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Original Article

Explainable AI for Financial Risk Mitigation: Governance, Compliance, and Customer Protection in the U.S. Economy

Norman Alfredo Gamboa Gamarra
Attorney (Colombia-licensed) & Enrolled Agent IRS certified. Financial Risk & Tax Compliance Consultant, Universidad Autonoma de Bucaramanga and CEO Momentum Factory LLC.

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Abstract *- The growing complexity of the U.S. financial system alongside quick digital transformation has exacerbated the demand to have smart and transparent risk management systems. This paper discusses the application of Explainable Artificial Intelligence (XAI) to improve financial risk management, specifically credit risk, detecting fraud, and compliance with regulations. Although the state-of-the-art machine learning (ML) and deep learning (DL) models, including Random Forest, LSTM, Graph Neural Networks and predictive analytics, considerably enhance the predictive accuracy and real-time risk monitoring, their black-box character causes some concerns about the transparency, accountability and compliance with regulations. To overcome this issue, the paper differentiates between interpretability and explainability and combines post-hoc explanation methods, such as LIME to understand model local interpretability and SHAP to understand the model global feature attribution to augment the model transparency. The study also examines AI-based risk identification, analysis, evaluation, and continuous monitoring frameworks in banking institutions. It also assesses the U.S. financial system governance and regulatory structure, as well as their adherence to the Dodd-Frank, Basel III regulations, AML, KYC, and CDD regulations. The results demonstrate that integrating sophisticated AI models with a well-developed explainability will increase institutional resilience, enhance the quality of decision-making, increase regulatory compliance, and foster systemic stability. The research is relevant in conceptualizing transparent AI systems, accountable AI systems, and governance-oriented AI systems to manage financial risk sustainably in the U.S. economy.*

Keywords *- Explainable Artificial Intelligence (XAI), Financial Risk Management, Credit Risk Assessment, Fraud Detection, Machine Learning (ML), Deep Learning (DL), U.S. Financial System, AI Governance.*

1. Introduction

Banks are subject to strict regulatory oversight, and compliance audits are crucial tools for guaranteeing ethical business activities. The risk management areas of financial institutions today are more dynamic and complex [1]. As much as the traditional risk management methods are still important, they are highly conservative in nature, depending on the traditional premises of manualization and slow turnover that disregards the dynamics of the contemporary financial system. A robust AI-based option is to use adaptive [2], data-driven, non-linear models to increase the precision and effectiveness of risk decisions.

Artificial intelligence has been extensively incorporated in the present financial risk management. Credit scoring, market risk forecasting, fraud detection, and operational risk monitoring are now commonly being done through ML models. These systems outperform typical statistical models in handling high-dimensional data, nonlinear interactions, and shifting market situations [3]. According to the best practices of Financial Risk Manager (FRM), a powerful data quality monitoring framework must be put in place. ML models, including autoencoders, isolation forests, and clustering algorithms, can recognise anomalous or missing values, spot odd patterns, and adjust dynamically to changing data distributions [4]. This practice is promptly embracing machine learning (ML) tools in enhancing and automating data validation processes. It can be a ML model, e.g. autoencoders, isolation forests, clustering algorithms, can identify anomalous or missing data, detect odd patterns [5], and adapt dynamically to changes in the data distribution. Explainable Artificial Intelligence (XAI) solves these problems and provides frameworks and tools that can assist humans in understanding AI decisions.

A deeper comprehension of the decision-making procedures and outcomes produced by black-box ML models is possible with XAI [6]. Here, we'll go over a few XAI strategies to give risk managers more comprehensible ML tools. This is illustrated by describing an application for improved paid-up risk management in insurance savings products [7].

The European Commission is putting out one of the world's first rules to control artificial intelligence (AI). Cross-sectoral AI regulation, or AI, promotes the adoption of principles that are consistent with the objective of creating reliable AI and focuses on governance needs for so-called high-risk AI systems. The fact that credit scoring algorithms are particularly cited as an example of a high-risk use case is intriguing [8].

