

Artificial Intelligence in Financial Risk Management

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Article Details	Abstract
Received: 18 July 2023 Accepted: 17 Oct 2023 Published: 19 Dec 2023	<i>Financial institutions are exposed to an increasing complex and fast-paced credit risk, market risk, liquidity risk, operational risk and fraud risk. Artificial intelligence (AI), machine learning, deep learning and natural language processing are providing new tools to more accurately measure and manage these risks than traditional statistical models. In this paper, we overview the use of AI in the primary risk areas and introduce a conceptual framework relating AI adoption and risk management effectiveness, along with an empirical example that compares model families in terms of their performance in credit default prediction, fraud detection, and market risk forecasting. The illustrative results demonstrate that the ensemble and neural models, as compared to logistic regression, provide better discrimination and fewer false positives without relaxing the constraints of explainability, model risk, data bias, or regulatory expectations. The paper concludes with a governance roadmap and recommendations for practitioners and regulators. Note: all numbers in the tables are examples and indicate the analysis structure, and must be changed to your experimental or institutional numbers prior to submission.</i>
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key words : AI, machine learning, credit risk, fraud detection, market risk, model risk, explainable AI.

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1-INTRODUCTION

Risk management is the essence of a financial institution. Banks, insurers and asset managers make money off of taking risk and they live off of measuring and controlling risk. The tool kit has been developed for decades using statistical techniques such as logistic regression scorecards, VaR models and rule-based monitoring. They are well known and easy to explain, but they are not so good at handling nonlinear relationships or dealing with high-dimensional data, unstructured text and rapidly changing circumstances.

What's possible has changed with the availability of large data sets, low-cost computers, and well-established machine-learning libraries. Lenders now evaluate applicants with thousands of behavioural metrics, payments systems quickly flag transactions, and risk teams are analyzing news and filings in real time to look for signs of trouble. Meanwhile, the regulators have expressed worries over unclear models, skewed results and the clustering of technology providers.

This paper looks at a real-life problem: where can AI really add value to financial risk management and what conditions must be fulfilled for institutions to use it safely? It does this by bringing together applications across different risk types, suggesting an algorithmic structure to connect AI capability with risk outcomes, and showing an example of a model comparison structure that a practitioner could reproduce.

1.1 Research Problem

There is some evidence for accuracy benefits, and the compromise on explainability and model risk, but the evidence is yet to be consolidated and/or is not comparable across risk areas.

1.2 Research Objectives

- 1.To map AI techniques to the main categories of financial risk.
- 2.To evaluate the performance of AI models against benchmark models on typical risk-related tasks.
- 3.To explore the impact of explainability, data quality and governance on the benefits of AI.
- 4.To make a governance plan for responsible adoption.

1.3 Research Questions

RQ1: Is there evidence that AI models are superior to traditional models in credit, fraud, and market risk applications?

What are the boundaries of safe use of AI in risk management?

How to manage the governing of AI models throughout their life cycle?

2. Literature Review and Theoretical Background

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2.1 Categories of Financial Risk

The most prevalent types of financial risk are credit risk (default by the borrower), market risk (losses arising from price changes), liquidity risk (difficulty in meeting obligations or trading positions), operational risk (failures in processes, people, systems or fraud) and compliance risk (violation of law or regulation). The type of data, length of time and type of loss distribution differ within each category, which affects the selection of model.

2.2 AI Techniques used in Risk Management

Supervised learning, such as logistic regression, random forests, gradient boosting, and neural networks predict labelled outcomes (default or fraud). Anomalies are identified in unsupervised learning such as clustering and autoencoders. Deep learning models are good for sequences and complex patterns, such as recurrent networks for volatility forecasting. NLP filters signals from news, earnings calls and complaints. Hedging and portfolio control using reinforcement learning and generative models for synthetic data generation and scenarios are discussed.

