

Retail Customer Retention Analytics – TESCO

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Overview

TESCO, a retail leader in the UK, operates across multiple cities through superstores, express outlets, and online channels. With growing competition and changing customer expectations, customer retention has become increasingly difficult. Although TESCO has access to rich data on customer transactions, store performance, and loyalty programs, its current reporting system lacks the analytical depth needed to:

- Understand why customers are churning? (Customer churn, the rate at which customers stop doing business with a company)
- Identify high-value customers and those at risk.
- Evaluate the impact of loyalty tiers and promotions.
- Guide store-specific retention strategies.

Goals

Develop a robust, Interactive Customer Retention Analytics Dashboard in Power BI using the provided data, which will:

- Consolidate customer demographics, transaction history, store performance, and loyalty program usage.
- Enable dynamic segmentation of high-value, repeat, and churned customers.
- Offer actionable insights for improving retention, loyalty program effectiveness, and regional store strategies.

Task 1: Data Modeling and Cleaning :

Use Power Query Editor to load and transform the datasets :

To ensure the integrity and reliability of the dataset for analysis, the following data cleaning tasks were performed:

- Duplicate Removal:** All duplicate rows were identified and removed based on key identifier columns (including Customer_ID and Store_ID) to prevent skewed results and ensure each entity is represented uniquely.
- Data Type Formatting:** Columns were systematically formatted to their correct data types. This included converting date-related strings into standardized date formats and ensuring that columns intended for numerical analysis (such as Amount and Points) were converted to numeric types.
- Handling Missing Values:** A review of missing (null) values was conducted. Based on the analysis, appropriate strategies, such as filtering out incomplete records or replacing nulls with a valid placeholder (e.g., zero, mean, or "Unknown"), were applied to maintain dataset completeness.

The screenshot shows the Microsoft Power BI Data Editor interface. The top navigation bar includes Home, Transform, Add Column, View, Tools, and Help. The ribbon below the bar contains various icons for managing queries, data sources, parameters, and transforms. On the left, a sidebar lists six queries: Customer_Demographics, Customer_Transactions, Store_Locations, Loyalty_Program, Churn_Labelled_Customers, and Measures (2). The main workspace displays a table titled "Table.TransformColumnTypes(#"Promoted Headers", [{"Customer_ID": type text}, {"Gender": type text}, {"Age": Int64.Type}, {"Membership_Since": type date}, {"Marital_Status": type text}, {"Region": type text}, {"Income_Group": type text}])". The table has 7 columns and 300 rows, showing data for Customer_ID, Gender, Age, Membership_Since, Marital_Status, Region, and Income_Group. The "APPLIED STEPS" pane on the right shows the history of changes made to the query, including "Changed Type" for the promoted headers and other steps like "Removed Duplicates" and "Added Custom".

	Customer_ID	Gender	Age	Membership_Since	Marital_Status	Region	Income_Group
1	C1000	Male	50	01-11-2020	Single	London	High
2	C1001	Female	18	05-07-2021	Divorced	London	Medium
3	C1002	Male	36	18-08-2021	Single	Birmingham	Medium
4	C1003	Male	19	01-02-2024	Married	Leeds	Medium
5	C1004	Male	70	15-10-2020	Married	Leeds	Medium
6	C1005	Female	61	19-11-2020	Single	Liverpool	High
7	C1006	Male	43	13-07-2021	Divorced	London	High
8	C1007	Male	49	16-03-2023	Married	London	Medium
9	C1008	Male	23	14-06-2022	Married	Manchester	Medium
10	C1009	Female	49	06-06-2024	Married	Liverpool	High
11	C1010	Male	21	03-05-2023	Single	Manchester	Medium
12	C1011	Male	28	07-07-2021	Married	Manchester	Low
13	C1012	Male	34	27-02-2023	Divorced	Manchester	Medium
14	C1013	Male	55	27-04-2023	Married	Birmingham	Medium
15	C1014	Female	41	20-01-2024	Married	Birmingham	Low
16	C1015	Male	22	15-11-2023	Divorced	Manchester	Low
17	C1016	Female	69	18-05-2023	Married	Liverpool	High
18	C1017	Female	51	11-07-2023	Single	London	High
19	C1018	Female	23	21-03-2024	Single	Liverpool	Low
20	C1019	Male	39	07-06-2023	Single	Leeds	Low
21	C1020	Female	28	04-05-2022	Divorced	Birmingham	High
22	C1021	Male	65	30-01-2022	Married	London	Medium
23	C1022	Female	33	19-12-2022	Single	London	Low
24	C1023	Female	50	02-10-2020	Divorced	Leeds	High

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Queries [6]

```
= Table.TransformColumnTypes(#"Promoted Headers",{{{"Transaction_ID", type text}, {"Customer_ID", type text}, {"Transaction_Date", type date}, {"Store_ID", type text}, {"Product_Category", type text}, {"Amount", type number}, {"Quantity", Int64.Type}, {"Promotion_Applied", type text}})
```

	A ^B _C Transaction_ID	A ^B _C Customer_ID	A ^B _C Transaction_Date	A ^B _C Store_ID	A ^B _C Product_Category	1.2 Amount	2 ³ Quantity
1	T20000	C1011	11-11-2024	S106	Bakery	249.6	
2	T20001	C1079	26-05-2025	S105	Beverages	431.22	
3	T20002	C1215	09-08-2024	S101	Beverages	233.28	
4	T20003	C1263	26-08-2024	S108	Beverages	470.27	
5	T20004	C1148	02-01-2025	S103	Electronics	254.48	
6	T20005	C1080	05-07-2024	S106	Grocery	474.85	
7	T20006	C1214	25-01-2025	S103	Bakery	417.25	
8	T20007	C1197	27-09-2024	S107	Electronics	184.4	
9	T20008	C1199	07-06-2025	S107	Clothing	432.5	
10	T20009	C1024	09-06-2025	S109	Bakery	59.48	
11	T20010	C1088	17-03-2025	S105	Bakery	462.9	
12	T20011	C1267	28-06-2024	S108	Bakery	317.66	
13	T20012	C1142	15-08-2024	S110	Beverages	31.92	
14	T20013	C1058	31-05-2025	S110	Bakery	323.91	
15	T20014	C1025	28-04-2025	S108	Grocery	487.25	
16	T20015	C1046	23-08-2024	S101	Bakery	39.55	
17	T20016	C1287	21-12-2024	S105	Beverages	279.57	
18	T20017	C1265	29-07-2024	S103	Bakery	375.16	
19	T20018	C1015	02-06-2025	S101	Clothing	406.08	
20	T20019	C1198	20-10-2024	S104	Clothing	209.84	
21	T20020	C1281	24-04-2025	S108	Beverages	106.06	
22	T20021	C1085	01-03-2025	S103	Grocery	25.96	
23	T20022	C1249	04-11-2024	S110	Grocery	291.96	
24	T20023	C1269	15-01-2025	S102	Electronics	229.19	
25							

8 COLUMNS, 999+ ROWS Column profiling based on top 1000 rows

Query Settings

Properties

Name: Customer_Transactions

All Properties

Applied Steps

Source: Promoted Headers

Changed Type: Removed Duplicates, Filtered Rows, Inserted Year, Renamed Columns, Inserted Month, Renamed Columns1

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Queries [6]

```
= Table.TransformColumnTypes(#"Promoted Headers",{{{"Store_ID", type text}, {"City", type text}, {"Region", type text}, {"Store_Type", type text}, {"Opening_Year", Int64.Type}})
```

	A ^B _C Store_ID	A ^B _C City	A ^B _C Region	A ^B _C Store_Type	1 ² Opening_Year
1	S101	Birmingham	London	Superstore	2021
2	S102	Leeds	London	Express	2020
3	S103	Birmingham	London	Express	2020
4	S104	Manchester	Leeds	Superstore	2010
5	S105	London	Birmingham	Express	2022
6	S106	Manchester	Manchester	Express	2010
7	S107	Manchester	London	Express	2019
8	S108	Leeds	Birmingham	Express	2018
9	S109	London	Birmingham	Superstore	2016
10	S110	London	Manchester	Superstore	2010

5 COLUMNS, 10 ROWS Column profiling based on top 1000 rows

Query Settings

Properties

Name: Store_Locations

All Properties

Applied Steps

Source: Promoted Headers

Changed Type: Removed Duplicates

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Screenshot of Power BI Desktop showing the Loyalty_Program query.

Query Settings:

- Name: Loyalty_Program
- All Properties

Applied Steps:

- Source: Promoted Headers
- Changed Type
- Removed Duplicates

Loyalty_Program Data:

Customer_ID	Loyalty_Tier	Points_Earned	Points_Redeemed	Last_Redemption_Date
C1000	Platinum	2209	820	02-09-2024
C1001	Silver	6153	2821	28-03-2025
C1002	Silver	5898	1055	10-04-2025
C1003	Platinum	3178	5439	05-01-2025
C1004	Gold	8610	5932	31-01-2025
C1005	Platinum	9895	1886	10-11-2024
C1006	Silver	3544	5263	03-11-2024
C1007	Silver	6522	3547	08-01-2025
C1008	Silver	3370	2927	30-08-2024
C1009	Silver	4281	7354	30-08-2024
C1010	Gold	5710	6538	17-09-2024
C1011	Gold	1328	2504	11-02-2025
C1012	Silver	6579	2430	03-11-2024
C1013	Gold	5228	5341	01-06-2025
C1014	Gold	7794	5270	10-07-2024
C1015	Gold	1120	2663	25-08-2024
C1016	Silver	7749	7248	15-08-2024
C1017	Platinum	1964	5661	26-01-2025
C1018	Platinum	5224	4367	21-07-2024
C1019	Platinum	4675	2926	04-11-2024
C1020	Silver	6694	4293	14-09-2024
C1021	Gold	3076	7873	20-08-2024
C1022	Gold	7865	3013	10-01-2025
C1023	Silver	6643	4303	29-06-2024

Screenshot of Power BI Desktop showing the Churn_Labelled_Customers query.

Query Settings:

- Name: Churn_Labelled_Customers
- All Properties

Applied Steps:

- Source: Promoted Headers
- Changed Type
- Removed Duplicates

Churn_Labelled_Customers Data:

Customer_ID	Last_Transaction_Date	Churned (Yes/No)	Days_Since_Last_Purchase
C1000	19-05-2025	No	37
C1001	26-05-2025	No	30
C1002	28-12-2024	No	179
C1003	14-08-2024	Yes	315
C1004	21-06-2025	No	4
C1005	30-10-2024	Yes	238
C1006	18-08-2024	Yes	311
C1007	24-05-2025	No	32
C1008	30-11-2024	Yes	207
C1009	03-09-2024	Yes	295
C1010	09-05-2025	No	47
C1011	29-04-2025	No	57
C1012	12-12-2024	Yes	195
C1013	07-02-2025	No	138
C1014	08-08-2024	Yes	321
C1015	10-06-2025	No	15
C1016	14-04-2025	No	72
C1017	06-03-2025	No	111
C1018	03-04-2025	No	83
C1019	08-07-2024	Yes	352
C1020	16-04-2025	No	70
C1021	16-01-2025	No	160
C1022	19-01-2025	No	157
C1023	22-07-2024	Yes	338

Create calculated columns:

Membership_Duration = Today - Membership_Since

```
= Table.AddColumn(#"Removed Duplicates", "Membership_Duration", each Date.From(DateTime.LocalNow()) - [Membership_Since])
```

The screenshot shows the Power Query Editor interface. On the left is a preview grid of data rows. To the right are several panes: 'Query Settings' (with 'Name' set to 'Customer_Demographics'), 'PROPERTIES' (listing 'Name' and 'Customer_Demographics'), 'APPLIED STEPS' (listing 'Source', 'Promoted Headers', 'Changed Type', 'Removed Duplicates', 'Added Custom', and 'Calculated Total Days' which is highlighted), and 'All Properties'. The main area shows a table with columns: Age, Membership_Since, Marital_Status, Region, Income_Group, and Membership_Duration. The 'Membership_Duration' column is highlighted.

	Age	Membership_Since	Marital_Status	Region	Income_Group	Membership_Duration
1	50	01-11-2020	Single	London	High	1800
2	18	05-07-2021	Divorced	London	Medium	1554
3	36	18-08-2021	Single	Birmingham	Medium	1510
4	19	01-02-2024	Married	Leeds	Medium	613
5	70	15-10-2020	Married	Leeds	Medium	1817
6	61	19-11-2020	Single	Liverpool	High	1782
7	43	13-07-2021	Divorced	London	High	1546
8	49	16-03-2023	Married	London	Medium	935
9	23	14-06-2022	Married	Manchester	Medium	1210
10	49	06-06-2024	Married	Liverpool	High	487
11	21	03-05-2023	Single	Manchester	Medium	887
12	28	07-07-2021	Married	Manchester	Low	1552
13	34	27-02-2023	Divorced	Manchester	Medium	952
14	55	27-04-2023	Married	Birmingham	Medium	893
15	41	20-01-2024	Married	Birmingham	Low	625
16	22	15-11-2023	Divorced	Manchester	Low	691
17	69	18-05-2023	Married	Liverpool	High	872
18	51	11-07-2023	Single	London	High	818
19	23	21-03-2024	Single	Liverpool	Low	564
20	39	07-06-2023	Single	Leeds	Low	852
21	28	04-05-2022	Divorced	Birmingham	High	1251
22	65	30-01-2022	Married	London	Medium	1345
23	33	19-12-2022	Single	London	Low	1022
24	50	02-10-2020	Divorced	Leeds	High	1830

Add a Transaction_Year and Transaction_Month column from Transaction_Date

The screenshot shows the Power Query Editor. The main area displays a table with columns: Date, Store_ID, Product_Category, Amount, Quantity, Promotion_Applied, and Year. The 'Year' column is highlighted. The 'APPLIED STEPS' pane shows steps like 'Source', 'Promoted Headers', 'Changed Type', 'Removed Duplicates', 'Filtered Rows', and 'Inserted Year' (which is highlighted).

