



# Home-Credit-Loan-Default-Risk-Analysis

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Analytical case study on Home Credit loan default risk: identifies key risk drivers using Chi-square tests and logistic regression. Includes actionable recommendations based on 307,511 loan applications.

# Home Credit Loan Default Risk Analysis: Case Study Workflow and Recommendations

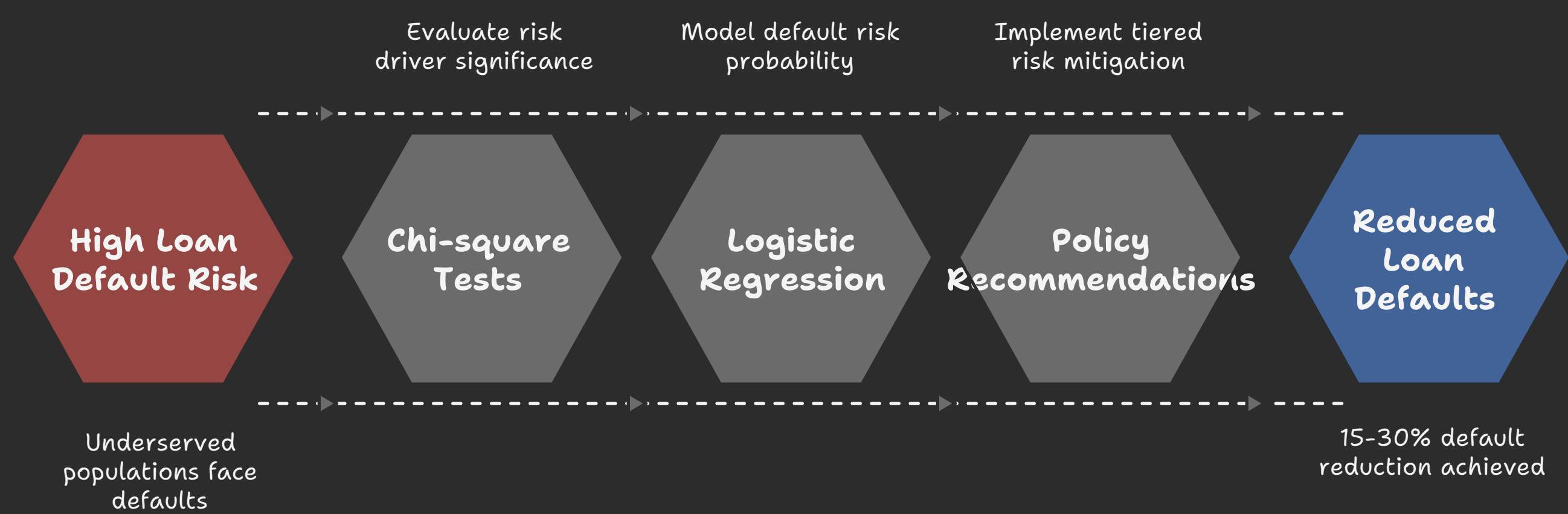
## Overview

This case study analyzes loan default risk for Home Credit, which serves financially underserved populations, using a dataset of 307,511 loan applications. The analysis leverages Chi-square tests and logistic regression to evaluate seven risk drivers: income type, regional rating, external credit scores, age cohorts, age segments, credit inquiries, and application weekdays. The objective is to provide evidence-based recommendations to reduce defaults by 15–30% while enhancing inclusion for low-risk groups.

Key objectives:

- Identify and rank impact of risk drivers on default odds.
- Propose targeted policy changes based on statistical findings.
- Estimate potential default reduction through tiered policies.

