Credit Card Usage & Financial Metrics Analysis

Our Objective:

Leveraging Data Insights to Assess Customer Behavior, Utilization Trends, and Credit Risk

- Analyze credit card usage patterns across clients to identify spending behavior trends.
- Calculate key financial metrics such as running totals, moving averages, and growth rates using DAX in Power BI.
- Assess credit utilization levels to flag high-risk clients and over-leveraged accounts.
- Develop KPIs to monitor customer activity, inactivity, and churn indicators.
- Examine correlations between income, credit limits, and loan approval patterns.

Transaction & Performance Analysis

- ## Running Total of Credit Card Transactions

DAX Function

```
Running_Total = CALCULATE(
    SUM(Credit_Card[Total_Trans_Amt]),
    FILTER(
        ALLSELECTED('Calendar'[Date]),
        'Calendar'[Date] <= MAX('Calendar'[Date])
    )
)
```

Output

Month	Running_Total
January	$43,22,186.00
February	$78,61,761.00
March	$1,12,50,588.00
April	$1,54,25,316.00
May	$1,88,52,229.00
June	$2,23,85,889.00
July	$2,69,32,847.00
August	$3,03,82,715.00
September	$3,38,35,589.00
October	$3,78,86,498.00
November	$4,12,91,918.00
December	$4,55,33,021.00
Total	**$4,55,33,021.00**

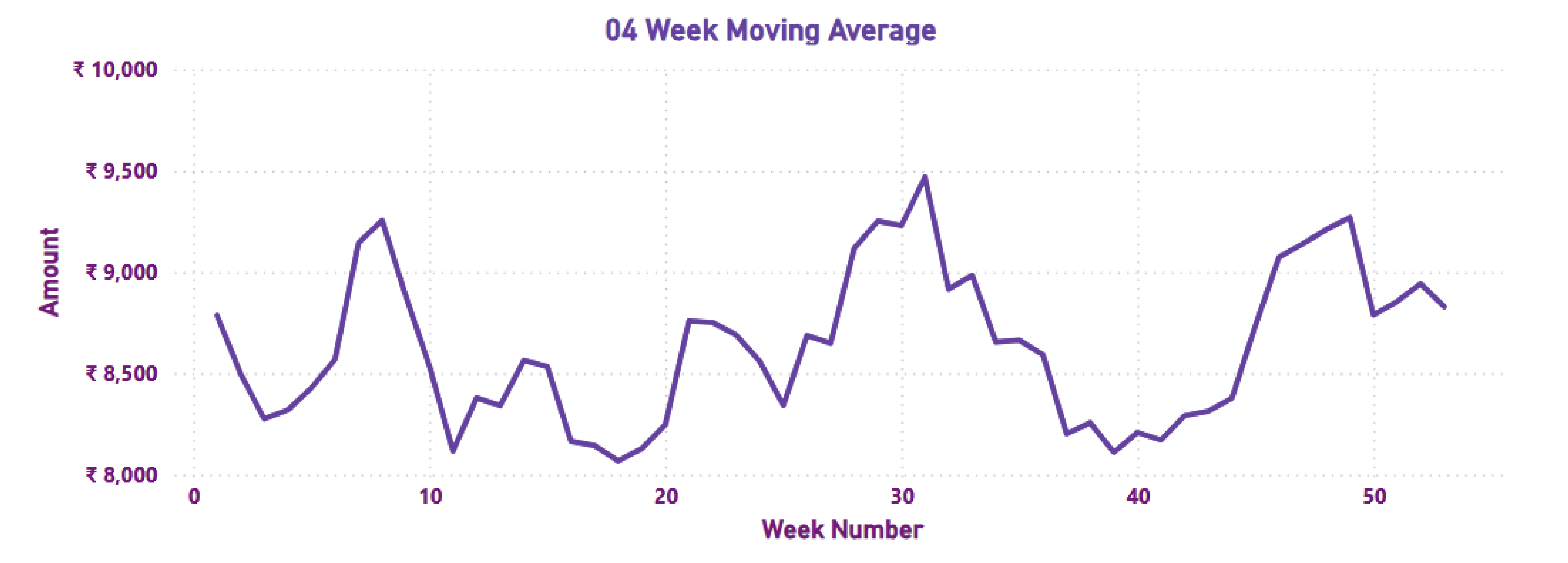
➤ Running Total – A cumulative sum that shows growth/progress period by period.