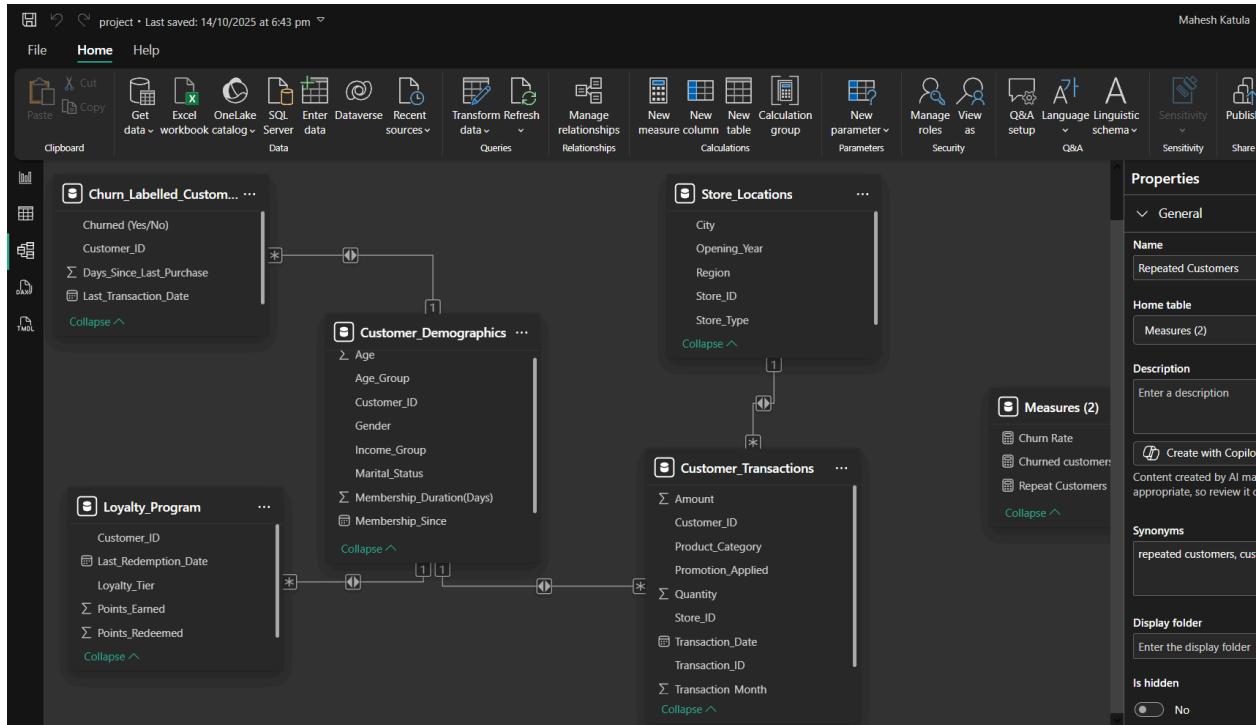
	Date	Store_ID	Product_Category	Amount	Quantity	Promotion_Applied	Year
1	11-11-2024	S106	Bakery	249.6	7	Yes	2024
2	26-05-2025	S105	Beverages	431.22	6	Yes	2025
3	09-08-2024	S101	Beverages	233.28	7	No	2024
4	26-08-2024	S108	Beverages	470.27	8	No	2024
5	02-01-2025	S103	Electronics	254.48	6	Yes	2025
6	05-07-2024	S106	Grocery	474.85	3	No	2024
7	25-01-2025	S103	Bakery	417.25	2	Yes	2025
8	27-09-2024	S107	Electronics	184.4	7	Yes	2024
9	07-06-2025	S107	Clothing	432.5	1	No	2025
10	09-06-2025	S109	Bakery	59.48	3	Yes	2025
11	17-03-2025	S105	Bakery	462.9	4	No	2025

The screenshot shows the Power Query Editor. The main area displays a table with columns: Product_Category, Amount, Quantity, Promotion_Applied, Transaction_Year, and Month. The 'Month' column is highlighted. The 'APPLIED STEPS' pane shows steps like 'Source', 'Promoted Headers', 'Changed Type', 'Removed Duplicates', 'Filtered Rows', 'Inserted Year', 'Renamed Columns', and 'Inserted Month' (which is highlighted).

	Product_Category	Amount	Quantity	Promotion_Applied	Transaction_Year	Month
1	Bakery	249.6	7	Yes	2024	11
2	Beverages	431.22	6	Yes	2025	5
3	Beverages	233.28	7	No	2024	8
4	Beverages	470.27	8	No	2024	8
5	Electronics	254.48	6	Yes	2025	1
6	Grocery	474.85	3	No	2024	7
7	Bakery	417.25	2	Yes	2025	1
8	Electronics	184.4	7	Yes	2024	9
9	Clothing	432.5	1	No	2025	6
10	Bakery	59.48	3	Yes	2025	6

Creating a basic Data Model view

- One-to-Many: Customer_Demographics → Transactions, Loyalty_Program, Churn_Labelled_Customers
- Many-to-One: Transactions → Store_Locations



Task 2: Churn and Retention Metrics :

Create a Churn Rate card: (Churned Customers / Total Customers) * 100

The screenshot shows the Power BI Report view. A card visualization displays the Churn Rate:

Churn Rate: 51.67%

The card contains the following calculated measure:

$$\text{Churned customers} = \text{CALCULATE}([\text{Total customers}], \text{Churn_Labelled_Customers}[\text{Churned (Yes/No)}] = "Yes")$$

Below the card, a table shows the breakdown of customers:

Total customers	Churned customers	Repeat Customers
300	155	254

Visualize churn rate by:

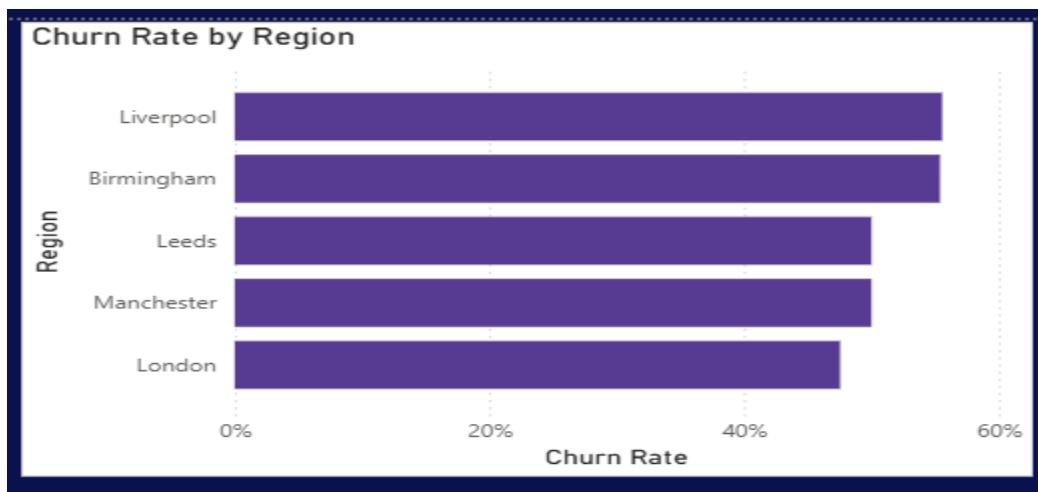
- Region
- Income Group
- Store Type
- Identify top 5 segments with highest churn %

The screenshot shows a Microsoft Power BI interface with the following details:

- Churn Rate by Region:** Horizontal bar chart showing Churn Rate for Liverpool, Birmingham, Leeds, Manchester, and London.
- Churn Rate by Income_Group:** Bar chart showing Churn Rate for High, Low, and Medium income groups.
- Churn Rate by Store_Type:** Pie chart showing the distribution of Store Type (Express and Superstore) with percentages: 49.30% (48.43%) for Express and 52.49% (51.57%) for Superstore.
- Data Grid:** A table listing Churn Rate data across various categories.
- Visualizations Pane:** Shows available visualization types like Bar, Line, Map, etc.
- Filters:** Options for Drill through, Cross-report, and Keep all filters.

Region	Income_Group	Gender	Churn Rate
Birmingham	Low	Female	80.00%
Liverpool	High	Female	75.00%
Manchester	Medium	Female	75.00%
Liverpool	High	Male	72.73%
Liverpool	Low	Male	71.43%
Birmingham	Low	Male	70.00%
Leeds	High	Male	66.67%
Leeds	High	Female	60.00%
Manchester	Medium	Male	60.00%
London	High	Male	57.14%
Birmingham	Medium	Female	55.56%
Leeds	Low	Male	55.56%
Manchester	High	Female	55.56%
Leeds	Medium	Female	54.55%
Birmingham	Medium	Male	52.94%

- Churn rate by Region

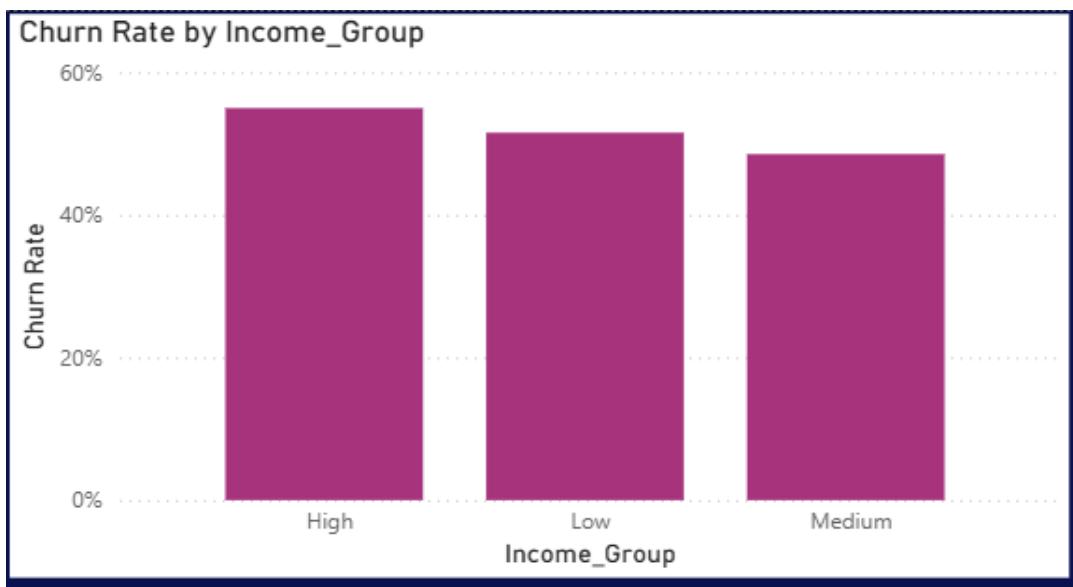


Key Insights from the Chart:

- **Highest Churn:** Liverpool and Birmingham have the highest churn rates, both appearing to be approximately 55%.
- **Mid-level Churn:** Leeds and Manchester have slightly lower but still high churn rates, both around 50%.
- **Lowest Churn (of this group):** London has the lowest churn rate among the regions shown, at approximately 47% or 48%.

In summary, the visual indicates that churn is a significant problem in all five regions (with all rates being close to 50% or higher), but it is most severe in Liverpool and Birmingham.

○ Churn rate by Income Group

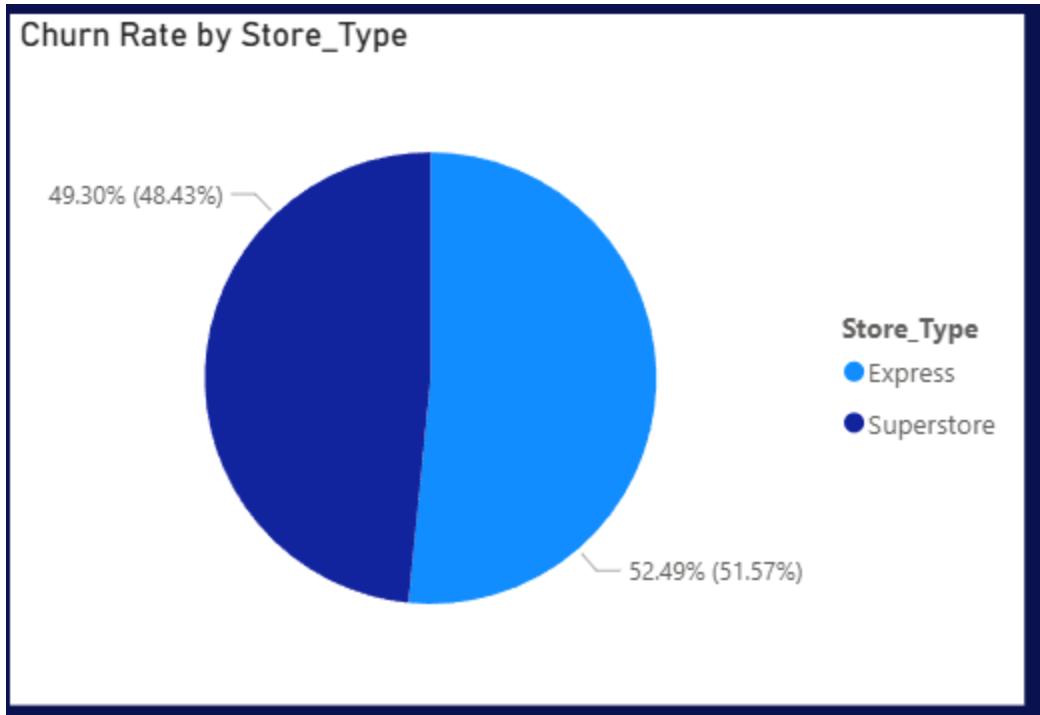


Key Insights from the Chart:

- **Highest Churn:** The "High" income group has the highest churn rate, at approximately 55%.
- **Mid-level Churn:** The "Low" income group has the next highest churn rate, at just over 50%.
- **Lowest Churn:** The "Medium" income group has the lowest churn rate of the three, at approximately 48%.

