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2026 Volume 11, Issue 2
Advances in Precision Medicine
ISSN: 2424-9106 (Online)
ISSN: 2424-8592 (Print)

Construction of Credit Evaluation Model for Rural Hypertensive Patients Based on AI Fundus Image Analysis and Its Application in Inclusive Finance

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Abstract: Against the background of the difficulty of rural hypertensive patients in obtaining credit services due to the lack of traditional credit collateral and the continuous promotion of inclusive finance, this study takes AI fundus image analysis technology as the entry point, integrates medical health indicators and traditional financial indicators, and constructs a credit evaluation model for rural hypertensive patients with the dual dimensions of "health-finance". On the basis of combing relevant theories such as financial exclusion and information asymmetry, this paper analyzes the feasibility, necessity, index selection logic and construction path of the model, discusses its application value in improving the accuracy of credit evaluation and expanding the coverage of inclusive finance, and identifies potential risks such as data security, algorithm fairness and model interpretability. The research aims to provide a new theoretical and practical path for solving the financial exclusion of rural chronic disease patients and promoting the integrated development of medical treatment and inclusive finance.

Keywords: AI fundus image analysis; rural hypertensive patients; credit evaluation model; inclusive finance; financial exclusion; medical-finance integration

Online publication: February 26, 2026

1. Introduction

1.1. Research Background

Inclusive finance, a core component of modern financial systems, aims to provide equitable and accessible financial services to all social groups, particularly vulnerable populations long excluded from traditional financial systems. Rural areas, hampered by unique economic structures, backward infrastructure, and uneven resource distribution, are key focuses for inclusive finance promotion. However, rural residents—especially those with chronic diseases like hypertension—often face severe financial exclusion, hindering personal and family economic development and restricting rural revitalization and inclusive finance progress.

Hypertension, one of the most prevalent rural chronic diseases, has a long course, requires long—term medication and regular check—ups, and imposes a continuous economic burden. Traditional credit evaluation relies on tangible collateral, stable income, and perfect credit records—all of which most rural hypertensive patients lack. Their health status is often labeled a “high-risk factor,” making credit access difficult. This exclusion exacerbates their medical and economic pressure, forming a vicious circle: poor health → difficulty obtaining credit → inability to invest in production → worse health.

The rapid development of artificial intelligence (AI) , especially in medical image analysis, has opened new avenues to address vulnerable groups’ financial exclusion. Fundus images, a non-invasive, low-cost examination, contain rich physiological and pathological information. Hypertension, a systemic disease, causes distinct fundus vascular lesions (arteriosclerosis, retinal hemorrhage, exudation) that reflect disease severity, course, and complication risk. AI enables accurate extraction and quantitative analysis of these features, offering an objective way to evaluate rural hypertensive patients’ health[1].

Against this backdrop, exploring AI fundus image analysis in rural hypertensive patients’ credit evaluation, constructing an inclusive scientific model, and promoting medical—health—inclusive finance integration hold significant theoretical and practical value. This study focuses on the cross-field of AI medical image analysis and inclusive finance, elaborating on the theoretical logic of model construction and discussing its application value and risks to support responsible AI use in medical—financial integration[2].

1.2. Research Significance

1.2.1. Theoretical Significance

First, this study enriches inclusive finance theory. Traditional research focuses on service channels, policy optimization, and product innovation, neglecting medical health data in credit evaluation. By integrating AI fundus image data, it expands credit evaluation data sources and dimensions, enriches inclusive finance’s connotation, and provides a new perspective to address chronic disease patients’ financial exclusion.

Second, it promotes cross-integration of AI medical technology and financial theory. AI medical image analysis is a medical research hotspot, but its financial application—especially in credit evaluation—is in its infancy. This study clarifies the mechanism linking health indicators to creditworthiness, fostering integration of medical, computer, and financial sciences to drive cross—field theoretical progress.

Third, it supplements algorithmic fairness research in finance. As AI algorithms are widely used in credit evaluation, algorithmic discrimination has become a key fairness issue. This study explores algorithmic fairness risks in health—data—based credit models, identifies discrimination mechanisms, and proposes solutions, enriching theoretical research on algorithmic fairness and supporting standardized AI application.

1.2.2. Practical Significance

First, it addresses rural hypertensive patients’ financial exclusion. By integrating AI health indicators and traditional financial indicators, the model objectively evaluates creditworthiness, identifies “invisible high-quality” borrowers rejected by traditional models, and helps more patients access credit, alleviating economic pressure and improving quality of life.

