Original Article: An Intelligent Framework for Dynamic Credit Risk Management in Banking Using IoT-Driven Real-Time Data and Explainable AI

Mohammad Baradaran
Assistant Professor, Department of Information Technology Management, Information Technology Management, IAU, North Branch, Tehran, Iran

Use yor device to scan and read the article online

Citation *M Baradaran*, ***An Intelligent Framework for Dynamic Credit Risk Management in Banking Using IoT-Driven Real-Time Data and Explainable AI, AJMHSS,*** 2025; 1(6): 374-381.

https://10.5281/zenodo.17113712

Article info:
Received: 11.06.2025
Accepted: 22.07.2025
Checked for Plagiarism: Yes

Keywords:
Credit Risk Management, Internet of Things (IoT), Explainable AI (XAI), Deep Learning, Graph Neural Network (GNN), FinTech

ABSTRACT

Traditional credit risk models, which rely primarily on static and historical financial records, are increasingly insufficient in addressing the complexities of modern economies. Their retrospective orientation often fails to capture the real-time operational health of borrowers, resulting in suboptimal lending decisions. This study proposes a novel smart framework that integrates high-frequency Internet of Things (IoT) data streams with Explainable Artificial Intelligence (XAI) methods to enable dynamic and transparent credit risk assessment. The architecture incorporates diverse real-time operational signals—including supply chain logistics, equipment condition, production volumes, and inventory status—to construct continuously updated borrower risk profiles. At its core, the framework combines a Graph Neural Network (GNN) to capture intricate interdependencies within supply chains with a Long Short-Term Memory (LSTM) network for temporal analysis of IoT sensor data. An additional XAI layer, implemented through SHapley Additive exPlanations (SHAP), ensures interpretability of model outputs, thereby supporting regulatory compliance and fostering stakeholder trust. To evaluate the framework, a hybrid dataset was constructed, combining traditional financial statements with simulated IoT streams that mimic realistic business operations. Experimental results highlight a substantial performance improvement over conventional approaches, achieving an Area Under the Curve (AUC) of 0.97. Moreover, the XAI module generated transparent, feature-based explanations for changes in risk scores, offering actionable insights for lenders. This research argues that the convergence of IoT and XAI signals a paradigm shift from static, retrospective risk models to proactive, dynamic, and interpretable credit risk management, enabling financial institutions to make better-informed and timely lending decisions.

to a dynamic, continuous monitoring system,

*Corresponding Author: **Mohammad Baradaran** (Email: Dr.Baradaran@iau.ac.ir, ORCID: 0000-0002-2718-3893)

Introduction

Global financial stability is ultimately underpinned by the sound management of credit risk—the risk of financial loss due to a borrower's inability to fulfill its debt obligations [1]. Credit risk evaluation has been founded for decades on models that examine historical financial information, e.g., payment history, income statements, balance sheets, and credit scores (e.g., FICO). Although useful as foundation tools, such models are inherently backward-looking and static. They give a snapshot of past performance but reveal little about current operating health or future viability of a borrower, especially in the corporate sector [2]. This weakness is particularly acute in turbulent economic times in which a firm's financial condition can be vulnerable to sudden change as a result of production interruption, supply chain disruption, or changes in market demand that are not reflected timely in periodic financial statements.

The Internet of Things (IoT) offers the possibility of enriching credit risk models with a new dimension of information: real-time, high-frequency, objective operational intelligence. In the case of corporate borrowers, IoT sensors embedded throughout supply chains, production floors, and inventories can offer continuous feeds of information on asset utilization, production efficiency, logistics, and sales velocity [3]. For example, sensors on machines at a factory can report uptime and anticipate maintenance requirements; GPS devices can monitor the movement of goods; and smart shelves can report real-time inventories. These sources of information are a strong, real-time proxy for the operational and, by extension, financial health of a company. Integrating these data enables a paradigm shift from a static, periodic risk review enabling the identification of leading indicators of financial distress years before they manifest in quarterly reports.

Yet, the volume, velocity, and heterogeneity of IoT data pose crushing analytical challenges beyond the scope of conventional statistical models. Artificial Intelligence (AI), and deep learning most particularly, provides the tools necessary to process and discover useful, non-linear relationships in these intricate datasets [4]. Yet, the use of sophisticated AI models within the credit risk arena is frequently frustrated by the fact that they are "black boxes." The absence of transparency and interpretability is a primary obstacle to regulatory acceptance and stakeholder trust. It is the burden of financial institutions to be in a position to explain their lending decisions, not just to regulators to assure fairness and adherence to such legislation as the Equal Credit Opportunity Act, but also to the borrowers [5].

