

TVS CREDIT

e.p.i.c⁷



ENRICH | PERFORM | INNOVATE | CHALLENGE

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#YourEPICMove

Analysis

Link: [Colab](#)

Data Assesment

- Assessed dataset shape
- Identified NULL values
- Data profiling

Descriptive Analysis & Visualization

- Calculated descriptive statistics
- Understood central tendency
- Visualized the feature distributions

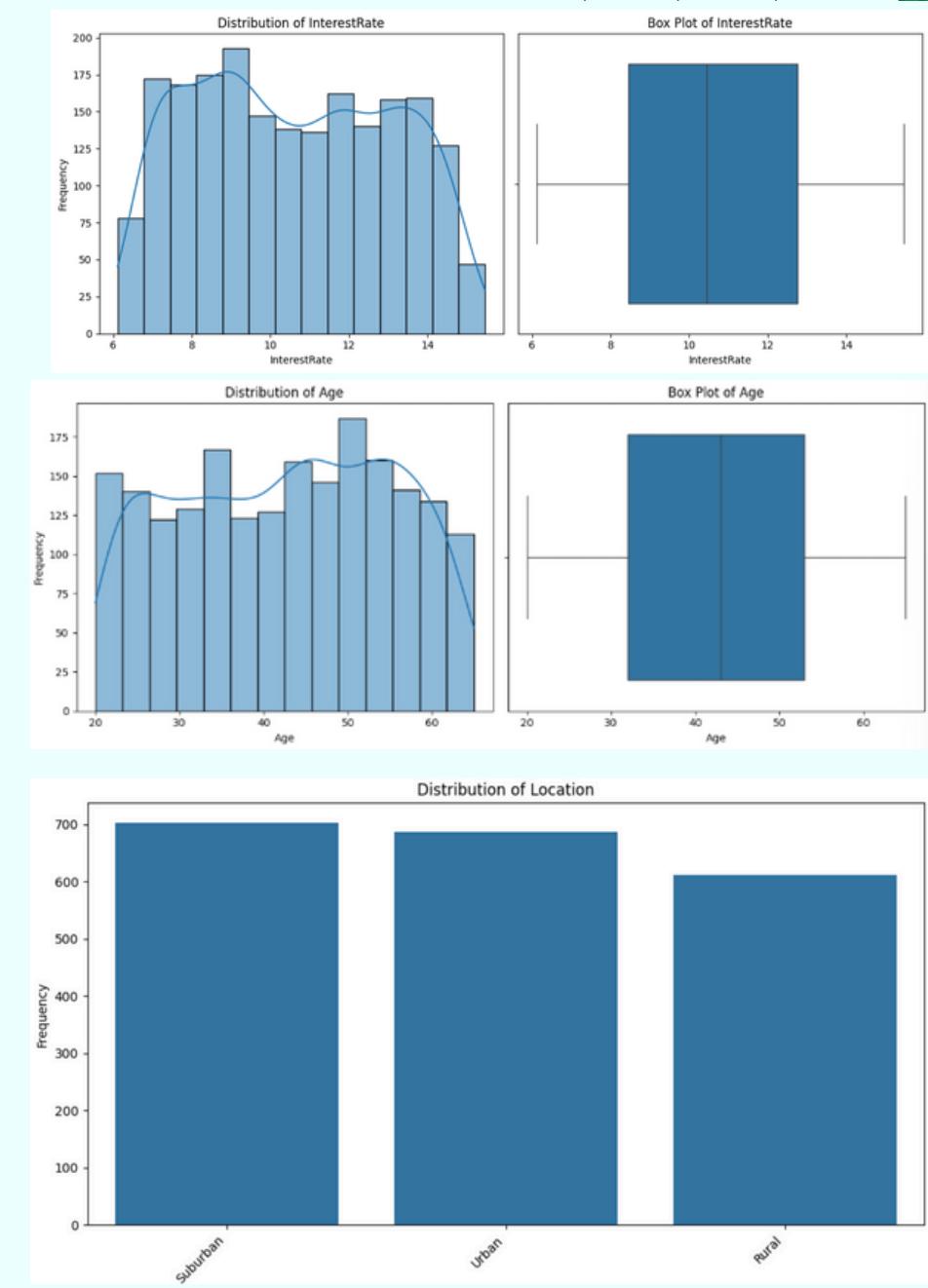
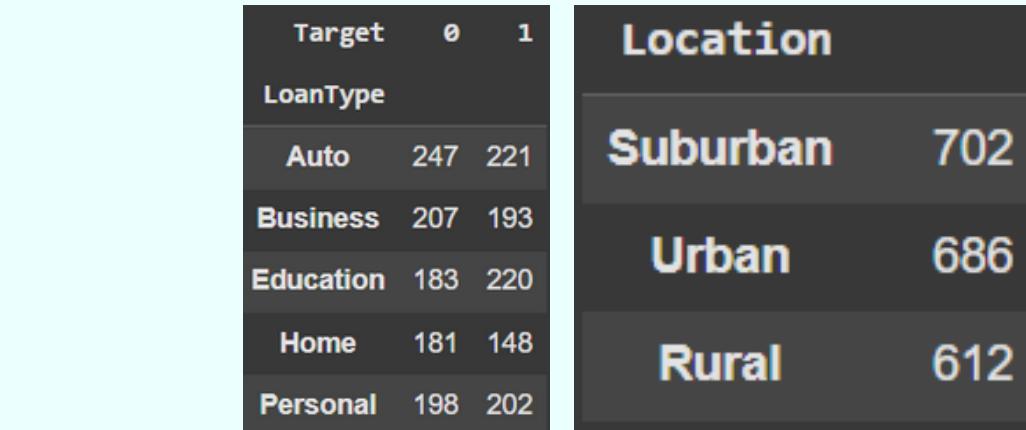
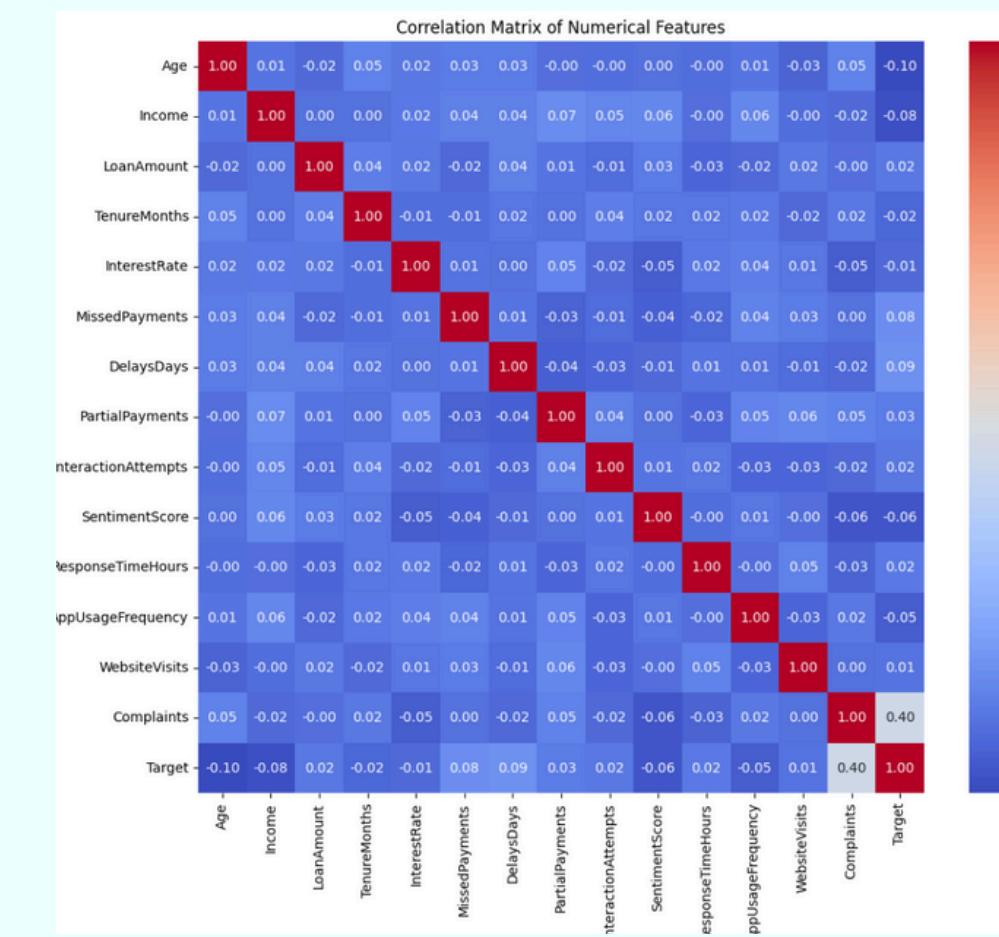
Categorical Analysis

- Analyzed the distribution
- Visualized the frequency among categories

Correlation & Target Analysis

- Created a correlation Heatmap
- Analysed target distribution among categories (percentiles & count)
- Categorical target distribution visualization

Insights for Modeling



Conclusion:

The target is strongly influenced by **complaints**, **delay days**, and **missed payments** (positive correlation), while **age** and **income** show a strong negative correlation.