1.1. Structure of the paper

The structure of this paper is as follows: Section II is devoted to the explainable AI in financial risk management. Section III outlines governance in the U.S. financial system. Section IV is an overview of regulatory and legal compliance. Section V is a literature review. Section VI summarizes the study and points out the future research directions.

2. Explainable AI in Financial Risk Management

Managing risks is one of the main issues facing financial institutions, particularly credit risk. Technology has made it possible for lenders to evaluate a wealth of client data and lower lending risk. The world is currently seeing the largest technological transformation in history because to artificial intelligence (AI) [9]. It provides the banking sector with excellent opportunities to democratise financial services, provide consumer protection, enhance customer experience, and improve risk management. Modern ML models may now be performed more easily than ever before, but it has proven difficult to build and execute systems that enable practical financial applications.

2.1. Implementation of Explainable AI in Credit Risk Modeling

In an attempt to illustrate the ways how Explainable Artificial Intelligence (XAI) can be used to improve financial risk assessment; the following section (Table I) provides illustrative credit risk modeling scenario that is a usual practice in banking institutions. The example demonstrates the way explainable tools like LIME and SHAP can assist risk managers in interpreting and improving machine learning models as applied to credit decision systems.

Examples A financial institution could have a machine learning model that assesses the creditworthiness of borrowers. The model examines some of them such as income level, years of employment, credit utilization ratio, debt-to-income ratio, and past repayment behavior. Although the model can be very predictive, some complex models like the Random Forest or deep learning networks can be black-box models and hence the regulators and risk managers cannot have an idea why some borrowers are considered as high-risk.

In that case, financially sound borrowers can be wrongly categorized as high-risk since the model places too much emphasis on some of the short-term behavioral factors, including temporary rises in credit utilization. This is not transparency and it poses problems to financial institutions trying to explain to regulators and customers why it made automated credit decisions.

These model decisions can be studied using explainable AI methods. Local explanations of individual predictions can be generated using LIME, making an analyst know what features contributed to the classification of a particular borrower. Simultaneously, SHAP can be used to globally understand the importance of features in the entire model, which can enable institutions to understand that some variables contribute to the predictions disproportionately.

Table 1: Role of Xai in Credit Risk Model Governance

Stage of Risk Modeling	Traditional AI Limitation	XAI Contribution
Credit Risk Prediction	Model decisions difficult to interpret	LIME explains individual predictions
Feature Importance	Hidden relationships between variables	SHAP identifies global feature impact
Model Validation	Hard for regulators to audit decisions	Explainability improves transparency
Compliance & Governance	Limited justification for automated decisions	Supports regulatory reporting and accountability

2.2. AI-Driven Risk Management Techniques

The use of AI in risk management in the banking industry has transformed traditional methodologies and structures used to recognize, evaluate, and address risks. Risk management approaches based on AI embrace the potential of sophisticated algorithms and ML models to quickly process extensive data in real-time and allow banks to react to new threats and make effective decisions. In this section, the author explores two of the most important areas in which AI has made significant contributions: real-time fraud detection and advanced credit scoring models. The AI on the risk management systems is displayed in Figure. 1.

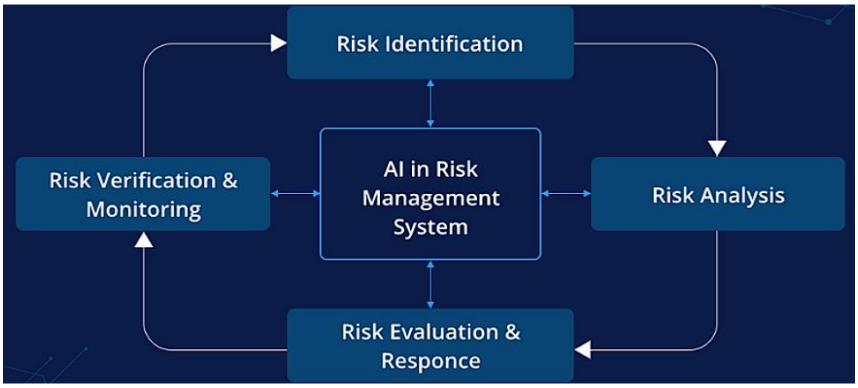

Fig 1: AI in Risk Management Systems.