Second, it offers a new path for inclusive financial innovation. AI fundus image technology breaks traditional credit evaluation limitations, improving accuracy and efficiency while reducing risk control costs. It also promotes medical—financial resource integration, data sharing, and the formation of a “medical + finance” inclusive service model.

Third, it provides practical guidance for responsible AI use in medical—financial integration. AI credit evaluation faces data security, privacy, and algorithmic discrimination risks. This study proposes targeted prevention measures, helping financial institutions, medical institutions, and regulators standardize AI application, ensure evaluation fairness and security, and promote healthy sustainable integration.

1.3. Research Framework and Content

This study is divided into six core parts:

Introduction: Elaborates on research background, significance, framework, and methods, clarifying core questions and objectives.

Literature Review: Systematically combs relevant research on inclusive finance, credit evaluation, AI fundus image analysis, and medical—financial integration, summarizing achievements and deficiencies to identify research gaps.

Theoretical Basis: Defines core concepts (inclusive finance, credit evaluation, etc.) and expounds on supporting theories (financial exclusion, information asymmetry, etc.) , laying the foundation for model construction.

Model Construction Theoretical Logic: Analyzes the feasibility and necessity of integrating AI health indicators into credit evaluation, clarifies indicator selection logic, and elaborates on the "health—finance" dual-dimensional model framework.

Application Value and Risks: Explores the model's value in improving inclusive finance coverage and accuracy, and analyzes potential risks (data security, algorithmic discrimination) and their formation mechanisms.

Conclusions and Policy Suggestions: Summarizes core viewpoints, proposes policy recommendations for responsible model application, and points out study limitations and future research directions.

1.4. Research Methods

This study adopts literature research, theoretical analysis, and logical deduction. Literature research sorts relevant literature to understand research status and deficiencies. Theoretical analysis clarifies core concepts and theories, and their logical relationships. Logical deduction infers model construction logic, indicator selection, and risk mechanisms, ensuring theoretical rigor and rationality[3].

2. Literature Review

2.1. Research on Inclusive Finance

2.1.1. Definition and Connotation of Inclusive Finance

Proposed by the United Nations in 2005, inclusive finance is a system providing equitable, accessible, affordable financial services (savings, loans, insurance, etc.) to all, focusing on "inclusiveness" and "equity" to eliminate exclusion and promote balanced development. Scholars worldwide emphasize its focus on low-income and vulnerable groups; Chinese scholars link it to rural revitalization, targeting rural areas, vulnerable groups, and micro-enterprises.

Digital inclusive finance, driven by the digital economy, uses the Internet, big data, and AI to expand coverage, reduce costs, and improve efficiency—offering new solutions to financial exclusion. However, it faces challenges like the digital divide, data security, and algorithmic discrimination.

2.1.2. Research on Financial Exclusion of Vulnerable Groups

Financial exclusion—geographical, information, condition, price, and self—exclusion—plagues rural residents, especially chronic disease patients. Foreign research attributes rural exclusion to backward financial infrastructure, lack of collateral, and information asymmetry; chronic disease patients' long-term medical costs and uncertain risks make them high-risk, exacerbating exclusion.

Domestic research notes rural hypertensive patients' low income, lack of collateral, and traditional credit models' neglect of their potential repayment ability. Low financial literacy and limited understanding of inclusive products also lead to self-exclusion.

2.1.3. Research on Medical—Financial Integration in Inclusive Finance

Medical—financial integration combines medical and financial resources to address vulnerable groups' medical and financial difficulties. Foreign research focuses on medical insurance and loans, showing medical insurance alleviates financial pressure and medical loans resolve temporary expenses. Domestic research emphasizes medical health data's role in credit evaluation but lacks in-depth study of AI medical image data application—creating a research gap.

2.2. Research on Credit Evaluatio

2.2.1. Evolution of Credit Evaluation Models

Credit evaluation (credit risk assessment) evaluates borrowers' creditworthiness to predict repayment ability and willingness. Early expert judgment was subjective; statistical models (logistic regression, decision trees) improved objectivity. Today, intelligent models (machine learning, deep learning) process multi-dimensional data, enhancing comprehensiveness and accuracy but facing data quality, fairness, and interpretability issues.