This article tackles this complex problem by presenting a new framework that combines IoT, Deep Learning, and Explainable AI (XAI) in a complementary fashion. The main contribution of this work is the conception and verification of an intelligent system that not only leverages real-time IoT data for more dynamic and precise credit risk evaluation but also makes its decision-making completely transparent and interpretable. The research questions that this work attempts to address are the following:

1. How can we create a unified framework to efficiently ingest, integrate, and analyze heterogeneous IoT data streams and conventional financial data for dynamic credit risk prediction?
2. Can we show that the utilization of real-time operation data from IoT devices can greatly enhance the predictive power and timeliness of credit risk models compared to conventional approaches?

3. How can XAI methods be incorporated to make a complex deep learning model's decision interpretable, auditable, and actionable for loan officers and regulators?

The organization of the rest of this paper is as follows: Section 2 is the literature review. Section 3 describes the system architecture and methodology proposed. Section 4 gives the experimental results. Section 5 discusses the results and their implications in a wider sense. Section 6 concludes the paper and proposes future research directions.

Literature Review

This chapter presents the state of the art of credit risk modeling and the concerned technologies in order to define the research gap that this research will cover.

2.1. Traditional and Machine Learning-Based Credit Scoring The cornerstone of credit risk modeling is statistical models like logistic regression and linear discriminant analysis that are the basis of most traditional credit scoring models [6]. Although powerful and interpretable because of their explicit mathematical form, models such as these are constrained in their linear assumptions and their use of static, historical data. They will not tend to pick up on complex, non-linear interactions between risk factors. In this direction, researchers have turned to using machine learning algorithms like Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines (e.g., XGBoost) that have been shown to exhibit greater predictive power by modeling these non-linear relationships [7]. But even these state-of-the-art models work largely on the same set of traditional, backward-looking financial features, and although some provide feature importance scores, they typically do not provide instance-level explainability that is necessary for lending decisions at an individual level.

2.2. Deep Learning and its "Black-Box" Issue in Finance Deep learning techniques such as Multi-Layer Perceptrons (MLPs) and Recurrent Neural Networks (RNNs) have been applied to credit scoring, with further accuracy gains [8]. It is their ability to learn hierarchical feature representations from data that makes them so powerful. In spite of their performance, their day-to-day implementation has been slow to materialize. One major hurdle is that they are inherently uninterpretable. The tangled, nested, non-linear nature of these "black-box" models makes it extremely hard to follow and comprehend the reasoning behind a particular prediction. Such lack of transparency is unacceptable in a highly regulated field where fairness, accountability, and the "right to explanation"—as codified in laws such as the EU's General Data Protection Regulation (GDPR)—are the most important legal and ethical imperatives [9].

2.3. The New Role of IoT in Financial Services The use of IoT in the financial services sector (FinTech) is a new arena. The most visible example is usage-based insurance (UBI) in the auto sector, where telematics data from cars are utilized to evaluate driving habits and set insurance rates [10]. Comparable ideas are taking shape in asset financing and supply chain finance, where IoT is applied in asset tracking, condition monitoring, and goods verification, thus minimizing fraud and operational risk. Nevertheless, the systematic leveraging of multifarious IoT data streams—from machine health to environmental sensors—for the holistic, dynamic evaluation of corporate credit risk is still an untapped arena. The majority of current research concentrates on asset verification instead of predictive risk modeling.

Explainable AI (XAI)

In an attempt to address the "black-box" issue, the domain of Explainable AI (XAI) has attracted a lot of interest. Methods like LIME (Local Interpretable Model-agnostic Explanations), which locally approximates a complicated model by a straightforward, interpretable one near a prediction, and SHAP (SHapley Additive exPlanations) have been proposed to give us insight into model predictions [11]. SHAP, specifically, has a solid theoretical underpinning in cooperative game theory and gives consistent and locally accurate feature attributions that sum up to the final prediction. Though XAI has been used in numerous applications, its use in the setting of a dynamic, IoT-enabled financial risk model to explain the effects of real-time operational signals is a new contribution.