## Reducing Loan Defaults at Home Credit



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## Project Structure

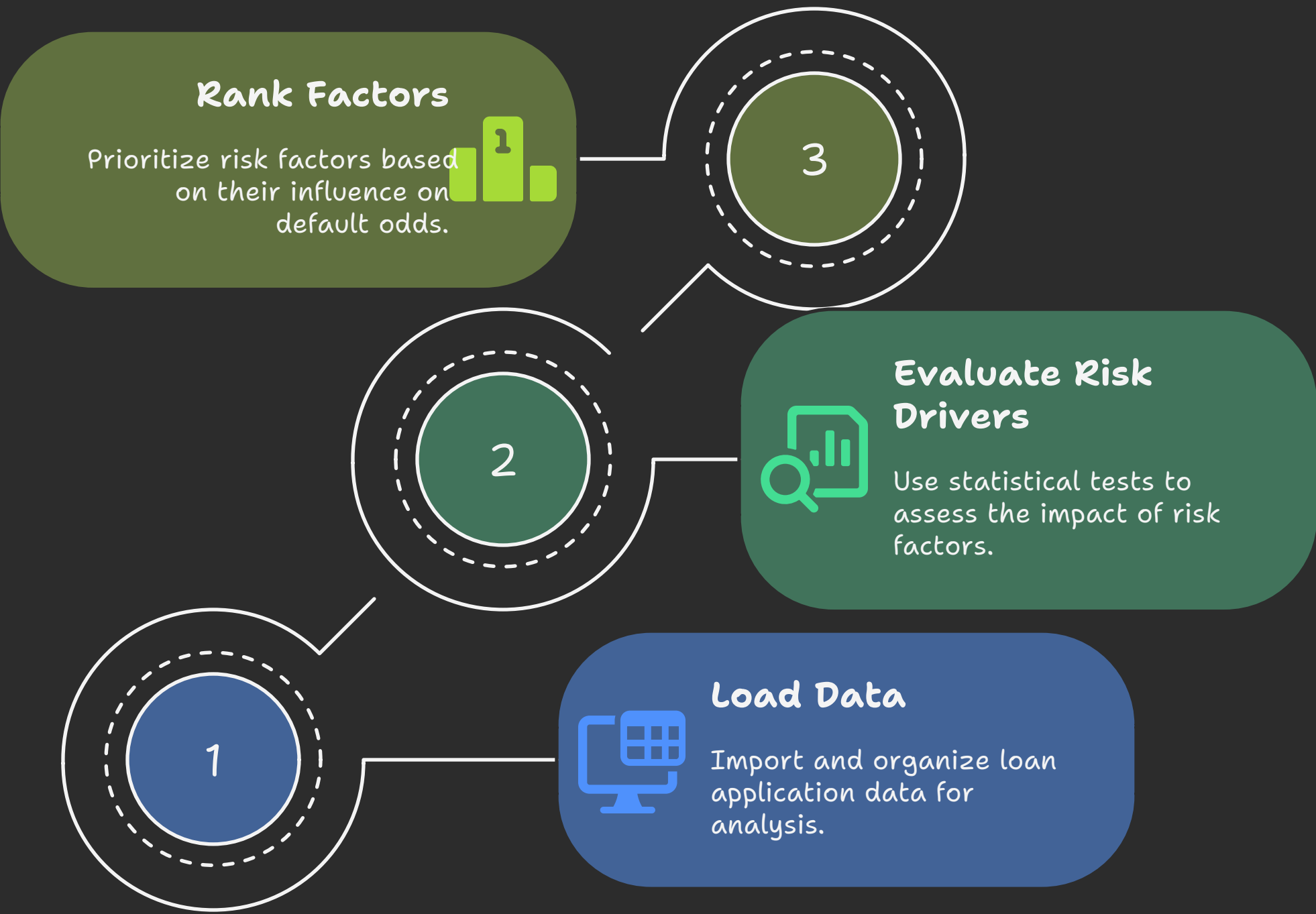
- **Data/**: Contains the dataset [not included here; derived from internal Home Credit records].
- **Docs/**: Includes the full case study report PDF ["case study report.pdf"].
- **Visuals/**: Logistic regression results [Figures A1-A8 in the appendix].

## Analytical Workflow

The project is divided into four phases:

### Phase 1: Data Loading & Analysis

- Analyzed 307,511 loan applications.
- Evaluated seven risk drivers using Chi-square tests and logistic regression.
- Ranked factors by impact on default odds.






