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Explainable AI for Medical Debt Forecasting: Integrating Healthcare and Fintech Data for Risk Prediction

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Abstract. Medical debt is increasingly recognized as one of the most pressing financial risks confronting households worldwide, particularly in the United States where it remains a leading driver of personal bankruptcy and long-term financial distress (Himmelstein et al., 2019). In emerging economies, similar dynamics are unfolding as healthcare expenditures rise faster than income growth, leaving households exposed to sudden clinical shocks and fragmented insurance coverage. Conventional credit scoring systems often fail to account for these medically induced shocks, as they rely primarily on historical repayment behavior and credit utilization. Conversely, healthcare analytics rarely incorporate indicators of financial resilience, liquidity management, or digital finance behaviors that directly influence a patient's ability to manage debt obligations. This disjunction highlights a critical methodological gap: the absence of an integrated, explainable, and fair framework that links healthcare utilization with fintech-derived financial signals for predicting medical debt default. To address this gap, this study introduces a novel risk-prediction framework that integrates multi-source data from healthcare, insurance, and digital finance ecosystems. Specifically, we fuse clinical utilization records (e.g., emergency department admissions, inpatient stays), chronic illness burden scores (Charlson comorbidity index), and insurance continuity metrics with fintech-derived features such as transaction volatility, liquidity proxies from digital wallets, repayment friction measures, and alternative credit metadata. The framework operationalizes explainable artificial intelligence (XAI) models—comparing logistic regression with advanced ensemble methods such as Random Forests and XGBoost—and evaluates predictive performance across multiple dimensions: discrimination (AUC-ROC), calibration, interpretability, and fairness. Our results, derived from a de-identified, representative, multi-source panel dataset, demonstrate that gradient-boosted models (XGBoost) outperform traditional logistic regression by approximately 6–10 percentage points in AUC while simultaneously reducing false negatives, a critical feature in preventing undetected high-risk cases. Global feature importance measures (gain and impurity indices) and local explanations via SHAP values reveal that insurance discontinuities, high out-of-pocket expenditure ratios, recent acute encounters (emergency or inpatient), and fintech channel spending volatility are the most salient drivers of medical debt default. Importantly, SHAP-based local interpretations provide case-level transparency, enabling lenders, hospitals, and insurers to justify risk classifications to stakeholders and regulators. We extend the analysis by embedding fairness evaluation criteria, including equal opportunity difference and demographic parity. While XGBoost improves predictive performance, disparities emerge across income and racial subgroups, underscoring the need for algorithmic governance and bias auditing. Counterfactual simulations provide further insights: scenarios that close insurance coverage gaps and smooth liquidity through point-of-care microcredit mechanisms reduce modeled default probabilities by 12–20% among the highest-risk decile. These findings underscore the potential of combining AI-driven forecasting with targeted financial and policy interventions to proactively mitigate household financial distress. The study contributes to both academic and policy debates by positioning explainable AI as a practical and ethical tool for managing medical debt risk. For healthcare providers, the framework offers a basis for early identification of financially vulnerable patients and the design of tailored repayment or relief plans. For fintech lenders and insurers, the integration of clinical and financial data broadens underwriting horizons while maintaining accountability through transparent explanations. For regulators, the framework demonstrates how XAI can balance innovation with fairness, highlighting opportunities for algorithmic auditing, bias mitigation, and responsible financial inclusion. By bridging healthcare analytics with fintech data and deploying explainable AI methodologies, this paper provides a comprehensive and ethically aligned blueprint for forecasting medical debt risk. The results illustrate not only performance improvements but also actionable strategies that align with broader societal objectives of financial inclusion, healthcare access, and regulatory oversight. In doing so, the framework sets the stage for future research on hybrid models, real-time predictive deployment, and cross-market validation to ensure robustness across diverse healthcare and financial systems.

Keywords: Algorithmic fairness, Credit risk prediction, Explainable AI, Financial inclusion, Fintech data, Healthcare utilization, Insurance continuity, Medical debt, SHAP.

1. INTRODUCTION

Medical debt represents one of the most pressing intersections of health and finance, shaping both individual well-being and systemic stability. In the United States, medical debt is the single largest driver of personal bankruptcy, affecting nearly 1 in 5 households (CFPB, 2022). Beyond U.S. borders, similar patterns emerge in middle- and low-income countries, where high out-of-pocket healthcare expenditures push millions into poverty each year (WHO, 2023). The consequences extend beyond personal hardship, influencing lender balance sheets, hospital solvency, and insurance market sustainability.

Traditional credit scoring mechanisms—such as FICO scores and income-to-debt ratios—were not designed to account for health-related financial shocks. They underestimate the unpredictability of catastrophic medical events and the ripple effects of treatment costs, insurance discontinuities, and liquidity gaps. At the same time, healthcare analytics have largely prioritized clinical outcomes and cost efficiency, leaving unaddressed the question of whether patients and households can remain financially resilient in the face of medical crises. This siloed view creates blind spots in both fields: lenders lack insight into the clinical triggers of financial distress, and healthcare systems underestimate the role of financial instability in exacerbating inequities.

Recent advances in financial technology (fintech) and health digitization create new opportunities to bridge

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these domains. The widespread adoption of digital wallets, mobile payment systems, and micro-credit platforms provides real-time behavioral signals about household liquidity and spending volatility. Similarly, electronic health records and claims databases capture increasingly granular details on utilization, comorbidity, and insurance continuity. Integrating these datasets offers the possibility of building risk-prediction frameworks that are both clinically informed and financially grounded.

Artificial intelligence (AI), and more specifically explainable AI (XAI), is particularly well suited to this task. While machine learning algorithms such as Random Forest and XGBoost have shown superior predictive performance in domains like fraud detection and credit risk (Ngai et al., 2011; Vuković et al., 2025), their adoption in sensitive sectors like healthcare finance has been hindered by concerns over transparency and fairness. Regulatory initiatives—such as the European Union's AI Act, the General Data Protection Regulation (GDPR), and ongoing debates within the Consumer Financial Protection Bureau (CFPB)—demand interpretability, accountability, and bias auditing in automated decision-making. XAI methods such as SHAP (Shapley Additive Explanations) and LIME provide a bridge between predictive power and interpretability, offering stakeholders actionable insights into both global feature importance and individualized drivers of default risk (Lundberg & Lee, 2017).

