

Retail customer Retention Analytics – ADIDAS(using power bi)

Task-1

Steps followed-

1. Removed duplicate rows, errors and ensured correct datatypes for all tables

Customer_ID	Age	Gender	Region	Income_Level	Membership_Since	Preferred_Channel	Membership_Duration
01000001	24	Female	North America	Medium	24-01-2023	Online	24-01-2023
01000002	32	Other	Middle East	High	14-02-2023	Online	14-02-2023
01000003	21	Other	Asia Pacific	High	24-03-2023	Online	24-03-2023
01000004	52	Female	South America	Premium	01-11-2023	Online	01-11-2023
01000005	22	Male	Asia Pacific	High	23-01-2024	Online	23-01-2024
01000006	40	Male	Middle East	Medium	29-03-2024	Store	29-03-2024
01000007	23	Male	North America	Medium	23-01-2024	Online	23-01-2024
01000008	49	Male	South America	Medium	14-03-2024	Store	14-03-2024
01000009	26	Other	Middle East	Medium	14-03-2024	Store	14-03-2024
01000010	29	Other	Middle East	Premium	27-12-2024	Online	27-12-2024
01000011	34	Female	South America	High	11-10-2024	Store	11-10-2024
01000012	63	Female	North America	Low	27-02-2023	Online	27-02-2023
01000013	22	Male	Middle East	Medium	15-04-2024	Store	15-04-2024
01000014	37	Other	Middle East	Low	26-04-2024	Store	26-04-2024
01000015	42	Other	North America	High	04-02-2024	Store	04-02-2024
01000016	57	Male	Asia Pacific	High	10-09-2024	Online	10-09-2024
01000017	35	Male	South America	Low	06-02-2024	Store	06-02-2024
01000018	45	Male	Asia Pacific	Low	09-09-2023	Online	09-09-2023
01000019	62	Female	North America	Premium	29-03-2024	Online	29-03-2024
01000020	30	Other	South America	Premium	10-03-2024	Online	10-03-2024
01000021	29	Male	North America	Medium	27-03-2024	Store	27-03-2024
01000022	14	Other	South America	Low	14-03-2024	Store	14-03-2024
01000023	48	Other	Europe	Premium	04-04-2024	Online	04-04-2024
01000024	54	Male	South America	Low	17-10-2023	Store	17-10-2023
01000025	42	Other	Asia Pacific	Premium	29-04-2024	Store	29-04-2024
01000026	25	Male	Europe	Low	24-02-2024	Store	24-02-2024
01000027	38	Other	Europe	Low	23-07-2024	Store	23-07-2024
01000028	27	Male	Middle East	Low	20-10-2023	Store	20-10-2023
01000029	22	Female	South America	High	07-03-2024	Store	07-03-2024

2. Created Three calculated columns Membership_Duration, Transaction_year, Transaction_Month

DAX Used- 1. Membership_Duration = DATEDIFF('Customer demographics adidas - Customer_Demographics (1)'[Membership_Since],Today(),Year)

2. Transaction_Month = Month('Adidas customer transactional - Customer_Transactions (1)'[Transaction_Date])

3. Transaction_Year = Year('Adidas customer transactional - Customer_Transactions (1)'[Transaction_Date])

Customer_ID	Age	Gender	Region	Income_Level	Membership_Since	Preferred_Channel	Membership_Duration	Total_Purchases	Segmented_Customers
01000001	24	Female	North America	Medium	24-01-2023	Online	24-01-2023	2	Low Tier (0-5)
01000002	32	Other	Middle East	High	14-02-2023	Online	14-02-2023	2	Low Tier (0-5)
01000003	21	Other	Asia Pacific	High	24-03-2023	Online	24-03-2023	2	Low Tier (0-5)
01000004	52	Female	South America	Premium	01-11-2023	Online	01-11-2023	2	Low Tier (0-5)
01000005	22	Male	Asia Pacific	High	23-01-2024	Online	23-01-2024	6	Mid Tier (6-10)
01000006	40	Male	Middle East	Medium	29-03-2024	Store	29-03-2024	5	Mid Tier (6-10)
01000007	23	Male	North America	Medium	23-01-2024	Online	23-01-2024	4	Mid Tier (6-10)
01000008	49	Male	South America	Medium	14-03-2024	Store	14-03-2024	5	Mid Tier (6-10)
01000009	26	Other	Middle East	Medium	14-03-2024	Store	14-03-2024	4	Mid Tier (6-10)
01000010	29	Other	Middle East	Premium	27-12-2024	Online	27-12-2024	2	Mid Tier (6-10)
01000011	34	Female	South America	High	11-10-2024	Store	11-10-2024	5	Mid Tier (6-10)
01000012	63	Female	North America	Low	27-02-2023	Online	27-02-2023	1	Low Tier (0-5)
01000013	22	Male	Middle East	Medium	15-04-2024	Store	15-04-2024	4	Mid Tier (6-10)
01000014	37	Other	Middle East	Low	26-04-2024	Store	26-04-2024	4	Mid Tier (6-10)
01000015	42	Other	North America	High	04-02-2024	Store	04-02-2024	4	Mid Tier (6-10)
01000016	57	Male	Asia Pacific	High	10-09-2024	Online	10-09-2024	1	Low Tier (0-5)
01000017	35	Male	South America	Low	06-02-2024	Store	06-02-2024	4	Mid Tier (6-10)
01000018	45	Male	Asia Pacific	Low	09-09-2023	Online	09-09-2023	4	Mid Tier (6-10)
01000019	62	Female	North America	Premium	29-03-2024	Online	29-03-2024	5	Low Tier (0-5)
01000020	30	Other	South America	Premium	10-03-2024	Online	10-03-2024	6	Mid Tier (6-10)
01000021	29	Male	North America	Medium	27-03-2024	Store	27-03-2024	5	Mid Tier (6-10)
01000022	14	Other	South America	Low	14-03-2024	Store	14-03-2024	1	Low Tier (0-5)
01000023	48	Other	Europe	Premium	04-04-2024	Online	04-04-2024	1	Low Tier (0-5)
01000024	54	Male	South America	Low	17-10-2023	Store	17-10-2023	4	Mid Tier (6-10)
01000025	42	Other	Asia Pacific	Premium	29-04-2024	Store	29-04-2024	4	Mid Tier (6-10)
01000026	25	Male	Europe	Low	24-02-2024	Store	24-02-2024	1	Low Tier (0-5)
01000027	38	Other	Europe	Low	23-07-2024	Store	23-07-2024	4	Mid Tier (6-10)
01000028	27	Male	Middle East	Low	20-10-2023	Store	20-10-2023	5	Low Tier (0-5)
01000029	22	Female	South America	High	07-03-2024	Store	07-03-2024	1	Low Tier (0-5)