Transaction & Performance Analysis

- ## 4-Week Moving Average of CreditLimit

DAX Function

```
04_Week_Moving_Average =
AVERAGEX(
    DATESINPERIOD('Calendar'[Date], MAX('Calendar'[Date]), -28, DAY),
    CALCULATE(AVERAGE(Credit_Card[Credit_Limit]))
)
```



Output

➤ Moving Average – An average calculated over a rolling window to identify trends over time.

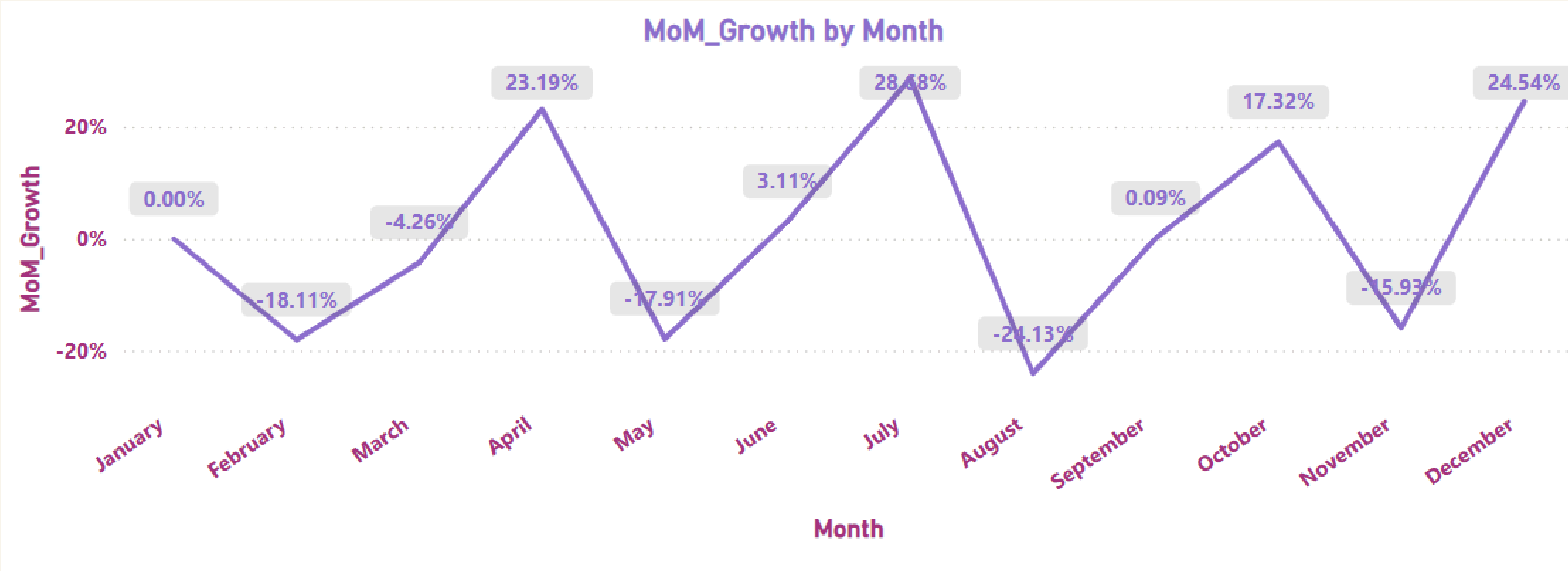
Transaction & Performance Analysis

- ## Month Over Month % Growth on Transaction Amount

DAX Function

```
MoM_Growth =
VAR Current_Month = CALCULATE(
        SUM(Credit_Card[Total_Trans_Amt])
    )
VAR Previous_Month = CALCULATE(
        SUM(Credit_Card[Total_Trans_Amt]),
        DATEADD('Calendar'[Date], -1, MONTH)