2.2.2. Research on Credit Evaluation Indicators

Traditional indicators focus on financial factors (income, assets, liabilities) . Non-financial indicators (social behavior, health) are increasingly important for vulnerable groups. Scholars find health status impacts repayment ability—good health means stable income and stronger repayment ability, while poor health increases default risk. However, research on specific health indicators for rural hypertensive patients and their integration into credit systems is insufficient.

2.2.3. Credit Evaluation of Rural Chronic Disease Patients

Rural chronic disease patients' long illness and high medical costs make their economic status fragile. Foreign research emphasizes health status, medical costs, and insurance coverage in credit evaluation. Domestic research notes traditional models' inadequacy but lacks in—depth study of health indicator selection and integration methods—providing a research direction.

2.3. Research on AI Fundus Image Analysis

2.3.1. Development of AI Medical Image Analysis

AI medical image analysis, a cross—field of AI and medical imaging, uses machine learning and deep learning to assist diagnosis. It has evolved from manual feature extraction (low efficiency) to shallow neural networks (improved accuracy) to deep neural networks (ResNet, VGG, AlexNet) for complex image analysis. Its high efficiency, accuracy, and low cost address rural medical resource shortages, improving rural health services[4].

2.3.2. Application in Hypertension Diagnosis

The fundus's visible blood vessels reflect hypertension's impact—arteriolar spasm, arteriosclerosis, and retinal lesions indicate disease severity and complication risk. AI fundus image models, developed globally, accurately identify these features to assist hypertension diagnosis. Chinese scholars have created models tailored to Chinese fundus characteristics, confirming fundus features reflect hypertension severity—laying a foundation for credit evaluation application.

2.3.3. Non-Medical Application Prospects

AI fundus image analysis is expanding to finance and insurance. Foreign insurers use it to evaluate insured health and adjust premiums, but its credit evaluation application—especially for rural hypertensive patients—is under—researched. This study addresses this gap, with innovative practical value[5].

2.4. Research on AI and Credit Evaluation Integration

2.4.1. AI Application in Credit Evaluation

AI is a financial industry trend, processing multi—dimensional data (financial, behavioral, health) to improve evaluation accuracy and efficiency, reducing risk control costs. Foreign scholars use machine learning (random forests, support vector machines) and deep learning to build models that reduce default rates. Domestic research focuses on digital inclusive finance, using AI to evaluate rural residents and micro—enterprises without traditional financial data, but faces data security, privacy, and fairness challenges.

2.4.2. Risks of AI in Credit Evaluation

AI brings efficiency and accuracy but also risks: data security (leakage, tampering), privacy violation (unlawful collection/use of sensitive data), algorithmic fairness (discrimination from biased data/design), and interpretability ("black boxes" hinder trust and supervision).

2.4.3. Algorithmic Fairness Research

Algorithmic fairness—individual (similar individuals get similar results), group (fair cross—group outcomes), and process (transparent, interpretable)—is critical. Foreign research identifies biased data, poor algorithm design, and incomplete features as discrimination causes, proposing data debiasing and algorithm optimization. Domestic research emphasizes fairness's role in inclusive finance, advocating algorithm review mechanisms and supervision.

2.5. Literature Review Summary

Existing research has achievements but key deficiencies: (1) Inclusive finance research lacks in—depth study of AI medical image data to address rural hypertensive patients' exclusion; (2) Credit evaluation research lacks specific health indicators for rural hypertensive patients and their integration methods; (3) AI—credit integration research lacks targeted fairness risk analysis and specific prevention measures. This study fills these gaps, providing theoretical support for responsible AI application in medical—financial integration.

3. Theoretical Basis

3.1. Core Concepts Definition

3.1.1. Inclusive Finance

Inclusive finance provides equitable, accessible, affordable services to all, eliminating exclusion, promoting equity, and supporting vulnerable groups. It includes savings, loans, insurance, and financial literacy education. In China's rural revitalization context, it focuses on rural areas, improving service coverage, narrowing urban—rural gaps, and providing targeted credit for rural hypertensive patients.

3.1.2. Credit Evaluation

Credit evaluation assesses borrowers' creditworthiness (repayment ability: income, assets, liabilities; repayment willingness: credit history, moral quality) to guide financial decisions. The credit evaluation model, a mathematical tool using statistical or AI methods, directly impacts evaluation accuracy and risk control.

3.1.3. AI Fundus Image Analysis

AI fundus image analysis uses machine learning/deep learning to process fundus images, extracting physiological/pathological features for disease diagnosis. Its core process: image preprocessing (noise reduction), feature extraction, classification, and result output. In this study, it extracts hypertension—related health indicators (arteriosclerosis degree, retinal hemorrhage) for credit evaluation.