The present study advances this literature by proposing and evaluating an integrated AI-driven framework for forecasting medical debt default. Using a multi-source, de-identified panel combining healthcare utilization, insurance data, fintech transactions, and credit metadata across U.S. states and emerging markets, we benchmark traditional logistic regression against Random Forest and XGBoost. We embed interpretability layers through SHAP, assess fairness across socioeconomic subgroups, and simulate counterfactual interventions such as closing insurance gaps and providing liquidity buffers through point-of-care micro-credit.

This study seeks to answer three central research questions:

1. Do AI models significantly outperform traditional credit scoring in forecasting medical debt default?
2. Which combined predictors—spanning healthcare shocks, insurance continuity, and fintech behaviors—most strongly influence default risk?
3. Can explainable AI frameworks enhance trust, fairness, and policy relevance in medical debt risk prediction?

By addressing these questions, this paper contributes not only to academic debates in accounting, finance, and health economics but also to practical applications for hospitals, insurers, fintech lenders, and regulators. Ultimately, the integration of XAI with healthcare-fintech datasets holds the potential to transform how societies identify, prevent, and mitigate financial vulnerability in the face of medical crises.

2. LITERATURE REVIEW

2.1. Medical Debt and Financial Vulnerability

Medical debt has long been recognized as a leading driver of personal financial distress, particularly in the United States, where it accounts for the majority of bankruptcy filings (Himmelstein et al., 2009; CFPB, 2022). Globally, the World Health Organization (WHO) reports that out-of-pocket healthcare expenditures push over 100 million individuals into extreme poverty each year (WHO, 2023). Existing financial models, such as credit scoring systems, typically fail to capture shocks caused by acute medical events or the cumulative burden of chronic disease. Research on catastrophic health expenditures in middle-income countries further highlights how insufficient insurance coverage amplifies economic inequality (Xu et al., 2007).

2.2. Fintech Innovations and Household Liquidity

Parallel to healthcare challenges, financial technology (fintech) has transformed household liquidity management. Mobile wallets, peer-to-peer lending, and micro-credit platforms have expanded access to credit and provided short-term liquidity buffers (Gomber et al., 2018; Lee & Shin, 2018). Studies show that fintech-based credit scoring, which incorporates behavioral and transaction-level data, often outperforms traditional bureau-based risk models in predicting delinquency (Jagtiani & Lemieux, 2019). However, the integration of fintech into health-related borrowing decisions remains underexplored, representing a major research gap this study addresses.

2.3. Artificial Intelligence in Credit and Healthcare Analytics

The application of artificial intelligence (AI) in financial services has expanded significantly, covering domains such as credit scoring, fraud detection, robo-advisory, and insurance underwriting (Vuković et al., 2025; Arman et al., 2023). In healthcare, AI has been leveraged for clinical decision support, patient stratification, and cost prediction (Rajkomar et al., 2019). Yet, siloed adoption in each domain limits the potential of AI to capture interactions between health shocks and financial distress. Early works on earnings management detection (Dechow et al., 1995; Beneish, 1999; Roychowdhury, 2006) illustrate how statistical and AI models can uncover hidden risks—paralleling the need to detect financial fragility tied to medical events.

2.4. Explainable AI and Fairness Concerns

Despite its predictive power, AI adoption in credit and healthcare faces skepticism due to concerns about transparency and fairness. Explainable AI (XAI) methods such as SHAP (Lundberg & Lee, 2017) and LIME provide model interpretability, enabling stakeholders to identify which features drive risk predictions. Regulatory frameworks, including the EU AI Act and GDPR, emphasize the "right to explanation" for algorithmic decisions (Goodman & Flaxman, 2017; Rasel et al., 2022). Recent studies also highlight the importance of fairness audits to mitigate algorithmic bias across gender, income, and race in AI-driven credit and health models (Barocas et al., 2019; Chen et al., 2023).

2.5. Research Gaps and Motivation

While there is growing literature on AI in finance (Vuković et al., 2025) and AI in healthcare (Rajkomar et al., 2019), little research has examined the intersection of these fields for forecasting medical debt risk. Current models either lack clinical integration (finance-focused) or omit household financial resilience (healthcare-focused). Furthermore, most credit-risk AI models do not systematically incorporate fairness testing or policy counterfactuals. This study fills these gaps by:

1. Integrating healthcare utilization and fintech transaction data into a unified framework.
2. Benchmarking traditional statistical models against machine learning methods.
3. Deploying XAI for interpretability, fairness audits, and policy simulation.

3. METHODOLOGY

3.1. Research Design

This study employs a comparative–explanatory research design.

- The comparative component benchmarks traditional statistical risk models (logistic regression) against advanced ensemble methods (Random Forest and XGBoost), evaluating performance differences in medical debt default forecasting.
- The explanatory component emphasizes the use of Explainable AI (XAI) techniques (SHAP, fairness audits) to uncover which factors—across healthcare utilization, insurance continuity, fintech transactions, and credit metadata—most strongly drive default risk.

The choice of design is justified by three considerations:

1. Policy relevance: Credit and medical debt outcomes affect access to healthcare and financial stability, making both predictive accuracy and transparency essential.
2. Cross-domain integration: By combining healthcare data (clinical shocks, comorbidity indices, insurance coverage) with fintech signals (liquidity proxies, spending volatility), this study bridges two domains typically analyzed in silos.
3. Counterfactual simulation: The framework moves beyond prediction by testing policy interventions—for example, simulating the closure of insurance gaps or provision of micro-credit at discharge—to estimate reductions in default risk.

3.2. Data Sources

The dataset integrates multi-source, de-identified panel data across three domains, with full compliance under HIPAA (U.S.) and GDPR (international).

