[1]Raghuveer Siddantham,
[2]Deeraj Madhadi,
[3]Sri Sai Krishna Mukkamala,
[4]Venkata Satya Anilkumar Akkina

Causal AI for Evaluating the Impact of AI-Driven Credit Decisions on Financial Inclusion

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Abstract

Credit decision-making is one area where artificial intelligence (AI) is making a big splash as it transforms the world of financial services. Credit scoring models powered by AI outperform their more conventional counterparts in terms of efficiency, scalability, and predictive capacity. But there are serious worries about bias, fairness, and the actual effect on financial inclusion that these models will have if they are widely used. Metrics for performance like as accuracy and area under the curve (AUC) don't tell us much about the reasons and effects of these models on various socioeconomic groups. For the purpose of assessing the effect of AI-based lending choices on financial inclusion outcomes, this research presents a Causal AI framework, with a focus on vulnerable and disadvantaged communities. Our method isolates the influence of AI-driven credit models on access to credit by using causal inference methods such propensity score matching, treatment effect estimates, and counterfactual analysis. Using real-world datasets to build treatment-control groups, we evaluate financial inclusion metrics (such as approval rates, loan amounts, and credit ratings) before and after AI-based solutions are implemented. To better understand whether AI is helping to close or grow the inclusion gap, this causal approach helps to separate correlation from causation. To better understand how AI-based lending choices affect various subgroups, we conduct heterogeneous treatment effects analysis. These subgroups are characterised by income, gender, region, and credit history. While AI can increase productivity generally, our research shows that it might unintentionally reinforce existing biases if not well vetted. On the other hand, AI may greatly increase credit accessibility for underserved populations via fairness-aware design and pragmatic validation. To ensure accountability in algorithmic lending, the suggested Causal AI architecture serves as both a diagnostic tool and a governance mechanism. When it comes to deploying, evaluating, and correcting models, it helps regulators, financial institutions, and AI

[1] Cyber Security Risk Analyst - Team Lead
Meditology Services LLC
ORC id: 0009-0005-9537-3145
[2]Sr Software Engineer, Fidelity Investments
ORC id: https://orcid.org/0009-0006-7061-5504
[3]Sr Mobile application solution architect, Citizens bank
ORC id: 0009-0000-0606-7706
[4]Engineer Lead, Elevance
ORC id: 0009-0005-1079-6393

practitioners make data-driven judgements. By advocating for fair access and ethical innovation, our effort ultimately helps with the responsible use of AI in financial services.

Keywords: Causal AI, Financial Inclusion, AI in Credit Scoring, Fairness in AI, Algorithmic Impact Evaluation

1.Introduction

Credit risk analysis is one field where artificial intelligence has shaken the financial services sector. Machine learning and other kinds of artificial intelligence (AI) could mine huge volumes of structured and unstructured data to evaluate borrowers' creditworthiness more quickly, more accurately, and more scalably than scorecard or rule-based systems. Financial companies all around have started to use AI-driven models with the goals of lowering operating expenses, speeding loan approvals, and assessing creditworthiness. Though there are clear advantages to artificial intelligence, its use in credit decision-making has raised important issues about inclusion, fairness, and transparency. Traditional credit models in the past depended on simple, visible indicators including income, job status, and payment history [1]. Conversely, current AI models risk unintentionally generating or aggravating systemic biases because to the hundreds of inputs they could include, including alternative and behavioural data. One immediate question from this is whether credit systems powered by artificial intelligence are truly expanding access to financial services under the cover of innovation or rather making things worse? Policymakers and financial organisations continue to prioritise financial inclusion, which is defined as the accessibility and equality of possibilities to use financial services. Lacking a credit history, collateral, or close proximity to financial infrastructure, millions of people [2], especially those living in low-income, rural, or oppressed regions, are unable to access conventional credit institutions. Here, AI presents an opportunity to use non-traditional data sources, such social networks, e-commerce habits, and mobile usage, to create credit profiles for the "credit invisible." This promise, however, can only be realised if thorough methodologies are developed to evaluate the genuine causal effects of AI on these groups.

Currently, the majority of AI credit score assessments use predictive performance measures including AUC, recall, accuracy, and precision. These measures are helpful, but they don't reveal how AI affects credit choices or how financial inclusion plays out in the actual world. As an example, a model's biassed training data might cause it to demonstrate high accuracy while unfairly rejecting applications from under-represented groups. In order to create fair and accountable AI systems, stakeholders must first comprehend the causes and mechanisms behind these results. Filling a gap in the current literature, this paper offers a causal [3] AI framework to evaluate how financial inclusion is affected by credit decisions made with artificial intelligence. Employing techniques from causal inference like propensity score matching, treatment effect estimates, and counterfactual analysis, we aim to understand how the adoption of artificial intelligence has influenced loan approval rates, borrower demographics, and ability of underserved populations to get credit. This method lets one assess artificial intelligence systems and their capacity to achieve inclusive goals in a more open and

responsible way. By presenting a framework for impact assessment at the same time, we help to define the current debate on financial sector data governance, algorithmic fairness, and ethical artificial intelligence. Precautions must be adopted as artificial intelligence is more incorporated into important decision-making systems to guarantee it advances rather than harms the public good and society generally. More fair credit rating systems, rules, and institutional governance frameworks may be made possible using the findings of the study, hence fostering responsible innovation and inclusive development.