2.3 Theoretical Foundations

The information asymmetry interpretation of the facts is that better information and better predictions diminish adverse selection and moral hazard in lending. Modern portfolio and risk theory would consider risk as a distribution of losses and requires an estimation that AI models can enhance the estimation of tails and dependency. The governance lens is given in model risk management guidance, such as the supervisory principles on model validation, where every model has the risk of error and misuse, and AI models are even more complex and opaque. Lastly, responsible AI principles outline the social licence of the models, which include fairness, accountability, transparency and robustness.

2.4 Empirical Evidence

Table 1. Brief overview of areas of representational research.

Risk Domain	Typical AI Approach	Reported Benefit	Main Limitation
Credit risk	Gradient boosting, neural networks, alternative data	Better default discrimination, increased access to credit	Opacity, bias to groups
Multivariate data quality and completeness	Anomaly detection, graph analytics, deep learning	Increased detection, reduced false alerts	Concept drift, adversarial adaptation
Market risk	LSM, ensemble volatility models	Better tail and volatility forecasts	Regime shifts, overfitting

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Liquidity risk Cash-flow forecasting using ML Early warning of stress
 Very few data for stress periods
 Operational and compliance risk NLP, process mining, AML screening
 Lower manual workload, faster alerts Explainability to regulators

2.5 Research Gap

Numerous studies test one model using one data set and only report accuracy. Few compare model families over multiple risk tasks and at the same time consider explainability, stability and governance cost. This paper will fill that void.

A conceptual framework and hypotheses were developed. A conceptual framework and hypotheses were developed.

The AI capability (data quality, model sophistication and computing infrastructure) is the enabler of risk management effectiveness in the framework. It is mediated by the predictiveness and the speed of detection, and moderated by model governance and model explainability: Strong governance preserves predictive gains, whereas weak governance allows model risk and model bias to erode predictive gains.

Figure 1. Every concept has an image used to help explain its meaning (see diagram below).

conceptual framework · 1 IV, 2 mediators, 1 moderator, 1 DV

The direct pathway is H1, while pathways through predictive accuracy and detection speed are H2-H4, and model governance is H5.

3.1 Hypotheses

- H2: AI boosts customer satisfaction among small businesses.
- H2: AI models predict better than statistical models.
- H3: AI makes the detection of risks quicker.
- H4: Predictive accuracy mediates the relationship between AI adoption and risk management effectiveness.
- H6: Model governance positively moderates the relationship between AI adoption and effectiveness.

4. Research Methodology

4.1 Research Design

The study involves quantitative research and comparative design experimental. The several model families are trained on the same data split for three tasks and evaluated on the same held-out data split with the same metrics. The process is as follows:

Figure 2. This is the AI Risk Modelling Pipeline as shown below.

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modelling pipeline is a 8 steps, 1 decision modelling pipeline.

If the model does not pass the stability or fairness test, it is returned to be revalidated before being chosen.

4.2 Data and Sample

The illustrative design assumes a retail loan portfolio of 30,000 loans, at an average default rate of approximately 8 percent, a card transaction dataset of 500,000 transactions and a fraud rate of approximately 0.4 percent, and a daily return of an equity index for 10 years for market risk. The split for each dataset is 70% training, 15% validation, 15% test – with time-based splits for market data to prevent look-ahead bias.

4.3 Models and Metrics

Table 2. Models and Evaluation Metrics by Task

Task	Model (1)	Model (2)	Primary Metrics
Loss functions	AUC, KS statistic, GiniBrier score	logistic regression score	Random forest score, XGBoost score, neural network score
Fraud detection	Rule-based and logistic regression	Isolation forest, XGBoost, autoencoder	Precision, recall, F1, false-positive rate
Market risk (1-day VaR)	Historical simulation, GARCH	LSTM, gradient boosting	Exceedance rate, RMSE of volatility

4.4 Validation and Robustness

The hyperparameters are optimized on the validation set via cross-validation. The population stability index quantifies stability, approval-rate differences across groups quantify fairness, and the SHAP value summaries quantify explainability. Paired comparisons of AUC are used to test results for significance.

5. Applications of AI in the risk domains

Table 3. Data, controls, and examples of AI use cases. Examples of AI use cases, data, and controls.

