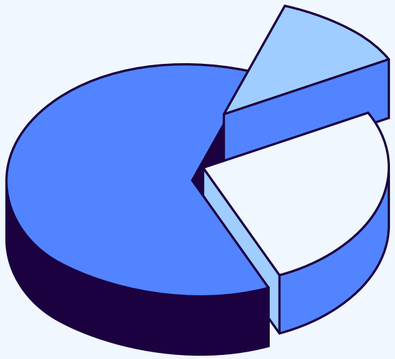
Financial Analysis using DAX Queries



by – Vikram Jakhar

Introduction

You are a Financial Data Analyst tasked with analyzing credit card usage and financial metrics for a banking institution. Using the provided data, you will create reports in Power BI by applying DAX functions. Your goal is to calculate financial metrics like running totals, moving averages, and growth rates, and generate KPIs that assess customer behavior, credit utilization, and delinquency risk. The analysis will provide key insights for improving customer retention and financial performance.

Problem Statement

- Running Total of Credit Card Transactions
- Calculate the 4-week moving average of the creditLimit for each client.
- Calculate the mom% growth and wow% growth on transaction amount.
- Calculate Customer Acquisition Cost (CAC) as a Ratio of Transaction Amount.
- Calculate the yearly average of avg_utilization_ratio for all clients.
- Calculate the percentage of Interest_Earned compared to Total_Revolving_Bal for each client.
- Calculate Top 5 Clients by Total Transaction Amount.
- Identify clients whose Avg_Utilization_Ratio exceeds 80%.
- Customer Churn Indicator: Create a KPI that flags clients who have not made any transactions (Total_Trans_Amt = 0) in the last 6 months.

- Delinquency Rate: Calculate the percentage of clients with Delinquent_Acc > 0.
- Credit Risk Score: Create a score for each client based on their Avg_Utilization_Ratio, Delinquent_Acc, and Total_Revolving_Bal.
- Income vs Credit Limit Correlation: Show the correlation between Income and Credit_Limit for all clients.
- Average Customer Satisfaction Score by Credit Card Category: Calculate the average Cust_Satisfaction_Score by Card_Category.
- Loan Approval vs Credit Limit: Analyze how Credit_Limit affects Personal_loan approval by calculating the average credit limit for clients with and without loans.
- High Risk Clients Flag: Create a flag for clients whose Total_Revolving_Bal exceeds 90% of their Credit_Limit and who have a high Avg_Utilization_Ratio.

DataSet Overview

DataSet Link

- This analysis consists **Credit_card** and **Customer** as separate tables in this data-set, which will be used to analyze Credit's Customer behavior , potential risk factors.

Credit_card

Key columns :

- Credit_Limit
- Total_Revolving_Bal
- Avg_Utilization_ratio
- Interest_Earned

Objectives :

- Tracking spending habits
- Credit utilization
- **To avoid risk factors (Delinquent acc)**

Customer

Key columns :

- Personal_loan
- Customer_Job
- Income
- Cus_satisfication_Score

Objectives :

- Overall Consumer Satisfication
- Potential_Churn
- **Forming better policies**

Transication & performace analysis

- Running Of Credit Card Transications

Dax Function

```
1 Running_total =
2 CALCULATE([total_Transction_amount]
3 ,FILTER(ALL(Credit_card),
4 Credit_card[Week_Start_Date]
5 <= MAX(Credit_card[Week_Start_Date])))
```

Output

Month	Sum of Total_Trans_Amt	Running_total
January	$4,322,186	$4,322,186
February	$3,539,575	$7,861,761
March	$3,388,827	$11,250,588
April	$4,174,728	$15,425,316
May	$3,426,913	$18,852,229
June	$3,533,660	$22,385,889
July	$4,546,958	$26,932,847
August	$3,449,868	$30,382,715
September	$3,452,874	$33,835,589
October	$4,050,909	$37,886,498
November	$3,405,420	$41,291,918
December	$4,241,103	$45,533,021
Total	**$45,533,021**	**$45,533,021**