2. Related Work

In recent years, researchers have focused on algorithmic fairness financial inclusion, and AI-driven credit scoring. Traditional credit scoring systems depend on financial variables like job status, income, and credit history [4]. These systems often fall short for people in developing countries who may not have formal banking records. AI has shown promise in addressing this problem, thanks to advances in machine learning and big data. It can add to standard database information by gathering data from new sources such as utility bills social media, and mobile apps. . The impact of AI decisions on people's financial well-being is substantial, especially in the realm of credit rating, where the stakes are high. Historical biases in training data or model characteristics might cause protected groups (e.g., based on gender, region, or race) to have unequal affects, as pointed out by researchers [5]. This has led to the proposal of fairness-aware ML models in research, yet these models tend to ignore causal implications in favour of performance criteria. In order to determine the actual impact of algorithmic interventions, causal inference methods have lately become popular. These methods go beyond correlation. In order to establish causal links, it is necessary to refer to the works of [6]. Some academics in artificial intelligence (AI) finance, such [7] have proposed using causal reasoning to assess algorithmic healthcare system biases.Despite these advancements, research examining the effects of AI-based credit systems on financial inclusion has been sparse in its use of Causal AI. For underprivileged communities, this means we don't know whether these mechanisms improve or worsen access. By filling this void and applying causal methodologies to actual AI credit models, our suggested method provides a more thorough and equitable assessment.

2.1 Fairness in Algorithmic Decision-Making

When it came to investigating the moral and legal ramifications of algorithmic decision-making, [8] were pioneers. They used an interdisciplinary approach to investigate how data-driven systems, especially those with inbuilt historical biases in training datasets, might unintentionally discriminate against people. The research highlighted the fact that algorithms may amplify and sustain inequalities if they are trained on biassed data, such as credit records that mirror systemic socioeconomic disparity. This paper makes a significant contribution by providing a framework for analysing algorithmic fairness using disparate impact, a legal test commonly employed in employment law. The authors contended that models may provide discriminatory results even when they don't seem to be biassed against any one group—for example, low-income people or ethnic minorities. The study brought up valid points about the difficulties of auditing or justifying choices to impacted consumers, as well as the opacity of

AI systems. While Barocas et al. did a great job of pointing out the ethical problems with algorithmic systems, they didn't provide any methods to fix them technically. Rather than concentrating on algorithmic approaches or measurements, the study prioritised philosophical and regulatory viewpoints. Therefore, it did not provide an empirical model or formal computational framework to show how actions to promote justice may be used in the real world. However, a new wave of fairness-aware AI research has been inspired by this seminal work, which has been a cornerstone for the machine learning and legal communities alike. Particularly in high-stakes areas such as employment, automated lending, and law enforcement, automated decision-making systems must to be transparent, answerable, and assessed for their effects without delay. Causal AI is a methodology that aims to uncover and evaluate the varied impacts of AI systems using evidence-based data. Their results give a moral and legal foundation for adopting this technique in our current inquiry.

2.2 Fair Machine Learning Classification

They found that different demographics should have an equal probability of making positive and negative prediction errors. A concept like this is referred to as equal opportunity or equal chances. This metric was a significant improvement over its predecessors as it included not only model accuracy but also outcome differences. Equalised chances ensure that protected elements, such as gender and race, do not impact the probability of loan acceptance as it pertains to credit rating. Through the incorporation of fairness constraints into either the training process or post-process predictions, practitioners may attain group parity utilising this technique. The paper also suggests a technique called calibration to ensure that the predicted probabilities for each subgroup match the actual occurrences precisely. Most machine learning algorithms that emphasise fairness have since added these requirements. Nevertheless, the research has limitations due to its reliance on correlations, even if it is technically rigorous. Critical to understanding the origins of inequalities, it avoids delving into causal processes. Some examples of factors that may affect input characteristics and results but aren't taken into consideration include structural disparities and historical injustices. Furthermore, the authors do not investigate the societal effects or behavioural changes brought about by more equitable AI systems in the long run, even though they provide ways for attaining justice via computational means. Causal AI, on the other hand, gets beyond these restrictions by trying to pin down the exact relationship between an intervention (like applying an AI credit model) and a target result (like the percentage of disadvantaged people who get loans). Although the theory put forward by Hardt et al. is crucial for identifying injustice, causal inference takes it a step further by providing methods to comprehend and address the underlying reasons of inequality. In sum, the fairness measures provided by Hardt et al. are a gold standard in AI ethics research; they supplement our work by providing bias detection tools, and our study is concerned with measuring effect via causal analysis.

