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by Sanaul Haque

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IARCO Research Proposal

Full Legal Name	**Katharina Alt**
Institution	**Munich International School**
Category	**Junior**
Class	**12th Grade**
Country Name	**Germany**
Registered Email	**katharina.alt13@gmail.com**
Date of Submission	**29/10/2024**
Research Topic	**Assessing Bias in AI Driven Credit Scoring Against Non-EU Immigrants in Germany**

Algorithmic Fairness in AI Driven Credit Scoring: Assessing Bias Against Non-EU Immigrants in Germany

Research Aim:

In Germany, credit bureaus are increasingly using AI scoring systems to determine the creditworthiness of an individual, as these models promise greater efficiency, consistency, and the ability to process large volumes of applications at speed. This study proposes to test the existence of barriers and biases within AI-based credit scoring systems in Germany that may disadvantage non-EU immigrants in accessing credit. Specifically, this study will analyse the following key issues: **(1)** the extent to which AI credit scoring models produce disparate outcomes for non-EU immigrants compared to EU native applications. **(2)** the underlying factors that contribute to any observed disparities. As the primary measure of disparity, the study will focus on home loan approval rate, as home ownership is a high-stakes financial milestone and the approval decisions are binary (either approved = 1 or denied = 0), making it a clear and direct indicator of access to credit.

Research Problem and Motivation:

The social consequences of biased AI credit scoring

AI-based credit scoring systems, used by banks, fintechs, and credit bureaus in Germany, play an important role in access to financial products like mortgages, credit, or loans. While efficient, these systems often rely on historical data and proxy variables—features that indirectly capture sensitive information without naming it directly. For example, a postcode may reflect neighborhood demographics, while documentation type (temporary vs. permanent residency) can signal immigration background. Such proxies can generate biased outcomes. Studies show that even without explicit attributes like nationality, machine learning models often reproduce disparities because other features such as postcode or employment type are statistically correlated with group identity [1, 2]. These risks are increased by opaque algorithms, where the feature weight and scoring processes are hidden, limiting applicants' ability to contest the outcome. In Germany, such biases may affect non-EU immigrants, excluding otherwise creditworthy individuals from access to loans or credit.

Regulatory context and urgency

Germany and the EU have recently tightened oversight over automated credit scoring. In 2023, the Court of Justice of the European Union (CJEU) ruled that if Germany's largest credit bureau, SHUFA, uses an AI-automated credit score as the decisive factor for accessing credit, it counts as automatic decision-making under Article 22 of the General Data Protection Regulation (GDPR). This gives applicants the right to human review and greater transparency [4–7]. Germany's financial regulator, BaFin, has also warned that AI can produce both direct and indirect discrimination, stressing that under the EU AI Act, credit scoring is classified as "high-risk," requiring strict governance and monitoring over bias [8]. However, independent groups like FinRegLab argue that this is insufficient and instead clearer denial notices are needed [9]. Beyond finance, German research on other AI applications, such as automated short-answer scoring in the educational PISA tests, has found disparities linked to students' language backgrounds. These systems are also treated as high-risk under the AI-Act, drawing a potential parallel to AI bias expectations for credit scoring [10].

Current gap in Germany

Despite these regulations, little empirical work investigates how AI-driven credit scoring interacts with non-EU immigrant profiles in Germany. This gap means bias may persist undetected, undermining both financial inclusion and compliance with EU requirements.

Research Questions:

1. *Do AI-based credit scoring models in Germany produce measurable differences in loan approval outcomes between non-EU immigrants and EU/native applicants?*

2. *Which features in credit scoring models function as proxy variables that indirectly influence approval outcomes and contribute to disparities for non-EU immigrants?*

Literature Review:

Recent Research on Algorithmic Bias in Credit Scoring

Within U.S. mortgage markets, fintech lenders charged Black and Hispanic applicants higher interest rates or fees than white borrowers, despite both groups having the same financial profile [3]. Kim et al. found the same subgroup applicants, such as young single mothers, in Spanish microfinance data even though the models seemed "fair" across agreegate categories (men vs women)[2]. As for methodological advances, more recent audit frameworks, as the BRIO framework, combine several fairness indicators into a single "unfairness risk" score. Using the UCI German Credit dataset (benchmark data set of 1000 German credit applications) BRIO's analysis showed that age-related bias was amplified in the model's predictions. This suggests that the algorithm introduced additional unfairness by further penalizing older applicants relative to others. [1].

Evidence and Mechanisms Relevant to Non-EU Immigrants in Germany

There are mechanisms and features by which non-EU immigrants may be disadvantaged:

- ***Thin files & short histories.*** Non-EU Immigrants often lack long credit records. EU studies note reliance on proxy factors like length of time of given address , phone contracts, or age of account, which correlate with recency of arrival and increase the chances of otherwise debt-free applicants being declined [9, 11].
- ***Proxying through correlated features***. Neighborhood default rates, employment duration or instability, and documentation type can indirectly suggest immigration status, which have been been raised as proxies and hence potential indicators of discrimination, as noted by BaFin[8].

Gaps in Prior Research

1. ***Fairness and lender economics.*** There is still know very little about how fairness measures affect lenders financially in Germany. The BRIO framework shows how fairness and performance trade-offs look on a test dataset, but there is almost no German evidence showing how specific fairness fixes like adjusting scoring models, or using constraints would reduce bank revenue or change how loans are priced under German rules Without this kind of evidence, it's hard for banks or regulators to judge whether fairness measures are both fair and financially workable. [3, 8–9].
2. ***Data governance under AI Act + GDPR***. There are few real-world examples of how lenders in Germany are putting new rules into practice after the SCHUFA ruling. For instance, we don't yet see systematic studies of how banks are updating disclosure templates, keeping records of human reviews, or building audit logs [4–8].
3. ***Causal attribution of proxy effects.*** Few studies use causal fairness tools like counterfactual fairness or mediation analysis to determine whether declines for recent non-EU immigrants are due to true risk or proxy-driven structural bias (e.g., address instability as an effect of recent arrival, not a risk cause).

Data and settings:

As a secondary source, this study will use the UCI German Credit dataset, compiled by Professor Hans Hofmann at the University of Hamburg. The dataset contains information on 1,000 credit applicants in Germany, including demographic features (e.g., age, marital status), financial indicators (e.g., credit history, loan amount, savings), and a "foreign worker" flag commonly used as a proxy for immigration status. Its strength is that its widely used as a benchmark in fairness research, making it useful for validation. However, it is small, dated, and lacks nuanced variables. To address these limits, the study will focus on using survey data and alternative-data indicators (rent, utilities, etc) collected directly from applicants using the UCI to audit and cross-check the findings.

Research Methodology:

Hypotheses:

H_1 **(Disparity impact)**: Non-EU immigrants have a lower home loan approval rate than native EU applicants, after controlling for debt to disposable income.
H_2 **(Proxy effects)**: Postcode, marital status, and documentation type act as proxy variables for immigration status, reducing the probability of home loan approval for non-EU immigrants even after controlling for debt-to-disposable-income.

Variables:

Hypothesis 1:

Dependent variables: home loan approval rate, measured as a binary outcome (approved = 1, rejected = 0). This directly captures access to credit, the most immediate and high-stakes decision in lending, providing a clear test of whether disparities exist in credit decisions themselves rather than in post-approval loan conditions.
Independent variables: immigration status, distinguishing between non-EU immigrants and EU/native applicants.
Control variables: debt-to-disposable-income ratio (DDI), household size, employment status, Loan-to-value (LTV) ratio, age, credit history length, Savings or asset holdings

Hypothesis 2:

Dependent variables: remains the home loan approval rate. This keeps the analysis consistent with Hypothesis 1 and ensures that any observed effects of proxy variables are directly tied to the same credit decision outcome.
Independent variables: proxy variables that may indirectly capture immigration status and contribute to disparities:

- **Postcode:** Reflects neighbourhood demographics (income, ethnicity, immigrant concentration), which may impact applicants from immigrant-dense areas.
- **Marital status:** Used as a signal of household stability but may correlate with immigration-related factors, such as higher rates of single parenthood or different family structures.
- **Documentation type:** Residency permits (temporary vs. permanent) vary systematically between citizens and immigrants and effect approval chances even with comparable financial profiles.

Together, these variables are not legally protected categories, but they may embed structural disadvantages that function as indirect pathways of bias. Their inclusion allows Hypothesis 2 to test whether disparities in approval are partly explained by proxies rather than legitimate measures of repayment risk.

Empirical Approach:

Hypothesis 1:
To test whether non-EU immigrants face significantly lower home loan approval rates than comparable EU/native applicants, this study will use a mixed data strategy combining survey data and secondary dataset analysis.

- **Sampling approach:** A survey will target approximately 500 recent credit applicants in Germany, recruited through financial literacy networks, immigrant associations, and social media platforms. Stratified sampling will be applied to ensure representation across immigrant status (non-EU vs. EU/native), income levels, and household structures. Control variables such as age, gender, employment status, and household size will also be collected to isolate the effect of immigration status.
- **Survey design:** Respondents will report their most recent loan application outcome, as well as income, debt obligations, household size, and property value. From these inputs, a debt-to-disposable-income (DDI) ratio will be calculated, which better reflects true repayment capacity by accounting for necessary household expenses. This will serve as a one of the other controlled variables that capture repayment capacity.
- **Statistical model:** A logistic regression model will be employed, as the dependent variable loan approval rate is binary. Logistic regression is appropriate because it estimates the probability of approval given predictor variables. This method allows coefficients to be interpreted as odds ratios, which makes results more intuitive.
- **Robustness check:** To ensure the model's results are not dependent on one specific sample, the analysis will apply k-fold cross-validation. Here the dataset is split into k parts, the model then is trained on k-1 parts and tests on the remaining one. Repeating this across all folds gives an average performance estimate, decreasing the risk that results are driven by random variation in the data. This strengthens confidence that any observed disparity is systematic rather than a statistical mistake.
- **Interpretation:** The test is whether the coefficient for non-EU immigrant status remains negative and statistically significant even after controlling for DDI. To aid interpretation, predicted probability plots based on estimated approval probabilities will illustrate whether, at equal levels of repayment capacity and collateral, non-EU immigrants are still less likely to be approved than comparable EU applicants.

Hypothesis 2 (Proxy Effects):
To evaluate whether postcode, marital status, and documentation type function as proxy variables for immigration status, the same regression framework from Hypothesis 1 will be extended. The dependent variable remains home loan approval.

- **Regression strategy:** After estimating the baseline disparity in Hypothesis 1, proxy variables will be introduced step-by-step. For example, Model 1 will include only immigrant status and DDI, Model 2 will add postcode; Model 3 will add marital status; and Model 4 will add documentation type. If the approval gap between EU/native and non-EU applicants shrinks as these variables are added, this would indicate that they function as indirect pathways of bias. A strong effect from temporary documentation status,for example, would suggest that document type acts as a proxy for immigration status rather than a legitimate measure of risk.
- **Sequential (added-variable) models:** Proxies will be added step by step to observe how the coefficient on non-EU status changes across models. Tracking these shifts provides a transparent way to identify which variables explain the largest share of the disparity. A significant drop in the non-EU coefficient after adding documentation type, for instance, would demonstrate its role as a proxy rather than a genuine risk factor.

- **Mediation and decomposition analysis:** To quantify "how much" each proxy contributes, the study will split the total approval gap into two parts: an explained portion (due to proxies such as postcode or documentation type) and an unexplained portion (residual bias). Mediation analysis will further test how much of the disadvantage of being non-EU flows indirectly through each proxy. These approaches provide clear numerical estimates (e.g., "documentation explains 30% of the gap"), showing which features drive inequality and which reflect bias that proxies cannot explain.
- **Qualitative Findings:** To complement the regression, 20–25 semi-structured interviews will be conducted with non-EU immigrant applicants to provide context for statistical findings. These will explore barriers such as difficulties with documentation, language, or the ability to contest automated rejections. Insights from these interviews will help interpret the statistical results by showing how proxy-related barriers affect applicants in practice.
- **Dataset linkage:** As a robustness check, the UCI German Credit dataset will be used to replicate proxy effects on a benchmark dataset widely cited in algorithmic fairness research. While this dataset is limited, it includes a "foreign worker" variable and demographic attributes such as marital status, which allow for partial testing of proxy effects and comparison with existing fairness audit studies.

Project Practicalities:

- Weeks 1-3:focus on survey design and distribution to about 500 loan applicants.
- Week 4-6: 20-25 interviews with non-EU immigrants.
- Week 7-9: cover regression analysis of survey results and thematic coding of interviews, with the UCI German Credit dataset used as a robustness check.
- Week 10-12: Final analysis and reporting.

All data will be anonymized, securely stored, and handled in accordance with GDPR and regulatory guidelines, with participants informed of their right to withdraw at any time.

Limitations and Improvements:

This study may face challenges in obtaining a representative sample, as survey participation could skew toward more digitally literate individuals. Response bias is another risk if applicants misreport income, debt, or loan outcomes due to privacy concerns; anonymization and careful framing will help mitigate this. The UCI German Credit dataset, used as a robustness check, despite being the largest available dataset is dated and not fully reflective of today's lending environment, so primary reliance will be on new survey and interview data. Finally, interviews may capture perceptions rather than objective processes, but triangulation with quantitative results will balance these limitations.

Conclusion:

This research tackles the urgent problem of bias in AI-based credit scoring. While these systems may improve efficiency, their potential bias can harm the livelihoods of non-EU immigrants in Germany by excluding otherwise creditworthy applicants from mortgages and home ownership. Looking ahead, future research could build on these findings by testing mitigation strategies such as incorporating alternative data or apply fairness modelling to explore how disparities might be reduced without sacrificing predictive accuracy.

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