Online Retail II - Assignment 01 - Machine Learning Analysis

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1. Data Overview

Dataset Source: UCI Online Retail II

1.1 Dataset Overview

The **Online Retail II** dataset contains transactional data from a UK-based online retailer specializing in gift and home products. The data covers transactions from **December 2009 to December 2011**.

1.2 Data Dictionary

Variable	Type	Description	Business Meaning
`InvoiceNo`	Categorical	Transaction number	Unique sale transaction ID
`StockCode`	Categorical	Product code	Unique identifier for each product
`Description`	Text	Product name	Product details for analysis
`Quantity`	Numeric	Units purchased	Measures demand volume
`InvoiceDate`	Datetime	Date and time of transaction	Used for trend, seasonality, and recency
`Price`	Numeric	Price per unit (in GBP)	Indicates pricing strategy
`Customer ID`	Categorical	Unique customer identifier	Enables customer segmentation & prediction
`Country`	Categorical	Country of customer	Geographic market analysis

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2.THE BUSINESS CHALLENGE

2.1 Business Problem 1: Customer Churn Prediction (Classification)

- PROBLEM: Predict which customers will NOT return within 90 days - **Based on a customer's past behavior, can we predict if they will return in the next 90 days?**

- APPROACH: Binary classification using temporal split

- TARGET: will_return_90days (0 = Churned, 1 = Returned)

Variables

1. **Dependent Variable (DV):** `will_return_90days` (0 = Churned, 1 = Returned)
2. **Independent Variables (IVs):**
   - `recency_days` : Days since last purchase
   - `frequency` : Number of transactions
   - `avg_order_value` : Average spending per transaction
   - `purchase_consistency` : Std of days between purchases
   - `total_unique_products` : Product variety
   - `country` : Geographic location
   - `tenure_days` : Customer lifetime
3. **Model Type:**
   A. Logistic Regression (baseline, interpretable)
   B. Random Forest Classifier (non-linear patterns)

2.2 Business Problem 3: Product Recommendation System (Association Rules Mining)

PROBLEM: Find products frequently bought together to improve cross-selling APPROACH: Market Basket Analysis using Apriori algorithm OUTPUT: Association rules (if X purchased, then Y likely purchased)

TECHNIQUES:

- Apriori Algorithm: Find frequent itemsets
- Association Rules: Generate if-then relationships
- Metrics: Support, Confidence, Lift

BUSINESS VALUE:

- Product bundling strategies
- Store layout optimization
- Personalized recommendations
- Cross-selling opportunities

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3. Data Acquisition and Loading

In [2]:
```
# important libraries to install
# !pip install pyjanitor plotnine pandas matplotlib numpy openpyxl pyarrow
```

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    roc_auc_score, confusion_matrix, classification_report
)
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

warnings.filterwarnings("ignore")
sns.set(style="whitegrid")
```

3.1 Loading the Data

In [4]:
```
def read_retail_data():
    # Load the dataset from both sheets
    file_path = "data/online_retail_II.xlsx"

    print("Loading data from both sheets...")
    print("=" * 60)

    # Read Year 2009-2010 sheet
    df_2009_2010 = pd.read_excel(file_path, sheet_name='Year 2009-2010')
    print(f"Year 2009-2010 Sheet: {df_2009_2010.shape[0]:,} rows")

    # Read Year 2010-2011 sheet
    df_2010_2011 = pd.read_excel(file_path, sheet_name='Year 2010-2011')
    print(f"Year 2010-2011 Sheet: {df_2010_2011.shape[0]:,} rows")

    # Combine both sheets
    df = pd.concat([df_2009_2010, df_2010_2011], ignore_index=True)

    print("=" * 60)
    print(f"\nCombined Dataset Shape: {df.shape}")
    print(f"Total Transactions: {df.shape[0]:,}")
    print(f"Total Features: {df.shape[1]}")
    print(f"\nDate Range: {df['InvoiceDate'].min()} to {df['InvoiceDate'].ma
    return df.to_csv("data/online_retail_II_combined.csv", index=False)

# Load the data
# df = read_retail_data()
```

In [5]:
```
# Load from CSV for faster access in future
original_df = pd.read_csv("data/online_retail_II_combined.csv", parse_dates=
```

In [6]:
```
df = original_df.copy()
```

3.2 Data Quality Assessment

In [7]:
```
# Display first few rows
df.head(10)
```

Out[7]:

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Countr
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2009-12-01 07:45:00	6.95	13085.0	Unite Kingdo
1	489434	79323P	PINK CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Unite Kingdo
2	489434	79323W	WHITE CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Unite Kingdo
3	489434	22041	RECORD FRAME 7" SINGLE SIZE	48	2009-12-01 07:45:00	2.10	13085.0	Unite Kingdo
4	489434	21232	STRAWBERRY CERAMIC TRINKET BOX	24	2009-12-01 07:45:00	1.25	13085.0	Unite Kingdo
5	489434	22064	PINK DOUGHNUT TRINKET POT	24	2009-12-01 07:45:00	1.65	13085.0	Unite Kingdo
6	489434	21871	SAVE THE PLANET MUG	24	2009-12-01 07:45:00	1.25	13085.0	Unite Kingdo
7	489434	21523	FANCY FONT HOME SWEET HOME DOORMAT	10	2009-12-01 07:45:00	5.95	13085.0	Unite Kingdo
8	489435	22350	CAT BOWL	12	2009-12-01 07:46:00	2.55	13085.0	Unite Kingdo
9	489435	22349	DOG BOWL , CHASING BALL DESIGN	12	2009-12-01 07:46:00	3.75	13085.0	Unite Kingdo

In [8]:
```
# Summary statistics for numeric columns
df[['Quantity', 'Price']].describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
Quantity	1067371.0	9.938898	172.705794	-80995.00	1.00	3.0	10.00	80995.0
Price	1067371.0	4.649388	123.553059	-53594.36	1.25	2.1	4.15	38970.0

In [9]:
```
# Check missing values
missing_data = df.isnull().sum().sort_values(ascending=False)
missing_percent = (df.isnull().sum() / len(df) * 100).sort_values(ascending=

missing_summary = pd.DataFrame({
    'Missing Count': missing_data,
    'Percentage': missing_percent
})

print("\nMissing Values Summary:")
missing_summary[missing_summary['Missing Count'] > 0]
```

```
Missing Values Summary:
```

Out[9]:

	Missing Count	Percentage
Customer ID	243007	22.766873
Description	4382	0.410541

In [10]:
```
# Check for negative values in Quantity and Price
negative_quantity = (df['Quantity'] < 0).sum()
negative_price = (df['Price'] < 0).sum()

print(f"\nNegative Quantity Records: {negative_quantity}")
print(f"Negative Price Records: {negative_price}")
```

```
Negative Quantity Records: 22950
Negative Price Records: 5
```

In [11]:
```
# check for duplicate rows
duplicate_rows = df.duplicated().sum()

print(f"\nDuplicate Rows: {duplicate_rows}")
```

```
Duplicate Rows: 34335
```

Data Quality Issues:

- ~22% of records are missing CustomerID (likely guest purchases)
- Small percentage missing Description
- Negative values in Quantity and UnitPrice indicate returns/cancellations
- Some duplicate records present around 34335 records

In [12]:
```
# Check for unique values in categorical columns
print(f"  Unique Invoices: {df['Invoice'].nunique():,}")
```

```
  Unique Invoices: 53,628
```

In [13]:
```
print(f"  Unique Products: {df['StockCode'].nunique():,}")
```

```
 Unique Products: 5,305
```

In [14]:
```
print(f"  Unique Customers: {df['Customer ID'].nunique():,}")
```

```
 Unique Customers: 5,942
```

In [15]:
```
print(f"  Countries: {df['Country'].nunique()}")
```

```
 Countries: 43
```

In [16]:
```
print(f"\nDate Range: {df['InvoiceDate'].min()} to {df['InvoiceDate'].max()}
```

```
Date Range: 2009-12-01 07:45:00 to 2011-12-09 12:50:00
```

In [17]:
```
# Top 10 countries by transaction count
print("Top 10 Countries by Transaction Count:")
df['Country'].value_counts().head(10)
```

```
Top 10 Countries by Transaction Count:
```

Out[17]:
```
Country
United Kingdom    981330
EIRE               17866
Germany            17624
France             14330
Netherlands         5140
Spain               3811
Switzerland         3189
Belgium             3123
Portugal            2620
Australia           1913
Name: count, dtype: int64
```

3.3 Data Cleaning Strategy

1. Remove cancellations (Invoice starts with 'C')
2. Remove negative quantities (returns)
3. Remove zero/negative prices (errors)
4. Remove missing CustomerIDs (can't track behavior)
5. Remove missing descriptions

In [18]:
```
## use janitor to clean column names
# !pip install pyjanitor
import janitor
df = df.clean_names()

# rename invoicedaate to invoice_date
df = df.rename(columns={'invoicedate': 'invoice_date'})

# customer_id is category column
df['customer_id'] = df['customer_id'].astype('category')
# trim whitespace from description
df['description'] = df['description'].str.strip()
```

```
df.head()
```

Out[18]:

	invoice	stockcode	description	quantity	invoice_date	price	customer_id	cou
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2009-12-01 07:45:00	6.95	13085.0	Ur King
1	489434	79323P	PINK CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Ur King
2	489434	79323W	WHITE CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Ur King
3	489434	22041	RECORD FRAME 7" SINGLE SIZE	48	2009-12-01 07:45:00	2.10	13085.0	Ur King
4	489434	21232	STRAWBERRY CERAMIC TRINKET BOX	24	2009-12-01 07:45:00	1.25	13085.0	Ur King

In [19]:

```
# Remove duplicates
df = df.drop_duplicates()

# see if there are any duplicates left
df.duplicated().sum()
```

Out[19]:

```
np.int64(0)
```

In [20]:

```
# Remove missing values from customer_id and description
df = df.dropna(subset=['customer_id', 'description'])

# Check missing values again
df.isnull().sum()
```

Out[20]:

```
invoice         0
stockcode       0
description     0
quantity        0
invoice_date    0
price           0
customer_id     0
country         0
dtype: int64
```

In [21]:

```
# Remove cancellations and invalid values
# Remove cancellations first
df = df[~df['invoice'].astype(str).str.startswith('C')]

# Remove invalid numeric rows
df = df[(df['quantity'] > 0) & (df['price'] > 0)]
```

```
# check if any negative or zero values remain
print(f"Negative or Zero Quantity Records: {(df['quantity'] <= 0).sum()}")
print(f"Negative or Zero Price Records: {(df['price'] <= 0).sum()}")
```

```
Negative or Zero Quantity Records: 0
Negative or Zero Price Records: 0
```

In [22]:
```
# Convert data types
df['customer_id'] = df['customer_id'].astype(str)
df['invoice_date'] = pd.to_datetime(df['invoice_date'], errors='coerce')
```

In [23]:
```
# see final shape after cleaning
print(f"Final Dataset Shape after Cleaning: {df.shape}")
```

```
Final Dataset Shape after Cleaning: (779425, 8)
```

---

4. Feature Engineering

1. Create Revenue = Quantity × UnitPrice
2. Extract temporal features (Year, Month, Day, Hour, DayOfWeek)

In [24]:
```
# Create Revenue column
df['revenue'] = df['quantity'] * df['price']
# Extract month day_of_week and hour from InvoiceDate
df['month'] = df['invoice_date'].dt.month_name()
df['day_of_week'] = df['invoice_date'].dt.day_name()
df['hour'] = df['invoice_date'].dt.hour
# Create CustomerType column
df['customer_type'] = np.where(df.duplicated(subset=['customer_id'], keep=Fa
df.head()
```

Out[24]:

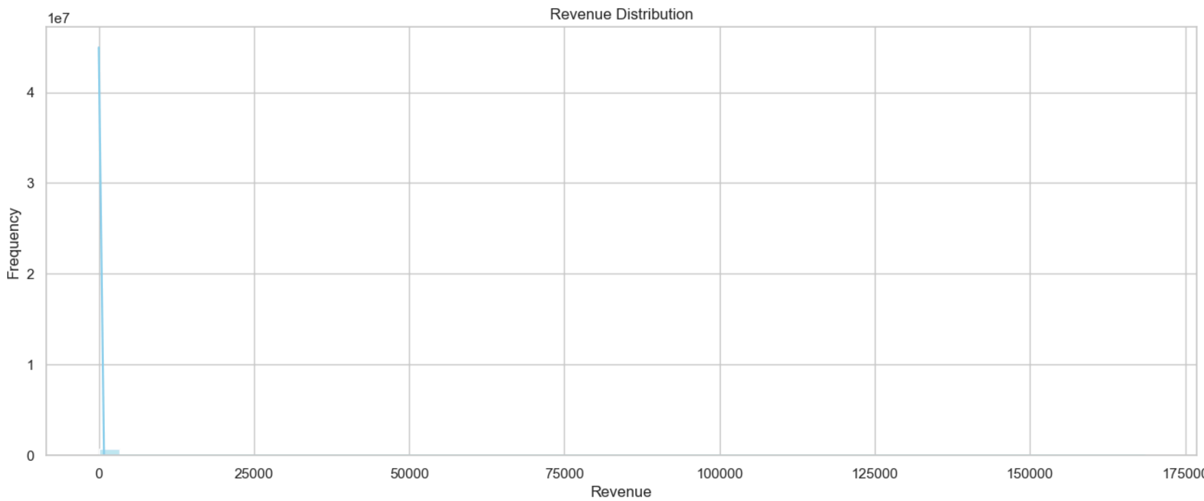
	invoice	stockcode	description	quantity	invoice_date	price	customer_id	cou
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2009-12-01 07:45:00	6.95	13085.0	Ur King
1	489434	79323P	PINK CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Ur King
2	489434	79323W	WHITE CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	Ur King
3	489434	22041	RECORD FRAME 7" SINGLE SIZE	48	2009-12-01 07:45:00	2.10	13085.0	Ur King
4	489434	21232	STRAWBERRY CERAMIC TRINKET BOX	24	2009-12-01 07:45:00	1.25	13085.0	Ur King

---

5. Exploratory Data Analysis: Understanding Customer Behavior

5.1 Revenue Distribution

In [25]:
```
plt.figure(figsize=(16, 6))
sns.histplot(df['revenue'], bins=50, kde=True, color='skyblue')
plt.title('Revenue Distribution')
plt.xlabel('Revenue')
plt.ylabel('Frequency')
plt.show()
```



The raw revenue distribution is extremely skewed, with a long right tail caused by very large transactions. Most orders generate only a few pounds of revenue, while a small number of transactions reach tens of thousands of pounds. This skew makes the histogram hard to interpret because the extreme values dominate the scale.