In summary, this chart indicates that customers in the "High" income group are the most likely to churn, while those in the "Medium" income group are the least likely (though all groups have a high churn rate close to 50%).

- Churn rate by Store Type



Key Insights:

- **Express (Light Blue):** This store type has a **churn rate of 52.49%**. These churned customers make up **51.57%** of the total churn.
- **Superstore (Dark Blue):** This store type has a **churn rate of 49.30%**. These churned customers make up **48.43%** of the total churn.

In summary, the churn rates for both store types are very high and relatively close (around 50%). The "Express" stores have a slightly higher churn rate than the "Superstores," and they also account for a slightly larger portion of the total churn.

- Identify top 5 segments with highest churn % :

Region	Income_Group	Store_Type	Gender	Churn Rate
Manchester	Medium	Superstore	Female	100.00%
Birmingham	Low	Express	Female	87.50%
Liverpool	High	Superstore	Female	87.50%
Birmingham	Low	Superstore	Female	83.33%
Liverpool	Low	Express	Male	80.00%
Leeds	High	Superstore	Male	75.00%
Liverpool	Low	Superstore	Male	75.00%
Manchester	Medium	Express	Female	75.00%
Birmingham	Low	Superstore	Male	71.43%
Leeds	High	Express	Male	71.43%
Liverpool	High	Express	Female	70.00%
Liverpool	High	Express	Male	70.00%
Birmingham	Low	Express	Male	66.67%
Leeds	High	Express	Female	66.67%
Manchester	Medium	Express	Male	61.20%

The analysis reveals several critical segments that are driving churn. The top 5 highest-risk groups are:

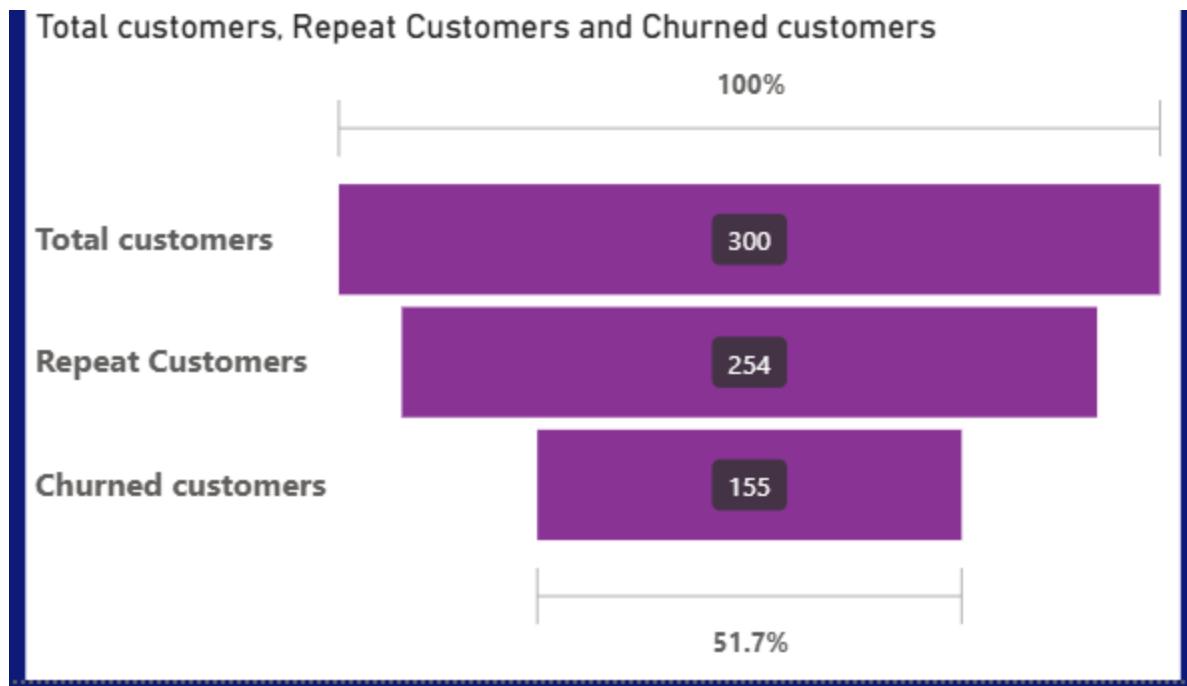
1. **Females** in the **Medium** income group shopping at **Superstores** in **Manchester** (100.00%)
2. **Females** in the **Low** income group shopping at **Express** stores in **Birmingham** (87.50%)
3. **Females** in the **High** income group shopping at **Superstores** in **Liverpool** (87.50%)
4. **Females** in the **Low** income group shopping at **Superstores** in **Birmingham** (83.33%)
5. **Males** in the **Low** income group shopping at **Express** stores in **Liverpool** (80.00%)

A significant pattern emerges from this data: **Female customers constitute four of our top five most at-risk segments.**

The 100% churn rate in the Manchester-based segment is a critical red flag. Furthermore, the Birmingham and Liverpool regions appear twice each within this top 5, indicating that retention issues are particularly severe in specific customer profiles within those areas.

These findings suggest we should prioritize immediate retention strategies targeting these specific high-risk female segments and investigate the root causes of dissatisfaction at the identified store types and regions.

Create funnel chart: Total Customers → Repeat → Churned



- Total Customers:** The funnel begins with a total of **300** customers, representing 100% of the customer pool for this analysis.
- Repeat Customers:** From this initial group, **254** customers (or 84.7%) became repeat customers, which shows a strong initial retention and engagement rate.
- Churned Customers:** The final stage of the funnel shows that **155** customers were ultimately churned.

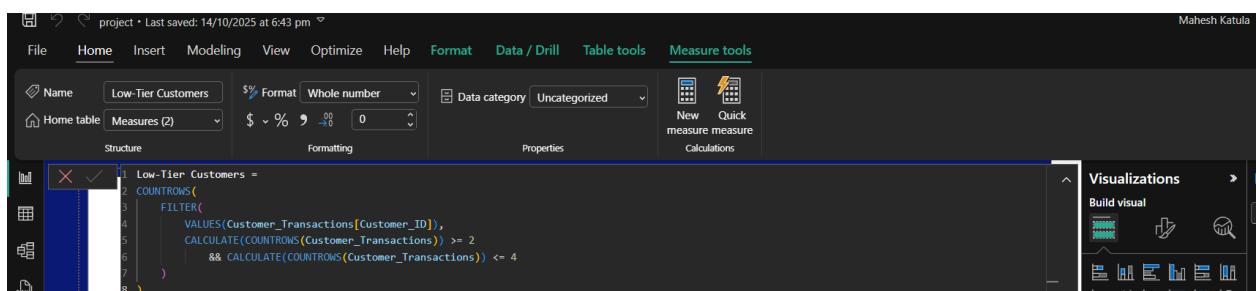
Summary Observation:

This visual provides a clear picture of our retention and churn. The key takeaway is that while we are effective at converting new customers into repeat customers (84.7% rate), we are losing a significant portion of our overall base.

The churn rate, calculated against the total initial customer pool, is **51.7%** (155 churned out of 300 total). This indicates that more than half of our customers are leaving, highlighting a critical need for long-term retention strategies, even for customers who have already become "repeat" buyers.

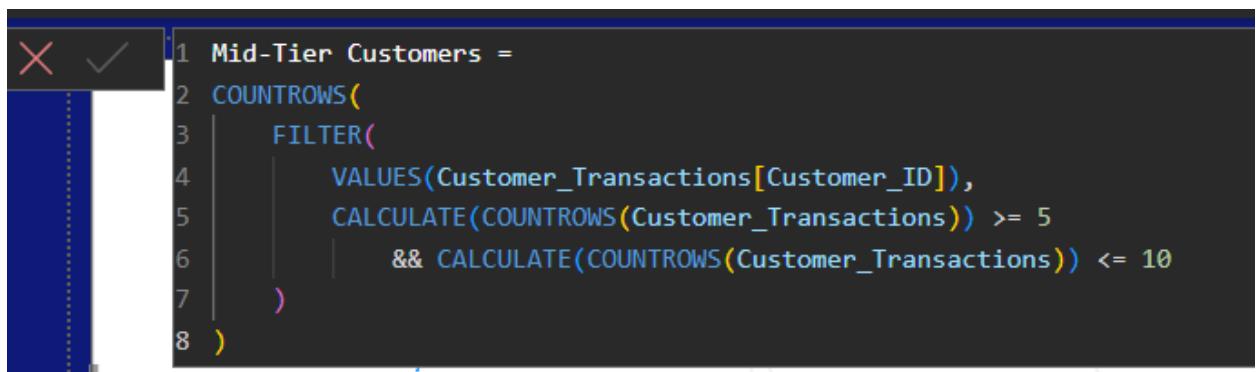
Task 3: Repeat Purchase Analysis

Create a measure: Low-Tier Customers: (2-4 purchases) Mid-Tier Customers: (5-10 purchases)
 High-Tier Customers: (11+ purchases)



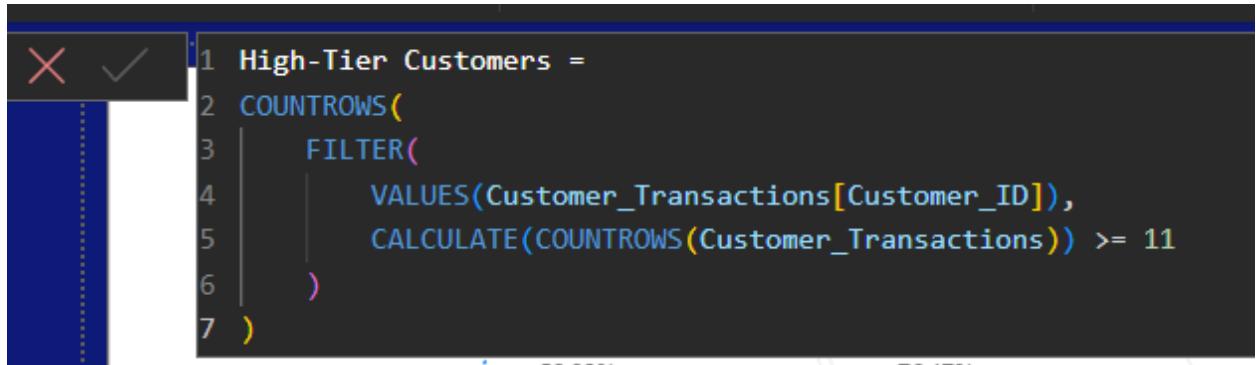
The screenshot shows the Power BI ribbon with the 'Measure tools' tab selected. A new measure named 'Low-Tier Customers' is being created. The formula bar contains the following DAX code:

```
1 Low-Tier Customers =
2 COUNTROWS(
3     FILTER(
4         VALUES(Customer_Transactions[Customer_ID]),
5         CALCULATE(COUNTROWS(Customer_Transactions)) >= 2
6         && CALCULATE(COUNTROWS(Customer_Transactions)) <= 4
7     )
8 )
```



The screenshot shows the Power BI ribbon with the 'Measure tools' tab selected. A new measure named 'Mid-Tier Customers' is being created. The formula bar contains the following DAX code:

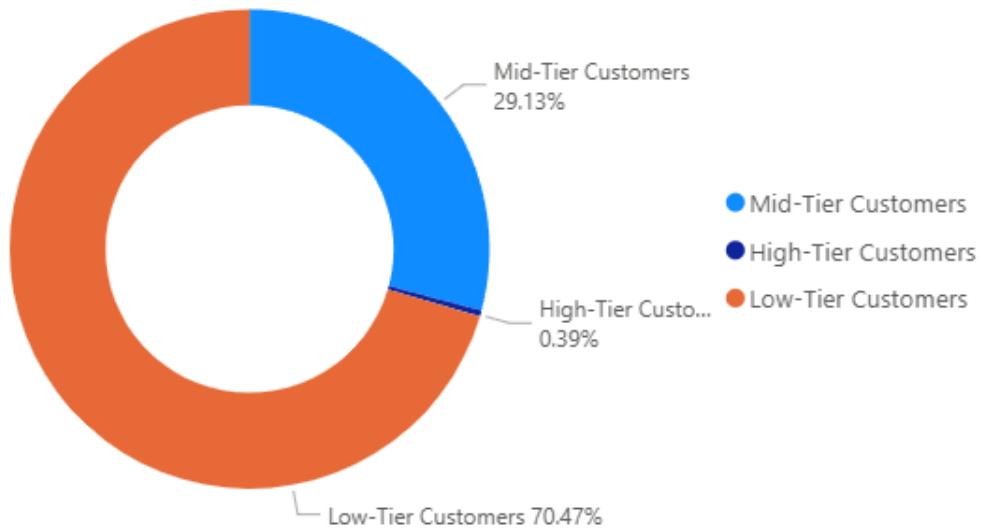
```
1 Mid-Tier Customers =
2 COUNTROWS(
3     FILTER(
4         VALUES(Customer_Transactions[Customer_ID]),
5         CALCULATE(COUNTROWS(Customer_Transactions)) >= 5
6         && CALCULATE(COUNTROWS(Customer_Transactions)) <= 10
7     )
8 )
```



