PRESENTATION CONTENT

Slide 1 — Title

AI Powered Lending Risk Intelligence Platform
Alternate & Behavioural Credit Assessment for Modern Banking

Team: The Optimizers
Objective: Intelligent loan decisioning using ML + alternative data

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Slide 2 — Problem Statement

Traditional credit scoring fails in modern lending:

- 40–60% applicants rejected due to no credit history
- Rule-based underwriting ignores behavioural patterns
- Static score cannot detect future default
- Banks suffer NPAs due to late risk detection
- Financial inclusion gap for young & gig-economy users

👉 Banks need dynamic, explainable & inclusive risk assessment

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Slide 3 — Project Objective

Build an intelligent lending decision engine that:

- Predicts probability of loan default
- Scores customers (300–850)
- Uses alternate data for thin-file users
- Segments risk levels for decision making
- Monitors behavioural risk after loan approval
- Provides explainable AI decisions

Slide 4 — Our Approach

We evaluate risk in **3 stages**

1. Application Risk (Can user repay?)
2. Alternate Data Risk (No credit history users)
3. Behavioural Risk (Will user default later?)

This converts static scoring → dynamic lending intelligence

Slide 5 — System Architecture

User Data → Feature Engineering → ML Models → Risk Engine → Decision Layer → Database

Modules:

- Preprocessing Engine
- Risk Prediction Model
- Credit Score Generator
- Behaviour Monitoring Engine
- Explainability Engine

Slide 6 — Input Data

Traditional Financial Data

- Income
- Loan amount
- Age
- Employment type
- Past loans
- Payment delays

Alternate Data (Thin File Users)

- UPI transaction frequency
- Utility bill payments
- Recharge regularity
- Spending consistency

Behavioural Data (Post-loan)

- EMI delay trend
- Balance drop pattern
- Spending spike

Slide 7 — Feature Engineering

We derive financial behaviour indicators:

- Debt-to-Income Ratio
- Loan Burden Ratio
- Payment Consistency Score
- Spending Volatility
- Credit Utilization

These features improve risk prediction accuracy significantly.

Slide 8 — Machine Learning Models

Two-layer modelling approach:

Logistic Regression

- Baseline probability estimation
- Regulatory interpretability

XGBoost

- Captures complex financial behaviour
- Final risk prediction

Evaluation Metrics:
Accuracy, Precision, Recall, ROC-AUC

Slide 9 — Credit Score Calculation

Model outputs Probability of Default (PD)

We convert PD → Credit Score:

Score = Offset + Factor × ln((1 − PD)/PD)

Result:

- Low risk → High score
- High risk → Low score

Score range: **300 – 850**

Slide 10 — Risk Segmentation Engine

Instead of only giving score → we give decision

Score	Risk Level	Decision
800+	Prime	Instant Approval
650–799	Near Prime	Normal Loan
500–649	Subprime	High Interest
<500	High Risk	Reject

Slide 11 — Behavioural Monitoring (Key Innovation)

After loan approval system keeps monitoring:

- Sudden spending increase
- Balance deterioration
- EMI delay trend

If detected → Early Default Alert

Banks can act before NPA occurs.

Slide 12 — Explainable AI

Using SHAP:

- Shows top factors affecting decision
- Transparent loan approval
- Regulatory compliance
- Builds customer trust

Example:
High DTI → Risk ↑
Stable payments → Risk ↓

Slide 13 — Technology Stack

Python, SQL
Scikit-learn, XGBoost, SHAP
Pandas, NumPy, Matplotlib
API ready architecture

Slide 14 — Benefits

- Better default prediction
- Reduced bad loans (NPA prevention)
- Financial inclusion for new users
- Transparent lending decisions
- Real-time risk monitoring

Slide 15 — Future Scope

- Real-time bank integration
- Fraud detection module
- Personalized loan pricing
- Dynamic credit limit adjustment

Slide 16 — Conclusion

We transform credit scoring into a continuous risk intelligence system.

From:
Static approval decision

To:
Dynamic lifecycle risk monitoring

🟩 SOLUTION EXPLANATION (FOR VIVA / REPORT)

You can speak this when asked **“Explain how your system solves the problem”**

Our Solution Logic

Banks traditionally check credit history once and approve/reject loan.
But risk changes over time.

So we designed a **3-layer risk intelligence system**

Step 1 — Application Risk Prediction

We first collect applicant financial data.

We calculate behavioural financial ratios:

- Debt to income
- Loan burden
- payment consistency

This data is passed to ML models.

Logistic Regression provides interpretable baseline risk.
XGBoost learns complex repayment behaviour patterns.

The model outputs Probability of Default (PD).

Step 2 — Credit Score Generation

We convert PD into a standardized credit score (300–850).

This helps bank officers understand risk easily and keeps system compatible with traditional lending workflows.