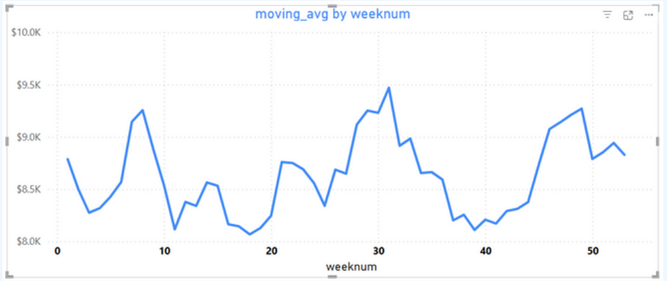
Running_Total :-The running total shows the cumulative amount spent on credit card transactions over time. It helps track how expenses are building up daily/monthly and identify spending trends.

Transication & performace analysis

- Calculate the 4-week moving average of the creditLimit for each client.

Dax Function

```
1 moving_avg =
2 AVERAGEX(DATESINPERIOD(Calender[Date],
3 MAX(Calender[Date]),-28,DAY),
4 CALCULATE(AVERAGE(Credit_card[Credit_Limit])))
```



Output

weeknum	moving_avg
1	$8,786.78
2	$8,498.42
3	$8,274.87
4	$8,318.39
5	$8,427.64
6	$8,568.25
7	$9,144.98
8	$9,254.75
9	$8,881.51
10	$8,536.63
11	$8,116.17
12	$8,377.95
13	$8,339.87
14	$8,563.55
15	$8,532.71
16	$8,164.81
17	$8,143.94
18	$8,067.50
19	$8,128.38

4_week moving _average:- This measure helps identify weekly trends in clients' credit limits over the past 4 weeks, allowing better risk analysis and credit behavior tracking.

Transication & performace analysis

- Calculate the mom% growth growth on transaction amount.

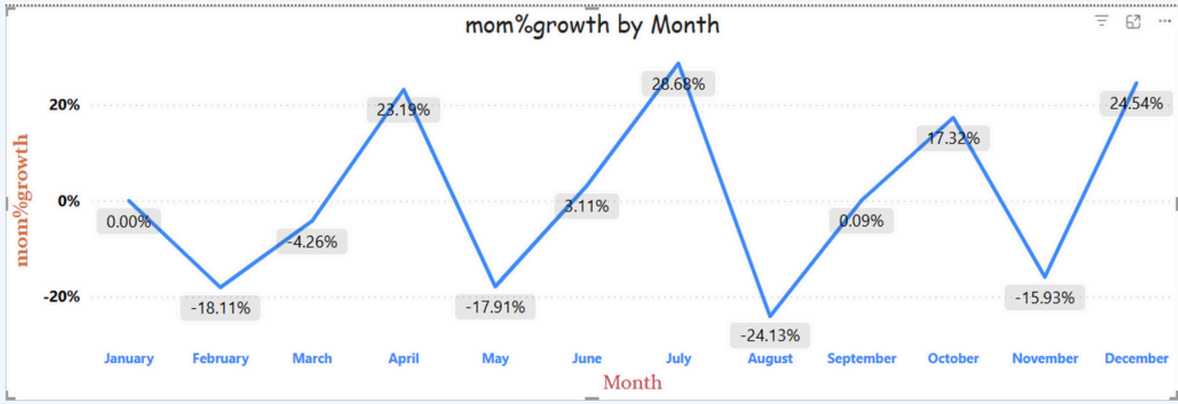
Dax Function

```
1 mom%growth =
2 var growth = CALCULATE([total_Transction_amount],
3 DATEADD(Calender[Date],-1,MONTH))
4 RETURN DIVIDE([total_Transction_amount]-growth,growth,0)
```

Output

Month	mom%growth	total_Transction_amount
January	0.00%	$4,322,186
February	-18.11%	$3,539,575
March	-4.26%	$3,388,827
April	23.19%	$4,174,728
May	-17.91%	$3,426,913
June	3.11%	$3,533,660
July	28.68%	$4,546,958
August	-24.13%	$3,449,868
September	0.09%	$3,452,874
October	17.32%	$4,050,909
November	-15.93%	$3,405,420
December	24.54%	$4,241,103
Total	**10.27%**	**$45,533,021**

MOM Growth:- MoM change in transaction amount shows monthly client spending trends, helping identify growth, decline, or anomalies in credit card usage.