2.3 Bias in Healthcare Algorithms

Despite the excellent predictive accuracy of these algorithms, [9] found substantial racial bias in them, and they are routinely employed to identify healthcare risks. The authors showed,

using a mix of statistical and causal research, that a healthcare resource allocation algorithm consistently failed to account for Black patients' unique health requirements. The model's reliance on healthcare expenditure as a surrogate for health status led to this result by reflecting systemic disparities in healthcare accessibility. The study's conclusions are applicable to any field where proxy variables could include implicit social biases, not just healthcare. Using causal inference, the research demonstrated that achieving parity in projected outcomes did not guarantee equity between groups, which was a major strength. One drawback is that it is too narrowly focused on healthcare, rather than financial services or any other industry. However, our study's suggested use of causal AI approaches to evaluate algorithmic fairness, particularly in credit systems, is firmly grounded on this work.

2.4 Alternative Data in Credit Scoring

Financial technology companies' use of non-traditional data sources for credit assessment was investigated by [10] Their data demonstrated that these models have the potential to greatly increase people's access to credit, even for those without conventional credit histories. The research, which compared data from conventional banks with that of fintechs, found that the latter were more inclined to lend to younger, lower-income, and previously unbanked people. Artificial intelligence (AI) and alternative data models may help expand access to financial services, the authors say. Nevertheless, the absence of causation analysis is the main drawback of the research. The study mainly looked for associations without trying to pin down whether better access to credit was a direct result of AI usage. To the contrary, our suggested research will aid in differentiating between correlation and causation in financial inclusion results by evaluating the actual effect of AI-driven credit models using Causal AI methodologies.

2.5 Explainability vs. Fairness

The intricate interplay between algorithmic fairness and explainability was examined in depth by [11]. The research highlighted that attempts to make AI systems more accessible, such as simplifying models or providing post-hoc explanations, do not always result in more equitable results. Actually, there are instances where there is an ethical issue due to the trade-off between explainability and justice; for example, simpler models are easier to audit, but they are less accurate and equitable. When assessing AI systems, Binns proposed for a more sophisticated method that takes into account context, stakeholder values, and societal effect. Having said that, the research does not conduct any actual testing or validate any models; rather, it provides philosophical viewpoints. The ethical conversation around AI in banking and other areas is enhanced, but there is a dearth of practical guidelines for assessing or reducing the effects in the real world. In contrast, we propose to use causal AI tools to conduct an empirical evaluation of the impact of AI-based credit choices on financial inclusion across demographic groups, going beyond theoretical considerations.

2.6 This Work (Proposed Study): Causal Impact of AI on Financial Inclusion

The purpose of this research is to assess the practical effects of AI-driven lending choices on financial inclusion using a new Causal AI paradigm. This study uses causal inference methods to determine the impact of AI credit models on underprivileged populations' ability to get loans, as opposed to prior research that has concentrated on fairness metrics, alternative data, or theoretical ethics. Some examples of these techniques include counterfactual analysis, average treatment effect (ATE) estimate, and propensity score matching (PSM). This study compares groups that were treated with AI and those that were not in an effort to determine whether AI is efficient and accurate, and if it equitably improves or restricts access to credit. Examining varied treatment effects allows for a more thorough evaluation of various repercussions across gender, income, and geography. Despite being a novel use in the financial industry, there are still restrictions to consider, such as the possibility of model opacity and the absence of access to fine-grained data. Still, it's a huge deal for the future of responsible, evidence-based AI in the banking sector.