- Risk Identification: Identifies and establishes possible financial, operational, compliance, or systemic risks based on the data with the help of the data-driven AI models.
- Risk Analysis: Evaluates the risk occurrence and its possible impact by predicting, recognising trends and analysing scenarios.
- Risk Evaluation & Response: Prioritizes risks in order of their severity and identifies proper mitigation measures, controls or corrective measures.
- Risk Verification & Monitoring: These are continuously monitored risk indicators, model performance, and emerging threats in order to maintain continuity.

2.3. Applications of AI in Bank Credit Management

The current world has made uncertainty more prevalent than ever in domains like politics, strategy, and society. This unpredictability increases the pressures on banks' credit management while also making the global situation more difficult. Credit management, a fundamental function of banks, must constantly enhance the accuracy of decision-making and risk alerts to ensure the stability of bank operations [10]. In this procedure, the use of AI technology is especially important.

2.3.1. Political Perspective

The global environment has presented hitherto unheard-of difficulties for bank credit management. The credit assets of banks are significantly impacted by geopolitical conflicts, increased trade protectionism, and global financial market volatility. Thus, in order to detect such dangers and implement suitable risk-response mechanisms, banks must employ AI to continuously monitor and assess the state of the world economy and politics.

2.3.2. Strategic Level

Banks must develop scientific management plans and credit policies at the strategic level to deal with the dynamic market environment. With the use of big data analysis and ML algorithms, AI technology may assist banks in more precisely determining borrowers' creditworthiness and forecasting future credit risk.

2.3.3. Societal Perspective

At the same time, AI technology may save operational costs, increase the efficiency of business processing, and optimise banks' credit business processes. From a sociological standpoint, there is a growing public need for stability and financial security. Maintaining financial stability must be the responsibility of banks, which are a crucial part of the financial system. Banks can better detect and manage credit risks, and prevent their amplification and spread within the financial system, by implementing AI technology. Furthermore, AI technology may boost client satisfaction, increase the competitiveness of banks, and improve the intelligence of financial services. With advances in computer simulation technology, simulation modeling for bank risk warning and decision-making has also emerged. Table II shows the applications of AI in the Bank Credit Management System.

Table 2: Multidimensional Applications of Artificial Intelligence in Bank Credit Management

Dimension	Contextual Challenges	AI-Driven Applications in Credit Management	Strategic Impact on Banks
Political Perspective	Geopolitical conflicts, trade protectionism, regulatory shifts, global financial volatility	Early warning systems for sovereign and cross-border credit risk; scenario analysis and stress testing; and real-time tracking of political and macroeconomic factors using predictive analytics	Enhances proactive risk mitigation, strengthens resilience against external shocks, and improves cross-border credit risk assessment
Strategic Level	Dynamic market competition, evolving borrower profiles, complex risk environments	Machine learning–based credit scoring models; big data–driven borrower profiling; predictive default modeling; AI-supported portfolio optimization	Improves accuracy of credit decisions, optimizes risk-adjusted returns, and supports evidence-based strategic planning
Societal Perspective	Rising demand for financial stability, transparency, efficiency, and customer-centric services	Automated credit evaluation systems; intelligent risk monitoring platforms; AI-powered fraud detection; simulation modeling for risk forecasting; personalized financial services	Increases consumer satisfaction, lowers expenses, increases operational effectiveness, fortifies the stability of the financial system, and encourages ethical lending practices.