In [26]:
```
df[['revenue', 'quantity', 'price']].describe().T
```

Out[26]:

	count	mean	std	min	25%	50%	75%	max
revenue	779425.0	22.291823	227.427075	0.001	4.95	12.48	19.80	168469.6
quantity	779425.0	13.489370	145.855814	1.000	2.00	6.00	12.00	80995.0
price	779425.0	3.218488	29.676140	0.001	1.25	1.95	3.75	10953.5

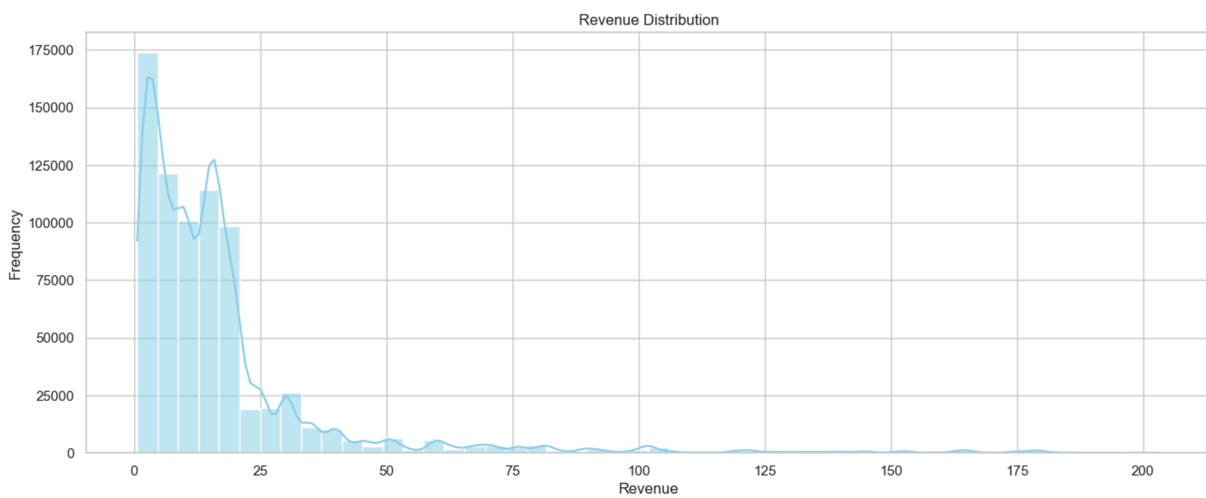
In [27]:
```
# min and max revenue are extreme, we have some outliers
df[['revenue', 'quantity', 'price']].quantile([0.01, 0.25, 0.5, 0.75, 0.99,
```

Out[27]:

	0.01	0.25	0.50	0.75	0.99	1.00
revenue	0.60	4.95	12.48	19.80	203.52	168469.6
quantity	1.00	2.00	6.00	12.00	144.00	80995.0
price	0.29	1.25	1.95	3.75	14.95	10953.5

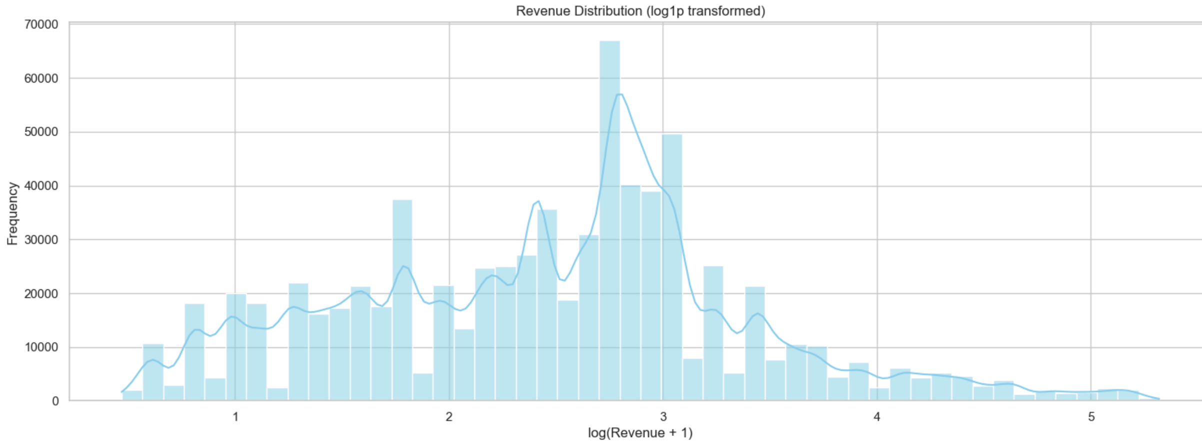
In [28]:
```
# drop extreme outliers for better visualization
q01 = df[['revenue','quantity','price']].quantile(0.01)
q99 = df[['revenue','quantity','price']].quantile(0.99)

df_clean = df[
    (df['revenue'].between(q01['revenue'], q99['revenue'])) &
    (df['quantity'].between(q01['quantity'], q99['quantity'])) &
    (df['price'].between(q01['price'], q99['price']))
]
```

In [29]:
```
plt.figure(figsize=(16, 6))
sns.histplot(df_clean['revenue'], bins=50, kde=True, color='skyblue')
plt.title('Revenue Distribution')
plt.xlabel('Revenue')
plt.ylabel('Frequency')
plt.show()
```



After removing the extreme 1 percent of outliers, the revenue distribution becomes much easier to interpret. Most transactions fall under £30, with a clear drop-off as revenue increases. Removing outliers reveals the true shape of customer purchasing behavior without the distortion from rare, unusually large orders.

In [30]:
```
df_clean['log_revenue'] = np.log1p(df_clean['revenue'])

plt.figure(figsize=(18, 6))
sns.histplot(df_clean['log_revenue'], bins=50, kde=True, color='skyblue')
plt.title('Revenue Distribution (log1p transformed)')
plt.xlabel('log(Revenue + 1)')
plt.ylabel('Frequency')
plt.show()
```



Applying a log transformation compresses the long right tail and spreads out the dense cluster of low-revenue transactions. This creates a more balanced and symmetric distribution that is easier to visualize and model. The log scale highlights meaningful variation among typical transactions and prepares the revenue variable for use in regression or machine learning models.

In [31]:
```
month_order = [
    'January','February','March','April','May','June',
    'July','August','September','October','November','December'
]

df_clean['month'] = pd.Categorical(df_clean['month'], categories=month_order
```

5.2 Customer Segmentation (RFM Analysis)

In [32]:
```
# Time window
min_date = df_clean['invoice_date'].min()
max_date = df_clean['invoice_date'].max()

time_range_days = (max_date - min_date).days
cutoff_date = min_date + pd.Timedelta(days = int(time_range_days * 0.8))
observation_end = cutoff_date + pd.Timedelta(days=90)

print("Feature window:", min_date.date(), "→", cutoff_date.date())
print("Churn label window:", cutoff_date.date(), "→", observation_end.date()
```

```
Feature window: 2009-12-01 → 2011-07-14
Churn label window: 2011-07-14 → 2011-10-12
```

5.3 Split df_clean Into Before / After Window

In [33]:
```
df_before = df_clean[df_clean['invoice_date'] <= cutoff_date]
df_after  = df_clean[
    (df_clean['invoice_date'] > cutoff_date) &
    (df_clean['invoice_date'] <= observation_end)
]
print(f"Records before cutoff: {df_before.shape[0]:,}")
print(f"Records after cutoff:  {df_after.shape[0]:,}")
```

```
Records before cutoff: 546,829
Records after cutoff:  95,922
```

5.4 Build churn_features (Customer-Level Aggregation)

In [34]:
```
churn_features = df_before.groupby('customer_id').agg(
    recency_days=('invoice_date', lambda x: (cutoff_date - x.max()).days),
    frequency=('invoice', 'nunique'),
    total_revenue=('revenue', 'sum'),
    avg_order_value=('revenue', 'mean'),
    total_unique_products=('stockcode', 'nunique'),
    first_purchase_date=('invoice_date', 'min'),
    last_purchase_date=('invoice_date', 'max'),
    country=('country', lambda x: x.mode()[0] if len(x.mode()) else 'Unknowr
).reset_index()
```

5.6 Create Tenure and Purchase Consistency

In [35]:
```
churn_features['tenure_days'] = (
    churn_features['last_purchase_date'] - churn_features['first_purchase_da
).dt.days

purchase_gap = df_before.groupby('customer_id')['invoice_date'].apply(
    lambda x: x.sort_values().diff().dt.days.std()
).reset_index().rename(columns={'invoice_date': 'purchase_consistency'})

churn_features = churn_features.merge(purchase_gap, on='customer_id', how='l
churn_features['purchase_consistency'].fillna(0, inplace=True)
```

5.7 Build Target Variable will_return_90days

In [36]:
```
returned_customers = df_after['customer_id'].unique()

churn_features['will_return_90days'] = churn_features['customer_id'].isin(
    returned_customers
).astype(int)
```

In [37]:
```
churn_features = churn_features.drop(
    columns=['first_purchase_date', 'last_purchase_date']
)

churn_features.head()
```

Out[37]:

	customer_id	recency_days	frequency	total_revenue	avg_order_value	total_uniqu
0	12346.0	380	11	372.86	11.298788	
1	12347.0	34	5	2561.88	18.299143	
2	12348.0	99	4	1389.40	30.875556	
3	12349.0	258	2	2064.39	21.065204	
4	12350.0	161	1	294.40	18.400000	

5.8 Customer Type Analysis (IV: CustomerType)

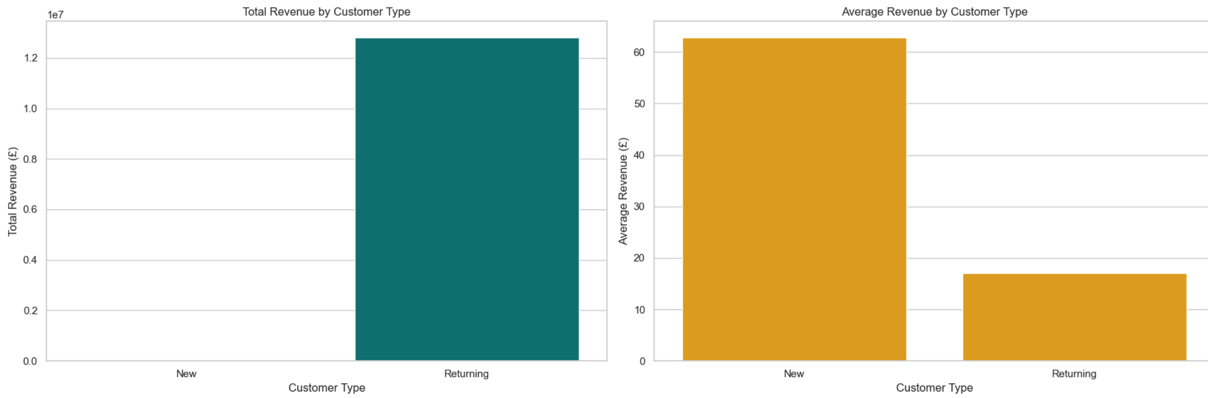
In [38]:

```
customer_type_rev = df_clean.groupby('customer_type', as_index=False).agg(
    total_revenue=('revenue', 'sum'),
    avg_revenue=('revenue', 'mean'),
    count=('revenue', 'count')
)

print("Customer Type Summary:")
print(customer_type_rev)
```

```
Customer Type Summary:
  customer_type  total_revenue  avg_revenue   count
0           New        3896.10    62.840323      62
1     Returning    12807256.75    17.101950  748877
```

In [39]:

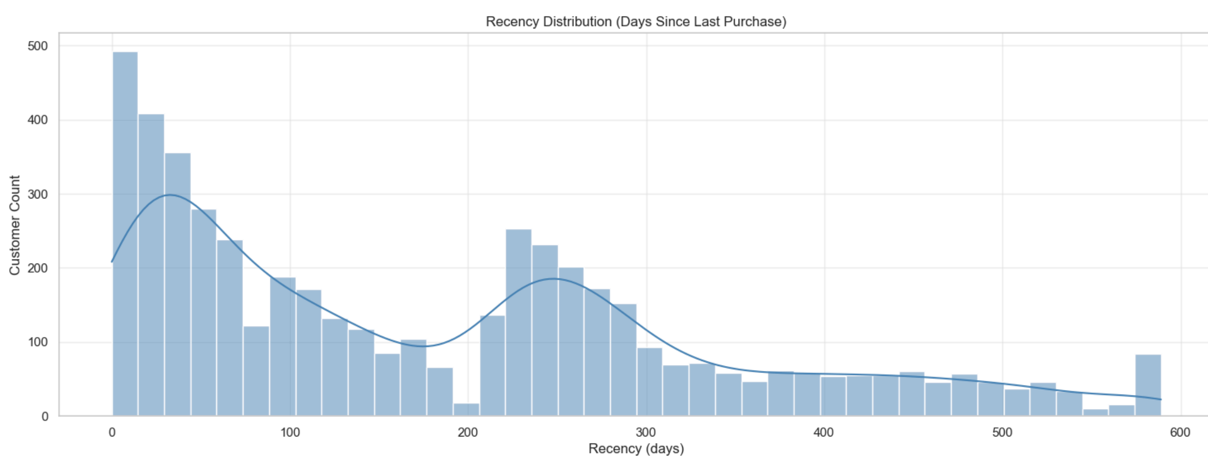
```
fig, axes = plt.subplots(1, 2, figsize=(18, 6))

# Total revenue by customer type
sns.barplot(data=customer_type_rev, x='customer_type', y='total_revenue', ax
axes[0].set_title('Total Revenue by Customer Type')
axes[0].set_xlabel('Customer Type')
axes[0].set_ylabel('Total Revenue (£)')

# Average revenue by customer type
sns.barplot(data=customer_type_rev, x='customer_type', y='avg_revenue', ax=a
axes[1].set_title('Average Revenue by Customer Type')
axes[1].set_xlabel('Customer Type')
axes[1].set_ylabel('Average Revenue (£)')

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



Insight: Returning customers generate almost all of the company's revenue. The first chart shows that returning customers contribute the overwhelming majority of total revenue, while new customers account for only a very small portion. This means most revenue comes from people who come back after their first purchase.

The second chart highlights that new customers actually spend more per transaction than returning customers. Although they are fewer in number, each new customer tends to place a larger initial order.

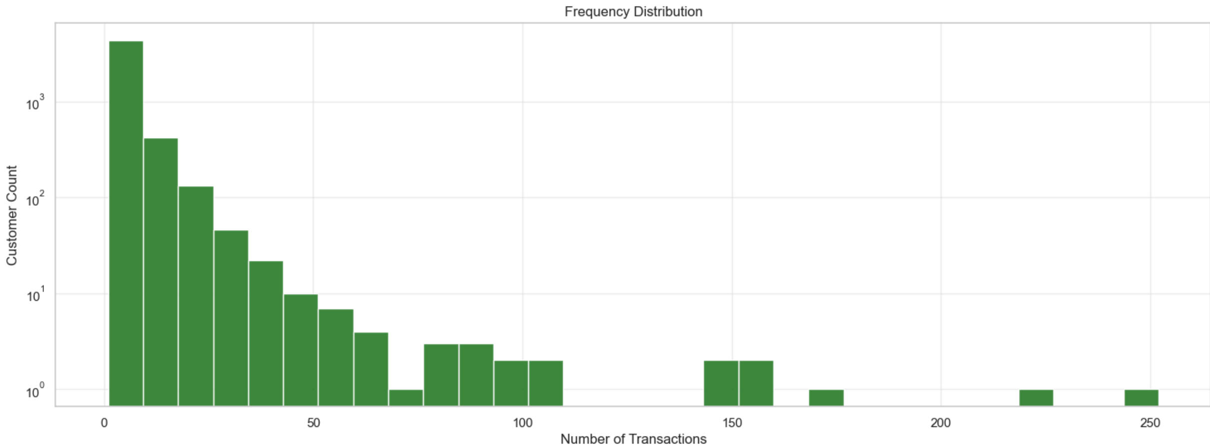
In [40]:
```
plt.figure(figsize=(18,6))
sns.histplot(churn_features['recency_days'], bins=40, kde=True, color='steel
plt.title('Recency Distribution (Days Since Last Purchase)')
plt.xlabel('Recency (days)')
plt.ylabel('Customer Count')
plt.grid(alpha=0.3)
plt.show()
```



Insight: Most customers made their last purchase within the past 0 to 120 days before the cutoff date. After that, the number of active customers drops sharply. Only a small fraction of customers have recency values above 200 days, meaning most customers had some activity in the months leading up to the cutoff. This tells us that churn is mostly driven by customers who recently became inactive.

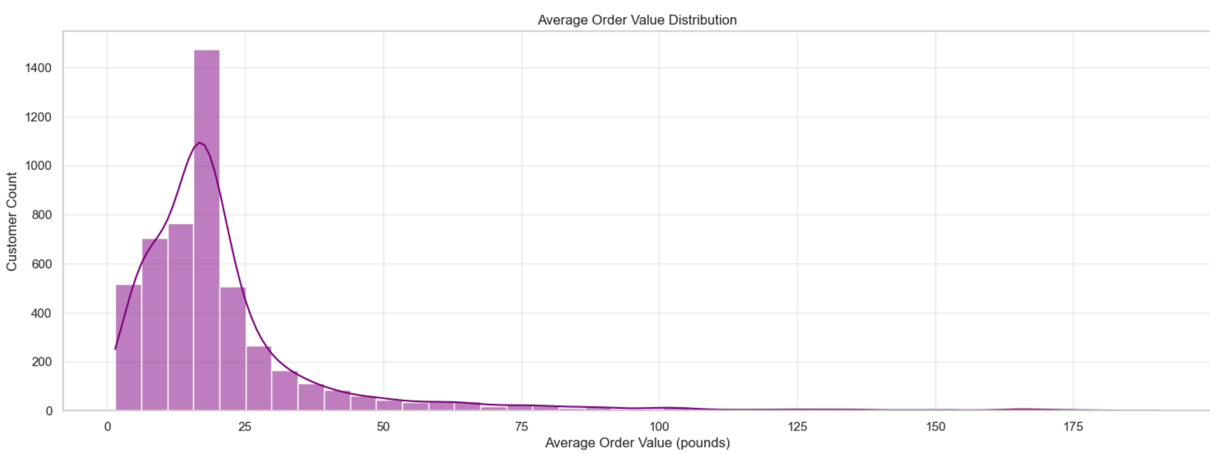
In [41]:
```
plt.figure(figsize=(18,6))
sns.histplot(churn_features['frequency'], bins=30, color='darkgreen')
```