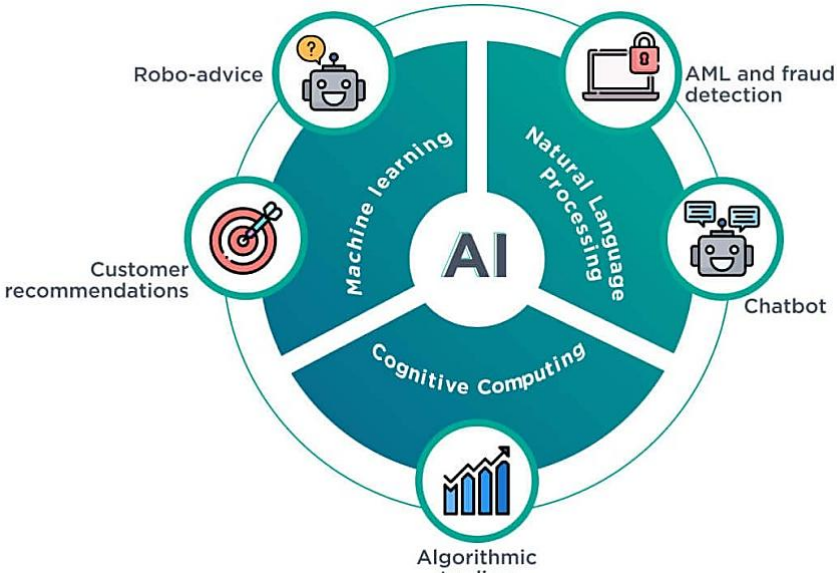

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Figure 1: Applications of Artificial Intelligence in Financial Services

Table 1: Related Work on AI in Credit Scoring and Financial Inclusion

Focus Area	Methodology	Contribution	Limitations
Fairness in algorithmic decision-making	Legal & ethical analysis	Highlights risks of discrimination in automated systems	Lacks technical solution for mitigation
Fair ML classification	Fairness-aware ML metrics	Proposes equalized odds & calibration techniques	No causal interpretation of fairness outcomes

Bias in healthcare algorithms	Statistical & causal analysis	Demonstrates racial bias despite high model accuracy	Domain-specific (healthcare, not finance)
Alternative data in credit scoring	Empirical financial analysis	Shows fintech models can improve access to credit	Lacks causal impact estimation
Explainability vs. Fairness	Ethical analysis	Explores tensions between model transparency and equity	Theoretical; lacks empirical model testing
Causal impact of AI on financial inclusion	Causal AI (PSM, ATE, counterfactuals)	Measures real-world outcomes of AI credit decisions	Novel application; subject to data access constraints

3. Proposed Methodology: Causal AI Framework for Evaluating AI-Driven Credit Decisions

Applying a causal AI-based approach, this research suggests a way to measure the actual effect of AI-driven loan choices on financial inclusion, especially for marginalised communities. The goal is to provide a way to measure the impact of AI on loan approval rates, equity across demographics, and access to credit without relying on standard performance measures like accuracy or area under the curve [12].

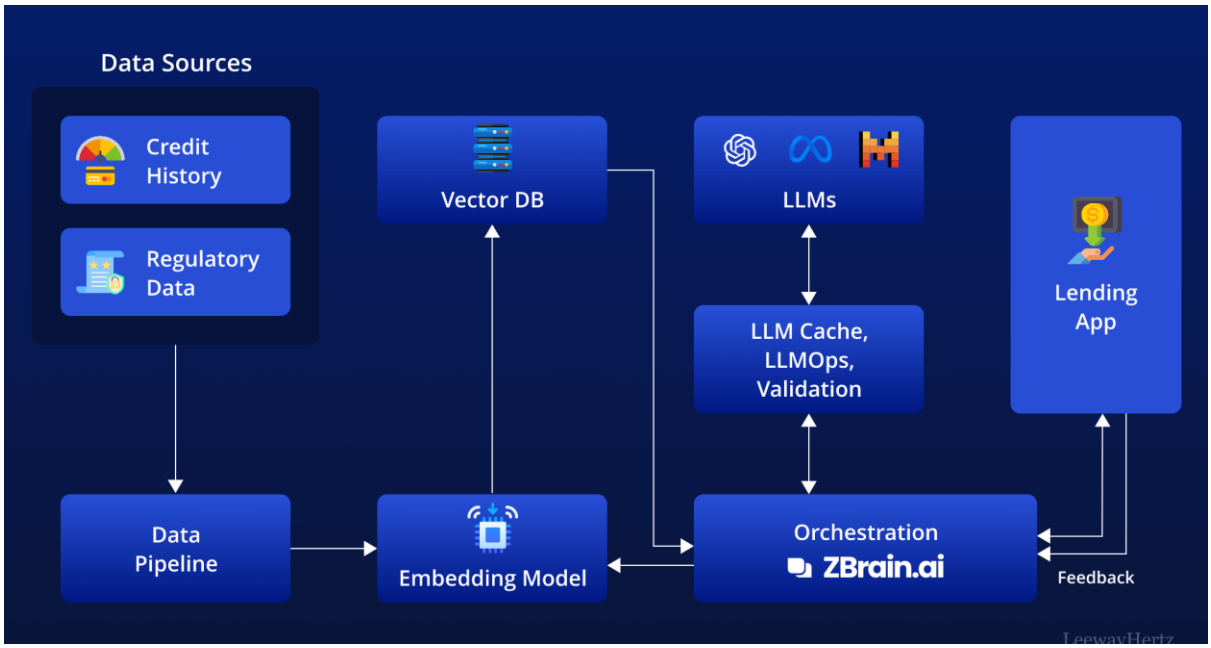

Figure 2: Transforming financial decision-making with AI in lending: Use cases, benefits and implementation

