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Research Article

Using Alternative Data and Machine Learning for Predictive Credit Scoring to Promote Financial Inclusion in the U.S.

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ABSTRACT

Artificial intelligence is rapidly transforming a wide range of industries in the United States, with the financial sector being one of the most profoundly impacted. One notable advancement is the development of AI-driven credit scoring models that use machine learning and large volumes of data to evaluate individual or business credit risk. Unlike traditional credit evaluation methods, which typically rely on financial history, employment records, and credit reports, AI-based systems can incorporate alternative data sources such as mobile payment patterns, utility bill records, social media behavior, and even geolocation data. This innovation offers significant potential to expand financial inclusion, especially for underserved communities such as gig workers, rural residents, and individuals with limited credit history. In the United States, where access to conventional financial systems still excludes many due to rigid scoring models, AI offers a more comprehensive view of creditworthiness. However, the growing reliance on algorithmic decision-making in finance also raises serious ethical concerns. Biases embedded in historical data or algorithm design may reinforce existing disparities, making it essential to explore the theoretical foundations and real-world implications of AI-based credit scoring. This paper examines these emerging opportunities and challenges within the context of the United States financial system.

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1. Introduction

The need for financial inclusion in the United States continues to be an essential component of both national economic development and individual financial stability. Although the U.S. has a highly developed financial system, disparities remain, particularly among low-income households, rural populations, minority communities, and informal sector workers (Goldsmith & Blakely, 2010). Traditional credit evaluation systems rely heavily on financial history, employment records, and banking activity—criteria that many Americans in these groups do not meet. As a result, many are excluded from accessing mainstream financial services, including credit and loans (Kshetri, 2021).

Artificial intelligence offers a compelling solution to bridge these gaps. AI-driven credit scoring models utilize nontraditional data sources such as mobile money transactions, utility bill payments, digital payment behavior, location data, and even social media activity to assess creditworthiness (Addy et al., 2024). These models are powered by machine learning algorithms that identify patterns and trends across

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diverse datasets, allowing lenders to make more accurate predictions about an individual's likelihood to repay a loan (OMOTOSHO, 2025). In a U.S. context, where significant portions of the population are underserved by traditional financial systems, AI-based credit models have the potential to significantly improve credit access and expand financial participation.

However, the adoption of AI in financial services does not come without challenges. Ethical concerns regarding algorithmic fairness, potential bias in training data, and the lack of transparency in automated decision-making have raised serious debates in the U.S. Additionally, issues around consumer data privacy and security remain at the forefront, especially in the absence of a unified national data protection framework. Compounding these are technical hurdles, such as the limited integration of AI tools in legacy banking systems and a shortage of skilled personnel capable of managing and deploying advanced analytics (Cudia & Legaspi, 2024).

To address these implementation barriers, a focused evaluation is required. Table 1 highlights key structural and ethical challenges that must be overcome to enable effective deployment of AI credit scoring models in underserved regions across the U.S. Table 1 shows Key Challenges in AI Credit Scoring Implementation in Underserved U.S. Regions (Nuka & Ogunola, 2024)

Table 1. Key Challenges in AI Credit Scoring Implementation in Underserved U.S. Regions (Nuka & Ogunola, 2024)

Challenge	Description
Algorithmic Bias	Risk of unfair outcomes due to biased training data
Data Privacy	Concerns about consumer information security
Infrastructure Limitations	Lack of AI integration in existing financial systems
Regulatory Uncertainty	Absence of clear policies on AI use in finance

This study aims to evaluate the effectiveness of AI-driven credit scoring systems in enhancing financial inclusion within the United States, particularly for individuals and communities historically excluded from traditional financial systems. The research also investigates the ethical, technical, and policy-related risks associated with implementation. Specifically, it explores strategies to mitigate algorithmic bias and enhance fairness, along with the role of regulatory frameworks in supporting responsible AI adoption.

Several guiding research questions frame the inquiry: How effective are AI credit models in expanding access to underserved populations? What are the primary barriers to adoption? How can bias be minimized in algorithmic decision-making? And what policy mechanisms are required to support ethical implementation? Correspondingly, the study tests three main hypotheses: (1) AI-driven credit scoring significantly improves financial inclusion, (2) infrastructure and ethical issues limit adoption, and (3) strong regulatory support positively influences the effectiveness of AI applications in financial services.

