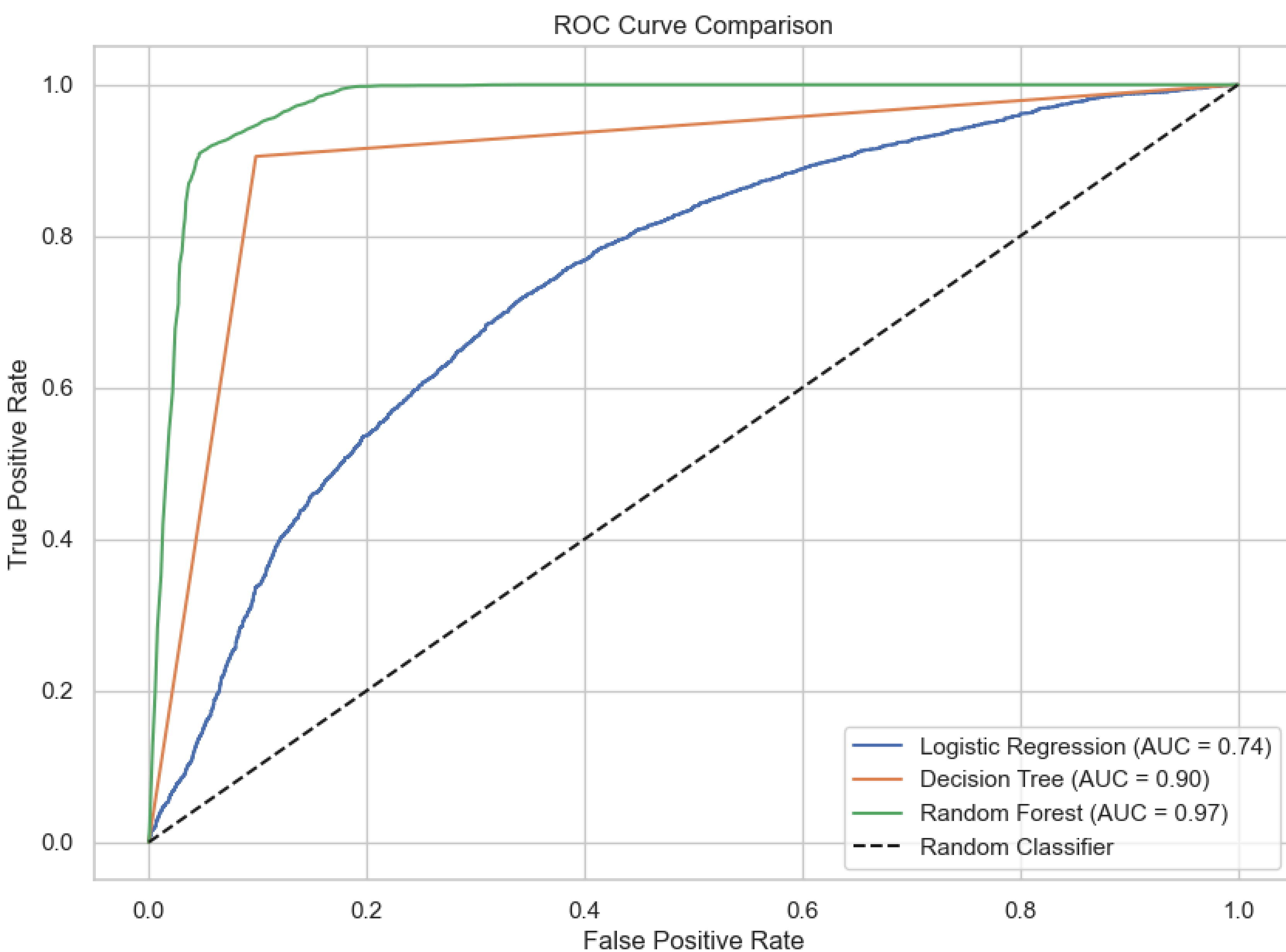
Check the evaluation metrics output

In [46]:
```python
metrics_df = pd.DataFrame(metrics)
print(metrics_df)
```

```
                 Model  Precision    Recall  F1 Score   ROC AUC
0  Logistic Regression   0.688081  0.790900  0.735917  0.742475
1        Decision Tree   0.916436  0.905271  0.910819  0.903479
2        Random Forest   0.923733  0.942566  0.933054  0.974643
```

Visual comparison of the models' performance using ROC curves. The Area Under the Curve (AUC) is a key metric for evaluating binary classification models.

In [47]:
```
# Plot ROC Curves
plt.figure(figsize=(10,7))
for name, model in trained_models.items():
    y_proba = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    auc_score = roc_auc_score(y_test, y_proba)
    plt.plot(fpr, tpr, label=f'{name} (AUC = {auc_score:.2f})')
plt.plot([0,1], [0,1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



Modeling & Evaluation Summary

1. Models Trained

Trained and evaluated three classification models

- Logistic Regression (Linear, interpretable)

- Decision Tree Classifier (non-linear, rule based)

- Random Forest Classifier (ensemble of decision trees for improved accuracy)

2. Cross-Validation Results

Used 5-fold cross-validation to assess model robustness and generalization using F1 Score (weighted)

Model	F1Score (Mean)	F1Score (Std)
Logistic Regression	~0.69	Higher Variance
Decision Tree	~0.91	Low Variance
Random Forest	~0.93	Very Low Variance

Findings:

- Random Forest consistently outperformed the others across all folds.

- Logistic Regression underperformed, possibly due to inability to model complex patterns.

3. Confusion Matrices

- Random Forest and Decision Tree had strong diagonals - they correctly predicted most churn vs non-churn cases

- Logistic Regression misclassified a larger number of churn cases (low recall)

Findings:

Random Forest minimized false negatives – critical in churn prediction, where missing a churner is costlier than flagging a loyal customer

4. Classification Metrics

Evaluated models using **Precision, Recall, F1Score and ROC AUC**

Model	Precision	Recall	F1 Score	ROC AUC
Logistic Regression	0.69	0.79	0.73	0.74
Decision Tree	0.92	0.90	0.91	0.90
Random Forest	0.92	0.94	0.93	0.97

Findings:

- **Random Forest:** Excellent across all metrics, particularly Recall (0.94) and ROC AUC (0.97), it is very good at correctly identifying churners

- **Logistic Regression:** Lower recall suggests many true churners are being missed

5. ROC Curve Analysis

- **Random Forest**'s curve hugged the top-left indicating excellent discrimination ability

- **Decision Tree** performed well, but slightly under Random Forest

- **Logistic Regression** had a curve closer to diagonal, indicating weaker performance

Findings:

Random Forest had the highest AUC and the most desirable ROC curve shape

---

Conclusion

Random Forest is the best performing model

1. Among the models tested, Random Forest delivered the highest performance across all key metrics like F1 Score, ROC AUC, and confusion matrix balance.
2. It also exhibited low variance across folds, indicating strong generalization and robustness.

Key Churn Drivers identified

The most important features contributing to churn are:

- Points_in_wallet – Low wallet balances correlate with higher churn.

- Membership_category – Certain membership types (lack thereof) ndrive churn risk.

- Avg_transaction_value and feedback – provide insight into engagement and satisfaction levels.

Visualization Supports Interpretability

1. Bar Plots, Scatterplots clearly show how behavioral and transactional patterns differ across churn outcomes,
2. Feature importance visualizations provide business insights for customer retention strategies.

Dataset was Model Ready with minor adjustments

1. The churn label was already binary.
2. Minimal preprocessing (encoding, missing value imputation) and feature engineering were required to enhance model performance.

Recommendations

Launch a Wallet bonus campaign

a. Customer with low wallet balances is more likely to churn.

b. Offer loyalty credit, point-matching, or wallet recharge bonuses to high-risk customers.

Segment and Engage Based on Membership

a. Customers with no or low tier memberships churn more.

b. Provide proactive upgrade incentives or early engagement for non-members.

Targeted Outreach Using Feedback

a. Prioritize customers who gave negative feedback for retention campaigns or follow-up support.

Real-Time Scoring dashboard

a. Integrate the trained Random Forest model into a CRM system to flag high-risk customers daily.

b. Setup automated alerts for customer support teams to intervene.

In [ ]:

```
```