Transaction_ID	Customer_ID	Store_ID	Product_Category	Transaction_Date	Amount	Promotion_Applied	Transaction_Year	Transaction_Month
01000001	01000001	STOR0001	Apparel	24 August 2023	433.22	Yes	2023	8
01000002	01000002	STOR0002	Apparel	06 January 2025	142.29	Yes	2025	1
01000003	01000003	STOR0003	Apparel	16 January 2023	411	Yes	2023	1
01000004	01000004	STOR0004	Apparel	05 April 2023	87.02	Yes	2023	4
01000005	01000005	STOR0005	Apparel	25 September 2022	295.55	Yes	2022	9
01000006	01000006	STOR0006	Apparel	14 November 2023	351.29	Yes	2023	11
01000007	01000007	STOR0007	Apparel	07 February 2024	104.43	Yes	2024	2
01000008	01000008	STOR0008	Apparel	23 March 2023	440.8	Yes	2023	3
01000009	01000009	STOR0009	Apparel	31 September 2023	31.65	Yes	2023	9
01000010	01000010	STOR0010	Apparel	15 July 2023	378.99	Yes	2023	7
01000011	01000011	STOR0011	Apparel	20 October 2024	54.98	Yes	2024	10
01000012	01000012	STOR0012	Apparel	03 October 2023	204.06	Yes	2023	10
01000013	01000013	STOR0013	Apparel	09 December 2024	652.86	Yes	2024	12
01000014	01000014	STOR0014	Apparel	11 December 2022	370.12	Yes	2022	12
01000015	01000015	STOR0015	Apparel	01 December 2022	250.33	Yes	2022	12
01000016	01000016	STOR0016	Apparel	20 July 2023	240.14	Yes	2023	7
01000017	01000017	STOR0017	Apparel	25 April 2023	301.85	Yes	2023	4
01000018	01000018	STOR0018	Apparel	01 May 2024	200.92	Yes	2024	5
01000019	01000019	STOR0019	Apparel	14 September 2022	195.71	Yes	2022	9
01000020	01000020	STOR0020	Apparel	21 July 2023	56.26	Yes	2023	7
01000021	01000021	STOR0021	Apparel	13 March 2024	131.71	Yes	2024	3
01000022	01000022	STOR0022	Apparel	16 October 2023	293.43	Yes	2023	10
01000023	01000023	STOR0023	Apparel	10 January 2023	447.65	Yes	2023	1
01000024	01000024	STOR0024	Apparel	02 November 2024	62.12	Yes	2024	11
01000025	01000025	STOR0025	Apparel	28 January 2024	457.6	Yes	2024	1
01000026	01000026	STOR0026	Apparel	04 April 2024	291.34	Yes	2024	4
01000027	01000027	STOR0027	Apparel	14 February 2024	495.78	Yes	2024	2
01000028	01000028	STOR0028	Apparel	20 June 2023	251.23	Yes	2023	6
01000029	01000029	STOR0029	Apparel	15 April 2025	207.62	Yes	2025	4
01000030	01000030	STOR0030	Apparel	06 January 2023	170.12	Yes	2023	1