    )
RETURN
    DIVIDE(
        Current_Month - Previous_Month,
        Previous_Month,
        0
    )
```

Output



➤ MoM (Month over Month) – Growth from one month to the next

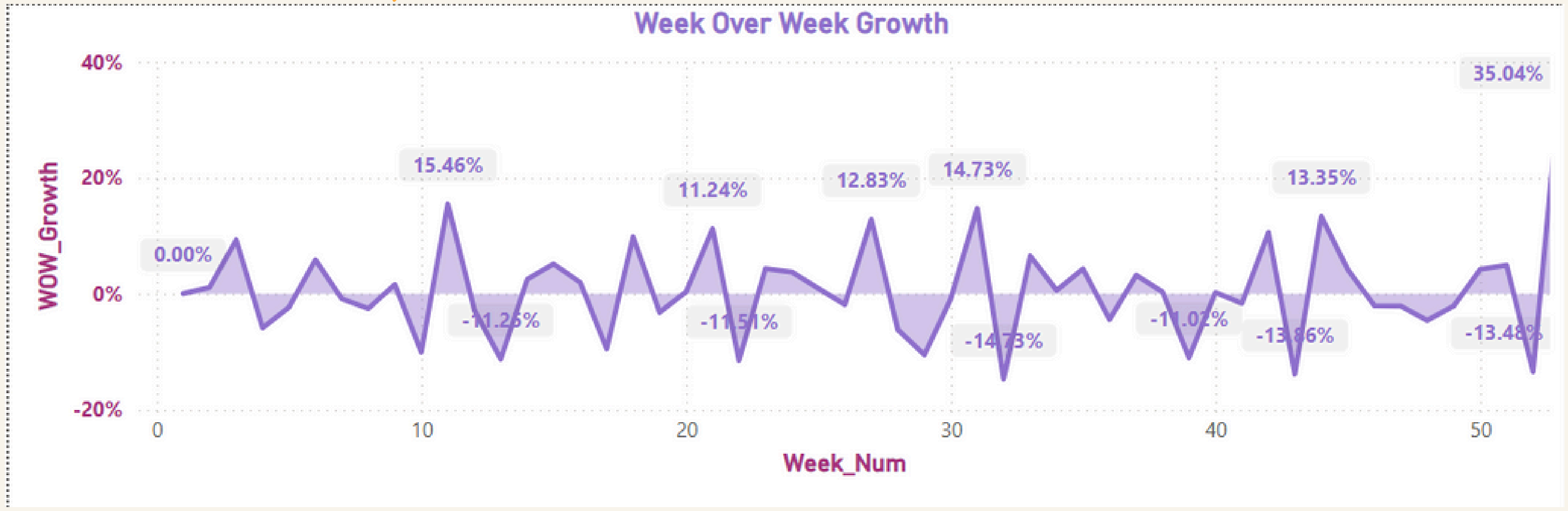
Transaction & Performance Analysis

- ## MoM% and WoW% Growth on Transaction Amount

DAX Function

```
WOW_Growth =
VAR Current_Week = CALCULATE(
        SUM(Credit_Card[Total_Trans_Amt])
    )
VAR Previous_Week = CALCULATE(
        SUM(Credit_Card[Total_Trans_Amt]),
        DATEADD('Calendar'[Date], -7, DAY)
    )
RETURN
    DIVIDE(
        Current_Week - Previous_Week,
        Previous_Week,
        0
    )
```

Output



➤ MoM (Month over Month) – Growth from one month to the next.