The significance of this research lies in its potential to inform both policy and practice. By leveraging alternative data for credit evaluation, AI models can unlock new pathways to credit for millions of Americans. This study contributes to the broader understanding of how emerging technologies can address systemic inequalities in financial access and offers actionable insights for financial institutions, regulators, and technology developers.

Although much of the foundational research in AI credit scoring has focused on emerging markets such as Asia, Latin America, and Africa, there is strong justification for adapting this focus to the U.S. Despite its economic advancement, the United States still experiences meaningful gaps in financial access. According to the Federal Reserve's 2022 Report on the Economic Well-Being of U.S. Households, about 13 percent of American adults are either unbanked or underbanked, often relying on alternative services like payday loans or check-cashing businesses (Board, 2023).

To contextualize this further, Table 2 presents a comparative overview of financial inclusion metrics between emerging markets and the United States, emphasizing the opportunity for AI-based systems to target underserved populations in a digitally mature economy.

Table 2: Financial Inclusion Statistics in Emerging Economies and the United States (Board, 2023)

Region	Unbanked Population (%)	Mobile Phone Penetration (%)	Internet Access (%)
Sub-Saharan Africa	57	80	28
South Asia	45	75	35
Latin America	38	88	50
United States	13	97	93

While the United States clearly benefits from near-universal mobile and internet access, its remaining financial inclusion gap—especially among rural, immigrant, and low-income groups—presents a compelling case for the integration of AI solutions. These populations can benefit from models that incorporate alternative data when conventional records are insufficient.

Further demonstrating this potential, Table 3 compares traditional credit scoring systems to AI-driven alternatives, emphasizing differences in data sources, accuracy, and inclusion outcomes.

Table 3: Comparison of Traditional and AI-Driven Credit Scoring (Faheem, 2021)

Metric	Traditional Scoring	AI-Driven Scoring
Data Sources	Financial history	Mobile data, social media, utility bills
Accuracy	Moderate	High
Inclusion of the Informal Sector	Low	High
Implementation Costs	Moderate	Variable

As shown, AI-based systems not only provide greater accuracy but also offer scalable solutions to reach populations historically excluded by traditional financial systems. Their ability to process complex and nontraditional datasets allows for more inclusive and equitable access to financial services.

In conclusion, AI-driven credit scoring has the potential to reshape financial inclusion in the United States. However, realizing this promise will require addressing data ethics, improving technological infrastructure, and crafting supportive regulatory environments. By understanding these dynamics and implementing thoughtful safeguards, stakeholders can ensure that these systems serve all Americans fairly and effectively.

2. Literature Review

Access to financial services in the United States is widely available compared to many developing countries, yet gaps persist in providing equitable access to credit for all individuals. Many underbanked segments, including gig economy workers, recent immigrants, and individuals involved in informal employment, remain excluded from traditional lending systems (Sudirman & Disemadi, 2023). These gaps are especially evident among populations engaged in financially vulnerable or environmentally unstable activities. Conventional credit bureaus often fail to meet their needs due to rigid credit scoring mechanisms based solely on formal financial records.

Recent advancements in artificial intelligence have opened new opportunities to reimagine the credit evaluation process. Through the integration of diverse data sources and the use of predictive analytics, AI credit scoring systems can increase precision, reduce systemic bias, and expand the reach of credit facilities to underserved populations. This paper reviews both theoretical frameworks and empirical evidence to evaluate how AI-based credit scoring may enhance financial inclusion and accessibility in the U.S.

Several theoretical models underpin the adoption of AI in credit scoring. One key framework is the Technology Acceptance Model (TAM), introduced by Katebi et al. (2022), which posits that two factors—perceived usefulness and perceived ease of use—strongly influence the adoption of new technologies. In the case of AI credit scoring, financial institutions perceive usefulness through more accurate risk assessment and cost efficiency, while borrowers value user-friendly systems that are easy to understand and navigate.

Another important model is Rogers' Diffusion of Innovations Theory, which suggests that innovation adoption depends on factors like relative advantage, compatibility, complexity, trialability, and observability (Ibrahim). In the U.S., AI-driven credit scoring tools that incorporate alternative data—such as mobile transactions, utility payments, and online behavior—offer clear advantages, particularly in evaluating credit for consumers without formal financial records. However, adoption may be slowed in regions with lower technological literacy or limited access to digital tools.