The screenshot shows the Power BI ribbon with the 'Measure tools' tab selected. A new measure named 'High-Tier Customers' is being created. The formula bar contains the following DAX code:

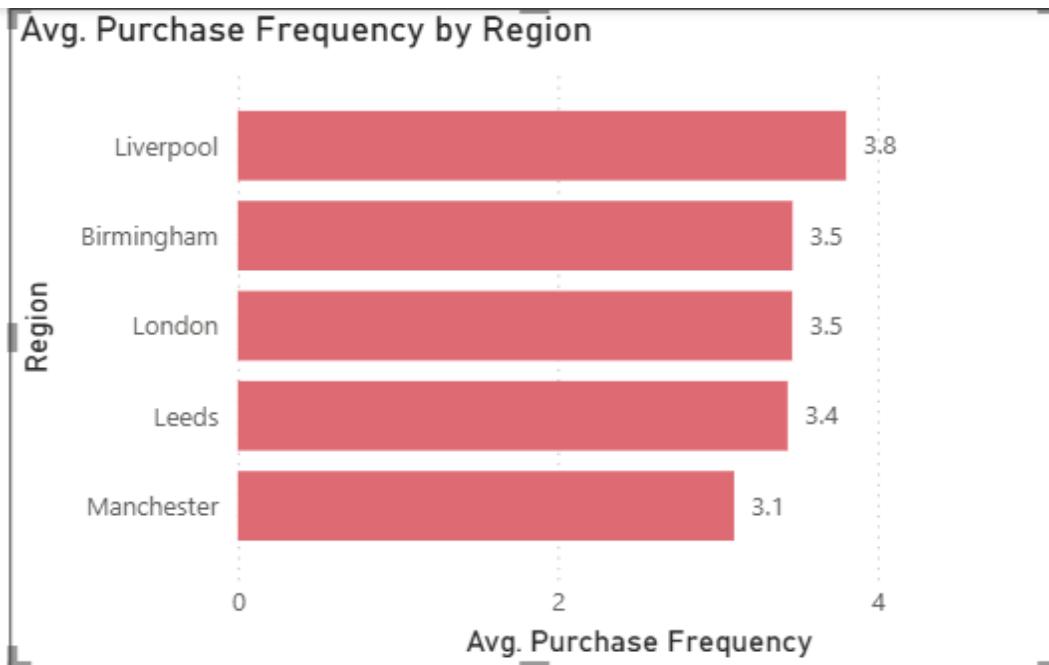
```
1 High-Tier Customers =
2 COUNTROWS(
3     FILTER(
4         VALUES(Customer_Transactions[Customer_ID]),
5         CALCULATE(COUNTROWS(Customer_Transactions)) >= 11
6     )
7 )
```

Mid-Tier Customers, High-Tier Customers and Low-Tier Customers



Compare avg. purchase frequency by:

- Region



Liverpool has the highest average purchase frequency, with customers making an average of **3.8** purchases.

Birmingham and **London** are tied for the second-highest frequency, with an average of **3.5** purchases each.

Leeds follows closely, with an average of **3.4** purchases.

Manchester has the lowest average purchase frequency among this group, with customers making an average of **3.1** purchases.

○ Age Group

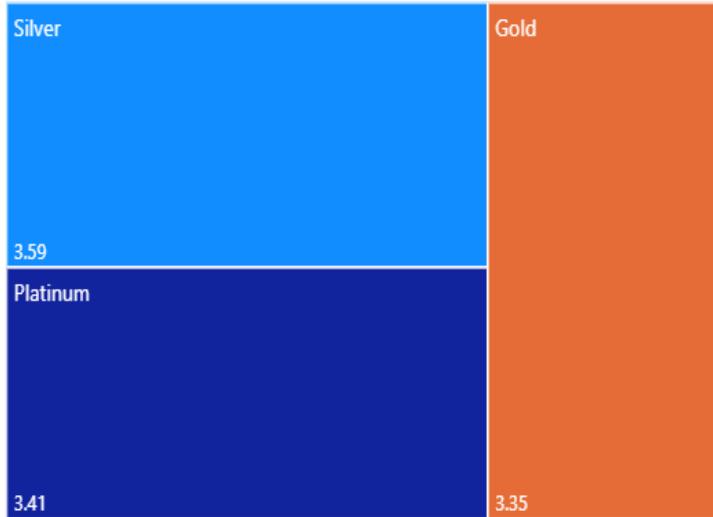


- **Highest Frequency:** The "**61-70**" age group has the highest average purchase frequency, at **3.88**.
- **Lowest Frequency:** The "**18-30**" age group has the lowest average purchase frequency, at **3.18**.
- **Mid-range Frequency:** The middle age groups ("**31-40**", "**41-50**", and "**51-60**") all have very similar purchase frequencies, ranging from **3.37** to **3.42**. The "**41-50**" group is the highest among these three.

In summary, the average purchase frequency generally increases with age, with the oldest group (61-70) purchasing the most often and the youngest group (18-30) purchasing the least often.

○ Loyalty Tier

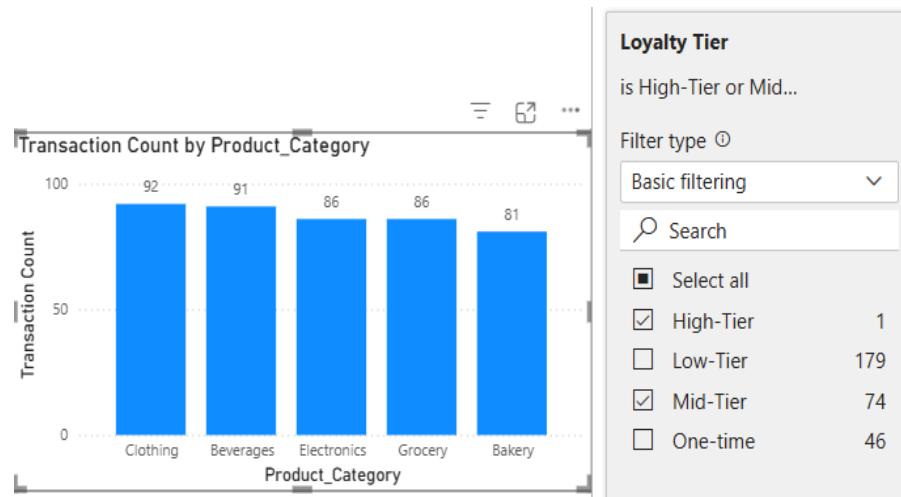
Avg. Purchase Frequency by Loyalty_Tier



- Silver (Light Blue):** This is the largest segment, indicating that **Silver** tier customers have the highest average purchase frequency at **3.59**.
- Platinum (Dark Blue):** This is the second-largest segment, with an average purchase frequency of **3.41**.
- Gold (Orange):** This is the smallest segment, representing the lowest average purchase frequency of the three tiers at **3.35**.

In summary, the visual shows that Silver-tier customers purchase the most frequently, followed by Platinum, and then Gold.

Identify product categories most frequently bought by loyal customers



- 
- **Most Popular: Clothing** is the most frequently purchased category, with **92** transactions.
 - **Second Most Popular: Beverages** is a close second, with **91** transactions.
 - **Middle Tier: Electronics** and **Grocery** are tied, both having **86** transactions.
 - **Least Popular: Bakery** has the lowest number of transactions in this group, with **81**.

In summary, all five categories have a relatively high and similar number of transactions, with Clothing and Beverages being the most popular.

Task 4: Promotion & Loyalty Impact

Create Measure:

- % of transactions where promotion was applied

```

1 % of Transactions with Promotion =
2 DIVIDE(
3     CALCULATE(
4         COUNTROWS(Customer_Transactions),
5         Customer_Transactions[Promotion_Applied] = "Yes"
6     ),
7     COUNTROWS(Customer_Transactions)
8 )

```

- Avg. purchase amount with vs without promotion

```

Promo Avg. Purchase =
CALCULATE(
    AVERAGE(Customer_Transactions[Amount]),
    Customer_Transactions[Promotion_Applied] = "Yes"
)

```

```

Non-Promo Avg. Purchase =  

CALCULATE(  

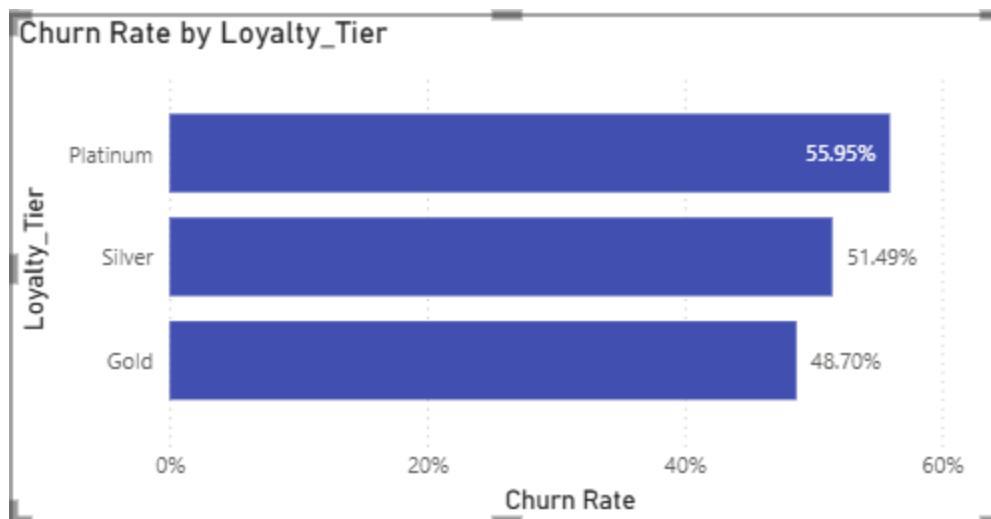
    AVERAGE(Customer_Transactions[Amount]),  

    Customer_Transactions[Promotion_Applied] = "No"  

)

```

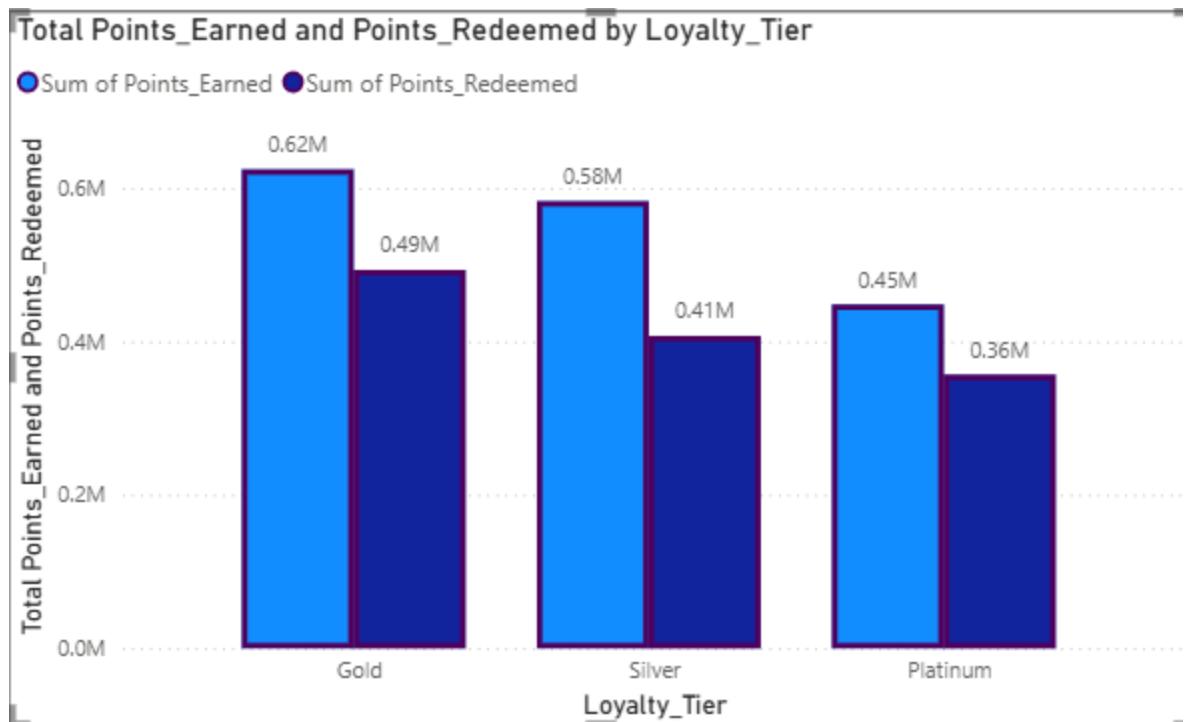
Compare churn rate across loyalty tiers :



- **Platinum** tier customers have the highest churn rate at **55.95%**.
- **Silver** tier customers have the next highest churn rate at **51.49%**.
- **Gold** tier customers have the lowest churn rate of the three, at **48.70%**.

In summary, the chart shows that churn is highest among Platinum members and lowest among Gold members.