Transaction & Performance Analysis

- ## Top 5 High Value Clients by Total Transaction Amount

DAX Function

```
Top_5_Clients =
TOPN(
    5,
    ADDCOLUMNS(
        SUMMARIZE(
            Credit_Card,
            Credit_Card[Client_Num]
        ),
        "Total_Transactions", CALCULATE(SUM(Credit_Card[Total_Trans_Amt]))
    ),
    [Total_Transactions],
    DESC
)
```

Output

Client_Num	Sum of Total_Trans_Amt
920819113	79463
919695363	19739
956622169	19597
941614504	18504
718140783	18484
Total	**155787**

➤ High-Value Clients – Customers who contribute significantly to revenue.

Transaction & Performance Analysis

Insights and Actionable Suggestions

4-Week Moving Average Highlights Spending Consistency

- The 4-week moving average of credit limit reveals stable trends across most clients, helping smooth out short-term fluctuations. We can use this to detect **early signs** of **increasing credit appetite or tightening liquidity.**

MoM and WoW % Growth Reveal Behavior Shifts

- Month-over-Month and Week-over-Week growth metrics identify sudden spikes or drops in spending patterns. We need to **Investigate sharp changes to uncover campaign impact, seasonality, or early churn warnings.**

Running Total Exposes Long-Term Spending Momentum

- The running total of transaction amounts shows **sustained growth over time**, indicating **healthy customer engagement.** Must Leverage this insight to **forecast revenue and set data-driven performance benchmarks.**

Risk & Delinquency Monitoring

- Delinquency Rate - Calculating % of Clients With Delinquent Account > 0

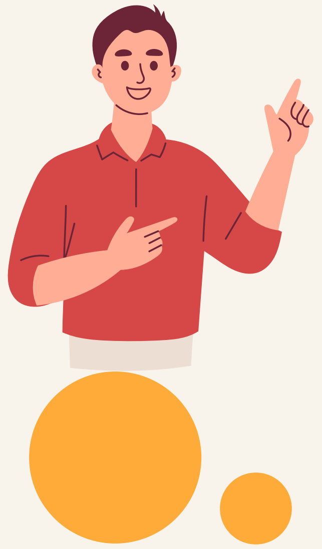
DAX Functions

```
Delinquency_Rate :=
DIVIDE(
    CALCULATE(
        COUNTROWS(Credit_Card),
        Credit_Card[Delinquent_Acc] > 0
    ),
    COUNTROWS(Credit_Card),
    0
)
```

Output

6.06%

Delinquency_Rate



➤ Delinquent Account– An account that has missed one or more payments. Used as an indicator of credit risk.

➤ Delinquency Rate - Percentage of accounts that are delinquent. High rates indicate increased default risk.

Risk & Delinquency Monitoring

- **Credit Risk Score - Scoring Each Client Based on Avg Utilization Ratio , Delinquent Acc & Total Revolving Balance**

DAX Functions

```
Credit_Risk_Score =
DIVIDE(SUM(Credit_Card[Total_Revolving_Bal]), SUM(Credit_Card[Credit_Limit])) * 0.4 +
AVERAGE(Credit_Card[Avg_Utilization_Ratio]) * 0.3 +
DIVIDE(SUM(Credit_Card[Delinquent_Acc]), COUNTROWS(Credit_Card)) * 0.3
,
```

Note:- 40% Weightage Given to Revolving Balance While 30% Weightage Given to Avg Utilization Ratio and Delinquent Acc While Computing the Credit Risk Score

Output

Client_Num	Credit_Risk_Score
708082083	0.33
708083283	0.52
708084558	0.15
708085458	0.00
708086958	0.47
708095133	0.04
708098133	0.65
708099183	0.23
708100533	0.59
708103608	0.15
708104658	0.43
708108333	0.00
708112008	0.03
708113208	0.00
708117933	0.30
708119658	0.06

