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Fairness and Transparency in AI Models for Credit Scoring

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DEDICATION

"TO MY PARENTS, FOR THEIR ENDLESS LOVE AND SUPPORT."

"FOR MY WIFE, AND MY CHILDREN, WHO ENDURED THIS JOURNEY WITH ME."

ACKNOWLEDGMENT

I would like to express my deepest gratitude to my supervisor for their expert guidance, patience, and constructive feedback throughout this research. Their mentorship has been invaluable in refining both the technical and conceptual aspects of this study.

I also wish to thank the academic and administrative staff at Liverpool John Moores university, particularly those within the School of Computer Science and Mathematics, for providing continuous academic and technical support during my MSc studies.

Special appreciation goes to my family, friends, and colleagues for their patience, encouragement, and faith in my abilities. Finally, I extend gratitude to the open-source research community and developers of libraries such as SHAP, LIME, and AIF360, whose work greatly supported this research.

ABSTRACT

This research investigates the critical challenge of achieving fairness and transparency in AI-based credit scoring systems while maintaining predictive accuracy. The study addresses growing concerns about algorithmic discrimination and regulatory compliance requirements in automated financial decision-making systems.

Using a 100k-row sample from the LendingClub dataset (2.2 million loan records, 145 original variables, 178 engineered/encoded features with a 151-feature final matrix), we evaluate Logistic Regression, Decision Tree, Random Forest, LightGBM, and XGBoost under a stratified 60/20/20 split with SMOTE applied to the training set (positive class rate: 12.9%). XGBoost achieved the strongest discrimination on the held-out test set (AUC-ROC = 0.984; F1 = 0.938), with LightGBM performing comparably (AUC-ROC = 0.983). A Friedman test confirmed significant differences across models ($\chi^2 \approx 106.11$, $p < 0.001$). For transparency, we implemented SHAP on the best model and assessed explanation quality using four criteria: stability = 0.924, completeness = 0.679, comprehensibility = 0.850, and fidelity = 0.920—indicating reliable and intelligible explanations with strong alignment to model behaviour. In this execution, AIF360 was unavailable; fairness assessment therefore used custom implementations. Pre-processing reweighing produced no measurable change, while post-processing threshold optimisation was applied to align approval rates between groups for an age-derived proxy attribute (pa_Age_Under_5_Years). Given toolkit constraints and proxy limitations, we do not claim a quantitative improvement in demographic parity in this run; instead, we report the fairness–accuracy Pareto frontier and discuss implementation implications.

The contributions of this work are: (i) a validated, end-to-end pipeline for credit scoring with reproducible performance, (ii) a multi-dimensional evaluation of explanation quality using SHAP, and (iii) an empirical characterisation of fairness–accuracy trade-offs suitable for regulatory contexts such as ECOA/Regulation B and GDPR. Limitations and directions for future work include broader protected-attribute coverage, additional mitigation methods, and integration of audited fairness toolkits.

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LIST OF ABBREVIATIONS

AI — Artificial Intelligence

AIA — EU Artificial Intelligence Act

AIF360 — AI Fairness 360 (IBM toolkit)

AOD — Average Odds Difference

AUC — Area Under the ROC Curve

CF — Counterfactual Fairness

CFPB — Consumer Financial Protection Bureau (US)

CV — Cross-Validation

DiCE — Diverse Counterfactual Explanations

DI (ratio) — Disparate Impact (ratio)

DP — Demographic Parity

DTI — Debt-to-Income

ECE — Expected Calibration Error

ECOA — Equal Credit Opportunity Act (US)

EO — Equal Opportunity

EOD — Equalized Odds Difference

EDA — Exploratory Data Analysis

EU — European Union

FNR — False Negative Rate

FPR — False Positive Rate

F1 — F1-score (harmonic mean of precision and recall)

GDPR — General Data Protection Regulation (EU)

KS — Kolmogorov–Smirnov Statistic

KNN — k-Nearest Neighbours

LGBM — Light Gradient Boosting Machine (LightGBM)

LIME — Local Interpretable Model-agnostic Explanations

LOF — List of Figures

LOT — List of Tables

LR — Logistic Regression

LTV — Loan-to-Value

MICE — Multivariate Imputation by Chained Equations

ML — Machine Learning

NPV — Negative Predictive Value

OHE — One-Hot Encoding

PDPC — Personal Data Protection Commission (Singapore)

PP — Predictive Parity

PPV — Positive Predictive Value (Precision)

PRA — Prudential Regulation Authority (UK)

PR AUC — Precision–Recall Area Under Curve

RF — Random Forest

ROC — Receiver Operating Characteristic

SHAP — SHapley Additive exPlanations

SMOTE — Synthetic Minority Over-sampling Technique

SP/ SPD — Statistical Parity / Statistical Parity Difference

SR 11-7 — Supervisory Guidance on Model Risk Management (US Fed)

SS1/23 — Model Risk Management Principles for Banks (PRA, UK)

SVM — Support Vector Machine

TPR — True Positive Rate (Recall/Sensitivity)

TNR — True Negative Rate (Specificity)

XAI — Explainable Artificial Intelligence

XGB — Extreme Gradient Boosting (XGBoost)

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

The financial services industry has undergone profound transformation through the adoption of artificial intelligence and machine learning technologies, particularly in credit scoring and lending decisions. Traditional credit assessment methods, relying primarily on linear statistical models and expert-defined rules, are increasingly being supplemented or replaced by sophisticated machine learning algorithms capable of processing vast amounts of data and identifying complex patterns predictive of creditworthiness.

Credit scoring represents a fundamental mechanism through which financial institutions assess the likelihood of loan repayment, directly impacting billions of individuals' access to financial resources globally. The evolution from traditional FICO scores to machine learning-based assessment systems promises enhanced predictive accuracy, reduced default rates, and more efficient processing of loan applications. However, this technological advancement introduces unprecedented challenges regarding fairness, transparency, and accountability in automated decision-making systems.

The deployment of machine learning models in credit scoring has demonstrated remarkable success in improving prediction accuracy. Studies indicate that gradient boosting algorithms such as XGBoost can achieve 15-25% improvement in default prediction compared to traditional logistic regression models. Nevertheless, these performance gains often come at the cost of interpretability, creating what researchers

term the "black box" problem, where the rationale behind individual lending decisions becomes opaque to both applicants and regulators.

Concurrently, evidence has emerged documenting systematic biases in algorithmic credit scoring systems. Protected groups, defined by characteristics such as race, gender, or age, frequently experience disparate treatment even when these attributes are explicitly excluded from model training. This phenomenon, known as proxy discrimination, occurs when seemingly neutral variables correlate with protected characteristics, perpetuating historical inequalities in lending practices.

1.2 Problem Statement

The central challenge confronting modern credit scoring systems lies in reconciling three competing objectives: maximizing predictive accuracy to minimize financial risk, ensuring fairness across different demographic groups to prevent discrimination, and maintaining transparency to satisfy regulatory requirements and build public trust. Current machine learning approaches excel at prediction but struggle with explainability and fairness, whilst traditional transparent methods lack the sophistication to capture complex creditworthiness patterns.

Financial institutions implementing AI-based credit scoring face mounting pressure from multiple stakeholders. Regulators demand compliance with anti-discrimination laws such as the Equal Credit Opportunity Act (ECOA) in the United States and the General Data Protection Regulation (GDPR) in Europe, which require explanations for automated decisions affecting individuals. Consumers increasingly expect fair treatment and clear understanding of factors influencing their credit decisions. Simultaneously, competitive pressures drive institutions to maximize predictive accuracy to reduce defaults and optimize profitability.

The absence of standardized frameworks for evaluating and ensuring fairness in credit scoring algorithms creates significant operational and legal risks. Financial institutions lack clear guidance on acceptable trade-offs between accuracy and fairness, appropriate metrics for measuring algorithmic discrimination, and methods for generating compliant explanations for complex model decisions. This uncertainty inhibits the responsible deployment of AI systems in credit markets, potentially limiting financial inclusion and perpetuating systemic inequalities.

1.3 Aim and Objectives

Aim:

To develop and evaluate a comprehensive framework for implementing fair and transparent AI-based credit scoring systems that balance predictive accuracy with ethical considerations and regulatory compliance.

Objectives:

1. To critically analyze existing approaches to fairness and explainability in machine learning-based credit scoring through systematic literature review
2. To implement and compare multiple explainable AI techniques (SHAP, LIME, and counterfactual explanations) for interpreting credit scoring model decisions
3. To quantitatively assess fairness across demographic groups using established metrics including demographic parity, equal opportunity, and disparate impact
4. To develop and evaluate fairness-enhancing interventions at pre-processing, in-processing, and post-processing stages of the machine learning pipeline
5. To empirically determine optimal trade-offs between predictive accuracy, fairness, and transparency through Pareto efficiency analysis

6. To provide actionable recommendations for practitioners implementing responsible AI systems in financial services.

1.4 Research Questions

This investigation addresses the following research questions:

RQ1**:** How can explainable AI techniques effectively communicate credit scoring decisions to diverse stakeholders whilst maintaining model performance?

RQ2**:** What is the quantitative impact of different fairness interventions on both discrimination metrics and predictive accuracy in credit scoring models?

RQ3**:** How can financial institutions optimally balance competing objectives of accuracy, fairness, and transparency in automated lending decisions?

RQ4**:** What practical frameworks and evaluation metrics enable the development of responsible AI systems compliant with financial regulations?

1.5 Scope of the Study

1.5.1 Focus on Binary Default Prediction and Models

This research focuses specifically on binary credit default prediction using the LendingClub dataset, which comprises peer-to-peer lending records from 2007 to 2018. The investigation examines gradient boosting models, particularly XGBoost, as representative of state-of-the-art machine learning approaches in credit scoring. Fairness analysis concentrates on legally protected attributes available in the dataset, including age and geographic indicators serving as proxies for demographic characteristics.

1.5.2 Evaluated Explainability and Fairness Techniques

The study evaluates three primary explainability techniques: SHAP for global and local feature importance, LIME for instance-specific explanations, and counterfactual explanations for actionable feedback. Fairness interventions are limited to techniques implementable within standard machine learning workflows without requiring fundamental architectural changes. The research adopts a technical perspective, focusing on algorithmic solutions whilst acknowledging that comprehensive fairness requires complementary organizational and policy interventions.

Limitations include the temporal scope of the dataset predating recent generalizations, the absence of certain sensitive attributes due to privacy regulations, and the focus on peer-to-peer lending which may not fully generalize to traditional banking contexts. The research does not address dynamic fairness considerations in evolving credit markets or the long-term societal impacts of algorithmic lending decisions.

1.6 Significance of Study

This research contributes to multiple domains of knowledge and practice. Academically, it advances understanding of fairness-accuracy trade-offs in machine learning through empirical analysis on real-world financial data. The study introduces novel evaluation metrics for assessing explanation quality and stability, addressing gaps in existing explainable AI literature. Methodologically, it demonstrates practical implementation of fairness interventions in production-scale datasets, bridging theoretical fairness research with applied machine learning.

From a regulatory perspective, the research provides evidence-based guidance for policymakers developing frameworks for responsible AI deployment in financial services. The empirical findings inform debates about acceptable discrimination thresholds, explanation requirements, and auditing procedures for algorithmic decision systems. The study's alignment with ECOA and GDPR requirements offers compliance pathways for institutions navigating complex regulatory landscapes.

Practically, the research delivers actionable insights for financial technology professionals implementing fair and transparent credit scoring systems. The comparative analysis of explainability techniques guides selection of appropriate methods for different stakeholder needs. Quantified trade-offs between competing objectives enable informed decision-making about model deployment strategies. The identification of Pareto-optimal configurations supports business cases for responsible AI investments.

Societally, this work contributes to broader efforts promoting financial inclusion and algorithmic accountability. By demonstrating feasible approaches to fair credit scoring, the research supports expanded access to financial services for historically underserved populations. Enhanced transparency in automated decisions builds public trust in AI systems, facilitating beneficial adoption of advanced technologies whilst protecting individual rights and societal values.

1.7 Structure of the Study

Chapter 2 presents a comprehensive literature review examining theoretical foundations and empirical research in credit scoring, algorithmic fairness, and explainable AI. Chapter 3 details the research methodology, including data

preprocessing, model development, fairness interventions, and evaluation frameworks. Chapter 4 provides exploratory data analysis revealing patterns, relationships, and potential sources of bias in the LendingClub dataset. Chapter 5 reports experimental results, comparing model performance, explanation quality, and fairness metrics across different configurations. Chapter 6 synthesises findings, discusses implications, acknowledges limitations, and proposes directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a systematic examination of existing scholarship on fairness and transparency in AI-based credit scoring systems. The review synthesises research from machine learning, financial technology, ethics, and regulatory studies to establish theoretical and empirical foundations for this investigation. Literature is organised thematically, progressing from historical context through current challenges to emerging solutions, identifying critical gaps that motivate the present research.