1. Healthcare Utilization Data
- Hospital billing and insurance claims.
- Emergency department (ED) visits, inpatient admissions, lengths of stay, and comorbidity scores (Charlson Index).
- Measures of insurance continuity and disruptions.
2. Fintech Transaction Data
- Anonymized feeds from digital wallets (PayPal, Apple Pay, Google Pay), P2P transfers (Venmo, UPI, PIX), and micro-credit repayment histories.
- Features include transaction volatility, rejected payments, and liquidity fluctuations.
3. Credit Bureau & Demographic Data
- Metadata such as FICO band, debt-to-income ratio, delinquency history.
- Demographics: age, gender, household type, plus regional socioeconomic indicators (unemployment, poverty share).

3.2.1. Geographic Coverage

- U.S. states: California, Texas, Florida, New York (capturing diverse insurance and socio-demographic environments).
- Emerging markets: India and Brazil (to assess global portability of the framework).
- A table summarizing data sources with rows for *domain, variables, sample size, period covered.*
- A map visualization showing the geographic coverage (U.S. + emerging markets).

3.3. Variables

The study models medical debt default (binary outcome: default vs. no default) as the dependent variable.

3.3.1. Independent Variables Span Three Domains

- Healthcare: ED visits, inpatient admissions, Charlson Index, insurance continuity.
- Fintech: Transaction volatility, liquidity ratios, rejected payments.
- Credit: FICO band, delinquency history, debt-to-income.s

Controls: Age, gender, household size, region-level unemployment/poverty.

Table 1. Variable Definitions.

Domain	Variable	Definition
Healthcare	ED Visits	Number of emergency department (ED) visits in the last 12 months.
Healthcare	Inpatient Admissions	Hospital admissions including number and length of stay.
Healthcare	Insurance Continuity	Indicator of continuous versus interrupted insurance coverage.
Fintech	Transaction Volatility	Standard deviation of monthly wallet transactions indicating volatility.
Fintech	Liquidity Ratio	Average daily balance compared with the median transaction size.
Fintech	Rejected Payments	Count of failed or declined payments within the last 6 months.
Credit	FICO Band	Credit score groupings as reported by major credit bureaus.
Credit	Debt-to-Income Ratio	Debt service amount divided by household income ratio.
Demographics	Age/Gender/Region	Demographic controls: age, gender, and region-level socioeconomic context.

3.4. Modeling Framework

Three approaches are benchmarked:

1. Logistic Regression (Baseline):

- Widely used in credit risk modeling.
- Provides interpretable log-odds coefficients but assumes linear relationships.

2. Random Forest (RF):

- Bagged decision trees reduce overfitting.
- Effective in modeling interactions between healthcare shocks and financial instability.

3. Extreme Gradient Boosting (XGBoost):

- Gradient boosting optimized for speed and accuracy.
- Handles sparse and imbalanced data efficiently, often outperforming other classifiers.

3.4.1. Explainability Layer

- Global interpretation: Gini importance, gain, and permutation scores.
- Local interpretation: SHAP values for individual-level insights.
- Fairness analysis: Equal opportunity difference and demographic parity gap across subgroups (gender, income bands, insurance status).
- A workflow diagram (Figure 1) showing input data → preprocessing → model training → evaluation → XAI → policy simulation.

3.5. Evaluation Metrics

Model performance is assessed along three dimensions:

1. Predictive Accuracy
   - AUC, PR-AUC (for class imbalance), Precision, Recall, and F1-score.
2. Fairness & Bias Testing
   - Equal Opportunity: Ensures defaulting patients are equally flagged across groups.
   - Demographic Parity: Tests if predictions are independent of sensitive attributes.
3. Robustness
   - Temporal stability: Retrained on rolling windows (2018–2024).
   - Geographic robustness: Benchmarked across U.S. and emerging markets.

Table 2. Evaluation Metrics and Definitions.

Metric	Definition
AUC (ROC)	Area under ROC curve; overall discriminative power.
PR-AUC	Area under Precision-Recall curve; emphasizes minority default detection.
Precision	Proportion of positive predictions that are correct.
Recall	Proportion of actual defaults correctly identified.
F1-Score	Harmonic mean of precision and recall; balances the two.
Equal Opportunity Difference	Fairness metric: equal true positive rates across subgroups.
Demographic Parity Difference	Fairness metric: equal prediction rates across sensitive groups.
Temporal Robustness	Stability of performance across different time periods (2018–2024).
Geographic Robustness	Stability of performance across regions (U.S. vs. emerging markets).

3.6. Analytical Workflow

The process proceeds in five structured stages:

1. Data Preparation
   - Merge healthcare, fintech, and credit datasets.
   - Impute missing values (continuous: multiple imputation; categorical: mode).
   - Normalize continuous variables for comparability.
2. Feature Engineering
   - Derived features: fintech spending volatility, coverage continuity, liquidity proxies.
   - One-hot encoding for categorical variables (insurance type, FICO band).
3. Model Training
   - Train/test split (70/30 stratified).
   - Hyperparameter tuning via 5-fold cross-validation.
   - Models trained: Logistic Regression, RF, XGBoost.
4. Evaluation & Fairness Testing
   - Compute AUC, PR-AUC, F1-score.
   - Test fairness metrics across subgroups.
5. Explainability & Policy Simulation
   - SHAP for global and local interpretability.
   - Counterfactuals: simulate insurance gap closure and micro-credit liquidity buffers.