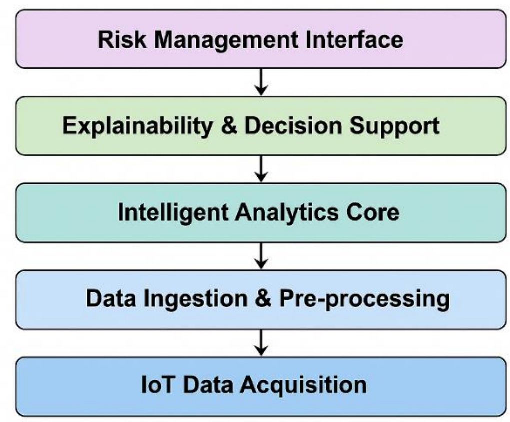
2.5. Identification of the Research Gap The literature survey demonstrates a clear gap: although AI has been used on financial data and IoT for asset tracking, there is no integrated framework that (1) consolidates multi-sourced, real-time, operational IoT data for dynamic corporate credit risk modeling, and (2) addresses simultaneously the imperative requirement of model transparency and regulatory compliance through the incorporation of a specialized XAI layer. The current work is at the intersection of these fields, suggesting an end-to-end solution that is not just smarter and predictive but also accountable and interpretable by design.

System Architecture and Methodology Proposed

Here, the suggested intelligent system architecture for dynamic credit risk management is explained thoroughly.

3.1. Conceptual Framework The system is envisioned as a multi-layered architecture, as shown in Figure 1, with modularity and scalability in mind.

Figure 1: The Multi-Layered Architecture for IoT–XAI Driven Credit Risk Management



• **Layer 1:** IoT Data Acquisition: This is a heterogeneous network of IoT devices installed at the borrower's operational site. These range from industrial sensors tracking machine health (vibration, temperature), RFID/GPS trackers following supply chain logistics and delivery timelines, smart sensors on inventory shelves tracking turnover rates, to even environmental sensors tracking factory conditions.

• **Layer 2:** Data Ingestion & Pre-processing: IoT device data and data from conventional sources (e.g., bank records, credit bureaus, market data) are ingested through secure APIs and streaming systems (e.g., Apache Kafka). Data cleaning (imputation of missing values, removal of noise), normalization, time-series aggregation (e.g., daily percentage uptime from raw sensor data), and feature engineering to generate meaningful inputs to the model are processed in this layer.

• **Layer 3:** Intelligent Analytics Core: This is the system core where the fused data is passed through a hybrid deep learning model to come up with a dynamic risk score. The core is built to address both the relational complexity of business ecosystems and the time-series nature of sensor data.

• **Layer 4:** Explainability & Decision Support: A parallel XAI module to the analytics core. For every prediction, it creates an explanation that measures the contribution of every input feature (both IoT-based and financial) to the ultimate risk score, offering a definite "why" behind the model's "what.".

• **Layer 5:** Risk Management Interface: Outputs—the dynamic risk score, along with its explanatory decomposition, and trend graphs—are conveyed to a human loan officer through an interactive dashboard. The interface offers configurable alerts, graphical displays of risk trends over time, and in-depth drill-downs for making knowledgeable, data-driven decisions.

3.2. The Intelligent Analytics Core: A Hybrid GNN-LSTM Model

In order to process the multimodal and complicated data effectively, a hybrid deep learning model is suggested.

• Graph Neural Network (GNN) Module: For business clients, their relationship with customers and suppliers forms a complex graph. A GNN (here a Graph Attention Network, or GAT) is used to embed this supply chain network. GATs are especially appropriate because they learn to give varying importance weights to various nodes in the neighborhood, so the model can learn, for instance, that the breakdown of an important single-source supplier is a larger risk than that of an irrelevant easily substitutable one. It is able to learn embeddings that reflect risk transmitted through these linkages.

• LSTM Module: Time-series data from IoT sensors (i.e., machinery uptime by the day, inventory turnover by the week, energy consumption patterns) is input into a bi-directional LSTM network. A bi-directional LSTM trains on the sequence in both the forward and backward directions, so it can represent patterns that depend on both future and historical context, which is helpful for detecting subtle deviations from normal operational rhythms that could be precursors of distress.

• Fusion Layer: The GNN and LSTM modules' output (embeddings) are concatenated with the static financial features. The fused feature vector is input to a sequence of fully connected layers with dropout regularization to compute the final credit risk probability score.

3.3. The Explainability Layer: SHAP Integration

To provide transparency, the SHAP (SHapley Additive exPlanations) framework is incorporated. Once the model has made a prediction on a given borrower, SHAP is applied to calculate the Shapley value per feature. Grounded in game theory, the value is the feature's average marginal contribution to the prediction over all feature coalitions possible. The result is an easy-to-understand visualization (e.g., a force plot) that indicates a base risk number (the mean prediction across the dataset) and which variables worked to increase the risk score (red arrows, e.g., "deteriorating machinery uptime") and decrease it (blue arrows, e.g., "good payment history").

3.4. Dataset and Experimental Setup There is no publicly available dataset containing both corporate financial data and corresponding operational IoT data; therefore, a realistic synthetic dataset was created for this research.