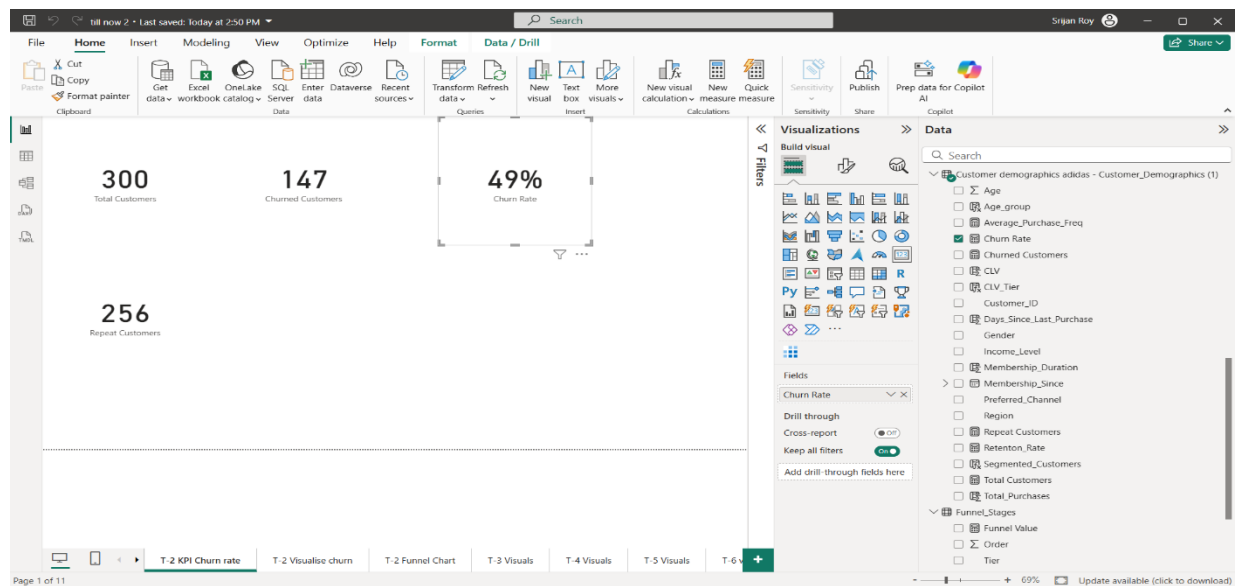
Task-2

Steps followed-

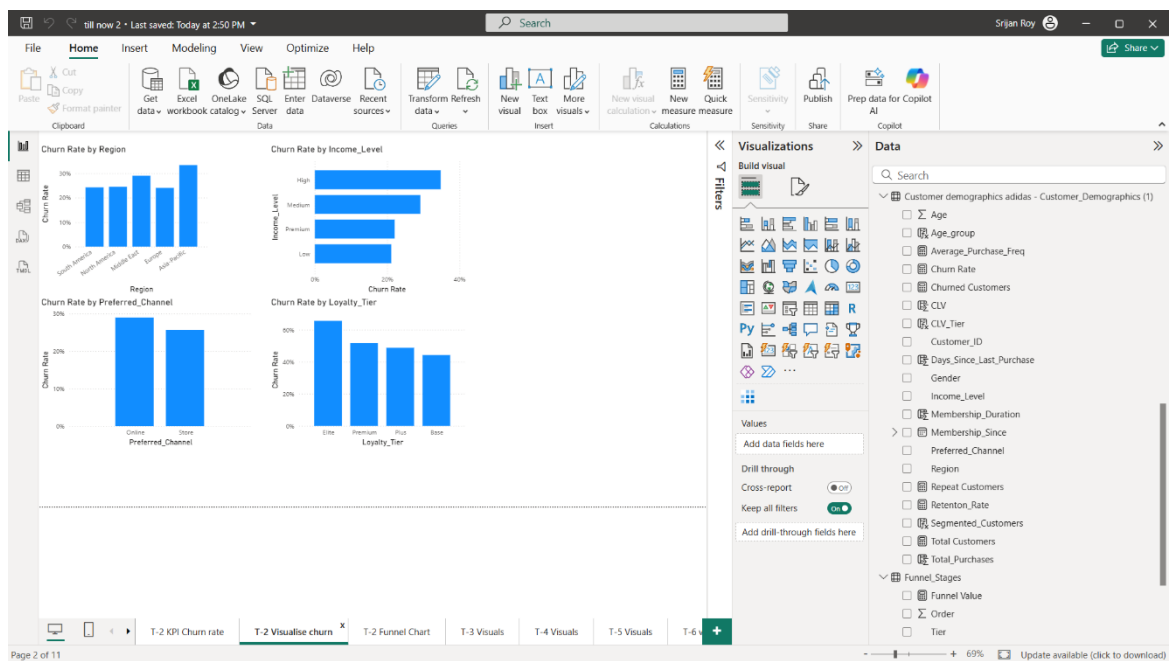
- Created 4 different measures named Churn rate, Churn Customers, Repeat Customers and Total Customers with following Daxes.

DAX used-

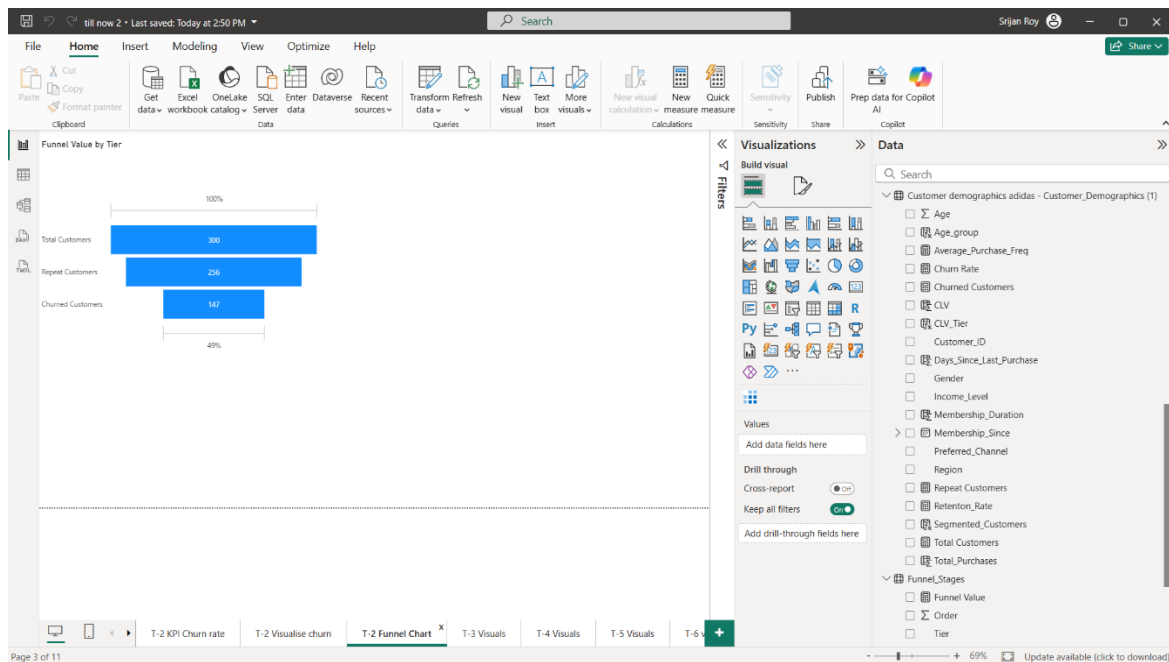
- Churn Rate = `DIVIDE([Churned Customers],[Total Customers])*100/100`
 - Churned Customers = `CALCULATE(DISTINCTCOUNT('customer churned - Churn_Labelled_Customers (1)'[Customer_ID]),'customer churned - Churn_Labelled_Customers (1)'[Churn_Flag]=1)`
 - Total Customers = `DISTINCTCOUNT('Customer demographics adidas - Customer_Demographics (1)'[Customer_ID])`
 - Repeat Customers = `VAR Who= SUMMARIZE('Adidas customer transactional - Customer_Transactions (1)', 'Adidas customer transactional - Customer_Transactions (1)'[Customer_ID], "Aight", COUNTROWS('Adidas customer transactional - Customer_Transactions (1)')) VAR Stm= FILTER(Who, [Aight]>1) RETURN COUNTROWS(Stm)`
- Created 4 card visuals then put all those measures in them which are now my Kpis.
 - Visualised churn rate using different charts.
 - Created funnel stages and funnel chart.