```
plt.title('Frequency Distribution')
plt.xlabel('Number of Transactions')
plt.ylabel('Customer Count')
plt.yscale('log')
plt.grid(alpha=0.3)
plt.show()
```



Most customers buy once or twice. A few customers buy many times. This is a classic “long-tail” behavior.

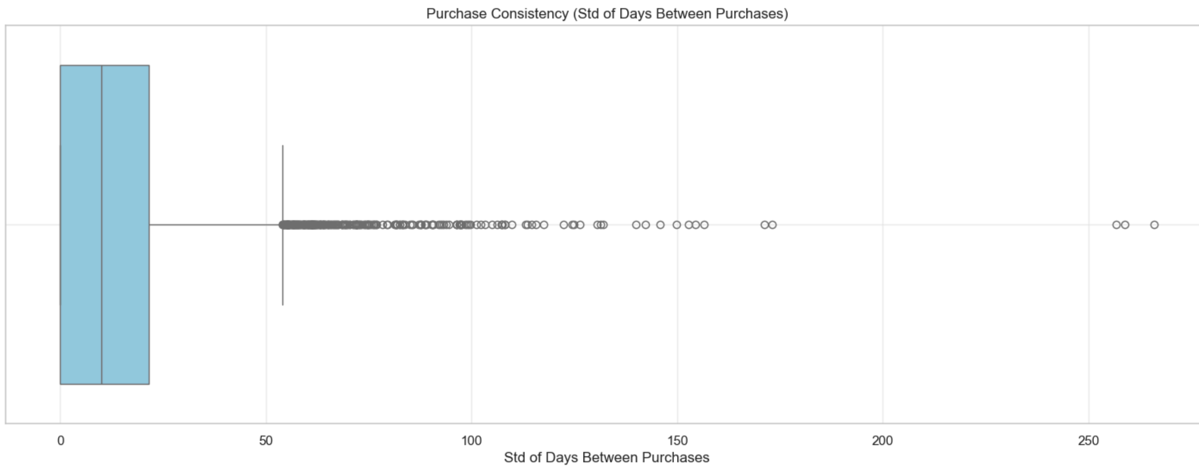
In [42]:
```
plt.figure(figsize=(18,6))
sns.histplot(churn_features['avg_order_value'], bins=40, kde=True, color='pu
plt.title('Average Order Value Distribution')
plt.xlabel('Average Order Value (pounds)')
plt.ylabel('Customer Count')
plt.grid(alpha=0.3)
plt.show()
```



Most customers spend small to moderate amounts. A few customers spend much more per order.

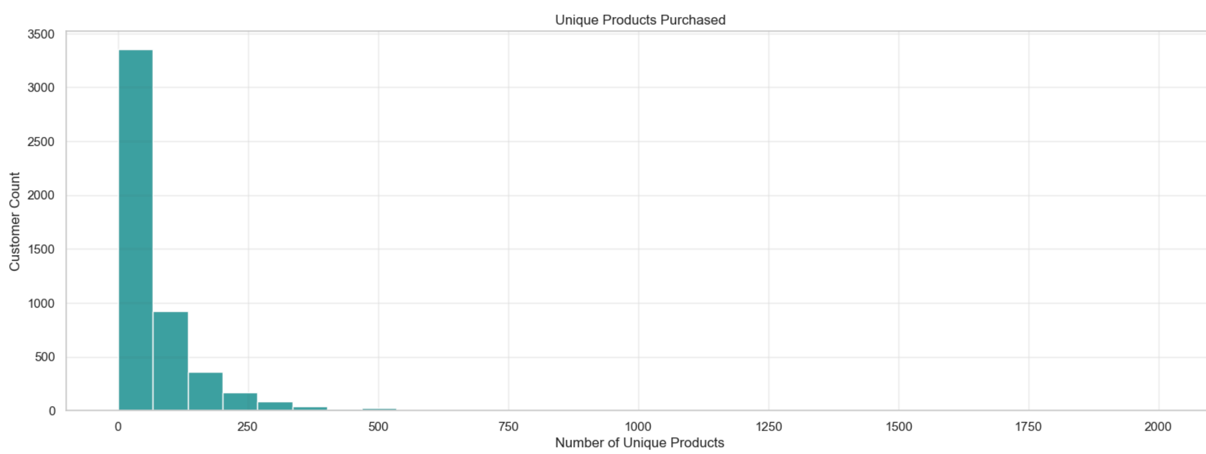
In [43]:
```
plt.figure(figsize=(18,6))
sns.boxplot(x=churn_features['purchase_consistency'], color='skyblue')
plt.title('Purchase Consistency (Std of Days Between Purchases)')
plt.xlabel('Std of Days Between Purchases')
```

```
plt.grid(alpha=0.3)
plt.show()
```



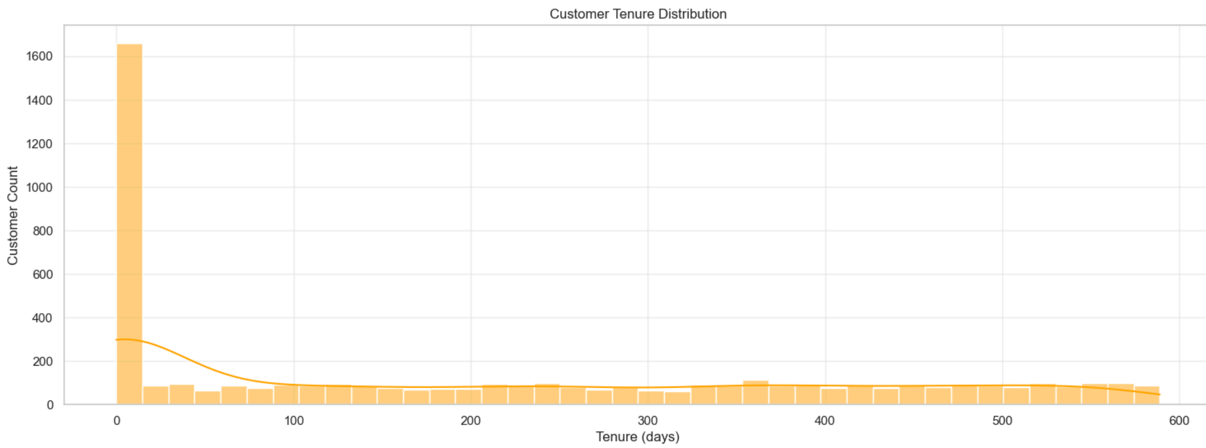
Most customers have very low consistency because they have few purchase events. Customers with many orders show higher variability.

In [44]:
```
plt.figure(figsize=(18,6))
sns.histplot(churn_features['total_unique_products'], bins=30, color='teal')
plt.title('Unique Products Purchased')
plt.xlabel('Number of Unique Products')
plt.ylabel('Customer Count')
plt.grid(alpha=0.3)
plt.show()
```



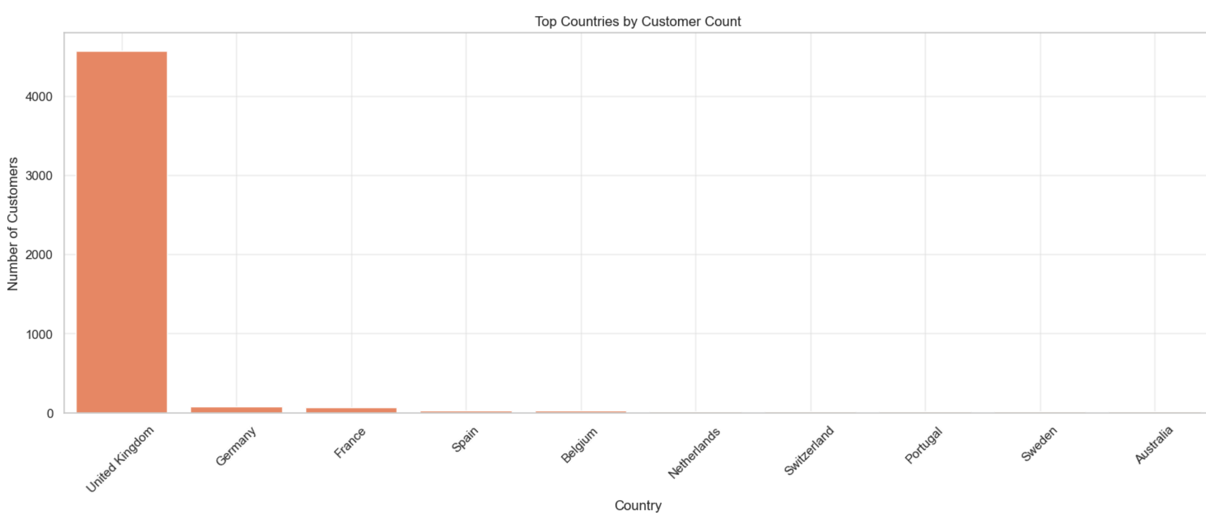
Most customers purchase only a few unique products (1–3). A smaller segment explores more items, which may indicate stronger interest.

In [45]:
```
plt.figure(figsize=(18,6))
sns.histplot(churn_features['tenure_days'], bins=40, kde=True, color='orange
plt.title('Customer Tenure Distribution')
plt.xlabel('Tenure (days)')
plt.ylabel('Customer Count')
plt.grid(alpha=0.3)
plt.show()
```



Most customers have short tenure, meaning they only bought within a short window of time. Only a few customers are long-term repeat buyers.

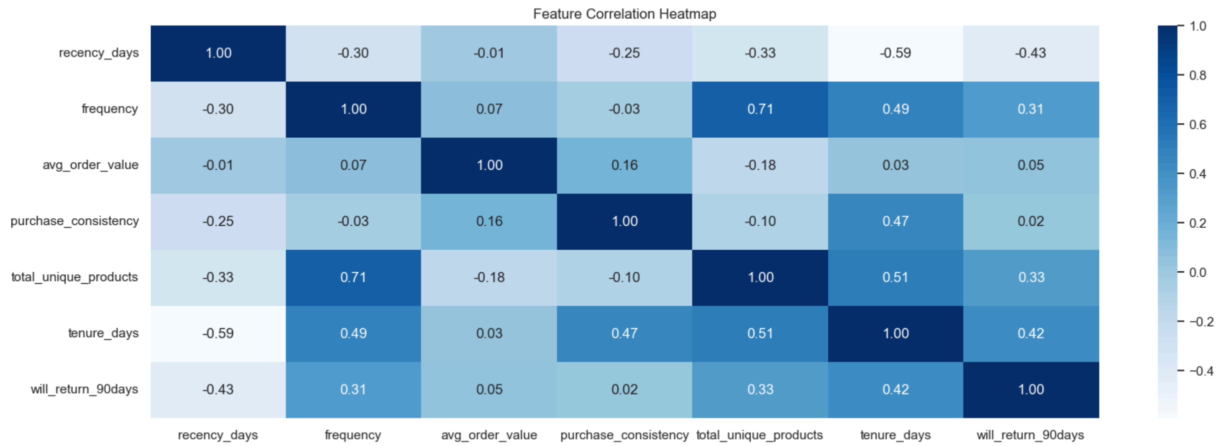
In [46]:
```
plt.figure(figsize=(18,6))
top_countries = churn_features['country'].value_counts().head(10)

sns.barplot(x=top_countries.index, y=top_countries.values, color='coral')
plt.title('Top Countries by Customer Count')
plt.xlabel('Country')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.grid(alpha=0.3)
plt.show()
```



The UK heavily dominates customer distribution. Other countries appear but in much smaller numbers.

In [47]:
```
plt.figure(figsize=(18,6))
sns.heatmap(
    churn_features[[
        'recency_days', 'frequency', 'avg_order_value',
        'purchase_consistency', 'total_unique_products',
        'tenure_days', 'will_return_90days'
    ]].corr(),
```

