Loan Analysis Dashboard

Presented by : K. Sabari Vasan

Table of Contents

Executive Summary / Overview

•*The analysis focuses on applicant demographics, financial attributes, credit scores, loan categories, and loan tenure to identify approval trends and risk indicators.*

•*This project provides a comprehensive analysis of secured and unsecured loan applications to understand the key factors influencing loan approval rates.*

•*Exploratory Data Analysis (EDA) was conducted to uncover patterns in customer behavior and loan performance, enabling data-driven decision-making.*

•*Results indicate that income levels, loan type, credit score range, and loan term duration have a significant impact on loan approval likelihood.*

•*Secured loans show higher approval rates among middle-aged, low-income applicants opting for short-term loans, while unsecured loans are predominantly approved for personal loan applicants with lower credit scores.*

Objective / Problem Statement

- *To identify the key demographic, financial, and behavioral factors that significantly influence loan approval decisions in secured and unsecured loan categories.*
- *To analyze patterns in customer profiles, loan types, credit scores, income levels, and loan tenure to understand their impact on approval rates.*
- *To uncover data-driven insights that can support financial institutions in minimizing loan default risks and optimizing approval strategies.*

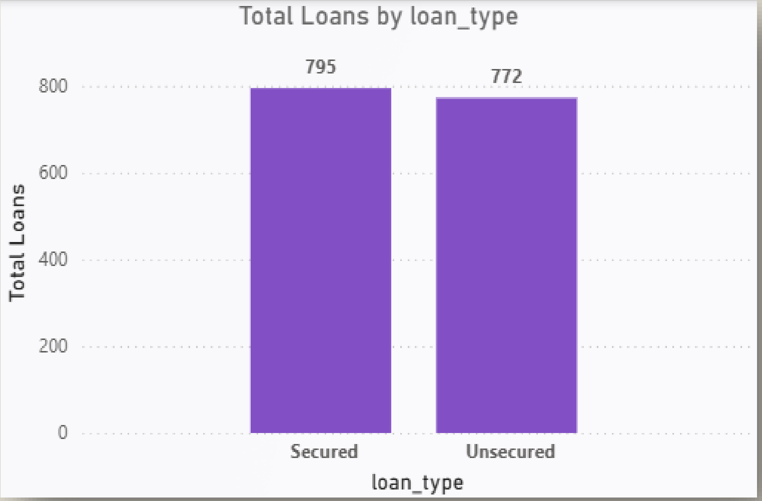
Data Cleaning and Preprocessing Steps

- *Removed null values*
- *Replaced null values with ‘**0**’for **Customer Income.***
- *Replaced null values with ‘ **Unknown** ’for **account type**.*
- *Replaced null values with ‘**in progress**’ for **Status.***
- *Created **calculated and conditional columns** such as age group , asset value , credit score , no of dependents and loan term bins.*

Methodology / Tools Used

- ***Step 1**: Data Import.*
- ***Step 2**: Data Transformation using Power Query.*
- ***Step 3**: EDA and DAX (Data Analysis Expression).*
- ***Step 4**: Dashboard Visualization and Insights.*

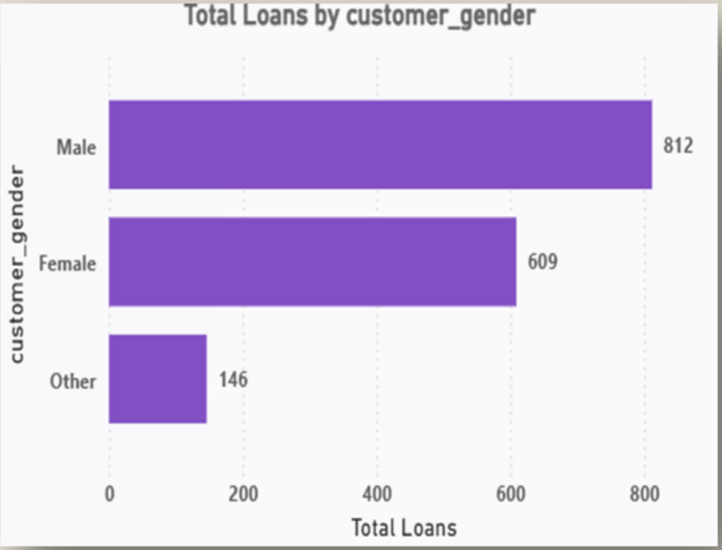
Exploratory Data Analysis (EDA) Findings