Churn rate visuals:



Funnel chart:



Task-3

Steps followed-

- Created a calculated Column as Segmented_Customers in customer demographics dataset where we Segmented customers in three different tiers "Low-Tier (0-3)", "Mid-Tier (4-8)" and "High-Tier (9+)"
- Crated a measure named avg_purchase_freq and visualize it by region, age group, loyalty tier using different charts

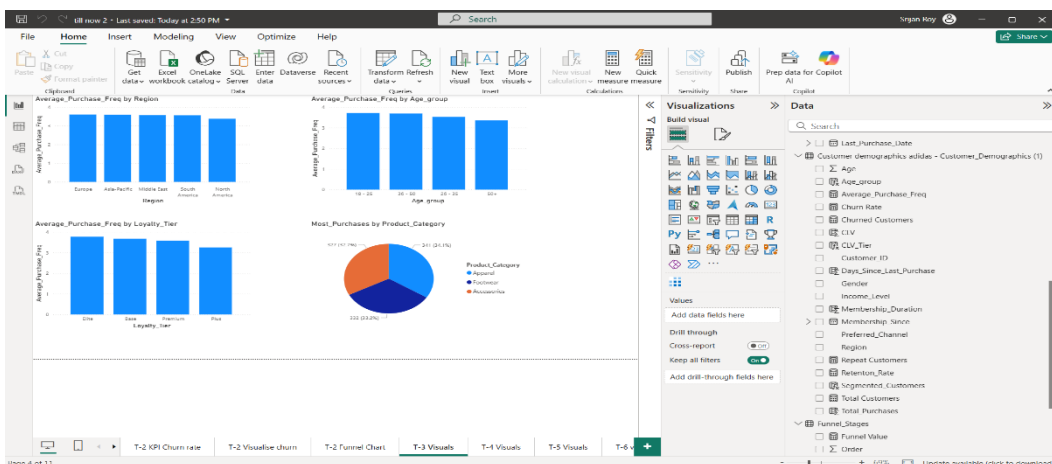
DAX Used-

- Segmented_Customers = SWITCH(TRUE(), 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] <= 3, "Low-Tier (0-3)", 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] <= 8, "Mid-Tier (4-8)", 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] >= 9, "High-Tier (9+)", "Unknown")
- Average_Purchase_Freq = AVERAGEX(VALUES('Customer demographics adidas - Customer_Demographics (1)'[Customer_ID]), CALCULATE(COUNTROWS('Adidas customer transactional - Customer_Transactions (1)')))

***MOST PURCHASED PRODUCT BY LOYAL CUSTOMERS =APPAREL

The screenshot shows the Power BI Desktop interface with the DAX formula bar. The formula for 'Segmented_Customers' is: `SWITCH(TRUE(), 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] <= 3, "Low-Tier (0-3)", 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] <= 8, "Mid-Tier (4-8)", 'Customer demographics adidas - Customer_Demographics (1)'[Total_Purchases] >= 9, "High-Tier (9+)", "Unknown")`. The table preview shows columns for Region, Age group, Loyalty tier, and Segmented Customers.

Region	Age group	Loyalty tier	Segmented Customers
Europe	18-24	Low	Low-Tier (0-3)
Europe	25-34	Low	Low-Tier (0-3)
Europe	35-44	Low	Low-Tier (0-3)
Europe	45-54	Low	Low-Tier (0-3)
Europe	55-64	Low	Low-Tier (0-3)
Europe	65-74	Low	Low-Tier (0-3)
Europe	75-84	Low	Low-Tier (0-3)
Europe	85-94	Low	Low-Tier (0-3)
Europe	95-104	Low	Low-Tier (0-3)
Europe	105-114	Low	Low-Tier (0-3)



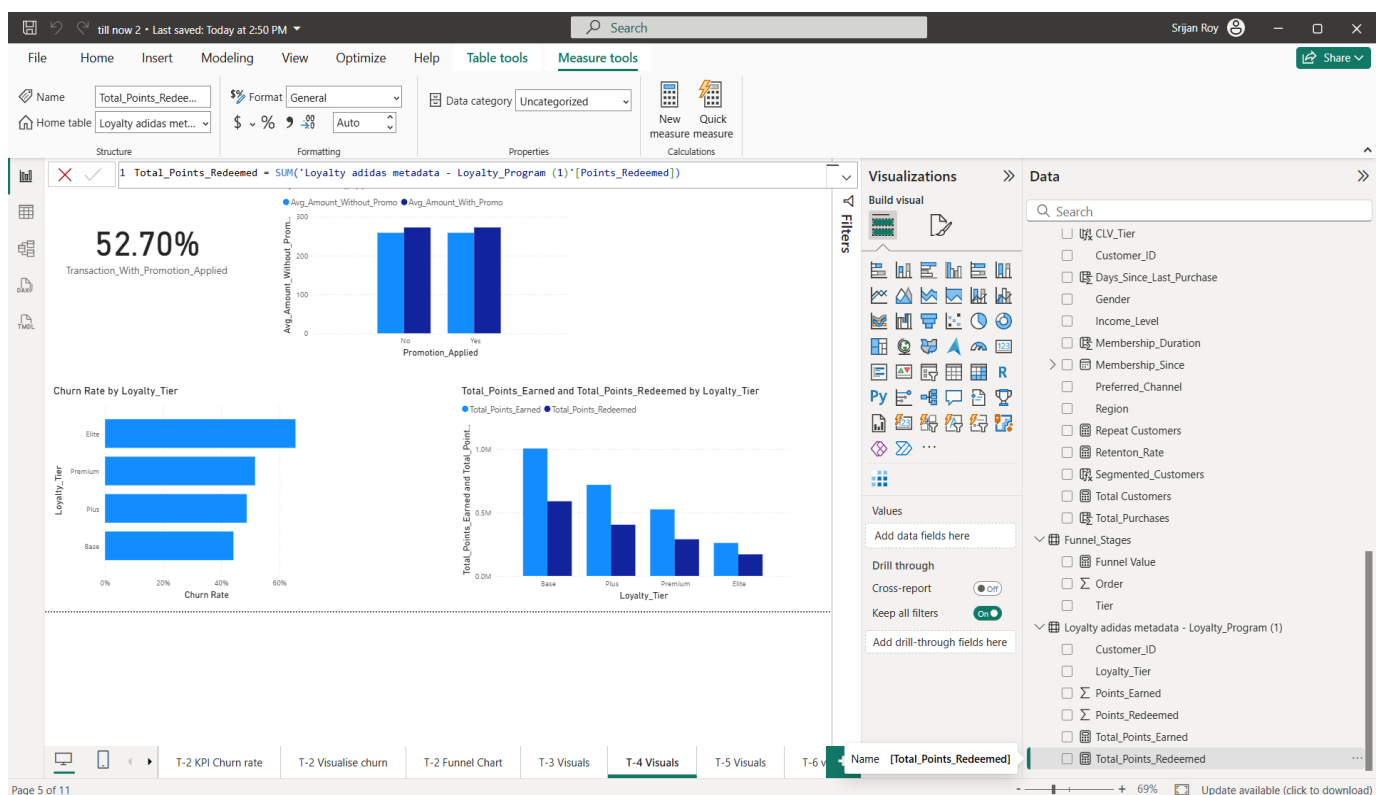
Task-4

Steps followed-

- Created a measure Transaction_With_Promotion_Applied =
 $\text{DIVIDE}([\text{Promotion_Transactions}], [\text{Total_Transactions}])$
And visualized it using card visual
- Created two different measures Avg. purchase amount with vs without promos and compare them using clustered column chart
- Visualised churn rate across loyalty tier
- Created two different measures , “points_earned” and “points _redeemed” and compare them across loyalty tier using clustered column chart