Transication & performace analysis

- Calculate the wow% growth growth on transaction amount.

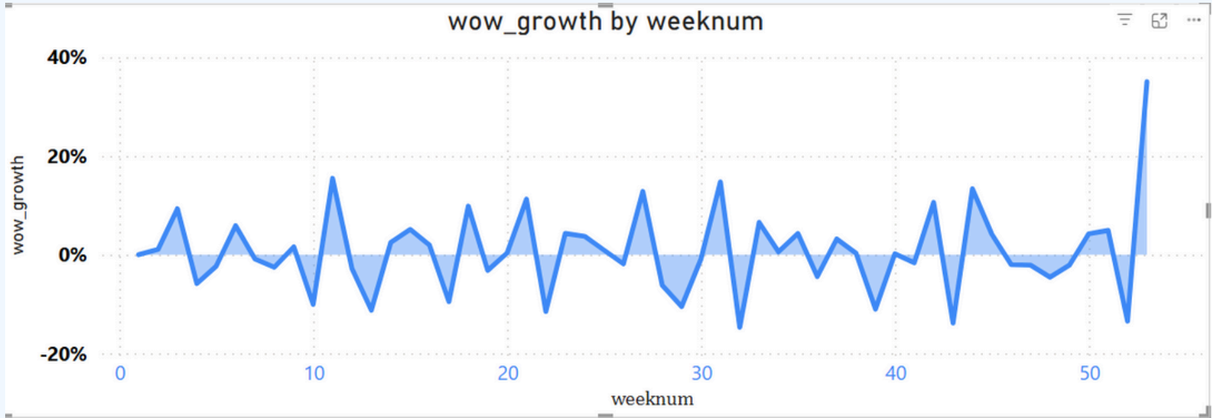
Dax Function

```
1 wow_growth =
2 var growth = CALCULATE([total_Transction_amount],
3 FILTER(ALLSELECTED(Calender),Calender[weeknum] =
4 MAX(Calender[weeknum])-1))
5 RETURN DIVIDE([total_Transction_amount]
6 -growth,growth,0)
```

Output

weeknum	wow_growth	total_Transction_amount
1	0.00%	$835,767
2	1.07%	$844,739
3	9.31%	$923,367
4	-5.86%	$869,235
5	-2.32%	$849,078
6	5.86%	$898,867
7	-0.90%	$890,756
8	-2.54%	$868,091
9	1.59%	$881,861
10	-10.07%	$793,080
11	15.46%	$915,725
12	-2.80%	$890,081

WOW Growth:- WoW change in transaction amount tracks weekly fluctuations in client spending, helping spot sudden surges, drops, or stable patterns.



Transication & performace analysis

- Calculate Top 5 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_transactions
718140783	$18,484
919695363	$19,739
920819113	$79,463
941614504	$18,504
956622169	$19,597
Total	$155,787

Top Clients :- High-value transactions are concentrated among the top these clients, showing dependency on a small client base.
Strategic engagement with them is crucial to maintain revenue stability.

Transication & performace 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.

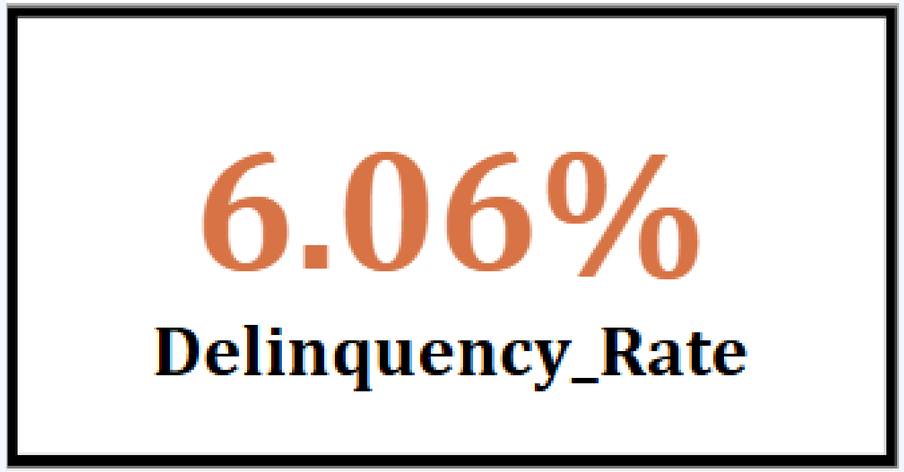
Risk & Delinquency Monitoring

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

Dax Function

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

Output



Delinquency Account :- Out of all credit card accounts, 6.06% are currently delinquent, indicating a moderate level of payment default. This suggests that around 6 out of every 100 users are not paying their dues on time, which may pose a potential risk to financial stability if not monitored closely.

Risk & Delinquency Monitoring

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

Dax Function

```
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
```

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

Credit_Risk_score :- We evaluated the credit risk of each client based on their Total Revolving Balance, Credit Limit, Average Utilization Ratio, and Delinquent Accounts. Using a weighted scoring model (40%-30%-30%)

Risk & Delinquency Monitoring

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

Dax Function

```
Churn_customer =
VAR Activity_window =
    CALCULATE(
        COUNTROWS(Credit_card),
        DATESINPERIOD(
            Calender[Date],
            MAX(Calender[Date]),
            -6,
            MONTH
        )
    )
RETURN
    IF(
        Activity_window = 0,
        "Churned",
        "Active"
    )
```

Output

Client_Num	Churn_customer
708082083	Churned
708083283	Churned
708084558	Churned
708085458	Churned
708086958	Churned
708095133	Churned
708098133	Churned
708099183	Churned
708100533	Churned
708103608	Churned

Churn_Customer :- We analyzed customer activity over the past 6 months to identify churned customers — i.e., those who have not made any transactions during this period.

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.

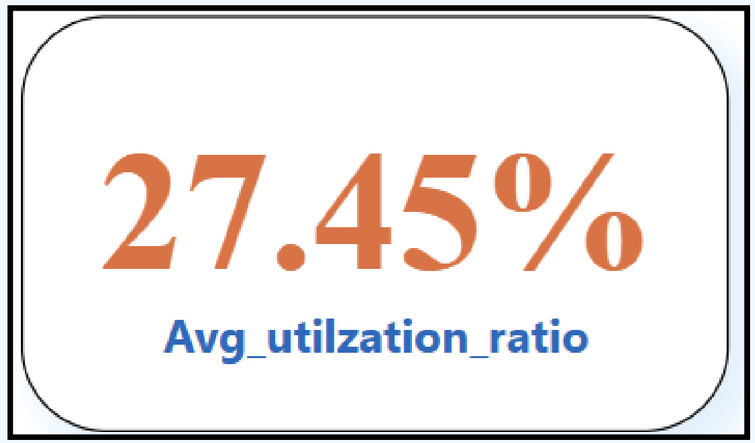
Credit Utilization & Limit Behavior

- Yearly Average of Average Utilization Ratio For All Clients

Dax Function

```
1 Yearly_Avg_utilization =
2 CALCULATE(
3     AVERAGE(Credit_card[Avg_Utilization_Ratio]),
4     VALUES('Calender'[Year])
5 )
6
```

Output



Yearly_Average_utilization :- The average credit utilization ratio has been tracked on a yearly basis to understand how customers are using their credit limits over time.