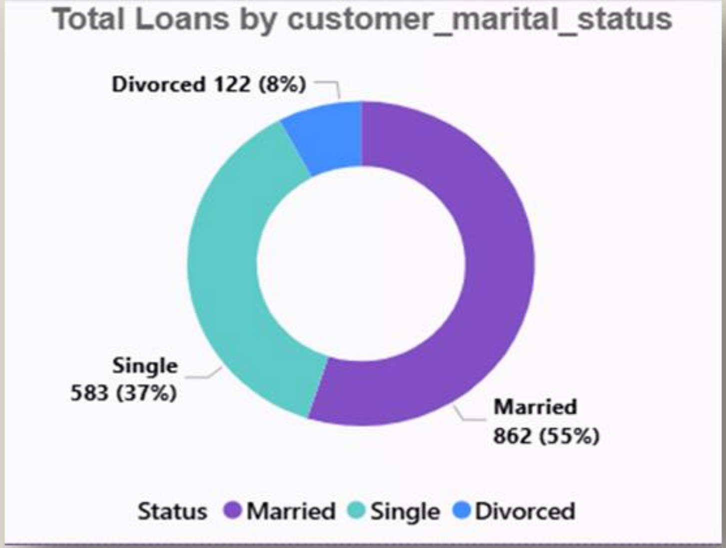
"The dataset shows the proportion of approved versus rejected loan applications, indicating the overall approval distribution."

"This chart illustrates the breakdown of different loan types in the dataset, indicating the most frequently applied loan categories."

Exploratory data Analysis(EDA)Findings



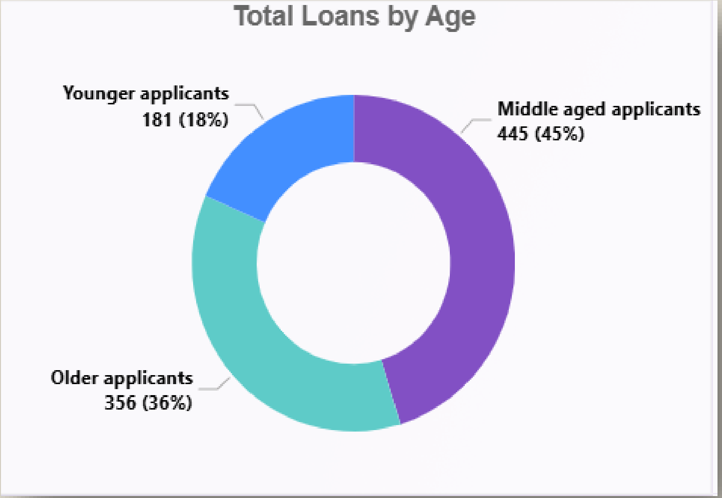
"This chart displays the count of loan applications received from male and female applicants, showing gender-based participation in the dataset."

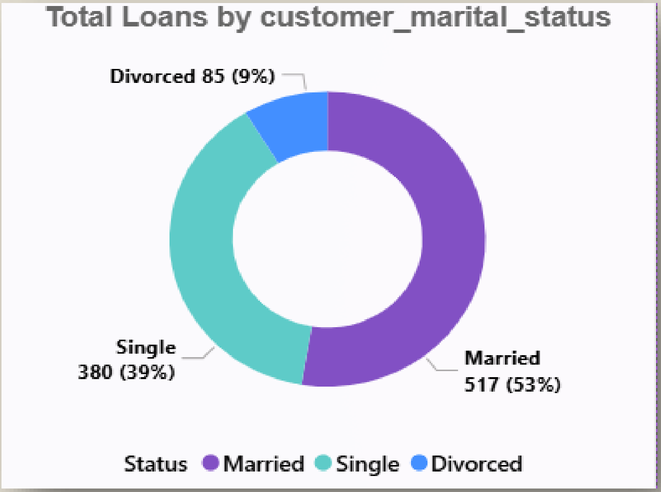


"This visualization represents the number of applicants based on marital status, highlighting the distribution between married and unmarried individuals."

Key Insights and Visualizations

Note: All visualizations are filtered to show the distribution among *approved loans only*, which helps in identifying which demographic and loan factors positively influence loan approval.