DAX Used-

1. Avg_Amount_With_Promo = $\text{CALCULATE}(\text{AVERAGE}('Adidas\ customer\ transactional - Customer_Transactions (1)')[Amount], 'Adidas\ customer\ transactional - Customer_Transactions (1)')[Promotion_Applied] = "Yes")$
2. Avg_Amount_Without_Promo = $\text{CALCULATE}(\text{AVERAGE}('Adidas\ customer\ transactional - Customer_Transactions (1)')[Amount], 'Adidas\ customer\ transactional - Customer_Transactions (1)')[Promotion_Applied] = "No")$
3. Total_Points_Earned = $\text{SUM}('Loyalty\ adidas\ metadata - Loyalty_Program (1)')[Points_Earned]$
4. Total_Points_Redeemed = $\text{SUM}('Loyalty\ adidas\ metadata - Loyalty_Program (1)')[Points_Redeemed]$



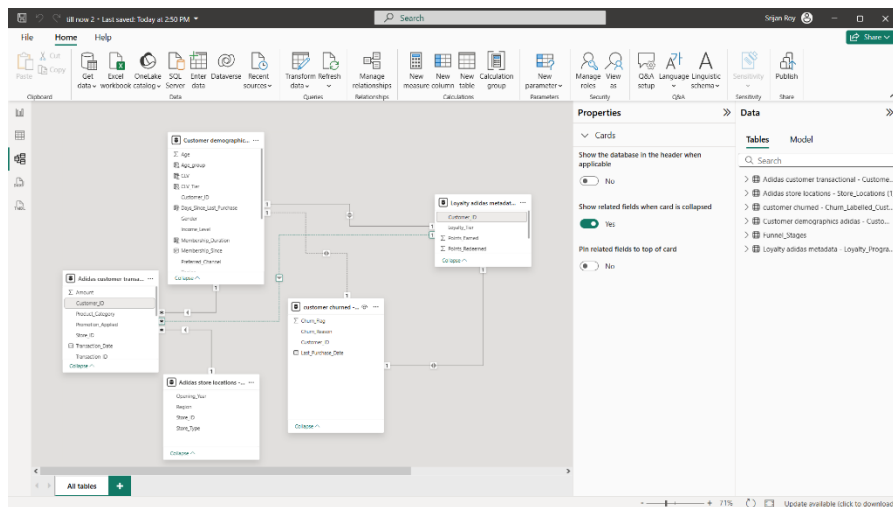
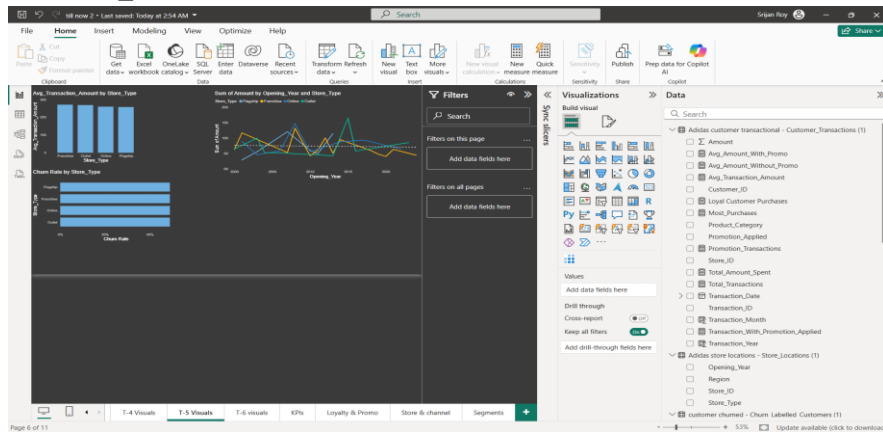
Recommendations to improve redemption & retention -

1. I'd suggest to increase rewards & awareness for that said rewards like customers aren't aware enough that they have unused points left so we can use reminders to let them know
2. Reduce hassle during transactions and redemptions and make it more fluid.
3. Give different tier-based customer more tier-based rewards and increasing frequency of rewards too.

Task-5

Steps followed-

- Checked the relationship between store data with transactions and made a many to one/ one to many relationships between both using store id as a key
- Visualised and computed Avg. Transaction Amount by store types
- Visualised churn rate by store type
- Created a measure named retention where retention is the opposite of measure or $\text{Retention_Rate} = 1 - [\text{Churn Rate}]$