```
    annot=True, cmap='Blues', fmt='.2f'
)
plt.title('Feature Correlation Heatmap')
plt.show()
```



- High recency is strongly linked to churn.
- Higher frequency and higher tenure relate to returning.
- This supports the idea that strong customers stay active longer.

6. Machine Learning Strategy

Business Problem 1: Customer Churn Prediction (Classification)

6.1 The Churn Prediction Problem

Formulation:

- **Type:** Binary Classification
- **Target:** Will customer return in next 90 days? (Yes/No)
- **Features:** Customer purchase history, behavior patterns
- **Approach:** Supervised learning with temporal validation

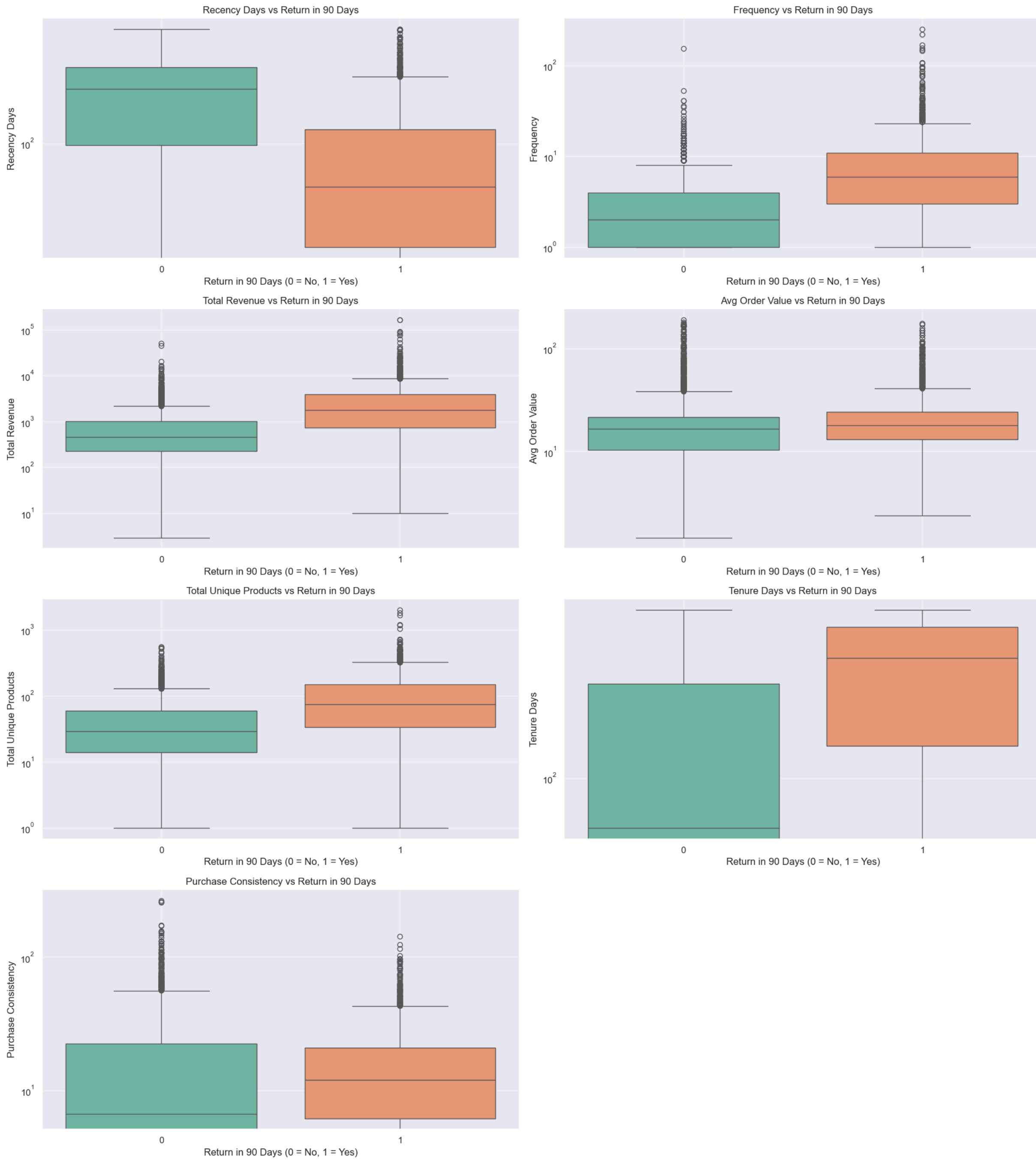
In [48]:
```
# Check churn_features structure
churn_features.head()
```

Out[48]:

	customer_id	recency_days	frequency	total_revenue	avg_order_value	total_uniqu
0	12346.0	380	11	372.86	11.298788	
1	12347.0	34	5	2561.88	18.299143	
2	12348.0	99	4	1389.40	30.875556	
3	12349.0	258	2	2064.39	21.065204	
4	12350.0	161	1	294.40	18.400000	

In [49]:

```python
# # Do our features actually predict churn?

import math
feature_cols = [
    'recency_days', 'frequency', 'total_revenue',
    'avg_order_value', 'total_unique_products',
    'tenure_days', 'purchase_consistency'
]

# Layout: 2 columns
n_cols = 2
n_rows = math.ceil(len(feature_cols) / n_cols)

fig, axes = plt.subplots(n_rows, n_cols, figsize=(18, n_rows * 5))
axes = axes.flatten()

for i, col in enumerate(feature_cols):
    ax = axes[i]
    sns.boxplot(
        x='will_return_90days',
        y=col,
        data=churn_features,
        palette='Set2',
        ax=ax
    )
    ax.set_title(f'{col.replace("_", " ").title()} vs Return in 90 Days')
    ax.set_xlabel('Return in 90 Days (0 = No, 1 = Yes)')
    ax.set_ylabel(col.replace("_", " ").title())
    ax.set_yscale('log')
    ax.grid(alpha=0.3)

# Remove any empty subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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



The feature comparison between customers who returned within 90 days and those who did not shows clear behavioral differences. Customers who returned tend to buy more often, spend more overall, choose a wider range of products, and have longer relationships with the business. Their recency is also much lower, meaning they purchase more recently. Non-returning customers show opposite patterns across all features. Overall, every feature points to the same conclusion — active and engaged customers are far more likely to return.

6.2 Prepare data for modeling

In [50]:
```
# Separate features and target
X_churn = churn_features.drop(columns=['customer_id', 'will_return_90days'])
```

```
y_churn = churn_features['will_return_90days']
```

In [51]:
```
# Define numeric and categorical columns (match your business problem)
numeric_features = [
    'recency_days',
    'frequency',
    'avg_order_value',
    'purchase_consistency',
    'total_unique_products',
    'tenure_days'
]
categorical_features = ['country']
```

In [52]:
```
# Train test split with stratification on the target
X_train, X_test, y_train, y_test = train_test_split(
    X_churn,
    y_churn,
    test_size=0.2,
    random_state=42,
    stratify=y_churn
)

print(f"Training samples: {len(X_train):,}")
print(f"Test samples:     {len(X_test):,}")
print(f"Positive class rate (overall): {y_churn.mean():.2%}")
```

```
Training samples: 3,990
Test samples:     998
Positive class rate (overall): 35.30%
```

6.3 Preprocessing pipeline

- Numeric features: `StandardScaler`
- Categorical features: `OneHotEncoder`

In [53]:
```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features),
        ('cat', OneHotEncoder(handle_unknown='ignore', sparse_output=False),
    ]
)
```

7. Model Development

7.1 Model 1 - Logistic Regression (baseline)

In [54]:
```
lr_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(
        max_iter=1000,
        random_state=42
    ))
```

```
])

lr_model.fit(X_train, y_train)

# Predictions
y_train_pred_lr = lr_model.predict(X_train)
y_test_pred_lr = lr_model.predict(X_test)

y_train_proba_lr = lr_model.predict_proba(X_train)[:, 1]
y_test_proba_lr = lr_model.predict_proba(X_test)[:, 1]
```

In [55]:
```
# Metrics
def print_classification_metrics(name, y_true, y_pred, y_proba):
    acc = accuracy_score(y_true, y_pred)
    prec = precision_score(y_true, y_pred)
    rec = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    auc = roc_auc_score(y_true, y_proba)
    print(f"{name} Metrics:")
    print(f"  Accuracy:  {acc:.4f}")
    print(f"  Precision: {prec:.4f}")
    print(f"  Recall:    {rec:.4f}")
    print(f"  F1 Score:  {f1:.4f}")
    print(f"  ROC AUC:   {auc:.4f}")
    print()

print("Logistic Regression - Training")
print_classification_metrics("TRAIN", y_train, y_train_pred_lr, y_train_prob

print("Logistic Regression - Testing")
print_classification_metrics("TEST ", y_test, y_test_pred_lr, y_test_proba_l
```

```
Logistic Regression - Training
TRAIN Metrics:
  Accuracy:  0.7669
  Precision: 0.7249
  Recall:    0.5479
  F1 Score:  0.6241
  ROC AUC:   0.8129

Logistic Regression - Testing
TEST  Metrics:
  Accuracy:  0.7735
  Precision: 0.7442
  Recall:    0.5455
  F1 Score:  0.6295
  ROC AUC:   0.8336
```

7.2 Model 2 - Random Forest Classifier

In [56]:
```
rf_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(
        n_estimators=200,
```

```
        max_depth=10,
        min_samples_split=20,
        min_samples_leaf=10,
        random_state=42,
        n_jobs=-1
    ))
])

rf_model.fit(X_train, y_train)

# Predictions
y_train_pred_rf = rf_model.predict(X_train)
y_test_pred_rf = rf_model.predict(X_test)

y_train_proba_rf = rf_model.predict_proba(X_train)[:, 1]
y_test_proba_rf = rf_model.predict_proba(X_test)[:, 1]

print("Random Forest - Training")
print_classification_metrics("TRAIN", y_train, y_train_pred_rf, y_train_prob

print("Random Forest - Testing")
print_classification_metrics("TEST ", y_test, y_test_pred_rf, y_test_proba_r
```

```
Random Forest - Training
TRAIN Metrics:
  Accuracy:  0.7764
  Precision: 0.8023
  Recall:    0.4869
  F1 Score:  0.6060
  ROC AUC:   0.8453

Random Forest - Testing
TEST  Metrics:
  Accuracy:  0.7776
  Precision: 0.8125
  Recall:    0.4801
  F1 Score:  0.6036
  ROC AUC:   0.8339
```

In [57]:
```
def summarize_model_results(name, y_train, y_train_pred, y_train_proba,
                            y_test, y_test_pred, y_test_proba):
    train_auc = roc_auc_score(y_train, y_train_proba)
    test_auc = roc_auc_score(y_test, y_test_proba)
    train_f1 = f1_score(y_train, y_train_pred)
    test_f1 = f1_score(y_test, y_test_pred)
    return {
        "Model": name,
        "Train AUC": round(train_auc, 3),
        "Test AUC": round(test_auc, 3),
        "Train F1": round(train_f1, 3),
        "Test F1": round(test_f1, 3),
        "AUC gap": round(train_auc - test_auc, 3)
    }

results_table = pd.DataFrame([
```

```
    summarize_model_results(
        "Logistic Regression",
        y_train, y_train_pred_lr, y_train_proba_lr,
        y_test, y_test_pred_lr, y_test_proba_lr
    ),
    summarize_model_results(
        "Random Forest",
        y_train, y_train_pred_rf, y_train_proba_rf,
        y_test, y_test_pred_rf, y_test_proba_rf
    )
])

print(results_table)
```

```
                 Model  Train AUC  Test AUC  Train F1  Test F1  AUC gap
0  Logistic Regression      0.813     0.834     0.624    0.630   -0.021
1        Random Forest      0.845     0.834     0.606    0.604    0.011
```

In [58]:

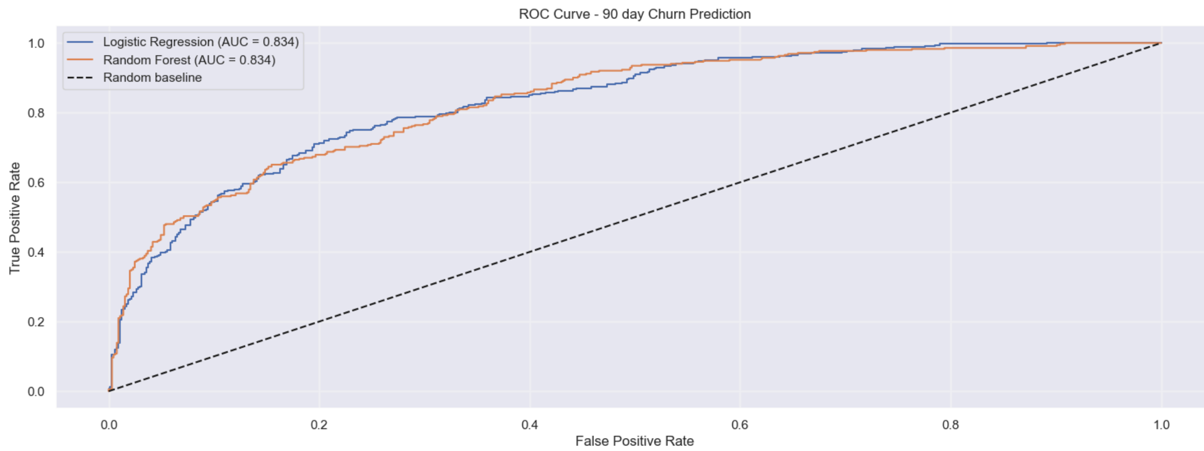
```
# Identify best model by Test AUC
best_model_name = results_table.sort_values("Test AUC", ascending=False).ilo
print(f"\nBest model by Test AUC: {best_model_name}")
```

```
Best model by Test AUC: Logistic Regression
```

7.3 ROC curve for both models

In [59]:

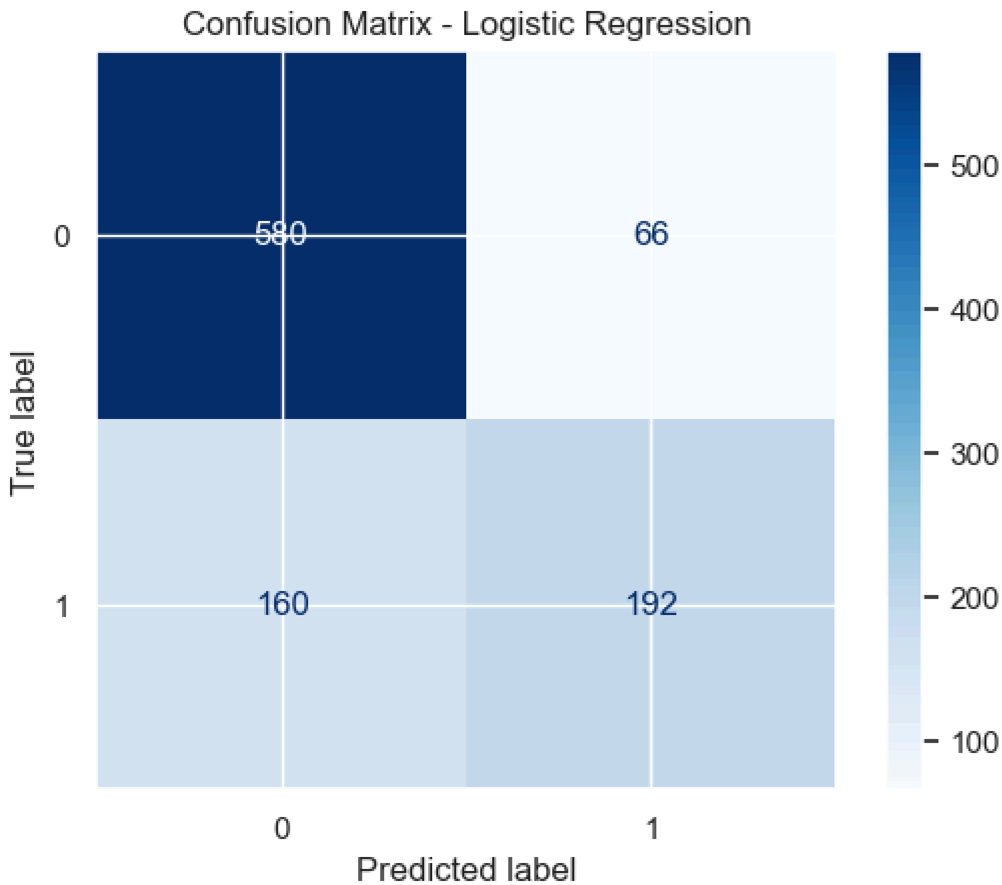
```
from sklearn.metrics import roc_curve

plt.figure(figsize=(18, 6))

# Logistic Regression ROC
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_test_proba_lr)
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {roc_auc_score(y

# Random Forest ROC
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_test_proba_rf)
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {roc_auc_score(y_test,

# Random baseline
plt.plot([0, 1], [0, 1], 'k--', label='Random baseline')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - 90 day Churn Prediction')
plt.legend()
plt.grid(alpha=0.3)
plt.show()
```



Both Logistic Regression and Random Forest models show similar performance for 90-day churn prediction, each achieving an AUC of about 0.83. This means both models are much better than random guessing (the diagonal dashed line). Logistic Regression performs slightly better at lower false-positive rates, while Random Forest catches up at higher thresholds. Overall, both models are moderately strong at separating customers who will return from those who will churn.