These insights guide feature selection for predictive modeling.

Prediction Modeling

- **One-hot encoded** categorical features into binary form.
- Created new features (eg Debt-to-Income Ratio, Delinquency Rate)
- Detected outliers with the **IQR technique**. Retained them to prevent dropping data. The chosen model could handle them.
- Normalised the dataset using **Min-Max Scaler** (range - 0 to 1)
- Split the data into training, validation and test sets.
- Chose the **Random Forest model** and performed hyperparameter tuning using **5-fold cross-validation** with GridSearchCV.
- Trained on full training set with optimal parameters.
- Assessed the model performance on the validation and test sets.
- Evaluated on validation and test sets using accuracy, precision, recall and **ROC-AUC**.
- Benchmarked against **XGBoost** and **LightGBM**.
- Fine-tuned tree threshold to improve metrics.
- Enhanced interpretability with **SHAP values** and dependence plots

Evaluation Metric

1. High precision

2. Low FN's(High Recall)

Random Forest Performance:
Accuracy: 0.8175
Precision: 0.8500
Recall: 0.9122

XGBoost Performance:
Accuracy: 0.8650
Precision: 0.9081
Recall: 0.8195

LightGBM Performance:
Accuracy: 0.8600
Precision: 0.9116
Recall: 0.8049

Performance Summary:
XGBoost has the highest accuracy.
LightGBM has the highest precision.
Random Forest has the highest recall.

Accuracy on the test set (threshold=0.37): 0.8725

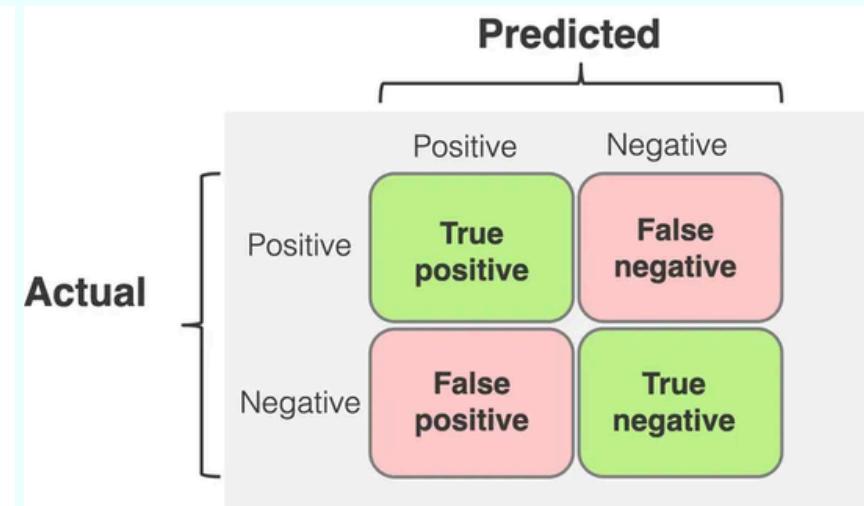
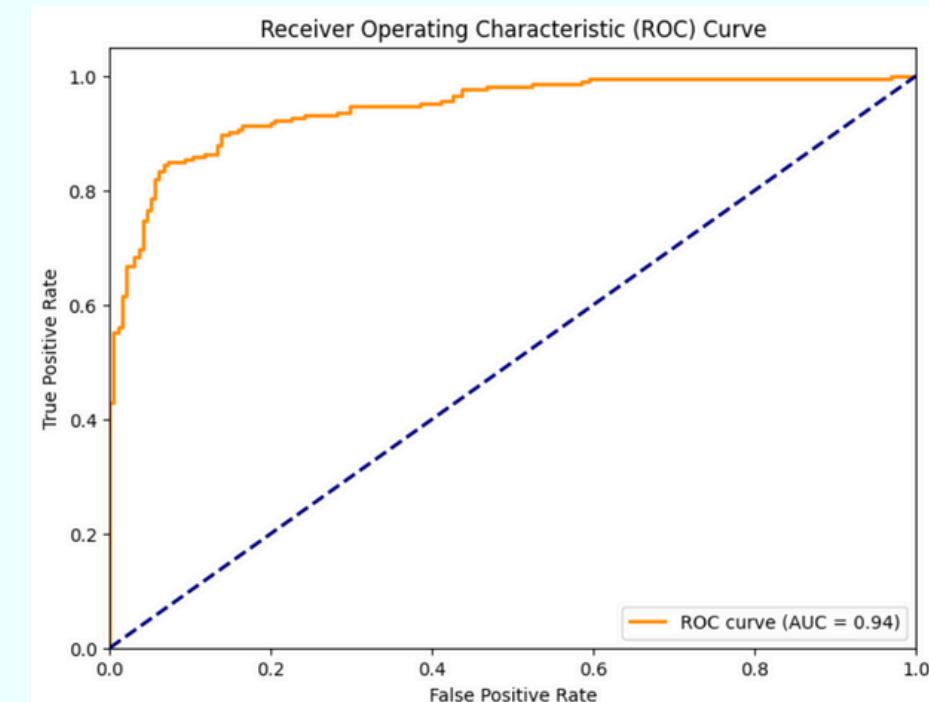
Accuracy on the Validation set (threshold=0.37): 0.8175

Test set

Validation set

Precision: 0.8500
Recall: 0.9122
Confusion Matrix:
[[187 18]
 [33 162]]

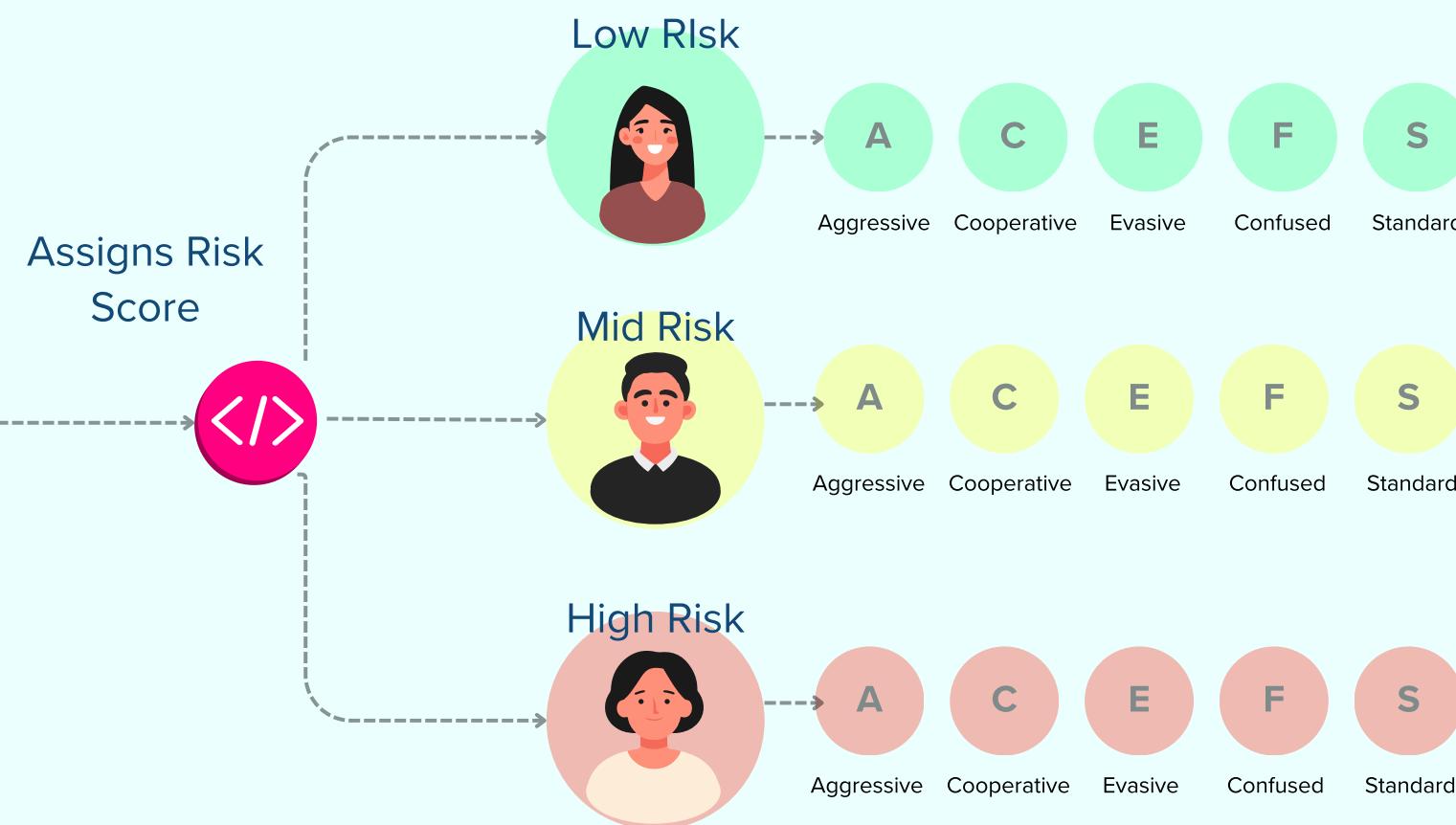
Precision: 0.7585
Recall: 0.9179
Confusion Matrix:
[[179 16]
 [57 148]]



