

The Current Status and Development Strategies of Artificial Intelligence Applications in Inclusive Finance in China—From the Perspective of the Rural Revitalisation Strategy

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Abstract

This article conducts an in-depth study on the application of artificial intelligence in China's inclusive finance sector. Presently, financial institutions are actively incorporating AI technologies to empower inclusive finance operations. AI-driven automated loan approvals, personalised financial solutions, and anti-fraud measures demonstrate the technology's positive impact. However, challenges such as algorithmic bias, insufficient computing power, and inadequate investment in AI-based rural inclusive finance hinder its advancement. Finally, this paper proposes countermeasures to address these issues and promote the healthy development of artificial intelligence within China's inclusive finance sector.

Keywords

Rural revitalization; Artificial Intelligence; Inclusive Financial

1. Introduction

Against the backdrop of the rural revitalisation strategy and the rapid advancement of artificial intelligence, digital finance has entered a new phase, profoundly reshaping our lifestyles and socio-economic structures. In recent years, the state has placed high importance on the application and development of AI technology within the financial sector, successively introducing a series of development plans and policy measures. These aim to drive high-quality development in the financial industry through technological innovation, particularly by achieving creative breakthroughs in the field of inclusive finance. General Secretary Xi Jinping has repeatedly emphasised: 'We must promote the deep integration of modern information technologies such as the internet, big data, and artificial intelligence with the real economy.' To revitalise China's rural areas, continuous technological transformation across fields such as the internet and artificial intelligence is required, weaving technology into the fabric of the financial system. At this critical juncture of socio-economic transformation, the demand for financial services in rural areas is growing. However, traditional service models struggle to meet the evolving needs of the rural economy. Consequently, our research focuses on leveraging artificial intelligence to address current challenges and further enhance and develop financial services.

This paper delves into the current application and future development of artificial intelligence within inclu-



sive finance, particularly examining how AI technology can be better harnessed to promote socio-economic development in rural areas under the rural revitalisation strategy.

2. Literature review

Currently, the application of artificial intelligence in inclusive finance is advancing rapidly. Existing research on the role of AI primarily focuses on technological implementation, economic impacts, and societal implications. Regarding technological application, AI is employed in intelligent investment advisory services to conduct risk assessments for clients, intelligently recommend investment products, and provide financial consultation and guidance. This approach guides clients towards rational investment decisions, thereby enhancing capital returns (Han et al., 2024). By acquiring vast datasets, AI can build submodels for credit risk prediction and integrate them into learning processes to derive comprehensive credit scores. This enables more effective user analysis during risk assessment, thereby improving credit evaluation efficiency (Liao & Li, 2023). Moreover, intelligent customer service systems can automate diverse processes, analyse client data, recommend tailored financial products, track financial decisions, and continuously refine investment advice data, thereby reducing service costs (Xu & Zhang, 2022). They play a pivotal role in fraud detection, with numerous financial institutions extensively adopting AI applications to enhance consumer protection, improve user experience, manage risks, and detect fraudulent activities (Yang, 2024).

Whilst artificial intelligence technology provides powerful enablement for inclusive finance development, several issues remain unignorable. The rapid advancement of AI technology poses significant challenges to financial sector stability, information security, and financial practitioners (Office Research Team of the Wuhan Branch of the People's Bank of China et al, 2016). AI faces issues such as algorithmic bias and the "algorithmic black box" (Li, 2024), high computational costs, algorithmic precision, and algorithmic resonance (Li, 2020), which can readily lead to outcome distortions. The application of AI in inclusive finance also faces obstacles to innovation, including multi-dimensional complex data formats and massive data volumes, inadequate computing processing capabilities, and insufficient financial data sharing (Wang & Xiao, 2017). Furthermore, insufficient foundational technological R&D capabilities weaken its core competitiveness (Ma & Wei, 2018). From a legal perspective, AI's automated decision-making fails to consider safeguards for human rights and interests, focusing solely on algorithmically defined objectives. All legal constraints are perceived as technical impediments to AI (Jiang & Li, 2025). The application of AI in finance also introduces information security risks, including cybersecurity vulnerabilities susceptible to exploitation (Yu & Peng, 2017) and information insecurity that fosters financial crime (Yi, 2023). Challenges include incomplete regulatory frameworks and elevated risks of system failure (Chen & Xu, 2019).

