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Leveraging Machine Learning in Bank Risk Management

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ABSTRACT: As markets evolve, so too must bank practice. The increase in complexity of financial markets, the volume of transactional data, and the demand for great transparency regarding bank operations all place pressure on bank risk management practices. Traditional methods of financial risk management, credit and liquidity risk more specifically, that rely on historical data and linear models, sometimes fail to capture the nonlinear and interconnected nature of risk. This paper displays that artificial intelligence (AI), namely supervised machine learning (ML) and neural networks, will become imperative in improving the methods banks employ to mitigate financial risk. This paper also addresses commonly expressed concerns within AI and ML research and bank risk management literature, such as explainability and implementation, and proposes a unique framework for regulatory compliance of banks with regulatory institutions. By reviewing documented AI applications in banking and other data-intensive fields, this review underscores successful use cases that can be extended into credit and liquidity risk management and identifies best practices when doing so. This work contributes to the literature mainly by proposing structured pathways to internal integration and regulatory compliance.

KEYWORDS: Robotics and Intelligent Machines, Machine Learning, Risk Management, Credit Risk, Liquidity Risk.

Introduction

Artificial intelligence (AI) is the wide-ranging field of science that describes computer algorithms that give non-human entities the ability to reason, solve, and compute with human-like or superior proficiency. Currently, we are witnessing the proliferation of AI and its subsectors, such as machine learning (ML), into many popular and relevant fields. In the past decade, AI has made exponential leaps in progress, from the founding of DeepMind, an AI research lab that was later acquired by Google, in 2010, to the recent release of OpenAI's GPT-5, available to their more than 700 million weekly users.

AI is actively playing a large role in banking, yet its role stands to become much larger. Data taken from major commercial banks show that AI is already being used to detect fraud in online banking and for digital chatbots that interact with clients and employees to provide information and feedback (Oyeniyi *et al.*, 2024).[1] Morgan Stanley, a large commercial bank, has implemented OpenAI's GPT-4 model into their workflows, which OpenAI says has "enhanced how financial advisors access the firm's knowledge base and respond to client needs."[2] Much of the integration by these firms is successful, with many banks exhibiting higher efficiency after implementing AI into internal operations.[3] Yet, banks still look for further opportunities to optimize their workflows and tasks with artificial intelligence, especially as financial markets expand.

Financial markets are expanding at extremely rapid paces, both in scale and complexity. In the early 2000s, technological change made it easier than ever for consumers to access many financial services and cheaper for providers to deliver them.[4] Lowering the threshold needed for someone to make a deposit or take out a loan, for example, allowed there to be a market response to meet lower-income consumers' demands and create exciting opportunities for new demographics. Emerging markets have also experienced substantial growth, increasing the level of integration and interconnectedness in our global market.[5] Markets in Asia, Latin America, and Africa experienced heightened foreign investment, robust economic development, and rising middle classes. However, these benefits brought along challenges, including increased market volatility and systemic risks. Increased interconnectedness and the emergence of larger consumer bases are in themselves both a benefit and a risk, as they give opportunities to new consumers but introduce higher chances of default, liquidity mismatches, and other contagion effects across institutions. The traditional methods to handle risk simply cannot keep up.

This paper offers artificial intelligence as the solution to mitigate bank risk more efficiently, as the successful use cases of AI decision making and fraud prevention suggest that it can be extended into credit and liquidity risk mitigation. This study also offers best practices when implementing AI practically into daily workflows and internal structures, and seeks to address commonly expressed concerns with AI in the financial industry.

The literature review covers traditional financial risk methodology and AI's current place in the risk management field. It covers fields such as stress-testing, early warning sign prediction, and credit risk evaluation. This is key for understanding why traditional financial risk methods cannot continue to withstand increasingly complex financial markets and how AI is currently being leveraged.