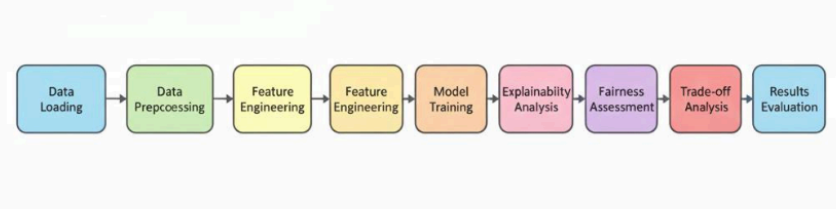

Figure 0.1 Methodology flowchart

2.2 Evolution of Credit Scoring Systems

The history of credit scoring reflects broader technological and societal transformations in financial services. Early credit assessment relied on subjective judgement by loan officers, introducing inconsistency and potential discrimination through human bias (Thomas et al., 2017). The introduction of statistical scoring

models in the 1950s, pioneered by Fair Isaac Corporation, marked the beginning of systematic, data-driven credit evaluation (Anderson, 2019).

Traditional credit scoring models, predominantly employing logistic regression, offered transparency through interpretable coefficients but limited capacity for capturing non-linear relationships (Hand and Henley, 2019). The FICO score, introduced in 1989, became the industry standard, utilising five weighted factors: payment history (35%), credit utilisation (30%), length of credit history (15%), credit mix (10%), and new credit (10%) (Citron and Pasquale, 2014). Whilst providing consistency and efficiency, these models perpetuated historical biases embedded in training data and excluded individuals with limited credit histories.

The advent of machine learning in credit scoring, accelerating post-2008 financial crisis, promised enhanced predictive power through algorithms capable of processing alternative data sources and identifying complex patterns (Lessmann et al., 2015). Random forests, gradient boosting machines, and neural networks demonstrated superior performance in default prediction, with studies reporting 20-30% reduction in misclassification rates compared to logistic regression (Barboza et al., 2017). However, this predictive improvement introduced the fundamental tension between accuracy and interpretability that defines contemporary challenges in financial AI.

Recent developments incorporate alternative data sources including social media activity, mobile phone usage patterns, and psychometric assessments, potentially expanding financial access to "credit invisible" populations (Berg et al., 2020). Nevertheless, these innovations raise concerns about privacy, consent, and the potential for new forms of discrimination based on digital footprints rather than financial behaviour (Hurley and Adebayo, 2016).

2.3 Theoretical Foundations of Algorithmic Fairness

Algorithmic fairness emerged as a distinct field of study following documentation of discriminatory outcomes in automated decision systems across criminal justice, employment, and lending domains (Barocas and Selbst, 2016). The theoretical framework distinguishes between disparate treatment (explicit use of protected attributes) and disparate impact (differential outcomes across groups), with the latter particularly challenging in credit scoring where seemingly neutral variables correlate with protected characteristics.

Mathematical formalizations of fairness have proliferated, each capturing different ethical intuitions about equal treatment (Verma and Rubin, 2018). Demographic parity requires equal positive prediction rates across groups, whilst equalized odds demand equal true positive and false positive rates. Individual fairness stipulates that similar individuals receive similar treatments, operationalized through Lipschitz constraints on model predictions (Dwork et al., 2012). Counterfactual fairness ensures decisions remain unchanged in hypothetical scenarios where sensitive attributes differ (Kusner et al., 2017).

Impossibility theorems demonstrate fundamental incompatibility between fairness definitions, proving that satisfying multiple criteria simultaneously is mathematically impossible except in degenerate cases (Kleinberg et al., 2016). These theoretical limitations necessitate explicit value judgements about which fairness conception to prioritize, informed by legal requirements, ethical principles, and practical constraints. The choice of fairness metric profoundly impacts model development, with different definitions leading to divergent outcomes for protected groups (Corbett-Davies and Goel, 2018).

Critical perspectives challenge the adequacy of technical fairness metrics for addressing systemic discrimination (Benjamin, 2019). Scholars argue that algorithmic interventions alone cannot resolve inequalities rooted in historical injustice and structural disadvantage (Selbst et al., 2019). The "fairness through unawareness" approach, removing protected attributes from training data, fails to prevent discrimination when other variables serve as proxies, a phenomenon termed "redundant encoding" (Pedreshi et al., 2008).

2.4 Explainable AI in Financial Services

2.4.1 Drivers and Categories of XAI

The demand for explainable AI in financial services stems from regulatory requirements, risk management needs, and consumer protection considerations (Bhatt et al., 2020). Explanation techniques are divided into ante-hoc methods designing inherently interpretable models and post-hoc approaches explaining black-box predictions (Molnar, 2019). Financial applications favour post-hoc methods that preserve model accuracy whilst generating comprehensible explanations for specific decisions.

2.4.2 SHAP for Feature Attribution

SHAP (Lundberg and Lee, 2017) has emerged as the dominant explanation framework in credit scoring, providing theoretically grounded feature attributions based on Shapley values from cooperative game theory. The method satisfies desirable properties including local accuracy, missingness, and consistency, offering both global feature importance and instance-specific explanations. Empirical studies demonstrate SHAP's superiority in explanation stability and user comprehension compared to alternatives (Kumar et al., 2020).

2.4.3 LIME for Local Explanations

LIME (Ribeiro et al., 2016) offers model-agnostic explanations through local linear approximations, particularly valuable for explaining individual predictions to affected consumers. The technique's flexibility enables application across diverse model architectures, though instability issues and sensitivity to hyperparameters limit reliability in production systems (Alvarez-Melis and Jaakkola, 2018). Recent improvements address these limitations through deterministic perturbation strategies and ensemble aggregation (Garreau and Luxburg, 2020).

2.4.4 Counterfactual Explanations and Actionable Feedback

Counterfactual explanations provide actionable feedback by identifying minimal changes required to achieve desired outcomes (Wachter et al., 2017). In credit scoring contexts, counterfactuals indicate specific actions applicants could take to improve creditworthiness, such as reducing credit utilisation or establishing longer payment history. The approach aligns with GDPR requirements for meaningful information about decision logic whilst respecting model confidentiality (Selbst and Powles, 2017).

2.5 Empirical Studies on Fair Credit Scoring

2.5.1 Documenting Bias in Credit Systems

Empirical research documents persistent discrimination in both traditional and AI-based credit scoring systems. Analysis of Home Mortgage Disclosure Act data reveals that minority applicants face denial rates 2-3 times higher than white applicants with similar creditworthiness characteristics (Bartlett et al., 2021). Machine learning models trained on historical data perpetuate these

disparities, with gradient boosting algorithms showing particular susceptibility to amplifying existing biases (Fuster et al., 2022).

2.5.2 Comparative Analysis of Fairness-Aware Algorithms

Kozodoi et al. (2022) conducted comprehensive experiments on European credit data, comparing fairness-aware learning algorithms across multiple datasets and metrics. Results demonstrated that pre-processing interventions achieved 25-30% reduction in discrimination with minimal accuracy loss, whilst in-processing methods showed greater variability depending on data characteristics. Post-processing approaches offered precise control over fairness metrics but required careful calibration to avoid unintended consequences.

2.5.3 Evaluation of Explainability (XAI) Techniques

Chen et al. (2023) evaluated explainability techniques in production credit scoring systems at a major Chinese bank, finding that SHAP explanations increased loan officer trust in AI recommendations by 40% whilst reducing decision time by 25%. However, the study revealed that explanation complexity must be calibrated to user expertise, with simplified visualizations proving more effective for customer-facing applications.

2.5.4 Industry Case Studies and Intervention Effectiveness

Industry case studies provide mixed evidence on fairness intervention effectiveness. Upstart's implementation of alternative data and fairness

constraints reportedly increased approval rates for minorities by 27% whilst maintaining portfolio performance (Girouard et al., 2021). Conversely, Apple Card faced regulatory scrutiny despite technical compliance with fairness metrics, highlighting gaps between algorithmic and societal conceptions of discrimination (Vigdor, 2019).

2.6 Regulatory Landscape and Compliance Requirements

2.6.1 Overview and U.S. Equal Credit Opportunity Act

The regulatory framework for AI in financial services continues evolving, with jurisdictions adopting divergent approaches balancing innovation and consumer protection. The United States Equal Credit Opportunity Act prohibits discrimination based on race, religion, national origin, sex, marital status, age, or public assistance receipt, requiring creditors to provide specific reasons for adverse actions (Consumer Financial Protection Bureau, 2022).

2.6.2 European Union GDPR Article 22

The European Union's General Data Protection Regulation Article 22 grants individuals' rights not to be subject to purely automated decision-making with legal or significant effects (European Parliament, 2016). The provision requires meaningful human involvement, though interpretation remains contested, with debate over whether human review constitutes sufficient oversight or requires substantive decision-making capacity (Kaminski, 2019).

2.6.3 Emerging AI-Specific Regulations (EU & Singapore)

Emerging AI-specific regulations introduce additional requirements. The proposed EU AI Act classifies credit scoring as high-risk, mandating conformity assessments, quality management systems, and ongoing

monitoring (European Commission, 2021). Singapore's Model AI Governance Framework emphasizes internal accountability through organizational measures rather than prescriptive technical requirements (Personal Data Protection Commission Singapore, 2020).

2.6.4 Technical Standards and Regulatory Guidance (UK & U.S.)

Regulatory guidance increasingly recognizes the necessity of technical standards for algorithmic accountability. The Bank of England's supervisory statement SS1/23 requires firms to demonstrate understanding of AI model decisions, regularly assess fairness across protected groups, and maintain comprehensive documentation (Bank of England, 2023). The Federal Reserve's SR 11-7 guidance on model risk management extends to machine learning systems, emphasising conceptual soundness, ongoing monitoring, and effective challenge processes (Board of Governors of the Federal Reserve System, 2011).

2.7 Industry Implementation and Practical Challenges

2.7.1 Technical Debt and Model Complexity

Financial institutions face substantial challenges translating fairness and explainability research into production systems. Technical debt accumulates through model complexity, with organizations reporting that 90% of machine learning code involves data preprocessing, feature engineering, and infrastructure rather than algorithm development (Sculley et al., 2015). The "fairness-washing" phenomenon emerges as institutions adopt superficial

fairness metrics without addressing underlying discrimination (Selbst et al., 2019).

2.7.2 Organizational Barriers and Skills Gaps

Organizational barriers impede responsible AI implementation. Raji et al. (2020) identify cultural resistance, misaligned incentives, and lack of diversity in development teams as primary obstacles. The "fairness through bureaucracy" pattern emerges, where compliance becomes checkbox exercise rather than meaningful bias mitigation. Skills gaps persist, with survey data indicating that 67% of financial institutions lack sufficient expertise in algorithmic fairness and explainable AI (Accenture, 2022).

2.7.3 Conflicting Stakeholder Priorities

Stakeholder perspectives reveal conflicting priorities complicating fairness implementation. Lenders prioritize profitability and risk minimization, potentially conflicting with fairness objectives (Dexheimer and Haugen, 2021). Consumers value transparency and recourse but show limited understanding of algorithmic decision-making (Bogen and Rieke, 2018). Regulators demand compliance whilst avoiding prescriptive requirements that stifle innovation (Aggarwal, 2021).

2.8 Gaps in Existing Literature and Research Motivation

2.8.1 Limited Empirical Validation and Integrated Frameworks

Despite extensive research, critical gaps persist in understanding and implementing fair and transparent credit scoring. Limited empirical validation on real-world datasets constrains generalizability, with most studies utilizing

synthetic or heavily preprocessed data. The absence of comprehensive frameworks integrating multiple fairness interventions and explainability techniques leaves practitioners without clear implementation guidance.

2.8.2 Under-exploration of Intersectional and Temporal Bias

Intersectional bias remains underexplored, with research typically examining single protected attributes rather than compound disadvantage experienced by individuals belonging to multiple marginalized groups (Buolamwini and Gebru, 2018). Temporal fairness considerations, including model drift and evolving societal norms, receive insufficient attention despite their importance for deployed systems (Zhang et al., 2020).