3. Current Applications of Artificial Intelligence in Inclusive Finance

3.1 AI-Driven Loan Process Automation

Traditional lending procedures are often complex and time-consuming, failing to meet the 'short-term, small-scale, frequent, and urgent' financing needs of farmers and micro-enterprises. Currently, financial institutions integrating 'AI + finance' predominantly employ machine learning algorithms to analyse and learn

from multi-dimensional data—including loan histories, transaction records, asset information, and corporate financial status—of individual farmers and micro-enterprises. This enables precise assessment of clients' repayment capacity and creditworthiness, alongside predicting their default probability. This approach not only incorporates traditional financial assessment metrics but also integrates unstructured data such as social network interactions and consumer behaviour, resulting in more comprehensive and accurate risk evaluations. Furthermore, it automates loan approval processes and optimises risk pricing mechanisms, enhancing approval efficiency while effectively reducing operational errors and moral hazards stemming from human factors.

3.2 AI-Empowered Personalised Financial Solutions

The implementation of the rural revitalisation strategy demands greater personalisation in financial services. Diverse financial needs among farmers and micro-enterprises render traditional uniform service models inadequate. Financial institutions are now exploring AI-driven user profiling to develop tailored services, analysing farmers' consumption patterns and operational data to create precise user profiles and recommend suitable financial products. Intelligent customer service and investment advisory systems, powered by natural language processing, overcome spatial and temporal constraints to address individual queries, recommend wealth management products, and deliver faster, more convenient services. These personalised service models not only enhance user satisfaction but also stimulate rural economic development. Most financial institutions' intelligent product recommendation systems have entered a foundational development phase, exploring the optimal personalised financial product recommendations for clients. For instance, they propose tailored solutions addressing the financing needs of rural tourism projects.

3.3 AI-Empowered Financial Fraud Prevention

By analysing customer transaction histories, social media data, and anomalous behaviour patterns, artificial intelligence employs image recognition technology to detect insurance fraud schemes such as duplicate claims and exaggerated loss reports. This enables real-time, precise identification of potential fraudulent activities, empowering financial institutions to promptly detect and prevent scams while purifying the agricultural finance ecosystem. AI technology uses algorithms to flag anomalous transactions, enabling financial institutions to detect and prevent fraud promptly. This safeguards both low-income client groups and corporate assets, achieving a fraud prevention rate exceeding 95% and ensuring the security of digital inclusive finance. (Liu & Jia, 2023)

4. Challenges Faced by Artificial Intelligence in Inclusive Finance Applications

4.1 Hidden Algorithmic Bias in AI Models

In the era of big data, algorithmic bias is challenging to avoid, posing a significant constraint on the sustainable development of inclusive finance. During the transition towards financial inclusion, the inherent flaws of algorithmic bias have gradually permeated operational processes, leading to unfair credit assessments and inadequate financial services. Beneath its rational and objective façade, this bias perpetrates more covert infringements upon the equitable rights of financially vulnerable groups. The emergence of algorithmic bias



stems from the combined influence of technological and human factors. Technologically, algorithms, through data learning and analysis, readily conflate correlation with causation, thereby triggering discriminatory decisions based on correlation. In credit services, algorithms may learn from data that applicants with rural household registrations exhibit higher loan default rates. Consequently, they may attribute this higher default rate to the rural household registration itself, subsequently discriminating against applicants from rural areas by offering lower loan amounts or demanding higher collateral requirements.

Regarding human factors, algorithm designers' biases are embedded within the algorithms themselves. These algorithms are further influenced by biased data during training, thereby fostering algorithmic discrimination. The opacity of algorithms prevents decision recipients from understanding the basis and process of decisions, making it difficult to determine whether unfair treatment exists. This situation deprives recipients of discriminatory decisions of the information and capacity to lodge appeals or seek redress at the source, concealing such decisions and actions within the complex, incomprehensible operation of algorithms.