The evaluation criteria is chosen for the following Business Goals

1. Correctly identify actual defaulters as Default (**True Positives**)
2. Minimise cases where defaulters are predicted as Not Default (**False Negatives**), the riskiest scenario for the firm which means we in turn need to increase Recall
3. Prioritise **high precision** and **low False Negatives** in the confusion matrix

Recommendation Engine



- Assigned a **risk score** to each customer based on the predictive model.
- Built a **rule-based engine** to generate personalised recommendations
- Classified** customers into three categories, based on risk scores
 - Low Risk
 - Mid Risk
 - High Risk
- Defined **personas** to customers based on interaction history, complaints and other engagement signals
- Designed a **matrix to map strategies** for each risk persona combination
- Ran a script to generate sub-datasets based on customer behaviour and persona (e.g., aggressive customers, silent churners, loyal advocates etc.)

Note -

- Problem Encountered** - Hardcoded the comparison thresholds, but the thresholds would only work on this dataset and not on any other dataset if there were variations in ranges.
- Solution** - Shifted to percentile-based thresholds for features with a lower bound and upper bound percentile values. This made the thresholds dynamic, which adjusted to the dataset, leading to more robust recommendations.
- Future Improvement** - In the future, the model can be trained to predict these thresholds automatically.

Dynamic Thresholds

```
sentiment_low = df['SentimentScore'].quantile(0.25)
sentiment_high = df['SentimentScore'].quantile(0.75)
complaints_high = df['Complaints'].quantile(0.75)
interaction_high = df['InteractionAttempts'].quantile(0.75)
response_high = df['ResponseTimeHours'].quantile(0.75)
website_visits_high = df['WebsiteVisits'].quantile(0.75)
```

Recommendations were designed to leverage the chatbot for **friendly** and **empathetic** engagement with low-risk, cooperative customers, while **escalating** to human intervention as risk levels and customer aggression increases.

Strategy Matrix

Risk Level \ Behavior	Aggressive	Cooperative	Evasive	Confused	Standard
High	Senior Escalation & Pause Automated Contact	Empathetic Call from Human Agent to Offer Solutions also for settlement option	Assertive Human Follow-up & Multiple Channels	Problem-Solving Call from Human Agent	Firm Human Call to Discuss Payment
Medium	Immediate Handoff to Human Agent	Chatbot with Flexible Payment Options with loan restructuring	Automated Follow-up via SMS/Email	Ask Chatbot to help with Step-by-Step Payment Guide	Assertive Chatbot Reminder
Low	Formal but Automated Notice	Gentle Chatbot Nudge and early repayment option with discount etc	Proactive Chatbot Nudge with Direct Payment Link	Informative Chatbot to Explain Bill	Standard Automated Reminder

ChatBot Bot Link

- Name of the bot : **TVS Sahahyak**
- Goal: To build a production-ready NBFC support chatbot that remembers users and fetches their financial data.
- Platform of Choice: Started with WhatsApp, switched to Telegram for faster setup.

Detailed Description

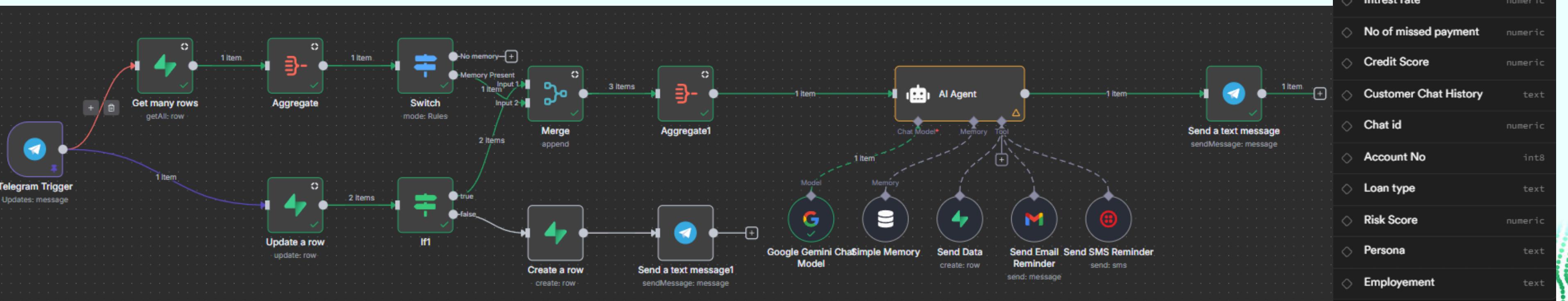
Database Design

- Customer Data → stores financial details.
- Conversation Memories → remembers chat history & key user info.

Tech-Stack



n8n workflow



Conversational memory	
id	int8
created_at	timestamptz
Message	text
Sender First name	text
Sender Last name	text
Agent Response	json
Chat id	int8

Customer Data	
id	int8
created_at	timestamptz
First Name	text
Last Name	text
Loan amount	int8
Address	text
EMI	numeric
Interest rate	numeric
No of missed payment	numeric
Credit Score	numeric
Customer Chat History	text
Chat id	numeric
Account No	int8
Loan type	text
Risk Score	numeric
Persona	text
Employement	text