3.Governance Frameworks for AI in the U.S. Financial System

The increasing intricacy and interdependence of the American financial systems has made risk management a concerning concern for market stability and institutional resilience. With the adoption of digital transformation and increased dependence on interconnected technologies by financial organizations, the risk environment has been transformed by multifaceted cyber and systemic risks, as opposed to the conventional credit and market exposures. This growth necessitates a more dynamic, intricate, and evidence-based approach to risk governance. AI is a concept that has shifted the paradigm whereby financial institutions forecast, analyze and manage risks in real-time [11]. AI use in the American financial market is not only concerning the efficiency, but has a solid foundation in the change of the risk management approach. The use of heavy historical data and linear risk assessment models as the basis of conventional models is becoming impractical in modern conditions of advanced cyberattacks, volatility of high-frequency trading, and geopolitical unknowns. AI technologies ML, DL and NLP have more intricate analytical abilities, which can identify obscure associations and novel weaknesses before it becomes a crisis. It is a step toward predictive and adaptive risk management, which can assist financial institutions improve cybersecurity and systemic stability.

3.1. Machine Learning in the U.S. Financial Systems

In the U.S. financial systems, credit risk assessment is operationalized through credit scoring or default predictive modeling in which lenders manage to estimate the probability of default, delinquency or failure by a borrower to pay within a specified period of time [12]. This task is extended by the output of a more complex machine-learning (ML) model, which learns non-linear correlations between the characteristics of the borrower, macro-financial indicators and behavioural track recordings, but once again, a rigorous holdout testing and stability tests are still required. These frameworks are useful in practice, since they are complex threshold effects (simplified by the debt-to-income ratios being different across income groups), and interaction effects (utilization risk being mitigated by the length of employment).

- Regression analysis is one of the main methods of ML that can be applied to financial prediction. Stock price predictions were made using Linear Regression, Random Forest Regression (RFR), and Support Vector Regression (SVR). These methods are particularly helpful when dealing with nonlinear financial data, which can be better forecasted based on the historical patterns on the market trends.
- The application of DL models, especially Long Short-Term Memory (LSTM) networks, is another essential method in ML-based financial prediction. Prediction of stock trends with the use of LSTM [13], as well as other algorithms such as Auto-ARIMA, Linear Regression, Random Decision Forest, Prophet (Automated Forecasting Procedure), k-Nearest Neighbours (KNN), and Moving Average, which comprises SMA and EMA.

3.2. Deep Learning in the U.S. Financial Systems

Systems for finances Fraud detection is a high-stakes use of DL architectures, like sequential decision making, where the context needed to discern between legitimate and fraudulent activities is provided by the temporal course of transactions [14]. Rule-based and statistical-based systems have difficulty in keeping up with the changing nature of fraud trends as a consequence of scammers' constant enhancement of their techniques to evading detection [15]. The DL architectures get around these problems by learning intricate models of normal behaviour and spotting minute irregularities that can indicate fraud.

- The temporal dynamics of transactional information render the RNN based architectures especially apt since they are able to capture the temporal relationships and evolving patterns of user behaviour over time. LSTM networks are now an essential part of the contemporary fraud detection systems since they can keep in mind the historical information that is relevant and forget irrelevant information behind the gated mechanisms.
- Graph-based DL systems have also expanded the power of fraud detection systems to include network structure beyond time information. Naturally, financial transaction data takes the form of a graph, with nodes standing in for entities or accounts and edges illustrating the relationships between transactions. The representations of each node's attributes and location inside the transaction network may be learned using GNNs. GNNs can be coupled with the temporal model to form an architecture that is able to identify fraud rings, or groups of accounts that collaborate to commit a coordinated fraud.

4. Regulatory Compliance and Legal Implications

The current high-paced financial landscape, has underscored the importance of preventive mechanisms to reduce risks and enhance the stability of financial institutions. Preventive strategies refer to measures implemented to detect, assess and reduce any possible threat before it becomes a reality. The importance of such strategies is that they protect financial institutions against fraud, money laundering, cyberattacks, and other financial crimes. The significance of compliance and legal issues cannot be overestimated, and all regulatory authorities of the world introduce strict standards and rules to preserve the integrity of the financial system.