4.2 Computational Power Bottlenecks in AI Models

As demand increases, expectations for AI models grow ever more demanding. As a critical enabler of artificial intelligence development, AI models currently face multi-faceted challenges. Regarding algorithmic efficiency, while hardware performance continues to advance, computational efficiency has failed to keep pace. Many models remain constrained by inherent limitations, persisting with traditional computational approaches such as brute-force methods—including but not limited to brute-force optimisation, Monte Carlo simulations, or large-scale matrix operations. These techniques exhibit high computational complexity, significant time expenditure, and substantial resource consumption. To address computational demands, distributed computing and edge computing are gaining prominence. However, current technologies struggle to support the mature development of these approaches fully. Moreover, the expansion of AI models presents significant technical challenges regarding storage capacity.

From the perspective of computational investment costs, cultivating superior AI models that advance in waves and spiral upwards necessitates the support of infrastructure such as data centres. This implies substantial capital expenditure for continuous data upgrades. For small and medium-sized financial institutions, however, the increased costs represent a considerable burden. Furthermore, in line with national requirements concerning 'carbon peaking and carbon neutrality' and 'environmental protection strategies', Environmental considerations represent an inviolable corporate baseline. The computational upgrades required for AI models consume substantial energy resources, exerting considerable pressure on the environment. Consequently, computational bottlenecks persist in AI model development, constraining the deeper integration of AI with inclusive finance.

4.3 Low Enthusiasm for AI Applications in Rural Areas

Technology has endowed AI with formidable capabilities. However, existing AI models are predominantly trained on large-scale datasets from urban or developed regions, rendering them ill-suited to the actual needs of rural areas. Targeted parameter adjustments or retraining are required before deployment in rural contexts. Currently, AI applications remain concentrated in a limited number of sectors such as agricultural production, government advisory services, and tourism promotion. This narrow coverage struggles to address the diverse

requirements of rural communities adequately. From a cost-benefit perspective, rural areas lag behind urban centres in economic development, exhibit lower population density, have smaller markets, and face limited consumer spending power. Given the relatively high computational costs of AI models and their extended investment return cycles, enterprises adopt a wait-and-see approach regarding AI's market potential when evaluating capital investment-to-output ratios. This significantly dampens investor willingness and enthusiasm for such ventures.

Inadequate existing infrastructure in rural areas, including incomplete network coverage and the absence of connectivity in some underdeveloped regions, has hindered AI adoption and resulted in low penetration rates. Furthermore, the scarcity of specialised talent persists, with rural areas still lacking professionals who possess both AI expertise and agricultural knowledge. The attractiveness of related welfare incentive mechanisms remains insufficient, and inadequate policy support has collectively diminished enthusiasm for investing in AI applications.

5. Policy Recommendations for Promoting AI Application and Development in Inclusive Finance

5.1 Multi-dimensional Strategies to Advance Algorithmic Fairness

To address latent algorithmic bias within AI models, a multi-faceted approach is required to establish a reliable AI application ecosystem. We shall explore advancing algorithmic fairness through three dimensions: diversified data collection, algorithmic design and optimisation, and enhanced algorithmic governance. Diversified data collection forms the foundation of algorithmic fairness. Such data must encompass diverse user groups and multiple scenarios, preventing content bias arising from excessive or insufficient representation of specific demographics within the database. During data collection, consideration must be given to underserved populations in inclusive finance—such as urban low-income groups, persons with disabilities, the elderly, and ethnic minorities—to ensure comprehensive data. Advanced techniques like big data analytics and machine learning should be employed for pre-processing to eliminate latent biases, thereby enhancing algorithmic accuracy and fairness.