Show Points Earned vs Redeemed by Tier using clustered column chart :



- Gold Tier:** This group is the most active in the loyalty program. They have the highest number of points both earned (0.62M) and redeemed (0.49M).
- Silver Tier:** This group is in the middle, having earned 0.58M points and redeemed 0.41M.
- Platinum Tier:** This group shows the lowest engagement with the points system, having earned the least (0.45M) and redeemed the least (0.36M).

Overall Observation: Across all three loyalty tiers, more points are consistently earned than are redeemed. The level of engagement with the points system (both earning and spending) directly corresponds with the tier, with Gold being the most engaged and Platinum the least.

Recommend how to improve redemption and retention :

1. Re-evaluate the Platinum Tier Value Proposition

Problem: Our "Platinum" members are leaving at the highest rate (55.95%) because they are the *least* engaged with the points system. This implies the perks of being "Platinum" are not valuable enough to keep them.

Recommendation: We must immediately re-assess the benefits for our Platinum tier. Since they are not engaging with points, they may value tangible, immediate perks more. Consider offering:

- **Non-point-based rewards:** Free shipping, exclusive early access to new **Clothing** collections, or a complimentary **Beverage** per store visit.
- **Proactive "At-Risk" Offers:** Target this 55.95% group with a special "We value you" offer, designed to remind them of their status and prevent churn.

2. Create Targeted Redemption Campaigns for Popular Products

Problem: Customers are earning far more points than they redeem, and we know they buy **Clothing** and **Beverages** most frequently.

Recommendation: Connect the unredeemed points to the products they already love. Launch marketing campaigns with a clear call to action:

- "*You have [X] points! Use them for \$10 off any purchase in our **Clothing** department this weekend.*"
- "*Redeem 200 points at checkout to get a free **Beverage** or **Bakery** item.*"

This makes the points feel tangible and valuable by tying them to a desired product, which will increase redemption rates.

3. Launch a "Platinum Rescue" Redemption Campaign

Problem: Platinum members are the least engaged *and* churn the most. We need to solve both problems at once.

Recommendation: Create a high-value, exclusive redemption offer *only* for Platinum members. Since they have the lowest redemption, the value proposition must be high:

- "*As a Platinum member, your points are worth 2x more for the next 30 days.*"
- "*An exclusive offer for our Platinum members: Redeem your points on any **Electronics** purchase and get an instant 25% discount.*"

This strategy serves two purposes: it makes them feel valued for their status and gives them a compelling, time-sensitive reason to engage with the loyalty program, which the data shows is a key factor in retention.

Task 5: Store Performance vs Retention

Merge Store_ID from transactions with Store_Locations

Merge

Select tables and matching columns to create a merged table.

Customer_Transactions							
Transaction_ID	Customer_ID	Transaction_Date	Store_ID	Product_Category	Amount	Quantity	Pro
T20000	C1011	11-11-2024	S106	Bakery	249.6	7	Ye
T20001	C1079	26-05-2025	S105	Beverages	431.22	6	Ye
T20002	C1215	09-08-2024	S101	Beverages	233.28	7	No
T20003	C1263	26-08-2024	S108	Beverages	470.27	8	No

Store_Locations				
Store_ID	City	Region	Store_Type	Opening_Year
S101	Birmingham	London	Superstore	2021
S102	Leeds	London	Express	2020
S103	Birmingham	London	Express	2020
S104	Manchester	Leeds	Superstore	2010
S105	London	Birmingham	Express	2022

Join Kind

Left Outer (all from first, matching from second)

Use fuzzy matching to perform the merge

Fuzzy matching options

The selection matches 1000 of 1000 rows from the first table.

OK **Cancel**

"Store_Locations", JoinKind.LeftOuter)

1 Transaction_Month ▾ 2 Store_Locations

Search Columns to Expand A Z

Expand Aggregate

(Select All Columns)

Store_ID

City

Region

Store_Type

Opening_Year

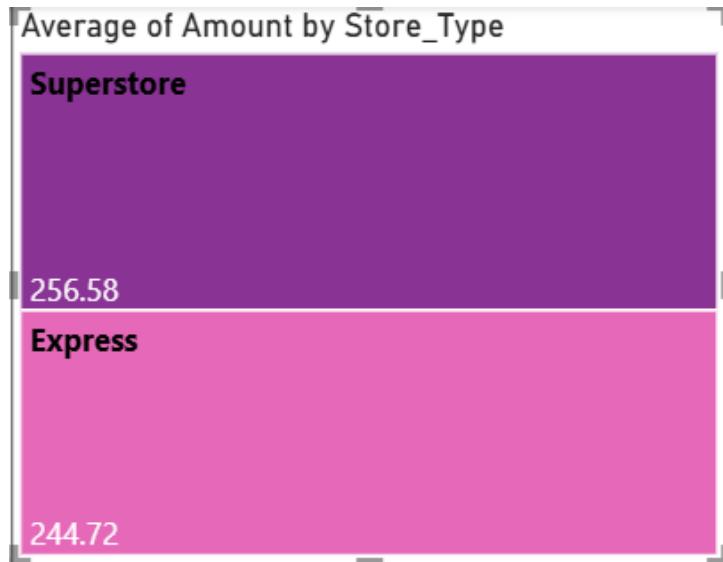
Use original column name as prefix

OK **Cancel**

2024 8 Table

Visualize:

- Avg. transaction amount by store type



- **Superstore (Purple):** This segment has the higher average transaction amount, at **256.58**.
- **Express (Pink):** This segment has a slightly lower average transaction amount, at **244.72**.

In summary, customers at Superstores spend slightly more on average per transaction than customers at Express stores.

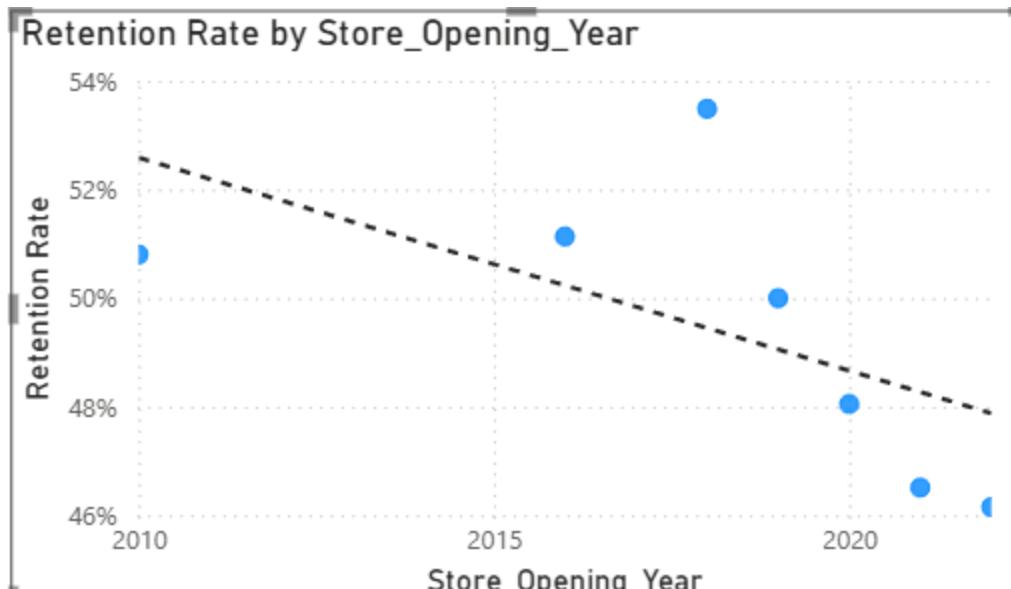
- Churn rate by store region



- **London** has the highest churn rate at **53.71%**.
- **Manchester** and **Birmingham** have very similar, high churn rates at **51.41%** and **50.79%**, respectively.
- **Leeds** has the lowest churn rate of the group, at **47.56%**.

In summary, all four regions are experiencing a high churn rate, at or above 47.5%, with London showing the most significant problem.

- Correlation between store opening year and retention



The downward-sloping trend line indicates a **negative correlation**. This means that, on average, **stores opened more recently have a lower customer retention rate** compared to stores that were opened in earlier years (like 2010).

Suggest where to run store-specific campaigns :

Based on these findings, I recommend three distinct, targeted campaigns:

1. The "London Rescue" Campaign (Retention Focus)

- **Where:** All stores (both Superstore and Express) in the **London region**.

- **Why:** London has the highest churn rate at 53.71%. We are losing customers here faster than anywhere else and must act aggressively to stop the bleeding.
- **Campaign Idea:** A geo-targeted "We Value Our London Customers" campaign. Offer bonus loyalty points for their next visit, launch a region-exclusive promotion, or send "we miss you" offers to customers who haven't shopped in 30 days.

2. The "New Store Loyalty" Campaign (Loyalty Focus)

- **Where:** All stores opened in the last 3-5 years (e.g., stores from **2019, 2020, 2021, etc.**).
- **Why:** The scatter plot shows a clear trend that our newer stores are failing to retain customers. We need to build loyalty from the ground up in these locations.
- **Campaign Idea:** An in-store campaign focused on loyalty program sign-ups. Offer an immediate incentive (e.g., "10% off today when you join") and a clear reward for their second and third visits to build an early habit of retention.

3. The "Superstore Upsell" Campaign (Value Focus)

- **Where:** All **Superstores**, with a special focus on those in high-churn regions like London and Manchester.
- **Why:** Customers are already willing to spend more at Superstores. We can leverage this to increase basket value while simultaneously offering a reward that improves loyalty.
- **Campaign Idea:** A store-specific promotion like "Spend £75, get a £5 voucher for your next visit" or "Buy 2, Get 1 Free" on high-margin categories. This increases the average transaction value and provides a strong incentive to return, directly fighting churn.

Task 6: Customer Value (CLV) Analysis

Calculate CLV = Total Amount Spent / Membership Duration (in years)

```

1 CLV =
2 DIVIDE(
3     CALCULATE(SUM(Customer_Transactions[Amount])) + 0,
4     Customer_Demographics[Membership_Duration(Years)], 0
5 )

```

... + 0 (The Numerator): Adding `+ 0` to the `SUM(...)` is a classic DAX method. It coerces (forces) any `BLANK()` value to become a `0`. This solves the problem for non-purchasing customers.

... , 0) (The Alternate Result): The `DIVIDE` function can take a third argument, which is the "result to return if division by zero occurs." By adding `, 0` at the end, we are telling DAX, "If the membership duration is 0, just return 0 instead of blank."

Segment customers into:

- Low (Bottom 25%)
- Medium (Mid 50%)
- High (Top 25%)

```

1 CLV_Tier =
2 // --- Finding percentile values ---
3 VAR P25 =
4     CALCULATE(
5         PERCENTILE.INC('Customer_Demographics', 'Customer_Demographics'[CLV], 0.25),
6         ALL('Customer_Demographics'), // <-- The secret: tells DAX to look at the WHOLE table
7         'Customer_Demographics'[CLV] > 0 // For new cus/cus without purchase CLV value is 0
8     )
9 VAR P75 =
10    CALCULATE(
11        PERCENTILE.INC('Customer_Demographics', 'Customer_Demographics'[CLV], 0.75),
12        ALL('Customer_Demographics'), // <-- The secret: tells DAX to look at the WHOLE table
13        'Customer_Demographics'[CLV] > 0 // For new cus/cus without purchase CLV value is 0
14    )
15
16 // --- CLV for the current row ---
17 VAR CurrentCustomerCLV = 'Customer_Demographics'[CLV]
18
19 // --- Assign the tier ---
20 RETURN
21     SWITCH(
22         TRUE(),
23         CurrentCustomerCLV >= P75, "High (Top 25%)",
24         CurrentCustomerCLV >= P25, "Medium (Mid 50%)",
25         "Low (Bottom 25%)"
26     )

```

project • Last saved: 27/10/2025 at 4:32 pm

Mahesh Katula

File Home Help Table tools Column tools

Name CLV Tier **Format Text** **Summarization Don't summarize** **Data category Uncategorized** **Sort by column** **Groups** **Relationships** **New column**

Structure **Formatting** **Properties** **Sort** **Groups** **Relationships** **Calculations**

Customer ID **Gender** **Age** **Membership Since** **Marital Status** **Region** **Income Group** **Membership Duration(Years)** **Age Group** **CLV** **CLV Tier**