3.1.4. Hypertension

Hypertension, a prevalent rural chronic disease, is characterized by elevated blood pressure (90% primary, caused by genetics/lifestyle; 10% secondary, caused by other diseases) . It has a long course and high complication risk (heart disease, stroke) , imposing heavy economic burdens. Rural patients have low control rates due to poor medical conditions and low health awareness.

3.2. Financial Exclusion Theory

Proposed by Leyshon and Thrift (1995) , financial exclusion is the inability to access fair financial services due to geographical, information, condition, price, or self—exclusion. Rural hypertensive patients face multiple exclusions: few rural financial outlets (geographical) , low financial literacy (information) , lack of collateral (condition) , high service costs (price) , and fear of default (self—exclusion) . This study's core goal is to address this via an inclusive credit model, using AI health indicators to reduce condition and information exclusion.

3.3. Information Asymmetry Theory

Proposed by Akerlof, Spence, and Stiglitz, information asymmetry (unequal transaction information) causes adverse selection (high—risk borrowers dominate credit applications) and moral hazard (post—transaction risky behavior) in credit markets. Rural hypertensive patients have more information about their health and income, while financial institutions lack accurate data—leading to conservative credit policies and exacerbated exclusion. AI fundus image analysis extracts objective health indicators, alleviating asymmetry and improving evaluation accuracy[6].

3.4. Signal Transmission Theory

Proposed by Spence (1973) , signal transmission reduces information asymmetry by enabling informed parties to signal quality. Rural hypertensive patients lack traditional credit signals (collateral, stable income), but AI—extracted fundus features serve as new signals: mild hypertension and normal fundus features indicate stable repayment ability (positive signal); severe hypertension and abnormal features indicate high risk (negative signal). This helps financial institutions identify creditworthiness and promote credit transactions.

3.5. Algorithmic Fairness Theory

Algorithmic fairness requires AI to treat all fairly, including individual, group, and process fairness. In health—data—based credit models, unfair algorithms cause "health discrimination," excluding poor—health patients—violating inclusive finance principles. Fairness is achieved via representative training data, fair algorithm design, and real—time fairness monitoring.

3.6. Deep Learning Theory

Deep learning, a machine learning branch using deep neural networks (input, hidden, output layers) , automates feature extraction and classification. It enables accurate, efficient fundus image analysis (using ResNet, VGG, AlexNet) to extract hypertension—related features, providing a technical basis for the credit model[7, 8].

4. Theoretical Logic of Credit Evaluation Model Construction

4.1. Feasibility and Necessity of Integrating AI Health Indicators

Feasibility analysis

Integration is feasible for three reasons: (1) Correlation: Fundus features reflect hypertension severity and complication risk, linking to repayment ability (mild hypertension = stable repayment; severe = high risk) . (2) Technological maturity: AI fundus image models are accurate and stable, with low—cost, convenient fundus examinations suitable for rural areas. (3) Data accessibility: Rural medical institutions offer fundus examinations and store standardized data (desensitized for AI analysis) .

4.1.2. Necessity Analysis

Integration is necessary: (1) Addresses traditional indicator insufficiency: Rural hypertensive patients lack traditional financial indicators; AI health indicators expand evaluation dimensions. (2) Alleviates information asymmetry: Objective AI indicators help financial institutions assess risk and make scientific decisions. (3) Promotes inclusive finance: Identifies "invisible high—quality" borrowers, expanding credit access and advancing inclusive goals.

4.2. Selection Logic of Credit Evaluation Indicators

The "health—finance" dual—dimensional system selects indicators based on scientificity, comprehensiveness, operability, and relevance.

4.2.1. AI Fundus Image Health Indicators

Indicators are selected based on: (1) Correlation with hypertension (arteriolar spasm, arteriosclerosis, retinal lesions). (2) Link to repayment ability (reflecting disease severity and complication risk). (3) Quantifiability and extractability (clear features, easy AI identification). Key indicators: fundus arteriosclerosis degree, retinal hemorrhage/exudation presence, retinal edema degree, retinal nerve fiber layer thickness.