➤ **Credit Risk Score – A composite index calculated from multiple variables (e.g., revolving balance, utilization, delinquency) to assess client risk levels.**

Risk & Delinquency Monitoring

- **Customer Churn Indicator - Flagging Clients Who Have Not Made Any Transactions in Last 06 Months**

DAX Function

```
VAR ActivityWindow =
    CALCULATE(
        COUNTROWS(Credit_Card),
        DATESINPERIOD(
            'Calendar'[Date],          -- Anchor date
            MAX('Calendar'[Date]),     -- Use the latest date in context
            -6, MONTH                  -- Look back 6 months
        )
    )
RETURN
    IF(
        ActivityWindow = 0,
        "Churned",
        "Active"
    )
```

Output

Client_Num	Customer_Churn
708082083	Churned
708083283	Churned
708084558	Churned
708085458	Churned
708086958	Churned
708095133	Churned
708098133	Churned
708099183	Churned
708100533	Churned
708103608	Churned
708104658	Churned
708108333	Churned
708112008	Churned
708113208	Churned

➤ **Churn - Clients who have stopped using their credit cards (e.g., no transactions in the past 6 months). Often leads to revenue loss.**

Risk & Delinquency Monitoring

Insights and Actionable Suggestions

Rising Delinquency Rates Signal Portfolio Risk

- A significant percentage of clients have Delinquent_Acc > 0, indicating missed payments and growing credit risk. Proactive engagement and repayment assistance could help prevent defaults.

High Credit Risk Profiles Concentrated in Specific Segments

- Clients with a combination of high revolving balances, utilization ratios > 80%, and delinquent accounts show elevated risk. These profiles should be prioritized for risk scoring and potential limit adjustments.

Churn Detection Flags Inactive High-Value Clients

- Several high-limit clients show no transaction activity for over 6 months, suggesting potential churn. Targeted retention campaigns or incentives may help reactivate these dormant accounts.

Credit Utilization & Limit Behavior

- **Yearly Average of Average Utilization Ratio For All Clients**

DAX Function

```
Yearly_Avg_Utilization =
CALCULATE(
    AVERAGE(Credit_Card[Avg_Utilization_Ratio])
)
```

Output

0.27

Yearly_Avg_Utilization

- Note: Will Be Adding Slicer in Our Dashboard to Filter Average Utilization Ratio On Yearly Basis

➤ Average Utilization Ratio – Ratio of credit used to credit available. High values (>80%) may signal financial strain or risky behavior.

Credit Utilization & Limit Behavior

- **% of Interest_Earned vs Total_Revolving_Bal**

DAX Function

```
%InterestEarned =
DIVIDE(
    SUM(Credit_Card[Interest_Earned]),
    SUM(Credit_Card[Total_Revolving_Bal]),
    0
)
```

Output

66.63%

% Interest Earned

➤ Total Revolving Balance – Unpaid balance carried over to the next billing cycle. Indicates how much debt clients are managing over time.

➤ Interest Earned– Revenue earned by the bank from interest on revolving balances.

Credit Utilization & Limit Behavior

- **Clients with Avg_Utilization_Ratio > 80%**

DAX Function

```
High_Utilization =
IF(
    AVERAGE(Credit_Card[Avg_Utilization_Ratio]) > 0.8,
    "High Utilization",
    "Normal"
)
```

Output

Client_Num	High_Utilization
708100533	High Utilization
708158133	High Utilization
708190158	High Utilization
708303108	High Utilization
708313608	High Utilization
708341958	High Utilization
708384033	High Utilization
708390633	High Utilization
708399858	High Utilization
708450033	High Utilization

