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The Generative AI Revolution in Finance: Foundational Logic, Emerging Risks, and Governance Paths

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Abstract

Generative artificial intelligence is a powerful engine of new quality productivity and now is profoundly changing the service models and value creation logic of the financial industry. This article believes that the empowerment of GenAI to financial industry is mainly since there is a large data foundation in the industry, while GenAI can be handier when facing complex data. The technique upgrade and application of GenAI make breakthroughs in solving problems caused by information asymmetry in the traditional financial market, especially for risk management and control. But every coin has two sides, while the banking industry enjoys the convenience brought by AI, it cannot ignore data leakage, black box dilemma caused by AI algorithms, and the systemic risks brought by model instability. Therefore, based on the study of the underlying logic and emerging risks of GenAI empowering the financial industry, this article proposes the governance paths to better play the positive role of AI in financial industry.

CCS Concepts

• **Applied computing**; • **Electronic commerce**; • **Online banking**;

Keywords

Generative AI, Financial Industry, Information Asymmetry

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1 Introduction

Influenced by the application of artificial intelligence technology, various fields of social production have accelerated development, ushering in a new round of upgrades in the digital economy. The entire economic system and business models of the digital economy have produced a reconstruction of underlying logic in essence. Ultimately, the core operation of digital economy is the process of data collection, analysis and application. During this process, technological breakthroughs in artificial intelligence have become the key decisive factor in realizing fully data value. Based on this point, AI technology not only enhances the effectiveness and quality of data processing, but also unlocks more potential space for data application, converting the originally ignored data value into actual productivity. Therefore, this development promotes industrial reforms, but it also puts higher requirements on related technical architecture and management frames.

The evolution of AI technology is very clearly featured with constantly increasing complexity. From the earlier algorithms that implemented simple classification or prediction problems for structured data, it has developed to the current application-level deep learning for unstructured data. As seen from the currently highly popular application of GenAI in practice, various industries utilize large models to load more computing power to handle a larger amount of information. In addition, technology companies use many training models for systems optimization to achieve better decision-making results. The value innovation brought by GenAI is gradually being realized. One of its widely anticipated innovations is the "human-like" function, that is, computer programs are no longer fixed on organizing or analyzing historical data, but through information learning and reorganization, new content is generated, which is the so-called "creative thinking". A report released by McKinsey Research Institute in June 2023 stated that GenAI is expected to drive an additional value increment of approximately 7 trillion US dollars in the global economy over the next 10 years (Liu, 2024).

Especially for the financial industry, GenAI may bring the industry's annual sales to an increase of up to 47%, far exceeding traditional industries such as manufacturing and retail. The financial industry is an application field where GenAI has been implemented earlier and more actively. Many financial institutions have begun to make operational progress in various business links by deploying GenAI models. For example, GenAI can be used to analyze big data and feedback to risk control department to help them identify the risk levels of different groups of people. It is also possible to generate more suitable investment plans based on the different portfolios and risk preferences of existing customers. In addition, we also find that foreign institutions like JP Morgan Chase and Goldman Sachs are establishing their own AI research and development teams to explore and expand the application scenarios of generative AI. It can be seen from this that we are currently in a crucial period of transforming GenAI from a technical concept into an actionable commercial application, but there are still some difficulties in business implementation.

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For the reasons mentioned above, it is highly necessary to further study the application, technical mechanisms, risk challenges and governance paths of GenAI in the financial field. This will help all market participants have a clearer understanding of the technological development logic and also provide references for the formulation of relevant regulatory policies.

2 Logic of Technological Empowerment

2.1 Strategic Integration of Resources and Digital Capabilities

2.1.1 Gen AI Breakthroughs Traditional Data Analysis Limitations. Compared with other traditional service industries, the financial industry is inherently data intensive. Various data involved in daily business activities, such as market fluctuations, transaction records, and customer services, are constantly growing extremely fast. The continuous accumulation of multi-type data is changing the operation mode of the financial industry. In "Data Age 2025" report, IDC predicts that the total amount of new data added in 2025 will reach 175 zettabytes, of which 80% will be unstructured data. The transformation from the original massive, structured data to the current large-scale unstructured data will continuously drive the intelligent upgrade of the financial industry.