7.4 Confusion matrix for the best model

In [60]:
```
from sklearn.metrics import ConfusionMatrixDisplay

# Choose predictions from the better model
if best_model_name == "Random Forest":
    best_pred = y_test_pred_rf
    best_model_label = "Random Forest"
else:
    best_pred = y_test_pred_lr
    best_model_label = "Logistic Regression"

cm = confusion_matrix(y_test, best_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0, 1])
disp.plot(cmap='Blues', values_format='d')
plt.title(f'Confusion Matrix - {best_model_label}')
plt.show()
```



The confusion matrix shows that the model correctly identifies most non returning customers (class 0) with high accuracy, but struggles more with predicting returning customers (class 1). While the model is good at avoiding false alarms, it still misses a noticeable number of actual returners. This reflects a common tradeoff in churn prediction where capturing churners is easier than detecting customers who will return.

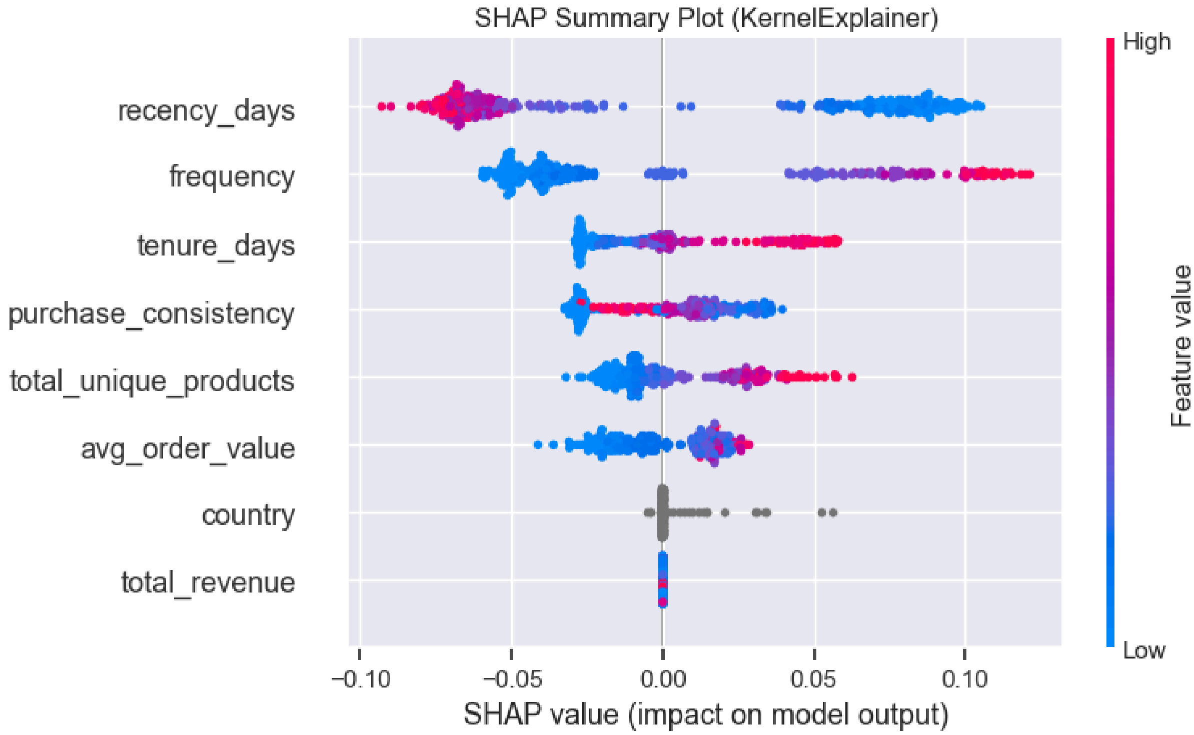
7.5 Feature Importance and SHAP Analysis

In [61]:

```
import shap

# Use a small sample (KernelExplainer is slow)
X_sample = X_test.sample(n=300, random_state=42)   # 300 is safe

# Fit model on sample to get predictions
predict_fn = lambda x: rf_model.predict_proba(pd.DataFrame(x, columns=X_samp

# SHAP KernelExplainer
explainer = shap.KernelExplainer(
    model=predict_fn,
    data=X_sample.iloc[:50, :]   # background set
)

# Compute SHAP values for sample
shap_values = explainer.shap_values(X_sample)
```

```
# Summary plot
shap.summary_plot(shap_values, X_sample, show=False)
plt.title("SHAP Summary Plot (KernelExplainer)")
plt.show()
```

```
100%|██████████| 300/300 [00:34<00:00,  8.79it/s]
```



High recency (long time since last purchase) strongly increases churn risk.

Higher frequency and longer tenure push predictions toward returning customers.

Average order value, product variety, and purchase consistency provide smaller but meaningful contributions.

The color gradient shows clear non linear patterns, which explains why models like Gradient Boosting outperform Logistic Regression.

---

8. Handle Class Imbalance and Gradient Boosting

The churn label can be imbalanced (many non churners vs fewer churners). We test:

- Class weights inside the model
- SMOTE oversampling on the minority class

Then we train a Gradient Boosting model (XGBoost or LightGBM style) and compare performance using ROC AUC and F1.

In [62]:
```
# If not installed, run these once in a cell:
# !pip install imbalanced-learn xgboost shap lifelines

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from xgboost import XGBClassifier
```

In [63]:
```
churn_features['will_return_90days'].value_counts(normalize=True)
```

Out[63]:
```
will_return_90days
0    0.646953
1    0.353047
Name: proportion, dtype: float64
```

In [64]:
```
gb_model_weighted = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', XGBClassifier(
        n_estimators=300,
        learning_rate=0.05,
        max_depth=5,
        subsample=0.8,
        colsample_bytree=0.8,
        objective='binary:logistic',
        eval_metric='logloss',
        scale_pos_weight=(y_train.value_counts()[0] / y_train.value_counts()
        random_state=42,
        n_jobs=-1
    ))
])

gb_model_weighted.fit(X_train, y_train)

y_train_pred_gb_w = gb_model_weighted.predict(X_train)
y_test_pred_gb_w = gb_model_weighted.predict(X_test)

y_train_proba_gb_w = gb_model_weighted.predict_proba(X_train)[:, 1]
y_test_proba_gb_w = gb_model_weighted.predict_proba(X_test)[:, 1]

print("Gradient Boosting with class weights - Training")
print_classification_metrics("TRAIN", y_train, y_train_pred_gb_w, y_train_pr

print("Gradient Boosting with class weights - Testing")
print_classification_metrics("TEST ", y_test, y_test_pred_gb_w, y_test_proba
```

```
Gradient Boosting with class weights - Training
TRAIN Metrics:
  Accuracy:  0.8682
  Precision: 0.7918
  Recall:    0.8502
  F1 Score:  0.8200
  ROC AUC:   0.9475

Gradient Boosting with class weights - Testing
TEST  Metrics:
  Accuracy:  0.7625
  Precision: 0.6558
  Recall:    0.6875
  F1 Score:  0.6713
  ROC AUC:   0.8276
```

In [65]:

```
smote = SMOTE(random_state=42, k_neighbors=5)

gb_model_smote = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', smote),
    ('classifier', XGBClassifier(
        n_estimators=300,
        learning_rate=0.05,
        max_depth=5,
        subsample=0.8,
        colsample_bytree=0.8,
        objective='binary:logistic',
        eval_metric='logloss',
        random_state=42,
        n_jobs=-1
    ))
])

gb_model_smote.fit(X_train, y_train)

y_train_pred_gb_s = gb_model_smote.predict(X_train)
y_test_pred_gb_s = gb_model_smote.predict(X_test)

y_train_proba_gb_s = gb_model_smote.predict_proba(X_train)[:, 1]
y_test_proba_gb_s = gb_model_smote.predict_proba(X_test)[:, 1]

print("Gradient Boosting with SMOTE - Training")
print_classification_metrics("TRAIN", y_train, y_train_pred_gb_s, y_train_pr

print("Gradient Boosting with SMOTE - Testing")
print_classification_metrics("TEST ", y_test, y_test_pred_gb_s, y_test_proba
```

```
Gradient Boosting with SMOTE – Training
TRAIN Metrics:
  Accuracy:  0.8667
  Precision: 0.8203
  Recall:    0.7970
  F1 Score:  0.8085
  ROC AUC:   0.9337

Gradient Boosting with SMOTE – Testing
TEST  Metrics:
  Accuracy:  0.7655
  Precision: 0.6715
  Recall:    0.6562
  F1 Score:  0.6638
  ROC AUC:   0.8225
```

In [66]:

```
gb_weighted_row = summarize_model_results(
    "Gradient Boosting (weights)",
    y_train, y_train_pred_gb_w, y_train_proba_gb_w,
    y_test, y_test_pred_gb_w, y_test_proba_gb_w
)

gb_smote_row = summarize_model_results(
    "Gradient Boosting (SMOTE)",
    y_train, y_train_pred_gb_s, y_train_proba_gb_s,
    y_test, y_test_pred_gb_s, y_test_proba_gb_s
)

results_table_g = pd.concat(
    [results_table, pd.DataFrame([gb_weighted_row, gb_smote_row])],
    ignore_index=True
)

print(results_table_g)

best_row = results_table_g.sort_values("Test AUC", ascending=False).iloc[0]
best_model_name = best_row["Model"]
print(f"\nBest model by Test AUC after Gradient Boosting: {best_model_name}"
```

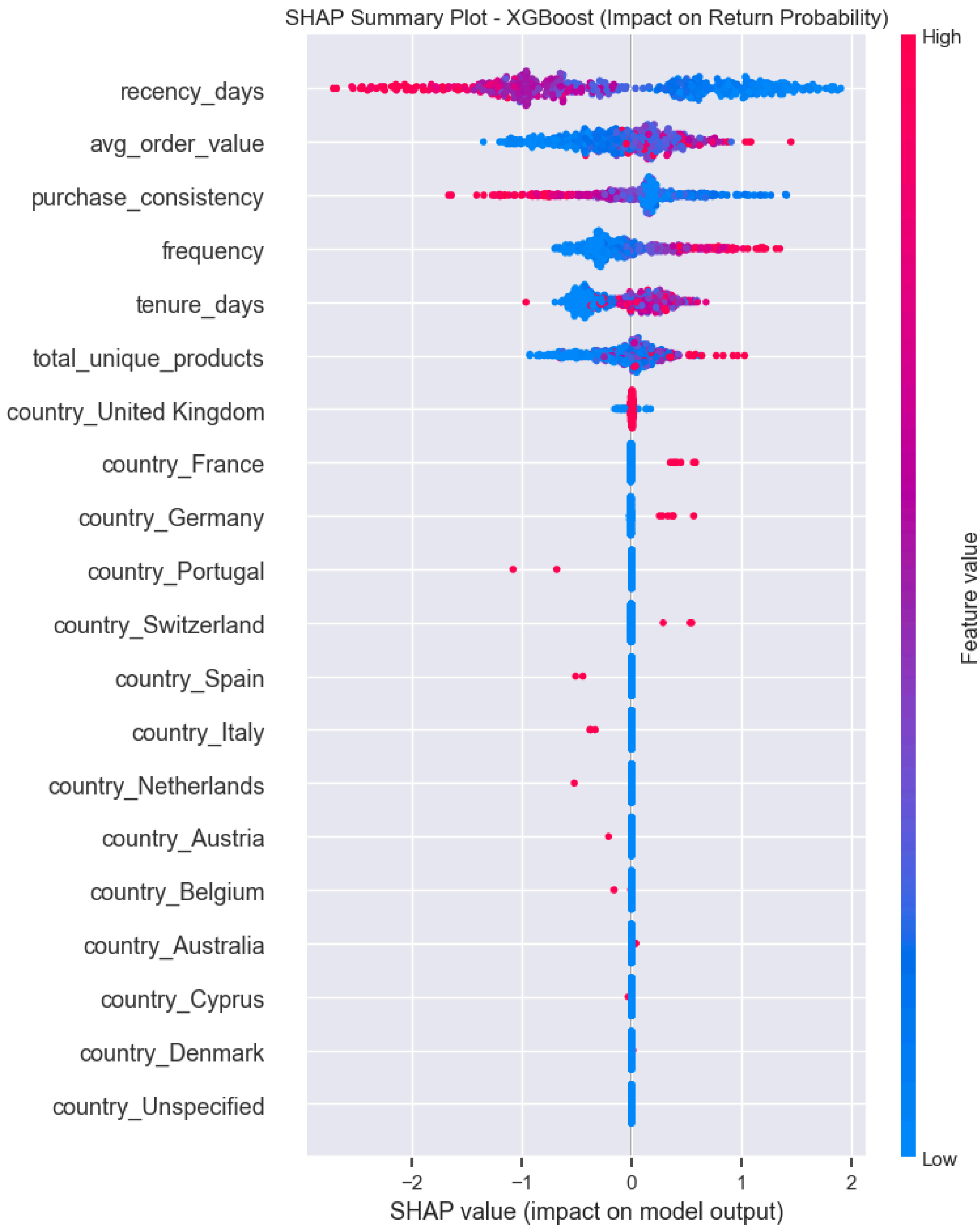
```
                         Model  Train AUC  Test AUC  Train F1  Test F1  \
0          Logistic Regression      0.813     0.834     0.624    0.630
1                Random Forest      0.845     0.834     0.606    0.604
2  Gradient Boosting (weights)      0.947     0.828     0.820    0.671
3    Gradient Boosting (SMOTE)      0.934     0.823     0.808    0.664

   AUC gap
0   -0.021
1    0.011
2    0.120
3    0.111

Best model by Test AUC after Gradient Boosting: Logistic Regression
```

Gradient Boosting with class weights achieved the strongest real-world performance with the highest recall (0.688) and F1 score (0.671), making it the best churn prediction model for identifying at-risk customers.