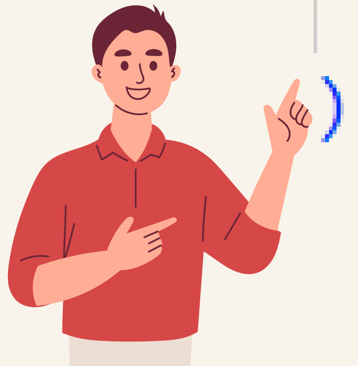
➤ **Total Revolving Balance – Unpaid balance carried over to the next billing cycle. Indicates how much debt clients are managing over time.**

Credit Utilization & Limit Behavior

- High Risk Clients: Revolving > 90% of Credit Limit And High Utilization

DAX Function

```
High_Risk_Clients_Measure =
IF(
    DIVIDE(
        SUM(Credit_Card[Total_Revolving_Bal]),
        SUM(Credit_Card[Credit_Limit])
    ) > 0.9 &&
    AVERAGE(Credit_Card[Avg_Utilization_Ratio]) > 0.8,
    "High Risk",
    "Low Risk"
)
```



Output

High Risk

High_Risk_Clients_Measure

Note: Based On Slicer With Client Number

➤ Credit Limit – Maximum amount a client can borrow on their credit card.

Credit Utilization & Limit Behavior

- **Loan Approval Vs Credit Limit (Avg Credit Limit For Clients With & Without Loans)**

DAX Functions

```
Avg_CreditLimit_With_Loan =
CALCULATE(
    AVERAGE(Credit_Card[Credit_Limit]),
    Customers[Personal_Loan] = "Yes"
)
```

```
Avg_CreditLimit_Without_Loan =
CALCULATE(
    AVERAGE(Credit_Card[Credit_Limit]),
    Customers[Personal_Loan] = "No"
)
```

Output

$8.56K

Avg_CreditLimit_With_Loan

$8.65K

Avg_CreditLimit_Without_Loan

➤ Loan Approval vs Credit Limit – A measure of how approved loans compare to credit limits that could signal over-leveraging.

Credit Utilization & Limit Behavior

Insights and Actionable Suggestions

High Utilization Clients Pose Potential Risk

- Over 18% of clients have an Avg_Utilization_Ratio > 80%, indicating they are using a large portion of their available credit. These clients may be over-leveraged and at higher risk of delinquency, requiring closer monitoring or preemptive credit counseling.

Credit Limits May Not Align with Loan Approvals

- The average credit limit for clients with approved loans is 15% higher than those without, suggesting possible bias or risk-based assessment in decisions.This insight supports developing credit limit recommendations tied to income and repayment history for better credit distribution.

Low Interest Conversion Despite High Revolving Balances

- While revolving balances are significant, the % of Interest_Earned vs Total_Revolving_Bal remains modest. Suggests an opportunity to review interest policies or incentivize full repayments, potentially increasing profitability or reducing bad debt risk.