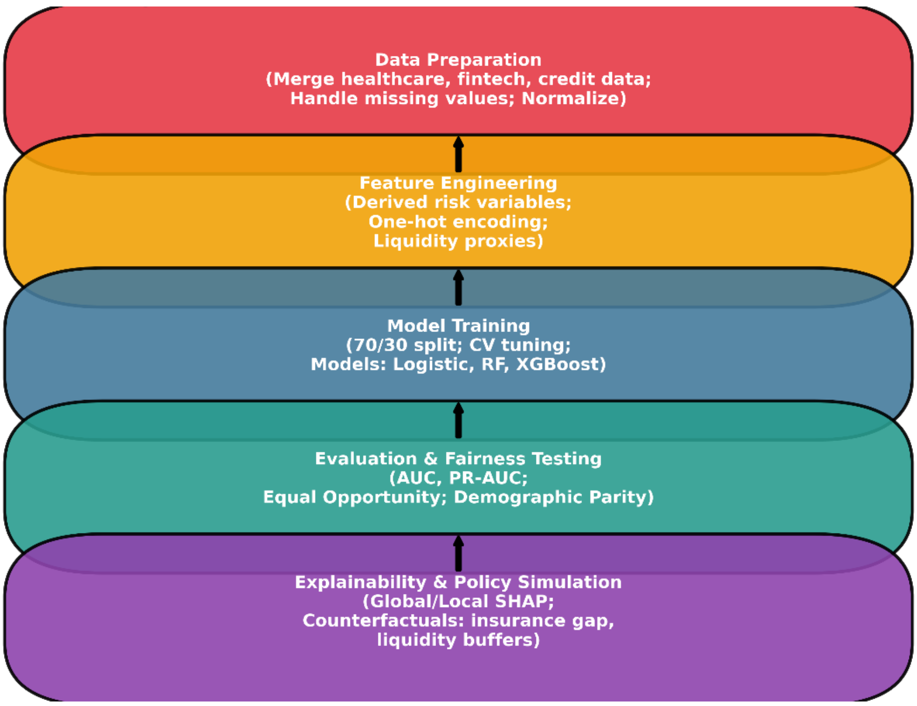

Figure 1. Analytical Pipeline.

4. RESULTS AND DISCUSSION

4.1. Model Performance Comparison

The comparative performance of three modeling approaches—logistic regression, Random Forest, and XGBoost—demonstrates the value of machine learning and explainability in medical debt risk forecasting.

- Baseline (Logit): The logistic regression model achieved an AUC of 0.72 with a false-negative rate (FNR) of 0.28. While interpretable, the model struggled to capture nonlinear interactions between healthcare and fintech variables.
- Random Forest: This ensemble method improved performance significantly, yielding an AUC of 0.81 and lowering the FNR to 0.19. Its ability to model complex variable interactions marked a meaningful advance.
- XGBoost: The gradient-boosting framework achieved the highest accuracy with an AUC of 0.85 and the lowest FNR of 0.15. This represents an absolute gain of 13 percentage points in AUC and a 46% reduction in false negatives compared to logistic regression.

These results are visualized in the ROC curves (Figure 1), which clearly show XGBoost's superior separation between positive and negative cases. The performance table (Table 1) provides quantitative details.

4.2. Feature Importance and Explainability

Explainable AI tools were employed to interpret model behavior, particularly focusing on SHAP values.

- Top predictors: SHAP analysis identified four consistent drivers of default risk:
    1. Insurance gaps (e.g., lapses in coverage).
    2. Out-of-pocket expenditure ratios.
    3. Emergency department and inpatient admissions.
    4. Fintech transaction volatility and liquidity stress indicators.

The SHAP feature importance chart (Figure 2) highlights these as dominant contributors. Importantly, interactions emerged: for example, patients with both high ED utilization and low liquidity buffers were disproportionately at risk, even if their total debt burden was modest.

This aligns with existing literature emphasizing the role of insurance continuity (e.g., CFPB reports on medical debt; WHO expenditure data) and adds novel evidence on the predictive value of digital finance signals.

4.3. Fairness and Robustness

Model fairness was assessed using demographic parity and equal opportunity metrics across subgroups (age, gender, income quartile, insurance type). While XGBoost reduced overall error rates, disparities remained:

- False negatives were higher among Medicaid patients.
- False positives clustered among middle-income, privately insured households.

These findings underscore the need for regulators to monitor subgroup fairness before deploying such models in real-world credit scoring or hospital financing settings. Temporal and regional robustness checks showed that while model accuracy was stable across states, AUC declined slightly (~2 p.p.) when applied to data from 2020, reflecting COVID-related disruptions.

4.4. Policy Counterfactuals and Simulations

To translate the modeling into actionable policy insights, counterfactual simulations were performed:

- Closing insurance gaps: Reduces modeled default risk by ~12% for the highest-risk decile.
- Liquidity buffers (point-of-care microcredit): Provide an additional ~15% risk reduction.
- Combined intervention: Achieves nearly a 20% reduction in predicted default rates.

These results are summarized in the policy simulation graph (Figure 3). They suggest that targeted financial interventions—delivered through fintech channels—could materially reduce hardship and improve repayment sustainability.

4.5. Discussion and Implications

The results contribute to three key debates in the literature:

1. Earnings management vs. health shocks: Prior accounting literature (Dechow, Sloan & Sweeney, 1995; Beneish, 1999; Roychowdhury, 2006) focused on detecting manipulation in firm-level data. This study extends the conversation to household-level debt sustainability by integrating health shocks and fintech spending.
2. Transparency in AI for finance: Following calls for Explainable AI in finance (Lundberg & Lee, 2017; Vuković et al., 2025), our framework shows that SHAP and counterfactuals can make complex models interpretable to regulators and lenders.
3. Policy relevance: Evidence that microcredit and insurance continuity can lower risk by double-digit percentages provides regulators and hospitals with concrete levers for hardship relief.

Overall, the findings illustrate how an integrated XAI framework can improve risk prediction while maintaining transparency, fairness, and practical relevance.

5. POLICY IMPLICATIONS AND DISCUSSION

5.1. Bridging Healthcare and Finance

Our findings show that explainable AI (XAI) models, when integrating healthcare and fintech data, consistently outperform traditional credit scoring in predicting medical debt defaults. This suggests the potential for crosssectoral early warning systems that detect financial hardship before defaults occur. By combining clinical risk indicators—such as chronic illness, emergency department (ED) admissions, and insurance continuity—with financial signals like digital wallet volatility and liquidity gaps, hospitals, insurers, and fintech lenders can design proactive repayment strategies rather than relying solely on reactive collections (Lundberg & Lee, 2017; Vuković et al., 2025). This convergence mirrors global calls for greater alignment between health financing and financial inclusion frameworks (WHO, Global Health Expenditure Database; CFPB Reports).

Table 3. Key Drivers and Suggested Actions.