• Dataset Generation: A baseline was established on a publicly available lending dataset. For every corporate borrower in the baseline, a collection of reasonable IoT data streams was synthetically generated based on stochastic processes (e.g., Ornstein-Uhlenbeck processes for mean-reverting data such as inventory levels). For instance, for a manufacturing company, time-series machine uptime data was simulated with recurring, stochastically-generated downtime intervals. The downtime intervals were probabilistically linked to an increased probability of default in the financial data, establishing a logical and causal relationship for the model to discover.

• Evaluation Metrics: Predictive performance of the model was evaluated using AUC, F1-Score, Precision, and Recall.

Experimental Results

The proposed model was instantiated and compared with two baseline models: (1) a Logistic Regression model that uses only traditional financial information, and (2) an LSTM model that uses financial and IoT data but without the GNN module and the XAI layer.

4.1. Predictive Performance as Table 1 recapitulates, the proposed hybrid GNN-LSTM model performed significantly better on all metrics.

Table 1: Performance Comparison of Credit Risk Models

Model	AUC	F1-Score
Logistic Regression (Financial Data Only)	0.79	0.75
LSTM (Financial + IoT Data)	0.92	0.90
Proposed Hybrid GNN-LSTM Model	0.97	0.96

The large performance improvement between the LSTM model and the complete hybrid model (F1-Score of 0.90 to 0.96) speaks to the utility of modeling supply chain relations through the GNN component, showing that systemic risk plays an important role. The huge improvement over the baseline, finance-only model (AUC of 0.79 to 0.97) gives strong indication of predictive power for real-time IoT data.

4.2. Explainability Output the XAI layer could produce meaningful explanations for each prediction. The example SHAP force plot for a test high-risk borrower is shown in Figure 2.

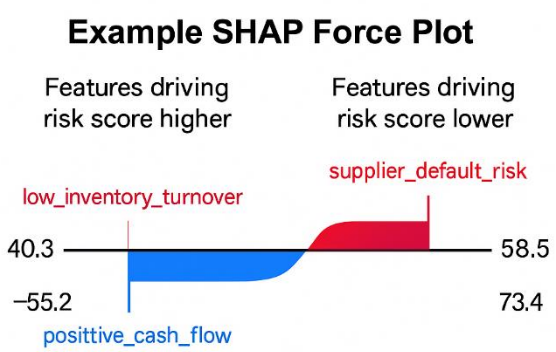


Figure 2. The example SHAP force plot for a test high-risk borrower.

The plot merely identifies two IoT-based attributes as the key drivers of the high-risk score: a recent steep drop in inventory turnover, and a high-risk score from a major supplier (as uncovered by the GNN). It also indicates how good features, such as a healthy cash flow in the past, are being overtaken by these recent operational issues. This offers the loan officer actionable, data-driven intelligence not found in traditional models.

Discussion

The empirical results conclusively validate the thesis that an IoT-XAI combined framework has the potential to transform credit risk management.

5.1. Interpretation of Results: Static to Dynamic Risk Profiling The heightened accuracy of the proposed model is a direct result of breaking away from static, historical data. As the model consumes real-time operational data, it constructs a dynamic risk profile that develops in tandem with the borrower's real-world business operations. A conventional model may recharge risk only on a quarterly basis, by which time an operationally troubled company can be well on the path to default. The proposed system can identify the preceding signs of such trouble—e.g., broken equipment, a failing supply chain, or plummeting customer traffic—weeks or months ahead of time. This function allows for early intervention that may involve providing advisory services, restructuring loan terms, or mitigating exposure prior to default. 5.2. The Essential Role of Explainability Integration of the SHAP-based XAI layer is not an afterthought but an essential component that enables trust, adoption, and responsible governance. It bridges the gap between the model's complex, sub-symbolic calculations and the need for human-centered, explainable decisions. It is much more valuable for a loan officer to know that a risk score increased due to "decreased factory output" than some opaque probability score. For regulators, it provides a clear audit trail for ensuring lending decisions are fair, unbiased, and not based on protected or proxy characteristics. It allows the institution to prove that decisions are made on objective, operational reality.