1 CLV Tier =

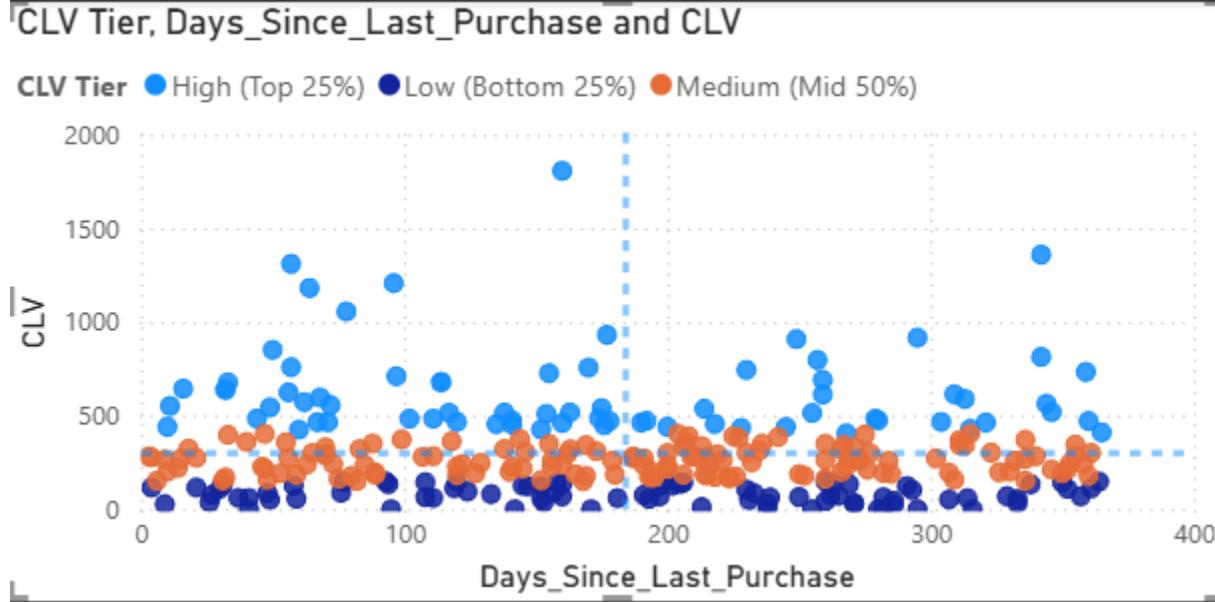
Customer ID	Gender	Age	Membership Since	Marital Status	Region	Income Group	Membership Duration(Years)	Age Group	CLV	CLV Tier	
C1000	Male	50	01 November 2020	Single	London	High		5.07	41-50	60.93	Low (Bottom 25%)
C1002	Male	36	18 August 2021	Single	Birmingham	Medium		4.22	31-40	259.05	Medium (Mid 50%)
C1005	Female	61	19 November 2020	Single	Liverpool	High		4.96	61-70	0.00	Low (Bottom 25%)
C1010	Male	21	03 May 2023	Single	Manchester	Medium		2.57	18-30	402.67	Medium (Mid 50%)
C1017	Female	51	11 July 2023	Single	London	High		2.32	51-60	60.93	Low (Bottom 25%)
C1018	Female	23	21 March 2024	Single	Liverpool	Low		1.62	18-30	321.50	Medium (Mid 50%)
C1019	Male	39	07 June 2023	Single	Leeds	Low		2.41	31-40	212.84	Medium (Mid 50%)
C1022	Female	33	19 December 2022	Single	London	Low		2.88	31-40	91.46	Low (Bottom 25%)
C1026	Female	33	24 November 2023	Single	Birmingham	Medium		1.95	31-40	691.14	High (Top 25%)
C1027	Female	46	08 September 2021	Single	Birmingham	High		4.16	41-50	38.15	Low (Bottom 25%)
C1028	Female	20	30 August 2021	Single	Liverpool	Low		4.18	18-30	246.84	Medium (Mid 50%)
C1031	Male	36	26 November 2023	Single	Manchester	Medium		1.94	31-40	440.27	High (Top 25%)
C1033	Female	20	02 August 2022	Single	Birmingham	High		3.26	18-30	200.72	Medium (Mid 50%)
C1034	Female	36	26 August 2023	Single	Birmingham	Low		2.19	31-40	166.45	Medium (Mid 50%)
C1037	Male	24	05 April 2023	Single	London	Low		2.59	18-30	286.59	Medium (Mid 50%)
C1038	Male	69	10 February 2024	Single	London	Medium		1.73	51-60	1181.51	High (Top 25%)
C1042	Female	56	26 February 2024	Single	London	Low		1.69	51-60	486.68	High (Top 25%)
C1047	Male	45	08 October 2023	Single	London	High		2.08	41-50	30.17	Low (Bottom 25%)
C1049	Female	67	14 September 2023	Single	London	Low		2.14	61-70	644.10	High (Top 25%)
C1056	Female	33	10 September 2021	Single	Leeds	Low		4.15	31-40	0.00	Low (Bottom 25%)
C1059	Male	69	30 June 2022	Single	Birmingham	High		3.35	61-70	274.80	Medium (Mid 50%)
C1061	Male	19	29 June 2021	Single	London	Low		4.35	18-30	281.82	Medium (Mid 50%)
C1063	Male	65	26 December 2022	Single	Liverpool	High		2.86	61-70	58.85	Low (Bottom 25%)
C1064	Male	29	07 September 2023	Single	Liverpool	Medium		2.16	18-30	265.89	Medium (Mid 50%)
C1065	Female	22	01 October 2022	Single	London	Medium		3.10	18-30	229.07	Medium (Mid 50%)
C1066	Female	54	04 August 2020	Single	Birmingham	High		5.25	51-60	144.81	Low (Bottom 25%)
C1067	Male	49	10 May 2024	Single	Birmingham	Medium		1.49	41-50	536.84	High (Top 25%)
C1069	Female	58	21 November 2023	Single	Leeds	Medium		1.96	51-60	155.77	Medium (Mid 50%)
C1070	Female	52	28 December 2020	Single	Manchester	High		4.85	51-60	45.32	Low (Bottom 25%)

Data **Search**

Measure Churn Customer Age Group CLV Cus Gen Income Mar ... Member Reg ... Custom ... Amer Cus Pro ... Pro ... Qual Stor Tran ... Tran ... Tran ...

Visualize:

- CLV vs Days Since Last Purchase



Top-Left (High CLV, Low Days): "Champions"

- *Insight:* These are your best customers. They have high value and have purchased recently. Your goal is to keep them happy.

Top-Right (High CLV, High Days): "At-Risk Champions"

- *Insight:* This is your most critical group. They are high-value customers who haven't bought anything in a while. They are at high risk of churning.
- *Action:* Target them immediately with a "we miss you" campaign or a special offer to bring them back.

Bottom-Left (Low CLV, Low Days): "New Customers / Potential"

- *Insight:* These are new or low-value customers who are actively purchasing.
- *Action:* Your goal is to increase their average order value and nurture them into becoming "Champions."

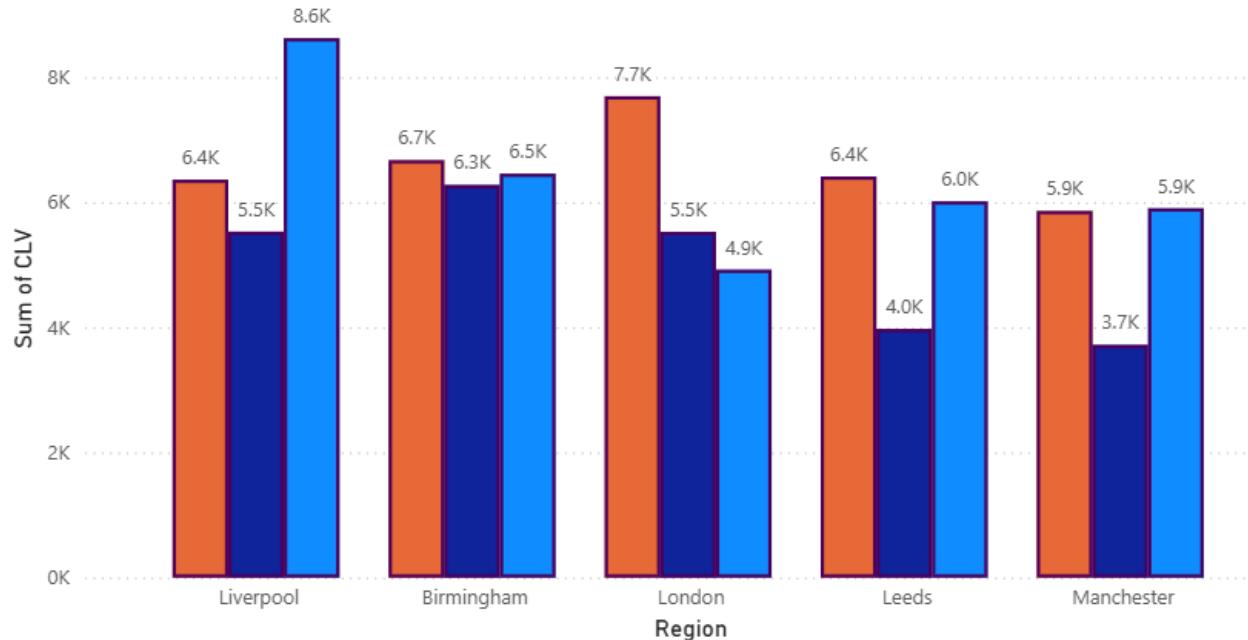
Bottom-Right (Low CLV, High Days): "Lost / Churned"

- *Insight:* These are low-value customers who are inactive. They have likely churned.
- *Action:* It's generally not worth spending much to re-acquire this group. Focus your efforts on the other three.

- CLV by Loyalty Tier and Region

CLV by Region and Loyalty_Tier

Loyalty_Tier ● Gold ● Platinum ● Silver



Insights :

Highest Value Segment: The single most valuable customer segment on the entire chart is **Silver** in **Liverpool**, with a CLV of **8.6K**. This is a significant outlier.

Second Highest Value Segment: The next most valuable segment is **Gold** in **London**, with a CLV of **7.7K**.

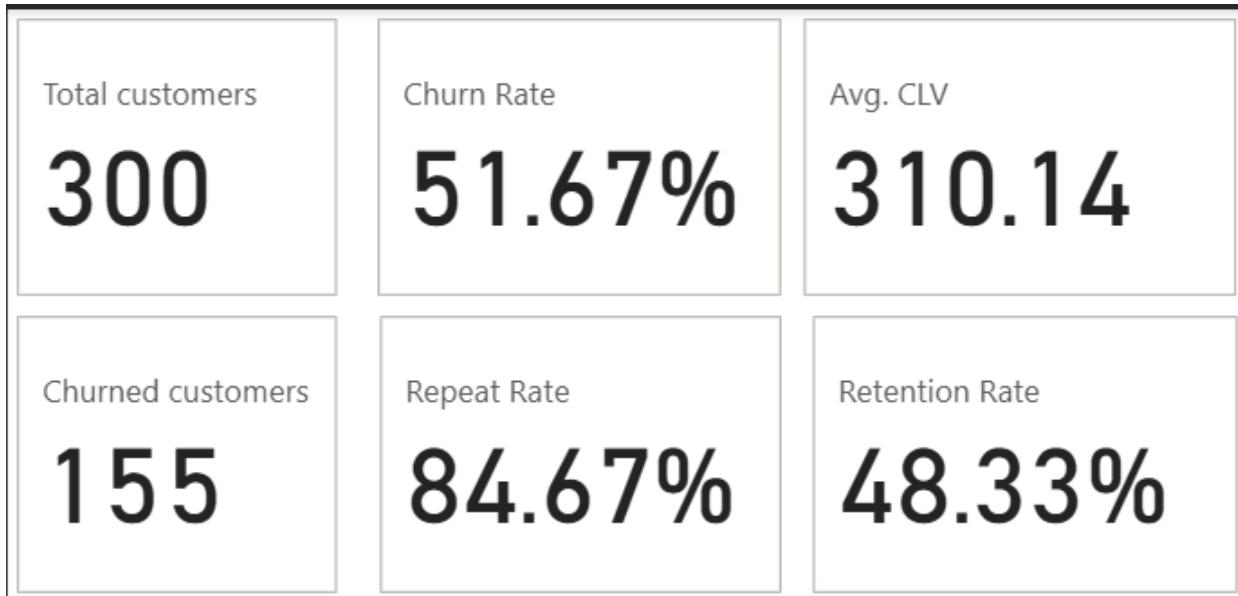
The Platinum Problem: A key insight is the consistent underperformance of the **Platinum** tier. In four out of the five regions (all except Birmingham), the Platinum tier has the *lowest* CLV.

Lowest Value Segments: The two worst-performing segments are both Platinum: **Manchester Platinum** (3.7K) and **Leeds Platinum** (4.0K).

Most Consistent Region: **Birmingham** shows the most balanced and consistently high CLV across all three tiers (6.7K, 6.3K, 6.5K), with very little variation between them.

Task 7: Final Dashboard and Executive summary

Create a multi-page Power BI report:

Overview KPIs (Churn, CLV, Repeat Rate) :

Dashboard Summary

This dashboard provides a high-level overview of key customer performance indicators (KPIs) for a specific cohort.

Key Metrics Displayed:

- **Total Customers:** 300
- **Churned Customers:** 155
- **Churn Rate:** 51.67%
- **Retention Rate:** 48.33%
- **Repeat Rate:** 84.67%
- **Average CLV:** 310.14

This analysis covers a cohort of 300 total customers, highlighting critical metrics for loyalty and value. The dashboard indicates a significant churn challenge, with 155 customers having left, resulting in a **Churn Rate of 51.67%**. This is directly mirrored by the **Retention Rate of 48.33%**. Despite the high churn, the data also shows a strong **Repeat Rate of 84.67%** among the customers who were retained. Financially, the **Average CLV** for this group is **310.14**.