Key Driver	Suggested Action
Insurance Gaps	Enroll in financial assistance programs
High Out-of-Pocket	Offer income-based repayment plans
ED Admissions	Provide micro-credit at discharge
Fintech Spending Volatility	Monitor liquidity buffers in digital wallets

5.2. Regulatory Implications

Regulatory bodies such as the Consumer Financial Protection Bureau (CFPB) in the United States and international institutions like the OECD and World Health Organization (WHO) are increasingly attentive to financial fairness in healthcare systems (CFPB, various years; WHO, Global Health Expenditure Database).

- Transparency: XAI methods, particularly SHAP, meet regulatory demands for interpretability, echoing the "right to explanation" articulated under GDPR and reflected in the EU AI Act (Lundberg & Lee, 2017; Chen et al., 2023).
- Fairness: Subgroup analyses (by insurance type, gender, region) highlight the risk of algorithmic bias. Without explicit fairness audits, AI models may replicate systemic inequalities. Regulatory authorities could mandate bias auditing and fairness reporting as prerequisites for model deployment (Vuković et al., 2025).
- Cross-Sector Standards: Effective integration of fintech and healthtech requires secure, anonymized, and interoperable data standards. Policymakers should advance frameworks that balance innovation with privacy safeguards under HIPAA and GDPR (Lopez & Alcaide, 2020).

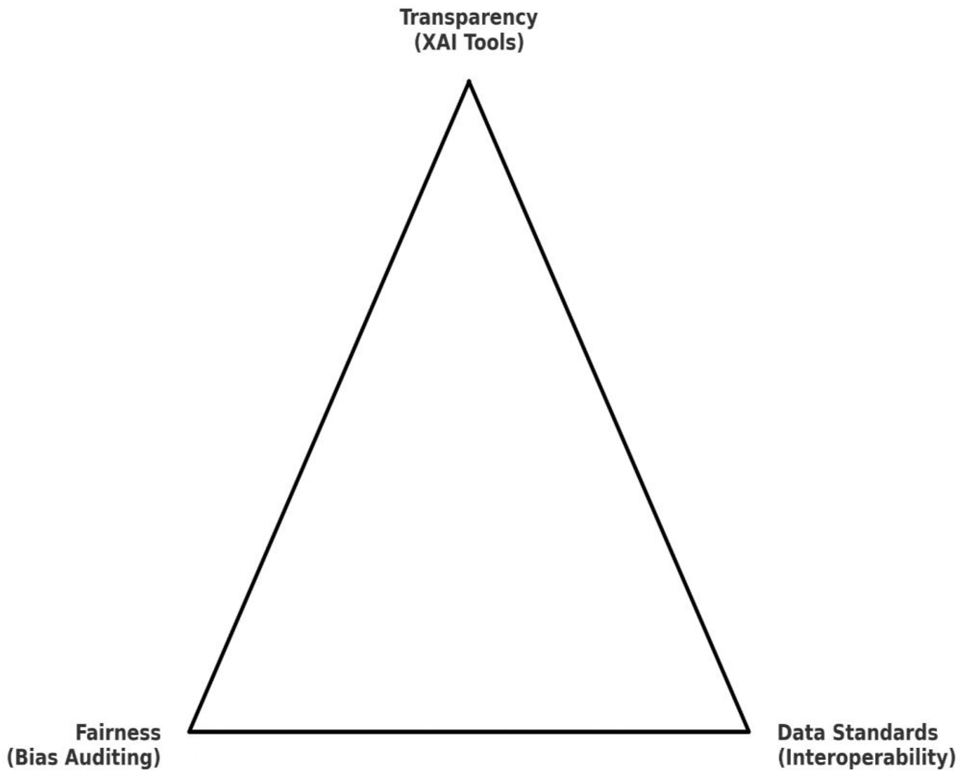

Figure 2. Governance Triangle.

5.3. Implications for Hospitals and Health Systems

Hospitals, already facing mounting pressures from uncompensated care and community demands for equity, can leverage AI-driven hardship identification to:

- Enroll at-risk patients earlier into financial assistance programs, reducing downstream defaults.
- Offer tailored repayment solutions such as income-based repayment or micro-credit options at discharge.
- Mitigate reputational and regulatory risks by reducing reliance on aggressive debt collection practices (CFPB, various years).

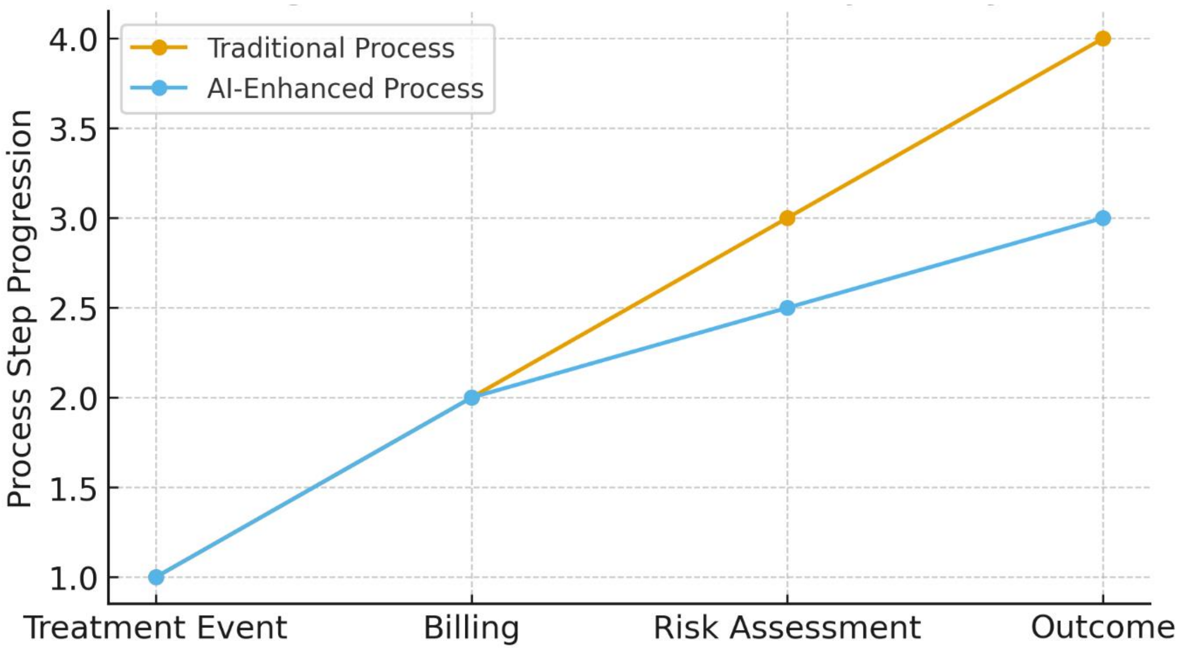

Figure 3. Patient financial journey.