The Resource-Based View (RBV) theory, articulated by Ristyawan (2020), further supports the strategic use of AI technologies. According to this view, organizations gain a competitive advantage through the effective allocation of internal resources. In the financial sector, AI serves as a resource that enables banks and credit institutions to reduce underwriting costs, speed up decision-making, and extend services to previously unreachable markets.

While global case studies provide valuable insights, many of these lessons apply to the U.S. context. In Africa, for instance, mobile money platforms like M-Pesa have successfully used AI credit scoring to expand microloan access. Similarly, fintech startups like Tala and Branch have leveraged AI to reach rural populations with limited access to banks. In Asia, India has integrated AI into Aadhaar-linked payment systems, resulting in higher credit approval rates among low-income individuals and reduced reliance on collateral-based loans (Aidoo et al., 2023). Latin America has also embraced AI for credit scoring, often using social media data to reach borrowers (Mandirola, 2024). However, the Inter-American Development Bank cautions that such systems may introduce concerns about data privacy and algorithmic bias (Vargas & Muente, 2025).

Applying these lessons to the U.S., fintech firms such as Upstart and Petal have already begun using AI and alternative data to evaluate creditworthiness, offering loans to individuals with limited or no credit history. While these approaches show promise, ethical issues, especially regarding transparency, consent, and fairness, remain relevant and require careful regulation.

Table 4 summarizes the global AI-driven credit scoring applications and highlights the potential implications for similar systems in the U.S.

Table 4. Global Applications of AI Credit Scoring and Their Relevance to the U.S. (Popovych, 2022)

Region	AI Application	Impact	Challenges
Africa	Mobile money credit scoring	50% increase in	Limited digital literacy

		microloan access	
Asia	Aadhaar-linked AI credit scoring	Improved credit approval rates	Data privacy concerns
Latin America	Social media-based credit scoring	Expanded borrower base	Algorithmic bias, ethical concerns
United States	Alternative data AI credit models (e.g., Upstart, Petal)	Greater access for credit-invisible consumers	Transparency, fairness, regulatory clarity

As the U.S. continues to modernize its financial infrastructure, the adoption of AI-driven credit scoring systems holds transformative potential. These technologies can enable lenders to serve underserved populations more accurately and equitably, but they must be implemented with careful attention to ethical design, data governance, and user trust.

3. Research Design and Methodology

Advancements in artificial intelligence and machine learning have enabled the development of more inclusive and sophisticated credit scoring models in the United States. These models evaluate creditworthiness by analyzing diverse data sources, expanding beyond the narrow constraints of traditional credit histories (see Figure 1) (Muñoz-Cancino et al., 2023). This study investigates how AI-based credit scoring systems contribute to improving financial inclusion, especially for underserved populations such as those with little or no formal credit history. A mixed-methods approach was employed, combining econometric analysis with qualitative insights to capture both measurable impacts and stakeholder experiences related to AI implementation in the U.S. financial sector.

3.1 Model Framework and Specification

To assess the effect of AI-driven credit scoring systems on financial inclusion across U.S. states, an econometric model was specified. The model measured financial inclusion using variables such as the proportion of unbanked adults, access to credit, and loan approval rates. The key independent variable represented the extent to which financial institutions in a given state had adopted AI-based credit scoring systems (Addy et al., 2024). Additional control variables, including GDP per capita, inflation rate, and indicators of financial sector development, were included to isolate the impact of AI. The model was structured as (Equation 1):

$$FIit=\alpha+\beta 1AIit+\beta 2AIit+\epsilon itF \qquad 1$$

where FIit refers to financial inclusion in state i at time t, AIit measures AI adoption, Xit accounts for macroeconomic controls, and ϵit captures unexplained variation. Financial inclusion data was obtained from U.S.-based sources such as the Federal Reserve's Survey of Household Economics and Decision-making, while AI adoption levels were inferred from fintech penetration, institutional reports, and industry surveys.