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### Phase 2: Key Findings - Statistical Tests

- **Income Type:** Highest impact (up to +551% odds), with unstable income sources (e.g., Unemployed +551%, Maternity Leave +61%) driving extreme risk.
- **Regional Rating:** High impact (up to +146% odds), with poorer regions (Region 3 +146%) showing higher defaults.
- **External Credit Scores:** High impact (−73.5% odds), with scores >0.5 reducing default risk significantly.
- **Age Cohorts (12 Bands):** High impact (−61.7% odds), risk declines steadily with age.
- **Broad Age Segments:** Medium impact (−53.2% odds), seniors (>50) are safest.
- **Credit Inquiries:** Low impact (+3.7% odds), multiple inquiries slightly raise risk.
- **Application Weekday:** Lowest impact (±5.2% odds), minimal variation with Tuesday slightly riskier.

Impact of Factors on Default Risk

	<div> Impact Level</div>	<div> Riskiest Group</div>	<div> Safest Group</div>
Income Type	Highest	Unemployed (+551%), Maternity Leave (+61%)	Stable income sources
Regional Rating	High	Region 3 (+146%)	Wealthier regions
External Credit Scores	High	Low scores	Scores >0.5 (-73.5%)
Age Cohorts	High	Younger cohorts	Older cohorts (-61.7%)
Broad Age Segments	Medium	Younger segments	Seniors (>50) (-53.2%)
Credit Inquiries	Low	Multiple inquiries (+3.7%)	Few inquiries
Application Weekday	Lowest	Tuesday (+5.2%)	Other weekdays

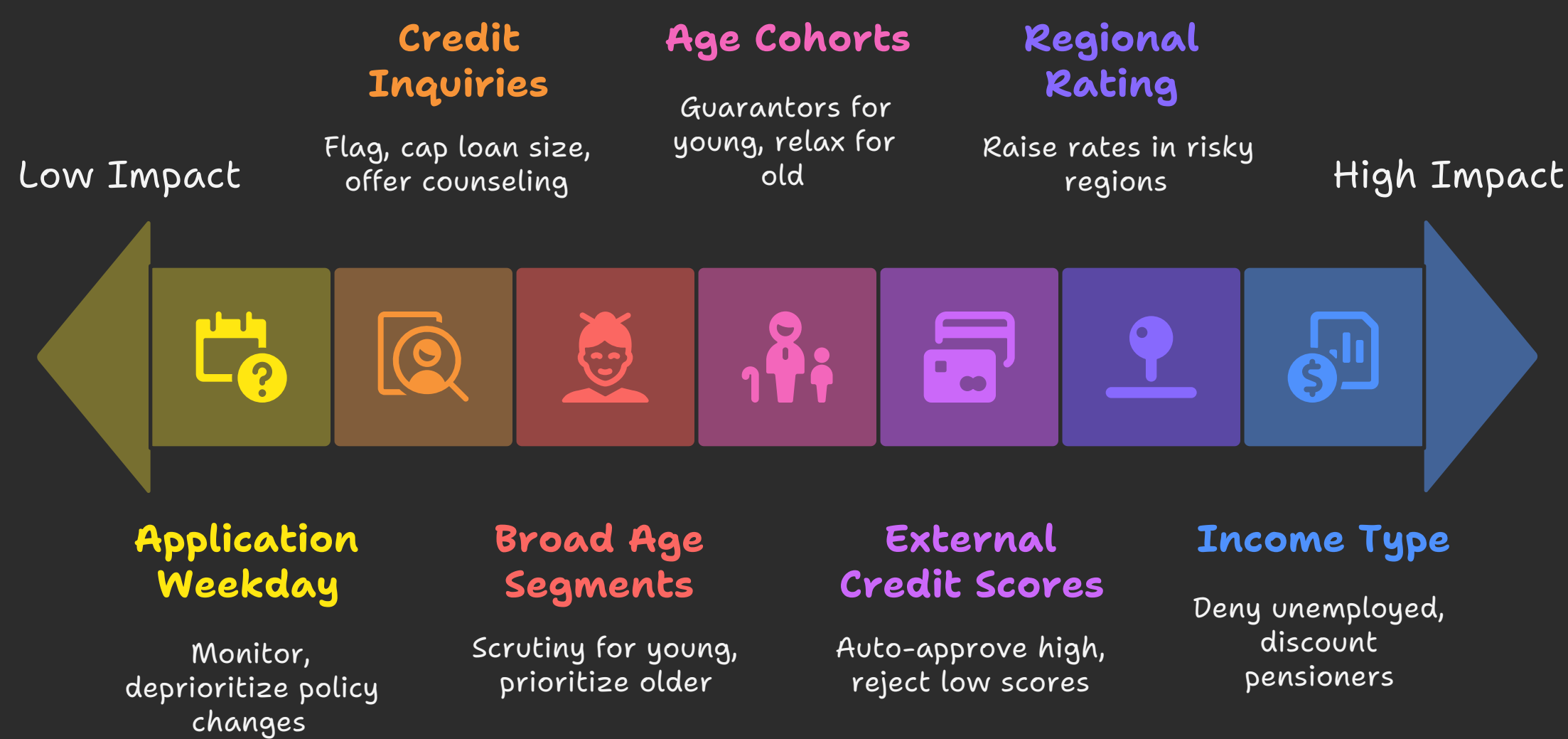
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### Phase 3: Conclusion & Recommendations