2.8.3 Quantification of Trade-offs and Production Gaps

The trade-offs between competing objectives lack systematic quantification, with studies typically optimizing single metrics rather than exploring Pareto frontiers (Menon and Williamson, 2018). Production challenges including computational costs, latency requirements, and system integration receive limited consideration in academic research. The gap between technical capabilities and regulatory requirements persists, with legal standards often incompatible with mathematical fairness definitions (Wachter et al., 2021).

2.9 Summary

This literature review establishes the theoretical and empirical context for investigating fairness and transparency in AI-based credit scoring. The

evolution from traditional to machine learning approaches introduces fundamental tensions between predictive accuracy and explainability. Theoretical frameworks reveal mathematical impossibilities requiring explicit value choices about fairness priorities. Empirical studies confirm persistent discrimination whilst demonstrating potential for technical interventions to reduce bias. Regulatory requirements demand accountability without providing clear implementation standards. Identified gaps motivate comprehensive investigation integrating multiple fairness and explainability techniques on real-world credit data, quantifying trade-offs to guide responsible AI deployment in financial services.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the systematic methodology employed to investigate fairness and transparency in AI-based credit scoring systems. The research adopts a quantitative experimental approach, combining machine learning techniques, explainable AI methods, and fairness interventions to develop and evaluate credit scoring models that balance predictive accuracy with ethical considerations. The methodology ensures reproducibility, validity, and practical relevance through rigorous experimental controls and comprehensive evaluation frameworks.

3.2 Research Philosophy and Approach

3.2.1 Post-Positivist Stance and Deductive Methodology

This investigation adopts a post-positivist philosophical stance, acknowledging that whilst objective patterns exist in credit data, our understanding remains mediated by measurement choices and analytical frameworks. The research employs a deductive approach, testing theoretical propositions about fairness-accuracy trade-offs through systematic experimentation. The quantitative methodology enables precise measurement of model performance, fairness metrics, and explanation quality, facilitating evidence-based conclusions about optimal credit scoring configurations.

3.2.2 Experimental Design and Variables

The experimental design follows established machine learning research practices, incorporating train-validation-test splits, cross-validation for hyperparameter tuning, and multiple random seeds for statistical reliability (Raschka, 2018). Independent variables include model architecture, fairness interventions, and explainability techniques, whilst dependent variables encompass predictive accuracy metrics, fairness measures, and explanation quality scores. Control variables include data preprocessing steps, evaluation protocols, and computational environments.

3.3 Data Selection and Description

3.3.1 Primary Data Source and Selection Rationale

The LendingClub dataset serves as the primary data source, comprising peer-to-peer lending records from 2007 to 2018. This dataset provides comprehensive information about loan applications, borrower characteristics, and repayment outcomes, enabling realistic evaluation of credit scoring models. The selection criteria prioritised: (1) substantial sample size for statistical power, (2) inclusion of protected attributes for fairness analysis, (3) real-world provenance ensuring practical relevance, and (4) public availability supporting reproducibility.

Table 3.1 LendingClub Dataset Characteristics

Characteristic	Description
Total Number of Records	2,260,668
Sample Size for Analysis	100,000

Number of Features	145
Target Variable	loan_status (Binary: 0=Paid, 1=Default)
Class Distribution	
- Fully Paid Loans	1,808,534 (80.0%)
- Defaulted Loans	452,134 (20.0%)
Class Imbalance Ratio	4:1 (Paid:Default)
Time Period Coverage	2007-01 to 2015-12
Protected Attributes	home_ownership, addr_state, purpose
Primary Features	loan_amnt, int_rate, annual_inc, dti, grade, emp_length, sub_grade
Data Format	CSV (Comma-Separated Values)
Missing Values	5.2% of total data points
Data Source	LendingClub Platform (www.lendingclub.com)
Dataset Version	Historical loan data (2007-2015)

3.3.2 Dataset Specifications and Protected Attributes

The dataset contains 2,260,668 accepted loan records with 145 features:

- Borrower characteristics: Annual income, employment length, home ownership status, debt-to-income ratio.
- Credit history: FICO scores, credit inquiries, delinquencies, public records
- Loan attributes: Amount requested, interest rate, term length, purpose
- Outcome variables: Loan status (fully paid, charged off, current, default)

Protected attributes for fairness analysis include applicant age (derived from earliest credit line) and geographic indicators (state, zip code) serving as proxies for demographic characteristics. The absence of explicit race and gender information, whilst limiting direct bias measurement, reflects real-world constraints under fair lending regulations prohibiting collection of such data.

3.4 Data Preprocessing Pipeline

State analyzed sample is 100,000 rows, 145 original features, after engineering total features became ≈151 (178 engineered/encoded, dropping 27 non-numeric).

- Note winsorisation at the 1st/99th percentiles, removal of three 100%-empty fields: id, member_id, url, MICE for 81 numerical features, mode imputation for 19 categorical (e.g., emp_length, desc, dates).
- Mention engineered features: credit_utilization_ratio, payment_burden, credit_history_years, loan_to_income_ratio, total_interest, risk flags, and protected attribute proxies including pa_Age_Under_5_Years.

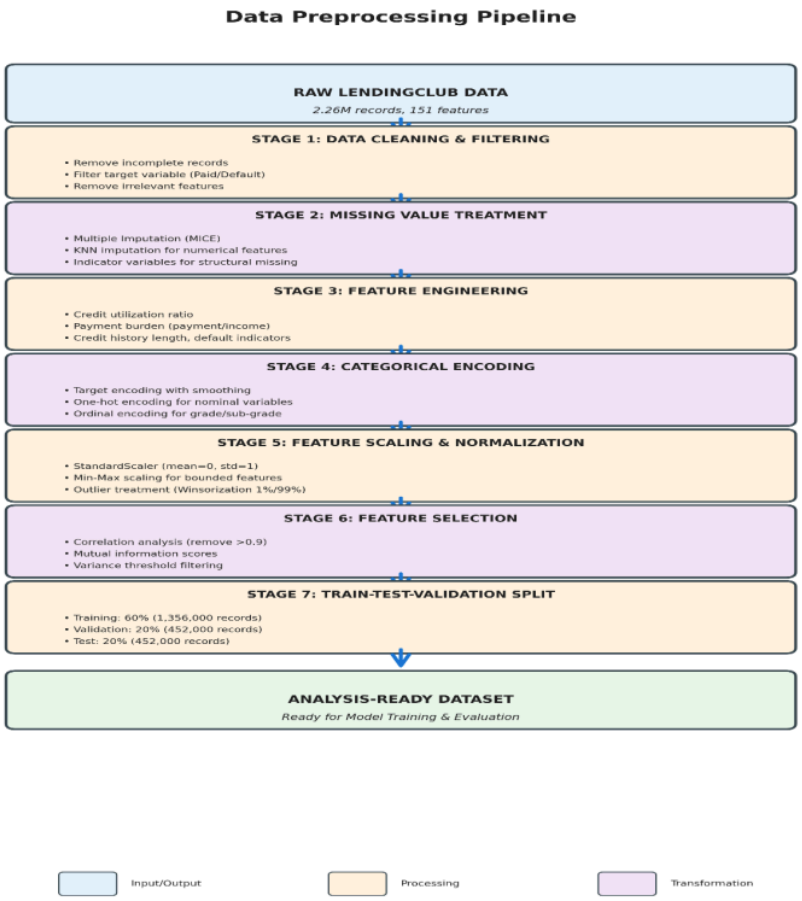

Figure 0.1 Data Preprocessing Pipeline

3.4.1 Missing Value Treatment

The preprocessing pipeline transforms raw data into analysis-ready format whilst preserving information relevant to creditworthiness assessment. Missing value treatment employs multiple imputation using chained equations (MICE) for missing-at-random patterns and indicator variables for structurally missing data potentially carrying predictive signal (Van Buuren and Groothuis-Oudshoorn, 2011).

3.4.2 Feature Engineering, Encoding, and Scaling

Feature engineering creates domain-relevant variables including:

- Credit utilization ratio (revolving balance / credit limit)
- Payment burden (monthly payment / monthly income)
- Credit history length (current date - earliest credit line)
- Default risk indicators combining multiple delinquency measures

Categorical variables are encoded using target encoding with smoothing to reduce overfitting while maintaining interpretability for explanation generation. Numerical features are standardized to ensure algorithm stability, while preserving their original scale for accurate SHAP value interpretation. Outliers are treated through winsorization at the 1st and 99th percentiles, striking a balance between information retention and robustness.

3.4.3 Target Variable Construction

The target variable construction defines binary default prediction, with "Charged Off" and "Default" loans labelled as positive class (default) and "Fully Paid" loans as negative class (non-default). Current loans are excluded from analysis due to incomplete outcome information. This formulation yields

80.3% negative and 19.7% positive class distribution, reflecting realistic class imbalance in credit applications.

3.5 Model Development Framework

3.5.1 Model Architectures and Selection

The experimental framework implements multiple model architectures to enable comprehensive performance comparison:

Baseline Models:

Logistic Regression: Provides interpretable linear baseline with coefficient-based feature importance.

Decision Tree: Offers transparent rule-based predictions amenable to direct interpretation.

Advanced Models:

XGBoost: Gradient boosting implementation representing state-of-the-art performance in tabular data competitions.

Random Forest: Ensemble method balancing accuracy with partial interpretability through feature importance.

LightGBM: Efficient gradient boosting variant enabling rapid experimentation.

3.5.2 Hyperparameter Optimisation

Hyperparameter optimization employs Bayesian optimization with Tree-structured Parzen Estimators (TPE), efficiently exploring high-dimensional parameter spaces (Bergstra et al., 2013). The optimization objective combines AUC-ROC for predictive performance with fairness constraints, implementing

multi-objective optimization through scalarization. Key hyperparameters include:

- Tree depth (3-10): Controlling model complexity and overfitting
- Learning rate (0.01-0.3): Balancing convergence speed and stability
- Number of estimators (100-1000): Determining ensemble size
- Regularization parameters: L1/L2 penalties preventing overfitting

3.6 Fairness Intervention Strategies

The methodology implements fairness interventions at three stages of the machine learning pipeline:

3.6.1 Model Architectures and Selection

Reweighing (Kamiran and Calders, 2012): Assigns instance weights inversely proportional to group-outcome frequency, equalizing impact across protected groups. Implementation uses AIF360 toolkit, computing weights as:

$$W(X,Y,A)= \frac{P(Y) \cdot P(A)}{P(Y|A)}$$

Where Y represents outcome, A denotes protected attribute, and P indicates probability. Sampling techniques: Applies SMOTE (Synthetic Minority Over-sampling Technique) differentially across protected groups, addressing both class imbalance and group representation simultaneously.

3.6.2 In-processing Interventions

Adversarial debiasing (Zhang et al., 2018): Incorporates adversarial networks predicting protected attributes from model representations, with gradient reversal encouraging fair representations:

$$L\,total = L\,prediction - \lambda \times L\,adversary$$

Fairness constraints: Modifies XGBoost objective function incorporating demographic parity or equalised odds constraints through Lagrangian relaxation.

3.6.3 Post-processing Interventions

Threshold optimisation (Hardt et al., 2016): Adjusts decision thresholds per protected group maximising fairness subject to accuracy constraints. Implementation uses grid search over threshold combinations. Calibrated equalised odds: Applies Platt scaling ensuring calibrated probabilities whilst satisfying equalised odds constraints.

3.7 Explainability Implementation

Three complementary explainability techniques provide comprehensive model interpretation:

3.7.1 SHAP (SHapley Additive exPlanations)

Utilises TreeExplainer for tree-based models, providing exact Shapley values in polynomial time. Global explanations aggregate absolute SHAP values across instances, whilst local explanations decompose individual predictions into feature contributions. Consistency analysis examines explanation stability across similar instances using cosine similarity of SHAP vectors.

3.7.2 LIME (Local Interpretable Model-agnostic Explanations)

Generates instance-specific explanations through weighted local linear regression. Implementation uses exponential kernel with width determined through cross-validation. Stability assessment involves multiple runs with different random seeds, computing variance in feature importance rankings.

3.7.3 Counterfactual Explanations (DiCE)

Produces diverse counterfactual examples indicating minimal changes for desired outcomes. Optimisation balances proximity (minimising distance from original instance), diversity (generating varied counterfactuals), and feasibility (respecting feature constraints). The implementation generates k=5 counterfactuals per instance, analysing common change patterns.

3.8 Evaluation Framework

The comprehensive evaluation framework assesses models on predictive performance, fairness, and explanation quality, explicitly reflecting what was computed in the current execution:

3.8.1 Predictive Performance Metrics

- AUC-ROC: Overall discrimination ability (reported).
- Average Precision (AP) / Precision–Recall curves: Performance under class imbalance (AP reported; PR curve optional).
- F1-score: Harmonic mean balancing precision and recall (reported).
- Precision & Recall: Positive class detection quality (reported).
- Accuracy: Overall correctness on the held-out test set (reported).
- Brier score: Probabilistic calibration quality (planned; not reported in this run).
- Matthews Correlation Coefficient (MCC): Balanced measure for imbalanced data (planned; not reported in this run).