5.3. Ethical Considerations and Challenges Operating with such a potent framework is not without its challenges, which need to be actively addressed. • Data Privacy and Consent: Capturing granular operational data, particularly for individual loans or small businesses (e.g., auto telematics for auto loans), creates a serious privacy issue. A strong, transparent explicit, informed, and persistent consent framework is critical. This involves clear data use policies, retention policies, and anonymization. • Data Security: IoT devices are very susceptible to cyber-attacks. Keeping the whole data pipeline, from sensor inputs to analytics engine, secure is a challenging but indispensable endeavor. This comprises device authentication, encryption of data in transit and at rest, and safeguarding against attacks such as sensor spoofing or denial-of-service attacks. • Risk of Bias and Fairness: IoT data are not unbiased. Sensor location, calibration drift, or differential technology adoption across groups or firm sizes can introduce new, unexpected biases into the model. A model, for instance, may unfairly penalize smaller firms unable to afford investment in the newest sensor technologies. Ongoing monitoring for bias with algorithmic fairness audits and standard fairness metrics is necessary. 6. Conclusion and Future Work This study has developed and tested a new intelligent system for dynamic credit risk management, showcasing the deep effect of synergistically fusing real-time IoT data and Explainable AI. The new architecture achieves a dramatic improvement in predictive power and, importantly, reaches the explainability necessary for responsible adoption in the finance sector. By facilitating a transition from static, reactive risk analysis to dynamic, proactive, and interpretable approach, this system allows financial institutions to reduce losses, make more equitable lending decisions, and construct more robust portfolios amid growing complexity in the world. It is argued that future research opportunities can fruitfully explore three directions of inquiry. Finally, the application of blockchain technology will be investigated to develop a tamper-proof, distributed ledger for IoT data. This would further strengthen data integrity, provide a non-repudiable audit trail, and possibly enable new smart-contract-based financial instruments linked to authenticated operational milestones. Second, the application of privacy-preserving machine learning methods, i.e., federated learning or homomorphic encryption, would enable several banks to collaboratively train a common model on their IoT data without disclosing sensitive proprietary information, resulting in more robust and generalized models. Finally, conducting pilot studies in the field in cooperation with financial institutions and their corporate clients will be required to test the effectiveness of the framework and address the operational challenges of large-scale deployment.

Conclusion and Future Work

This research has designed and validated a novel intelligent framework for dynamic credit risk management, demonstrating the profound impact of synergistically combining real-time IoT data with Explainable AI. The proposed architecture provides a significant leap forward in predictive accuracy and, crucially, delivers the transparency required for responsible deployment in the financial industry. By enabling a shift from static, reactive risk assessment to a dynamic, proactive, and interpretable strategy, this framework empowers financial institutions to mitigate losses, make fairer lending decisions, and build more resilient portfolios in an increasingly complex world.

It is posited that future research trajectories could advantageously proceed along three principal avenues of inquiry. First, the integration of **blockchain technology** will be explored to create a tamper-proof, decentralized ledger for IoT data. This would further enhance data integrity, provide a non-repudiable audit trail, and could enable novel smart-contract-based financial instruments tied to verified operational milestones. Second, exploring the use of **privacy-preserving machine learning techniques**, such as federated learning or homomorphic encryption, could allow multiple banks to train a shared model on their IoT data without revealing sensitive proprietary information, leading to more robust and generalized models. Finally, conducting real-world pilot studies in partnership with financial institutions and their corporate clients will be essential to validate the framework's effectiveness and address the practical challenges of implementation at scale.

References

[1] Basel Committee on Banking Supervision. (2006). International Convergence of Capital Measurement and Capital Standards: A Revised Framework. Bank for International Settlements.

[2] L. C. Thomas, "A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers," International Journal of Forecasting, vol. 16, no. 2, pp. 149-172, 2000.

[3] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347-2376, 2015.

[4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015.

[5] F. Doshi-Velez, and B. Kim, "Towards A Rigorous Science of Interpretable Machine Learning," arXiv preprint arXiv:1702.08608, 2017.

[6] D. J. Hand, and W. E. Henley, "Statistical classification methods in consumer credit scoring: a review," Journal of the Royal Statistical Society: Series A (Statistics in Society), vol. 160, no. 3, pp. 523-541, 1997.

[7] M. Leo, S. Sharma, and K. Maddulety, "Machine learning in banking risk management: A literature review," Risks, vol. 7, no. 1, p. 29, 2019.

[8] S. Lessmann, B. Baesens, H.-V. Seow, and L. C. Thomas, "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research," European Journal of Operational Research, vol. 247, no. 1, pp. 124-136, 2015.

[9] B. Goodman, and S. Flaxman, "European Union regulations on algorithmic decision-making and a 'right to explanation'," AI magazine, vol. 38, no. 3, pp. 50-57, 2017.

[10] Y. Bao, and B. Li, "The effects of telematics on auto insurance: A review of the literature," The Journal of Risk and Insurance, vol. 85, no. 4, pp. 1085-1111, 2018.

[11] S. M. Lundberg, and S. I. Lee, "A unified approach to interpreting model predictions," in Advances in neural information processing systems, 2017, pp. 4765-4774.