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ADVANCING CREDIT RISK MODELING THROUGH GENERATIVE ARTIFICIAL INTELLIGENCE: METHODS, APPLICATIONS, AND CHALLENGES

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ABSTRACT

Credit risk modeling is an important component of the financial decision-making process because it determines whether or not credit is given and whether or not the credit given is appropriately used. Classical approaches to logistic regression, scorecards, and sophisticated machine learning techniques have proven helpful in providing institutions with practical prediction capabilities. The same issues, however, confuse these models: unstructured financial data cannot be modelled, rare default events are challenging to model, and there is always a trade-off between model accuracy and model explainability. Recent breakthroughs in generative artificial intelligence (AI) provide a new potential pathway to overcome such inadequacies.

The paper explores the potential use of generative models such as generative adversarial networks (GANs), variational autoencoders (VAEs), transformer-based language models, and some of the newer diffusion methods to create more advanced credit risk models. Generative AI practices are assessed on their capability to produce realistic borrower data, model rare credit occurrences, credit scoring with multi-modal *data, and dynamic stress testing conditions. It also discusses how generative models can support and augment the existing methodologies in portfolio-level fraud detection, anomaly detection, and risk assessment. Given these opportunities, its adoption in practice presents a challenging problem. Compliance with Basel III/IV and data protection regulations, algorithmic bias and unfair lending outcomes, extensive computational needs, and interpretability of black-box models have become of concern. The barriers to these must be overcome by designing explainable generative AI, Just and Equal education systems, and a governing construct that addresses institutional and regulatory requirements.*

A synthesis of current approaches, applications, and issues is presented in this paper to consider the role of generative AI as not being merely a technical innovation but also a future opportunity in credit risk modeling, as it mandates a fine line between innovation and trust and compliance in the global financial system.

Keywords: Credit Risk Modeling, Generative Artificial Intelligence, Synthetic Data in Finance, Financial Risk Management, Explainable AI in Banking, Regulatory Compliance in AI, Machine Learning for Credit Scoring

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1. INTRODUCTION

The model of credit risk will continue to be a staple of financial risk management, as it allows financial institutions to assess the reliability of borrowers, price credit accordingly, and comply with regulatory capital requirements (Bhat, Ryan, and Vyas, 2019; Rampini, Viswanathan, and Vuillemey, 2020). Formal and quantitative approaches to default forecasting and exposures management in institutions have been and still are required over the past decades as a result of recurring financial crises and heightened regulatory pressures (Bülbül, Hakenes, and Lambert, 2019; Kiptoo, Kariuki, and Ocharo, 2021).

1.1 Methods of Credit Risk Modeling Used in Classical

Standard credit risk evaluation models are statistically and econometrically based. The original scorecard models were transparent and explainable, and accordingly, they could be applied to the retail banking and credit card portfolios (Sousa, Gama, and Brandao, 2016). The logistic regression model that fails to account for the non-linearity and gets stifled by the non-homogeneous factors among the borrowers is the most prevalent model and tool to estimate the probability of default (PD) (Yaneko et al., 2021). Predictive accuracy has improved, and the handling of raw high-dimensional datasets has become feasible with the introduction of machine learning (ML)-based algorithms, including Random Forests (RF), Support Vector machines (SVM), and ensemble learning (Papouskova & Hajek, 2019; Mashrur et al., 2020).

However, despite such developments, there are continued restrictions on current practices. The organization and past data also limit the possibility of identifying nonlinear borrower behaviour, unstructured financial information, and relatively small numbers of defaults as those created by systemic shocks such as COVID-19 (Telg, Dubinova, and Lucas, 2023). In addition, its problem also lies in the fact that most machine learning models cannot be interpreted or trusted, which is controlled by the character of their application (Mishchenko et al., 2021; Singh, 2024).