Features & USP

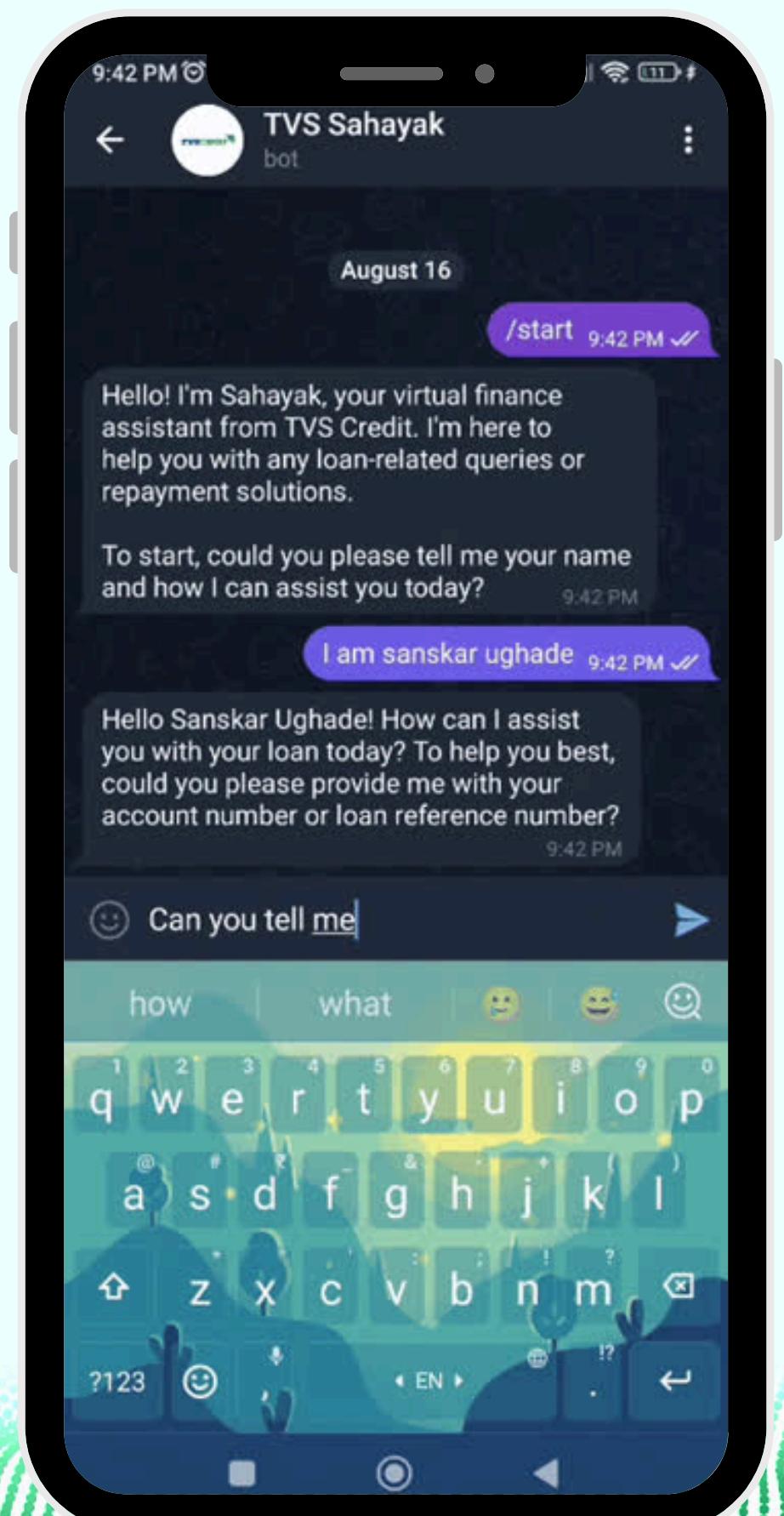
- 1. Context Aware Responses** - Remembers past conversations to provide relevant answers without repeating questions.
- 2. Direct Financial Data Access** - Instantly fetches customer information for faster resolution.
- 3. Personalised Assistance** - Tailors replies based on user profile and past interactions.
- 4. Seamless Onboarding** - Automatically identifies and saves new users without manual data entry.
- 5. Robust Identification System** - Uses unique chat ID for accurate, consistent user recognition.
- 6. Multi Case Handling** - Adapts to users with or without stored data and keeps workflow smooth.
- 7. Optimized Workflow** - Built to eliminate duplicate responses and handle edge cases efficiently.
- 8. Send Email and SMS reminders** - automate personalized emails with dynamic fields, reliable delivery, and opt-out handling.

Ensuring Data Privacy & Security

- Encrypt all data in transit (TLS 1.3) and at rest (AES-256)
- Mask or tokenise sensitive fields like account number & personal information before model input
- Enforce RBAC (role-based access) & strict access logging
- Keep PII (Personally Identifiable Information) within India to comply with DPDP Act 2023 & RBI guidelines

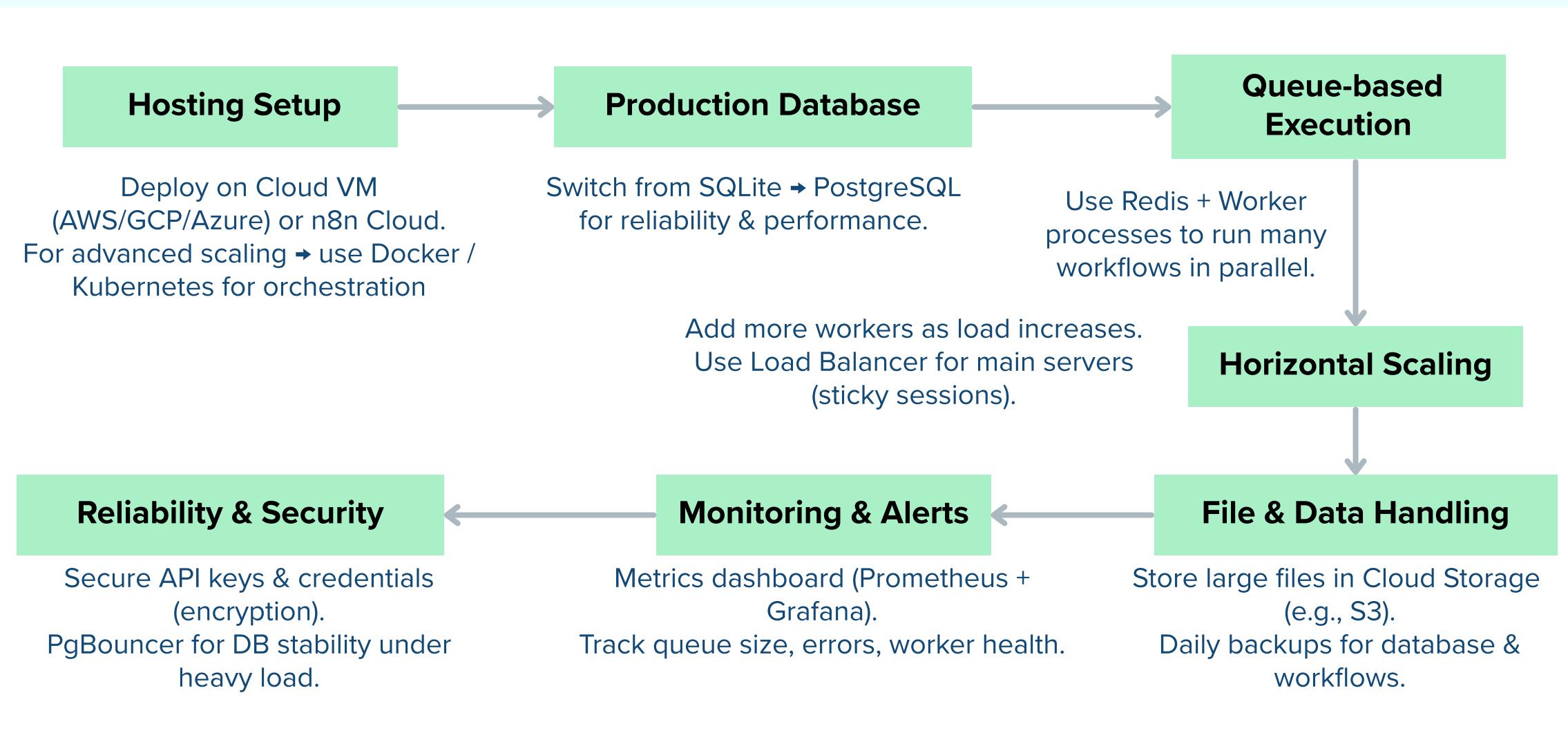
Data-flow

- User Interaction → Chatbot UI captures queries (WhatsApp/Web/App).
- n8n Workflow Orchestration → Routes requests, manages logic & privacy.
- Mask/Tokenize PII → Replace sensitive info (e.g., account numbers) with tokens before sending to Gemini.
- Gemini API for Language → Handles natural conversation, never sees raw PII.
- Secure Backend (India Servers) → n8n maps tokens back to real data and fetches loan/account details.
- Merge Responses → Combine Gemini's reply with masked account details (e.g., account ending 7890).
- Compliance Ensured → PII stays in India (DPDP Act 2023 & RBI guidelines).
- Scalable → n8n workflows can scale via Docker/Kubernetes, handle multiple users in parallel.