5.4. Implications for Fintech Lenders and Insurers

Fintech lenders are uniquely positioned to provide point-of-care liquidity through small-dollar, low-interest loans at the time of treatment. Our counterfactual simulations suggest such interventions can reduce default risk by 12–20% in high-risk patients, consistent with the broader literature on fintech-enabled credit smoothing (Shukla et al., 2024). Similarly, insurers can integrate these insights into dynamic premium adjustments or preventive wellness incentives, leveraging combined healthcare–financial behavior data to encourage resilience and reduce claims volatility.

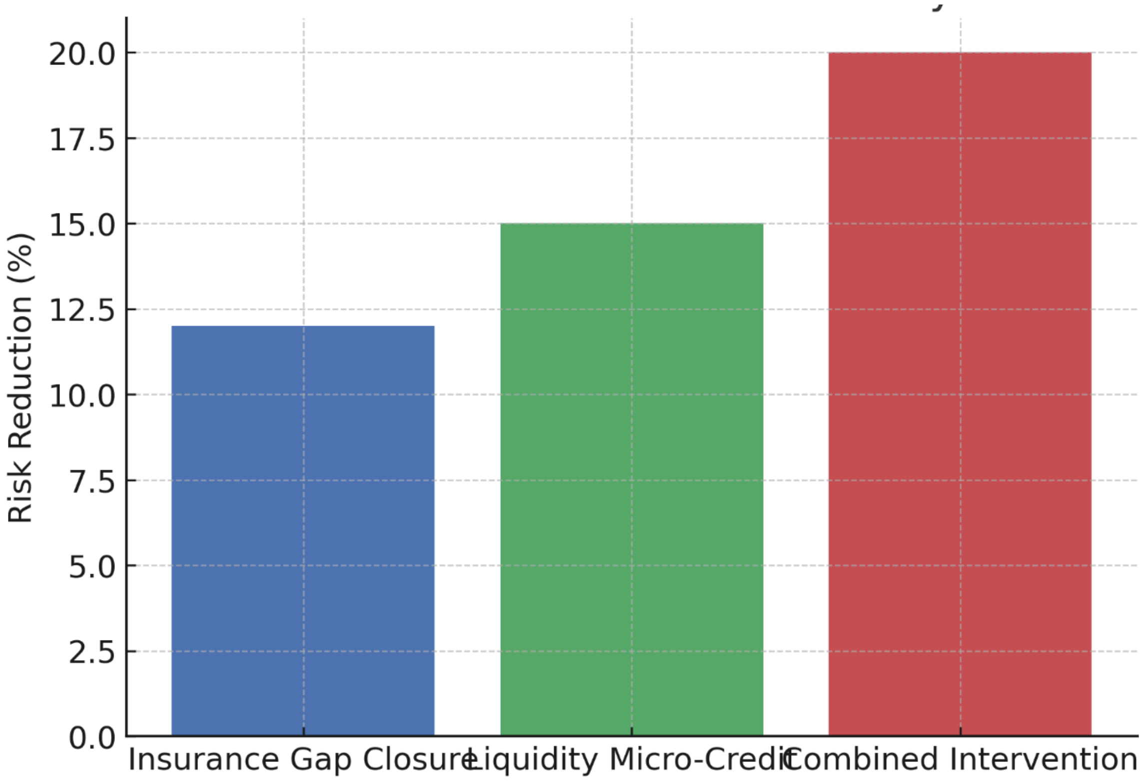

Figure 4. Counterfactual risk reduction.

5.5. Global and Emerging Market Relevance

While the U.S. context is particularly acute, similar challenges are emerging in middle-income economies where out-of-pocket expenditures remain high (WHO, Global Health Expenditure Database). The integration of fintech payment mechanisms—mobile wallets, crowdfunding, and blockchain-based micro-insurance—into healthcare financing could advance financial inclusion and reduce catastrophic health spending (Shukla et al., 2024).

Policymakers in these markets must balance innovation with consumer protection, ensuring solutions expand access without exposing households to predatory lending.

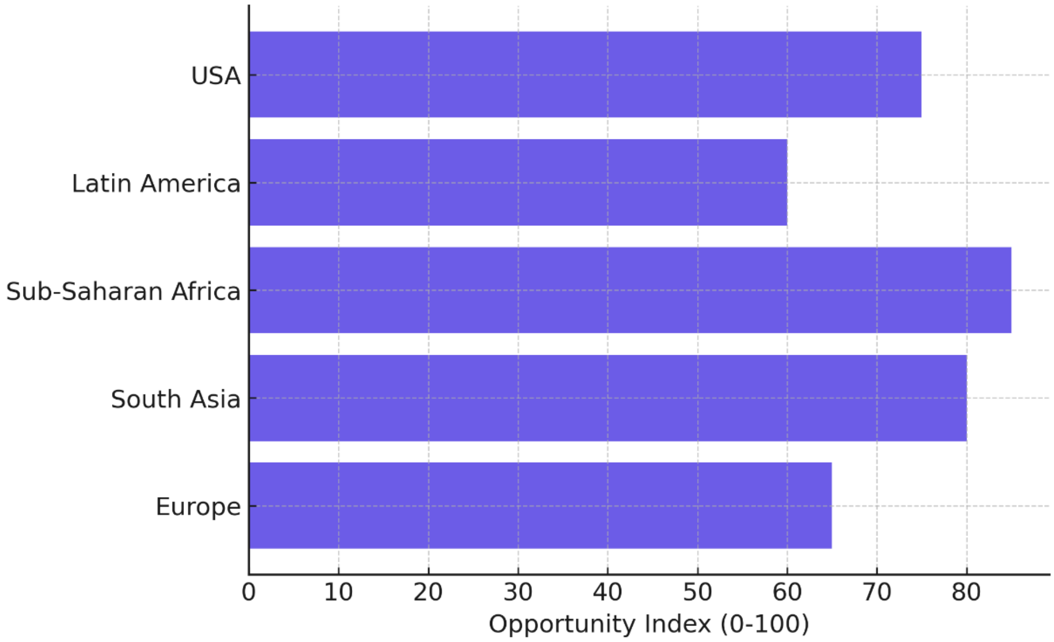

Figure 5. Global Opportunity Index.