TASK-6

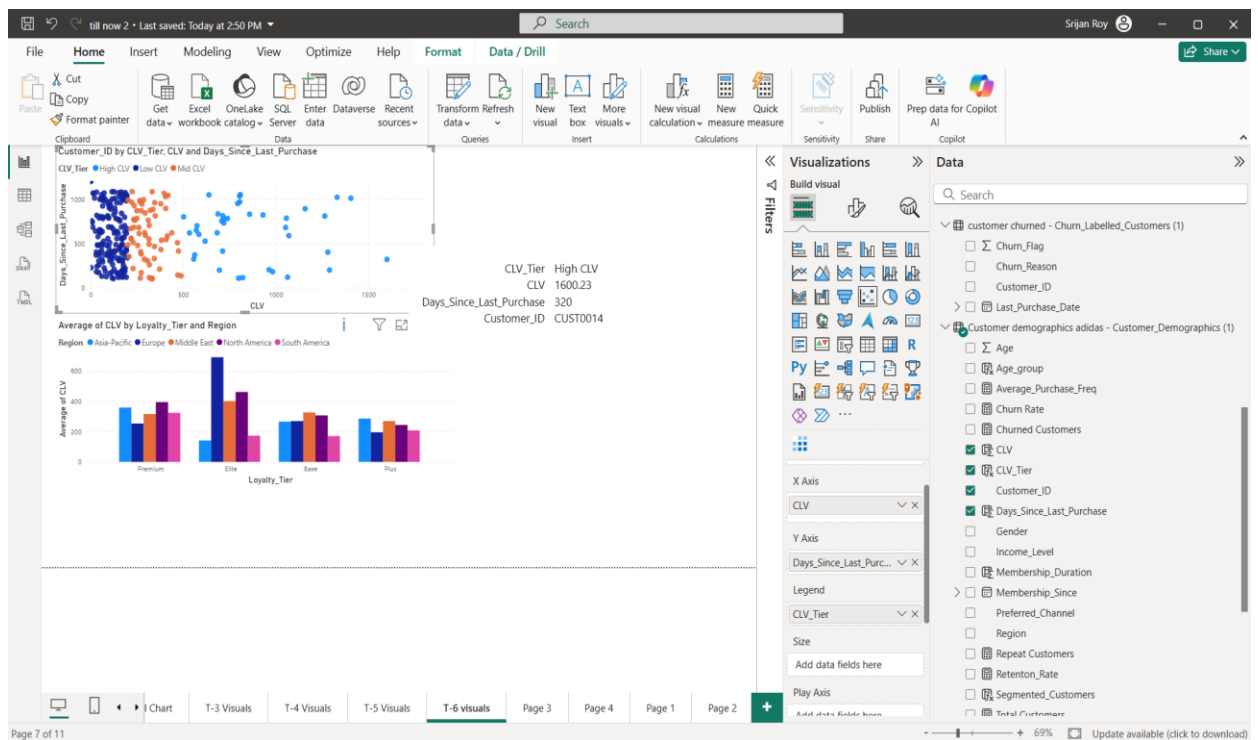
Steps followed-

- Created a Calculated column as CLV where $CLV = \text{Total amount spent} / \text{Membership Duration}$
- Segmented customers (calculated column) into Low, Medium and High CLV and naming it as CLV tier (denoting $[CLV] < 200$, "Low CLV", $[CLV] < 500$, "Mid CLV" and $[CLV] > 500$, "High CLV").
- Visualised CLV vs Days since last purchase into a scatter chart where x axis is CLV, y axis is Date_since_last_purchase and putting CLV_Tier into legends and Customer_id into tooltips which perfectly segments individual customers with their CLV_tier and how many days it's been from their last purchase.
- Visualised CLV by Loyalty Tier and Region using clustered column chart putting Loyalty_Tier in X axis and CLV(Average) in Y axis while putting region into legends which computes CLV by loyalty tier per region flawlessly.

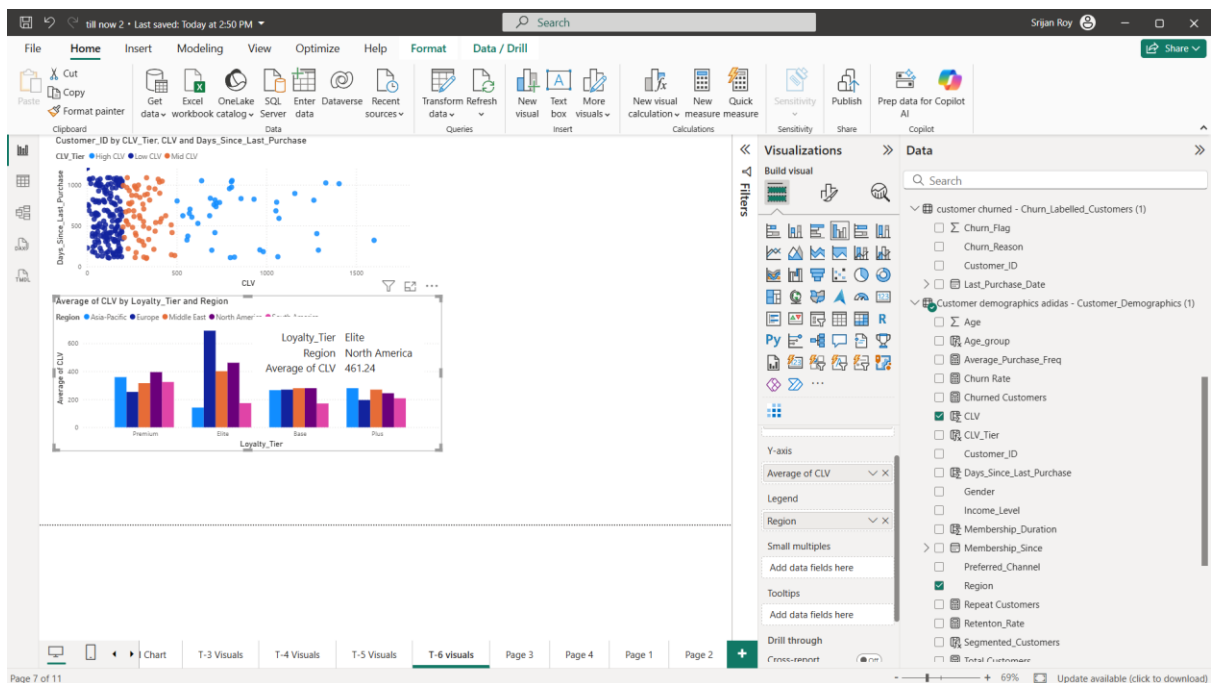
DAX Used-

1. `CLV = DIVIDE([Total_Amount_Spent], 'Customer demographics adidas - Customer_Demographics (1)'[Membership_Duration])`
2. `CLV_Tier = SWITCH(TRUE(), 'Customer demographics adidas - Customer_Demographics (1)'[CLV] < 200, "Low CLV", 'Customer demographics adidas - Customer_Demographics (1)'[CLV] < 500, "Mid CLV", 'Customer demographics adidas - Customer_Demographics (1)'[CLV] > 500, "High CLV")`