Table 1: Comparison of Traditional Credit Risk Models

Model Type	Strengths	Weaknesses	Typical Use Cases
Scorecards	Simple, interpretable	Limited with complex/non-linear data	Retail banking, credit cards
Logistic Regression	Strong baseline, easy to explain	Struggles with non-linear relationships	Default prediction, SME lending
Machine Learning (RF, SVM)	Higher accuracy, handles big data	Opaque, prone to overfitting, less transparent	Large loan portfolios

1.2 The Emergence of Generative Artificial Intelligence

Generative Artificial Intelligence (GenAI) is a new paradigm shift in the capability of modeling financial risk. New data can be generated through generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), transformer-based large language models (LLMs), and diffusion models, which may also learn latent borrower patterns and combine multimodal data (text-rich financial disclosures, customer communications, and macroeconomic narratives) (Kalota, 2024; Yu & Guo, 2023). These solutions are becoming a topic of discussion in both practitioner and scholarly settings as a transformative data generation, fraud detection, and regulatory reporting tool (Karangara, Shende, and Kathiriya, 2024; Mullankandy, 2024; Padmanaban, 2024).

Until then, the generative AI dualism of innovation and increased flexibility is rather an academic/business generalization: the new applications of ethics, explainability, and adherence to regulations and sustainability objectives will have to be negotiated (Barros, Prasad, and Śliwa, 2023; Truby, 2020; Liu & Huang, 2022). The key research question as institutions go digital is:

What are the best ways that generative AI can improve credit risk modeling without sacrificing innovation, interpretability, or regulatory compliance?

To answer this question, this paper synthesizes approaches, applications, and issues by offering a systematic framework of how generative AI can transform financial risk management.

2. GENERATIVE AI METHODS FOR CREDIT RISK

Recent accelerated progress in Generative Artificial Intelligence (GenAI) has brought a novel set of modeling instruments, which can solve decades-old credit risk analysis challenges, including data scarcity, rare-event forecasting, and unstructured borrower information integration. In contrast to classical predictive models, which are based on historical data and deterministic models (Sousa, Gama, and Brandao, 2016; Yanenko et al., 2021), generative models acquire data distribution information and even generate new and realistic borrower or default situations (Mashrur et al., 2020; Parbat, 2024). The subsections below identify the most applicable generative approaches used on credit risk: Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), transformer-based large language models (LLMs), diffusion models, and hybrid systems combining generative methods with known approaches to machine learning.

2.1 GAN on Synthetic Borrower Data and Default Data

GANs are especially useful in credit risk environments with a small amount of default data or a skewed collection of borrowers. A different way GANs can be used is to augment credit scoring models, or to simulate rare events like default in stressful conditions, by generating artificial, yet statistically plausible samples (Kalota, 2024; Barros, Prasad, and Śliwa, 2023). The second drawback of financial institutions is the low default portfolio, and the rules will require them to estimate risk based on limited risk observation (Bhat, Ryan, and Vyas, 2019). This kind of model would make GANs workable because realistic distributions of infrequent defaults among borrowers would be produced, but our model will suffer from training instabilities and mode collapses that would reduce the fidelity (Papouskova & Hajek, 2019).

2.2 Variational Autoencoders (VAEs) for Probability Distributions

VAEs are generative models trained over latent representations of the attributes of the borrower, as well as the latent structure of repayment patterns. In contrast to GANs, VAEs are more interested in estimating a probability distribution. They can thus be extended to predict the probability of default (PD) of non-homogeneous groups of customers (Yanenkova et al., 2021). Their produced samples may be less fiducial than GANs, but their probabilistic behaviour meets regulatory requirements of risk parameter estimation (Rampini, Viswanathan, and Vuillemey, 2020). Ensemble learning can also be applied with VAEs to model consumer risk in two phases with a trade-off between statistical discipline and flexibility (Papouskova & Hajek, 2019).

2.3 Text-Rich-Data Transformers

Transformer-based LLMs use generative AI on unstructured textual domains like loan applications, customer communication, and contractual documentation. This ability to extract and model the semantic meaning of natural language also allows financial institutions to analyze creditworthiness beyond numbers (Kelly, Sullivan, and Strampel, 2023; Yu & Guo, 2023). Indeed, an LLM can be employed to detect delicate signals of a distressed client in the correspondence of the borrower, or detect sophisticated conditions in legal contracts. They also need big data in training and computing, making it challenging to apply to the resource-restricted environment (Mishchenko et al., 2021; Singh, 2024).

2.4 Diffusion Models as Emerging Tools

Diffusion models are a relatively new invention, but perform well in high-dimensional data distributions. They are relatively new to financial applications but demonstrate potential in all three portfolio-wide tests, stress testing, and systemic risk propagation tests (Karangara, Shende, and Kathiriya, 2024). More stable diffusion models can benefit GANs by refining noisy data to structured outputs, which are more expensive to compute (Mullankandy, 2024). Additional techniques to embed diffusion models in credit risk models would continue to contribute to the literature on macroprudential oversight in the future, as they can help represent systemic processes (Liu & Huang, 2022; Truby, 2020).

2.5 Generative and Hybrid ML

Combination methods involving traditional ML and generative methods are starting to be studied in credit risk cases. The generative models applied with ensemble methods will help institutions to achieve the predictive power and, at the same time, interpretability (Papouskova & Hajek, 2019; Telg, Dubinova, and Lucas, 2023). One such example is GAN-generated borrower sets that can be used as inputs to either gradient boosting models or neural networks, which positively impact performance without affecting the transparency criteria regulators require (Singh, 2024; Padmanaban, 2024). The given dual framework helps fill the gap between the innovative implementation of AI and the compliance-driven culture of financial institutions (Kiptoo, Kariuki, and Ocharo, 2021; Mishchenko et al., 2021).

Table 2. Generative AI Techniques in Credit Risk Modeling

Method	Key Strengths	Limitations	Example Application
GANs	Synthetic rare-event data	Training instability, mode collapse	Default event simulation
VAEs	Captures latent borrower features	Lower fidelity compared to GANs	Probability of default distributions
Transformers	Handles unstructured text	Requires large training data, expensive	Credit history & loan doc interpretation
Diffusion	High-dimensional modeling	Still emerging, computationally heavy	Portfolio-wide stress testing
Hybrid ML+GenAI	Balances interpretability & power	Complexity in integration	Ensemble credit scoring

3. APPLICATIONS IN FINANCIAL PRACTICE

GenAI has progressed beyond theoretical exploration and is being successfully applied in financial risk management, where the upside of its application is far more than incremental efficiency improvements. GenAI allows financial institutions to model complex realities, create synthetic data, and respond to emerging uncertainties in a way that traditional models do not, compared to traditional credit risk tools (logistic regression, cost-risk modeling, or heterogeneous ensembles), which are highly dependent on past, structured data (Papouskova & Hajek, 2019; Yanekova et al., 2021). This area discusses the key areas in which GenAI is transforming credit risk modeling and practice.

3.1 Synthetic Data Generation for Low-Default Portfolios and Rare Events

One overriding weakness of credit risk management is the lack of data on defaults, particularly on portfolios where default has historically been low. This is a limitation on the calibration of default probability (PD), loss given default (LGD), and exposure at default (EAD) models (Sousa, Gama, and Brandao, 2016; Bhat, Ryan, and Vyas, 2019).

Generative AI can be used in this regard to:

- Synthetic borrower data created with Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) recreate statistical default characteristics.

- Greater machine learning model training to support greater resilience to extreme yet realistic events (Parbat, 2024; Mashrur, Luo, Zaidi, and Robles-Kelly, 2020).
- Regulatory judgment is important because institutions can access more of the what-ifs, which helps them plan capital adequacy.
- Tail-risk reduction, reducing the under-statement of the extreme performance of low-default portfolios.

3.2 Credit Scoring Enhancement with Multi-Modal Datasets

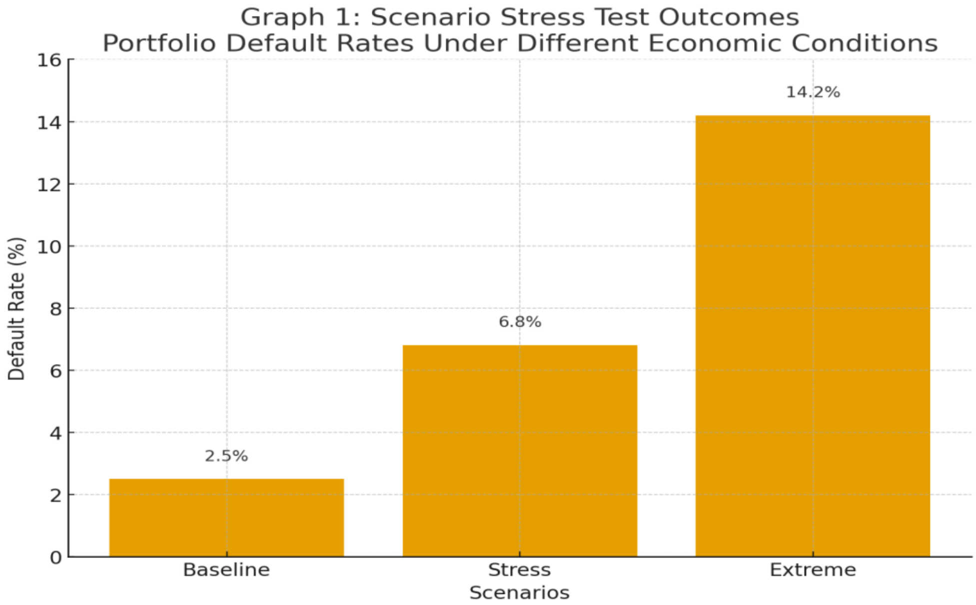
Conventional credit rating has been restricted to structured entities like income, debts, and repayments. The financial participants are more incentivized to utilize the unstructured and semi-structured information to operate the new digital finance (Mishchenko et al., 2021).

The AI-generated can add to credit scoring by:

- Combining multi-modal information, such as text loan applications, customer communications, and online transaction patterns.
- Applying transformer-based models and LLM to make sense of unstructured text and behavioral data.
- Aside from a linear model, more effective scoring engines need to be built to differentiate high- and low-risk borrowers more effectively via flexible and situational scoring (Kelly, Sullivan, and Strampel, 2023; Garcia-Penalvo, Llorens-Largo, and Vidal, 2024).
- Decreased information asymmetry allows for fairer credit analysis when dealing with various borrower populations.

3.3 Scenario Generation and Stress Testing for Regulatory Compliance

Basel Accords also ban stress testing that would have the institutions test the strength of their portfolios in periods of economic slowdown, unemployment shocks, or liquidity crises (Rampini, Viswanathan, and Vuillemey, 2020). Both classical scenarios and the models are narrow-ranged and linear as they generate estimates of risk exposure of low scope (Telg, Dubinova, and Lucas, 2023). GenAI allows auto-generating macro-economic and borrower-specific scenarios and lets institutions simulate cascading portfolio effects more faithfully. Not only can it increase the level of compliance with regulations, but it also allows adopting aggressive approaches to allocating capital (Karangara, Shende, and Kathiriya, 2024; Singh, 2024).



Graph 1: Scenario Stress Test Outcomes

A comparative stress-testing chart would display portfolio default rates (%) under three conditions:

- **Baseline Scenario** – reflecting normal economic stability.
- **Stress Scenario** – simulating a moderate downturn.
- **Extreme Scenario** – capturing systemic shocks such as combined market crash and high unemployment.

The illustration underscores how GenAI models can generate non-linear, fat-tailed outcomes that traditional stress models may overlook, revealing vulnerabilities hidden under "average-case" assumptions.

3.4 Fraud Detection and Anomaly Monitoring

Fraud credit activity and abnormal borrower behaviours remain among the most burning issues in the financial services sector. As the scale and speed of digital banking ecosystems grow, and fintech innovation intensifies, the variety and scale of fraud escalate, including identity theft and account takeovers, more sophisticated, biased scams with synthetic identity, and organized lending fraud. Conventional detection systems (typically hard-wired machine rule architectures) have since been found to be inefficient when responding to such adaptive threats. They are also frail because they steal some previous knowledge, a collection of pre-established thresholds, and that is how they give out fake positive and negative outputs in a real-life setting (Mullankandy, 2024; Padmanaban, 2024).

The Generative Artificial Intelligence offers a more agile and resilient way of identifying anomalies. Using generative adversarial networks (GANs) and similar models, financial institutions can be trained to discover the latent statistical distributions of typical transaction and borrower behavior. After these baseline patterns are set, the models can warn of anomalies that indicate fraudulent intent, even in cases where the baseline patterns have never been observed in historical data. This capability to detect new and emerging fraud schemes is an enormous breakthrough relative to the limitations of traditional channels.

In addition to increasing accuracy, GenAI is also used to facilitate real-time fraud detection in large streams of transactions. Models used in institutions can track lending applications, payment transactions, and use of credit within near-instantaneous cycles, and create alerts that compliance teams can act on within the institution. This would reduce the duration of exposure during which an act of fraud will go viral and, correspondingly, reduce the losses incurred by an institution and protect consumers (Truby, 2020; Liu & Huang, 2022). The generative models are also general, giving them resilience toward adversarial efforts to bypass detection systems because the models continue to improve as the methods used by criminals change over time. The other important element is how GenAI can improve customer trust and performance. Rule systems tend to over-trigger alarms, resulting in false alarms that drain investigative resources and interrupt legitimate customers. In comparison, GenAI-based anomaly detection is an enhanced and context-dependent analysis of suspicious activity that leaves behind significant unnecessary noise in the name of control. This two-fold privilege of accuracy and scale will allow generative AI to not only contribute to its role as a deterrent to fraud, but to form the foundation of a rebranding of financial security processes.

3.5 Portfolio-Level Risk Management and Diversification

Indeed, some of the best approaches to reducing systemic risk exposures in a volatile market are portfolio diversification. Traditional portfolio analysis depends on a back-test of history and assumes that the risks in the future will be similar to the past. They are inadequate accounts of systemic shocks and relations that become apparent in the events of the crisis (Yanenkova et al., 2021).

Generative AI is potent to support portfolio-level risk management, as it:

- A stress factory, allowing financial managers to experiment with resilience in the face of market crashes, liquidity crises, and geopolitical upheavals.
- Probabilistic simulations expose latent vulnerabilities by modelling fat-tailed risk events and not assuming normal distributions.

- Dynamical correlation modeling, in which GenAI learns how the correlation between assets evolves in extreme cases, which can provide richer information than past correlations.
- The arrangement of capital sufficiency is preserving a sufficient buffer against the worst-case scenario risks (Kiptoo, Kariuki, and Ocharo, 2021).
- Long-term stability testing assists banks, insurers, and investment companies in developing robust and diversified portfolios for new economic conditions.

It would transform the reactive into a more proactive portfolio and future resilience model. Generative AI supports adopting risk management practices aligned to regulatory expectations and long-term investor trust by capturing systemic interconnections and extreme-event risk.

3.6 Integration with Real-World Banking and Fintech Systems

The last GenAI frontier in fintech and banking practice is implementation into live banking and fintech ecosystems. The system must be compatible with governance, compliance, and reporting systems to be adopted, although technical superiority is also required (Barros, Prasad, and Sliwa, 2023). Because regulators continue to focus on financial institutions, innovation and transparency should be included in the GenAI building process as something that can be explained to regulators and customers (Singh, 2024). The fact that new fintech companies are testing embedded GenAI to rate credit in real-time and micro-lend is a sign that the technology is already a driver of financial inclusion, and that regulatory oversight is essential (Yu & Guo, 2023).