The discussion of AI methods and future pathways posits that AI is the future of bank risk management. This section not only explains the most applicable AI and ML algorithms, but works to address explainability and interpretability concerns, regulatory compliance concerns, and issues regarding real-world accuracy. Currently, AI is most leveraged in sensor

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networks, wireless networks, and even accounting to process and analyze large amounts of data.[6-9] AI undoubtedly has the capacity to better serve us than traditional methods in bank risk management, and its adoption should be made immediately.

The last section concludes.

This paper aims to contribute to the literature by addressing the most expressed concerns when discussing the feasibility of AI being applied to banking. It prescribes future steps to ensure that banks can integrate these AI models smoothly into their existing internal operations, maintain constant oversight of their models, interact with their regulatory counterparts, and address all explainability and interpretability roadblocks.

■ Literature Review

The following literature review can be considered as both reviewing how AI is being used in the banking industry more broadly and establishing the urgency for AI to expand further into risk management, where traditional methods will not suffice as markets expand. It also sets the groundwork for the subsequent discussion of AI and ML models that is more in-depth.

AI in Banking:

Prediction, the fundamental premise of risk management, is becoming a strong suit of AI in banking. ML can make increasingly accurate predictions in areas such as asset risk premiums,[10] financial credit risk,[11,12] and liquidity risk via stress testing and advanced decision networks and modeling.[13,14] Supervised machine learning methods allow for more efficient adaptation and accuracy in prediction, as it uses data sets with pre-marked data. This makes it one of the most common forms of ML.[15] Ensemble learning, which compiles a group of individual algorithms, and hybrid models, which compile different ML models, have been explored in predicting default.[16,17]

AI is also being experimented with in bank stress-testing. Stress-testing is a primary tool used by commercial banks to understand the level of capital resources to undergo certain levels of risk, should they take it on. A support vector machine (SVM) modeled to forecast risk in a sample of 1443 U.S. banks, including 481 that failed from 2007-2013, was 99.22% overall accurate in predicting insolvency in banks.[18] Other supervised ML models have also been highly successful in interpreting risk in bank stress-testing.[19,20]

Explainability, however, is a common challenge that has been acknowledged within the financial industry and elsewhere. The application of neural networks and DL is the next step after implementing ML algorithms, as they can drastically improve beyond the capabilities of general ML.[15,21] However, DL networks and algorithms have encountered issues with being "black box" and incomprehensible in their decision-making.[22,23] The "black box" problem needs to be solved for banks and large financial institutions to rely on their decisions for risk mitigation. Banks, ultimately, must understand the rationale behind decisions before they act, especially in domains such as risk management.

Traditional Financial Risk Management Methods:

Traditional financial risk management methods involve large amounts of historical data, simplified statistical models, and regulatory frameworks that aim to protect banks from liquidity and credit risk.

In credit, classic approaches to mitigating risk rely on linear statistical techniques such as logistic regression to analyze financial ratios and large data sets. Doko *et al.* verified that across numerous types of credit risk assessment, including credit scoring and loan approvals, logistic regression and linear regression models were among the most common.[24] These models are reliable when it comes to transparency and consistency with linear assumptions in data sets and are suitable for regulatory and supervisory purposes. Yet, these models' dependence on linear assumptions limits their ability to capture nonlinear relationships, a crucial element in improving validity measures.[25]

Liquidity risk management traditionally subsists on liquidity regulations and quantitative buffers. Metrics introduced by the Basel Committee on Banking Supervision, such as the Liquidity Coverage Ratio (LCR), help banks withstand short- and medium-term disruptions.[26] The LCR maintains that banks with more than $50 billion in total assets (LCR banks) must hold a portfolio of high-quality liquid assets large enough to sustain a 30-day stress period of high cash outflows. Macchiavelli and Pettit find that regulations regarding metrics such as the LCR can slow efficiency, as liquidity holdings and maturities are increased.[27] These measures improve stability by preparing financial institutions for worst-case scenarios, yet they can constrain credit supply.

Another vein of literature underscores the role of transparency in risk management. Ratnovski argues that transparency plays a central role in covering large shocks to liquidity, and that liquidity requirements should be complemented by measures that increase bank incentives to adopt transparency.28 Risk management is not solely a matter of analyzing historical data trends and maintaining buffers, but of information disclosure and appropriate governance quality. However, transparency and governance will not be able to fully mitigate spikes in financial risk.

These studies highlight the strengths and weaknesses of traditional methods. They provide standardized frameworks that fit well with regulatory needs, but they struggle when forced to grapple with nonlinear and complex data sets and the adaptive nature of modern financial markets. These shortcomings motivate interest in AI and ML practices, which this paper discusses as more flexible and accurate tools for credit and liquidity risk management.

■ Discussion of AI Methods and Future Pathways

Simply put, the future of bank risk management — in general, but, for this paper, in credit and liquidity risk — is AI. ML algorithms, and DL trees and networks that can consume and learn from more data than is currently possible, will allow banks to not only keep up with the bank risk management crisis but advance past it. This section will cover solutions to credit and liquidity risk that are currently explored, as well as make suggestions for implementing new methods in the future and avoiding challenges that banks will encounter.

AI in Credit and Liquidity Risk Management:

Risk management for credit risk and liquidity risk is not so dissimilar. Mitigating credit and liquidity risk requires ensuring borrowers are capable of and willing to repay and securing reliable funding sources to meet short-term and unforeseen obligations, even in turbulent macroeconomic conditions. In the case that many borrowers withdraw from a bank, banks need to be liquid enough to meet these demands. Bank credit and liquidity risk are intertwined, and it is for these reasons that the methods to mitigate both risks will be quite similar.

In the domain of credit risk, Generative AI and ML algorithms have been utilized to increase accuracy in default predictions through more accurate risk modeling and scenario analysis. A systematic review of default prediction models in 250 published research papers conducted by Alvi *et al.* discovered highly successful predictive models.[29] From neural networks, with prediction accuracy as high as 96.15%, to combinations of hybrid models (AI techniques — ML and DL) and traditional methods (e.g., logistic regression) that report superior accuracy to traditional methods alone, AI and ML outperform benchmark models consistently.[29] Random forest models, formally introduced by Breiman, use an ensemble learning method that compiles multiple decision trees.[30] They, too, outperform baseline models such as autoregressive ones in areas such as predicting market conditions in the money market and FX (foreign exchange) markets.[31] This ability to accurately predict market conditions allows banks to make better-informed decisions when it comes to risk management.

As for liquidity risk, multiple models are used for discovering hidden patterns and outlining relationships in liquidity behavior. While supervised learning methods use pre-labeled data in training, unsupervised learning uses unmarked data. ML clustering methods, a form of unsupervised learning, are particularly useful in identifying hidden patterns and have been widely utilized in financial risk analysis.[32] Kou *et al.* utilized a multiple criteria decision making (MCDM) approach to evaluating clustering methods in financial risk and found the method to be effective.[33] Since liquidity risk is inherently relationship-driven, Graph Neural Networks (GNNs) are also useful in anticipating its dynamics. GNNs do not only observe individual pieces of data, but the relationships between them (like a function on a graph) and have thus become a leading approach for building predictive models.[34] An experiment conducted by Xu *et al.* modeled the entire financial market in a graph and used a GNN to predict market volatility.[35] The results showed that the GNN was superior in the field of financial volatility prediction. While the model in the experiment predicted market volatility, the broader implications are that GNNs have a superior ability to make accurate predictions despite complex relationships in data sets. GNNs that predict market volatility could, too, be influential in mitigating liquidity risk, given the traditionally inverse relationship between volatility and liquidity,[36] and the inverse relationship between market liquidity and liquidity risk.[37]

Recommended AI Methods for Risk Mitigation:

There is an extensive list of AI models that could be used in bank risk management. This section will cover a smaller selection of the models that may be more appropriate for risk management in the financial industry, divided into two categories. The first category consists of more classical supervised ML algorithms, namely GBMs (Gradient Boosting Machines) and RFs (Random Forests). The second category consists of deep learning (DL) neural network systems, namely LSTM (Long Short-Term Memory) and CNNs (Convolutional Neural Networks).

Classical Supervised ML Algorithms:

Supervised learning requires human-labeled input and output data sets to learn.[38] Classical supervised learning algorithms are more traditional methods of pattern recognition, such as decision trees, GBMs, RFs, and logistic regression, and they contrast with newer neural network models that analyze more complex relationships.

GBMs should be widely adopted in credit and liquidity risk management, given their ability to iteratively minimize prediction error. Gradient boosting is an ensemble learning method that compiles multiple decision trees. The idea of this algorithmic approach to predictive modeling was introduced by Jerome H. Friedman, and the method has since proven to excel at predictive modeling tasks.[39] The individual decision trees are not highly accurate on their own, and are prone to making mistakes, yet when combined in a method called “boosting,” the sum of these less accurate decision trees is one large tree that has learned from the previous trees’ mistakes and is thus far more accurate.[40,41]

The most popular GBMs are eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM). XGBoost expands its decision trees level by level (Figure 1), keeping them stable, whereas LightGBM expands its decision trees using leaf-wise tree growth (Figure 2), developing leaves in the tree that will result in the greatest error reduction.[42,43] Level-wise tree growth keeps trees balanced but is slower than leaf-wise tree growth. However, it increases stability and reduces the chance of overfitting, which is a risk that increases as trees grow deeper due to leaf-wise expansion.[44]

As for applications of both XGBoost and LightGBM to financial risk management, a credit risk assessment in digital lending platforms conducted by Ying *et al.* found that a hybrid ML model centered around LightGBM was highly effective in predicting borrower default risk and filtering key borrower attributes.[45] XGBoost and LightGBM were also cited as being highly trustworthy and accurate in predicting loan defaults, illustrating their promising nature in the realm of mitigating credit risk.[29] Banks should implement multiple types of GBMs to leverage the full adaptability and prediction accuracy of these models. It is also important to keep in mind that diversity of models is crucial as well, as the tree growth methods employed by specific GBMs can result in overfitting, while others can result in a slower adjustment to new data.

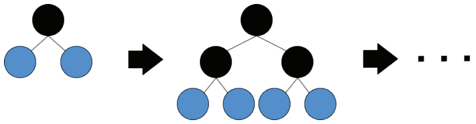

Figure 1: Level-wise tree growth in GBMs. This figure depicts how the decision trees are improved layer by layer, in tandem with each other. The primary benefit of this tree growth method is that it keeps the rate of evolution stable.

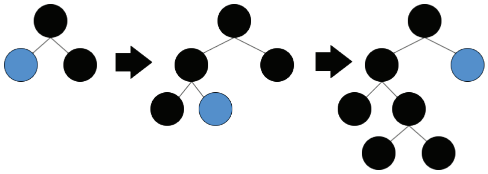

Figure 2: Leaf-wise tree growth in GBMs. This figure illustrates a model with more pointed development of decision trees. This targeted approach helps eliminate errors at a quicker rate than the level-wise growth method.

Another classical supervised ML method that would be highly effective is RFs, as their ensemble learning and voting system offers high adaptability and can reduce variance and overfitting. RFs, unlike GBMs, utilize, loosely put, a voting committee. The decision trees that compose each RF are trained with samples from a training set with replacement, called a bootstrap sample.[46] Then, bagging – a process in which more data with replacement is injected – reduces correlation between the individual trees. Finally, RFs have two methods when making decisions. If they are presented with a classification task, the individual trees will take a vote, and the majority vote will yield the predicted class, whereas for a regression task, the votes from individual decision trees will be averaged.[46] This allows RFs to majorly reduce the issue of overfitting, becoming too familiar with the training data and performing poorly when given new data. GBMs will make one ensemble of decision trees to perform tasks, so if that model becomes too comfortable with its training data, the entire algorithm has succumbed to overfitting. The RF, because of its voting system, surpasses other methods, including GBMs, in its ability to handle model overfitting, as one decision tree does not hold all the deciding power.[47]

As for applications of RFs in bank risk management, a study of early liquidity risk warnings done by Drudi and Nobili found that random forests, especially when combined with XGBoost and the logistic LASSO, are highly effective in preventing overfitting and achieve low percentages of false negatives and false positives.[48] In terms of readability, a significant attribute of RFs is their voting system and non-correlated decision trees, making their outputs easily interpretable.[49] In areas of financial risk where transparency is a primary concern for AI models, RFs will be a good fit. In liquidity risk specifically, RFs can be trained on institutional net flows, loan demand, market funding conditions, and more to help banks predict early warning signs of liquidity risk.

Supervised DL Models:

Supervised deep learning models are a subset of supervised machine learning methods that use artificial neural networks to process and analyze information,[50] often complex and non-linear relationships. Some common types of DL models include feedforward neural networks, LSTMs, CNNs, and Generative Adversarial Networks (GANs), though this section will focus solely on LSTMs and CNNs.

Two supervised DL models that can be adopted by banks to combat credit and liquidity risk are LSTMs and CNNs. Both are neural networks able to identify dependencies and relationships within data, though they have their differences. LSTMs have memory cells and use a three-gate system (input/forget/output) that determines what information should impact the input, whether the internal state should be reset to 0 or forgotten, and what should be allowed to impact the cell's output.[51] The three-gate system and usage of memory cells allow for the LSTM model to adapt to dependencies over long periods of time.

CNNs are not too dissimilar. They consist of three main layers: input, hidden, and output.[52] There are also other classifications of the layers into what are convolutional layers and pooling layers,[15] yet the essence of the model remains the same. An input, such as an image or signal, will be broken down in a process called convolution, where each part of the input will be reassigned a mathematical value, combined with other values called weights, and ultimately yield a two-dimensional array called a filter (Figure 3). These filters search for different things within the input (for an image, maybe one filter searches for curved lines, another for straight, another for color, etc.), pool the information together in the pooling layers, and then output a classification or identify a motif within the input information (Figure 4). A CNN's framework can allow it to identify local patterns within data sets using its learnable filters and down-sample with its pooling layers.

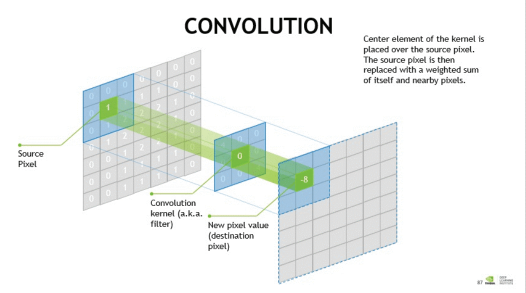

Figure 3: The process of convolution. A kernel, or filter, is placed over a source pixel or subsection of data and performs a weighted sum at the position, resulting in a new value for the pixel or subsection. This process helps reduce the number of trainable parameters significantly when performing hierarchical feature extraction, increasing efficiency.

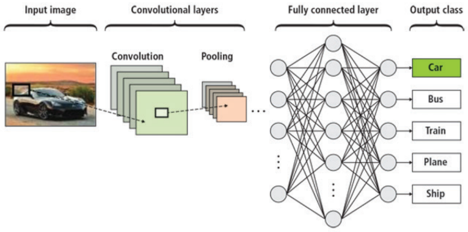

Figure 4: Layers and architecture of a convolutional neural network. After the CNN is given an input, multiple layers begin the process of convolution (Figure 3), piece together information in the pooling layers, and work to classify some pattern or identity of the input. This architecture underpins the model's ability to learn discriminative features.

LSTMs and CNNs can be used for time series forecasting, and outperform many other models, with LSTMs obtaining the most accurate forecasts (Lara-Benítez *et al.*, 2021).[53] Zhang *et al.* predicted price movements from limit order book data of cash equities in the London Stock Exchange, using convolutional layers to capture the spatial structure of the limit order books as well as LSTM modules to capture longer time dependencies.[54] The model delivered remarkably stable results and outperformed many other algorithms on the benchmark data set. LSTMs and CNNs can be paired in financial risk management to identify shifts in intraday flows, wholesale funding spreads, and even the news (using convolutional filters). Market microstructures can be monitored, and asset prices can be tracked following the same LSTM-CNN stack structure that Zhang *et al.* employed. Teams in banks will be able to identify early warning signs in both liquidity and credit risk with a combination of both LSTM and CNN models.

Best Practices and Possible Challenges:

Many challenges will arise when attempting to effectively implement AI into banks' internal structures. As it stands, AI is still a relatively new technology, and it is advancing at an extremely rapid pace. If we fail to take certain precautions when introducing AI and ML into workspaces within large financial institutions, or an institution for that matter, we may end up being unable to control what the outcomes are.[55]

One pressing challenge that must be dealt with is the "black box" problem. Explainability and transparency are crucial not just for regulatory compliance but for sound decision-making within the financial industry. Many researchers have expressed their concerns about the need for explainability in bank risk AI.[29,56,57] A feasible solution to this issue is the implementation of explainability frameworks such as SHAP (SHapley Additive exPlanations) by Lundberg and Lee in post-hoc justifications of model predictions.[58] The traditional Shapley value by Lloyd Shapley was popular in game theory (1952).[59] It used a mathematical formula to find the average contribution by multiple players to the outcome of the game. However, it wasn't well-suited for ML predictions, so SHAP restructured the traditional value to arrive at weighted averages for multiple features in a model that drove its prediction. What researchers have found is that SHAP is highly accurate and effective when it comes to model interpretability.[29] Best practice for the sake of full transparency is for SHAP's discoveries to be presented alongside visual output plots and with simple language.[60] Utilizing SHAP and eventually future explainability frameworks in post-hoc justification of model prediction will slowly remove the concern of a lack of transparency and explainability in leveraging AI in risk management.

Another frequently expressed concern is that of regulatory compliance.[56,61,62] The financial industry is characterized by strict compliance with both federal and international regulations. AI will need to fit into this web of regulations as well (Figure 5). A recommendation that many have is forming an "AI strategy."[63] This section will build on the idea of an AI strategy and highlight core elements of what the standard AI strategy for bank risk management should look like. One element of the banks' AI strategy is to have a human team that provides constant oversight of models to ensure effectiveness, explainability, and prevent the model from deviating from its intended purpose (this could look like bias or some form of misinformation). Another large element would be for banks and agencies to collaborate on developing proper regulations for AI models. The current Federal Reserve Supervision and Regulation Letter, SR 11-7, of Guidance on Model Risk Management was last updated on April 4, 2011.[64] There is no mention of AI within the document, though it should be noted that the letter itself is quite broad and could be argued as applying to any method, AI or not. Not only should there be a development of regulatory frameworks for AI models, but there should be a framework for the official auditing of said models. Auditing is crucial in the financial industry and will be useful in monitoring AI and keeping it on track with its intended purposes. Agencies need to create branches designated to perform AI audits, similar to how the International Atomic Energy Agency audits and inspects virtually every country's nuclear program. The same agencies that perform audits should also meticulously record each bank's model within a registry for ease of access and to ensure transparency and consistency in compliance assessments. Finally, proper documentation and public reporting of how AI models are being used and advanced is necessary for public transparency.

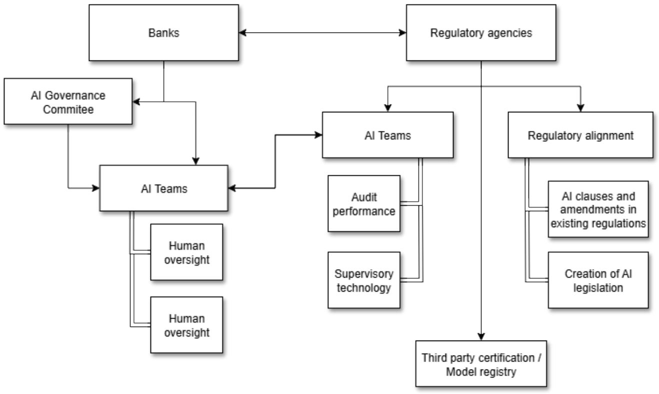

Figure 5: Proposed AI regulatory compliance framework for banks and regulatory agencies. This figure depicts the relationship that banks and regulatory agencies will have on multiple levels. This proposed structure synthesizes regulatory, technical, and human governance mechanisms into a unified model.

Banks also need to ensure that their models are effective in real-world situations, not just in simulations. This issue goes hand in hand with ensuring there is adequate availability of high-quality data to train these models. AI Teams need to be integrated seamlessly with the rest of a bank's existing segments and must be able to freely and easily draw upon information in the firm's databases. The best way for banks to increase the certainty of successful performance of AI models in real-world scenarios is by feeding them and training them on as much available, diverse, realistic information as possible.[56] The best way for this to occur is if the AI Teams that provide human oversight to and train these AI models can be integrated smoothly into the established operational structure of the bank.

Finally, banks will need to ensure that AI is implemented practically and smoothly into existing operational frameworks. AI Teams need to roll out models in tandem with introducing the best practices for usage. Banks can also create "AI sandboxes,"[65] where AI tools can be experimented with in safe environments with practice data, giving humans who will work side-by-side with these models an opportunity to grow comfortable with how these models work. Dashboards need to be developed to not only ensure proper interpretability and readability, but also quick and easy access to AI risk management tools. The AI Team in the above framework should be able to address any concerns that arise. In essence, banks must ensure that they introduce AI risk management tools in an appropriate fashion and utilize the best practices when doing so.

Conclusion

The results of this paper suggest that banks need to implement AI into their internal structures to improve risk mitigation. AI and ML models, namely GBMs, RFs, LSTMs, and CNNS, can be leveraged in credit and liquidity risk management. These methods present highly advanced ways of consuming and interpreting high quantities of complex, non-linear data, which is abundant in finance. Models such as GBMs and CNNs can identify complex and hidden relationships in large data sets, allowing banks to identify trends in borrower behavior and funding source stability. There are also upsides to having a diversity of AI models, as each has its own downsides that can be compensated for by another's strengths. However, it is key for banks to understand that there is a plethora of challenges that will arise in adopting AI strategies in risk management. Commonly expressed issues, such as explainability, data availability, public transparency, and regulatory compliance, will need to be addressed and handled accordingly. However, there are many feasible solutions to each of these problems, such as interpretability methods like SHAP and readability frameworks that can be implemented to ensure there is no confusion. Banks must also take the necessary precautions in implementing AI risk tools into the existing operational taxonomy and allow AI Teams the full bandwidth of correcting complications that arise. With time, the financial industry will be able to employ AI strategies in internal risk management structures to combat the impending global risk management crisis.

There are, inevitably, issues that will arise that were not addressed in this paper. For one, ethical concerns were not discussed. There are possibilities yet to be seen for data breaches when it comes to risk management models and the data sets that they work on. Banks must also work to ensure there is sufficient accountability should their models develop biases or deviate from their intended purpose, and future research can address how this developing method of risk management will affect the job market and future workforce in banks. Many of these issues have yet to become pressing, though they will be poignant as time passes, and will be better served in future research.

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