Scaling process

Scaling Guide



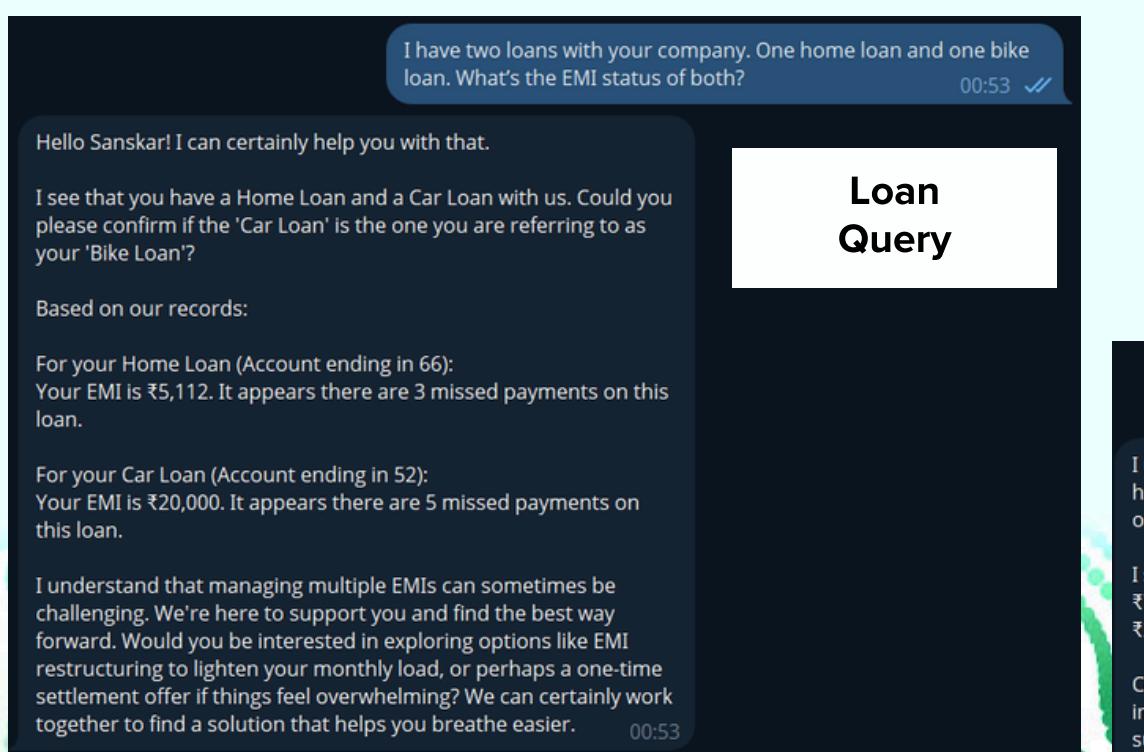
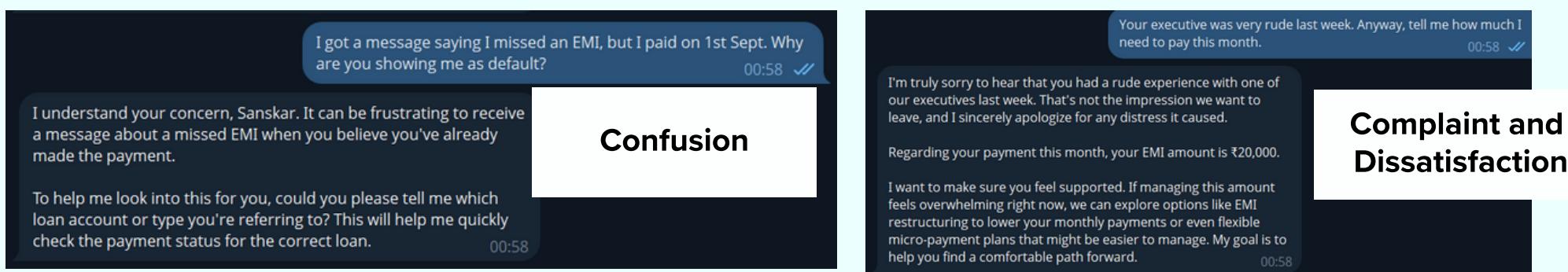
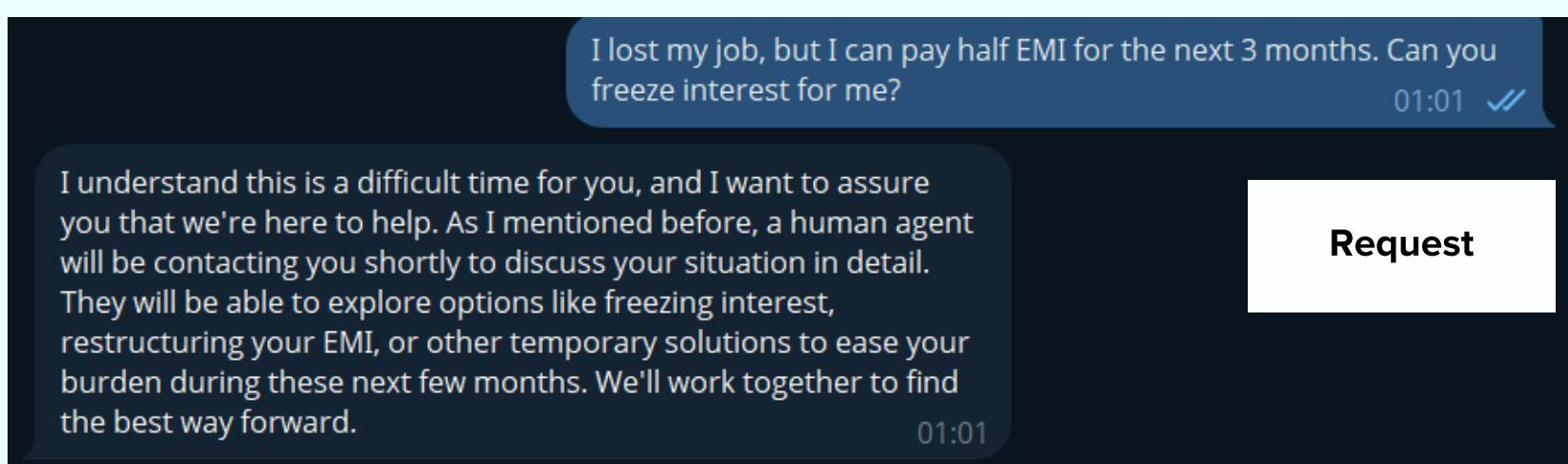
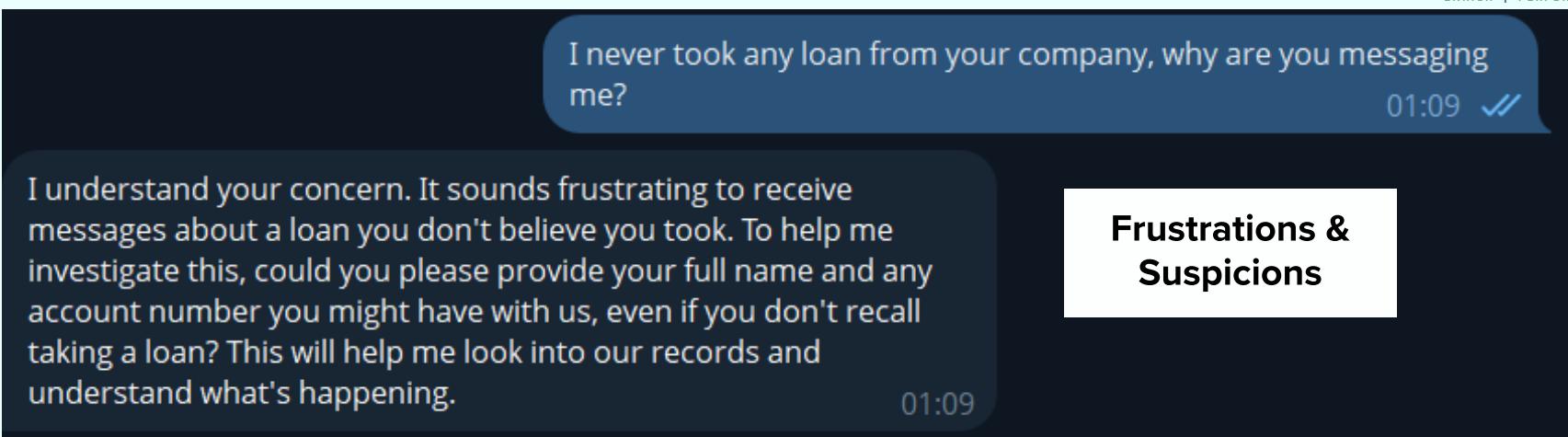
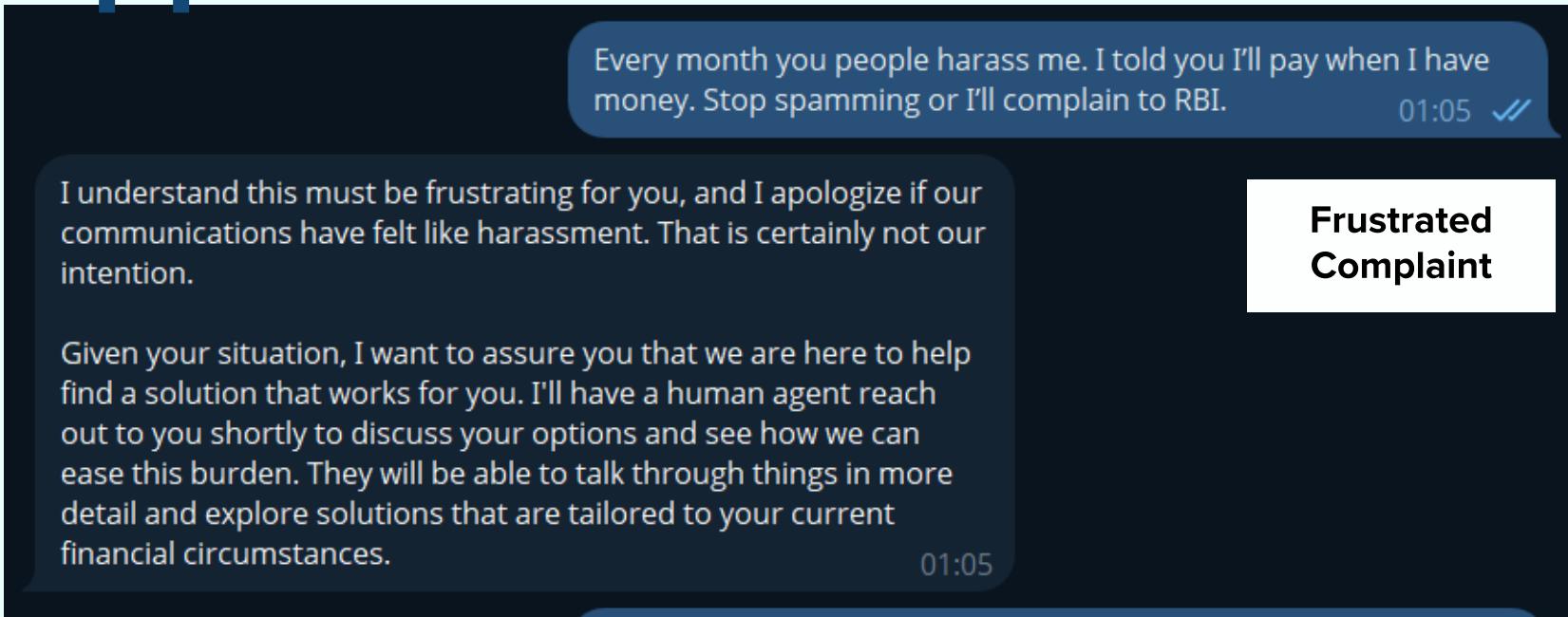
Cost Benefit Analysis