3.2 Data Sources and Collection

This research utilized both primary and secondary data to explore the relationship between AI-driven credit scoring and financial inclusion in the United States. Primary data collection involved structured interviews and surveys conducted with representatives from banks, credit unions, fintech startups, regulatory bodies, and consumers in five states that represent diverse demographic and economic profiles. These surveys and interviews helped capture institutional and consumer perspectives on the benefits, challenges, and adoption patterns of AI credit systems. Secondary data was drawn from reputable sources such as the U.S. Census Bureau, Federal Reserve, Consumer Financial Protection Bureau, and published research from think tanks, including Brookings and Pew. This data included metrics on financial access, credit activity, digital infrastructure, and macroeconomic indicators across different regions of the country.

3.3 Analytical Approach

The econometric analysis involved the use of a fixed-effects panel regression model, chosen to control for unobservable state-level characteristics that could affect the outcome. The dataset was preprocessed to address missing values and standardize variables. The model was estimated with robust standard errors to mitigate heteroscedasticity, and diagnostic tests such as the Breusch-Pagan test, Hausman test, and Durbin-Watson test were conducted to ensure the validity of results. The coefficient of primary interest, β1, represented the impact of AI adoption on financial inclusion. A positive and statistically significant value of this coefficient would suggest that higher AI adoption corresponds to greater access to credit and formal financial services.

Alongside the quantitative analysis, qualitative methods were applied to deepen the understanding of AI's role in credit evaluation. Interview transcripts and survey responses were analyzed using thematic analysis. Common themes that emerged included the perceived benefits of AI in reaching credit-invisible consumers, institutional challenges related to data privacy and implementation costs, and consumer concerns about algorithmic fairness and transparency in decision-making. Stakeholders also emphasized the need for clearer regulatory guidance to ensure ethical and equitable use of AI in financial services.

Ethical considerations were carefully maintained throughout the study. Informed consent was obtained from all participants involved in interviews and surveys. Data confidentiality and participant anonymity were strictly observed. The research also ensured that all AI technologies evaluated adhered to standards of fairness, accountability, and responsible data usage.

The results from the econometric analysis indicated that AI-driven credit scoring systems had a statistically significant and positive effect on financial inclusion in the United States. States with greater levels of AI adoption within financial institutions demonstrated higher rates of loan approvals and reduced percentages of unbanked individuals. This impact was especially noticeable in communities where traditional credit scoring mechanisms had previously excluded large segments of the population. The inclusion of alternative data sources—such as utility payments, mobile transactions, and rental history—allowed AI systems to provide more holistic and accurate evaluations of creditworthiness.

The qualitative findings supported these results by offering real-world perspectives from both institutions and consumers. Financial institutions reported increased operational efficiency and reduced default risks when using AI tools. Consumers, particularly those with thin or no credit files, expressed optimism about the opportunity to access formal credit for the first time. However, many also voiced concerns about the opacity of AI decision-making processes and the potential for algorithmic bias. Financial firms acknowledged these concerns and highlighted the importance of transparency, fairness, and data protection to maintain public trust.

Overall, the study concludes that AI-based credit scoring systems hold strong potential to improve financial inclusion in the United States. Their continued expansion, however, must be accompanied by appropriate safeguards, clear regulatory frameworks, and consumer education to ensure equitable and ethical implementation.