Step 3 — Thin-File Customer Handling

For users without credit history:

We use alternate behavioural indicators like:

- bill payments
- transaction consistency
- recharge behaviour

This allows inclusion of new-to-credit population.

Step 4 — Decision Engine

Instead of just score → we segment risk levels.

Each segment maps to lending action:
approve, higher interest, collateral, or reject.

This makes the system directly usable by banks.

Step 5 — Behavioural Risk Monitoring (Key Part)

After loan approval system continues monitoring account behaviour.

If repayment capacity deteriorates:
→ early default alert generated

Bank can intervene before loan becomes NPA.

Step 6 — Explainability

Using SHAP we show which factors affected decision.

This ensures transparency, regulatory compliance and customer trust.

Final Outcome

Our system is not just a prediction model.
It is a **complete lending lifecycle intelligence platform**:

Before loan → risk prediction
During loan → behaviour monitoring
After loan → default prevention

🧠 1) ARCHITECTURE DIAGRAM

AI Lending Risk Intelligence Architecture

```pgsql
                 USER / BANK PORTAL
                        ↓
                 Data Input Layer
       (Financial + Alternate + Behavioural Data)
                        ↓
                 Data Preprocessing
      (Cleaning, Encoding, Scaling, Feature Engineering)
                        ↓
                   Feature Store
                        ↓
        -----------------------------------
        |                                 |
 Logistic Regression (Baseline Risk)   XGBoost (Final Risk)
        |                                 |
        ----------- Risk Probability --------
                        ↓
             Credit Score Generator (300-850)
                        ↓
                  Risk Segmentation Engine
           (Prime / Near Prime / Subprime / Reject)
                        ↓
              Behaviour Monitoring Engine
          (Detect future default early warning)
                        ↓
                 Explainability (SHAP)
                        ↓
                     SQL Database
                        ↓
                Dashboard / Bank Decision
```

🔁 2) FLOW CHART

You can draw decision diamonds in PPT.

Loan Decision Workflow

```pgsql
Start
  ↓
User submits loan application
  ↓
Collect financial & alternate data
  ↓
Preprocess data
  ↓
Calculate financial ratios
  ↓
Predict Probability of Default (ML Model)
  ↓
Convert PD → Credit Score
  ↓
Is Score > 800?
   → Yes → Instant Approval
   → No ↓
Is Score between 650–799?
   → Yes → Standard Loan
   → No ↓
Is Score between 500–649?
   → Yes → High Interest / Collateral
   → No remind Reject Loan

After approval →
Start Behaviour Monitoring
  ↓
Risk detected?
   → Yes → Early Warning Alert
   → No → Continue Monitoring
  ↓
End
```

📱 3) WIREFRAMES (UI Screens)

Screen 1 — Loan Application Form

Fields:

- Name
- Age
- Monthly Income
- Loan Amount
- Employment Type
- Existing Loans
- Monthly Expenses

Button: **Check Eligibility**

Screen 2 — Credit Risk Result

Display:

Credit Score: 742
Risk Level: Near Prime
Decision: Approved with Standard Interest