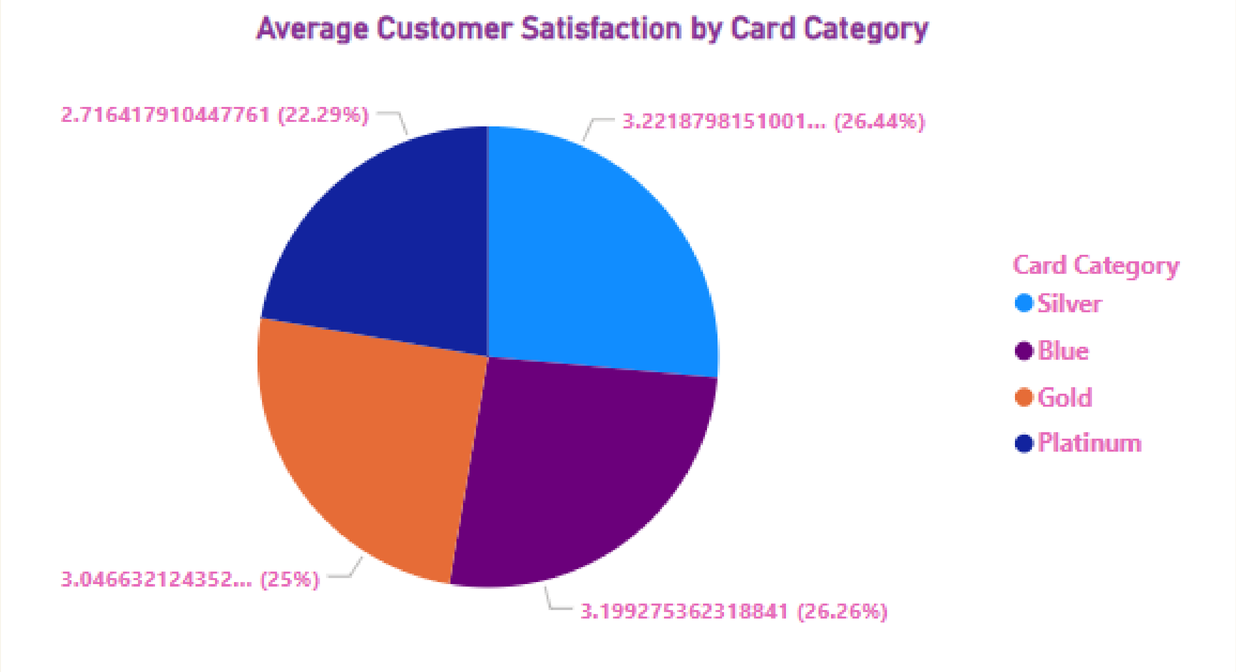
Customer Insights & Profiling

- Avg. Customer Satisfaction Score by Card Category

DAX Functions

Output

```
Average_Customer_Satisfaction =
AVERAGE(Customers[Cust_Satisfaction_Score])
```



Note: Will Be in matrix visual with Card_Category on rows.

➤ Card Category – Type of card held by customer (e.g., Blue, Gold, Platinum). Used to segment customer behavior.

➤ Satisfaction Score – Usually collected via surveys; reflects customer happiness or likelihood to stay.