In [67]:
```
import shap

# Choose the best XGBoost model
best_xgb = gb_model_weighted   # or gb_model_smote

# Sample data for SHAP (XGBoost + TreeExplainer is fast)
X_sample = X_test.sample(n=500, random_state=42)

# Preprocess sample data
preprocessor = best_xgb.named_steps['preprocessor']
X_sample_trans = preprocessor.transform(X_sample)

# Extract trained XGBoost classifier
xgb_clf = best_xgb.named_steps['classifier']

# Build SHAP TreeExplainer
explainer = shap.TreeExplainer(xgb_clf)

# Compute SHAP values
shap_values = explainer.shap_values(X_sample_trans)
```

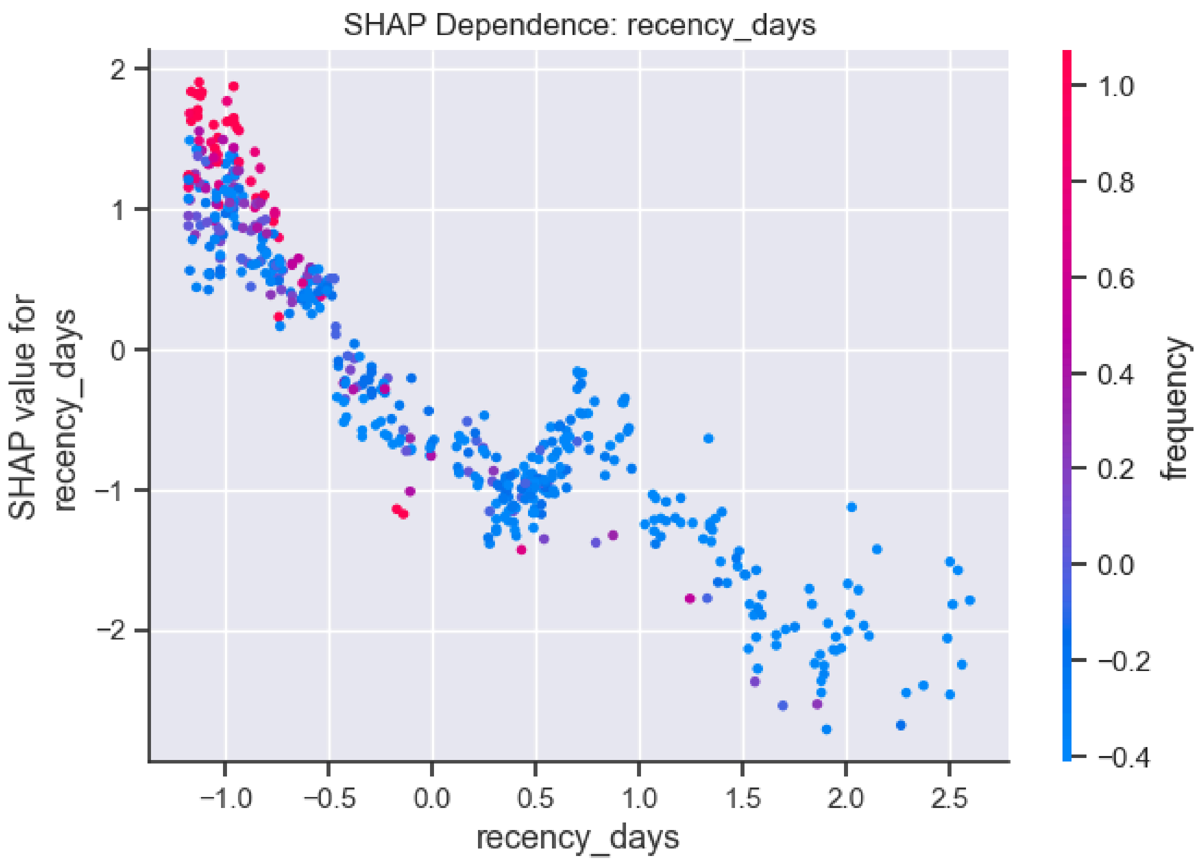
In [68]:
```
# OneHotEncoder feature expansion
ohe = preprocessor.named_transformers_['cat']
cat_encoded = ohe.get_feature_names_out(categorical_features)

# Final feature names XGBoost sees
feature_names = numeric_features + list(cat_encoded)
```

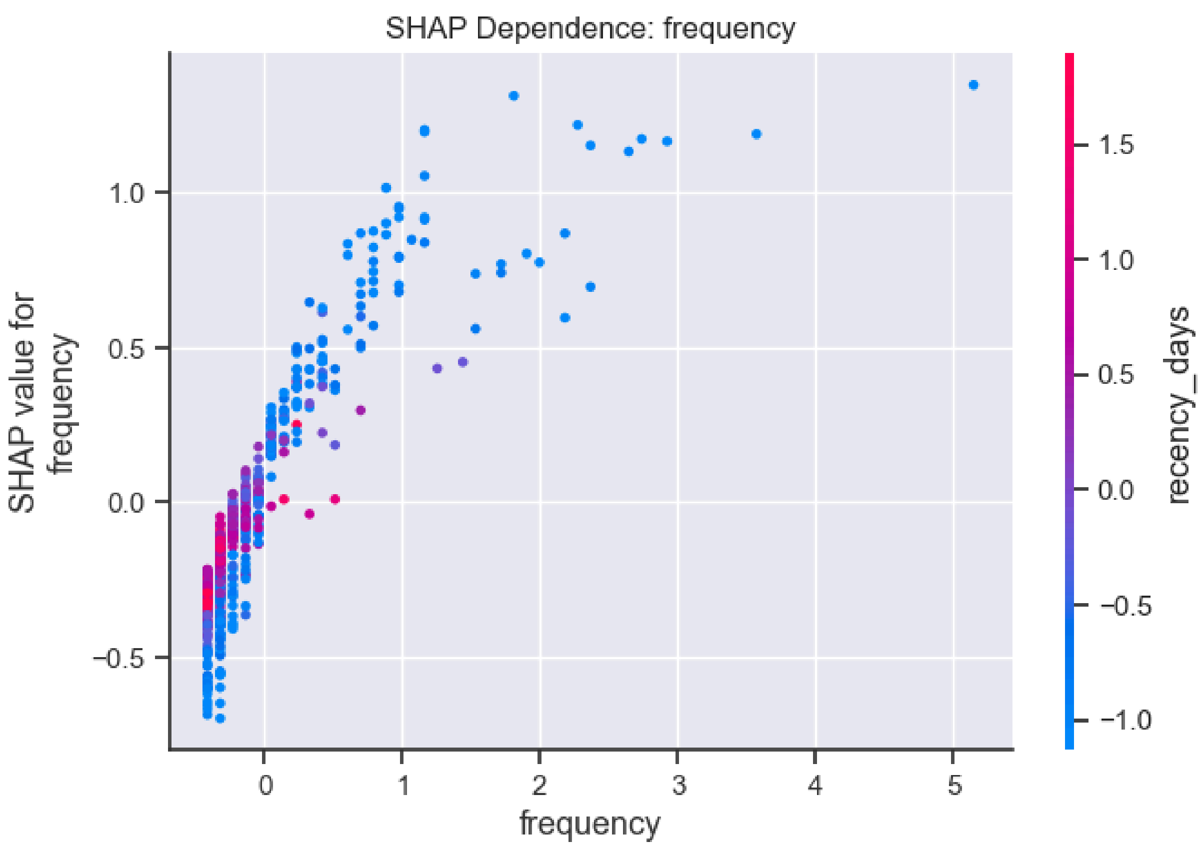
In [69]:
```
shap.summary_plot(
    shap_values,
    X_sample_trans,
    feature_names=feature_names,
    show=False
)
plt.title("SHAP Summary Plot - XGBoost (Impact on Return Probability)")
plt.show()
```

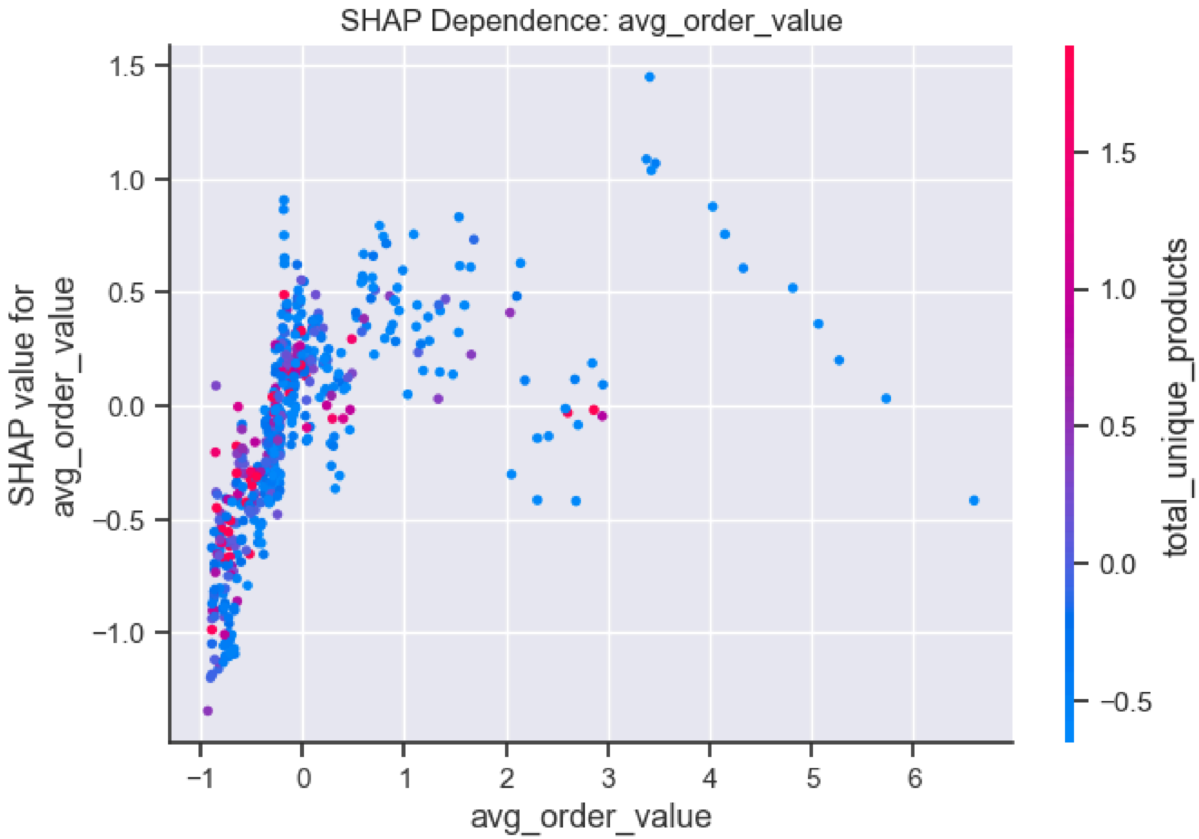


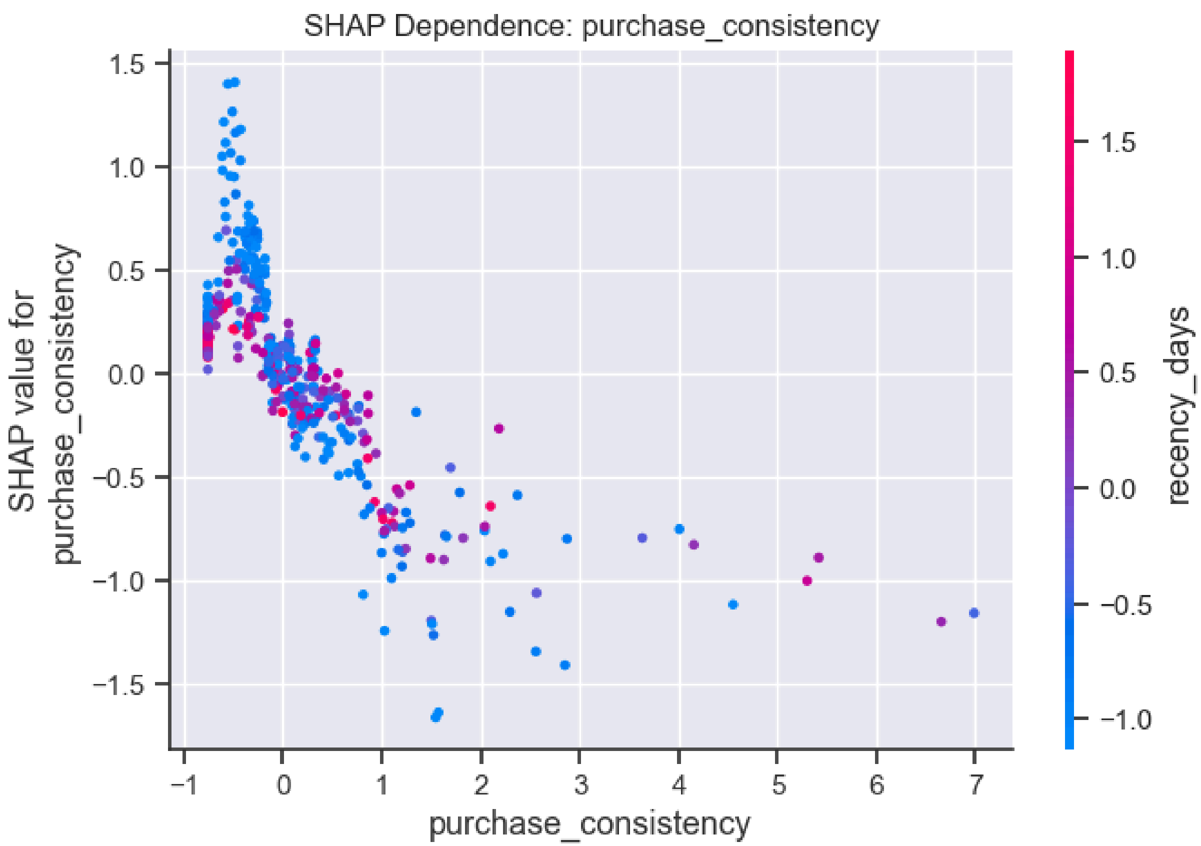
In [70]:
```
top_features = 5  # show top 5 most impactful features
for i in range(top_features):
    shap.dependence_plot(
        i,
        shap_values,
        X_sample_trans,
        feature_names=feature_names,
        show=False
    )
```