Top Risk Factors:
- High loan amount
- Moderate income
- Stable payment history

Button: Download Report

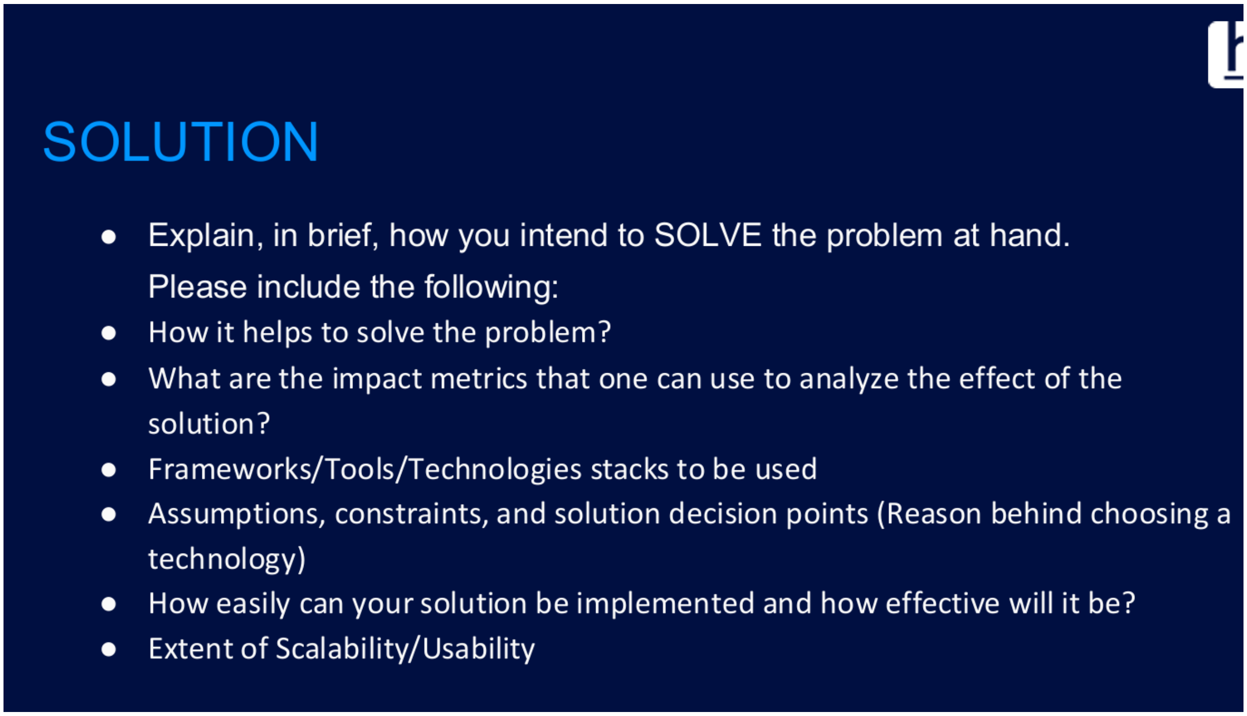
Screen 3 — Bank Dashboard

Table:

Customer	Score	Risk	Status
A	812	Prime	Approved
B	540	Subprime	Review
C	420	High Risk	Reject

Alert Section:
⚠ Early Default Warning: Customer B

SOLUTION SLIDE CONTENT:



Below is **ready-to-paste content** exactly according to the format shown in your slide 👇

SOLUTION

1. How we solve the problem

We propose an **AI-Powered Lending Risk Intelligence Platform** that evaluates a borrower across the complete loan lifecycle instead of a one-time static score.

The system works in three stages:

1. **Application Risk Assessment**
   - Machine Learning predicts Probability of Default using financial attributes

    - Generates standardized credit score (300–850)
2. **Alternate Data Assessment**
    - Evaluates thin-file users using behavioural indicators (payment consistency, spending pattern)
    - Enables financial inclusion for users without credit history
3. **Behavioural Monitoring**
    - Continuously tracks post-loan behaviour
    - Detects early signs of future default
    - Sends risk alerts to bank before NPA occurs

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2. How it helps solve the problem

- Improves accuracy compared to rule-based credit scoring
- Approves new-to-credit customers safely
- Detects risky customers early instead of after default
- Reduces Non-Performing Assets (NPAs)
- Provides explainable decisions for regulatory compliance

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3. Impact Metrics

The effectiveness of the system will be evaluated using:

Model Performance Metrics

- Accuracy
- Precision & Recall
- ROC-AUC Score

Business Impact Metrics

- Reduction in default rate
- Increase in approval rate for thin-file users
- Early risk detection rate
- Portfolio risk distribution improvement

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4. Frameworks / Tools / Technology Stack

- **Language:** Python

- **Machine Learning:** Scikit-learn, XGBoost
- **Explainability:** SHAP
- **Database:** SQL
- **Visualization:** Matplotlib / Seaborn
- **Deployment/UI:** Streamlit

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5. Assumptions, Constraints & Decision Points

Assumptions

- Historical credit data reflects repayment behaviour
- Behavioural patterns correlate with future default

Constraints

- Limited real banking transaction data
- Privacy & regulatory requirements

Technology Decisions

- XGBoost chosen for high predictive performance
- Logistic Regression for interpretability
- SHAP for regulatory transparency
- Streamlit for rapid prototype deployment

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6. Ease of Implementation & Effectiveness

- Modular architecture allows quick bank integration via API
- Requires only customer form data initially
- Real-time prediction within seconds
- High effectiveness due to combined financial + behavioural risk analysis

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7. Scalability & Usability

- Can handle unlimited users after deployment
- Supports periodic retraining with new data
- Easily extendable to fraud detection & dynamic credit limits
- Simple dashboard usable by bank officers without technical knowledge

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🔎 Search for Problem Evidence (why solution needed)

Financial inclusion / thin file users

Search:

- `percentage of Indians without credit history RBI report`
- `new to credit customers statistics India`
- `financial inclusion credit access statistics India banking`
- `how many people in India have CIBIL score statistics`

You'll get:
→ Proof many users get rejected because no credit history

Loan defaults / NPA problem

Search:

- `NPA rate India banks RBI statistics 2024`
- `loan default rate retail lending India report`
- `bank losses due to bad loans statistics`
- `global consumer loan default rate statistics`

You'll get:
→ Why banks need better risk prediction

Search for Impact Metrics

Search:

- `how much NPA reduced using AI in banking`
- `AI fraud detection banking statistics`
- `digital lending growth statistics India`