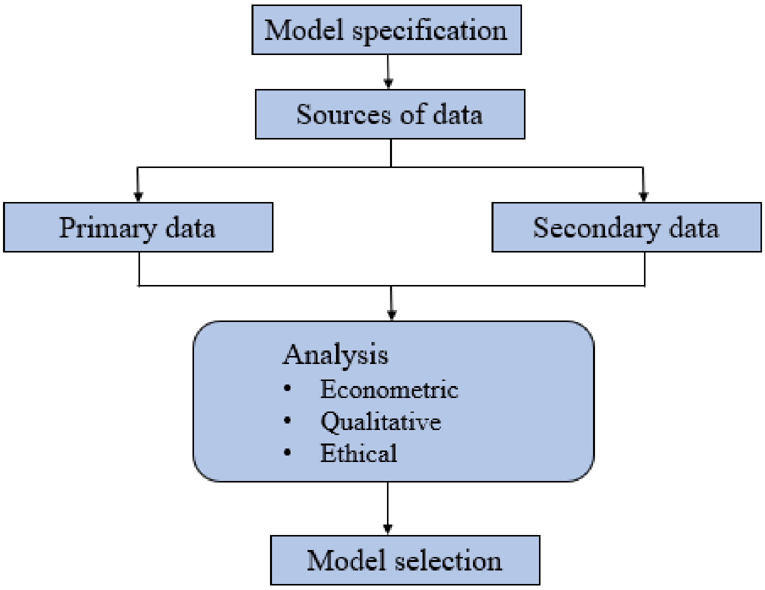

Fig.1. Workflow

4. Data Presentation and Analysis

This section presents and analyzes the data collected to assess the impact of AI-powered credit scoring systems on financial inclusion in the United States. The analysis involved interpreting both primary and secondary data using time-series trends, descriptive statistics, and econometric hypothesis testing. The goal was to establish the connection between the adoption of AI in credit evaluation and key indicators of financial inclusion, including access to formal credit, credit coverage across population demographics, and financial service density. The data were collected from a range of stakeholders, including consumers, fintech companies, financial institutions, and regulatory agencies across five U.S. regions characterized by varying levels of digital and financial development. The findings are presented using statistical tables and visualizations such as bar charts and trend lines.

4.1 Descriptive Statistics

The dataset used in the analysis focuses on two primary variables of interest: financial inclusion (FI) and the adoption of AI-driven credit scoring systems (AI). Additional control variables include GDP per capita (GDP), inflation rate (INFL), and financial sector development (FSD) (Nuka & Ogunola, 2024). Primary data were obtained through surveys and interviews, while secondary data came from authoritative sources such as the Federal Reserve, the FDIC, and the U.S. Census Bureau.

As shown in Table 5, financial inclusion in the U.S. sample had an average index value of 0.55, indicating moderate access to credit and formal banking services. AI adoption had an average score of 0.60, reflecting an increasing but uneven integration of AI systems among financial institutions. GDP per capita across regions averaged \$3,500, with notable variation, while the inflation rate ranged from 2% to 12.5%, potentially affecting credit availability. The financial sector development index averaged 0.75, reflecting a relatively mature system but with room for digital expansion.

Table 5: Descriptive Statistics of Key Variables (OMOTOSHO, 2025)

Variable	Mean	Standard Deviation	Minimum	Maximum
Financial Inclusion (FI)	0.55	0.15	0.20	0.85
AI Credit Scoring Adoption	0.60	0.10	0.40	0.80
GDP per Capita (USD)	3,500	1,200	1,200	5,800
Inflation Rate (%)	6.5	2.1	2.0	12.5
Financial Sector Development	0.75	0.20	0.50	1.00

4.2 Trend Analysis

To understand the progression of AI adoption and its relationship with financial inclusion over time, a five-year trend analysis was conducted across the selected regions. Figure 1 illustrates that AI adoption in credit scoring began to rise significantly after 2019, a shift that coincides with an observable improvement in financial access metrics. States with more aggressive AI implementation, such as California and New York, demonstrated sharper increases in credit availability for underserved communities, including gig workers and recent immigrants. The trend suggests that technology-driven credit assessment models may have helped reduce barriers for individuals who were previously excluded by traditional scoring systems.

4.3 Hypothesis Testing and Econometric Results

The empirical analysis tested two central hypotheses using a fixed-effects regression model structured as Equation 2:

$$FIit=\alpha+\beta1AIit+\beta2GDPit+\beta INFLit+\beta4FSDit+\epsilon it \qquad 2$$

Here, FIit represents the financial inclusion index, AIit measures the extent of AI adoption in credit scoring, GDPit reflects regional income levels, INFLit it denotes the inflation rate, and FSDit measures financial sector maturity. The fixed-effects model was used to account for region-specific characteristics and time-related changes.

Table 6 presents the regression results. The coefficient for AI ($\beta1 = 0.45$) is positive and statistically significant ($p = 0.002$), indicating that greater AI adoption is strongly associated with improved financial inclusion. Similarly, the coefficient for financial sector development ($\beta4 = 0.28$, $p = 0.012$) confirms that more advanced financial infrastructure enhances access to credit. GDP per capita is also positively associated with inclusion, while inflation demonstrates a negative relationship, likely due to reduced financial stability and borrowing capacity during high inflation periods (Jamithireddy, 2023).