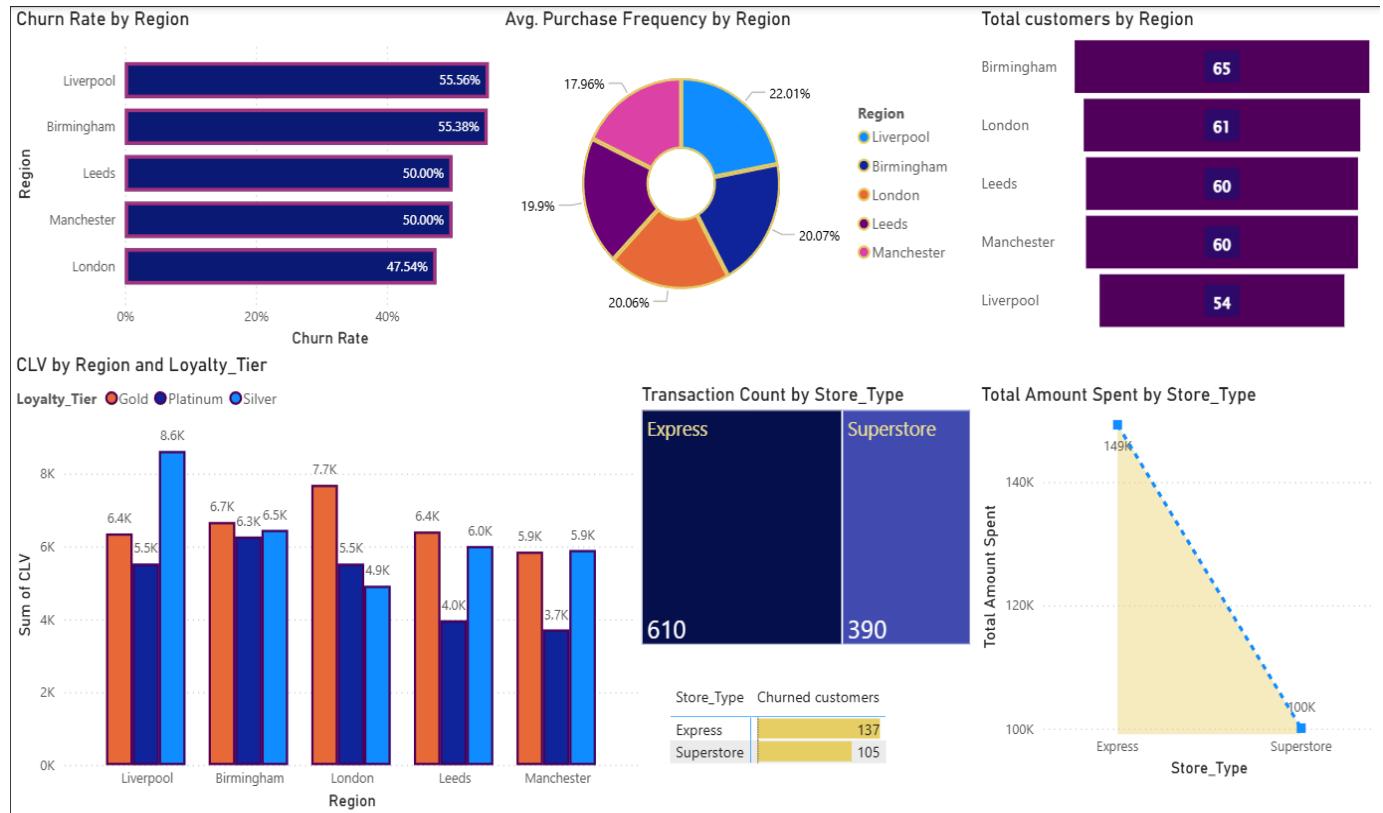
Loyalty & Promotion Impact :



Key Insights

- **Churn Rate by Loyalty_Tier:** Shows a counter-intuitive trend where the top-tier **Platinum** members churn the most (55.95%), while the base-tier **Gold** members are the most loyal (48.70% churn).
- **Total Points (Earned vs. Redeemed):** Reinforces the churn data. Gold members are the most engaged (earning 0.62M, redeeming 0.49M), while Platinum members are the least engaged.
- **Total Customers by Loyalty_Tier:** The customer base is fairly distributed, with Gold (38.33%) as the largest segment and Platinum (28%) as the smallest.
- **Average Purchase (With vs. Without Promo):** Demonstrates that promotions are largely ineffective at increasing spending, adding only 1.39 to the average purchase.
- **Transaction Count by Product_Categories:** Indicates a balanced product interest from customers, with Clothing (92) and Beverages (91) being the most frequently purchased categories.
- **Transaction Count by Loyalty_Tier and Promotion_Applied:** Shows that promotion usage is nearly identical across all three tiers, hovering around 46-52%.

Store and Region Insights :



The analysis reveals that regional performance varies dramatically. Liverpool (55.56%) and Birmingham (55.38%) suffer from the highest customer churn rates, while London (47.54%) performs the best in retention. Despite high churn, Liverpool boasts the single most valuable customer segment (Silver tier, 8.6K CLV). This suggests that even high-risk regions contain highly valuable customer groups.

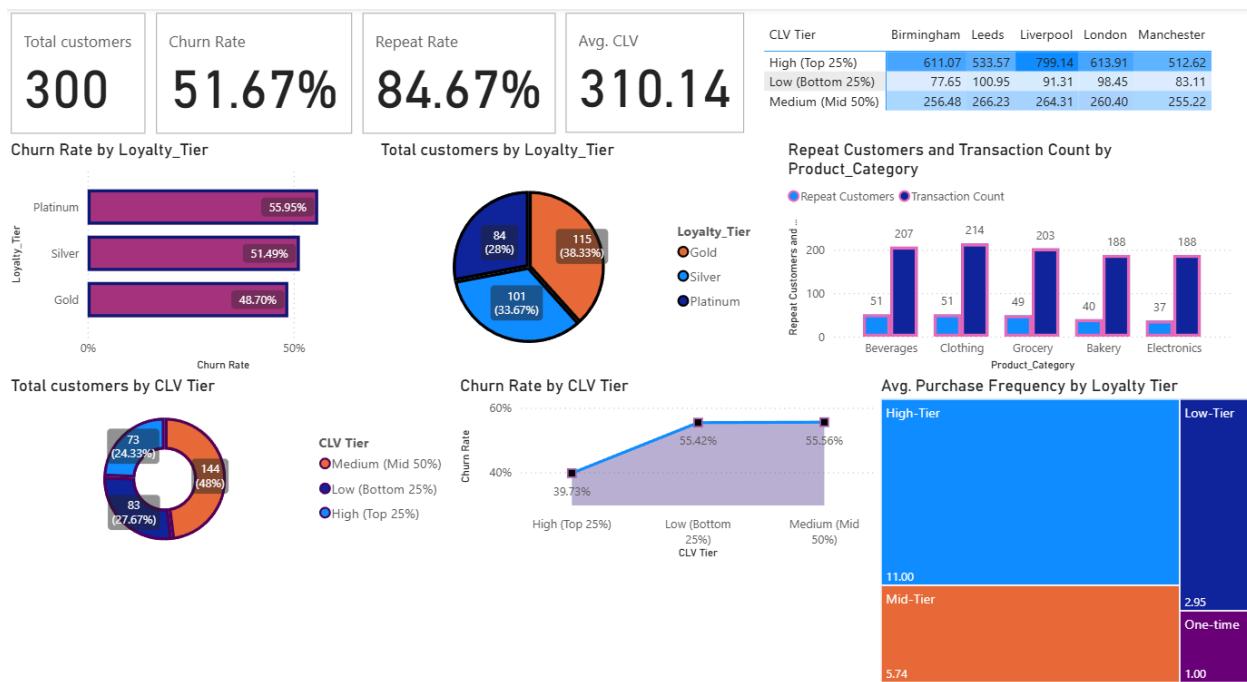
In the store-type analysis, Express stores are the clear engine for volume and revenue, driving 610 transactions and 146K in spending, compared to the Superstore's 390 transactions and 100K in spending. However, this high volume comes with a retention cost, as Express stores also account for a higher number of churned customers (137) than Superstores (105).

Key Insights

- **Regional Churn:** Liverpool and Birmingham are critical problem areas, with churn rates significantly above 50%. London is the strongest-performing region in terms of customer retention.

- Customer Distribution: The total customer base is fairly evenly distributed across all five regions, indicating the high churn rates are not simply due to a larger customer pool.
- CLV & Loyalty: The 'CLV by Region' chart shows that the 'Platinum' tier is not always the most valuable. In several regions (like London and Leeds), 'Gold' and 'Silver' tiers contribute more to Customer Lifetime Value, with Liverpool's 'Silver' tier being the highest single segment on the chart.
- Store Type Performance (Express): Express stores are the primary driver of transactions (610) and total spending (146K).
- Store Type Risk (Express): This high traffic comes at a cost. Express stores also have a higher absolute number of churned customers (137) compared to Superstores (105), suggesting a more transactional and less "sticky" customer relationship.

Customer Segmentation (Churned, Repeat, High-Value) :

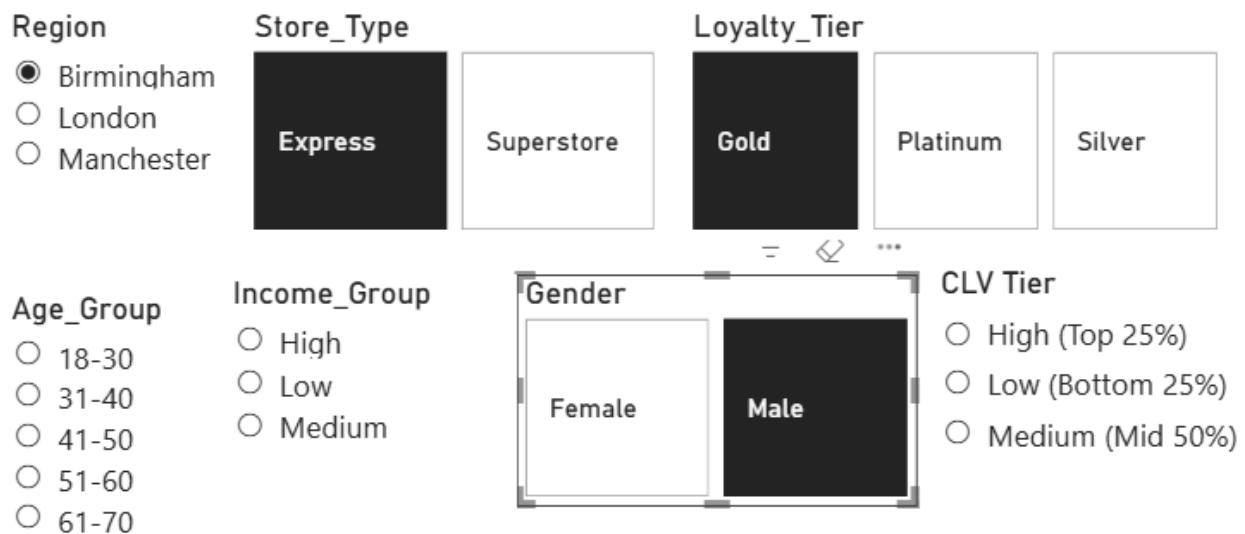
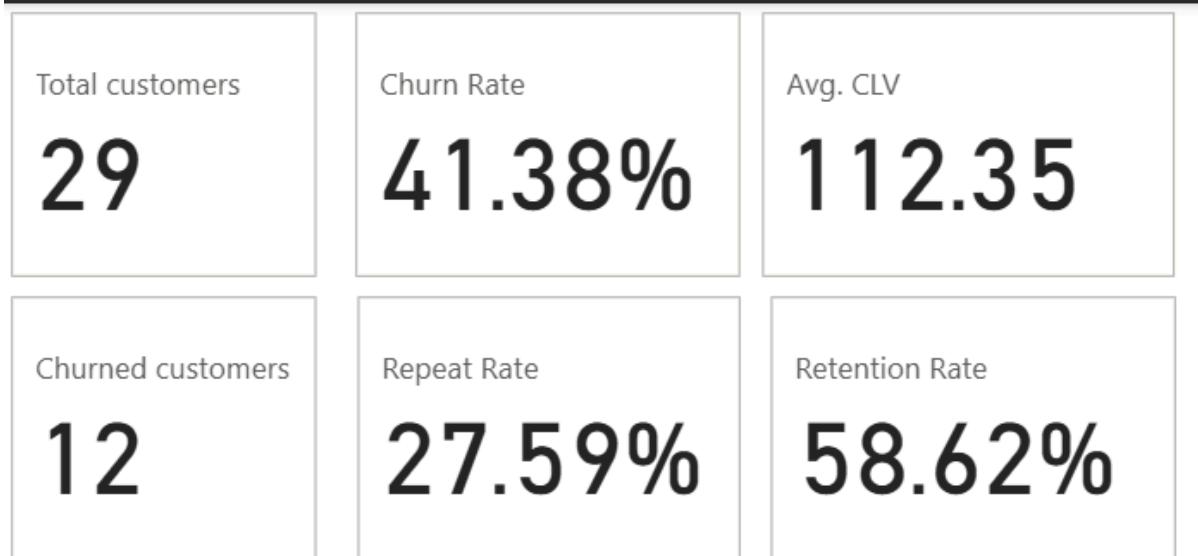