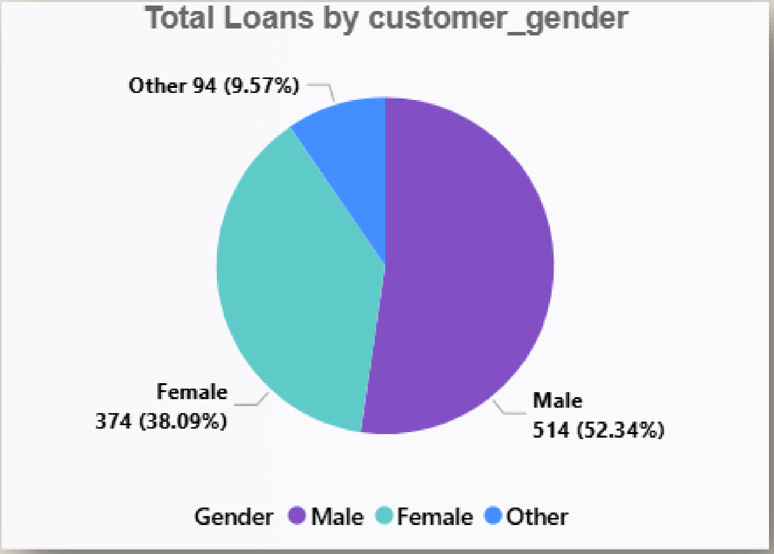


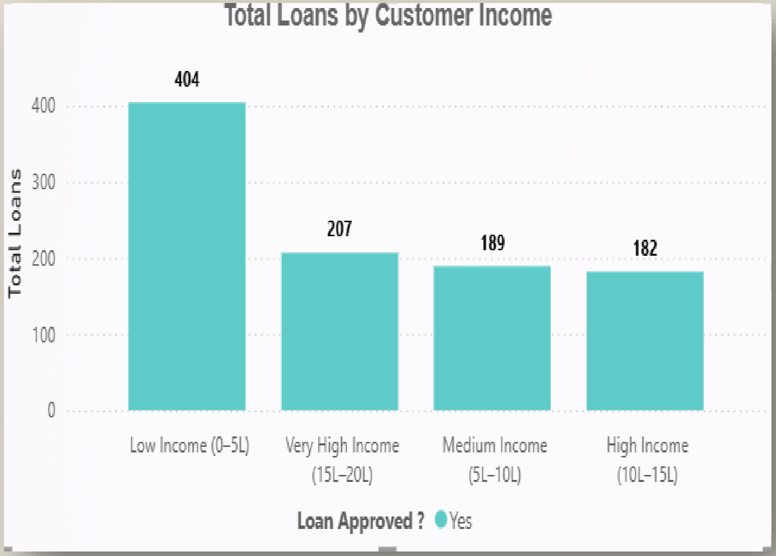


Middle-aged applicants receive the most loans, reflecting their higher creditworthiness and stable income stage.

Married individuals account for the majority of loans, suggesting higher financial stability and approval likelihood.

Key Insights and Visualizations

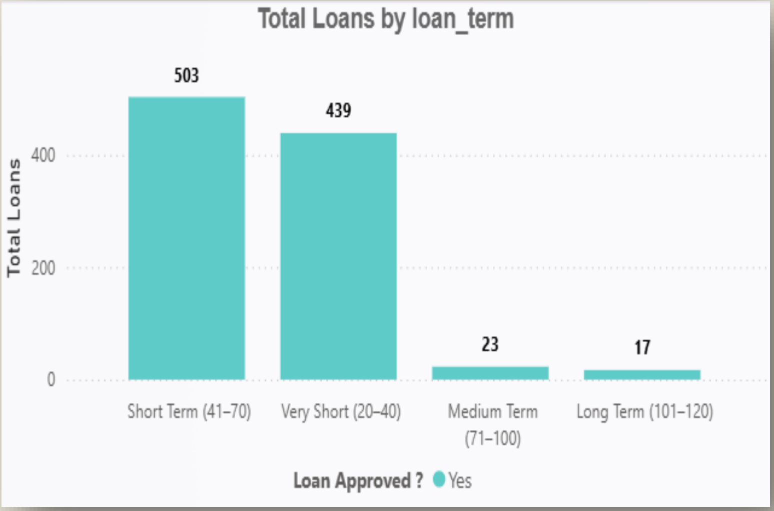


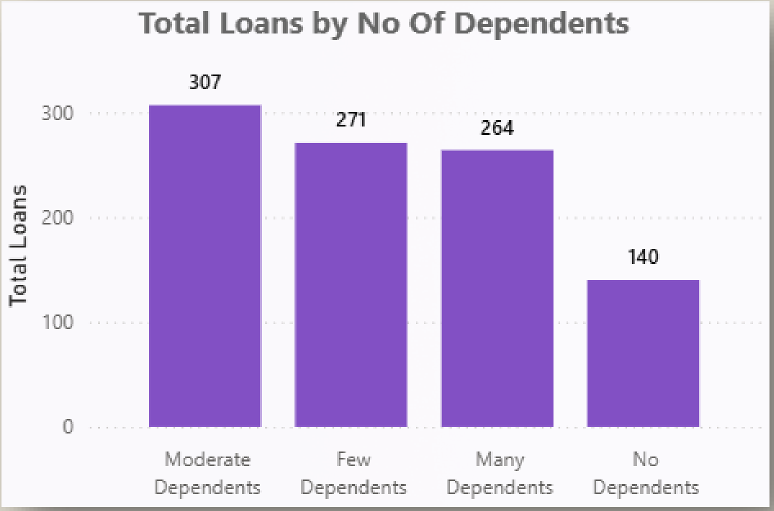


Male applicants have the highest share of total loans, indicating slightly higher participation or approval preference.