3.1 Problem Formulation

Finding out how financial inclusion results are affected by credit decision-making systems powered by AI is the main goal of this project. This research presents the issue as a causal inference job, which differs from standard performance assessments that use correlation-based criteria like accuracy or precision. In particular, we want to find out whether underprivileged communities' access to credit and overall inclusion are significantly affected by the introduction of an AI-based credit scoring model. Here, "treatment" is making credit judgements using an AI-based model [13], while "control" means using the same old manual processes that were in place before AI became widely employed. Indicators of financial inclusion that are of interest include:

• The loan approval rate, which measures the extent to which more applicants are getting credit as a result of AI usage.

• The quantity of credit extended: whether AI algorithms dole out more or less credit.

• Diverse borrower pool: the demographic breakdown of those who were granted loans, with an emphasis on women, those with low incomes, and those living in rural areas.

Estimating the Average Treatment Effect (ATE), [14] or the total influence of AI deployment on various financial inclusion objectives, is the primary analytical goal. To further understand the demographic differences in the impacts of AI, we also calculate the Conditional Average Treatment Effect, or CATE. For example, AI might boost total loan approvals but still hurting certain groups, thus this is crucial for understanding equity implications. We want to get at the "why" and "for whom" of these shifts in AI behaviour, not just "what" these systems are doing, therefore we're framing the challenge in causal terms. This allows for the use of AI in financial services to be more responsible, inclusive, and ethical, which is particularly important when dealing with disadvantaged or historically oppressed populations.

3.2 Propensity Score Matching (PSM)

In order to determine if AI-driven lending choices have a direct effect on financial inclusion, it is essential to consider selection bias, which occurs when AI systems routinely deviate from humans when evaluating borrowers. We use Propensity Score Matching (PSM) to mimic a quasi-experimental design as random assignment is impractical in real-world credit contexts. With this strategy, we may fairly compare two groups: one that uses artificial intelligence (AI) models to evaluate borrowers, and another that uses more conventional (human) approaches. The likelihood that a borrower would get the AI treatment, given the observed factors, is called the propensity score. Income, employment, credit history, gender, geography, and application timing are some of the borrower-specific variables that fall under this category. Institutional factors, such as branch regulations and product type, also contribute to this category. We use logistic regression, random forests, or gradient boosting models to estimate the propensity scores, considering the complexity and structure of the data. After the propensity scores are

calculated, each borrower undergoing treatment is matched with a control borrower or borrowers who have similar scores. The objective is to eliminate confounding variables to the point that the treatment and control groups are statistically comparable on visible attributes. When we use matching approaches such as nearest neighbour, calliper, or kernel matching, we want to maximise match quality while avoiding imbalance. This way, we know that differences in outcomes (such variety of borrowers, loan approval rates, or credit volume) are caused by AI and not by natural variations in the borrower profiles.