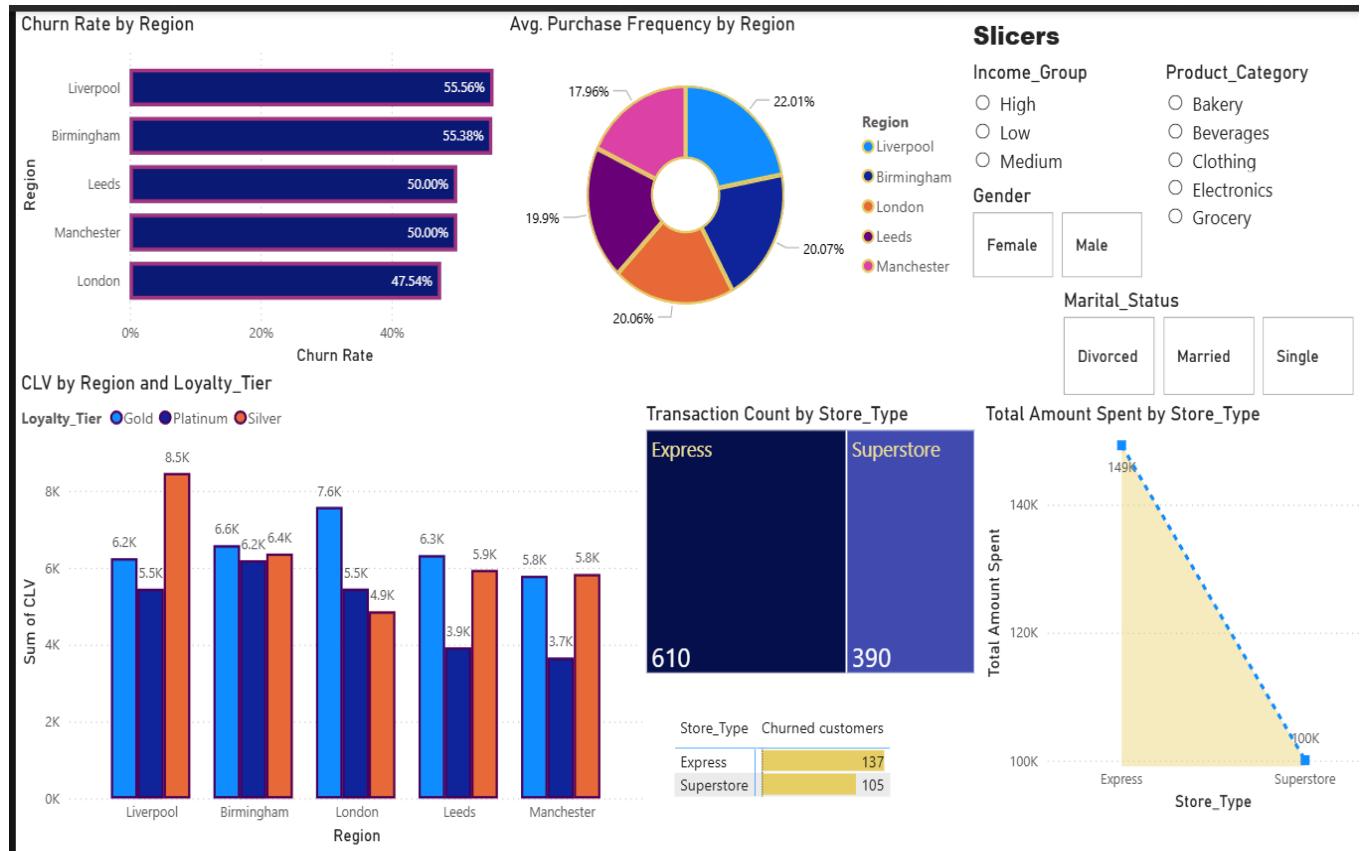
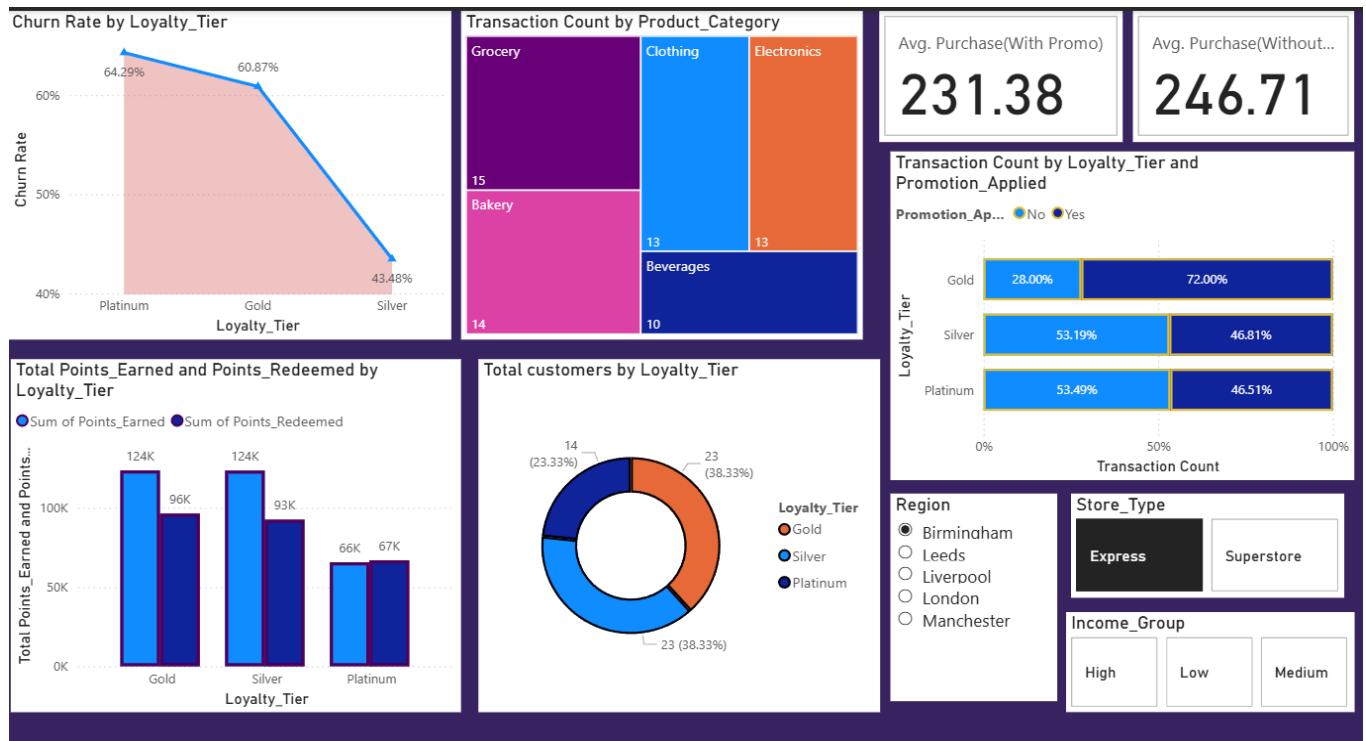
Key Insights by Chart

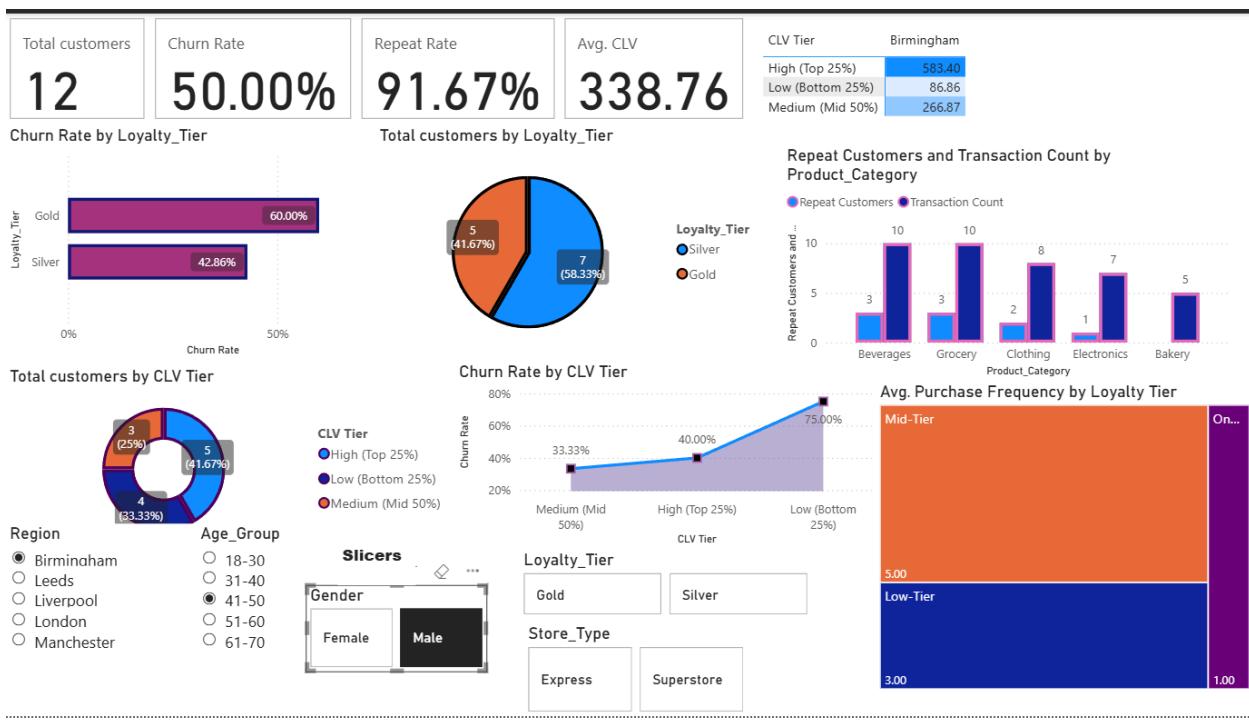
- **Churn Rate by CLV Tier:** This shows the *opposite* trend. The "High (Top 25%)" CLV customers are the most loyal (39.73% churn), while "Medium" and "Low" CLV groups are churning at over 55%.
- **Avg. Purchase Frequency:** High-tier customers (11.00) are significantly more active than mid-tier (5.74) and low-tier (2.95) customers.

- **Product Categories:** Clothing (214) and Grocery (203) are the primary drivers for transactions and repeat customers.

Add slicers: Region, Income Group, Loyalty Tier, Store Type :







To enhance the dashboard's interactivity, a set of slicers has been implemented. These slicers allow for dynamic filtering of all visuals on the pages, enabling a deeper analysis of specific segments. The dashboards can now be filtered by:

- Region
- Store Type
- Loyalty Tier
- CLV Tier
- Age Group
- Gender
- Marital Status

Summarizing the top 3 recommendations:

Top 3 recommendations:

Based on the insights, here are the three most urgent, high-impact recommendations:

- 1- Fix the Inverted Loyalty Program:** The **Platinum tier is failing**. The visuals show this tier has the **highest churn rate (55.95%)**, the **lowest CLV** in most regions, and the **lowest engagement** with the points system. Tesco must immediately re-evaluate the Platinum value proposition. We recommend shifting its perks away from points (which they don't use) and toward tangible, immediate benefits like free delivery, exclusive access to **Clothing** or **Beverage** partner products, or in-store "skip the queue" perks.
- 2- Launch Hyper-Targeted "Rescue Campaigns":** The data identifies segments with 100% churn. The immediate priority is a segment identified in the table analysis: **Females with Medium Income shopping at Superstores in Manchester**. A second priority, **Aged 31-40 in Liverpool and Leeds**. We must launch targeted marketing campaigns to these specific, high-risk groups now to prevent further losses.
- 3- Prioritize High-Risk, High-Value Locations:** The **London** region has the highest churn (53.7%) but also contains one of the highest CLV segments ("London Gold"). This combination of high value and high risk makes London the #1 priority for regional intervention. Separately, we must launch a "New Store Loyalty Onboarding" program, as the scatter plot shows a clear trend of **lower retention at newer stores**.

What should TESCO do to retain more customers?

To retain more customers, Tesco must move from a one-size-fits-all approach to a deeply segmented strategy focused on demonstrated value and engagement.

- **Make the Loyalty Program Valuable:** As established, the Platinum tier is broken. The program must be redesigned so that the "best" tier *feels* the most valued. Since the "Gold" tier is the most engaged with points, keep their points-based rewards. For Platinum, add experiential benefits that don't require them to bank and redeem points.
- **Drive Point Redemption:** The data shows a large gap between points earned and redeemed. It also shows that **Clothing** and **Beverages** are the most popular transaction categories. Tesco should launch campaigns that directly link points to these popular items (e.g., "Use 500 points for £5 off any Clothing purchase"). This increases engagement, which is correlated with retention.
- **Segment by Behavior, Not Just Tier:** We know the "**61-70**" age group has the highest purchase frequency, and the "**Silver**" loyalty tier (in Liverpool) has the highest CLV. We should be targeting these groups with "thank you" offers and incentives to protect their high-value, high-frequency behavior.
- **Fix Leaky Store Locations:** Implement the "London Rescue" and "New Store Loyalty" campaigns recommended above. The data on store-opening years shows that customer loyalty is not being successfully transferred to new locations.

Where should they focus next?

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1. **Immediate Focus (Next 3 Months): The Platinum Tier.** This is the most urgent problem. The company is losing its highest-designated customers at a faster rate than any other group. The immediate focus must be on redesigning the Platinum tier's benefits to stop this high-value churn.
 2. **Secondary Focus (Next 6 Months): High-Value, High-Risk Segments.** Focus retention efforts on the segments with the highest CLV that are in high-churn regions. The data identifies these as "**Liverpool Silver**" (8.6K CLV) and "**London Gold**" (7.7K CLV). These are the most valuable customer groups; protect them at all costs.
 3. **Long-Term Focus (Next 12 Months): New Stores & Inconsistent Regions.** The long-term focus should be on standardizing the customer experience to fix the two biggest inconsistencies:
 - **New Stores:** Implement a new, standard onboarding process for all stores opened since 2019 to reverse the trend of low retention.
 - **Underperforming Regions:** Analyze why regions like **Manchester** and **Leeds** have the lowest CLV segments (e.g., "Manchester Platinum" at 3.7K). This will require a deeper, region-specific analysis.

Task 8: Video explanation: Expressing the finding and actionable insights

Drive Link :

https://drive.google.com/file/d/1dqVPpB4avuPCHDjwl0mK_5PcmDv8wGy2/view?usp=sharing

 BI_Project_Video.mp4