- **Conclusion:** Top levers for risk reduction are income type, regional rating, external scores, and age.
- **Evidence-Based Recommendations:**
  - **Income Type:** Deny/cap loans for Unemployed & Maternity Leave; offer 1–2% rate discounts to Pensioners/State Servants; tighten income verification for Working/Commercial Associates.
  - **Regional Rating:** Raise rates or collateral in Region 3 by ~25%; fast-track approvals in Region 1; cap Region 3 loan amounts at 70% of standard.
  - **External Credit Scores:** Auto-approve >0.5 with minimal checks; require collateral or reject ≤0.5; expand bureau partnerships.
  - **Age Cohorts:** Require guarantors for youngest cohorts [0–3]; relax terms for oldest [9–11]; build age-based risk models.
  - **Broad Age Segments:** Extra scrutiny & financial literacy for <30; prioritize >50 in portfolio mix; limit <30 exposure to ~25%.
  - **Credit Inquiries:** Flag >2 for manual review; cap loan size; offer credit counseling.
  - **Application Weekday:** Increase Tuesday checks; promote low-risk days; monitor but deprioritize for major policy changes.

- **Expected Impact:** Tiered policies could cut defaults by 15–30% while improving inclusion for low-risk groups.

Risk reduction levers ranked by impact on loan defaults



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### Phase 4: Limitations & Future Work

- **Limitations:**
  - Data scope limited to provided dataset; may not capture macroeconomic shocks or post-loan behavioral changes.
  - Missing variables [e.g., debt-to-income ratio, employment tenure].
  - Model simplification assumes linear log-odds relationships.
  - Multicollinearity and lack of time-series modeling.
- **Future Work:**
  - Incorporate additional borrower metrics [e.g., payment history, debt ratios].
  - Test advanced models [XGBoost, LightGBM, survival analysis].
  - Develop multi-factor risk tiers and behavioral tracking.
  - Conduct A/B testing and enhance explainability with SHAP/partial dependence plots.

# Enhancing Loan Risk Assessment: Limitations and Future Directions



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## ## Technologies Used

- Statistical tools: Chi-square tests, logistic regression.
- Software: Python-based analysis.

## ## Getting Started

1. Review the case study report PDF ["case study report.pdf"].
2. Implement recommendations based on organizational needs and data availability.

## ## Contributing

Contributions welcome! Suggest improvements or additional analyses via feedback channels.

## ## License

MIT License – feel free to use and adapt.

Made with  by Gajarajan V Y. Inspired by standard dataset for educational purposes.