4.1. Legal and Regulatory Compliance Obligations in Financial Risk Prevention

It is mandatory for financial organisations to implement a complex system of risk-reduction measures. To combat illegal activity, the most significant legislation, such as the Foreign Account Tax Compliance Act (FATCA), the Bank Secrecy Act (BSA), and the Anti-Money Laundering (AML) laws, are stringent and mandate stringent standards. These rules require that organisations possess effective internal controls, perform due diligence and keep track of transactions that could raise some suspicions. Financial institutions have to adhere to the preventative steps in case they wish to retain the trust and the licence of the clients. Good risk-indicating compliance processes ensure the stability of financial operations, as it helps the institutions to determine and deter risks. One of the legal consequences of non-compliance includes heavy penalties, suspension of licence, and probable criminal charges against executives.

4.2. Legal Framework

Financial institutions are subject to a complex combination of national and international compliance regimes that seek to minimize risks and enhance their compliance. This section discusses the frameworks, including regulating agencies and some legislative requirements that should be satisfied by different types of institutions.

4.2.1. National Regulatory Frameworks

- The Dodd-Frank act (U.S., 2010) mandates intensive preventive measures to decrease systemic risks and improve the stability of the economy.
- It has dramatically reorganized financial regulation after the global financial crisis.

4.2.2. International Regulatory Standards

- The Basel Committee on Banking Supervision released Basel III, which establishes global guidelines for stress testing, capital adequacy, and liquidity risk management.
- These changes are intended to improve risk management procedures and the banking sector's resilience.

4.2.3. Global Regulatory Coordination

- The Basel Committee on Banking Supervision works to standardize global banking practices.
- Cross-border regulatory alignment streamlines compliance for multinational financial institutions.

4.3. Compliance Requirements

Several compliance standards have been established to ensure that financial systems are secure and free of irregularities. These include Know Your Customer (KYC), Customer Due Diligence (CDD) and Anti-Money laundering (AML) programs.

4.3.1. Customer Due Diligence (CDD)

The purpose of CDD processes is to gather sufficient information about clients in order to assess their risk profiles. CDD entails understanding the nature of the business connection and confirming the customer's identification.

4.3.2. Know Your Customer (KYC)

KYC policies are essential parts of the compliance frameworks of financial firms. Institutions must check the identity of their clients, evaluate any dangers, and make sure their data is accurate and up to date.

Table III provides a summary of Legal and Compliance Architecture in Financial Institutions.

Table 3: Integrated Legal and Compliance Architecture Governing Financial Institutions

Domain	Regulatory Instrument / Mechanism	Core Requirements	Institutional Obligations	Strategic & Risk Implications
Legal Framework	Dodd–Frank Act (U.S., 2010)	Systemic risk oversight; enhanced prudential standards; stress testing; consumer protection reforms	Banks and financial institutions must implement stronger capital controls, risk governance structures, and reporting mechanisms	Reduces systemic risk exposure; strengthens financial stability; enhances transparency and accountability
	Basel III Standards (Basel Committee on Banking Supervision)	Minimum capital requirements, limitations on leverage ratios, liquidity coverage ratios (LCR), and stress test frameworks	Banks must maintain adequate capital buffers and adopt robust risk measurement systems	Improves resilience to financial shocks; promotes global risk harmonization; mitigates liquidity crises
	Global Regulatory Coordination	Cross-border supervisory cooperation; harmonized banking standards; consolidated supervision	Multinational institutions must align compliance systems across jurisdictions	Streamlines international compliance; reduces regulatory arbitrage; strengthens global financial integration
Compliance Requirements	Customer Due Diligence (CDD)	Risk-based customer identification; beneficial ownership verification; ongoing risk assessment	Institutions must collect, verify, and periodically review customer information	Mitigates fraud and illicit financing; enhances early risk detection capabilities
	Know Your Customer (KYC)	Identity authentication; client risk profiling; continuous monitoring and data updating	Financial entities must implement robust onboarding and monitoring systems	Strengthens transparency; reduces reputational and regulatory risk; supports responsible lending
	Anti-Money Laundering (AML) Programs	Transaction monitoring; suspicious activity reporting (SAR); internal controls and compliance audits	Mandatory reporting to regulatory authorities; establishment of compliance officers and AML programs	Prevents financial crime; avoids legal penalties; safeguards institutional credibility and trust