Algorithm design and optimisation are pivotal to advancing fairness. Through technological innovation, anti-discrimination tools can be designed. For instance, we incorporate human-centred modifications into model design—embedding fairness-constraint modules. Prior to model training, feature masking techniques can process and obscure raw sensitive information. During training, group fairness thresholds can be set, with elastic constraints applied as data evolves, alongside developing real-time monitoring interfaces for discrimination risks. Within the model's structural design, a 'fairness brake system' can be added. For instance, when the operational velocity of digital systems for inclusive financial services exceeds manual oversight thresholds, multi-dimensional algorithmic correction protocols should automatically activate. Such technical interventions block the propagation of algorithmic black-box risks, thereby mitigating hazards.

Refining algorithmic governance constitutes the institutional safeguard for promoting algorithmic fairness. Firstly, explicit regulations should categorise data pertaining to sensitive attributes—such as race and reli-



gious beliefs—as prohibited for collection, disclosure, or utilisation, thereby strictly defining data acquisition boundaries. Secondly, appropriate accountability frameworks should be designed for both 'algorithm designers' and 'algorithm users'. A tiered penalty system should be established to address violations involving the improper acquisition or misuse of sensitive information, with severe cases subject to restrictions on professional qualifications. Finally, legislation should mandate that entities using algorithms provide corresponding algorithmic explanations, such as algorithm development logs and testing records. Alternatively, relevant industry associations could be encouraged to publish protocols for detecting algorithmic discrimination and accountability principles, thereby informing the legal sector in formulating corresponding policies and regulations.

5.2 Introducing Sparse Models to Optimise AI Computing Power

The application of artificial intelligence technology is becoming increasingly widespread, with computing power demands exhibiting a significant upward trend. For instance, the emergence of DeepSeek, an innovative AI model, has caused considerable volatility in the stock market. Consequently, introducing sparse models, such as DeepSeek, to optimise AI computing power is an effective solution to address computational resource constraints.

Optimising algorithmic efficiency and actively investing in AI algorithm research to identify more efficient computational methods, thereby reducing reliance on hardware performance. For instance, deploying the DeepSeek model achieves higher inference efficiency with lower computational power. Its success stems primarily from sparse models and distillation techniques. Such sparse models (MoE), exemplified by DeepSeek, utilise parameter-sharing mechanisms that require computation only on partial network activations, thereby reducing unnecessary computational expenditure. Distillation techniques, meanwhile, transfer data from large models to smaller ones, preserving performance while lowering resource demands. This demonstrates that complex AI models can operate effectively even in resource-constrained environments, thereby alleviating computational pressures in inclusive financial services.

Increase investment in research and development for distributed computing models, including edge and cloud computing. Processing tasks closer to data sources reduces transmission latency while distributing computational load, further alleviating data analysis pressures. Concurrently, explore novel algorithms and technologies—including neural architecture search (NAS) and automated machine learning (AutoML)—to discover more efficient computational models.

5.3 Optimising Capital Allocation for Rural AI

Optimise market resource allocation to attract investor capital. Markets play a decisive role in resource allocation by achieving efficiency through three mechanisms: price regulation, supply-and-demand dynamics, and competition. Prices reflect supply-demand equilibrium, which in turn influences pricing, while competition directs resource flows, thereby enabling the survival of the fittest among AI models. For instance, rural markets can lower costs and entry barriers by adjusting prices and supply-demand dynamics, thereby introducing more AI models for rural applications. Encouraging competitive comparison among diverse AI models drives continuous improvement in data quality while phasing out underperforming configurations. This demonstrates profitable opportunities to external investors, attracting greater capital into rural AI. Given the

inherent spontaneity, blindness, and lag in market mechanisms, stakeholders, including enterprises and external investors, must adhere to market rules.

Furthermore, the state may implement appropriate macroeconomic regulation, employing economic, legal, and administrative measures to intervene and maintain equilibrium in market resource allocation indirectly. Steady fiscal policies should stabilise pricing for AI models deployed in rural areas; additional specialised laws and regulations should be enacted, with policy implementation directing local resource allocation to enhance capital mobility and efficiency; government support should be amplified through dedicated funds for rural infrastructure development; talent training programmes and improved welfare benefits should be rolled out to cultivate local expertise while attracting urban professionals with multidisciplinary skills to rural areas.

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