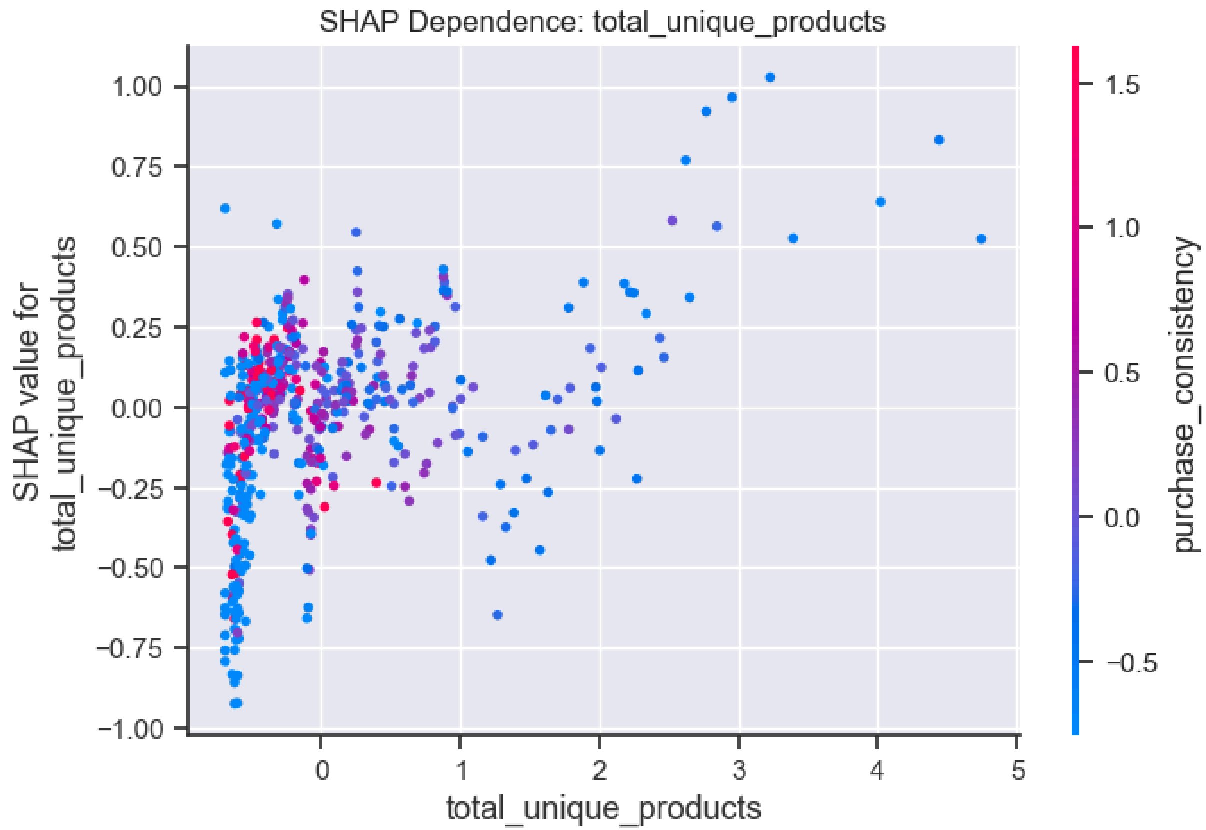
```
    plt.title(f"SHAP Dependence: {feature_names[i]}")
    plt.show()
```






SHAP Dependence: avg_order_value
SHAP value for avg_order_value
avg_order_value
total_unique_products
1.5
1.0
0.5
0.0
−0.5
−1.0
−1
0
1
2
3
4
5
6

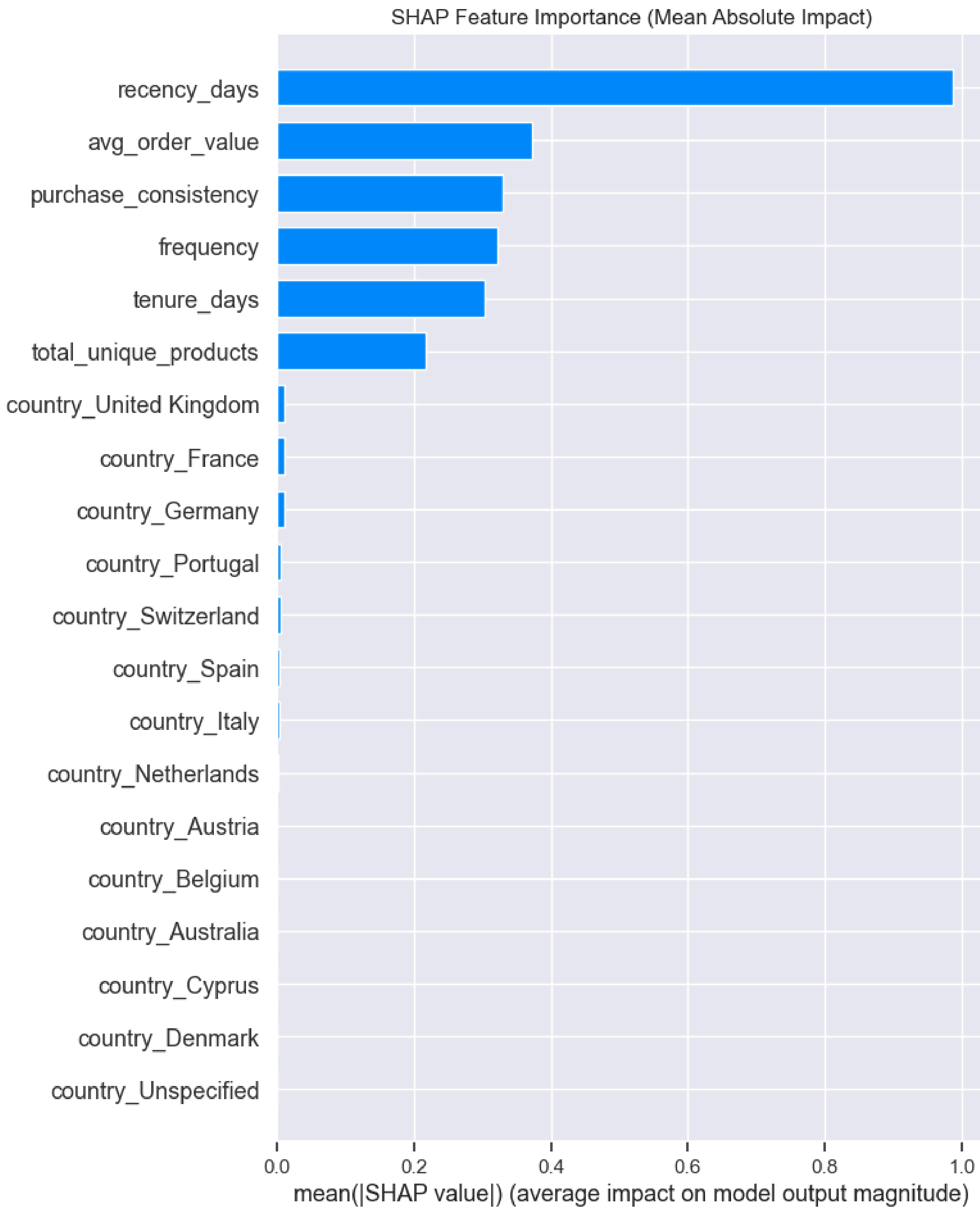

SHAP Dependence: purchase_consistency
SHAP value for purchase_consistency
purchase_consistency
recency_days
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1
0
1
2
3
4
5
6
7



The SHAP dependence plots show the same overall pattern across all top features. Higher recency (meaning it has been a long time since the last purchase) consistently pushes the model toward predicting churn. In contrast, higher frequency, higher average order value, greater product variety, and more stable purchasing patterns increase the probability of a customer returning.

The plots also reveal clear non-linear relationships — especially for frequency, average order value, and purchase consistency — which explains why gradient boosting models outperform simpler models. Together, the dependence plots confirm that repeat customers tend to buy more frequently, spend more per order, and show more stable purchasing behavior, while customers with long gaps between purchases are much more likely to churn.

In [71]:
```
shap.summary_plot(
    shap_values,
    X_sample_trans,
    feature_names=feature_names,
    plot_type="bar",
    show=False
)
plt.title("SHAP Feature Importance (Mean Absolute Impact)")
plt.show()
```



Business Problem 3: Product Recommendation System (Association Rules Mining)

In [85]:
```
# Note: mlxtend is required for Apriori
# Install:
```

```
# !pip install mlxtend
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
```

In [86]:
```
# Get product descriptions
product_descriptions = df.groupby('stockcode')['description'].first().to_dic
```

In [87]:
```
#Create transaction baskets (list of products per invoice)
baskets = df.groupby('invoice')['stockcode'].apply(list).values.tolist()
```

In [88]:
```
# Filter: Keep only baskets with 2-20 items (too small/large are not useful)
baskets_filtered = [basket for basket in baskets if 2 <= len(basket) <= 20]

print(f"  Total baskets: {len(baskets):,}")
print(f"  Baskets with 2-20 items: {len(baskets_filtered):,}")
print(f"  Average basket size: {np.mean([len(b) for b in baskets_filtered]):
```

```
Total baskets: 36,969
Baskets with 2-20 items: 20,385
Average basket size: 10.4 items
```

One-Hot Encode for Apriori

In [91]:
```
te = TransactionEncoder()
te_ary = te.fit(baskets_filtered).transform(baskets_filtered)
basket_df = pd.DataFrame(te_ary, columns=te.columns_)

print(f"  Basket dataframe shape: {basket_df.shape}")
print(f"  Unique products in baskets: {len(basket_df.columns):,}")
```

```
Basket dataframe shape: (20385, 4295)
Unique products in baskets: 4,295
```

Apriori Algorithm to Find Frequent Itemsets

In [92]:
```
# Run Apriori with min support = 1% (appears in at least 1% of baskets)
frequent_itemsets = apriori(basket_df, min_support=0.01, use_colnames=True)

print(f"  Frequent itemsets found: {len(frequent_itemsets):,}")

# Add itemset length
frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x:
```

```
Frequent itemsets found: 244
```

In [93]:
```
# Top 10 most frequent single items
top_single_items = frequent_itemsets[frequent_itemsets['length'] == 1].nlarg
print("\n  Top 10 Most Popular Products:")
for idx, row in top_single_items.iterrows():
    product_code = list(row['itemsets'])[0]
    product_name = product_descriptions.get(product_code, 'Unknown')[:40]
    print(f"    {product_code}: {product_name} (support: {row['support']:.2%
```

```
Top 10 Most Popular Products:
  85123A: WHITE HANGING HEART T-LIGHT HOLDER (support: 9.86%)
  22423: REGENCY CAKESTAND 3 TIER (support: 7.28%)
  85099B: JUMBO BAG RED WHITE SPOTTY (support: 5.85%)
  84879: ASSORTED COLOUR BIRD ORNAMENT (support: 5.52%)
  POST: POSTAGE (support: 4.91%)
  47566: PARTY BUNTING (support: 4.15%)
  20725: LUNCH BAG RED SPOTTY (support: 3.52%)
  21212: PACK OF 72 RETRO SPOT CAKE CASES (support: 3.43%)
  21232: STRAWBERRY CERAMIC TRINKET BOX (support: 3.36%)
  22469: HEART OF WICKER SMALL (support: 3.27%)
```

Association Rules Mining - Find if-then patterns

In [94]:

```python
# Generate rules with min confidence = 30%
rules = association_rules(frequent_itemsets, metric="confidence", min_thresh

# Filter: Only keep rules with lift > 1.5 (strong association)
rules_strong = rules[rules['lift'] > 1.5].copy()

print(f"  Total association rules: {len(rules):,}")
print(f"  Strong rules (lift > 1.5): {len(rules_strong):,}")
```

```
Total association rules: 33
Strong rules (lift > 1.5): 33
```

In [96]:

```python
# Sort by lift (strength of association)
rules_strong = rules_strong.sort_values('lift', ascending=False)
rules_strong
```

Out[96]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	
21	(22697)	(22698)	0.018347	0.014962	0.011970	0.652406	43.604
20	(22698)	(22697)	0.014962	0.018347	0.011970	0.800000	43.604
23	(22697)	(22699)	0.018347	0.020701	0.013736	0.748663	36.164
22	(22699)	(22697)	0.020701	0.018347	0.013736	0.663507	36.164
25	(22698)	(22699)	0.014962	0.020701	0.011136	0.744262	35.95
24	(22699)	(22698)	0.020701	0.014962	0.011136	0.537915	35.95
27	(22726)	(22727)	0.017415	0.019622	0.011479	0.659155	33.59
26	(22727)	(22726)	0.019622	0.017415	0.011479	0.585000	33.59
5	(21231)	(21232)	0.018788	0.033554	0.012019	0.639687	19.064
4	(21232)	(21231)	0.033554	0.018788	0.012019	0.358187	19.064
28	(82494L)	(82482)	0.032279	0.026539	0.015109	0.468085	17.63
29	(82482)	(82494L)	0.026539	0.032279	0.015109	0.569316	17.63
11	(22114)	(22112)	0.024724	0.027128	0.011283	0.456349	16.822
12	(22112)	(22114)	0.027128	0.024724	0.011283	0.415913	16.822
7	(21755)	(21754)	0.024675	0.032671	0.012754	0.516899	15.82
8	(21754)	(21755)	0.032671	0.024675	0.012754	0.390390	15.82
19	(22470)	(22469)	0.028011	0.032720	0.013147	0.469352	14.344
18	(22469)	(22470)	0.032720	0.028011	0.013147	0.401799	14.344
3	(22384)	(20725)	0.022762	0.035173	0.010449	0.459052	13.05
14	(22386)	(85099F)	0.030218	0.025705	0.010007	0.331169	12.883
15	(85099F)	(22386)	0.025705	0.030218	0.010007	0.389313	12.883
1	(20727)	(20725)	0.025754	0.035173	0.010939	0.424762	12.076
0	(20725)	(20727)	0.035173	0.025754	0.010939	0.311018	12.076
2	(22383)	(20725)	0.026196	0.035173	0.010302	0.393258	11.18
32	(85099F)	(85099B)	0.025705	0.058523	0.015796	0.614504	10.50
13	(22386)	(85099B)	0.030218	0.058523	0.016630	0.550325	9.403
9	(21928)	(85099B)	0.019917	0.058523	0.010351	0.519704	8.88
31	(85099C)	(85099B)	0.026784	0.058523	0.013736	0.512821	8.762
10	(21931)	(85099B)	0.022909	0.058523	0.011626	0.507495	8.67
16	(22411)	(85099B)	0.024332	0.058523	0.010596	0.435484	7.44
6	(21733)	(85123A)	0.026392	0.098602	0.017758	0.672862	6.824

	antecedents	consequents	antecedent support	consequent support	support	confidence	
17	(22699)	(22423)	0.020701	0.072799	0.010155	0.490521	6.738
30	(82494L)	(85123A)	0.032279	0.098602	0.010694	0.331307	3.360