5. Literature Review

This section provides a systematic review of the studies on explainable AI for financial risk management in the U.S. Economy. Table IV provides the AI/ML Techniques employed, dataset characteristics, risk type, comparison with traditional methods, benefits and research gaps.

He (2025) purpose of this article is to study the enterprise financial risk assessment and pre-alarm model based on machine learning (ML) algorithm, in order to raise the level of enterprise risk management's intelligence and sophistication. An efficient enterprise financial risk assessment and pre-alarm system is constructed by comprehensively applying random forest (RF) algorithm, data preprocessing technology and feature selection method. In the process of model construction, firstly, the collected financial data of enterprises are comprehensively cleaned and standardized, and then the model is trained and optimized by RF algorithm [16].

Katamaneni et al. (2024) investigated a variety of AI techniques, such as ML algorithms, NLP procedures, and predictive analytics. AI models can provide real-time insights and predictions, which are often lacking in conventional methods. These abilities are realized by means of analysis of the historical data, trends in transactions and markets. Within the scope of this research project, the effectiveness of AI-driven approaches is compared to that of traditional risk management tactics. Particular attention is paid to improvements in accuracy, efficiency, and scalability [17].

Qiao et al. (2024) proposed an approach known as Long-term Payment Behaviour Sequence Folding (LBSF). Without depending on outside information, LBSF allows for informative parallelism by folding payment behaviour sequences according to merchants utilising the merchant field as an inherent grouping criteria. In the meanwhile, they use a multi-field behaviour encoding approach to optimise the usefulness of payment information. Following merchant-level behaviour aggregation, relationship learning across merchants enables thorough user financial representation. The financial risk assessment task is used to test LBSF using a sizable real-world dataset [18].

Guo (2023) suggests doing research on the applicability of the Apriori algorithm in information management systems. Apriori algorithms may significantly lower calculation complexity and speed up computations in financial risk (FR) information management systems. For storage, it converts transaction databases into Boolean matrices. An association analysis is conducted in this study used the Apriori method in the Statistical Package for the Social Sciences Clementine 12.0 program. It is indicated in the results of the research that the Apriori algorithm is superior to the traditional algorithms by 164%, but it can process client data at a rate of approximately 9000 transactions [19].

Wanjale et al. (2023) Financial corporations can evaluate the risk of providing credit to customers with the help of financial risk prediction, which is why it is an important task in the financial sphere. ML algorithms have become increasingly popular for financial risk prediction because they can analyze large amounts of customer data and generate reliable predictions. This presentation highlights the advantages and disadvantages of several approaches as part of the overall review of financial risk prediction. Several techniques are covered in the paper, including LR, NB, DT, RF, XGBoost, and KNN. The prediction of financial risk uses a variety of consumer data types, such as income, credit limit, and payment history [20].

Yu et al. (2022) can achieve this purpose by examining the pertinent element data and particular account features in order to monitor the account's danger of money laundering. Customer attributes, geographic location, and business growth, and industry circumstances are the four fundamental components of the method of client classification indicators and risk assessment for accounts. Risk indicators for account money laundering include a number of fundamental components and their risk sub-items. It is advised that financial institutions use an aspect-based (aspect-level) graph CNN to measure the risk of money laundering, starting from a variety of angles [21].