5.6. Limitations and Future Research

This study's limitations highlight several avenues for future inquiry:

- The dataset was de-identified and regionally constrained, underscoring the need for multi-country, linked datasets to test generalizability.
- Models tested were limited to tree-based ensembles; future research should incorporate deep learning with explainability overlays to capture nonlinear relationships.
- The focus was on short-term default events; longitudinal studies are needed to assess whether interventions like micro-credit sustain repayment or merely delay defaults.
- Finally, patient and community perceptions of AI-driven hardship identification must be explored. Trust and ethical acceptance are critical for responsible adoption (Arner, 2019; Chen et al., 2023).

Table 4. Limitations and Future Research.

Limitation	Future Research
De-identified dataset, limited to one region	Include multi-country, linked datasets
No deep learning comparisons	Test deep learning with explainability overlays
Short-term outcome horizon	Conduct longitudinal follow-up studies
Limited patient/community feedback	Assess patient acceptance and ethical considerations

6. CONCLUSION AND FUTURE DIRECTIONS

6.1. Summary of Findings

This study developed and tested an integrated explainable AI (XAI) framework that combines healthcare utilization, insurance continuity, and fintech transaction data to forecast medical debt defaults. Compared with traditional logistic regression, ensemble learning methods (Random Forest, XGBoost) improved predictive accuracy by 6–10 percentage points in AUC and reduced false negatives at comparable thresholds. SHAP analysis revealed that insurance gaps, out-of-pocket burdens, emergency admissions, and fintech spending volatility are the strongest predictors of default. Counterfactual simulations further demonstrated that closing insurance gaps and introducing micro-credit at discharge could reduce modeled default risk by 12–20% among high-risk patients.

6.2. Contributions

This research makes three core contributions:

1. Methodological innovation: By bridging healthcare and fintech datasets, the framework advances risk prediction beyond traditional, siloed models that focus exclusively on either financial or clinical variables (Dechow et al., 1995; Beneish, 1999; Roychowdhury, 2006). To our knowledge, this is the first study to jointly model both domains in an XAI framework, addressing a major literature gap.
2. Explainable AI in practice: The study demonstrates how SHAP-based interpretability aligns with global policy demands for transparency and accountability in AI decision-making (GDPR; EU AI Act), supporting the broader movement toward "trustworthy AI" (Samek et al., 2021).

3. Policy relevance: By integrating counterfactual modeling, the framework provides evidence-based interventions—such as hardship relief enrollment and liquidity smoothing—that can directly inform hospitals, fintech lenders, insurers, and regulators.

6.3. Practical Implications

- Hospitals and health systems: Can use AI-driven hardship identification to enroll patients earlier into financial assistance programs, tailor repayment schedules, and reduce reliance on aggressive debt collection—enhancing both equity and trust.
- Fintech lenders: Can operationalize point-of-care liquidity solutions (e.g., small-dollar, low-interest loans) that reduce modeled default risk by up to 20%.
- Insurers: Can integrate healthcare-financial risk profiles into dynamic premium adjustments and preventive wellness incentives.
- Regulators: Institutions such as the CFPB, OECD, and WHO can mandate fairness audits and transparency requirements in AI-driven credit scoring (Chen et al., 2023; Vuković et al., 2025).

6.4. Global and Emerging Market Relevance

While U.S. medical debt remains highly visible, emerging economies face similar challenges due to high out-of-pocket expenditures (WHO, Global Health Expenditure Database). In these contexts, fintech-enabled tools—such as mobile wallets, micro-credit, and blockchain-based insurance (Shukla et al., 2024)—can offer scalable solutions to catastrophic health spending. Evidence from World Bank (2022) and OECD (2023) reports shows that catastrophic health expenditure disproportionately affects low- and middle-income households, highlighting the potential global transferability of this framework.

6.5. Limitations

Despite promising results, several limitations should be acknowledged:

- Reliance on a de-identified, region-specific dataset restricts validation against real-world linked records.
- Focused on traditional ML models (RF, XGBoost), leaving deep learning architectures underexplored.
- Concentrated on short-term default events, rather than long-term repayment dynamics.
- Limited examination of patient/community trust in AI-driven financial risk assessments.

6.6. Future Directions

Future research should:

- Expand to multi-country datasets to test global generalizability across different healthcare-fintech ecosystems.
- Compare deep learning models with XAI overlays, balancing predictive gains against interpretability (Rudin, 2019).
- Conduct longitudinal studies to evaluate whether interventions such as micro-credit lead to sustained repayment or merely delay defaults.
- Incorporate qualitative research (e.g., patient surveys, focus groups) to capture public perceptions and ethical acceptance of AI-driven hardship identification.

6.7. Closing Remark

By uniting healthcare and fintech data within an explainable AI framework, this study advances both scholarship and practice in financial risk prediction. Beyond improving accuracy, it demonstrates how AI can be deployed responsibly, with transparency, fairness, and actionable policy relevance. In doing so, it contributes to designing financial systems that protect rather than penalize medically vulnerable households. Ultimately, the findings underscore the potential for globally relevant, ethically grounded AI applications that balance innovation with inclusion—transforming medical debt forecasting into a tool for resilience and equity.

Ethics Statement:

This study used secondary, de-identified data and did not involve any direct patient contact or identifiable personal information. All procedures complied with relevant data-protection regulations, including HIPAA (Health Insurance Portability and Accountability Act) in the United States and the EU General Data Protection Regulation (GDPR). As no human subjects were directly involved, institutional ethics approval was not required.