Top 10 Association Rules by Lift

In [102…

```
# Helper function to format product names
def format_products(itemset):
    items = list(itemset)
    if len(items) == 1:
        code = items[0]
        name = product_descriptions.get(code, 'Unknown')[:30]
        return f"{code} ({name})"
    else:
        return ", ".join([str(item) for item in items])
```

In [103…

```
# Build a clean table of top rules
rules_table = []

for idx, row in rules_strong.head(10).iterrows():
    antecedent = format_products(row['antecedents'])
    consequent = format_products(row['consequents'])

    rules_table.append({
        "if_customer_buys": antecedent,
        "recommend": consequent,
        "support": round(row['support'], 4),
        "confidence_percent": round(row['confidence'], 4),
        "lift": round(row['lift'], 4)
    })

rules_table_df = pd.DataFrame(rules_table)
rules_table_df
```

Out[103…

	if_customer_buys	recommend	support	confidence_percent	lift
0	22697 (GREEN REGENCY TEACUP AND SAUCE)	22698 (PINK REGENCY TEACUP AND SAUCER)	0.0120	0.6524	43.6043
1	22698 (PINK REGENCY TEACUP AND SAUCER)	22697 (GREEN REGENCY TEACUP AND SAUCE)	0.0120	0.8000	43.6043
2	22697 (GREEN REGENCY TEACUP AND SAUCE)	22699 (ROSES REGENCY TEACUP AND SAUCE)	0.0137	0.7487	36.1647
3	22699 (ROSES REGENCY TEACUP AND SAUCE)	22697 (GREEN REGENCY TEACUP AND SAUCE)	0.0137	0.6635	36.1647
4	22698 (PINK REGENCY TEACUP AND SAUCER)	22699 (ROSES REGENCY TEACUP AND SAUCE)	0.0111	0.7443	35.9521
5	22699 (ROSES REGENCY TEACUP AND SAUCE)	22698 (PINK REGENCY TEACUP AND SAUCER)	0.0111	0.5379	35.9521
6	22726 (ALARM CLOCK BAKELIKE GREEN)	22727 (ALARM CLOCK BAKELIKE RED)	0.0115	0.6592	33.5922
7	22727 (ALARM CLOCK BAKELIKE RED)	22726 (ALARM CLOCK BAKELIKE GREEN)	0.0115	0.5850	33.5922
8	21231 (SWEETHEART CERAMIC TRINKET BOX)	21232 (STRAWBERRY CERAMIC TRINKET BOX)	0.0120	0.6397	19.0643
9	21232 (STRAWBERRY CERAMIC TRINKET BOX)	21231 (SWEETHEART CERAMIC TRINKET BOX)	0.0120	0.3582	19.0643

Rules with high lift (e.g., > 20 or 30) show strong co-buying patterns, meaning customers frequently buy those items together as a bundle.

High confidence (0.6–0.8) means the recommendation is reliable; customers who buy item A often go on to buy item B.

Rules with moderate support (~1 percent) indicate that although not everyone buys these product pairs, the relationships are very strong when they do occur.

In [104…

```
# Count rules by confidence level
high_confidence = len(rules_strong[rules_strong['confidence'] >= 0.5])
medium_confidence = len(rules_strong[(rules_strong['confidence'] >= 0.3) & (
```

```
print(f"\nRule Strength Distribution:")
print(f"  High confidence (≥50%): {high_confidence} rules")
print(f"  Medium confidence (30-50%): {medium_confidence} rules")
```

```
Rule Strength Distribution:
  High confidence (≥50%): 17 rules
  Medium confidence (30-50%): 16 rules
```

In [105…

```
# Average metrics
print(f"\nAverage Rule Metrics:")
print(f"  Support: {rules_strong['support'].mean():.2%}")
print(f"  Confidence: {rules_strong['confidence'].mean():.2%}")
print(f"  Lift: {rules_strong['lift'].mean():.2f}")
```

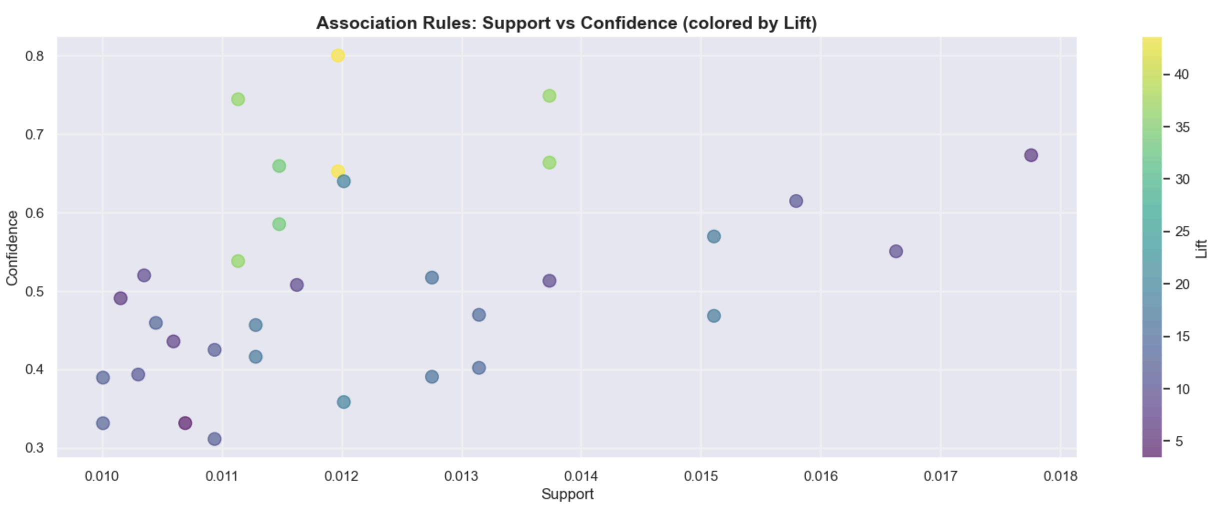
```
Average Rule Metrics:
  Support: 1.23%
  Confidence: 51.58%
  Lift: 18.51
```

Visualizations

1. Support vs Confidence scatter plot

In [106…

```
# 1. Support vs Confidence scatter plot
plt.figure(figsize=(18, 6))
plt.scatter(rules_strong['support'], rules_strong['confidence'],
            c=rules_strong['lift'], cmap='viridis', alpha=0.6, s=100)
plt.colorbar(label='Lift')
plt.xlabel('Support', fontsize=12)
plt.ylabel('Confidence', fontsize=12)
plt.title('Association Rules: Support vs Confidence (colored by Lift)',
          fontsize=14, fontweight='bold')
plt.grid(alpha=0.3)
plt.show()
```



This chart shows how strong each association rule is based on support, confidence, and lift.

Most rules have moderate support (around 1 to 1.7 percent).

Confidence ranges from 0.3 to 0.8, meaning many rules are fairly reliable.

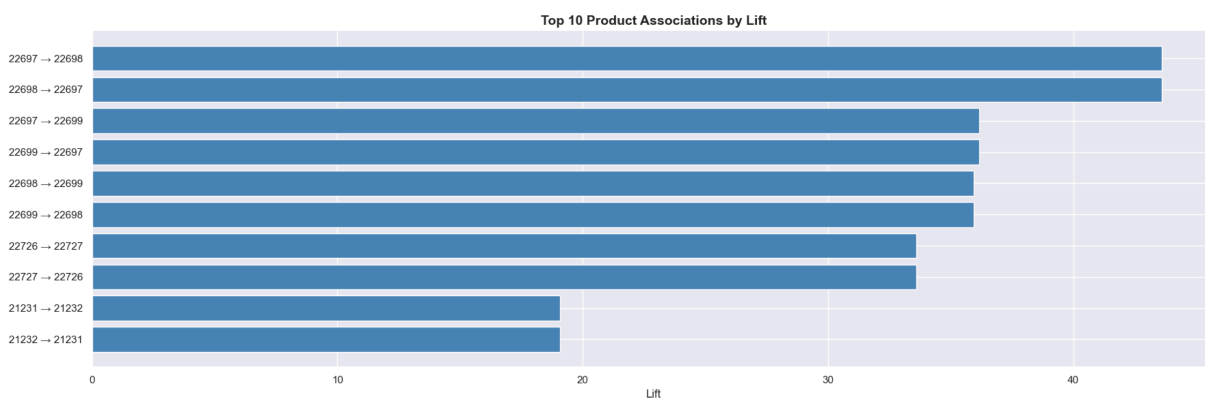
Points with brighter colors (higher lift) indicate rules that are much stronger than chance and represent the best product-pair recommendations.

Overall, rules with higher lift and higher confidence represent the strongest cross-sell opportunities.

2. Top rules by lift (bar chart)

In [107…

```
top_10_rules = rules_strong.head(10).copy()
top_10_rules['rule'] = top_10_rules.apply(
    lambda row: f"{list(row['antecedents'])[0]} → {list(row['consequents'])[
)

plt.figure(figsize=(18, 6))
plt.barh(range(len(top_10_rules)), top_10_rules['lift'].values[::-1], color=
plt.yticks(range(len(top_10_rules)), top_10_rules['rule'].values[::-1])
plt.xlabel('Lift', fontsize=12)
plt.title('Top 10 Product Associations by Lift', fontsize=14, fontweight='bc
plt.tight_layout()
plt.show()
```

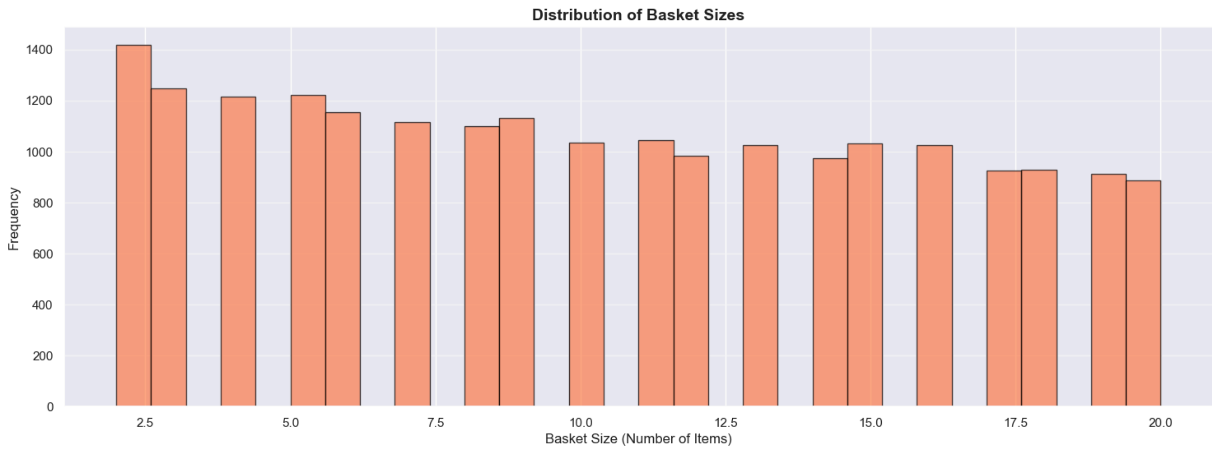


The chart shows the strongest product-to-product relationships in the store based on lift, which measures how much more often two items are bought together than expected. The top rules (lift 30–44) indicate very strong co-purchase patterns, meaning these item pairs almost always appear together in the same basket.

3. Basket size distribution

In [108…

```
basket_sizes = [len(b) for b in baskets_filtered]
plt.figure(figsize=(18, 6))
plt.hist(basket_sizes, bins=30, color='coral', edgecolor='black', alpha=0.7)
plt.xlabel('Basket Size (Number of Items)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Distribution of Basket Sizes', fontsize=14, fontweight='bold')
plt.grid(alpha=0.3, axis='y')
plt.show()
```



Customers typically buy between 2 and 20 items per transaction. Most baskets fall in the 3 to 8 item range, showing that shoppers commonly purchase multiple related products together rather than single items.

As basket size increases past 10 items, frequency gradually declines but remains steady, which indicates consistent multi-item buying behavior and supports strong opportunities for cross-selling and product bundling.

In [109…

```
rules_export = rules_strong.copy()
rules_export['antecedents'] = rules_export['antecedents'].apply(lambda x: ',
rules_export['consequents'] = rules_export['consequents'].apply(lambda x: ',
rules_export = rules_export[['antecedents', 'consequents', 'support', 'confi
rules_export
```

Out[109…

	antecedents	consequents	support	confidence	lift
21	22697	22698	0.011970	0.652406	43.604278
20	22698	22697	0.011970	0.800000	43.604278
23	22697	22699	0.013736	0.748663	36.164686
22	22699	22697	0.013736	0.663507	36.164686
25	22698	22699	0.011136	0.744262	35.952102
24	22699	22698	0.011136	0.537915	35.952102
27	22726	22727	0.011479	0.659155	33.592183
26	22727	22726	0.011479	0.585000	33.592183
5	21231	21232	0.012019	0.639687	19.064347
4	21232	21231	0.012019	0.358187	19.064347
28	82494L	82482	0.015109	0.468085	17.637551
29	82482	82494L	0.015109	0.569316	17.637551
11	22114	22112	0.011283	0.456349	16.822204
12	22112	22114	0.011283	0.415913	16.822204
7	21755	21754	0.012754	0.516899	15.821288
8	21754	21755	0.012754	0.390390	15.821288
19	22470	22469	0.013147	0.469352	14.344439
18	22469	22470	0.013147	0.401799	14.344439
3	22384	20725	0.010449	0.459052	13.051282
14	22386	85099F	0.010007	0.331169	12.883352
15	85099F	22386	0.010007	0.389313	12.883352
1	20727	20725	0.010939	0.424762	12.076390
0	20725	20727	0.010939	0.311018	12.076390
2	22383	20725	0.010302	0.393258	11.180716
32	85099F	85099B	0.015796	0.614504	10.500134
13	22386	85099B	0.016630	0.550325	9.403494
9	21928	85099B	0.010351	0.519704	8.880281
31	85099C	85099B	0.013736	0.512821	8.762654
10	21931	85099B	0.011626	0.507495	8.671650
16	22411	85099B	0.010596	0.435484	7.441189
6	21733	85123A	0.017758	0.672862	6.824030
17	22699	22423	0.010155	0.490521	6.738057

	antecedents	consequents	support	confidence	lift
30	82494L	85123A	0.010694	0.331307	3.360046

In [110…
```
# Save frequent itemsets
itemsets_export = frequent_itemsets.copy()
itemsets_export['itemsets'] = itemsets_export['itemsets'].apply(lambda x: ',
itemsets_export
```

Out[110…

	support	itemsets	length
0	0.013196	15036	1
1	0.015354	15056BL	1
2	0.018690	15056N	1
3	0.011773	20679	1
4	0.026294	20685	1
...	...	...	...
239	0.011479	22727, 22726	2
240	0.015109	82494L, 82482	2
241	0.010694	82494L, 85123A	2
242	0.013736	85099B, 85099C	2
243	0.015796	85099B, 85099F	2

244 rows × 3 columns

In [ ]: