Case on Banking Loan Risk (Dashboard)

I'll keep **simple English**, clear structure, and **business storytelling**

Project :- Loan Risk & Churn Analysis

Achieved

"Built an end-to-end loan risk and churn analytics solution using Python, MySQL, and Power BI, identifying 13% high-risk customers and delivering actionable insights through a 6-page executive dashboard."

End-to-End Data Analytics Project (Jupyter Notebook→ MySQL → Power BI)

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1. Problem Statement

Banks face significant financial losses due to **loan defaults and customer churn**.
While most customers repay loans responsibly, a **small group of high-risk customers** can create **disproportionate risk** for the organization.

The key challenges addressed in this project are:

- Identifying **high-risk loan customers**
- Understanding **why customers churn or default**
- Segmenting customers into **Low, Medium, and High Risk**
- Presenting insights clearly to **non-technical stakeholders**
- Supporting **data-driven decision making** using dashboards

This project aims to build a **data-driven loan risk and churn monitoring system** using Python, SQL, and Power BI.

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2. **Objective (WHAT you want to achieve)**

To analyze customer financial behavior, build a loan risk model, and identify high-risk churn customers using data analytics and Power BI.

Created by :- Sandeep Kumar Singh

Thought Process and Approach :-

- First of all , after get to know the issue/problem then starts to find the solution/goal.
  set the goals (what to achieve ?).
- Find /gather or collecting the data from different sources.
- Once , collected the data then create a new relational database in MySQL ,
- By using connector and SQL alchemy ,import engine to extract the Raw data (tables) from MySQL to Jupyter Notebook.
- Then start normalize the raw data (after data cleaning),
- Next, do all EDA(Exploratory data analysis) like perform all necessary step which is required for this project like creating or adding new columns , feature engineering etc.
- After this all extract the new and cleaned table into the MySQL database for dashboard creation in Power BI.

<u>I'll describe in brief , and step by step</u>

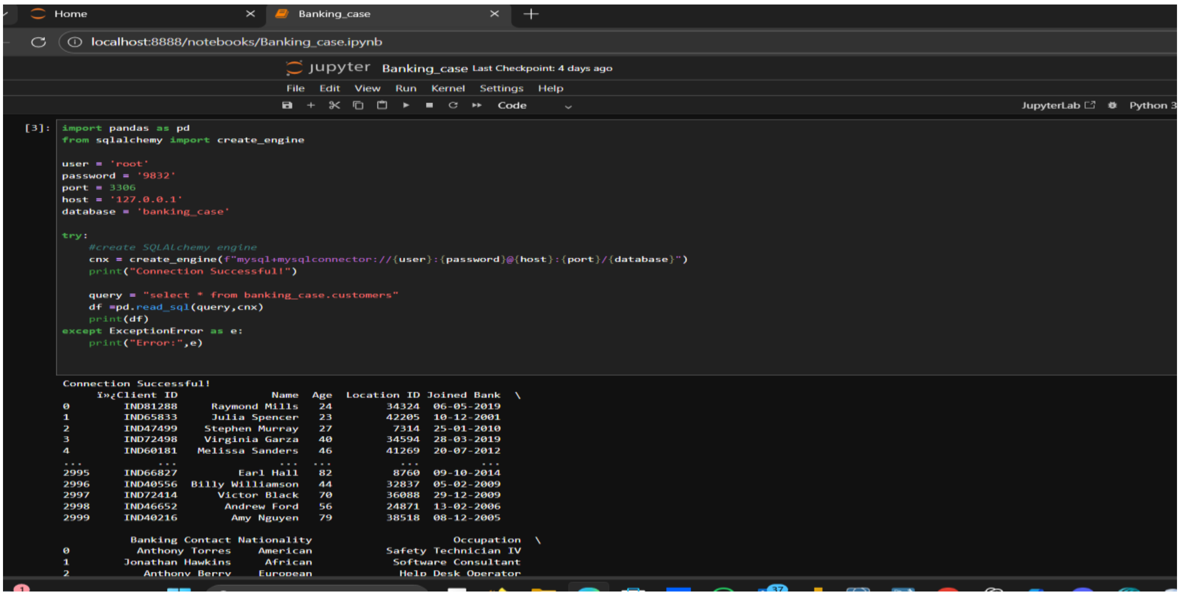
1. **About Dataset (Dataset Overview) –**

This dataset basically contains information about bank details ,various client details which consists of multiple tables which are interlinked with each other through keys like primary key and foreign key.

The various tables are Banking Relationship, Client-Banking, Gender, Investment Advisor and Period.

The dataset contains **3,000 banking customers** with financial and behavioral attributes.

The data represents a **typical retail banking portfolio**.



```
[3000 rows x 25 columns]
[5]: df.head(5)
[5]:
```

	ï»¿Client ID	Name	Age	Location ID	Joined Bank	Banking Contact	Nationality	Occupation	Fee Structure	Loyalty Classification	...	Bank Deposits	Checking Accounts	Saving Accounts	Foreign Currency Account	Business Lending	Properties Owned	Risk Weighting	BRId	GenderId	IAId
0	IND81288	Raymond Mills	24	34324	06-05-2019	Anthony Torres	American	Safety Technician IV	High	Jade	...	1485828.64	603617.88	607332.46	12249.96	1134475.30	1	2	1	1	1
1	IND65833	Julia Spencer	23	42205	10-12-2001	Jonathan Hawkins	African	Software Consultant	High	Jade	...	641482.79	229521.37	344635.16	61162.31	2000526.10	1	3	2	1	2
2	IND47499	Stephen Murray	27	7314	25-01-2010	Anthony Berry	European	Help Desk Operator	High	Gold	...	1033401.59	652674.69	203054.35	79071.78	548137.58	1	3	3	2	3
3	IND72498	Virginia Garza	40	34594	28-03-2019	Steve Diaz	American	Geologist II	Mid	Silver	...	1048157.49	1048157.49	234685.02	57513.65	1148402.29	0	4	4	1	4
4	IND60181	Melissa Sanders	46	41269	20-07-2012	Shawn Long	American	Assistant Professor	Mid	Platinum	...	487782.53	446644.25	128351.45	30012.14	1674412.12	0	3	1	2	5

5 rows × 25 columns

2. **Project Architecture (End-to-End Flow)**

This project follows a **real-world analytics workflow**:

1. **Data Processing & Feature Engineering**
   → Jupyter Notebook (Python)

2. **Data Storage & Aggregation**
   → MySQL Database

3. **Business Intelligence & Visualization**
   → Power BI Dashboard (6 Pages)

This architecture reflects how analytics projects are executed in **actual banking and financial organizations**.

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4. **Data Preparation & Feature Engineering (Jupyter Notebook)**

4.1 Data Cleaning

- Checked for missing values
- Verified numeric scales
- Normalized ratios (e.g., debt-to-income)
- Ensured consistency across financial variable
- Eleminate outliers

Home | Banking_case

localhost:8888/notebooks/Banking_case.ipynb

jupyter Banking_case Last Checkpoint: 4 days ago

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Code

Start to do the proper Data Cleaning

[9]:
```python
#standardize column names:-
#why:- lowercase + underscore avoids spaces/Unicode issues and is easiest to remember.
#Using single rule avoids typos.
df.columns = df.columns.str.strip().str.lower().str.replace("[^0-9a-z_]","",regex=True)


# to clean all white spaces of the value from each and every columns

for i in df.select_dtypes(include = ['object']).columns:
    df[i] = df[i].astype(str).str.strip()
df.info()
df.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 25 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   client_id                3000 non-null   object
 1   name                     3000 non-null   object
 2   age                      3000 non-null   int64
 3   location_id              3000 non-null   int64
 4   joined_bank              3000 non-null   object
 5   banking_contact          3000 non-null   object
 6   nationality              3000 non-null   object
 7   occupation               3000 non-null   object
 8   fee_structure            3000 non-null   object
 9   loyalty_classification   3000 non-null   object
 10  estimated_income         3000 non-null   float64
 11  superannuation_savings   3000 non-null   float64
 12  amount_of_credit_cards   3000 non-null   int64
 13  credit_card_balance      3000 non-null   float64
 14  bank_loans               3000 non-null   float64
 15  bank_deposits            3000 non-null   float64
 16  checking_accounts        3000 non-null   float64
 17  saving_accounts          3000 non-null   float64
 18  foreign_currency_account 3000 non-null   float64
 19  business_lending         3000 non-null   float64
```

[4]:
```python
df.rename(columns={df.columns[0]:"Client ID"},inplace=True)          #it is used to rename the first column name it was wrong
df.head(5)
```

[4]:

	Client ID	Name	Age	Location ID	Joined Bank	Banking Contact	Nationality	Occupation	Fee Structure	Loyalty Classification	...	Bank Deposits	Checking Accounts	Sa Acco
0	IND81288	Raymond Mills	24	34324	06-05-2019	Anthony Torres	American	Safety Technician IV	High	Jade	...	1485828.64	603617.88	60733
1	IND65833	Julia Spencer	23	42205	10-12-2001	Jonathan Hawkins	African	Software Consultant	High	Jade	...	641482.79	229521.37	34463
2	IND47499	Stephen Murray	27	7314	25-01-2010	Anthony Berry	European	Help Desk Operator	High	Gold	...	1033401.59	652674.69	20305
3	IND72498	Virginia Garza	40	34594	28-03-2019	Steve Diaz	American	Geologist II	Mid	Silver	...	1048157.49	1048157.49	23468
4	IND60181	Melissa Sanders	46	41269	20-07-2012	Shawn Long	American	Assistant Professor	Mid	Platinum	...	487782.53	446644.25	12835

5 rows × 25 columns

[12]:
```python
df.describe()          #to check the overview of the dataset
```

[12]:

	Age	Location_ID	Estimated_Income	Superannuation_Savings	Amount_of_Credit_Cards	Credit_Card_Balance	Bank_Loans	Bank_Deposits
count	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3.000000e+03	3.000000e+03
mean	51.039667	21563.323000	171305.034263	25531.599673	1.463667	3176.206943	5.913862e+05	6.715602e+05
std	19.854760	12462.273017	111935.808209	16259.950770	0.676387	2497.094709	4.575570e+05	6.457169e+05
min	17.000000	12.000000	15919.480000	1482.030000	1.000000	1.170000	0.000000e+00	0.000000e+00
25%	34.000000	10803.500000	82906.595000	12513.775000	1.000000	1236.630000	2.396281e+05	2.044004e+05
50%	51.000000	21129.500000	142313.480000	22357.355000	1.000000	2560.805000	4.797934e+05	4.633165e+05

Home
Banking_case
localhost:8888/notebooks/Banking_case.ipynb
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Code

```
[11]: df['client_id'] = df['client_id'].astype(str).str.strip()
      df['name'] = df['name'].astype(str).str.strip()
      print(df['client_id'].head().tolist())
      print(df['name'].head().tolist())

      ['IND81288', 'IND65833', 'IND47499', 'IND72498', 'IND60181']
      ['Raymond Mills', 'Julia Spencer', 'Stephen Murray', 'Virginia Garza', 'Melissa Sanders']

[12]: # Handle missing values - we have (1190 non-null values out of 3000) , it means we have more then 50% null values in joined_dat
      #create a flag "joined_known"
      #Flag missing "joined_bank"
      df['joined_known'] = df['joined_bank'].notna().astype(int)

      #Impute numeric columns if needed (example: estimated_income)
      df['estimated_income'] = df['estimated_income'].fillna(df['estimated_income'].median())
```

Deal or remove outliers

```
: def remove_outliers_iqr(series,k=1.5):
      q1 = series.quantile(0.25)
      q3 = series.quantile(0.75)
      iqr =q3 - q1
      lower = q1 - k*iqr
      upper = q3 + k*iqr
      return series.clip(lower,upper)

  #Clip extreme estimated income to reasonable range

  df['estimated_income_clipped'] = remove_outliers_iqr(df['estimated_income'])
```

4.2 Loan Risk Churn Definition

Two churn modeling approaches were tested:

Method 1: Rule-Based Risk Paths (Final Choice)

Customers are flagged as high-risk churn if they meet **any of the following**:

- High debt-to-income + high risk score
- Low deposits + high total debt + low income
- New customer with high risk score

This method produced a **realistic churn rate (~13%)**, which aligns with real banking scenarios.

Chosen because it is **interpretable**, **business-friendly**.

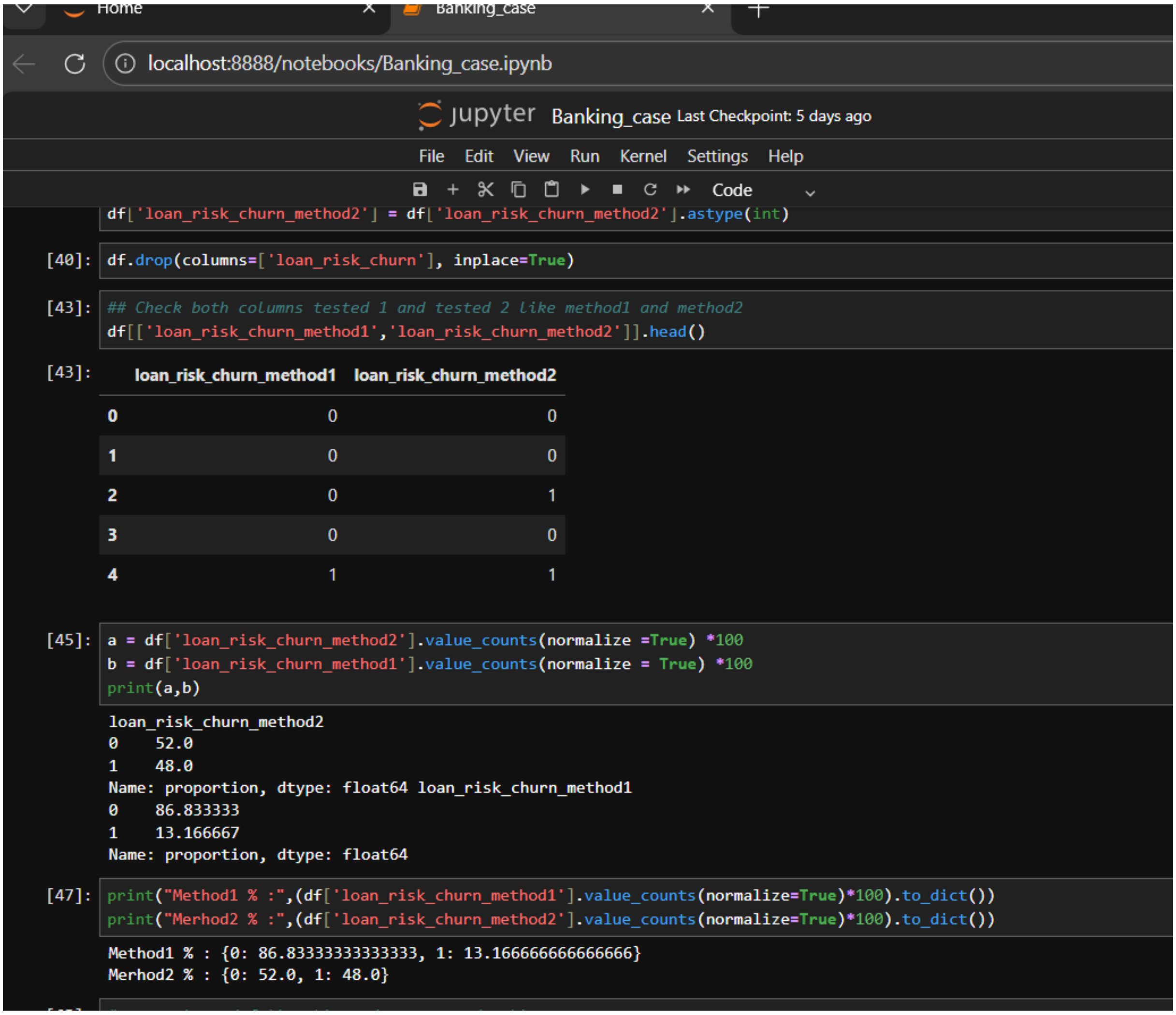
```python
[61]: import numpy as np
import pandas as pd

# ---------- 1) percentile thresholds (method1) ----------
dti_80 = np.percentile(df["debt_to_income"], 80)
risk_80 = np.percentile(df["risk_score"], 80)
deposit_20 = np.percentile(df["bank_deposits"], 20)
debt_80 = np.percentile(df["total_debt"], 80)
income_20 = np.percentile(df["estimated_income"], 20)
years_20 = np.percentile(df["years_with_bank"], 20)

# ---------- 2) loan_risk_churn_method1 (binary flag using percentile paths) ----------
df['loan_risk_churn_method1'] = np.where(
    # Path 1 : High DTI + High Risk
    ((df['debt_to_income'] > dti_80) & (df['risk_score'] > risk_80)) |

    # Path 2 : Low deposits + Low income + high debt
    ((df['bank_deposits'] < deposit_20) & (df['total_debt'] > debt_80) &
     (df['estimated_income'] < income_20)) |

    # Path 3 : New customers with high risk
    ((df['years_with_bank'] < years_20) & (df['risk_score'] > risk_80)),
    1, 0
)

# ---------- 3) loan_risk_churn_method2 (alternate scoring approach you had earlier) ----------
# Keep the previous metric approach (if you also made method2 earlier).
# If method2 isn't present, you can compute it similarly. Here assume it already exists.
# df['loan_risk_churn_method2'] = ...   # (skip if already exists)

# ---------- 4) Build a clean, bounded risk_model_score (0-100) ----------
# We'll normalize each numeric component safely (avoid divide-by-zero),
# then combine using weights (weights add to 1), and scale to 0-100.

# pick the numeric features we want to use
num_cols = {
    'debt_to_income': 0.30,       # weight 30%
    'risk_score': 0.40,           # weight 40% (risk_score is already 0-100)
```

```python
# pick the numeric features we want to use
num_cols = {
    'debt_to_income': 0.30,       # weight 30%
    'risk_score': 0.40,           # weight 40% (risk_score is already 0-100)
    'bank_deposits': 0.15,        # weight 15% (we invert deposits: less deposit => higher risk)
    'total_debt': 0.15            # weight 15%
}

# compute safe max (replace 0 with small number to avoid division by zero)
safe_max = {}
for c in ['debt_to_income','risk_score','bank_deposits','total_debt']:
    m = df[c].max()
    safe_max[c] = m if m and m > 0 else 1.0

# normalized components (0..1)
# - for debt_to_income: bigger → worse → keep as-is
# - for risk_score: it's 0..100 → normalize by 100
# - for bank_deposits: bigger → better → we invert to make bigger → lower risk
# - for total_debt: bigger → worse
df['norm_dti'] = df['debt_to_income'] / safe_max['debt_to_income']
df['norm_risk_score'] = (df['risk_score'] / 100.0)  # already 0-100
df['norm_deposits_inv'] = 1.0 - (df['bank_deposits'] / safe_max['bank_deposits'])
df['norm_total_debt'] = df['total_debt'] / safe_max['total_debt']

# ensure no NaN and clip 0..1
for col in ['norm_dti','norm_risk_score','norm_deposits_inv','norm_total_debt']:
    df[col] = df[col].fillna(0).clip(0,1)

# weighted sum (weights sum to 1)
w_dti = num_cols['debt_to_income']
w_risk = num_cols['risk_score']
w_dep = num_cols['bank_deposits']
```

```python
# weighted sum (weights sum to 1)
w_dti = num_cols['debt_to_income']
w_risk = num_cols['risk_score']
w_dep = num_cols['bank_deposits']
w_debt = num_cols['total_debt']

df['risk_model_score'] = (
    df['norm_dti'] * w_dti +
    df['norm_risk_score'] * w_risk +
    df['norm_deposits_inv'] * w_dep +
    df['norm_total_debt'] * w_debt
) * 100.0   # scale to 0-100

# Clip strictly to 0..100 (safety)
df['risk_model_score'] = df['risk_model_score'].clip(0, 100)

# ---------- 5) Create categorical segments from score ----------
bins = [0, 40, 70, 100]
labels = ['Low Risk', 'Medium Risk', 'High Risk']
df['risk_segment_final'] = pd.cut(df['risk_model_score'], bins=bins, labels=labels, include_lowest=True, right=True)

# ---------- 6) Check results ----------
print("loan_risk_churn_method1 distribution (%)")
print(df['loan_risk_churn_method1'].value_counts(normalize=True) * 100)

if 'loan_risk_churn_method2' in df.columns:
    print("\nloan_risk_churn_method2 distribution (%)")
    print(df['loan_risk_churn_method2'].value_counts(normalize=True) * 100)

print("\nRisk model score stats:")
print(df['risk_model_score'].describe())
```

```python
if 'loan_risk_churn_method2' in df.columns:
    print("\nloan_risk_churn_method2 distribution (%)")
    print(df['loan_risk_churn_method2'].value_counts(normalize=True) * 100)

print("\nRisk model score stats:")
print(df['risk_model_score'].describe())

print("\nRisk segments counts:")
print(df['risk_segment_final'].value_counts(dropna=False))

# ---------- 7) OPTIONAL: delete the old column 'loan_risk_churn' if you want ----------
if 'loan_risk_churn' in df.columns:
    df.drop(columns=['loan_risk_churn'], inplace=True)
    print("\nDropped old column 'loan_risk_churn'.")
```

```
loan_risk_churn_method1 distribution (%)
loan_risk_churn_method1
0    86.833333
1    13.166667
Name: proportion, dtype: float64

loan_risk_churn_method2 distribution (%)
loan_risk_churn_method2
0    52.0
1    48.0
Name: proportion, dtype: float64

Risk model score stats:
count    3000.000000
mean       34.514360
```



4.3 Risk Model Score Creation

A **custom weighted risk score (0–100)** was developed using:

- Debt-to-income ratio
- Risk score
- Bank deposits (inverse effect)
- Total debt

This score provides a **continuous measure of customer risk**, rather than a simple yes/no label.

4.4 Risk Segmentation

Customers were classified into:

- **Low Risk** (Score < 40)
- **Medium Risk** (40–70)
- **High Risk** (>70)

This segmentation enables **targeted business actions**.

```
[66]: agg = df.groupby('risk_segment_final', observed=False).agg(
          customers_count=('client_id','nunique'),
          avg_risk=('risk_model_score','mean'),
          pct_churn_method1=('loan_risk_churn_method1','mean')
      ).reset_index()

      agg.to_sql('customers_risk_agg', engine, if_exists='replace', index=False)

[66]: 3
```

5. Data Storage (MySQL)

Two tables were created:

a) First Table :- customers_cleaned

- Customer-level detailed data
- Used for deep analysis and Power BI visuals

b) Seccond Table :- customers_risk_agg

- Aggregated KPIs by risk segment
- Optimized for dashboard performance

Using MySQL reflects **enterprise-level data pipelines**, where Power BI connects to structured databases.

```
]: # save cleaned full table and aggregated table
   df.to_sql('customers_cleaned', engine, if_exists='replace', index=False)

]: 3000

]: agg = df.groupby('risk_segment_final', observed=False).agg(
       customers_count=('client_id','nunique'),
       avg_risk=('risk_model_score','mean'),
       pct_churn_method1=('loan_risk_churn_method1','mean')
   ).reset_index()

   agg.to_sql('customers_risk_agg', engine, if_exists='replace', index=False)
```

Safe way to create a pipeline

Created by :- Sandeep Kumar Singh

```python
from sqlalchemy import create_engine

user = 'root'
password = '9832'
host = '127.0.0.1'
port = 3306
database = 'banking_case'

engine = create_engine(f'mysql+mysqlconnector://{user}:{password}@{host}:{port}/{database}')

# 1) customer_cleaned
df.to_sql('customer_cleaned',engine,if_exists='replace',index=False)

# 2) customer_agg
agg = df.groupby(['risk_segment','location_id']).agg(
    customers_count = ('client_id','nunique'),
    avg_risk = ('risk_score','mean'),
    avg_income = ('estimated_income','mean')
).reset_index()

agg.to_sql('customer_agg',engine,if_exists='replace',index=False)
```

```
2941
```

---

6. Power BI Dashboard Overview (6 Pages)

The dashboard is designed for **both executives and analysts**.

Page 1: Executive Overview

Purpose:

Provide a **high-level snapshot** of Customer loan risk.

Key Metrics:

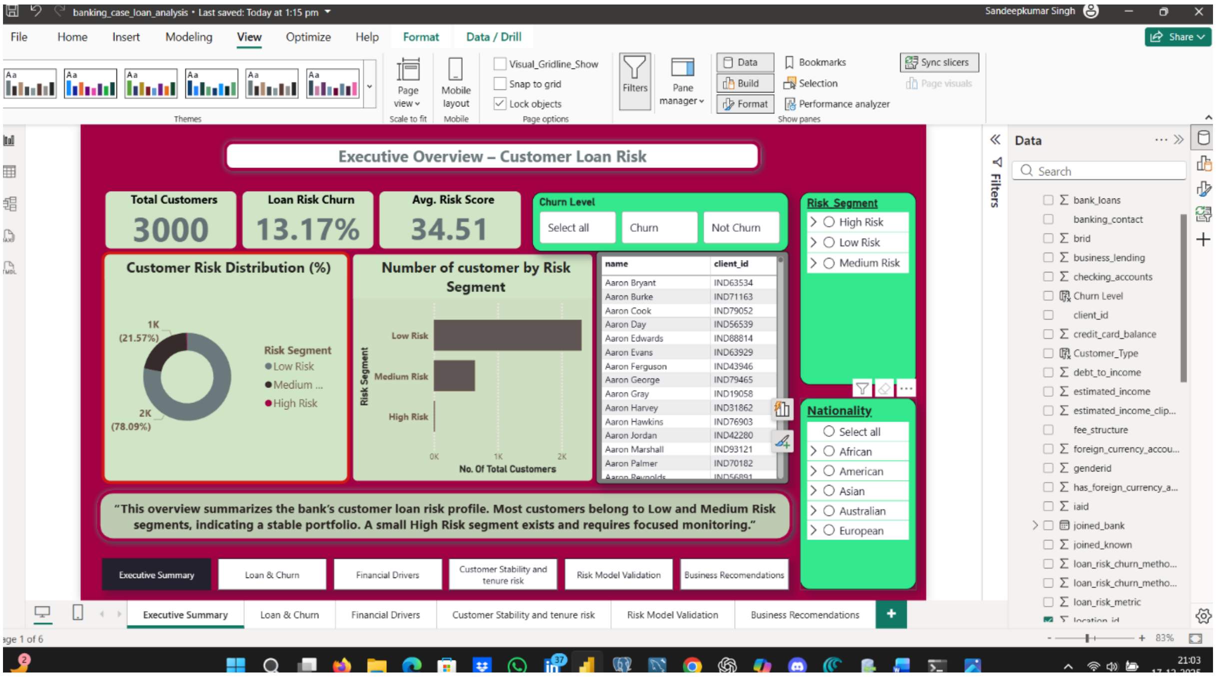
- Total customers
- Loan risk churn %
- Average risk score

Visuals:

- Donut chart: Customer distribution by risk segment
- Bar chart: Customer count by risk segment

Business Insight:

Most customers are low to medium risk, but a **small high-risk segment requires attention**.



Page 2: Loan Risk & Churn Analysis

Purpose:

Understand how churn is distributed across risk segments.

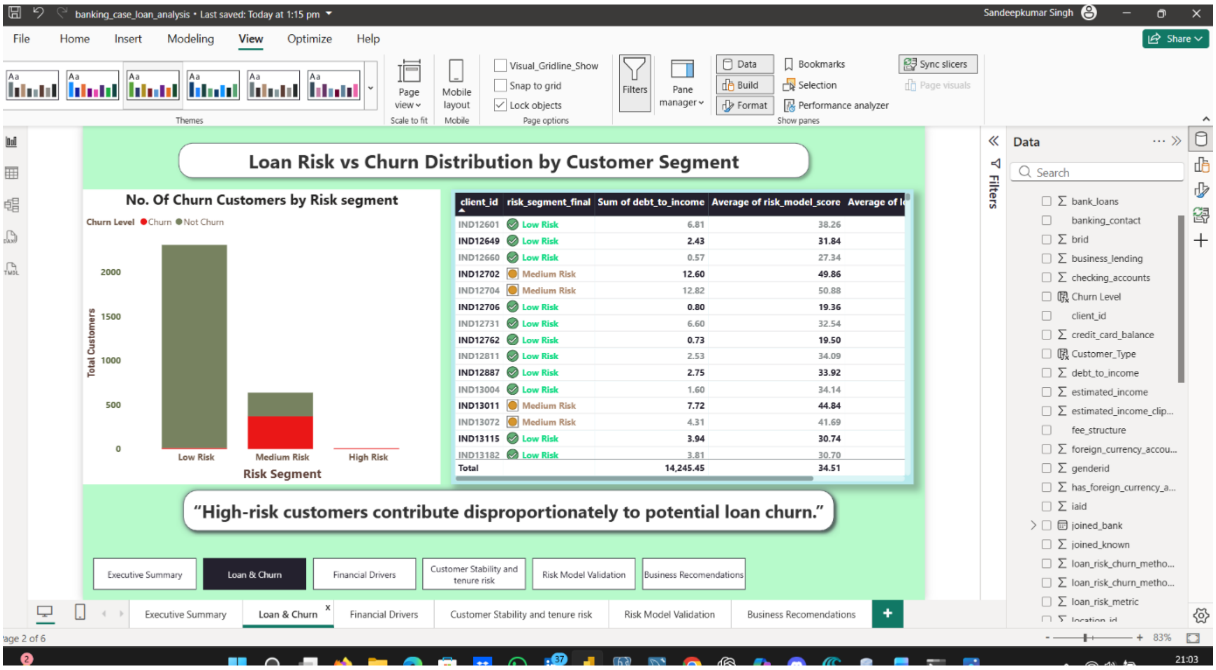
Visuals:

- Stacked column chart:
  Risk segment vs churned / non-churned customers

Insight:

Created by :- Sandeep Kumar Singh

Medium-risk customers show higher churn volume due to **larger population size**, while high-risk customers show **higher churn intensity**.



Page 3: Financial Drivers

Purpose:

Identify financial variables driving risk.

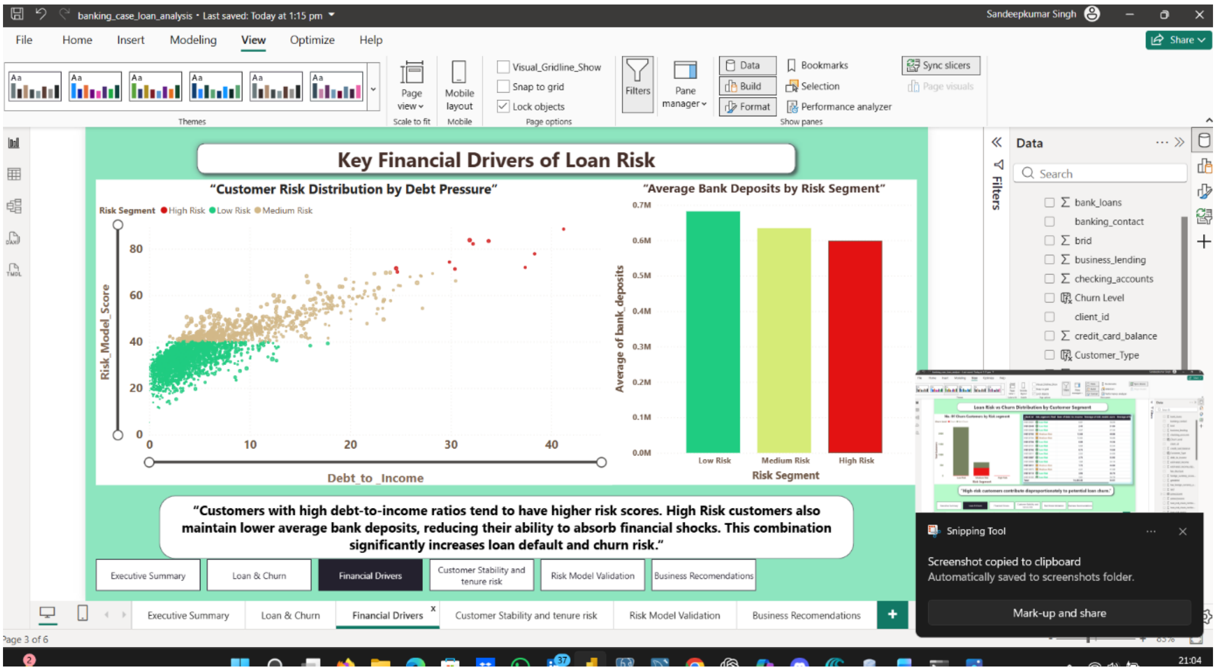
Visuals:

1. Scatter plot
   - X: Debt-to-income
   - Y: Risk model score
   - Size: Total debt
   - Color: Risk segment
2. Bar chart
   - Average bank deposits by risk segment

Insight:

Created by :- Sandeep Kumar Singh

Customers with **high debt burden and low savings** consistently appear in higher risk segments.



Page 4: Customer Stability

Purpose:

Analyze risk behavior over customer tenure.

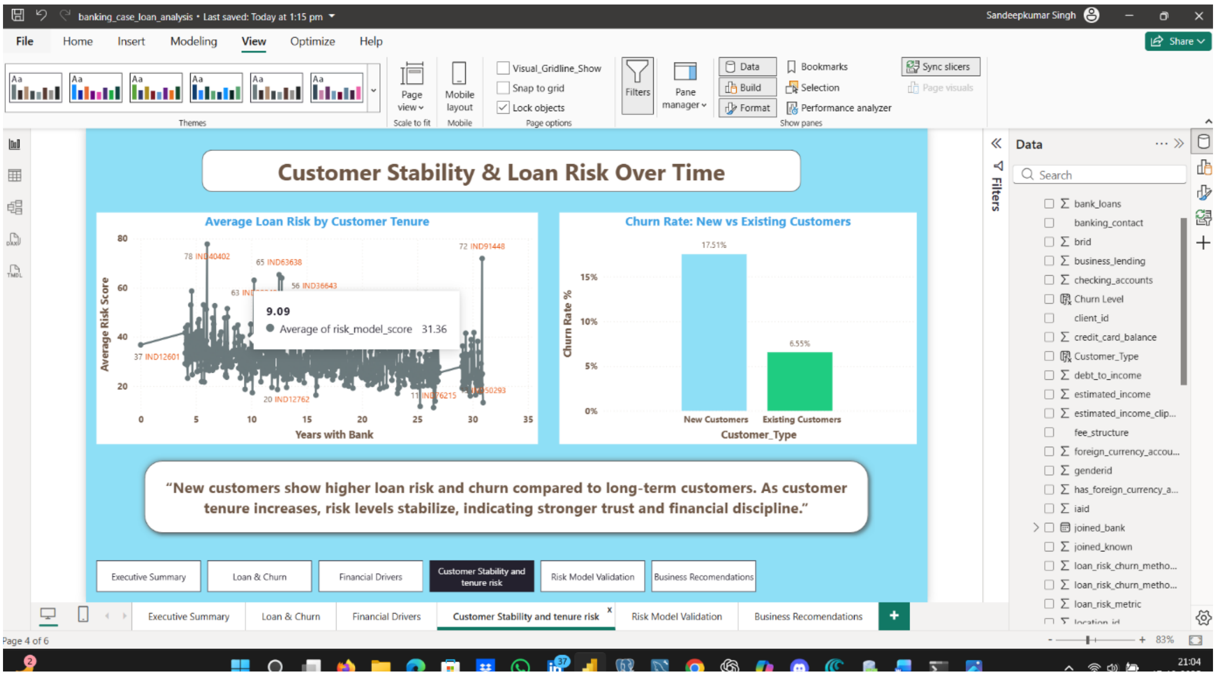
Visuals:

1. Line chart
   - Years with bank vs average risk score
2. Bar chart
   - Churn %: New vs long-term customers

Insight:

Created by :- Sandeep Kumar Singh

New customers tend to have **higher risk and churn**, indicating the need for stronger early engagement.



Page 5: Risk Model Validation

Purpose:

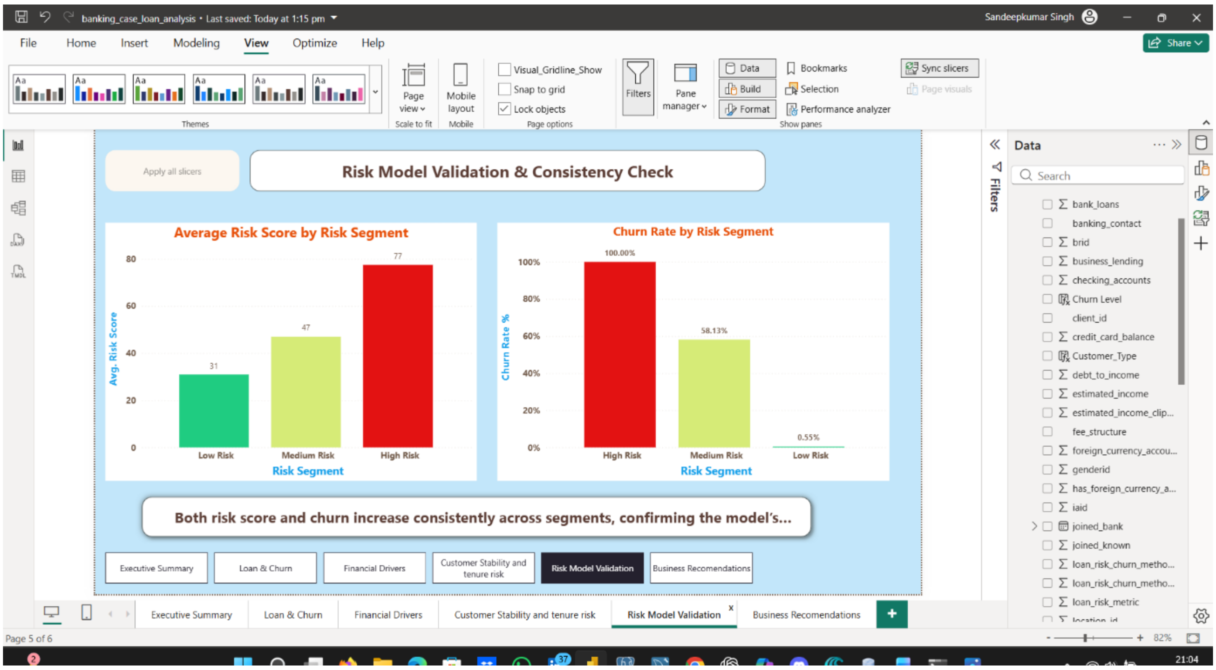
Validate whether the model segments customers meaningfully.

Visuals:

- Risk score distribution by segment
- Churn rate by risk segment
- Key Influencers visual (loan risk churn)

Insight:

Risk increases progressively from Low → Medium → High, confirming the model behaves logically.



Page 6: Business Recommendations

Purpose:

Convert insights into **actionable strategies**.

Example Actions:

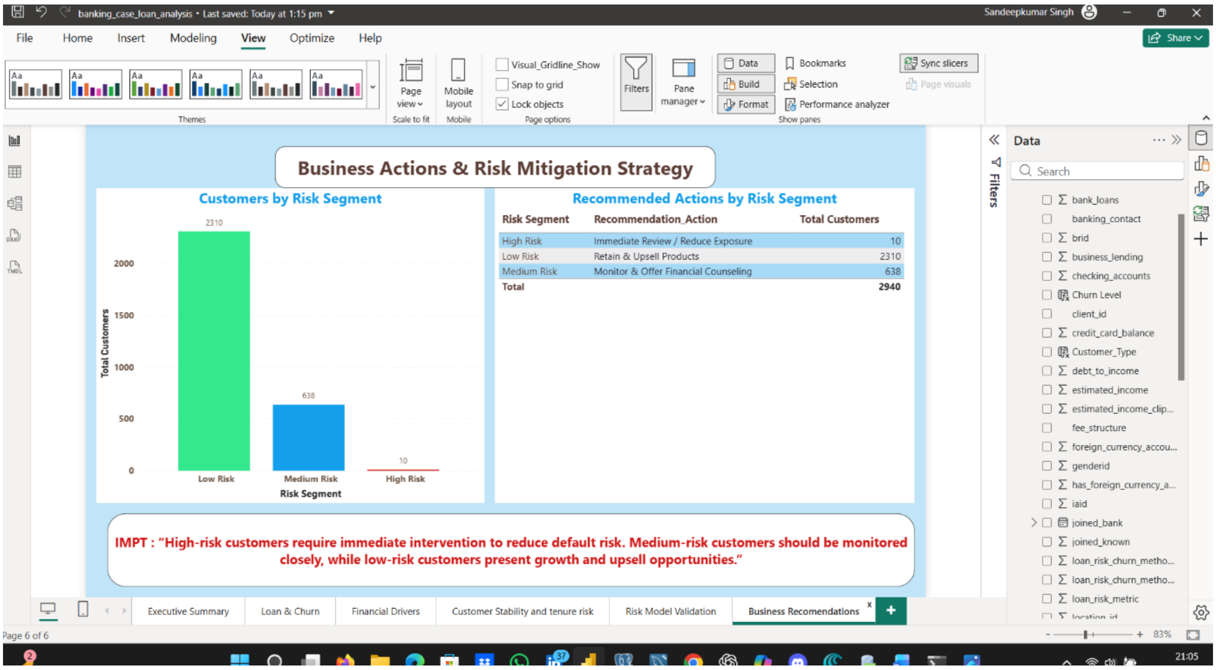
- **High Risk**: Reduce credit exposure, proactive monitoring
- **Medium Risk**: Retention offers, financial guidance
- **Low Risk**: Upsell opportunities

Visuals:

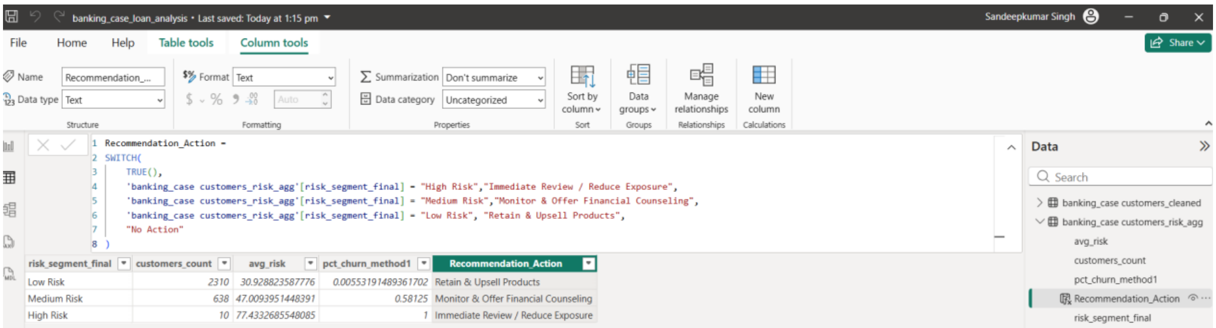
- Risk segment vs recommended action

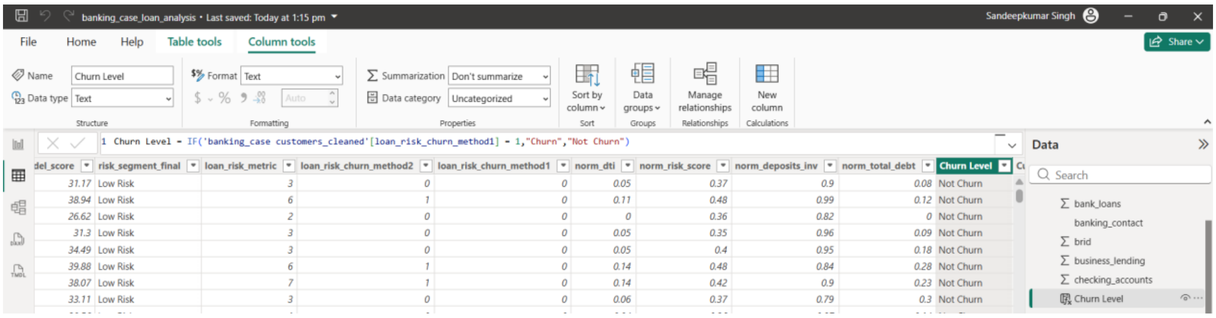
Created by :- Sandeep Kumar Singh

- KPI summary



Screenshots of some Calculate Columns and Measures are created on this project using DAX functions





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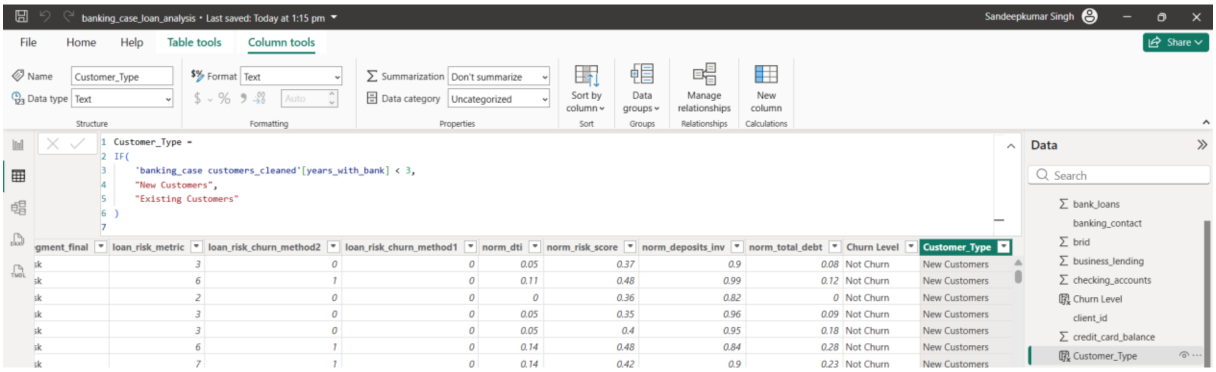

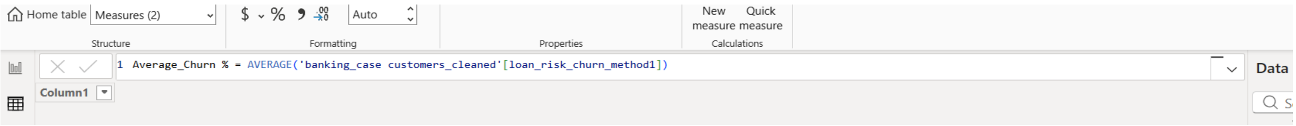

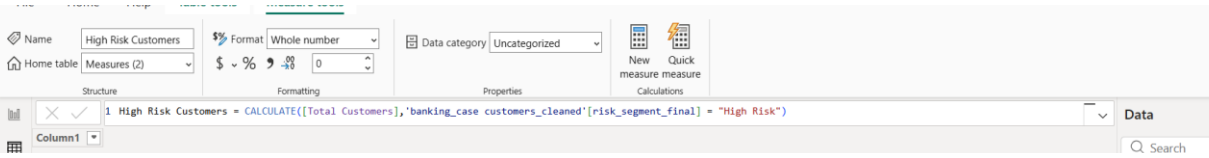

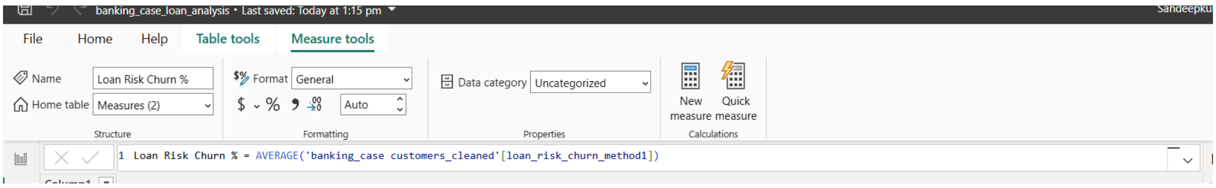

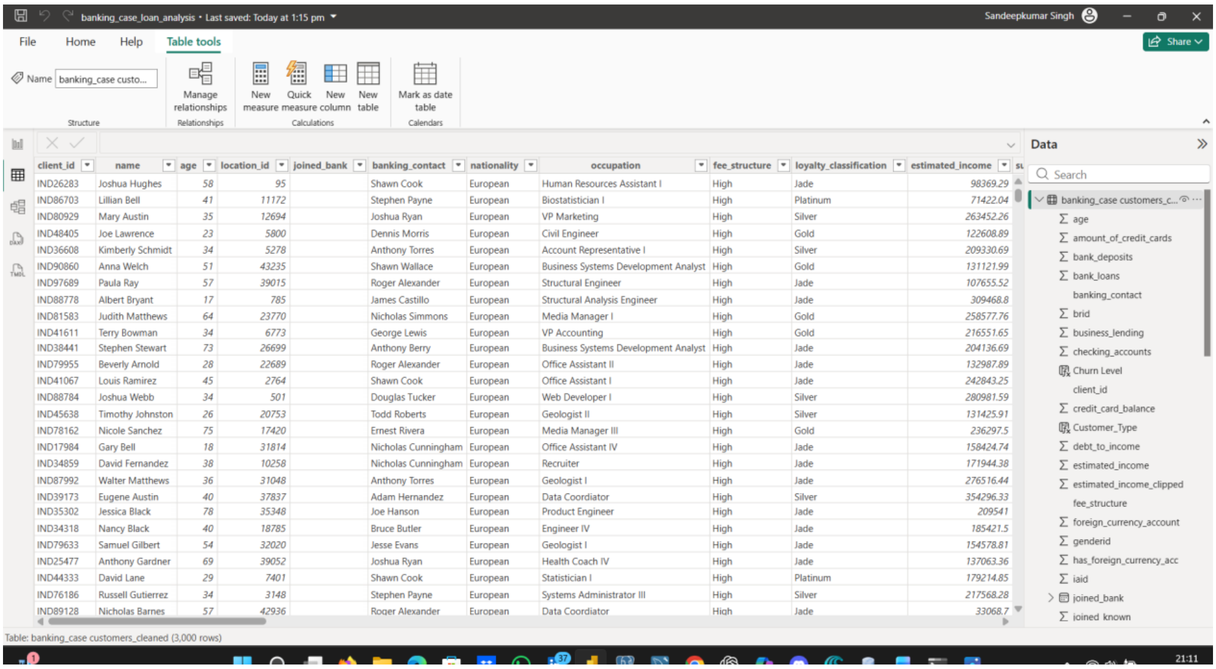

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7. Business Impact

This solution enables the bank to:

- Proactively identify risky customers
- Reduce loan default losses
- Improve customer retention
- Allocate resources efficiently
- Support data-driven executive decisions

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8. **Tools Used**

- Python (Pandas, NumPy,Scikit-learn)
- Jupyter Notebook
- MySQL
- Power BI
- SQLAlchemy

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9. **Conclusion**

This project demonstrates strong skills in:

- Data cleaning and feature engineering
- Risk modeling and segmentation
- SQL-based data pipelines
- Executive-level dashboard design
- Business storytelling with data

Created by :- Sandeep Kumar Singh