Use Case Type: Risk Domain/Typical Data/Key Control

Risk assessment Application scoring, early warnings, limit management
Bureau, transaction, behavioural, alternative data, fair lending tests, adverse-action reasons

The above-mentioned areas are particularly affected by the fraud category. Fraud is a specific area that is affected by the above mentioned areas particularly by real-time transaction screening, payments, device and network graphs, and human review of high impact alerts.

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Most of the above applies to the following types of series: Market
 Volatility and tail forecasting, stress scenarios Prices, volumes, macro
 series Backtesting and exceedance monitoring
 Liquidity Deposit outflow and cash-flow forecasting Balance and flow history
 Scenario overlays by treasury.
 Specific features Anomaly detection, incident triage, Logs, tickets, process
 data, Change control and audit trails
 Compliance AML alert prioritisation, document review Transactions, KYC
 files, text Documented rationale for alert closure

Figure 3. Real-Time AI Decision Flow for Transaction Risk (see diagram below)

The real-time transaction decision flow is a collection of 7 steps and 1 decision for making a real-time decision.

If the transaction is classified as low risk, it is passed, high risk is blocked, and medium risk transactions are passed on to analysts who add new labels to the learning set.

AI is not a decision-making entity in its own right, but rather an embedded part of the decision-making process. The model generates a score, apply business rules to thresholds, and cases are referred to human analysts, who provide new training labels.

6. Results and Analysis (Illustrative)

The analysis presented below is simulated and illustrates the expected format.

6.1 Dataset Description

Table 4. A description of the data sets is included. Data sets are described.

The classes that were observed were randomly chosen and verified by a sample of 150 students. 150 students were randomly sampled and verified to be the observed classes.

Retail loans	30,000	48	8.1%	5 years
Card transactions	500,000	32	0.4%	12 months
Net returns on equity index funds	2,520	days	12%	Not applicable for 10 years

6.2 Credit Default Prediction

Table 5. Test-Set Performance on Credit Default.

Model	AUC	KS Statistic	Gini	Accuracy
Logistic regression	0.742	0.368	0.484	0.912
Random forest	0.801	0.452	0.602	0.921
XGBoost	0.826	0.489	0.652	0.925
Neural network	0.812	0.470	0.624	0.923

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Gradient boosting gives the best discrimination, with an increase in AUC of approximately 0.08 over the logistic benchmark. When defaults have a low percentage, it does not impact accuracy much and AUC, KS, and Gini are the most popular metrics for this instance.

6.3 Fraud Detection

Table 6. Test-Set Performance: Fraud Detection

Model	Precision	Recall	F1	False-Positive Rate
Rule-based system		0.18	0.52	0.27 1.60%
Logistic regression		0.34	0.61	0.44 0.80%
Isolation forest	0.41	0.66	0.51	0.55%
XGBoost	0.67	0.78	0.72	0.15%
Autoencoder	0.58	0.74	0.65	0.24%

With fewer unnecessary customer declines, the supervised ensemble boosts precision more than triple times that of the rule-based system, and improves recall, too, which reduces the workload on analysts.

6.4 Market Risk Forecasting

Table 7. 25 percent VaR backtest = One-Day 99% VaR (2,520 days, 25 expected exceedances)

Model	Exceedances	Exceedance Rate	Volatility RMSE
Historical simulation	38	1.51%	0.0094
GARCH(1,1)	31	1.23%	0.0081
Gradient boosting	29	1.15%	0.0077
LSTM	27	1.07%	0.0072

The LSTM is closest to the expected exceedance rate of 1 percent, with the least volatility error; however, in the rare conditions of the crisis regime, this performance gap decreases.

6.5 Explainability and Fairness Diagnostics

Table 8. Governance Diagnostics for Credit Models

A sample of actual models is presented below: Examples of actual models are presented below:

Logistic regression	3.1 pts	Native coefficients	Low
Random forest	0.07	Medium	SHAP values 3.6 pts
SHAP values	0.09	4.0 pts	XGBoost
Neural network	0.12	4.4 pts	SHAP and surrogate model High

The more effective models exhibit a slightly greater degree of drift and a larger difference in the ratios of approval, so improvements in accuracy should take into account fairness and stability.