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

Credit Utilization & Limit Behavior

- % of Interest_Earned vs Total_Revolving_Bal

Dax Function

```
1 Interest_Earned_by_Rev_Bal =
2 DIVIDE(
3     SUM(Credit_card[Interest_Earned]),
4     SUM(Credit_card[Total_Revolving_Bal])
5 )
```

Output

Interest _Earned :- The bank earned interest equivalent to 66.63% of the total revolving balance, which reflects a strong interest yield performance

Credit Utilization & Limit Behavior

- Clients with Avg_Utilization_Ratio > 80%

Dax Function

```
1 High_utilization =
2 IF(
3     AVERAGE(Credit_card[Avg_Utilization_Ratio])
      > 0.8,
4     "High_utilization",
5     "Normal"
6 )
```

Output

Client_Num	High_utilization
708171858	Normal
708173433	Normal
708174708	Normal
708176208	Normal
708177333	Normal
708178608	Normal
708185208	Normal
708186933	Normal
708190158	High_utilization
708193008	Normal
708195633	Normal

Avg_Utilization_Ratio:- We identified customers with an average credit utilization ratio above 80% as high utilization clients. These individuals are heavily reliant on their credit limits, which may indicate financial stress or over-leveraging.

Credit Utilization & Limit Behavior

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

Dax Function

```
Avg_credit_limit_without_loan =
CALCULATE(
    AVERAGE(Credit_card[Credit_Limit]),
    Customer[Personal_loan] = "No"
)
```

```
Avg_credit_limit_without_loan =
CALCULATE(
    AVERAGE(Credit_card[Credit_Limit]),
    Customer[Personal_loan] = "Yes"
)
```

Output

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

Credit Utilization & Limit Behavior

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

Dax Function

```
High_risk_client_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

Note :- Based On Slicer With Client Number

Credit_Limit :- **These clients are heavily reliant on credit and may be close to maxing out their available limit.**

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.

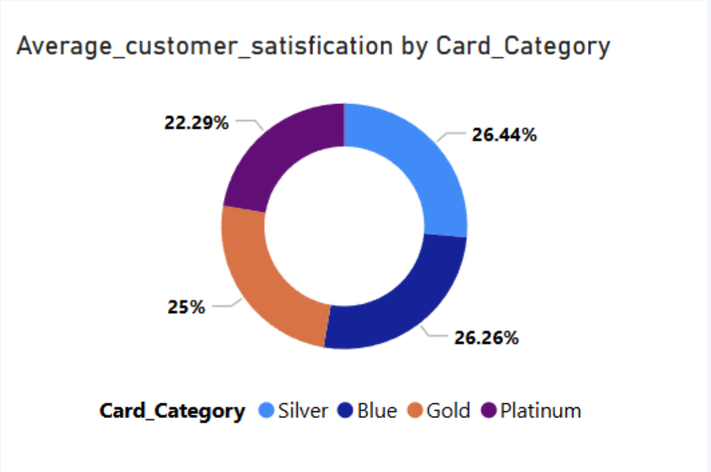
Customer Insights & Profiling

- Avg. Customer Satisfaction Score by Card Category

Dax Function

```
1 Average_customer_satisficatio
2 AVERAGE(Customer
3 [Cust_Satisfaction_Score])
```

Output



Credit_Limit :- These clients are heavily reliant on credit and may be close to maxing out their available limit.

Customer Insights & Profiling

- Calculate Customer Acquisition Cost (CAC) as a Ratio of Transaction Amount.

Dax Function

```
1 Customer_Acquisition_Ratio =
2 DIVIDE(
3     SUM(Credit_card[Customer_Acq_Cost]),
4     SUM(Credit_card[Total_Trans_Amt]),
5     0
6 )
```

Output

Calculate_Customer_Acquisition :- A low ratio like 0.02 implies that the cost of acquiring customers is well justified by their transaction activity.

Customer Insights & Profiling

Insights and Actionable Suggestions

Customer Satisfaction Varies by Card Category

- Focused improvements in services for Platinum users could lead to better retention of high-value clients. Conduct deeper analysis (like feedback sentiment) to understand their pain points

- The Platinum card category shows a slightly lower satisfaction (22.29%), which may suggest higher expectations from premium customers are not being fully met.

Efficiency of Customer Acquisition Strategy

- A low Customer Acquisition Ratio of 0.02 indicates that the cost of acquiring customers is very low compared to their transaction volume, highlighting a highly efficient and profitable acquisition strategy.
- This low ratio suggests that the customer acquisition cost is minimal compared to how much customers transact, indicating a strong return on investment (ROI) in acquisition efforts.

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.

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