Low-income group shows the highest number of approved loans, indicating strong demand or targeted financial inclusion.

Key Insights and Visualizations





Short-term loans dominate approvals, showing preference for lower repayment duration and reduced risk.

Applicants with moderate and few dependents receive more loans, suggesting that a balanced family responsibility is viewed favorably in the approval process.

The insights from this analysis can be leveraged to optimize loan strategies, enhance customer targeting, and improve risk assessment models for better decision-making.

KPIs and Metrics

982
Total Loans

₹ 1.33M
Average Loan Approved

52.65
Married Applicants %

63.30
Male Approval %

50.31
Secured Loan %

Average Credit Score
566

Interpretation of Results

•The analysis clearly shows that loan approval likelihood is influenced by key demographic and financial attributes such as age, income level, marital status, dependents, and loan type.
•Middle-aged, married, and male applicants have the highest loan approval percentages, suggesting these groups are perceived as financially stable and reliable by lenders.
•Short-term and very short-term loans dominate approvals, indicating that both customers and lenders prefer lower repayment duration and reduced lending risk.
•Low-income applicants (0–5 LPA) also have a significant share of approvals, possibly due to smaller loan sizes and inclusive lending policies.
•Both secured (gold, home, vehicle) and unsecured (personal) loans show similar patterns — approvals are concentrated among middle-aged applicants with moderate dependents.
•Credit scores across categories show approvals even for lower ranges, implying that factors like income and loan term may offset the risk of low credit scores in some cases.

Recommendations / Actionable Insights

- ***Target reliable customer segments** : Focus marketing and loan products toward middle-aged, married applicants with moderate dependents, as they show the highest approval and repayment potential.*
- ***Promote short-term loan products** : Since most approvals are for short and very short-term loans, financial institutions can emphasize these offerings to ensure quicker recovery and lower risk.*
- ***Enhance financial inclusion** : Given that low-income applicants have a considerable approval rate, continue supporting them with small-ticket, low-risk loan options and flexible repayment plans.*
- ***Strengthen risk assessment for low credit scores** : Although approvals exist across credit ranges, stricter monitoring or tailored interest rates can help mitigate risks for applicants with poor or fair credit.*
- ***Optimize loan product mix** : Encourage secured loan products (home, gold, vehicle) where approval likelihood and repayment confidence are higher, while refining unsecured loan evaluation criteria.*

Assumptions

- *Considered **“Closed” Account Status** and **“In Progress” Loan Status** to investigate why some loans remain active even after account closure.*
- *Compared **Loan Approved Date (AD)** and **Account Last Active Date (LA)** to identify timing relationships and potential inconsistencies.*
  - *If LA < AD → Normal case (loan approved when account was active).*
  - *If LA > AD → Possible timing or data mismatch.*
- *Observed that **Loan Application ID** and **Loan Account ID** differ across all records, suggesting separate identifiers for the application and the approved loan.*
- *Found that in most “In Progress” loans, **Customer ≠ Co-Applicant**, indicating that repayment continues through a **co-applicant’s or linked account**.*
- *Concluded that loans marked In Progress after account closure are **valid cases**, where repayment is tied to another active account or co-applicant.*
- *Noted that the majority of these cases involve **unsecured loans** (e.g., education or personal loans).*

Limitations

*•Some assumptions are **based on logical inference**, as original business rules or system documentation were not available.*
*•The dataset may contain **temporal mismatches** (e.g., approval vs. activity dates) due to record entry delays.*
*•Lack of unique **relational mapping** between customer and co-applicant accounts may limit accuracy in tracking linked loan repayments.*
*•The replacement of missing values could **introduce bias** in future modeling or trend analysis if not revalidated with domain experts.*
•Certain fields like “Loan Purpose” or “Repayment Channel” were not available, limiting deeper behavioral insights.