6.6 Mediation and Moderation

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Figure 4. Mediate and Moderate Model (see diagram below)

mediation and moderation model · path estimates

None of the two indirect effects exceeds 46 percent of the total effect; the accuracy indirect effect (0.21) is 46 percent of the total effect (0.46); the governance interaction is 0.15.

Table 9. Path Estimates for Risk Management Effectiveness

Path	Estimate	95% CI	
AI adoption → Effectiveness (total)	0.46	0.34 to 0.58	H1 supported
For every question, the support for each answer follows the adoption of AI.			
AI adoption → Predictive accuracy	0.58	0.46 to 0.70	H2 supported
Improved detection speed with AI	0.52	0.39 to 0.65	H3 supported
Indirect effect (partial mediation) through accuracy	0.21	to 0.31	H4 was supported (indirect effect).
AI adoption × Governance	0.15	0.04 to 0.26	H5 supported

The positive interaction effect indicates that institutions with better governance reap greater benefits, while the predictive accuracy effect indicates that it transmits about half of the total effect.

6.7 Summary of Hypotheses

Table 10. Hypothesis Outcomes

Hypothesis	Statement	Outcome
H1	AI has successfully promoted more effective risk management.	H1 AI has been effective in enhancing risk management effectiveness.
R2	AI models are more accurate than traditional models	Supported
H3	AI use accelerates risk identification	Sustained
H4	The AI effect is mediated by accuracy.	H4 Accuracy is a mediator of the AI effect.
H5	Governance strengthens the AI effect	Supported

7. Discussion

The results shown in the illustrations are consistent with the opinion that AI can enhance risk measurement when data are abundant and relationships are nonlinear, such as in credit and fraud. In market risk, regimes change and tail events are rare, with smaller gains and less stability. For each domain, the only thing that matters is accuracy; a model that, for whatever reason, cannot be communicated to a customer, tested by an independent group, or presented to a supervisor is a liability, no matter how good its AUC is.

Model risk due to complexity and drift, bias from historical datasets, manipulation by adversaries, third-party concentration risk, and over-reliance

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on automated decision making are the major risks for AI in risk management. With institutions adopting a lifecycle approach to AI models, rather than a one-off project, these risks can be managed.

Figure 5. AI Model Governance Lifecycle (as shown in the diagram below)

This is the model governance lifecycle, which captures the six stages of a governance cycle and one loop.

There is no model deployment without independent validation and monitoring results determine if it is retrained or retired.

7.1 Managerial Implications

1. Begin in domains where there is a lot of data labeled and decisions made often, like fraud or retail credit.

2. Ensure that a benchmark model is included with each complex model and provide a documented rationale for any override of the benchmark model.

3. Track stability, fairness and performance continuously and automatically trigger stability or rollback procedures.

4. Ensure human involvement in high impact or low confidence decisions.

5. Spend money on data quality and lineage as most failures in the model are the result of data.

7.2 Policy Implications

To enable safe adoption, supervisors can establish expectations on how to validate and explain AI, mandate inventories of AI models and material vendors, advocate for regulatory sandboxes, and encourage common standards for tests of fairness. Smaller institutions can profit without the compliance burden without having to pay proportionate costs.

8. Constraints and further studies

The illustrative results are based on simulated values and a limited number of families of models. In a real deployment, data drift, labelling delays, and adversaries who adapt occur. Future research could involve testing generative AI and LLM in credit analysis and compliance, federated learning for privacy-preserving risk models, causal and counterfactual explanations, and systemic risk (when many institutions use similar models).

9. Conclusion

AI enhances financial risk management by boosting the precision, speed, and extent of risk measurement, especially in credit and fraud. The benefits are dependent: it relies on data quality, model explainability, and disciplined model governance. AI institutions with proven capabilities and lifecycle can secure accuracy benefits and maintain acceptable model risk, bias, and

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regulatory exposure. Regulators can support the financial system to benefit from AI, without exacerbating instability, by providing proportionate guidance and establishing shared standards.

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