CLV vs Days since Last purchase



CLV by Loyalty Tier & Region



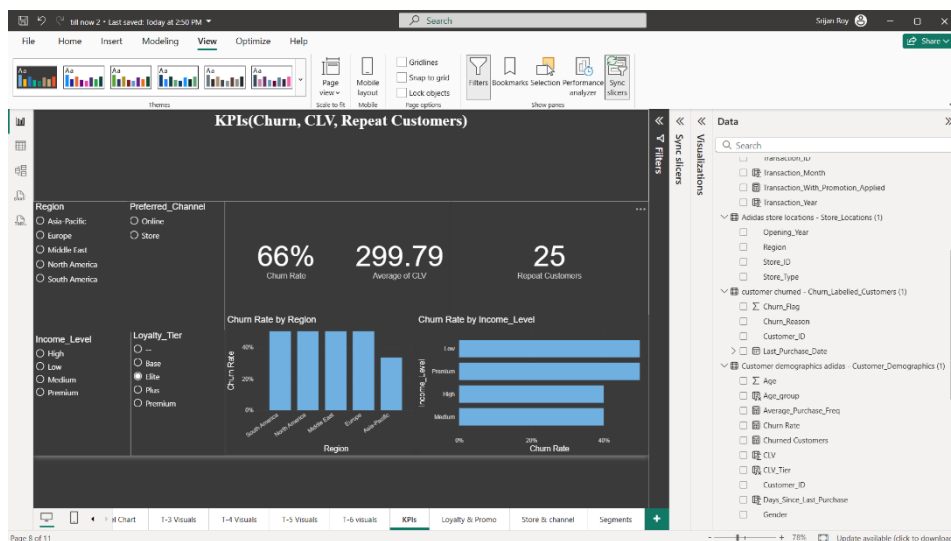
Task-7

Steps followed-

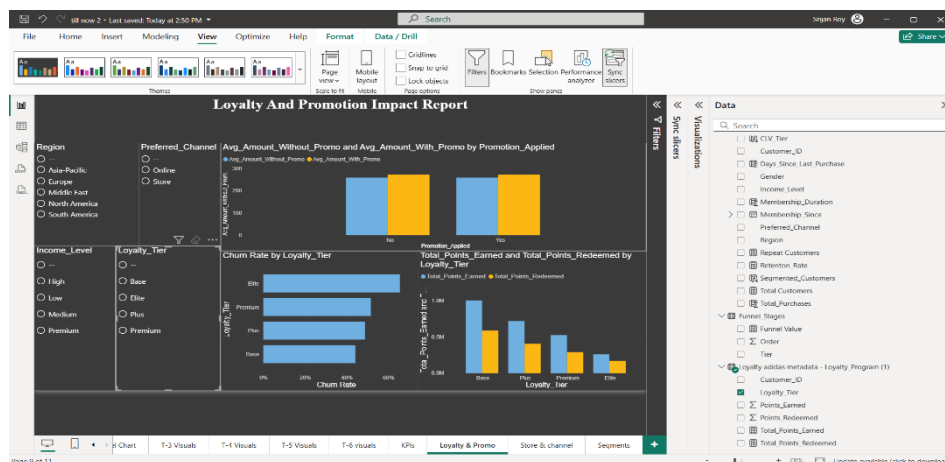
- Created a multi-Page Power Bi report where-
 - Page 1 contains All KPIs (Churn rate, CLV, Repeat customers) with visuals
 - Page 2 contains Loyalty and promo impact for the campaign
 - Page 3 contains all the stores and channel insights like where do customers want to prefer shopping and whether they prefer online channel or offline ones
 - Page 4 contains the segmentation part like CLV tier and how it effects the channel specific regions
- Added list slicers (Region, Channel, Income, Loyalty tier) are added and synced