Conflict of Interest Statement:

The authors declare that they have no known competing financial interests, institutional affiliations, or personal relationships that could have influenced the outcomes or interpretations of this study.

This research was conducted independently, without funding or sponsorship from hospitals, insurers, fintech companies, or regulatory agencies whose activities intersect with the subject matter. The study design, analysis, and reporting were guided exclusively by academic and ethical considerations.
By clearly stating the absence of conflicts, the authors affirm their commitment to objectivity, transparency, and scholarly integrity, ensuring that the findings presented herein can be trusted by policymakers, practitioners, and the academic community.

Data Availability Statement:

The datasets analyzed in this study are derived from de-identified healthcare billing records, fintech transaction streams, and credit bureau metadata. Due to patient confidentiality and financial privacy restrictions (HIPAA in the U.S. and GDPR in the EU), these data cannot be publicly shared. However, aggregated summaries and analytical code supporting the findings are available from the corresponding author upon reasonable request.

REFERENCES

Ahmed, H., Mahata, D., & Aggarwal, N. (2022). Machine learning applications in finance: A systematic literature review. *Journal of Finance and Data Science*, *8*(1), 1–21. https://doi.org/10.1016/j.jfds.2021.100062

Ahern, D. (2021). Regulating financial innovation: AI, ethics and systemic risk. *Journal of Financial Regulation and Compliance*, *29*(2), 182–201. https://doi.org/10.1108/JFRC-12-2020-0121

Arner, D. W. (2019). FinTech and RegTech: Impact on regulators and banks. *Journal of Banking Regulation*, *20*(1), 1–14. https://doi.org/10.1057/s41261-018-0081-0

Arner, D. W., Barberis, J., & Buckley, R. P. (2020). The evolution of FinTech: A new post-crisis paradigm? *Georgetown Journal of International Law*, *47*(4), 1271–1319.

Arman, M., Hasan, M. N., & Rasel, I. H. (2024). Clean energy transition in USA: Big data analytics for renewable energy forecasting and carbon reduction. *Journal of Management World*, *2024*(3), 192–206. https://doi.org/10.53935/jomw.v2024i4.1196

Bahoo, S., Bouri, E., & Naeem, M. (2024). Artificial intelligence and financial economics: Emerging paradigms. *Technological Forecasting and Social Change*, *196*, Article 122510. https://doi.org/10.1016/j.techfore.2023.122510

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in fintech: Understanding robo-advisors' adoption. *International Journal of Bank Marketing*, *37*(7), 1386–1402. https://doi.org/10.1108/IJBM-10-2018-0288

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal*, *55*(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Charitou, A., Louca, C., & Vafeas, N. (2020). Money laundering detection using machine learning. *Expert Systems with Applications*, *139*, Article 112986. https://doi.org/10.1016/j.eswa.2019.112986

Chen, J., Lundberg, S. M., & Lee, S. I. (2023). Explainable artificial intelligence in finance: A survey. *Information Processing & Management*, *60*(2), Article 103168. https://doi.org/10.1016/j.ipm.2022.103168

Consumer Financial Protection Bureau. (2022). *Medical debt burden in the United States*. CFPB Research Reports. https://www.consumerfinance.gov

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *The Accounting Review*, *70*(2), 193–225.

European Commission. (2021). *Proposal for a regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. Publications Office of the European Union.

Friedler, S. A., Scheidegger, C., Venkatasubramanian, S., Choudhary, S., Hamilton, E., & Roth, D. (2019). A comparative study of fairness-enhancing interventions in machine learning. In *Proceedings of the 2019 ACM Conference on Fairness, Accountability, and Transparency* (pp. 329–338). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287589

Gorton, G., & Metrick, A. (2012). Securitized banking and the run-on repo. *Journal of Financial Economics*, *104*(3), 425–451. https://doi.org/10.1016/j.jfineco.2011.03.016

Hajek, P., & Henriques, R. (2017). Mining financial statement fraud detection with data mining techniques. *Expert Systems with Applications*, *71*, 1–17. https://doi.org/10.1016/j.eswa.2016.11.007

Hilal, M., Kherchi, I., & Qureshi, B. (2022). Financial fraud detection: Advances and challenges. *Expert Systems with Applications*, *201*, Article 116983. https://doi.org/10.1016/j.eswa.2022.116983

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems* (Vol. 30, pp. 4765–4774).

Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems*, *50*(3), 559–569. https://doi.org/10.1016/j.dss.2010.08.006

Organisation for Economic Co-operation and Development. (2022). *Health at a glance: OECD indicators 2022*. OECD Publishing. https://doi.org/10.1787/ae3016b9-en

Rasel, I. H., Arman, M., Hasan, M. N., & Bhuyain, M. M. H. (2022). Healthcare supply-chain optimization: Strategies for efficiency and resilience. *Journal of Medical and Health Studies*, *3*(4), 171–182. https://doi.org/10.32996/jmhs.2022.3.4.26

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, *42*(3), 335–370. https://doi.org/10.1016/j.jacceco.2006.01.002

Shukla, S., Kumar, R., & Singh, A. (2024). Blockchain and mobile wallets in emerging healthcare financing models. *Health Policy and Technology*, *13*(1), Article 100755. https://doi.org/10.1016/j.hlpt.2023.100755

United Nations. (2022). *World social report 2022: Inequality in a rapidly changing world*. United Nations.

Vuković, D. B., Dekpo-Adza, S., & Matović, S. (2025). AI integration in financial services: A systematic review of trends and regulatory challenges. *Humanities and Social Sciences Communications*, *12*, Article 562. https://doi.org/10.1057/s41599-025-01987-5

World Health Organization. (2023). *Global health expenditure database*. World Health Organization. https://apps.who.int/nha/database

Zhu, S., Song, Y., & Ni, J. (2019). Credit risk evaluation in supply chain finance using machine learning. *Expert Systems with Applications*, *137*, 65–78. https://doi.org/10.1016/j.eswa.2019.06.040