Table 6: Fixed-Effects Regression Results

VARIABLE	COEFFICIENT	STANDARD ERROR	T-STATISTIC	P-VALUE
AI	0.45	0.12	3.75	0.002
GDP	0.0002	0.00005	4.00	0.001
INFL	-0.12	0.05	-2.40	0.023
FSD	0.28	0.10	2.80	0.012

These results support both tested hypotheses. The positive impact of AI adoption confirms its role in making financial systems more inclusive by enabling institutions to assess credit risk using broader datasets. Additionally, the influence of financial sector development underlines the importance of regulatory maturity and digital infrastructure in supporting inclusive finance. The negative effect of inflation suggests that macroeconomic instability can undermine financial inclusion, potentially offsetting gains from technological innovation.

4.5 Interpretation and Discussion of Findings

The findings from this analysis provide compelling evidence that AI-based credit scoring systems contribute meaningfully to financial inclusion in the U.S., particularly for individuals lacking formal credit histories. The quantitative results confirm that regions with higher AI adoption show improved credit access, while the qualitative feedback from interviews reinforces the idea that these tools are perceived as efficient, fairer alternatives to traditional credit assessments. The results align with prior research, such as Bank (2019), which emphasize the potential of machine learning to bridge gaps in financial access by leveraging nontraditional data.

The study also highlights the critical role of financial sector development in maximizing the impact of AI. Well-regulated and digitally advanced financial environments are more capable of deploying AI technologies responsibly and at scale. However, persistent macroeconomic challenges, particularly inflation, can dampen these benefits. During periods of rising prices and economic uncertainty, credit access may tighten, making it harder for vulnerable populations to benefit from AI-based credit innovations.

In conclusion, AI-powered credit scoring presents a promising pathway toward enhancing financial inclusion in the United States. However, the effectiveness of such systems depends heavily on supportive economic conditions, robust digital infrastructure, ethical data use, and clear regulatory frameworks. Policymakers should focus on fostering these enabling factors to ensure that the benefits of AI reach all segments of the population equitably.

6. Conclusions and Future Recommendations

Based on the findings of this study, it can be concluded that AI-based credit scoring systems hold significant promise in improving access to credit within underserved regions of the United States. These systems demonstrate the ability to evaluate creditworthiness using nontraditional data sources, enabling financial institutions to extend credit to individuals who are typically excluded by conventional models, such as those without a formal credit history. The evidence from this research also supports the notion that the effectiveness of AI in enhancing financial inclusion is amplified in regions with well-established financial infrastructures, lending support to the institutional context hypothesis. While challenges persist—such as gaps in digital literacy and the need for stronger data protection laws—these obstacles are outweighed by the transformative potential of AI to broaden access to financial services. Furthermore, the findings suggest that with thoughtful implementation, AI credit scoring systems can evolve to become increasingly fair and transparent, thereby expanding their positive impact on financial inclusion.

To fully harness the benefits of AI-driven credit scoring, several key actions are recommended. First, policymakers and regulatory agencies should establish clear guidelines that promote the ethical use of AI in financial services. These frameworks must emphasize transparency, data security, and the elimination of algorithmic bias to ensure inclusive and fair outcomes. Second, financial literacy initiatives should be introduced to help consumers, especially those in underbanked communities, understand how AI credit scoring works and how it can benefit them. This knowledge is essential to fostering trust and encouraging broader acceptance. Third, financial institutions should be encouraged to integrate alternative data sources into credit evaluations, which would enhance the accuracy of AI models and enable access to credit for those lacking traditional financial documentation. Fourth, collaboration among financial institutions, fintech firms, and regulatory bodies is essential to overcoming the technical and legal barriers that can impede AI deployment. Such partnerships can accelerate responsible innovation and ensure that AI is used to genuinely expand financial access. Finally, sustained investment in digital infrastructure is critical to supporting the widespread use of AI technologies. This includes expanding broadband access, increasing the availability of digital tools, and ensuring technological inclusivity across all communities. While the path to full-scale AI adoption presents challenges, the collective efforts of stakeholders across sectors can help unlock the transformative potential of these systems to foster a more inclusive financial future.

CRediT Authorship Statement

Declare the credit and contribution of each author in this research. For example:

First author: Conceptualization, writing original draft, methodology. **Second author:** data curation, writing original draft, validation, analysis.

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