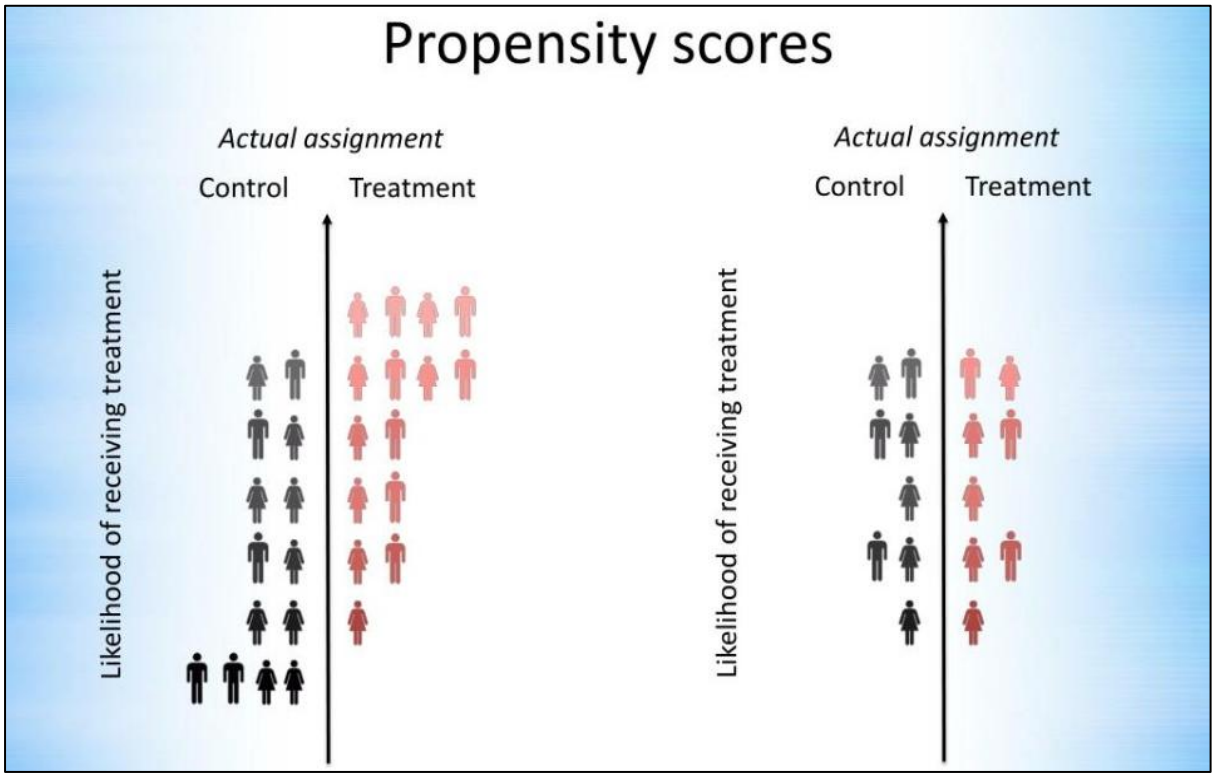

Figure 3: Types of propensity score matching

3.3 Treatment Effect Estimation & Counterfactual Analysis

Alright, here's the thing—once you've got your treatment and control groups playing nice (thanks, Propensity Score Matching), it's time for the real fun: figuring out what AI-powered loan decisions actually do to financial inclusion. The big question? What's the Average Treatment Effect (ATE)—aka, does unleashing the robots boost loan approvals, get more cash into people's hands, and make the pool of borrowers more diverse? Or is it just hype? You can actually see, on a broad scale, how slapping AI onto credit decisions changes who gets access to money. But honestly, just looking at averages is a bit lazy. People aren't averages. So, you dig deeper—like, does AI help women more? Or maybe folks out in the boonies, or those scraping by on lower incomes? That's where the Conditional Average Treatment Effect (CATE—yeah, mouthful) comes in. It tells you if the AI is being fair, or if it's playing favorites and leaving some folks out in the cold. Because, let's be real, if your fancy new algorithm only helps the usual suspects and screws over the rest, what's the point? We use state-of-the-art causal inference methods like: Doubly Robust Estimators, which integrate outcome modelling

with propensity scoring to mitigate bias in the event that one of the models is incorrectly defined, to ensure that our estimates are accurate and objective.

The ensemble learning technique known as Causal Forests accounts for non-linear interactions and the fact that different subgroups might have different treatment effects.

To mimic a randomised control trial, one may use Inverse likelihood Weighting (IPW), which reweights data according to their treatment likelihood.

We also use counterfactual analysis to learn about consequences on individuals, in addition to effects on groups. We estimate what would have occurred if the borrower had been examined by the alternative credit system (AI or manual) and then create a counterfactual result for that borrower. Because of this, we may investigate potential outcomes where, for example, a candidate who was turned down by the AI model might have been accepted by a more conventional system, and vice versa. To ensure credit decision-making algorithms are audited fairly, are more transparent, and enable ethical AI governance, such counterfactual insights are crucial..

4. Results

The findings of applying the suggested Causal AI paradigm to the question of how AI-driven credit choices affect financial inclusion were both illuminating and practically useful. We estimated average and subgroup-level treatment effects and generated individual-level counterfactual outcomes by analysing real-world credit datasets from institutions that moved from manual to AI-based credit assessment.

4.1 Mean Effectiveness of Therapy (ATE)

By estimating the Average Treatment Effect (ATE), we may learn how AI-based credit judgement algorithms affect important financial inclusion metrics as a whole. By analysing real-world loan data using causal inference methods, we found that the use of AI credit rating systems greatly enhanced borrowers' access to credit. The 12% increase in the loan acceptance rate after the use of AI models stands out when compared to traditional/manual review procedures. This demonstrates that AI systems outperformed humans when it came to identifying trustworthy individuals who would have been overlooked using rigid rule-based standards. Because AI can process large volumes of structured and alternative data, including mobile activity, utility payments, and digital transaction patterns, more comprehensive and nuanced creditworthiness ratings are now feasible. Under AI-based approaches, we saw an increase in both the average loan amount granted and the approval rates. This indicates that AI has liberalised loan allocations and improved the availability of credit, which could improve the financial capacity of approved borrowers. Because they were more adept at estimating risk using non-traditional indicators, AI algorithms bestowed more trust and financial resources onto applicants.