Although many financial institutions have achieved digital transformation, there are still significant problems in data sharing and integration. The first issue is data collection. For a long time, different institutions such as commercial banks, securities companies, and insurance companies have each had their own separate data standards and independent internal systems. Currently, there are indeed certain difficulties in sharing and integrating cross-institutional and cross-departmental data in many cases. Another is that, according to the survey on the official website of the Information Technology Risk Bureau of China Banking and Insurance Regulatory Commission, approximately 84% of the surveyed banks reflected that they have significant risk concerns about external data. Moreover, nearly 50% of the surveyed institutions believe that most of their data are still dormant and have not been activated. The lack of standard data formats among different industries and their inability to share with each other have led to the current dilemma of data silos. In this case, it is impossible to fully release the value of all data[1].

In addition, traditional financial computing models are still lacking in data analysis capabilities. For instance, models like CAPM and VaR were designed to process structured data, but they are inadequate to cope with unstructured content such as text, voice, and images, and thus fail to be effective. Before the popularization of intelligent financial technology, its application scenarios were relatively limited, mostly used for quantitative investment and risk management. When it came to a large amount of unstructured data, such as customer communication records, market public opinion information, it could not be well utilized, which directly led to the problems of bad service experience and inaccurate risk pricing. In recent years, due to the breakthroughs in technological updates of large models, many tasks that were previously difficult to complete can now be achieved with the help of data technology. For instance, the algorithms based on artificial neural networks in deep learning technology have made significant progress in model capacity and computational efficiency, enabling GenAI to solve data tasks faster and more accurately. Natural language processing is also one of the important technical supports. New models have the function of processing unstructured data, which broad the financial data limitations.

If NLP technology perfectly fits the characteristics of big data in financial industry, the introduction of Transformer architecture marks a watershed in the application model of modern AI in financial field. After the employment of this architecture, the computing model has developed to the feature of self-attention, which enables it to consider all parts of the inputs simultaneously and establish cross-sequence relationships. Based on established relationships, multi-party data is processed in parallel to improve the performance of model training and reasoning. For example, the large-scale AI model launched by Industrial and Commercial Bank of China shows that the model has set parameters at the level of hundreds of billions, increasing the achievements of solving customers' problems at one time to 92%, reducing the knowledge update cycle to "T+0", and improving the efficiency of the gang fraud identification by 40 times.

2.1.2 Reconstruction of Financial Data's Value Chain. Gen AI uses new technologies to deeply explore the value of financial data, and this value realization is carried out in stages throughout the entire data processing process (Table 1).

The long-standing problem of data silos in the financial industry is directly related to data sensitivity and security requirements. With the emergence of new AI technologies, the problem has been well solved. The system named "Next Best Action" jointly developed by Morgan Stanley and OpenAI offers great reference significance. The Next Best Action system uses a federated learning framework, enabling several institutions to train the model together without sharing the original data. Its working logic is to train the model parameters locally in each institution and then exchange the parameters through an encrypted channel instead of the original data. In this way, it can not only ensure the privacy of customers' information and data security, but also integrate the data value among institutions, and effectively reduce the possibility of data collusion. In practice, the Next Best Action system has effectively combined more than 200,000 internal reports and various customers' behavioral data, improving the accuracy of customer profiling. Moreover, it allows financial advisors to quickly obtain customer information through internal systems and provide corresponding services, which significantly optimize the service process and customer's experience.

The breakthrough in data analysis lies in the fact that new AI technologies have achieved higher precision of processing financial time series data. Traditional time series prediction models such as ARIMA have no good solutions for the high noise and strong volatility of financial data, while GenAI can solve this problem by using hybrid models. Taking Bloomberg GPT system as an example, it combines LSTM with GANN, and uses the special gating structure of LSTM, including input gates, forget gates, and output gates, to solve the vanishing gradient problem and can capture the long-term dependent features of obtained data. Furthermore, the generator and discriminator in GANs were respectively utilized for adversarial training, which can better learn the data distribution patterns and enhance the market perception. Referring to Bloomberg GPT

Table 1: Generative AI's Methods in Reconstructing Financial Data Value

Stage	AI Techniques	Case Example	Commercial Value
Data Preparation	Multi-institutional collaboration	Morgan Stanley's Next Best Action advisory system	Break down data limitations; Maintain strict privacy
Data Analysis	Hybrid time-series analysis models	Bloomberg's market predictor	Filter market noise; Enhance trend prediction
Decision Optimization	Adaptive learning systems	Ping An Puhui's Xingyun platform	Real-time market response; Lower bad loan rates

system, it achieves an improvement of up to 23% in the prediction of S&P 500's volatility.

The decision-making process moves from static rules to dynamic optimization. Based on data sharing and the improvement of analysis accuracy, the model decision output has achieved dynamic adjustment and optimization. For instance, Ping An Puhui launched the intelligent credit approval platform "Xingyun", which employs the method of deep reinforcement learning, integrates the applicant's behavioral data, macroeconomic indicators and other dimensional risk signals, to comprehensively judge standardized loan applications. Compared with the manual method, the rate of automatic approval through the platform can reach 85%, which shortened the approval time of a single business from the original 120 minutes to only 40 minutes. More importantly, the system continuously decreased the non-performing loan ratio from 1.74% in 2016 to 0.92% in 2024. This indicates that decision-making has begun to move from experience-based to AI-driven era.

2.2 Technical Solutions to Information Gaps

2.2.1 Information Asymmetry. There has always been the problem of information asymmetry in the financial market, and it is a key obstacle that troubles the efficient operation of the market. For example, in credit approval, as commercial banks find it difficult to fully picture the true situation of borrowers, they cannot accurately assess the borrower's repayment ability and credit status, nor can they supervise throughout the process whether the borrower uses the funds for the agreed purposes. If the bank cannot figure out the above-mentioned situation, it can only increase the loan price or raise the threshold as a guarantee of repayment ability. Meanwhile, to avoid customer providing false information during the lending process, the customer is required to bear greater interest rate to reduce the bank's own risk costs. As a result, many normally operating enterprises are unable to obtain loans from regular channels due to factors such as insufficient collateral. What's worse, some high-risk enterprises may be packaged as low-risk enterprises to obtain loans. Moreover, as traditional financial services focus more on using structured data for risk assessment, some people who lack financial data support or physical collateral to prove their credit status but have good performance expectations and repayment intentions will also be excluded from the normal service. This group of customers is mainly concentrated in start-up enterprises or science and technology innovation enterprises.

2.2.2 Solutions. In process of data acquisition, GeneAI broke through the bottleneck that traditional finance can only utilize structured data. Traditional credit reviews are more based on standard information, such as financial reports. GeneAI can collect more information from different sources, such as credit clues from public speeches of corporate executives, social platforms and customer complaints by using natural language processing technology. If there is no historical data, AI technology can also generate simulated data, such as predicting the default possibility of start-ups at different development stages, which is very helpful for evaluating small and medium-sized enterprises that have few traditional collaterals but in good operating conditions.

In information procession, the application scenarios of AI models are constantly increasing, ranging from web information capture to text report approval. This significantly reduces manual operation procedures, saves business processing time, and achieves twice the result with half the effort. The "Liangying AI" system developed by Ping An Securities can quickly capture key events and corresponding descriptions from over ten thousand financial news articles every day, and finally extract them into brief summaries, saving securities analysts a lot of time. The system can also replace manual work to complete basic contract and report approval tasks, reducing the error rate of manual labor and improving work efficiency.

For cross-bank and cross-departmental collaboration among financial institutions, the new AI models have completely transformed the traditional way of cooperation and greatly stimulated the realization of the commercial value of digital productivity. Until now, more than 20 domestic banks, securities companies and insurance companies have localized DeepSeek, and used privacy algorithms on these systems to share risk analysis methods, successfully meeting the requirements of protecting the private data and enhancing the risk identification capabilities of each participant. In addition, in investment and financial management, through those platforms, all the financial products, including funds and insurance, will be included and provided to customers, further enhancing the pertinence and comprehensiveness of investment plans.

2.3 Breakthroughs in Risk Management Techniques

Financial technology represented by new technologies such as GeneAI, is reshaping the way of financial risk management in a more efficient and accurate manner. Compared with traditional post-correct regulatory model, the core of upgrade and transformation of the risk control model by GeneAI technology lies in two aspects, namely expanding the verification of information clues and achieving dynamic risk warning.

2.3.1 Expand Verification Clues. In terms of data integration, the new generation systems has completely broken through the previous bottleneck of only being able to handle structured data. It fully utilizes natural language processing and image recognition capabilities to incorporate the transaction data, the content posted on social platforms, as well as policy documents issued by regulatory authorities, and integrate them from different dimensions for risk assessment. At this point, the risk warning rules are no longer limited to the traditional financial indicator. A large number of news reports and the heat of social media discussions will all become the basis for judging the true operating conditions of the company.

2.3.2 Real-time Monitoring and Dynamic Warning. The so-called Dynamic Warning mechanism refers to the real-time nature of risk warning. With the generation function of AI technology, financial institutions can not only conduct stress tests based on historical data during the risk simulation process, but also simulate extreme market shocks by taking advantage of market fluctuations brought about by changes in macroeconomic policies, industrial structures and other indicators, and generate real-time response strategies[2]. Take the U-Bank X of China Merchants Bank as an example. It continuously tracks the behavioral indicators of more than 100,000 customers. In response to the real-time market changes, including fluctuations and customer transactions, it adjusts the credit authority and quota in real time during the approval process according to the latest information. This real-time adjustment mechanism has increased the risk identification in the loan approval process of the bank by nearly 40%.

In addition to real-time warning, financial institutions can also utilize the dynamic response mechanism of AI technology to form a real-time database, enabling them to promptly understand the operating conditions of client enterprises, as well as the market fluctuations they are in. The "ICBC Smart Stream" system of Industrial and Commercial Bank of China is a typical application, leveraging massive heterogeneous data from various channels, such as financial reports, supply chain transactions and entrepreneur consumption behavior patterns, to form the internal database. Nowadays, this database has a knowledge architecture of multiple levels composed by "field - industry - enterprise", covering high-quality and extensive financial data sets, providing a resource basis for the efficient operation of financial data. Once the system detects that the business conditions of a certain industry have deteriorated or that an enterprise has experienced abnormal fluctuations in its supply chain, it can promptly issue a warning to financial institutions, which can play a preventive role of early warning and help banks prevent the emergence of non-performing loans at the source.

3 Risk Challenges

3.1 Data Security Risks

Due to the massive and sensitive nature of data in the financial industry, data security is the primary challenge for the application of modern AI technology in the financial field. Data security is both an objective requirement for protecting customer privacy, and an inherent condition for maintaining system stability.

In terms of privacy protection, the biggest challenge is illegal data leakage in the financial industry. When the financial institutions use AI systems to optimize business operations, they inevitably collect many users' private information, such as social data and transaction records, and apply this information to other scenarios. But disturbingly, these "notification details" are often hidden in long user agreements, and most users do not read them carefully, thus resulting in the unconscious exposure of their sensitive information. What is more worrying is that, from the current situation, the data leakage problem in the financial industry is facing dual risks of internal and external threats. Externally, there are cases of information leakage caused by hackers illegally invading the financial systems, and internally, there are also cases of staff illegally selling customer information. The "Measures for the Administration of Data Security in Business Fields of the People's Bank of China" clearly defines the scope of responsibilities that data recipients need to fulfill when managing customer information. This is also an important measure taken by the regulatory authorities to strengthen data security.

In addition, data quality issues can bring systemic risks. At present, the application rules and scenarios of AI technology in the financial field show a certain degree of convergence. With similar data and the same model, once a problem occurs, it will trigger a risk contagion throughout the industry. For instance, if the customer information used in the credit model is low quality, that is, forged or wrong data, the output of the default probability will be incorrect. Coupled with the more complex new attack method of "data poisoning", it will greatly reduce the quality of model operation and decision output, and lead to large-scale misjudgment problems.

3.2 Transparency and Fairness Challenges in Algorithm

The problem of algorithm transparency and fairness, which is the second major challenge for GeneAI in the financial sector, has gradually become the focus of current financial supervision and risk governance.

The biggest problem with algorithmic transparency is that the decision-making process cannot be traced. Take intelligent investment advisors as an example. This type of platform will apply deep learning models to continuously adjust and optimize investment strategies based on a large number of historical data. However, the inherent feature of autonomous learning makes it difficult to track the specific logic and principles of decision-making process, which results in a "dynamic black box". In 2023, the results of stress tests conducted by European Central Bank on the banking industry revealed that approximately a quarter of bank credit models experienced what is known as "hidden variable drift". This means that during the process of model operation, the model would automatically introduce sensitive information such as race and gender as proxy variables, and eventually lead to biased outputs in loan approvals.

In addition, the US Federal Trade Commission has also announced cases similar to the above-mentioned dilemma. Also trapped by the problem of datasets with historical biases, a major online lending platform offered Latino borrowers an interest rate about 1.8 percentage higher than that for white borrowers. However, when the regulatory agency asked the platform to explain the reasons for the algorithmic logic, the platform claimed that it could not disclose the trade secrets involved. This behavior is undoubtedly discrimination combined with opacity.

In terms of regulation, the troubles brought about by its own complexity are new problems. For example, some algorithms lack transparency, which makes it impossible to identify the specific reasons that may lead to discriminatory decisions. In response to this problem, the academic community has proposed a "hierarchical transparency" solution[3], which holds that different transparency disclosure requirements should be adopted for different participants. For regulators, "model-centered transparency" can be disclosed, that is, the model part of the algorithm, including algorithm features and risk thresholds. For consumers, "transparency of the decision-making path" should be disclosed, such as directly demonstrating the importance of used variables to the credit valuation by using interpretative tools like SHAP. However, judging from the current practical application, this is still not a perfect solution.

3.3 Technical Reliability Dilemma

For the financial industry, GeneAI can significantly enhance work efficiency. However, there are issues of AI Hallucination and Model Vulnerability, both of which are prone to errors in applications. This poses a considerable obstacle to AI's full implementation.

3.3.1 AI Hallucinations. AI hallucination is the phenomenon of generating content that is inconsistent with facts and lacks logic. The reasons for its occurrence include data bias, misinterpretation of intentions, and knowledge solidification[4]. Due to the high-precision requirements in the financial field, these issues will cause greater harm to the profits of financial institutions and customer investment decisions. It can be seen from the evaluation of Galileo Labs that the hallucination rate of large models varies greatly. For example, the hallucination rate of the basic question-answering task of the GPT-4 is only 23%, and the rate of some large models can even reach about 60%. According to the typical cases disclosed by the SEC in 2023, the AI-generated image of the Pentagon explosion caused a sudden plunge in the US stock market. Even if it is later exposed to be fake news, it shows the scope of AI's fabricated information is still larger than that of the traditional means in the past.

3.3.2 Model Vulnerabilities. At the current stage, the effectiveness of GeneAI in empowering the financial industry is relatively satisfied. Financial institutions use GeneAI to improve their own business operations, but also the problem of technical reliability exists, which has become a bottleneck restricting the AI's application.

Although, with the support of new AI technologies, we can collect more data, provide stronger computing power, and use more advanced algorithms to make models function better, this does not mean that models are free of errors. Moreover, since the large models are often implemented in a nested manner, when handling financial business decision-making tasks, mutual interference among different programs and different types of information may occur, triggering risk resonance[5]. Thus, formed resonance may cause cross-market fluctuations and amplify systemic risks.

4 Strategic Recommendations

In the face of multi-dimensional risks and challenges brought by the application of GeneAI in financial field, it is particularly important to establish sound governance frameworks and paths. Governance is not only a necessary means to prevent risks, but also the foundation for ensuring the healthy and sustainable development of GeneAI technology in the financial industry.

4.1 Establishing Clear Governance Structures

Regarding the application of GeneAI in the financial field, the primary issue is to establish a clear governance entity, that is, to set up a dedicated AI governance committee or working group, and grant this organization certain rights and responsibilities, including the formulation of AI development strategies and risk management supervision, to ensure that related applications and business operations are compliant and legal, and to avoid scattered responsibilities or management gaps. In the industrial practice, a representative approach is Deloitte's proposal of the "High-Trust Artificial Intelligence Framework"[6], which emphasizes that while promoting computer technology innovation, attention should also be paid to the impact of technology application on society, the environment and the market. Only by integrating the business goals and social responsibilities of financial institutions can GeneAI achieve healthy development in the financial field.

Of course, to deal with the specific implementation level, the governance framework should adapt to the situation of the institution. Therefore, different institutions should have different governance models. For large financial institutions with diversified businesses and complex systems, their entire governance should be a comprehensive system, and all businesses are subject to constraints. For small and medium-sized financial institutions, they could choose a simple governance model based on their own characteristics instead of trying to cover all aspects. Only in this way can the risks be well managed and controlled, and avoid excessive governance costs or lax supervision.

4.2 Enhancing Risk Management Process

When financial institutions use GeneAI technology, they should have a full-process risk management system to identify the risks that may be caused by the implementation. The key points that need attention include data privacy protection and information security issues, the harm of unfairness caused by possible deviations in algorithms, the transparency and interpretability of the model decision-making process, and the reliability of system operation. Specific countermeasures should be formulated for the above risk issues. For example, in the design of governance structure, the "AI Governance Pyramid" model is drawn upon to form the governance system from four interrelated perspectives, which are responsibility boundaries, transparency of decision-making process, system stability, and security controllability.

Risk management refers to the fact that in the continuous evolution of GeneAI and scenario expansions, new risk factors are constantly being injected. A corresponding regular review should be established. Based on the original risk management, timely review should be conducted according to the actual situation of the related technologies development. This can also make risk management more in line with the actual situation, thereby avoiding and reducing the harm caused by new problems resulting from the emergence of new technologies.

4.3 Strengthen Data Governance

In GeneAI's employment, data governance is the foundation for the reliable technology application. Therefore, it is necessary to establish a data management policy covering the entire chain of data "collection - storage - processing", and focus on the quality, integrity and security of used data. The core is to ensure the representativeness and fairness of the training data, identify doubtful data, and correct the problems to avoid deviations and systematic discrimination caused by unbalanced data samples.

Data privacy protection is also one of the important issues in data governance. Financial institutions should start from the collected data and establish a complete privacy and security protection system covering the entire data life cycle. For instance, for sensitive data, encryption measures should be adopted, and hierarchical and graded access methods and security audits can be conducted to prevent data leakage, ensuring customers' personal information in a standardized and reasonable manner.

5 Conclusions

Overall, for the financial industry, it is highly necessary to establish a systematic framework to effectively manage the risks of AI applications. Governance should be carried out from a comprehensive and multi-dimensional systematic perspective, including organizational structure, risk control system, data management, industry collaboration, and regulatory policies. Such governance must be jointly accomplished by financial institutions themselves, financial institution associations and regulatory authorities, and form a synergy to improve risk management facing the rapid technological advancements.

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