4.2.2. Traditional Financial Indicators

Traditional financial indicators reflect financial status and repayment ability, selected for comprehensiveness and operability. Core indicators include: (1) Income indicators (annual household income, income stability) to reflect repayment capacity. (2) Asset—liability indicators (fixed assets, liabilities ratio) to measure solvency. (3) Credit history indicators (past repayment records, default history) to reflect repayment willingness. These indicators form the foundation of the credit model, complementing AI health indicators to ensure comprehensive evaluation.

4.3. Theoretical Framework of the "Health—Finance" Dual-Dimensional Model

The model integrates AI health indicators and traditional financial indicators, following a three—step theoretical framework: indicator normalization, weight assignment, and comprehensive credit scoring.

First, indicator normalization eliminates dimensional differences between health and financial indicators, converting raw data into a unified range (0—1) using min—max normalization. This ensures indicators are comparable and avoids bias from different units.

Second, weight assignment reflects indicator importance. AI health indicators and traditional financial indicators are assigned weights based on theoretical analysis and expert consultation: health indicators (40%) reflect rural hypertensive patients' unique characteristics, while financial indicators (60%) maintain the core of credit evaluation. Within each category, weights are assigned based on correlation with credit risk (e.g., fundus arteriosclerosis degree has higher weight than retinal edema in health indicators) .

Third, comprehensive credit scoring combines normalized indicators and weights to calculate a total credit score (0—100) . Scores are divided into credit levels (excellent, good, general, poor) to guide financial institutions' credit decisions. Excellent scores indicate strong repayment ability and low risk; poor scores indicate high risk, requiring more conservative policies.

4.4. Construction Path of the Model

The model's construction follows four steps: (1) Data collection: Gather fundus images (from rural medical institutions) , health records, and financial data (from financial institutions and rural households) after desensitization to protect privacy. (2) AI health indicator extraction: Use deep learning models to process fundus images, extract and quantify health indicators. (3) Indicator integration: Combine health indicators with traditional financial indicators, normalize and assign weights. (4) Model validation and optimization: Test the model's rationality using theoretical analysis, adjust weights and indicators based on feedback, and ensure it meets inclusive finance goals.

5. Application Value and Potential Risks of the Model in Inclusive Finance

5.1. Application Value

The model has significant inclusive finance value: (1) Improves credit evaluation accuracy: Integrating health and financial indicators provides a comprehensive view of creditworthiness, reducing misjudgment of "invisible high—quality" borrowers. (2) Expands inclusive finance coverage: Helps financial institutions serve rural hypertensive patients previously excluded, narrowing the rural—urban financial gap. (3) Promotes medical—financial integration: Drives collaboration between medical and financial institutions, realizing data sharing and resource optimization, and fostering a "medical + finance" service model. (4) Reduces financial institution risks: Accurate risk assessment reduces default rates, lowering credit risk control costs.

5.2. Potential risks and formation mechanisms

5.2.1. Data security and privacy risks

Data security risks arise from fundus image, health, and financial data leakage, tampering, or destruction during collection, storage, and processing. Privacy risks stem from unlawful collection or use of sensitive personal data (health records, financial information) . Formation mechanisms include inadequate data protection systems, loose access controls, and lack of standardized data management[9].

5.2.2. Algorithmic fairness risks

Algorithmic fairness risks lead to "health discrimination": Biased training data (e.g., over—representing mild hypertension patients) or inappropriate algorithm design (overweighting health indicators) may exclude severe hypertension patients, violating inclusive finance principles. Formation mechanisms include biased data, insufficient algorithm fairness design, and lack of real—time fairness monitoring[10].

5.2.3. Interpretability Risks

AI models (especially deep learning) are"black boxes," making it difficult to explain credit score origins. This reduces borrower trust and hinders financial institution supervision. Formation mechanisms include the complexity of deep learning models and lack of interpretability design in model construction.

6. Research Conclusions

This study elaborates on the theoretical logic of constructing a rural hypertensive patient credit evaluation model based on AI fundus image analysis, drawing key conclusions: (1) Integrating AI fundus image health indicators into credit evaluation is feasible (correlation, technological maturity, data accessibility) and necessary (addressing indicator insufficiency, alleviating asymmetry, promoting inclusive finance). (2) The "health—finance" dual—dimensional model, combining AI health indicators (arteriosclerosis degree, etc.) and traditional financial indicators (income, assets, etc.), is scientific and inclusive. (3) The model has significant inclusive finance value but faces data security, algorithmic fairness, and interpretability risks. (4) Algorithmic fairness, data security, and privacy protection are critical for responsible AI application in medical—financial integration.

Disclosure statement

The author declares no conflict of interest.

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