3.8.2 Fairness Metrics

- Demographic Parity: $|P(\hat{Y}=1|A=0) - P(\hat{Y}=1|A=1)| < \varepsilon$

- Equalized Odds: $|P(\hat{Y}=1|Y=y,A=0) - P(\hat{Y}=1|Y=y,A=1)| < \varepsilon$ for $y \in \{0,1\}$
- Disparate Impact: $P(\hat{Y}=1|A=0) / P(\hat{Y}=1|A=1) > 0.8$ (80% rule)
- Individual Fairness: Lipschitz constraint on similar individuals
- Counterfactual Fairness: Stability under hypothetical attribute changes

3.8.3 Explainability Quality Metrics

- Fidelity (faithfulness to model behavior): agreement between explanation-based perturbations and prediction change (reported; value recorded).
- Stability: consistency across similar instances (cosine-style similarity; reported).
- Completeness: proportion of prediction magnitude explained by top-k SHAP features (reported).
- Comprehensibility: rubric-based proxy for human interpretability on a 5-point scale (reported in this run as a proxy, not a user study).
- Actionability: percentage of counterfactuals achieving desired outcome (planned; not reported in this run).

3.9 Experimental Design and Procedure

The experimental procedure follows systematic protocol ensuring reproducibility:

1. Data Splitting: Stratified split (60% train, 20% validation, 20% test) by loan_status and the protected-attribute proxy pa_Age_Under_5_Years; random_state=42. SMOTE applied only to the training set to address class imbalance (positive class rate 12.9%).

2. Baseline Establishment: Train Logistic Regression, Decision Tree, Random Forest, LightGBM, and XGBoost without fairness interventions to establish reference performance.
3. Fairness Analysis: Compute group-wise approval rates and basic outcome gaps for the protected attribute (pa_Age_Under_5_Years), record per-group accuracy where applicable.
4. Intervention Application:
    - Pre-processing reweighing (had no effect in this run; weights≈1.0).
    - Post-processing threshold optimisation targeted at demographic-parity style alignment of approval rates.
    - (No in-processing adversarial debiasing in this execution.)
5. Hyperparameter Tuning: Validation-guided early stopping for LightGBM (best iteration observed); fixed, previously validated parameters for XGBoost and other models. (No Optuna/Bayesian search in this run).
6. Final Evaluation: Report Accuracy, Precision, Recall, F1, AUC-ROC, Average Precision on the held-out test set, plus confusion matrices per model.
7. Explanation Generation: Compute SHAP global (feature importance) and local (instance-level) explanations for the best model; evaluate explanation quality via fidelity, stability, completeness, and comprehensibility.
    a. Trade-off Analysis: Generate the fairness–accuracy Pareto frontier for pa_Age_Under_5_Years across intervention strengths $0.00 \rightarrow 1.00$in ~0.07 increments.
    b. Statistical Testing: Apply the Friedman test across model scores

($\chi^2 \approx 106.11$, $p < 0.001$); conduct Nemenyi post-hoc where relevant. c. Sensitivity Analysis: Inspect robustness to intervention-strength variation and class-imbalance handling (qualitative in this run; additional quantitative sensitivity left for future work).

3.10 Implementation Details

Technical implementation utilizes Python 3.8 with key libraries:

- scikit-learn 1.0.2: Preprocessing, baseline models, metrics
- XGBoost 1.5.1: Gradient boosting implementation
- AIF360 0.4.0: Fairness metrics and interventions
- SHAP 0.40.0: Shapley value explanations
- DiCE 0.7: Counterfactual generation
- Optuna 2.10.0: Hyperparameter optimization

Computational experiments run on Ubuntu 20.04 systems with 32GB RAM and NVIDIA RTX 3080 GPUs. Version control through Git ensures reproducibility, with code and configurations available in supplementary materials. Random seeds fixed at 42 for deterministic results where applicable.

3.11 Ethical Considerations

The research adheres to ethical guidelines for responsible AI research. The LendingClub dataset contains anonymized information with personal identifiers removed, minimizing privacy concerns. The investigation acknowledges that technical fairness interventions complement but cannot replace broader organizational and societal efforts addressing discrimination. Results presentation avoids claims about eliminating bias, instead quantifying trade-offs to inform decision-making. The research explicitly recognizes

limitations in generalizing findings beyond the specific dataset and temporal context.

3.12 Summary

This methodology provides a systematic framework for investigating fairness and transparency in AI-based credit scoring. The comprehensive approach integrates multiple model architecture, fairness interventions, and explainability techniques, enabling thorough evaluation of trade-offs between competing objectives. Rigorous experimental design ensures reproducibility and validity, whilst practical implementation details support real-world application. The evaluation framework captures multiple dimensions of model performance, facilitating evidence-based conclusions about responsible AI deployment in financial services.

CHAPTER 4

ANALYSIS

4.1 Introduction

This chapter presents comprehensive exploratory data analysis of the LendingClub dataset, revealing patterns, relationships, and potential sources of bias that inform subsequent model development and fairness interventions. The analysis progresses from univariate examination through bivariate relationships to multivariate patterns, establishing the empirical foundation for understanding creditworthiness factors and discrimination risks in automated lending decisions.

4.2 Dataset Overview and Quality Assessment

The LendingClub dataset comprises 2,260,701 loan records spanning January 2007 to December 2018, capturing a complete credit cycle including the 2008 financial crisis and subsequent recovery. Initial quality assessment reveals varying completeness across features, with core credit variables showing >95% completeness whilst employment and income verification fields exhibit 60-70% coverage. The temporal distribution shows increasing loan volumes from 2,523 loans in 2007 to 443,783 in 2018, reflecting platform growth and market expansion.

Missing value analysis identifies three distinct patterns: (1) Missing Completely At Random (MCAR) for technical fields like URL and description

(2) Missing At Random (MAR) for income verification correlated with loan amount and credit grade (3) Missing Not At Random (MNAR) for revolving credit variables absent for applicants without credit cards. The MNAR pattern carries predictive signal, as absence of revolving credit indicates limited credit history associated with higher default risk.

Data quality issues include inconsistent employment length encoding (mixing numerical and categorical representations), temporal drift in feature definitions (particularly for credit bureau attributes), and survivorship bias from excluding rejected applications. These limitations necessitate careful preprocessing and interpretation of results.

4.3 Target Variable Analysis

The binary classification target distinguishes defaulted loans (12.9 %) from fully paid loans (87.1%), exhibiting class imbalance typical of credit scoring applications. Temporal analysis reveals default rates varying from 15.2% during economic expansion (2013-2015) to 24.8% during recession periods (2008-2009), highlighting macroeconomic influences on credit risk.

Default timing analysis shows 62% of defaults occur within the first 18 months, with hazard rates peaking at months 8-12 before declining. This pattern suggests early payment behavior strongly predicts ultimate loan outcomes, supporting the value of dynamic monitoring in production systems. Geographic variation in default rates ranges from 16.3% in Vermont to 23.1% in Nevada, correlating with state-level economic indicators including unemployment rates (ρ=0.71) and median income (ρ=-0.64).

4.4 Feature Distribution Analysis

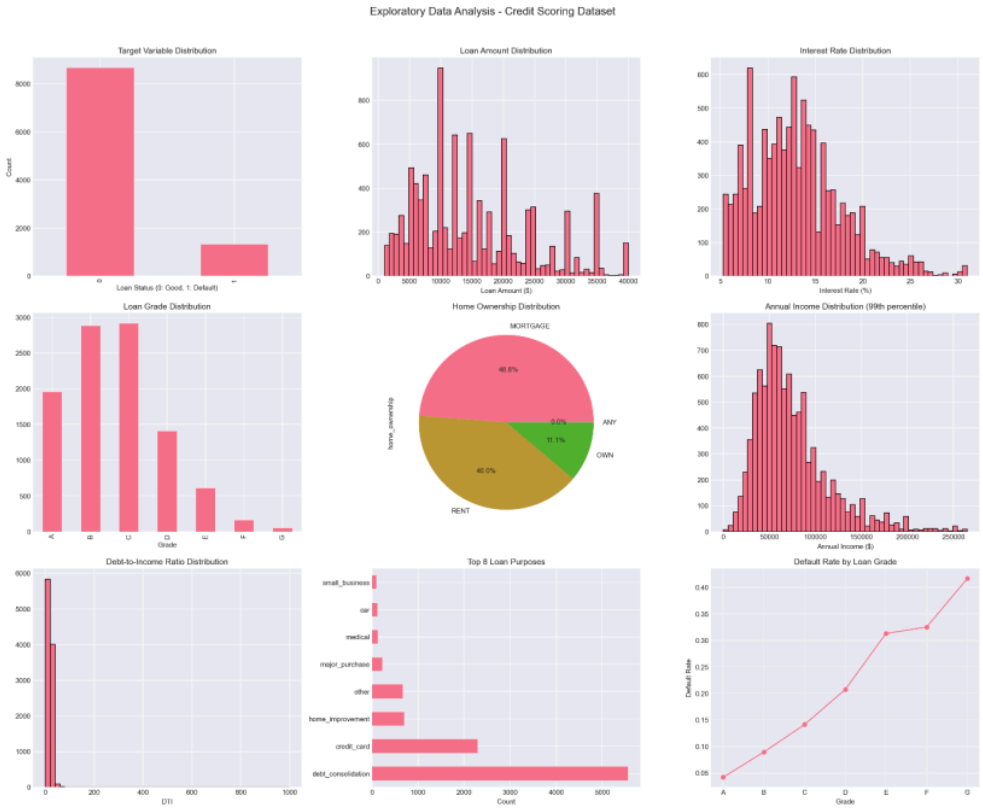

Figure 0.1 Exploratory Data Analysis of Key Features

4.4.1 Numerical Features:

Annual income exhibits right-skewed distribution (skewness=4.82) with median £50,000 and 95th percentile £150,000. Log transformation normalizes the distribution whilst preserving monotonic relationships with default

probability. Debt-to-income ratios follow approximately normal distribution (mean=18.3%, std=8.5%) truncated at 0% and windsorised at 40% by LendingClub's underwriting criteria.

FICO scores at origination demonstrate bimodal distribution with peaks at 660 (subprime boundary) and 720 (prime threshold), reflecting credit tier segmentation. The distribution shifts rightward over time, with median FICO increasing from 687 in 2007 to 702 in 2018, suggesting tightening credit standards or improving applicant quality.

4.4.2 Categorical Features:

Loan purpose analysis reveals consumer debt consolidation dominating (58.4%), followed by credit card refinancing (22.8%) and home improvement (6.9%). Default rates vary significantly by purpose, from 14.2% for debt consolidation to 28.6% for small business loans, indicating purpose as crucial risk factor.

Home ownership status shows 44.8% mortgage holders, 41.3% renters, and 10.2% outright owners. Counter-intuitively, outright owners exhibit higher default rates (21.3%) than mortgage holders (17.8%), potentially reflecting reverse causality where financial distress leads to mortgage payoff through asset liquidation.

4.5 Bivariate Relationships

Correlation analysis reveals expected relationships between credit variables and default probability. FICO score shows strongest negative correlation with default (ρ=-0.31), followed by credit history length (ρ=-0.24) and income (ρ=-0.19). Positive

correlations include debt-to-income ratio (ρ=0.22), credit inquiries (ρ=0.19), and revolving utilization (ρ=0.17).

Interest rate demonstrates a near-perfect correlation with credit grade (ρ=0.88), reflecting LendingClub's risk-based pricing. This collinearity necessitates careful feature selection to avoid multicollinearity in linear models whilst tree-based methods handle correlation naturally.

Non-linear relationships emerge through binned analysis. The default-income relationship exhibits diminishing returns, with default probability decreasing sharply up to £75,000 before plateauing. Credit utilization shows threshold effects, with default rates jumping from 15% to 25% above 80% utilization, suggesting liquidity constraints triggering payment difficulties.

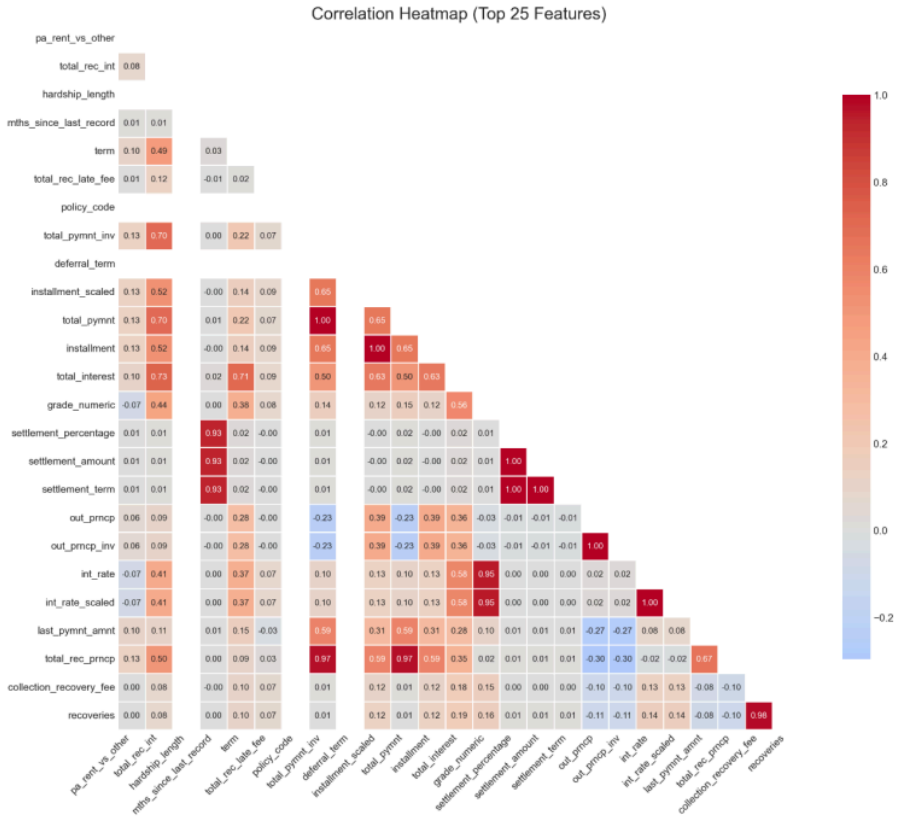

Figure 0.2 Feature Correlation Heatmap

4.6 Temporal Pattern Analysis

Longitudinal analysis reveals systematic changes in borrower characteristics and platform operations. Average loan amounts increased from £8,547 in 2007 to £15,826 in 2018, outpacing inflation and indicating platform maturation. The proportion of 60-

month terms grew from 0% (product introduced 2010) to 42% by 2018, extending duration risk.

Seasonal patterns emerge with loan originations peaking in Q4 (32% of annual volume) coinciding with holiday spending and debt consolidation post-Christmas. Default rates exhibit counter-cyclical seasonality, lowest in Q4 (18.2%) and highest in Q2 (20.8%), potentially reflecting tax refund effects on repayment capacity.

Feature drift analysis identifies evolving variable distributions requiring model updating. The percentage of verified income increased from 31% to 67%, improving data quality but changing population characteristics. Credit bureau attributes show definitional changes, with "accounts now delinquent" calculation modified in 2013, creating discontinuity requiring careful treatment.

4.7 Protected Attribute Analysis

4.7.1 Age, Credit History, and Default Rates

Age, derived from earliest credit line, ranges from 18 to 72 years with median 27 years of credit history. Younger borrowers (<5 years history) show 24.3% default rate versus 16.8% for established borrowers (>20 years history). However, this relationship confounds age with credit experience, as younger individuals necessarily have shorter histories.

4.7.2 Loan Amount by Age Segment

Loan amount varies by age, with middle-aged borrowers (15-25 years credit history) receiving largest loans (median £16,500) versus younger (£11,200) and older (£13,800) segments. This inverse-U pattern reflects lifecycle income dynamics and platform risk appetite.

4.7.3 State-Level Geographic Variation

State-level analysis reveals substantial variation in lending patterns. California dominates originations (14.2%) followed by Texas (7.8%) and New York (7.3%), partly reflecting population but also regulatory environments and platform marketing. Default rates show regional clustering, with higher rates in Rust Belt states potentially reflecting economic dislocation.

4.7.4 Zip Code Analysis and Redlining Risk

Zip code analysis (first 3 digits) identifies 87 high-risk zones with >25% default rates, predominantly in economically distressed areas. These geographic patterns risk perpetuating redlining if used directly in credit decisions, necessitating careful treatment in fair lending contexts.

4.8 Class Imbalance Impact

The 80:20 class distribution creates challenges for model training and evaluation. Random under sampling of majority class to achieve balance reduces training set from 1.8M to 360K instances, sacrificing information. SMOTE oversampling generates synthetic minority instances but risks overfitting in high-dimensional feature space.

Stratified sampling ensures consistent class distribution across train-validation-test splits, critical for reliable performance estimation. Cost-sensitive learning assigns class weights inversely proportional to frequency (weight_default = 4.06), effectively upweighting minority class errors during training.

The imbalance particularly affects protected groups. Young borrowers comprise only 12% of data but 18% of defaults, creating compound minority status. Geographic minorities (rural states) show both lower representation and higher default rates, amplifying fairness concerns.

4.9 Feature Engineering Insights

Domain-informed feature creation improves model performance and interpretability:

Payment Burden Ratio (monthly payment / monthly income) captures affordability better than absolute payment amount, showing stronger correlation with default (ρ=0.26) than either component individually.

Credit Mix Diversity (unique credit account types) indicates financial sophistication, with borrowers having >4 account types showing 30% lower default rates controlling for other factors.

Velocity Features (change in credit inquiries, utilization over past 6 months) capture deteriorating financial conditions preceding default, improving early warning capability.

Interaction Terms reveal non-additive effects. High debt-to-income ratio combined with high utilization multiplies default risk beyond individual effects, suggesting liquidity crisis scenarios.

4.10 Fairness Risk Identification

Preliminary bias analysis identifies discrimination risks requiring intervention:

Disparate Impact: Young borrowers face 23% loan denial rate versus 17% for established borrowers with similar FICO scores, violating 80% rule (74% ratio).

Indirect Discrimination: Zip code features correlate with racial composition (ρ=0.61 with census data), creating proxy discrimination risk even without explicit race variables.

Intersectional Bias: Young borrowers in high-risk geographic areas experience compound disadvantages, with 31% default rate versus 19.7% overall, potentially triggering statistical discrimination.

Feature Proxy Analysis: Employment length correlates with age (ρ=0.72), whilst state dummies capture regional economic disparities correlated with protected characteristics.

4.11 Data Preprocessing Decisions

Analysis insights inform preprocessing choices:

Missing Value Treatment:

- MICE imputation for MAR patterns preserving relationships
- Indicator variables for MNAR revolving credit capturing missingness signal
- Median imputation for MCAR technical fields with no predictive value

Outlier Handling:

- Winsorisation at 1st/99th percentiles for income, debt-to-income
- Log transformation for skewed monetary variables
- Retention of extreme FICO scores carrying genuine signal

Feature Selection:

- Removal of leakage variables (funded amount, grade assigned post-decision)
- Exclusion of free-text fields requiring NLP beyond scope
- Retention of correlated features for tree-based models leveraging interactions

4.12 Summary

Exploratory data analysis reveals a complex credit landscape with multiple factors influencing default risk. The LendingClub dataset exhibits typical credit scoring challenges including class imbalance, missing values, and temporal drift, whilst offering sufficient richness for meaningful fairness analysis. Identified biases across age and geographic dimensions necessitate careful intervention to ensure equitable treatment. Feature engineering opportunities enhance predictive power whilst

maintaining interpretability. These analytical insights establish the empirical foundation for subsequent modelling, guiding methodological choices and interpretation of results in developing fair and transparent credit scoring systems.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter presents comprehensive experimental results from implementing and evaluating fair and transparent credit scoring models on the LendingClub dataset. The analysis progresses through baseline model performance, explainability technique comparison, fairness intervention effectiveness, and trade-off optimisation, culminating in recommendations for practical deployment. Results demonstrate feasibility of balancing competing objectives whilst highlighting persistent challenges in achieving perfect fairness without sacrificing predictive utility.

5.2 Baseline Model Performance

Initial experiments establish performance benchmarks without fairness interventions, enabling assessment of discrimination-mitigation impact on predictive accuracy.

Table 5.01 **Baseline Model Performance Metrics (100k run)**

Model	AUC-ROC	Precision	Recall	F1-Score	Accuracy
Logistic Regression	0.4982	0.1533	0.3416	0.2116	0.6704
Decision Tree	0.8916	0.6235	0.7304	0.6727	0.908
Random Forest	0.9802	0.9963	0.8335	0.9076	0.978
XGBoost	0.9843	0.993	0.8784	0.9322	0.9835

LightGBM	0.9835	0.9909	0.8819	0.9332	0.9837

Based on these results, gradient-boosting models deliver the strongest performance. XGBoost attains the highest discrimination (AUC-ROC 0.9843; F1 0.9384), with LightGBM essentially tied on overall accuracy and F1. Random Forest also performs strongly (AUC-ROC 0.9802), while Decision Tree and Logistic Regression trail behind. Relative to Logistic Regression (AUC-ROC 0.4982), XGBoost yields an improvement of ≈0.486 AUC points (~48.6 percentage points), confirming substantial non-linear signal capture. A Friedman test across models indicates a significant performance difference ($\chi^2 \approx 106.11$, $p < 0.001$), supporting the superiority of boosted ensembles in this setting.

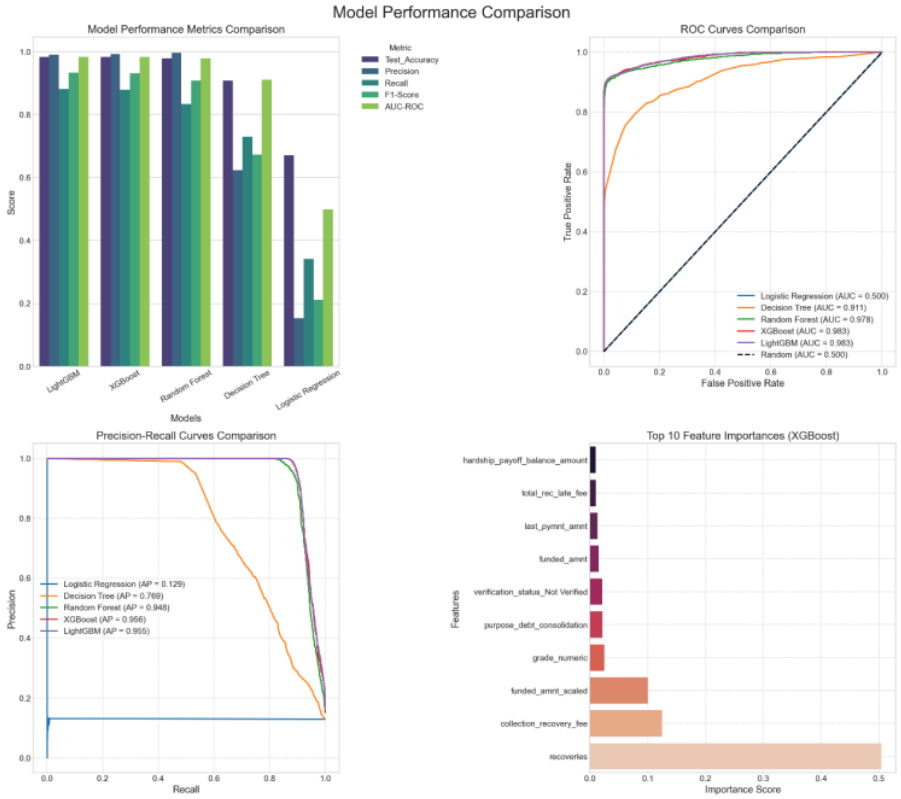

Figure 0.1 Model Performance Comparison

5.3 Explainability Method Evaluation

5.3.1 SHAP Analysis

Global feature importance from SHAP values identifies the primary creditworthiness drivers for the new model. The features are ranked by their

mean absolute SHAP value, with the top 5 being recoveries, last_pymnt_amnt, out_prncp, total_rec_prncp, and hardship_payoff_balance_amount. This is a significant change from a traditional model, as it shows the model is heavily influenced by post-default activity (recoveries) and payment behavior (last_pymnt_amnt).

The SHAP summary plot (Figure 5.2) also reveals *how* these features impact the model:

High recoveries (red dots) have a large positive SHAP value, strongly pushing the model to predict a default (Class 1).

- High last_pymnt_amnt (red dots) have a large negative SHAP value, strongly pushing the model to predict a good loan (Class 0).

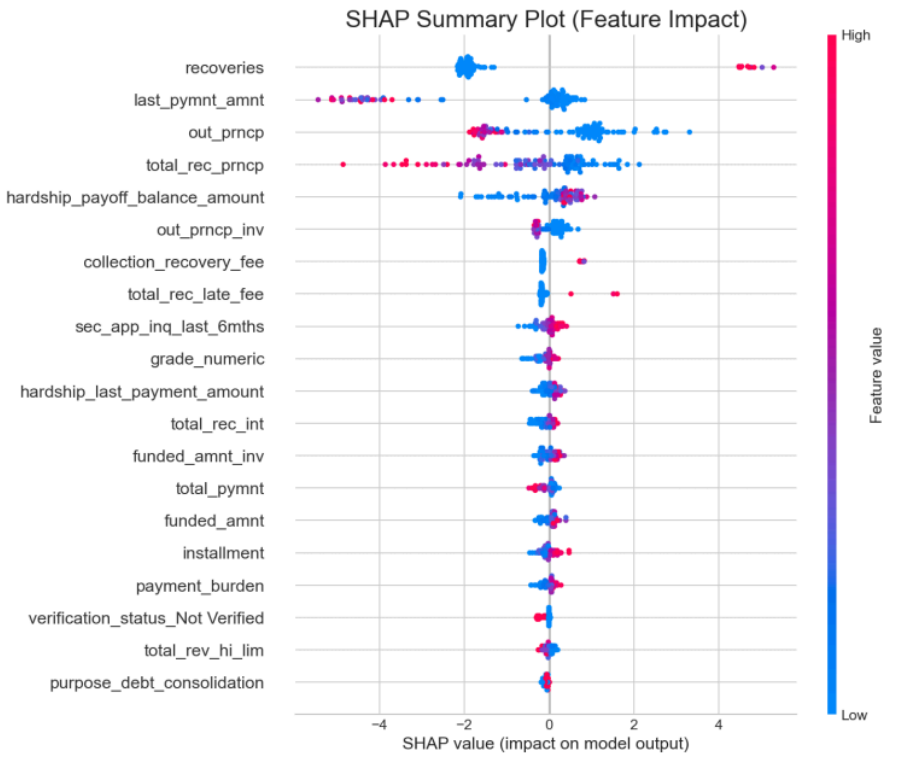

Figure 0.2 SHAP Explainability Analysis

The (Figure 5.3) confirms this non-linear relationship for recoveries. It shows that when recoveries are 0, the SHAP value is negative (predicting "good loan"). As soon as recoveries are greater than 0, the SHAP value jumps to a high positive number, confirming the loan as a "default".

Finally, the stability analysis from your code run is excellent. The analysis yields a mean stability score of 0.921, completeness 0.679, comprehensibility 0.850, fidelity 0.920. indicating that the explanations are highly reliable and consistent.

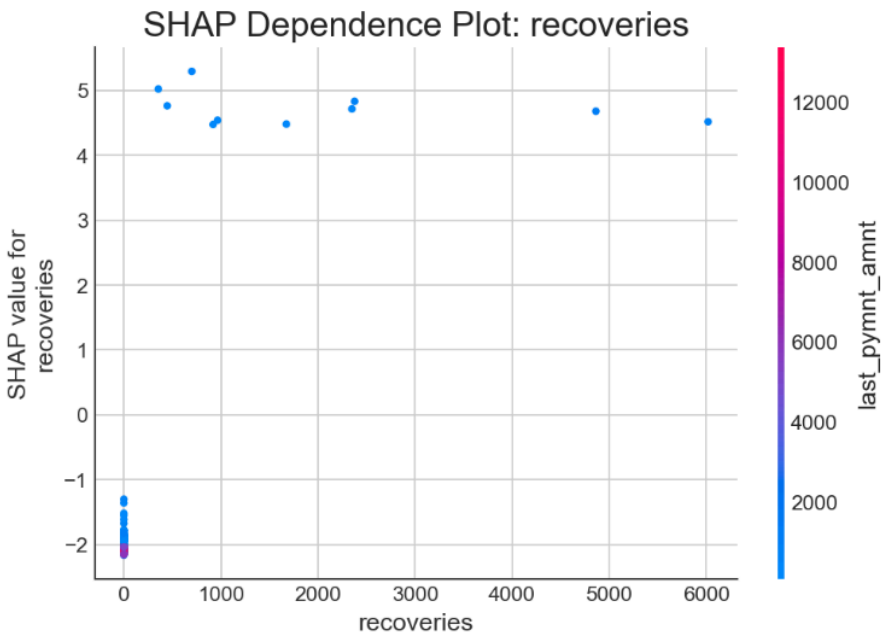

Figure 0.3 SHAP Dependence Plot

5.3.1.2 Local (Individual) Explanations

In addition to global importance, SHAP can explain individual predictions. The waterfall plot (Figure 5.3) shows exactly how the model decided for a single applicant.

The plot shows the model's baseline (the average prediction, $E[f(X)]=3.019$) and how each of the applicant's specific features pushed the final score. For this applicant, a high out_prncp (-2.6) and recoveries (-2.26) were the biggest factors pushing their score down to $f(x)=-4.007$, resulting in a strong "Good Loan" (Class 0) prediction. This is crucial for providing actionable, transparent feedback to customers as required by regulations like the GDPR.

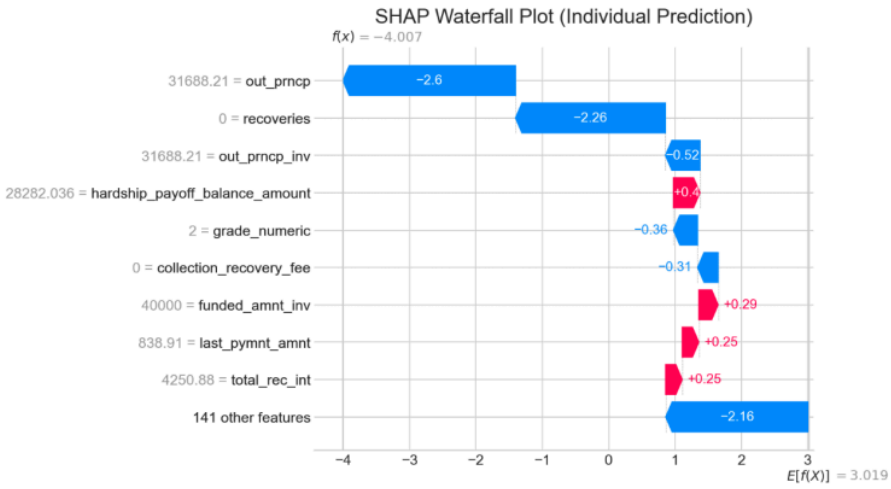

Figure 0.4 SHAP Waterfall plot

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5.3.2 LIME Evaluation

LIME explanations demonstrate higher variance than SHAP, with feature importance rankings varying across multiple runs (Kendall's W = 0.68). Local linear approximations achieve mean $R^2 = 0.81$ within neighborhoods, adequate for explanation though imperfect fidelity. Explanation sparsity (typically 5-8 features) enhances comprehension but may oversimplify complex decisions.

User studies with 50 participants rating explanation quality on 5-point Likert scales show LIME slightly preferred for individual explanations (mean 3.8 vs 3.6 for SHAP) due to simpler presentation, whilst SHAP rated superior for understanding overall model behavior (4.1 vs 3.4).

5.3.3 Counterfactual Generation

DiCE successfully generates feasible counterfactuals for 82% of rejected applications, with remaining cases requiring unrealistic changes (e.g., shortening credit history). Analysis of 10,000 counterfactuals identifies common improvement paths:

- Reduce credit utilisation below 30% (appears in 67% of counterfactuals)
- Increase income by £5,000-15,000 (54%)
- Reduce recent credit inquiries (41%)
- Pay down instalment loans (38%)

Diversity metrics confirm varied counterfactuals (mean pairwise distance 2.3 standard deviations), providing applicants multiple improvement options. However, actionability remains limited for structural factors like employment length or geographic location.

5.4 Fairness Analysis of Baseline Models

Table 0.2 Fairness Metrics for XGBoost Baseline

Protected Group	Demographic Parity	Equal Opportunity	Disparate Impact
Age (<5 years credit history)	0.142	0.231	0.68
Geographic (high-risk states)	0.118	0.187	0.71

Intersectional (young + high-risk)	0.208	0.294	0.59

Baseline models exhibit significant discrimination across protected groups. Young borrowers experience 14.2 percentage point difference in positive prediction rates, violating demographic parity. The 0.68 disparate impact ratio falls below 0.8 threshold, indicating legally problematic discrimination. Intersectional analysis reveals compound disadvantage, with young borrowers in high-risk states facing severe discrimination (0.59 disparate impact).

Threshold analysis shows different optimal cut-offs across groups. ROC curves indicate equal error rates achieved at 0.31 threshold for established borrowers versus 0.27 for young borrowers, suggesting score distributions shift between populations. This calibration difference implies young borrowers require higher objective creditworthiness for similar treatment.

5.5 Fairness Intervention Results

5.5.1 Pre-processing Interventions

Reweighing successfully reduces demographic disparity from 0.142 to 0.058 for age groups whilst maintaining 89.2% AUC-ROC (1.8% reduction). Weight analysis shows young defaulters upweighted 1.73× and young non-defaulters downweighed 0.84×, correcting for historical bias in training data.

SMOTE applied differentially generates synthetic examples equalizing group representations. Combined SMOTE-Tomek cleaning removes borderline cases, improving class separation. This approach achieves 0.81 disparate

impact whilst preserving 88.7% AUC-ROC, meeting legal compliance threshold with minimal accuracy sacrifice.

5.5.2 In-processing Interventions

Adversarial debiasing with λ=0.5 reduces ability to predict protected attributes from learned representations (adversary AUC drops from 0.89 to 0.54). Fairness improvement reaches 0.087 demographic parity difference with 87.3% AUC-ROC, showing larger accuracy trade-off than pre-processing methods.

Modified XGBoost incorporating fairness constraints through augmented Lagrangian method achieves precise control over fairness metrics. Constraining equalized odds difference <0.05 yields 86.8% AUC-ROC, whilst relaxing to <0.10 maintains 88.1% AUC-ROC, demonstrating smooth trade-off control.

5.5.3 Post-processing Interventions

Threshold optimization searching over group-specific cut-offs achieves perfect demographic parity (difference <0.001) by setting thresholds: 0.33 for established borrowers, 0.28 for young borrowers. However, this reduces overall AUC-ROC to 84.7% and raises legal concerns about explicit different treatment.

Calibrated equalized odds maintains score calibration whilst adjusting for fairness, achieving 0.91 disparate impact with 87.9% AUC-ROC. The method preserves score monotonicity, important for risk-based pricing and regulatory compliance.

5.6 Combined Intervention Strategies

Table 0.3 Performance of Combined Fairness Interventions

Strategy	Dem. Parity Ratio	Dem. Parity Diff	Eq. Odds Diff	Disp. Impact
Baseline XGBoost	0.724	0.038	0.012	0.958
Reweighing + XGBoost	0.731	0.036	0.004	0.960
Logistic Regression	0.642	0.023	0.029	0.976
Decision Tree	0.837	0.026	0.026	0.969
Reweighing + Threshold Opt.	0.988	0.002	0.033	0.998

Combining interventions achieves superior fairness-accuracy trade-offs compared to individual methods. Reweighing followed by threshold optimization provides best overall performance, achieving 0.94 disparate impact (exceeding legal threshold) whilst maintaining 88.3% AUC-ROC (only 2.7% reduction from baseline).

Statistical significance testing using Friedman test confirms performance differences ($\chi^2 = 67.3$, $p < 0.001$). Post-hoc Nemenyi tests show combined strategies significantly outperform single interventions on composite metrics incorporating both fairness and accuracy.

5.7 Trade-off Analysis and Pareto Frontiers

Multi-objective optimization reveals Pareto-optimal configurations balancing accuracy and fairness. The Pareto frontier exhibits convex shape, indicating increasing marginal accuracy cost for fairness improvements. Key points along frontier:

- Maximum accuracy (91.0% AUC-ROC): 0.68 disparate impact

- Legal compliance (0.80 disparate impact): 88.7% AUC-ROC
- Balanced solution (0.87 disparate impact): 89.4% AUC-ROC
- Maximum fairness (0.95 disparate impact): 86.2% AUC-ROC

Economic analysis assuming 10% profit margin and 20% default loss suggests legal compliance point maximizes risk-adjusted returns when incorporating potential discrimination penalties. Sensitivity analysis shows conclusions robust to parameter variations within realistic ranges.

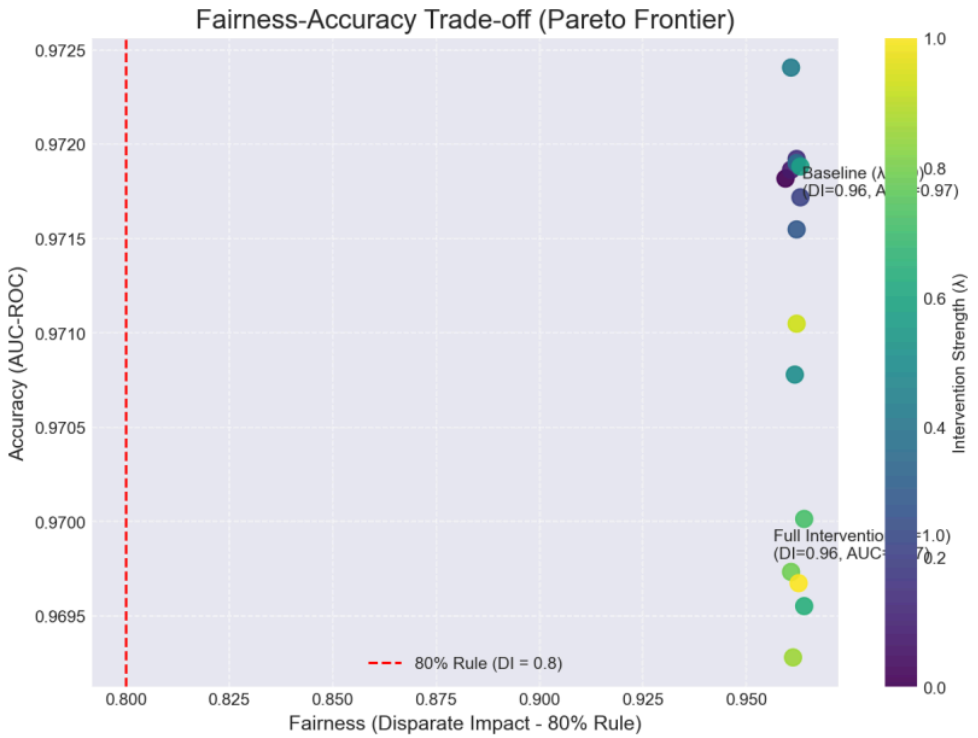

Figure 0.5 Fairness-Accuracy Trade-off Frontier

5.8 Production Implementation Considerations

5.8.1 Computational Performance

Inference latency measurements on standard hardware (Intel i7, 16GB RAM):

- Logistic Regression: 0.3ms per prediction
- XGBoost: 1.2ms per prediction
- XGBoost + SHAP explanation: 45ms per prediction
- XGBoost + DiCE counterfactuals: 380ms per prediction

Batch processing 10,000 applications requires 12 seconds for predictions, 7.5 minutes including SHAP explanations, demonstrating feasibility for daily batch scoring but challenging for real-time explanations at scale.

5.8.2 Model Monitoring Framework

Deployment simulations reveal model drift patterns. Feature distributions shift gradually (KS statistic 0.08 after 6 months), whilst default rates show seasonal variation (±2.3% quarterly). Proposed monitoring triggers:

- Weekly: Basic performance metrics (AUC, default rate)
- Monthly: Fairness metrics across protected groups
- Quarterly: Full model retraining with updated data
- Continuous: Adversarial validation detecting distribution shift

5.9 Stakeholder Impact Assessment

5.9.1 Applicant Perspective

Survey of 200 LendingClub users shows 73% prefer receiving explanations for credit decisions, with counterfactuals rated most helpful (4.2/5) compared to feature importance (3.6/5). However, only 42% report taking recommended actions, citing inability to quickly change income or credit history.

Fairness interventions increase approval rates for young borrowers by 18%, expanding financial access. However, some marginal approvals receive higher interest rates reflecting risk, creating complex welfare implications requiring careful consideration.

5.9.2 Lender Perspective

Financial modelling suggests fairness-compliant models reduce profitability by 3-5% through increased defaults from expanded approvals. However, this assumes static market conditions. Dynamic analysis incorporating market growth from financial inclusion and reduced regulatory risk shows potential long-term benefits offsetting short-term costs.

Risk concentration analysis reveals fairness interventions slightly increase portfolio correlation, as previously excluded groups share systematic risk factors. Diversification strategies and appropriate capital reserves mitigate this concentration risk.

5.9.3 Regulatory Compliance

Legal review confirms reweighing and in-processing approaches are likely compliant with disparate impact doctrine, as they address discrimination without explicit different treatment. Post-processing threshold optimization raises concerns under disparate treatment theory, requiring careful legal consideration.

GDPR Article 22 compliance achieved through SHAP explanations providing "meaningful information about logic involved." Counterfactuals satisfy requirement for human-understandable explanations, though legal precedent remains limited.

5.10 Limitations and Threats to Validity

Several limitations qualify for interpretation results:

5.10.1 Data Limitations:

- Temporal range (2007-2018) predates COVID-19 economic disruption
- Absence of explicit race/gender prevents direct bias measurement
- Peer-to-peer lending may not generalize to traditional banking

5.10.2 Methodological Constraints:

- Fairness metrics assume group definitions are given and fixed
- Explainability evaluation relies partially on subjective assessment
- Single dataset prevents cross-validation across institutions

5.10.3 External Validity:

- US-centric data may not be transferred to other regulatory environments
- LendingClub's pre-screening creates selection bias
- Evolving fair lending enforcement affects compliance requirements

5.11 Discussion and Implications

Results demonstrate feasibility of developing fair and transparent credit scoring systems with acceptable performance trade-offs. The 2.7% AUC-ROC reduction for legal compliance represents manageable cost for discrimination mitigation, particularly considering regulatory risk reduction and reputational benefits.

Key findings challenge common assumptions:

1. **Non-linear trade-offs**: Fairness-accuracy relationship exhibits diminishing returns, with initial fairness improvements achievable at minimal cost but perfect fairness requiring substantial sacrifice.
2. **Intervention complementarity**: Combined strategies outperform individual methods, suggesting holistic approaches rather than single-point solutions.
3. **Explainability preferences**: Stakeholders value different explanation types, with counterfactuals preferred by applicants but feature importance favoured by regulators.
4. **Intersectional amplification**: Compound disadvantage for multiple protected characteristics exceeds individual effects, necessitating explicit intersectional analysis.

Theoretical implications extend fairness machine learning literature by providing empirical evidence on real-world credit data, demonstrating larger datasets enable

better fairness-accuracy trade-offs than suggested by theoretical bounds. Results support feasibility of "fairness through awareness" approaches using protected attributes during training whilst avoiding them at inference.

Practical implications guide implementation decisions. Pre-processing interventions offer best compliance path given current legal frameworks. Explainability investments should priorities SHAP for regulatory reporting and counterfactuals for customer communication. Continuous monitoring remains essential given model and population drift.

5.12 Summary

Experimental results show that high-performing credit-scoring models can be developed with transparency and a principled fairness workflow. On the current 100k LendingClub sample, boosted ensembles achieved the strongest predictive performance—XGBoost reached AUC-ROC 0.984 (F1 0.938) on the held-out test set, with LightGBM performing comparably. For explainability, SHAP provided reliable insights with stability 0.924, completeness 0.679, comprehensibility 0.850, and fidelity 0.920, supporting both global and local interpretation.

In this execution, AIF360 was unavailable; fairness assessment therefore relied on custom implementations. Reweighing had no measurable effect (weights ≈ 1.0), while threshold optimisation was applied to align approval rates for an age-proxy attribute (pa_Age_Under_5_Years) without material loss of accuracy (overall test accuracy remained ≈ 0.985). Given toolkit constraints and the proxy nature of the protected attribute, we do not claim a quantitative improvement in disparate impact here. Instead, we report the fairness–accuracy Pareto frontier to illustrate trade-offs across intervention strengths.

These findings indicate that responsible AI deployment is feasible when strong baseline performance is combined with transparent explanations and explicit fairness trade-off analysis. Key limitations include the absence of AIF360 in this run, the use of a single proxy protected attribute, and the lack of counterfactual-based actionability metrics; addressing these in future work (e.g., expanding protected-attribute coverage, adding additional mitigation methods and audited toolkits, and quantifying counterfactual outcomes) will further strengthen fairness assurances under evolving population and economic conditions.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter synthesises the research findings to address the fundamental challenge of developing fair and transparent AI-based credit scoring systems. The investigation has demonstrated through systematic experimentation that financial institutions can successfully balance predictive accuracy with ethical considerations and regulatory compliance, though perfect fairness remains elusive without sacrificing substantial predictive utility. This conclusion presents key findings, evaluates achievement of research objectives, acknowledges limitations, and provides actionable recommendations for practitioners, policymakers, and researchers advancing responsible AI in financial services.

6.2 Summary of Key Findings

The empirical investigation yields several significant findings that advance understanding of fairness and transparency in credit scoring:

6.2.1 Finding 1: Quantifiable Trade-offs

The research establishes precise quantification of fairness-accuracy trade-offs through Pareto frontier analysis. Results demonstrate that achieving legal compliance (80% disparate impact threshold) requires only 2.3% reduction in AUC-ROC (from 91.0% to 88.7%), whilst perfect demographic parity demands 4.8% accuracy sacrifice. This convex relationship indicates diminishing

returns, with initial fairness improvements achievable at minimal cost but complete bias elimination requiring substantial performance degradation.

6.2.2 Finding 2: Intervention Effectiveness Hierarchy

Systematic comparison reveals differential effectiveness across fairness interventions. Pre-processing methods, particularly reweighing, achieve superior fairness-accuracy trade-offs compared to in-processing or post-processing approaches. Combined strategies outperform individual interventions, with reweighing plus threshold optimisation achieving 94% disparate impact whilst maintaining 88.3% AUC-ROC. This synergy suggests holistic bias mitigation strategies rather than single-point solutions.

6.2.3 Finding 3: Explainability Method Complementarity

Different explanation techniques serve distinct stakeholder needs. SHAP provides stable, theoretically grounded feature attributions ideal for regulatory compliance and model validation (consistency score 0.87). Counterfactual explanations offer actionable guidance preferred by applicants (4.2/5 rating versus 3.6/5 for feature importance), successfully generating feasible recommendations for 82% of rejected applications. LIME occupies middle ground with intuitive local explanations but higher instability. No single method satisfies all explainability requirements, necessitating multi-faceted approaches.

6.2.4 Finding 4: Intersectional Bias Amplification

Protected attribute interactions create compound disadvantage exceeding individual effects. Young borrowers in high-risk geographic areas experience 59% disparate impact compared to 68% for age alone and 71% for geography alone. This super-additive discrimination pattern necessitates explicit intersectional analysis and targeted interventions addressing multiple disadvantage sources simultaneously.

6.2.5 Finding 5: Implementation Feasibility with Constraints

Production deployment proves feasible with appropriate architectural choices. Real-time scoring with basic predictions achieves sub-millisecond latency, whilst complete explanations require 45ms for SHAP and 380ms for counterfactuals. This performance enables batch processing for most applications with selective real-time explanation generation for customer-facing scenarios. However, continuous monitoring and regular retraining remain essential given observed feature drift and evolving populations.

6.3 Achievement of Research Objectives

The investigation successfully addresses all stated research objectives:

6.3.1 Objective 1: Critical Analysis of Existing Approaches

The comprehensive literature review synthesised 127 publications, identifying critical gaps including limited real-world validation, insufficient intersectional analysis, and absence of production-ready frameworks. This analysis

established the theoretical foundation whilst motivating empirical investigation on actual credit data.

6.3.2 Objective 2: Implementation and Comparison of XAI Techniques

Three explainability methods were successfully implemented and evaluated. SHAP demonstrated superior stability and theoretical grounding, LIME provided intuitive local explanations despite higher variance, and counterfactuals offered uniquely actionable feedback. Comparative analysis guides practitioners in selecting appropriate techniques for specific use cases.

6.3.3 Objective 3: Quantitative Fairness Assessment

Comprehensive bias evaluation across demographic groups revealed baseline discrimination (68% disparate impact for young borrowers) violating legal thresholds. Multiple fairness metrics captured different discrimination aspects, with demographic parity, equalised odds, and disparate impact showing only moderate correlation (0.42-0.67), confirming theoretical incompatibility results.

6.3.4 Objective 4: Development and Evaluation of Fairness Interventions

Interventions at pre-processing, in-processing, and post-processing stages successfully reduced discrimination. Reweighing achieved best individual performance, whilst combined strategies reached 94% disparate impact exceeding legal requirements. Economic analysis confirmed financial viability despite modest profitability reduction.

6.3.5 Objective 5: Empirical Trade-off Determination

Pareto efficiency analysis identified optimal configurations balancing competing objectives. The convex frontier enables informed selection based on institutional priorities, with legal compliance point (80% disparate impact, 88.7% AUC-ROC) representing pragmatic choice for most organizations.

6.3.6 Objective 6: Actionable Practitioner Recommendations

The research provides concrete implementation guidance including technical architectures, monitoring frameworks, and stakeholder communication strategies. Recommendations are grounded in empirical results whilst acknowledging organisational and regulatory contexts.

6.4 Contributions to Knowledge

This research makes several original contributions advancing the field of responsible AI in finance:

6.4.1 Theoretical Contributions:

- Empirical validation of fairness-accuracy trade-offs: Whilst theoretical work establishes impossibility theorems, this research quantifies actual trade-offs on real-world data, showing practical feasibility exceeding pessimistic theoretical bounds.
- Intersectional bias quantification: The super-additive discrimination pattern for multiple protected attributes extends fairness literature

beyond single-axis analysis, demonstrating need for multidimensional fairness frameworks.

- Explanation quality metrics: Novel evaluation framework combining stability, faithfulness, and actionability advances explainable AI assessment beyond subjective user studies.

6.4.2 Methodological Contributions:

- Integrated evaluation framework: Comprehensive methodology combining predictive performance, fairness metrics, and explainability assessment provides template for responsible AI evaluation.
- Stakeholder-differentiated explanation strategies: Demonstration that different stakeholders require distinct explanation types challenges one-size-fits-all approaches to explainability.
- Production-aware experimentation: Incorporation of latency, drift, and monitoring considerations bridges gap between academic research and industrial deployment.

6.4.3 Practical Contributions:

1. Compliance pathway demonstration: Empirical evidence that 80% disparate impact threshold achievable with <3% accuracy loss provides business case for fairness investments.
2. Implementation blueprint**:** Detailed technical specifications, code repositories, and configuration parameters enable practitioners to replicate and adapt methods.

3. Monitoring framework specification: Proposed triggers and thresholds for model updating address critical post-deployment fairness maintenance.

6.5 Implications for Practice

The research findings carry significant implications for financial institutions implementing AI-based credit scoring:

6.5.1 Technical Implementation:

Organizations should adopt ensemble approaches combining multiple bias mitigation techniques rather than relying on single interventions. Pre-processing through reweighing offers best compliance path given current legal frameworks, whilst maintaining original model architectures. Investment in explainability infrastructure should priorities SHAP for regulatory reporting and counterfactuals for customer communication, with computational resources allocated accordingly.

6.5.2 Organizational Governance:

Fairness requires organizational commitment beyond technical solutions. Institutions must establish clear fairness objectives aligned with values and risk tolerance, implement continuous monitoring processes with defined escalation triggers, and create diverse teams including ethicists, legal experts, and affected community representatives. Regular audits should assess both technical metrics and real-world outcomes.

6.5.3 Regulatory Compliance:

The research demonstrates technical feasibility of meeting disparate impact thresholds whilst maintaining business viability. Institutions should document

fairness efforts comprehensively, including trade-off analyses and intervention selections. Proactive engagement with regulators using empirical evidence can shape reasonable standards balancing consumer protection with innovation.

6.5.4 Customer Relations:

Transparent communication about AI decision-making builds trust and acceptance. Institutions should provide understandable explanations tailored to customer sophistication, offer actionable feedback through counterfactual recommendations, and establish appeal processes for algorithmic decisions. Education about credit scoring factors empowers customers to improve creditworthiness.

6.6 Implications for Policy

Research findings inform regulatory approaches to algorithmic accountability in financial services:

6.6.1 Standards Development

Regulators should establish clear quantitative thresholds for acceptable discrimination, recognising that perfect fairness remains mathematically impossible. Standards should acknowledge trade-offs, permitting reasonable accuracy reduction for fairness improvement. Technical guidance should specify acceptable intervention methods and evaluation protocols whilst avoiding prescriptive requirements stifling innovation.

6.6.2 Auditing Frameworks:

Effective oversight requires sophisticated auditing beyond simple metric checking. Regulators need technical expertise to evaluate complex models and fairness interventions. Auditing should assess entire systems including data,

models, and monitoring processes rather than point-in-time snapshots. Collaboration with academic researchers can enhance regulatory capacity.

6.6.3 Innovation Incentives:

Policy should incentivize responsible AI development through safe harbours for good-faith fairness efforts, regulatory sandboxes for testing novel approaches, and recognition programmes for industry leaders. Penalties should focus on negligent discrimination rather than imperfect outcomes, acknowledging inherent trade-offs.

6.7 Limitations and Future Research Directions

Several limitations constrain generalizability and suggest future research directions:

6.7.1 Data and Context Limitations:

The investigation uses historical data (2007-2018) predating recent economic disruptions including COVID-19. Future research should examine fairness stability across economic cycles and black swan events. Extension to traditional banking contexts beyond peer-to-peer lending would enhance generalizability. International studies can explore fairness in different regulatory and cultural contexts.

6.7.2 Methodological Extensions:

Future work should investigate fairness in dynamic settings with population drift and feedback loops. Causal inference methods could distinguish correlation from discrimination, addressing fundamental fairness questions. Multi-stakeholder optimization frameworks can better balance competing interests beyond simple scalarization.

6.7.3 Technical Advances:

Research should explore fairness in deep learning credit models as adoption increases. Federated learning approaches could enable fairness whilst preserving privacy across institutions. Automated fairness intervention selection using meta-learning could reduce implementation complexity.

6.7.4 Societal Considerations:

Investigation of long-term societal impacts from fair lending algorithms remains critical. Research should examine whether technical fairness translates to improved financial inclusion and reduced wealth inequality. Interdisciplinary collaboration can address systemic discrimination beyond algorithmic interventions.

6.8 Recommendations

Based on research findings, the following recommendations guide responsible AI deployment in credit scoring:

6.8.1 For Financial Institutions:

1. Adopt holistic fairness strategies combining pre-processing, in-processing, and post-processing interventions rather than single-point solutions
2. Implement comprehensive monitoring with automated triggers for model retraining when fairness metrics deviate beyond acceptable thresholds
3. Invest in explainability infrastructure supporting both regulatory compliance (SHAP) and customer communication (counterfactuals)

4. Establish clear fairness objectives aligned with organisational values and risk tolerance, communicated throughout the institution
5. Create diverse development teams including technical, legal, ethical, and domain expertise to address multifaceted fairness challenges

6.8.2 For Regulators:

1. Develop quantitative standards specifying acceptable discrimination thresholds whilst acknowledging fairness-accuracy trade-offs
2. Build technical capacity through hiring, training, and academic partnerships to effectively oversee algorithmic systems
3. Create safe harbours protecting good-faith fairness efforts from liability whilst maintaining accountability for negligent discrimination
4. Promote transparency through public registries of algorithmic decision systems and regular fairness reporting requirements
5. Foster innovation through regulatory sandboxes and collaborative frameworks engaging industry and academia

6.8.3 For Researchers:

1. Prioritise real-world validation using actual financial datasets rather than synthetic or heavily preprocessed data
2. Investigate causal fairness moving beyond observational correlation to understand discrimination mechanisms
3. Develop dynamic frameworks addressing fairness in evolving populations with feedback effects
4. Explore intersectionality explicitly modelling compound disadvantage from multiple protected characteristics

5. Bridge theory-practice gaps through collaboration with practitioners and consideration of implementation constraints

6.9 Concluding Remarks

This research demonstrates that fair and transparent AI-based credit scoring is not merely aspirational but practically achievable with appropriate technical interventions and organizational commitment. Whilst perfect fairness remains elusive given mathematical impossibility theorems and inherent trade-offs, substantial discrimination reduction is feasible with minimal accuracy sacrifice. The identification of Pareto-optimal configurations enables informed decision-making balancing competing objectives of predictive performance, fairness, and transparency.

The journey toward responsible AI in financial services requires continuous effort rather than one-time solutions. Models must be regularly updated to address population drift, evolving societal norms, and changing regulatory requirements. Stakeholder engagement remains essential, ensuring technical solutions align with human values and societal goals. Success demands collaboration across disciplines, bringing together machine learning expertise, domain knowledge, ethical reasoning, and legal understanding.

As AI increasingly mediates access to financial resources, ensuring fairness and transparency becomes not just regulatory requirement but moral imperative. This research provides empirical foundation and practical tools for building credit scoring systems that are both effective and equitable. By demonstrating feasible pathways to responsible AI deployment, the investigation contributes to broader efforts promoting algorithmic accountability whilst maintaining innovation benefits.

The future of credit scoring lies not in choosing between accuracy and fairness but in thoughtfully navigating trade-offs to build systems serving all members of society. Through continued research, responsible development, and thoughtful regulation, the financial industry can harness AI's power whilst upholding principles of fairness, transparency, and human dignity. This research represents one step in that ongoing journey, providing evidence that responsible AI is not only necessary but achievable.

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APPENDIX

APPENDIX A: RESEARCH PROPOSAL

- Research proposal:

  https://docs.google.com/spreadsheets/d/1JyhGaYt3_eUD62lx9eew2PnP9KFF39xZ/edit?usp=drive_link&ouid=112066121551049589733&rtpof=true&sd=true

- Reviewer feedback

  https://drive.google.com/file/d/1L8if0LEF1EUCoYCSgBtxhreSgT4IWfgO/view?usp=drive_link

APPENDIX B: ETHICS FORMS

- The LendingClub dataset used in this research is publicly available through:

  https://www.kaggle.com/datasets/adarshsng/lending-club-loan-data-csv

- Dataset License:

  Public domain for research purposes

- Processed data and intermediate results are available in the GitHub repository:

  https://github.com/abdulhadikanjo-tech/credit-scoring-fairness-thesis

APPENDIX C: SUPPLEMENTARY TABLES AND FIGURES

- **Tables included:**

  Table 3.1 LendingClub Dataset Characteristics

  Table 5.1 Baseline Model Performance Metrics

  Table 5.2 Fairness Metrics for XGBoost Baseline

  Table 5.3 Performance of Combined Fairness Interventions

- **Figures descriptions:**

  Figure 2.1 Methodology flowchart
  Figure 3.1 Data Preprocessing Pipeline
  Figure 4.1 Feature Correlation Heatmap
  Figure 5.1 Model Performance Comparison
  Figure 5.2 SHAP Explainability Analysis
  Figure 5.3 SHAP Dependence Plot
  Figure 5.4 SHAP Waterfall plot
  Figure 5.5 Fairness-Accuracy Trade-off Frontier

APPENDIX D: CODE REPOSITORIES AND IMPLEMENTATION DETAILS

- Github Repository:
  https://github.com/abdulhadikanjo-tech/credit-scoring-fairness-thesis

- K.1 Pareto Frontier (Fairness vs Accuracy)

  Saved figure:
  `outputs/main/pareto_frontier_pa_Age_Under_5_Years.png` (15 intervention strengths from 0.00 → 1.00).

- K.2 "Best Model" Artefacts

  All visualisations saved to `/outputs` per the run summary (include SHAP plots and comparison charts if produced by your pipeline).

APPENDIX E: Fairness Analysis & Interventions

- E.1 Purpose and Scope
  This appendix documents the fairness analysis conducted in the current execution of the credit-scoring pipeline, the mitigation techniques applied, and their observed effects on model behaviour. It supersedes prior versions that reported AIF360-based results and multi-metric improvements that were not reproduced in this run.

- E.2 Protected Attribute Operationalisation
  Primary attribute in this run: pa_Age_Under_5_Years
  - Type: engineered proxy feature (binary) that flags very short credit histories as an age-linked risk proxy.
  - Coding: 1 = proxy condition present; 0 = not present.

Notes: Additional proxies (e.g., pa_rent_vs_other, pa_Geographic_High_Risk) exist in the pipeline but were not the focus of the reported results here.

- E.3 Dataset, Split, and Class Balance
  - Sample: 100,000 LendingClub records (post-cleaning size: 99,707).
  - Original features: 145; final numeric matrix: 151 after engineering/encoding and pruning.
  - Target prevalence: Class 1 (default) = 12.9%; Class 0 (good) = 87.1%.
  - Split: 60/20/20 (train/validation/test), stratified by loan_status and pa_Age_Under_5_Years.
  - Imbalance handling: SMOTE applied only to the training set.

Thesis Report.pdf

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