Conclusion

*•The project uncovered key **loan approval trends** — middle-aged, male, and moderate-income applicants show higher approval rates.*

*•**31% missing values** were handled logically to ensure data consistency and reliability.*

*•Analysis showed that **“In Progress” loans with closed accounts** are valid cases linked to **co-applicant accounts**.*

*•The study emphasizes the importance of **data validation and co-applicant tracking** in loan processing.*

*•Insights from this analysis can guide **future predictive modeling and business decisions**.*

Appendix (code snippets, formulas)

- **DAX Code Snippets / Syntax:**

```
Total Loans = COUNT('Loan Pred excel'[loan_account_id])

Percentage of loan_Approved =
DIVIDE(
   COUNTROWS(FILTER('Loan Pred excel', 'Loan Pred excel'[Loan Approved ?] = "Yes")),
   COUNTROWS('Loan Pred excel'),
   0
)


Loan term bin =

SWITCH(
   TRUE(),
   'Loan Pred excel'[loan_term] >= 20 && 'Loan Pred excel'[loan_term] < 41, "Very Short (20–40)",
   'Loan Pred excel'[loan_term] >= 41 && 'Loan Pred excel'[loan_term] < 71, "Short Term (41–70)",
   'Loan Pred excel'[loan_term] >= 71 && 'Loan Pred excel'[loan_term] < 101, "Medium Term (71–100)",
   'Loan Pred excel'[loan_term] >= 101 && 'Loan Pred excel'[loan_term] <= 120, "Long Term (101–120)",
   "Unknown"
 )
```

CustomerIncome_Bin =

```
SWITCH(
    TRUE(),
    'Loan Pred excel'[customer_income] >= 0 && 'Loan Pred excel'[customer_income] < 500000, "Low Income (0–5L)",
    'Loan Pred excel'[customer_income] >= 500000 && 'Loan Pred excel'[customer_income] < 1000000, "Medium Income (5L–10L)",
    'Loan Pred excel'[customer_income] >= 1000000 && 'Loan Pred excel'[customer_income] < 1500000, "High Income (10L–15L)",
    'Loan Pred excel'[customer_income] >= 1500000 && 'Loan Pred excel'[customer_income] <= 1999625, "Very High Income (15L–20L)",
    "Unknown"
)
```

Credit score bin =

```
SWITCH(
    TRUE(),
    'Loan Pred excel'[credit_score] >= 300 && 'Loan Pred excel'[credit_score] < 400, "Very Poor (300–399)",
    'Loan Pred excel'[credit_score] >= 400 && 'Loan Pred excel'[credit_score] < 500, "Poor (400–499)",
    'Loan Pred excel'[credit_score] >= 500 && 'Loan Pred excel'[credit_score] < 600, "Fair (500–599)",
    'Loan Pred excel'[credit_score] >= 600 && 'Loan Pred excel'[credit_score] < 700, "Good (600–699)",
    'Loan Pred excel'[credit_score] >= 700 && 'Loan Pred excel'[credit_score] <= 800, "Excellent (700–800)",
    "Unknown"
)
```

```
Average of credit score = AVERAGE('Loan Pred excel'[credit_score])



Asset Value Bin =

SWITCH(

    TRUE(),

    'Loan Pred excel'[asset_value] <= 2484755, "0 – 2.48M",

    'Loan Pred excel'[asset_value] <= 4969510, "2.48M – 4.96M",

    'Loan Pred excel'[asset_value] <= 7454265, "4.96M – 7.45M",

    'Loan Pred excel'[asset_value] <= 9939018, "7.45M – 9.93M",

    "Unknown"

)

Male Approval % =
DIVIDE(
    CALCULATE(
        COUNTROWS('Loan Pred excel'),
        'Loan Pred excel'[Loan Approved ?] = "Yes",
        'Loan Pred excel'[customer_gender] = "Male"
    ),
    CALCULATE(COUNTROWS('Loan Pred excel'),
        'Loan Pred excel'[customer_gender] = "Male"
    )
) * 100
```

Married Applicants % =
```
DIVIDE(
   CALCULATE(
      COUNTROWS('Loan Pred excel'),
      'Loan Pred excel'[Loan Approved ?] = "Yes",
      'Loan Pred excel'[customer_marital_status] = "Married"
   ),
   CALCULATE(
      COUNTROWS('Loan Pred excel'),
      'Loan Pred excel'[Loan Approved ?] = "Yes"
   )
) * 100
```

Secured Loan % =
```
DIVIDE(
   CALCULATE(
      COUNTROWS('Loan Pred excel'),
      'Loan Pred excel'[Loan Approved ?] = "Yes",
      'Loan Pred excel'[loan_type] = "Secured"
   ),
   CALCULATE(
      COUNTROWS('Loan Pred excel'),
      'Loan Pred excel'[Loan Approved ?] = "Yes"
   )
) * 100
```