Power Bi Report-

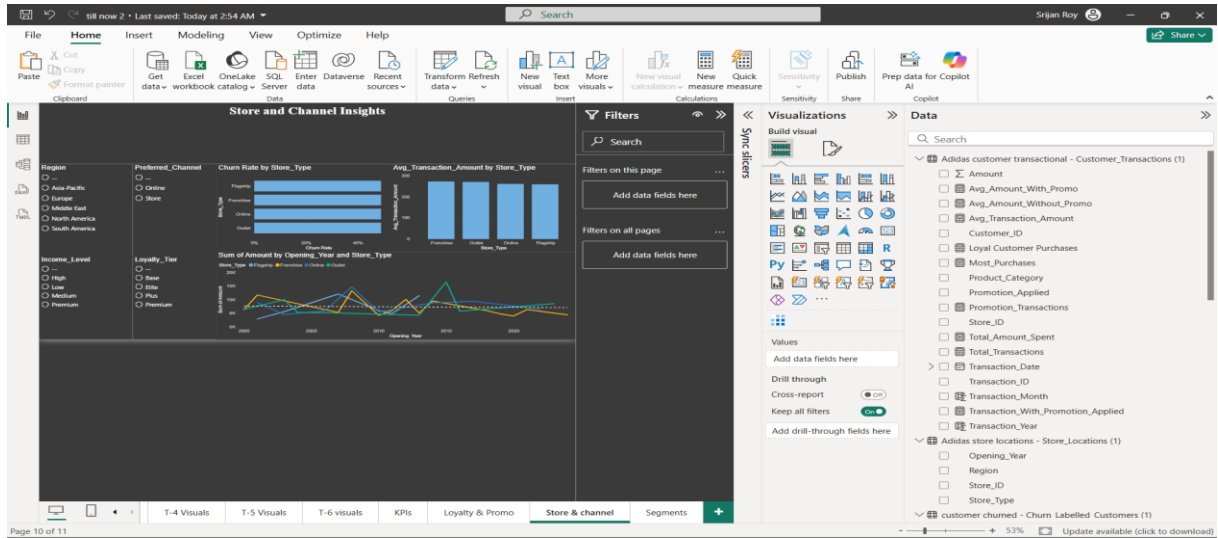
Page-1 KPIs



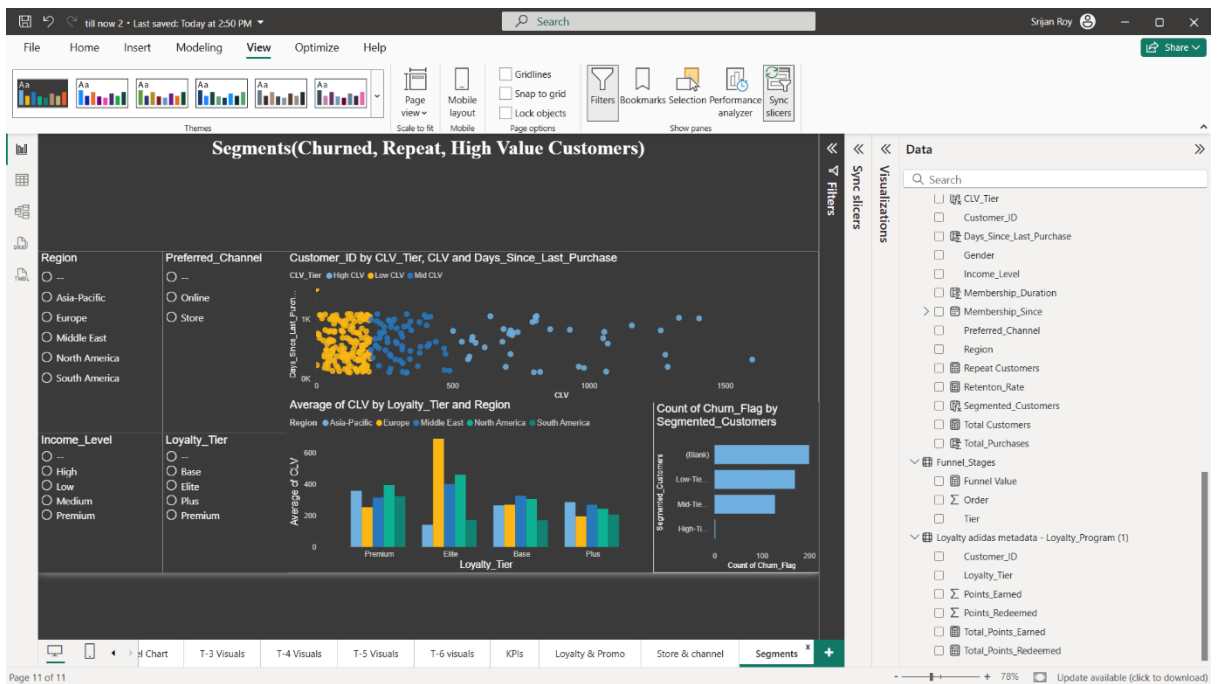
Page-2 Loyalty & Promotion Impact



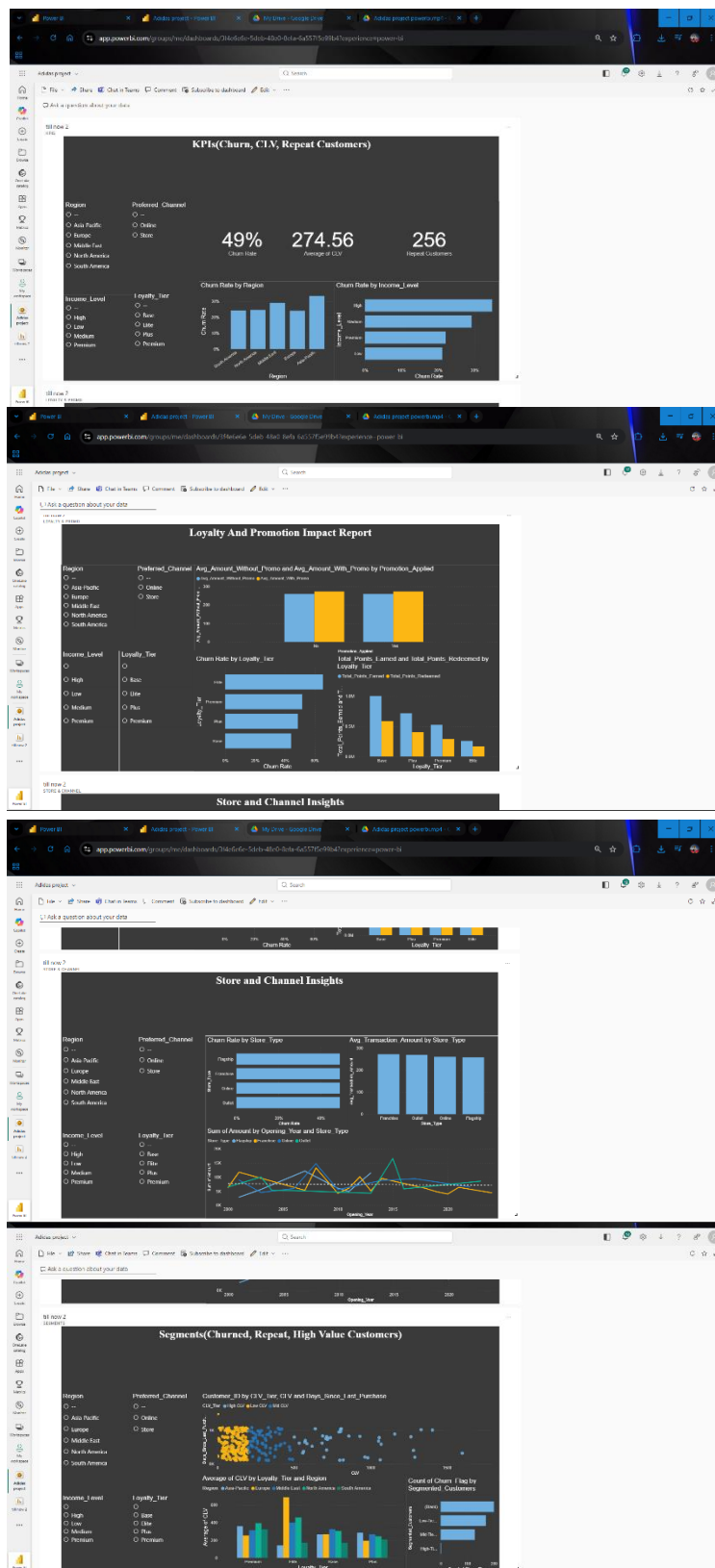
Page-3 Store/Channel Insights



Page-4 Segmentations (Churned, Repeat, High value customers)



Dashboard in power-bi service



Recommendations –

1. I'd suggest High CLV customers, High-Tier Loyalty members like Plus and premium ones, High tier customers as well as Mid tier customers with frequent purchases, customers churning due to competitor, inactivity or low engagement to prioritize for retention.
2. Franchise stores show highest average transaction amount. Online customers have higher volume with lower retention. Flagship stores show weakest performance as more people tend to buy online or other channels.
3. To strengthen loyalty programme – Make points more noticeable and viable to users as most users usually have unused points left, Make redemption easier and more friendlier whether it's online app optimisation or human interactions, Creating more opportunities like Exclusive tier base reward systems.

Task-8

Vid explanation link - <https://drive.google.com/file/d/1swrSr8m-xC6BPdvQNG0nq1xjK-w275KF/view?usp=sharing>