4. CHALLENGES AND FUTURE DIRECTIONS

Even though the application of generative artificial intelligence (GenAI) in modeling credit risk may potentially revolutionize this process, a set of structural, ethical, and regulatory challenges is linked to its application in financial institutions. The following challenges should be overcome to have GenAI rolled out responsibly and sustainably in high-stakes areas, such as lending and portfolio risk management.

4.1 Data Protection, Data Management, and Regulation

Financial institutions are governed in the most stressful environment, where data and customers' integrity, transparency, and privacy are vital. GenAI adoption also creates additional data governance challenges, including ingestion and anonymization of structured and unstructured borrower data. The General Data Protection Regulation (GDPR) and Basel III/IV regulations feature internal controls with extremely high expectations regarding using, storing, and managing model risk (Karangara, Shende, and Kathiriya, 2024; Singh, 2024). The failure to integrate GenAI systems into such frameworks may result in compliance penalties and reputational risk, as also identified in financial governance and sustainability literature (Liu & Huang, 2022; Mullankandy, 2024; Padmanaban, 2024).

4.2 Black Box vs Interpretability

The assessment of credit risks is one area where interpretability is as important as predictive accuracy. The traditional scorecards were limited but gave transparency to the decision-making process (Sousa, Gama, and Brandao, 2016; Papouskova & Hajek, 2019). In comparison, generative models, including GANs, transformers, and others, are black boxes that cannot be audited significantly and are largely untrustworthy to stakeholders (Mashrur et al., 2020). It also casts further doubt upon the responsibility of negative lending decisions, at least during macroeconomic turmoil (Rampini, Viswanathan, and Vuillemey, 2020; Telg, Dubinova, and Lucas, 2023).

4.3 Ethics: Prejudice, Equity, and Accountable AI

Lending practice-based GenAI systems are also more likely to strengthen structural biases against marginalized groups and raise concerns regarding fairness and fair access to credit. Regulating the implementation of AI and fairness-aware training systems is also viewed as part of the implementation of AI in the recent literature (Mishchenko et al., 2021; Truby, 2020). Lack of effective corrective mechanisms will ruin institutional legitimacy, and financial exclusion will increase, which is the entire concept of risk management.

4.4 Computational and Infrastructure Requirements

State-of-the-art Generative AI (GenAI) models can require significant computational resources to implement in credit risk management, which can pose a significant challenge to smaller institutions. The categories of computational and infrastructure considerations are described in the following subsections.

a) High-Performance Computing Needs

Complex generative artificial intelligence systems such as GANs, VAEs, and transformers can strain server processes, typically large-scale graphics processing units (GPUs) and dedicated cloud computing, by running in parallel (Kiptoo, Kariuki, and Ocharo, 2021). These facilities are incredibly costly, particularly to small financial institutions that may lack the funds to invest in such luxurious facilities. A solution capable of scaling to meet performance requirements at reasonable prices is critical for a broader audience to adopt these technologies.

b) Cloud Data and Infrastructure

Along with GPUs, secure cloud platforms are necessary to handle large volumes of data needed to execute GenAI applications. Cloud computing allows loading and processing large amounts of unstructured and structured information (Yanenkova et al., 2021). It is, however, also a requirement that financial institutions adhere to the stringent provisions of data privacy and data security, particularly sensitive customer financial data. The principles of data protection introduced by regulatory requirements like GDPR also introduce several additional compliance considerations, including the need to install an effective encryption system, anonymization, and access controls to eradicate the occurrence of data breaches.

c) Personnel and Skill Gaps

Another major challenge will be the unskilled workforce running and maintaining GenAI systems and infrastructure. Generative models can only be shaped and refined with the help of knowledge in AI, machine learning, and data science. Moreover, the model pipelines themselves are complex, the information supplied can be of poor quality, and the analysis of the choices taken by the AI will require an enormous amount of training and specialisation (Kelly, Sullivan, and Strampel, 2023). The lack of education and training on the application of AI in various areas also contributes to the widespread implementation of these technologies in smaller financial institutions and in emerging markets, where fewer resources are available to access cutting-edge ones (Garcia-Penalvo, Llorens-Largo, and Vidal, 2024; Yu & Guo, 2023).

4.5 Institutional Adoption Barriers

Although GenAI has a revolutionary potential in credit risk modeling, most financial institutions are not ready to implement it due to major hindrances. They are regulation uncertainties, integration and inertial organizational costs. We break down the significant adoption challenges below.

b) Concern and Uncertainty Regulatory

Banking organizations are highly regulated, and any emerging technology, particularly one as disruptive as GenAI, should face a challenging regulatory process. It is impossible to find untested guidelines through the regulatory agencies, and this situation can delay and even stop the process of institutions introducing new technologies. This is the reason why they do not like new technologies (Bülbül, Hakenes, and Lambert, 2019). The lack of a standardized system for implementing GenAI in financial decision-making creates a certain sense of uncertainty. Financial institutions fear not complying with the industry regulations, such as Basel III/IV, and the risk of a fine as the penalty for misusing the model.

b) Reputational Risks and Organizational Resistance

Financial institutions have reputational issues that dominate the decision-making process. Adopting a sophisticated AI-based approach, especially in the high-stakes sector, like credit risk, is associated with a certain degree of social examination and the risk of adverse reaction. There exist some risks, as with other technologies (e.g., AI in recruiting and lending), regarding how this model would be perceived by the population, regulators, and shareholders (Telg, Dubinova, and Lucas, 2023). In addition, internal stakeholders (management and risk teams) may be unwilling to utilize a new technology because they fear being viewed as overly complex or disruptive to existing processes.

c) Governance, Accountability, and Auditability

The ability to implement GenAI in financial institutions also depends on creating a proper governance structure. Institutions cannot win the goodwill of regulators and customers without systems to achieve accountability and transparency. Since GenAI models are still opaque and complex, model interpretability and audit trails are the most important questions to consider. In order to ensure the comfort of people with the AI models, the models must be clarified with the help of explainability models, fairness models, and bias reduction models (Barros, Prasad, and Śliwa, 2023). The other is that institutions should be able to make their AI systems auditable to meet the standards and financial regulatory requirements established by internal governance bodies (Kalota, 2024).

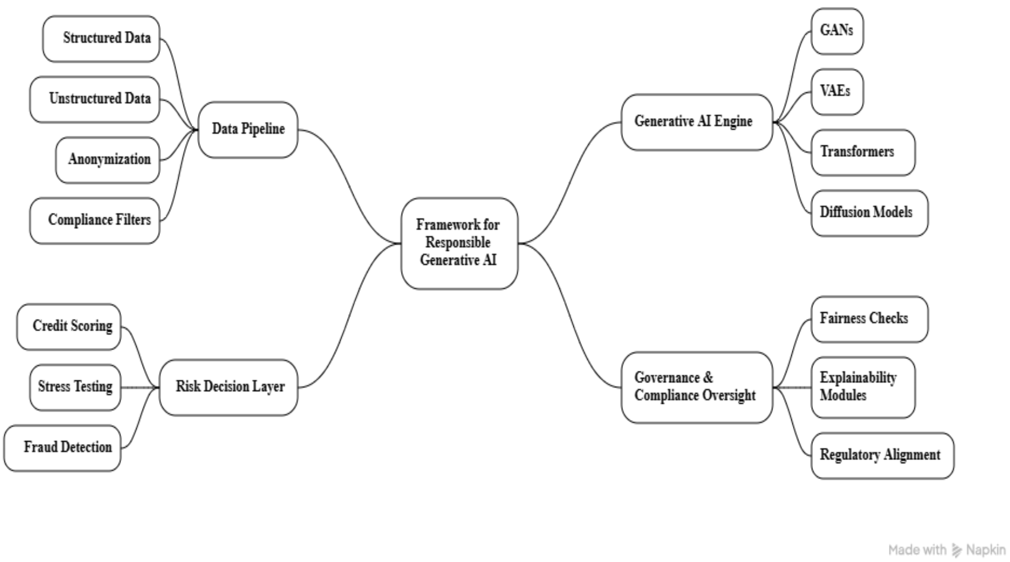


Diagram 1: Framework for Responsible Generative AI in Credit Risk

A conceptual framework is presented to illustrate responsible deployment. The pipeline proceeds in four stages:

1. **Data Pipeline** – ingestion of structured and unstructured borrower data with anonymization and compliance filters.
2. **Generative AI Engine** – model layer incorporating GANs, VAEs, transformers, and diffusion models for simulation and feature generation.
3. **Risk Decision Layer** – applications in credit scoring, stress testing, and fraud detection.
4. **Governance & Compliance Oversight** – fairness checks, explainability modules, and regulatory alignment ensuring accountability and trust.

4.6 Future Directions

The future of research and practice has three priorities. To begin with, the development of justifiable generative AI is needed to bridge the transparency gap between the regulator and the financial institution. Second, not only will the conscious training systems prevent the discrimination practised in the past, but they will also bring justice to lending practices (Singh, 2024; Parbat, 2024). Third, quantum finance and hybrid GenAI models will enable quantum optimization and the next stage of credit risk modelling (Yu & Guo, 2023). The given generative AI is a product of the risk management paradigm, which should be regulated ethically and imaginatively.

5. CONCLUSION

This paper has explored the changing nature of credit risk modeling when approached through generative artificial intelligence (GenAI) and its techniques, use cases, and challenges that underlie its use. Classical approaches to credit risk, such as logistic regression, ensemble learning, and cost-risk frameworks, have offered conceptualized tools against which to assess borrower defaults and portfolio risk. However, they fail to capture the dynamics of non-linear borrower behavior and low-default portfolios, as well as high-dimensional and unstructured data (Bhat, Ryan, and Vyas, 2019; Sousa, Gama, and Brandao, 2016; Papouskova & Hajek, 2019). In these aspects, GenAI has a radical potential that can generate synthetic data, simulate scenarios, and predict models that can more strongly reflect uncertainties in the financial system (Kalota, 2024; Mashrur et al., 2020; Parbat, 2024).

The financial institution applications of GenAI are diverse and multiple. In addition to predictive credit scoring, generative models also assist with stress testing, fraud detection, and automated regulatory reporting to increase the resilience of operations and compliance capacities (Karangara, Shende, and Kathiriya, 2024; Padmanaban, 2024; Mullankandy, 2024). In addition, the problem of the scarcity of data can be mitigated by modeling rare events and building synthetic borrower profiles that could also mitigate systemic risk (Yanenkova et al., 2021; Telg, Dubinova, and Lucas, 2023). Although promising, GenAI integration into credit risk modeling is still somewhat problematic. Another issue of specific importance in instances where the lending procedure is complex and has to be regulated by lending policies is its understandability, fairness, and amplification of bias (Singh, 2024; Mishchenko et al., 2021). Governance structures must also consider the barrier of adoption based on computational and technical complexity (Truby, 2020; Liu & Huang, 2022). Educational research also emphasizes the importance of re-skilling and institutional preparedness to reap the full benefits of generative models and reduce the risks that could arise (Kelly, Sullivan, and Strampel, 2023; Barros, Prasad, and Śliwa, 2023; García-Peñalvo, Llorens-Largo, and Vidal, 2024; Yu & Guo, 2023).

To sum up, general artificial intelligence combined with the conventional credit risk management functions is a paradigm shift in financial risk management. This study highlights the need to balance innovation, as it recommends methods to combine predictive and synthetic features of generative AI with strict requirements of interpretability, adherence to regulations, and trust in institutions. Technological progress and the ability to align it with ethical and practical restrictions can help financial institutions create safer, more equitable, more robust credit risk models that will eventually help make the financial ecosystem itself more stable and sounder (Rampini, Viswanathan, and Vuillemey, 2020; Bülbül, Hakenes, and Lambert, 2019; Kiptoo, Kariuki, and Ocharo, 2021).

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