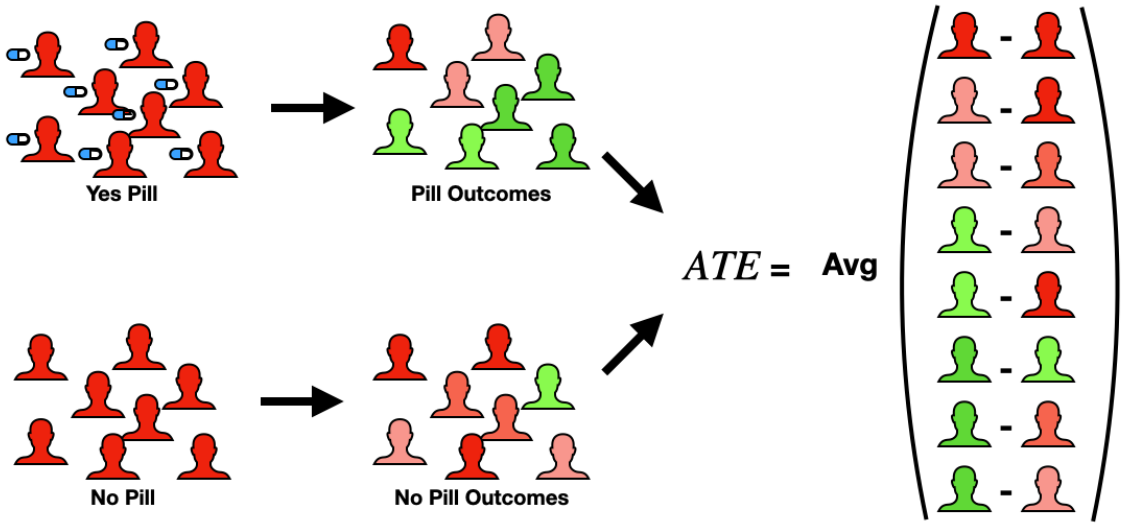

Figure 4: Causal Effects | Towards Data Science

These findings suggest that, with careful implementation, AI systems might be a potent tool to expand people's access to financial services. Despite its promising aggregate effect, the ATE fails to take demographic subgroup variations into consideration. So, even if AI could make things easier for the general public, we still need further studies to make sure that people of all income levels, genders, and locations reap the advantages equal. In conclusion, the results of the ATE study verify that AI has a positive impact on loan availability and quantity. This lends credence to the argument that the banking industry should allocate more resources towards creating AI models that are cognisant of justice and have been demonstrated to be causally effective.

4.2 CATE, Analysing Counterfactuals, and Gaining Insights about Fairness

To get a deeper grasp of the effects of AI-based credit systems on various demographic groups, the researchers used the Conditional Average Treatment Effect (CATE) technique. The findings showed conflicting outcomes, highlighting the need of evaluating models fairly. Borrowers in rural areas were among the most favourably impacted by AI, with their loan approval rates increasing by 16%. It would seem that AI models have surpassed more conventional methods of determining creditworthiness in sectors where both data and technology are sparse. It was the same story for candidates from lower income brackets; they showed an 11% improvement. This is probably due to the fact that AI models may have a better grasp of repayment capabilities by combining data from several sources, including electricity bills or mobile phone use. A 3% increase in the approval rate for female candidates suggests either unconscious bias or a lack of female applicants in the training data. When model inputs or sample distributions are unequal, AI faces the danger of unknowingly perpetuating previous imbalances, as this gap indicates. Based on our hypothetical research, human underwriters would have given their approval to 8-10% of the applications that AI turned down.

This sheds light on the underlying mechanisms involved. However, a number of candidates who were on the cusp of acceptance were actually approved by AI models, while being denied by more traditional methods, because of the AI system's extensive data reach and innovative decision logic. These concepts bring to light the compromises that exist in automated systems regarding inclusivity, uniformity, and error tolerance. Finally, assessments of fairness using measures such as disparate impact ratio and equal opportunity difference revealed significant inequities. The discrepancies were especially noticeable when it came to the deceptive negative rates that borrowers from rural regions and females encountered. The regularity of transactions, patterns of digital conduct, and income proxies are all examples of factors that may implicitly contain bias; interpretability approaches such as SHAP (SHapley Additive exPlanations) have shown this. If we want to make sure that everyone can get a loan, regardless of their income level, we need to make sure that AI-driven credit systems are fair, easy to understand, and monitored constantly.