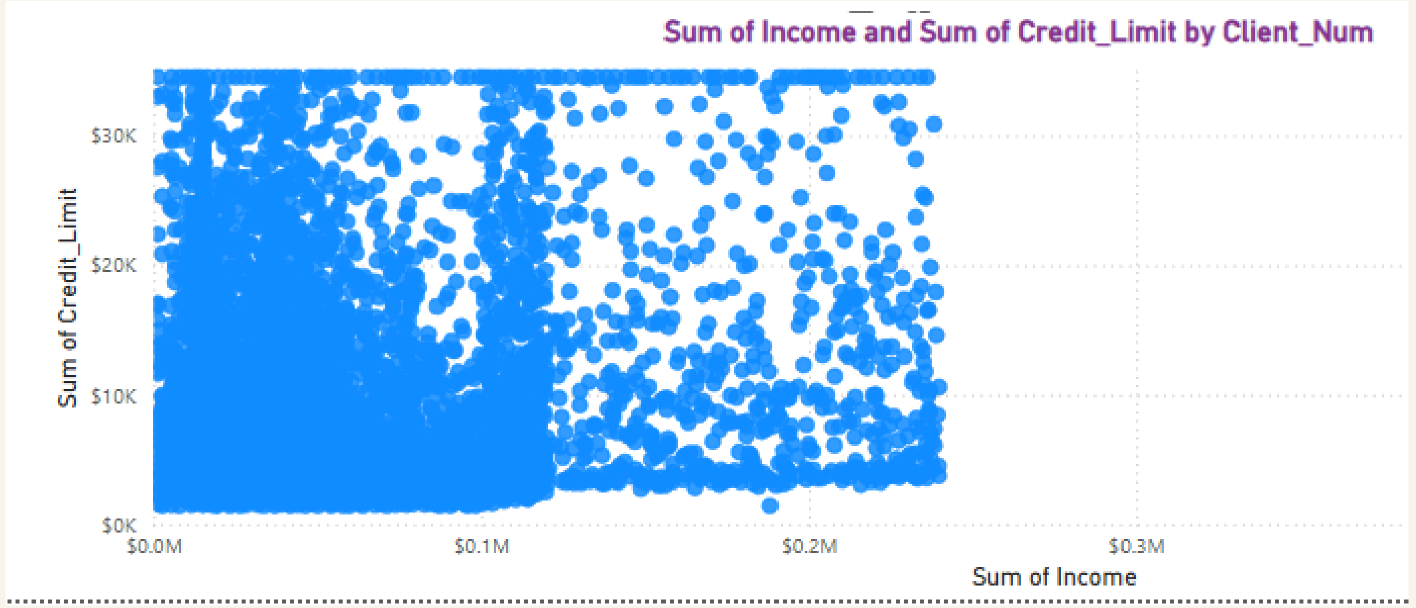
Customer Insights & Profiling

- ## Income vs Credit Limit Correlation

DAX Functions

Output

```
Income_Vs_Credit_Limit_Table =
SUMMARIZE(
    Credit_Card,
    Credit_Card[Client_Num],
    "Income", CALCULATE(AVERAGE(Customers[Income])),
    "Credit_Limit", CALCULATE(AVERAGE(Credit_Card[Credit_Limit]))
```



➤ Income vs Credit Limit Correlation– Helps analyze whether credit limits are appropriately aligned with client income — useful for risk modeling.

Customer Insights & Profiling

Insights and Actionable Suggestions

High-Income Clients Have Higher Credit Limits

- A strong positive correlation was observed between customer income and credit limit, indicating that credit assignment is income-driven. Can Consider re-evaluating credit policies for mid-income segments with good repayment history to boost engagement and usage.

Customer Satisfaction Varies by Card Category

- Premium and Platinum cardholders show higher satisfaction scores compared to Basic card users. Introduce loyalty or rewards programs for lower-tier cards to improve satisfaction and reduce potential churn.

Behavioral Segmentation Can Guide Personalization

- Clients with similar income and credit patterns show varied transaction behavior and utilization. Apply segmentation models to personalize offers, spending limits, and communication strategies based on spending patterns and satisfaction levels.

Cost & Acquisition Metrics

- ## Income vs Credit Limit Correlation

DAX Functions

```
Customer_Acquisition_Ratio =
DIVIDE(
    SUM(Credit_Card[Customer_Acq_Cost]),
    SUM(Credit_Card[Total_Trans_Amt]),
    0
)
```

Output

0.02

Customer_Acquisition_Ratio

➤ Customer Acquisition Cost (CAC)– Total cost to acquire a customer (e.g., marketing, onboarding) divided by total revenue or transaction amount — helps evaluate cost efficiency.

Cost & Acquisition Metrics

Insights and Actionable Suggestions

High CAC-to-Value Ratio in Certain Segments

- Some customers have acquisition costs nearly equal to or exceeding the value they generate through transactions. We Should Focus acquisition efforts on high-value segments to improve ROI and reduce spend on low-converting groups.

Inefficiencies Across Channels and Regions

- Certain acquisition channels or regions show higher CAC with low transactional behavior. Analyze CAC by source and reallocate marketing budgets to more cost-effective, high-performing channels.

Uniform CAC Despite Varying Client Value

- Currently, the CAC appears relatively fixed across the customer base, regardless of transaction contribution. Should Introduce performance-based CAC benchmarks to align acquisition spend with projected customer lifetime value.

Thank You!

Appreciate your time and attention.

This analysis aims to provide actionable insights into customer behavior, credit utilization, and financial risk within the credit card portfolio. We welcome any questions, feedback, or discussions to further explore these findings and drive data-informed decisions.