Table 4: Literature Studies on Explainable AI for Financial Risk Management in The U.S. Economy

Reference	AI / ML Technique Used	Data Type	Risk Type Addressed	Comparison with Traditional Methods	Advantages Identified	Research Gap Identified
He (2025)	Random Forest (RF), Feature Selection, Data Preprocessing	Enterprise financial statement data	Enterprise Financial Risk / Bankruptcy Warning	Compared implicitly with conventional financial risk assessment models	Improved prediction accuracy, intelligent pre-warning system, automated feature selection	Lack of explicit explainability techniques (e.g., SHAP/LIME); limited transparency analysis
Katamaneni et al. (2024)	Machine Learning, NLP, Predictive Analytics	Historical financial data, transaction patterns, market trends	General Financial Risk Management	Direct comparison with traditional risk management approaches	Real-time insights, improved scalability, higher efficiency and accuracy	Limited discussion on interpretability and model transparency
Qiao et al.	Long-term	Large-scale real-	Financial	Performance	Improved	Explainability of

(2024)	Payment Behavior Sequence Folding (LBSF), Behavioral Encoding, Relational Learning	world payment behavior data	Risk Assessment (User-level)	evaluated on real dataset; no deep benchmarking with classical statistical models	representation learning, enhanced predictive performance through behavioral aggregation	sequence folding and relational learning not addressed
Guo (2023)	Apriori Algorithm (Association Rule Mining)	Customer transaction database (Boolean matrix format)	Financial Risk Information Management	Compared with traditional processing methods (164% performance growth at 9000 transactions)	Reduced computational complexity, faster processing speed	Rule-based approach lacks predictive modeling depth and scalability; limited modern XAI integration
Wanjale et al. (2023)	Decision Tree, Random Forest, XGBoost, KNN, Naïve Bayes, and Logistic Regression	Financial information on consumers (income, credit limit, payment history)	Credit Risk / Financial Risk Prediction	Comparative discussion of multiple ML vs traditional credit scoring	High predictive capability, ability to process large datasets	No detailed explainability framework; limited focus on model interpretability
Yu et al. (2022)	Aspect-based Graph Convolutional Neural Network (GCN)	Account element data (customer characteristics, location, industry, business conditions)	Money Laundering Risk	Not explicitly compared with traditional AML statistical systems	Multi-perspective risk quantification, improved detection capability	Graph neural network interpretability challenges; lack of transparent explanation mechanisms

6. Conclusion and Future Work

Conventional methods of financial risk forecasting have been based on long-term statistical and econometric models which include time series analysis, regression analysis and discriminant analysis. This paper shows that the application of the Explainable Artificial Intelligence (XAI) to financial risk management substantially fosters both the effectiveness, transparency, and alignment of the governance of risk assessment systems in the U.S. financial landscape. Although more sophisticated ML and DL models, including the Random Forest, the LSTM, and the GNN, achieve better predictive accuracy when used in credit risk assessment, fraud detection, and systemic monitoring, they exhibit black-box properties that make them difficult to hold responsible and regulate. Using the explainability method of LIME to interpret instances and SHAP to attain a global attribute, financial institutions will be able to fill the gap between model performance and regulatory transparency. More importantly, systemic stability and organisational resilience are promoted when AI-enabled risk management systems are integrated with the required legal and compliance standards, including Dodd-Frank, Basel III, AML, KYC, and CDD requirements. Finally, the paper summarizes that sustainable financial risk management of the future is not in the development of sophisticated predictive features but in clear, readable, and governance-compliant AI systems that could encourage trust, regulatory compliance, and responsible research in the U.S. economy.

Further research should engage in designing natural deep learning implementations that can be interpreted into the financial risk management. More work is needed to unite real-time explainability with regulatory reporting systems, evaluate fairness and bias reduction strategies, and evaluate XAI models in a diverse range of financial institutions in the United States to strengthen it, make it more transparent and scalable.

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