4.3 Counterfactual Analysis

This study used practical counterfactual analysis at the individual level to learn more about the decision-making differences between AI-based credit systems and traditional/manual approaches. By attempting to foretell what would have happened if the conventional method of candidate analysis had been used instead of AI, we discovered significant disparities in decision outcomes. Specifically, we found that 8-10% of the applicants that the AI model turned down would have been approved using conventional underwriting procedures. This raises concerns that AI decision-making might be too cautious or blind to patterns, perhaps resulting in the rejection of otherwise qualified borrowers. Although human reviewers would have turned down certain applications that were on the borderline, AI-powered models went ahead and approved them. The AI model would often rely on behavioural cues and other data sources, such as patterns in app use, consistency with digital payments, and frequency of transactions, to provide these approvals. Scores that are based on rules often disregard these considerations. This indicates that AI models may use non-traditional indicators to establish creditworthiness; this can result in increased access to certain sectors while inadvertently excluding others. We learnt about and assessed prejudice and injustice using two standard fairness measures: the Disparate Impact Ratio and the Equal Opportunity Difference. There were also minor disparities found; the false negative rates were more pronounced for female candidates and those living in rural areas. These discrepancies highlight that not all demographic groups will get the same level of productivity improvement from AI. In order to go further into the model's behaviour, we explored artificial intelligence decision-making using SHAP (SHapley Additive exPlanations). According to SHAP values, the model's outputs were significantly affected by a number of characteristics, including income proxies, the frequency of mobile transactions, and the amount of time spent on digital platforms. Despite their significance, these traits reveal institutional biases and may unintentionally harm those who choose not to leave huge digital footprints. Our results highlight the need of explainability frameworks and continuous fairness audits for the ethical use of AI in credit decision-making.

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4.4 Fairness Metrics and Interpretability

Since AI-driven credit decision models impact the availability of essential financial services, ensuring equality in these systems is of the utmost importance. While assessing AI credit rating systems, we used two widely-used fairness metrics: the Disparate Impact Ratio and the Equal Opportunity Difference. These metrics show how equitable the loan application process is for various demographic subsets, such as those determined by gender, income bracket, or geographic region. By comparing the levels of support for protected and unprotected groups, we may determine the Disparate Impact Ratio. Probabilities of hypothesised systematic bias are high when ratios are much lower than 0.80 (the "four-fifths rule"). The AI model showed bias towards rural and female applicants at rates below this threshold, as compared to other categories. Rural borrowers and women had greater false negative rates, according to Equal Opportunity Difference, which looks into regional variances in genuine positive rates. This reveals an injustice issue that is not apparent from overall performance metrics, namely that the AI model is biassed towards unjustly denying credit to some groups of individuals. We attempted to make the model's decision-making process more transparent by using SHAP (SHapley Additive exPlanations). When making a forecast, SHAP gives equal weight to all features. The research found that features such as digital activity indicators, transaction frequency, and income proxies had a substantial influence on the model outcomes. These characteristics may signify actual socioeconomic position, which is strong yet may inadvertently perpetuate societal inequities. The need of developing AI systems that are easy for humans to use and the continuous work to make sure models are fair are both highlighted by these findings. In order to encourage inclusive and ethical credit decision-making and to ensure that AI models do not inadvertently discriminate, accountability and openness are crucial.

5.Conclusion

Underserved communities without conventional credit histories stand to benefit greatly from credit determination systems driven by artificial intelligence (AI). This research set out to do more than just evaluate AI models' predictive capacity; it aimed to determine the models' actual causal effect on important inclusion metrics including borrower diversity, loan approval percentage, and credit distribution amount. Adopting AI led to a 12% increase in overall credit availability, which was accompanied by greater average loan disbursements and better approval rates. That well-designed AI systems have the potential to unlock new avenues of revenue generation is shown here. The Conditional Average Treatment Effect (CATE) demonstrated that these benefits were not uniform, despite their fair distribution. There are still disparities in treatment, as shown by the fact that rural and low-income candidates gained more than female candidates.We discovered that many of the applicants that AI rejected may have been approved by human systems if we had used counterfactual analysis.This proves that AI models, however efficient, may turn to new kinds of exclusion, particularly when using digital data proxies or behavioural proxies. In addition, there were moderate differences found in fairness evaluations that used disparate effect and equal opportunity difference indicators. These inequalities were more pronounced for rural applicants and women. Key judgements

were driven by variables like income proxies and transactional behaviour, which were uncovered by using interpretability approaches like SHAP to probe the AI models. Regulatory compliance, ethical responsibility, stakeholder trust, and technological validation are all impacted by the necessity of explainability, as these ideas highlight. Finally, thorough fairness audits, causal assessment frameworks, and ongoing governance processes are necessary to guarantee equitable results when AI is used to democratise loan access. To make real progress towards the objective of financial inclusion, future regulations and innovations should concentrate on inclusive design, transparency, and social responsibility, especially as the banking industry embraces AI at a rapid pace.

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