Costs	Benefits
Development & Hosting - Cloud infra ₹15–25k/month, Dev & maintenance ₹5–10L/year	Financial Savings - 10–15% lower defaults → ₹10–15 Cr savings on ₹100 Cr portfolio
Integration & Training - System integration ₹2–3L Staff training ₹50k	Operational Efficiency - Automates 70–80% queries, frees staff for high-risk cases
Operational Costs - Monitoring & backups minor, optional enterprise scaling	Customer Experience - 24x7 support, faster resolutions, improved repayment rates
	Scalability & Readiness - Thousands of users handled without extra staff, extendable to WhatsApp/IVR/Email

ROI Under Different Scenarios

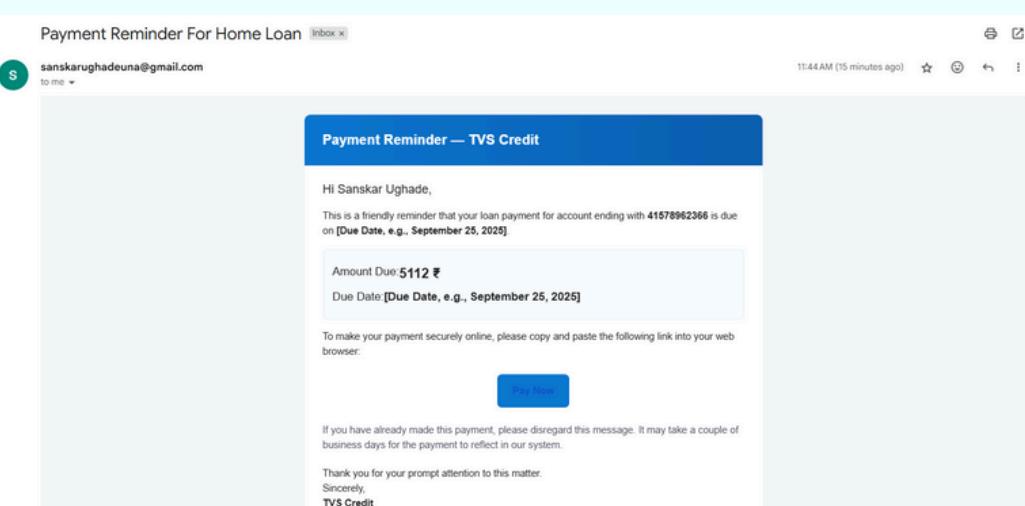
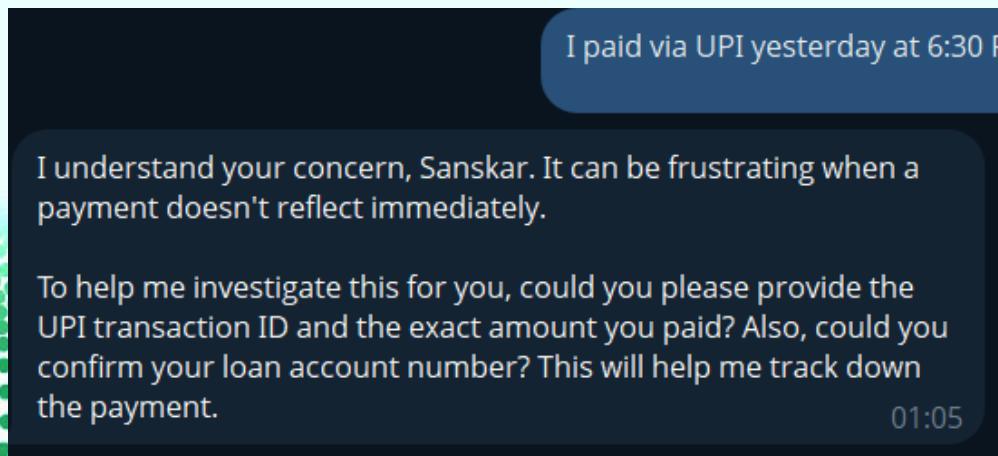
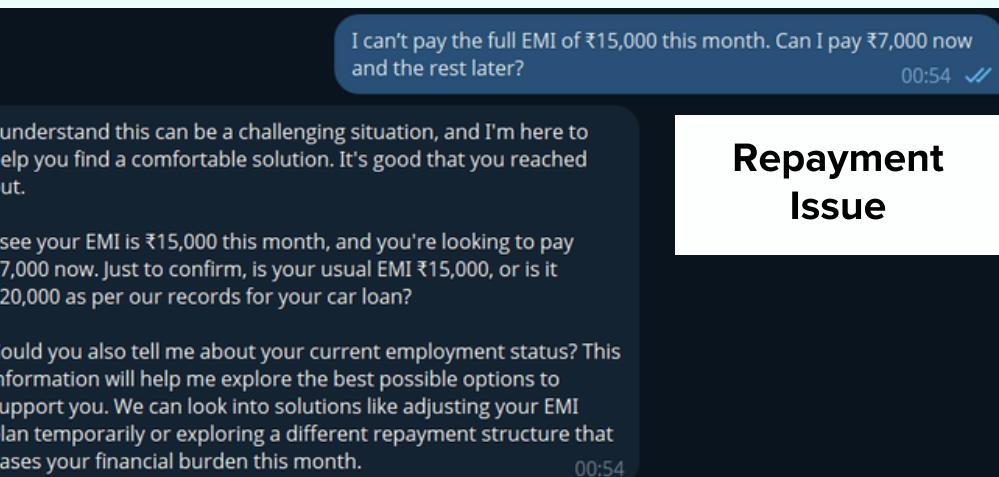
Case	Default Reduction (₹100 Cr portfolio)	Infra Cost	Net Benefit
Worst	5%	₹50k/month	~₹4.9 Cr
Base	10%	₹25k/month	~₹9.7 Cr
Best	20%	₹10k/month	~₹19.9 Cr

Appendix - I



ScreenShots

Bot-response in different situations



Appendix - II

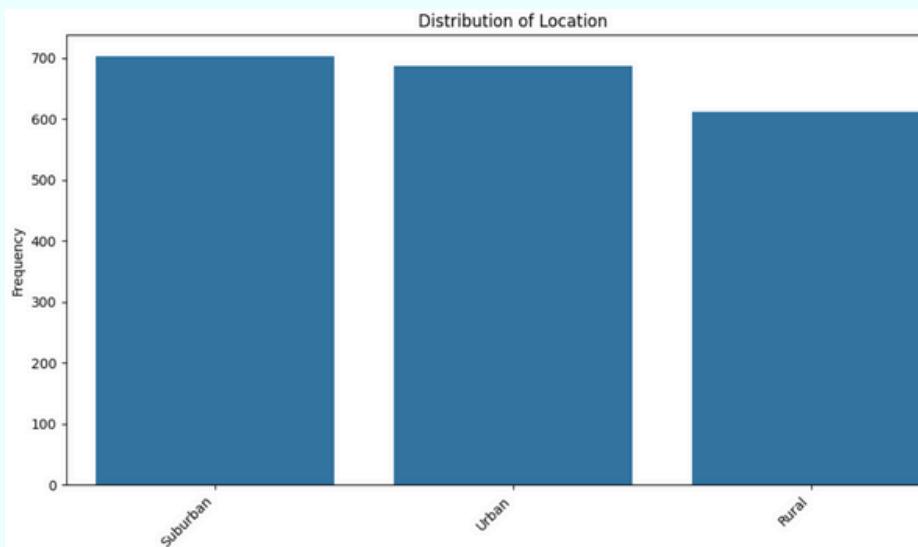
Analysis Category Distributions

Shape of Dataset
 (2000, 19)

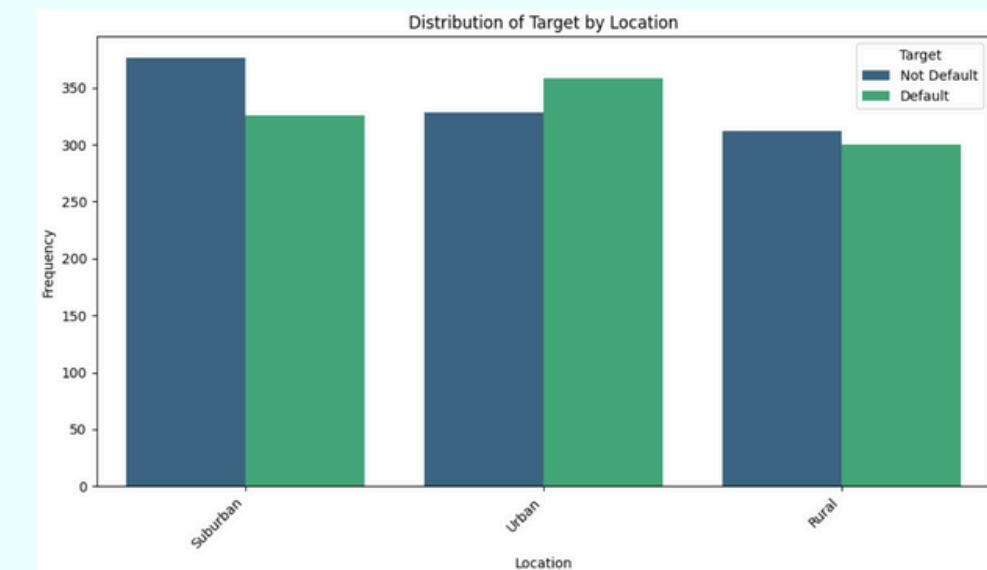
Missing Values
 No Null Values

CustomerID	0
Age	0
Income	0
Location	0
EmploymentStatus	0
LoanAmount	0
TenureMonths	0
InterestRate	0
LoanType	0
MissedPayments	0
DelaysDays	0
PartialPayments	0
InteractionAttempts	0
SentimentScore	0
ResponseTimeHours	0
AppUsageFrequency	0
WebsiteVisits	0
Complaints	0
Target	0

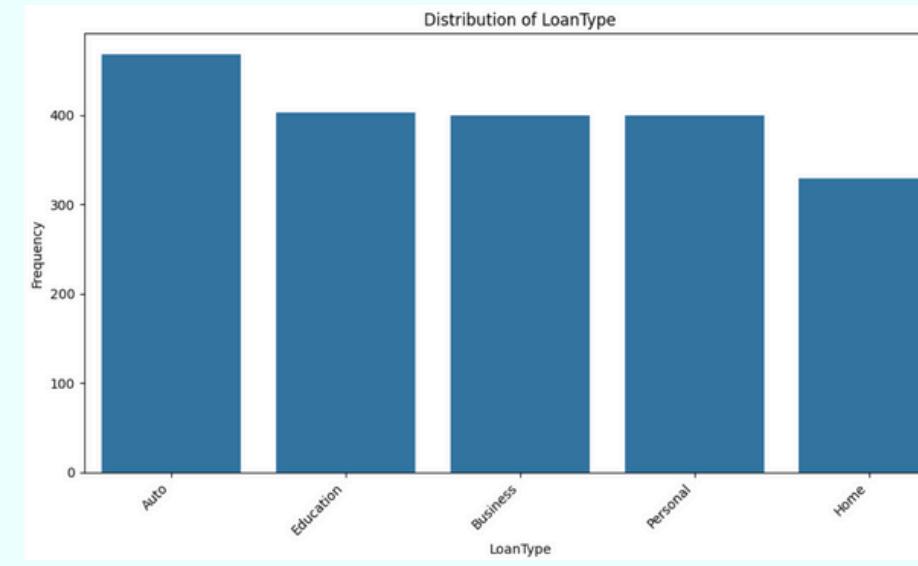
Location	
Suburban	702
Urban	686
Rural	612



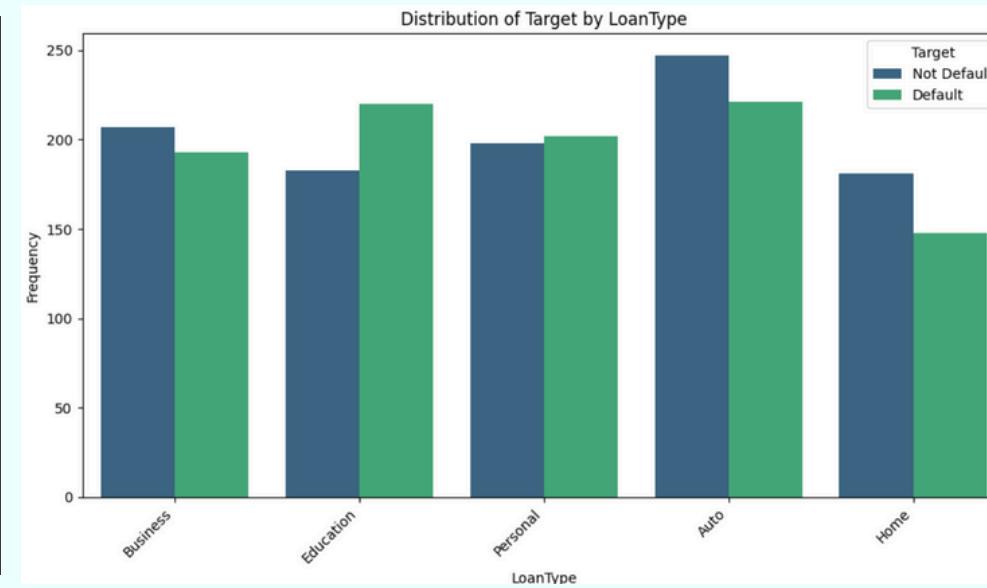
Target	0	1
Location		
Rural	312	300
Suburban	376	326
Urban	328	358



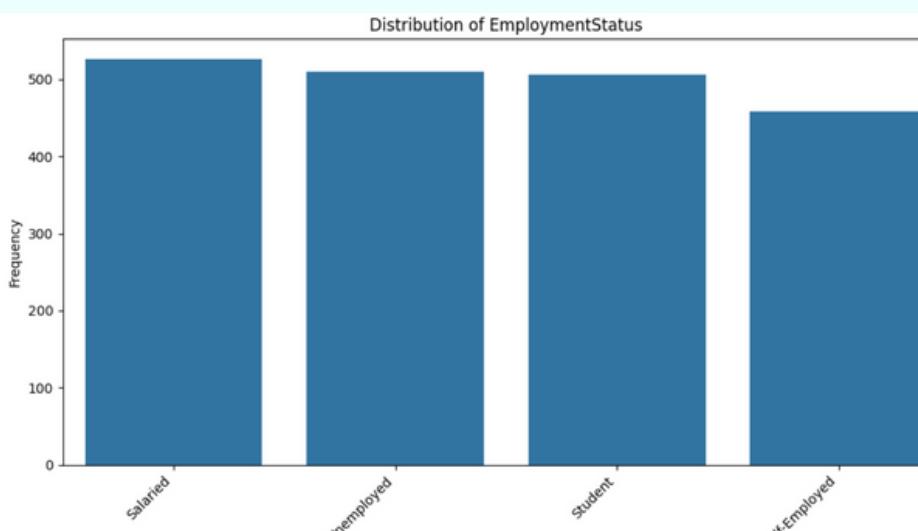
LoanType	
Auto	468
Education	403
Business	400
Personal	400
Home	329



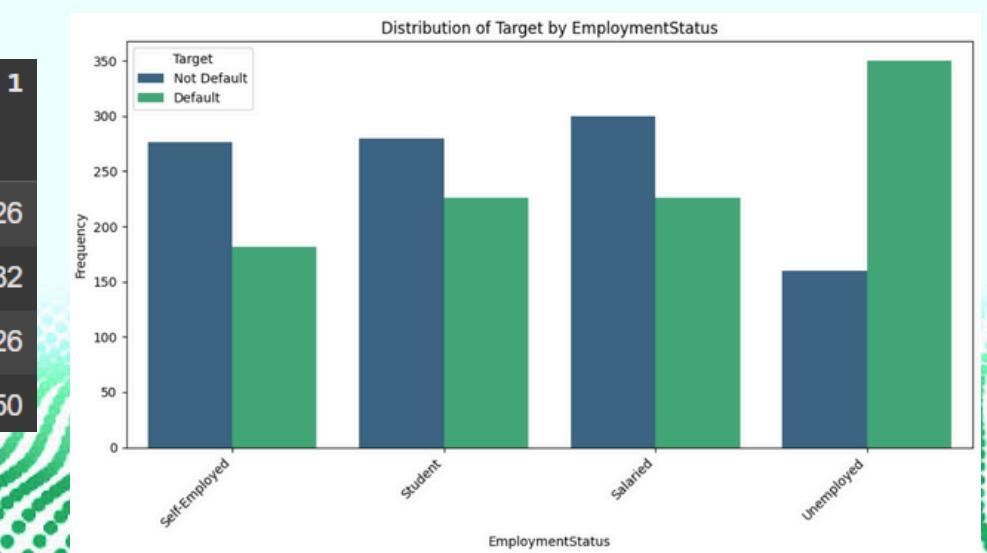
Target	0	1
LoanType		
Auto	247	221
Business	207	193
Education	183	220
Home	181	148
Personal	198	202



EmploymentStatus	
Salaried	526
Unemployed	510
Student	506
Self-Employed	458

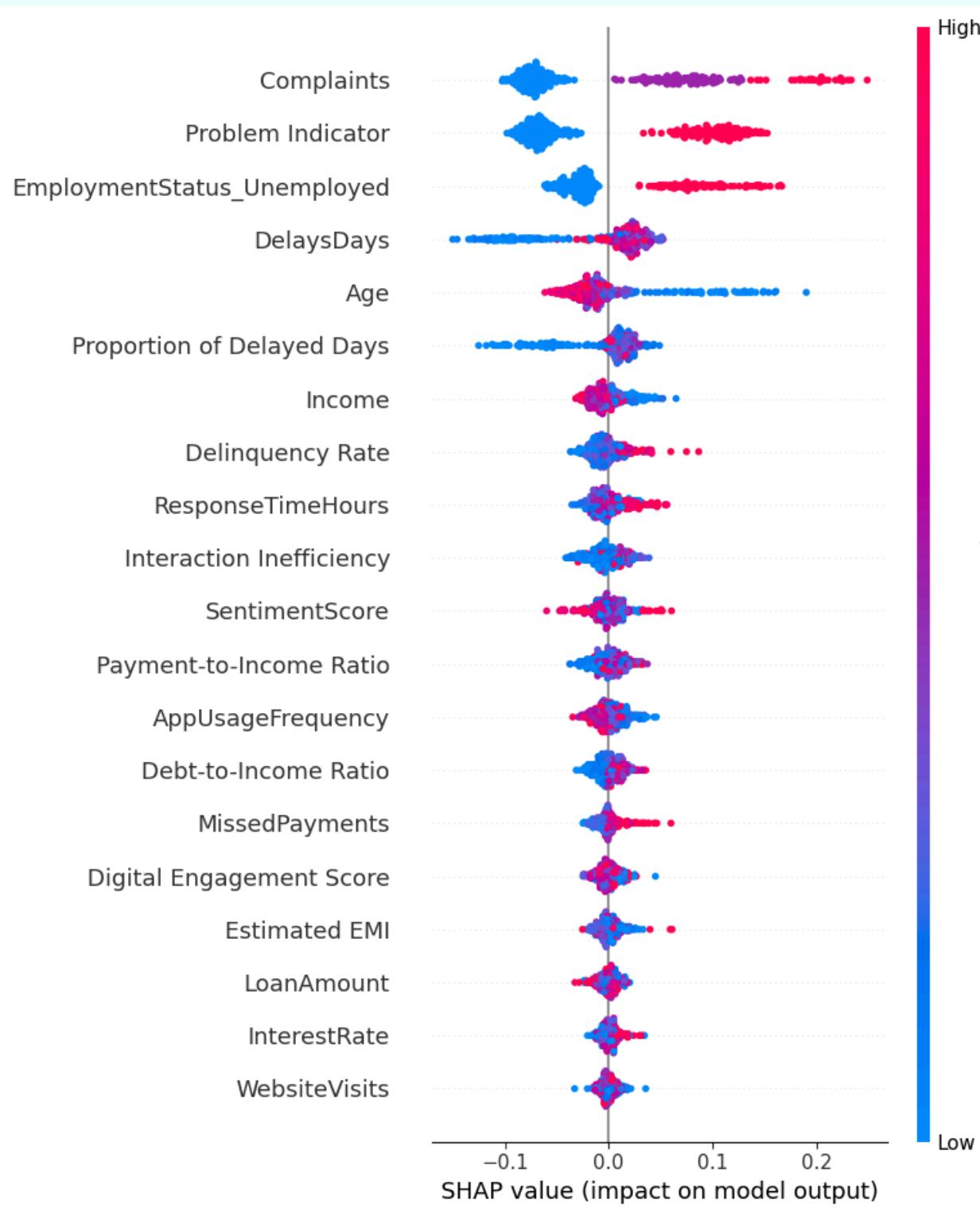


Target	0	1
EmploymentStatus		
Salaried	300	226
Self-Employed	276	182
Student	280	226
Unemployed	160	350



Appendix - III

SHAP Values



Links

- Analysis Notebook [Collab](#) | [Drive](#)
- Prediction Model Notebook [Collab](#) | [Drive](#)
- Recommendation Model Notebook [Collab](#) | [Drive](#)
- Chatbot (Sahayak) n8n workflow [Drive](#)
- Description of Building the Chatbot [Doc](#)
- Prediction with risk scores [Link](#)
- Ideations [Link](#)
- Recommendation Strategy Output [Link](#)



Thank You