

Generative AI in Financial Investment Research Applications and Risk Management

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Abstract. Generative Artificial Intelligence (GenAI) has gradually become one of the new-age technologies in the financial industry and is now being used in many places, such as investment research, risk control, etc. Although generative AI has enhanced the efficiency of information processing and analysis to some extent, problems such as data bias, model opacity, hallucination and systemic risk have arisen that existing risk management systems for traditional AI systems are not fully equipped to address. Given this deficiency, the present study has systematically reviewed 37 academic and industrial sources to explore the applications of Generative AI in financial investment research, identify the main risks associated with its deployment, and construct an all-encompassing risk management system. Based on the above, the three types of GenAI applications can be divided into investment research and analysis, risk assessment and forecasting, and customer interaction and advisory, and the four categories of associated risks are data-related risks, model-related risks, application-level risks, and systemic risks. Based on the above results, this paper proposes a three-tier risk management system that incorporates technical quality control, application-level risk management and institutional governance. This paper expands the new body of research on GenAI in finance by introducing an all-encompassing system of risk classification and governance, providing practical guidance for financial institutions in their application of GenAI.

Keywords: Generative AI, Financial investment research, Risk management framework, Large language models, Risk classification

1. Introduction

1.1. Research background and motivation

Artificial intelligence (AI) is a system that can carry out all sorts of work previously done by people, such as recognising patterns, making decisions and processing natural language [1, 2]. Among the various types of AI, generative AI (GenAI) is relatively new. Rather than classifying or predicting, GenAI models generate new content, such as text, synthetic data and structured analyses, by learning the underlying distributions of their training corpora [3, 4]. The main Generative AI technologies are large language models (LLMs), such as GPT-4 and BloombergGPT; generative adversarial networks (GANs); and multimodal Transformer architectures [5-7]. In research on

financial investment, GenAI has been used for automated analysis of financial reports, real-time sentiment monitoring, risk early warning, personalised robo-advisory, and multi-agent collaborative research [5, 8-10], etc., indicating a trend of moving from passive data processing to active knowledge generation [11, 12]. GenAI deployment in finance faces some serious problems. The volume of expanding financial data now exceeds the capacity for manual research [13]. Heterogeneous multi-modal data sources exceed the capacity of conventional analysis [8, 14]. The requirements for regulatory compliance are now more immediate, open and verifiable [15, 16]. Cognitive biases of people also harm fairness [17]. GenAI also has new problems that existing AI risk frameworks have not covered, such as hallucinations, model opacity, data privacy leakage and systemic cascading failures [16, 18]. If they are not handled, the risks will damage investor confidence and increase market volatility, resulting in regulatory penalties for the institution [15, 19]. This paper will systematically study the applications and risks of GenAI in financial investment research and put forward an all-encompassing three-level risk management system for its responsible use.

1.2. Literature review

In the past three to five years, a large number of studies have explored the application of artificial intelligence in finance, and many of these have been generative models. Gao and others have conducted an all-encompassing survey of machine learning in business and finance, identified deep neural networks and ensemble methods as the main directions, and also noted the problems of model explainability and cross-modal integration [2]. Kumar and Sinha have studied the start of generative AI in finance and pointed out its possible applications for improving customer service, risk control and algorithmic trading; however, they also noted that issues of transparency and accountability have not been resolved [3]. Chen and others have traced the origins of fiction in the application of generative AI to business, and they have shown that generative AI surpasses the performance of traditional natural language processing (NLP) in sentiment analysis, summarisation and financial statement interpretation [4]. Bhattacharyya et al. proposed a Wells Fargo model risk management system for generative AI and built a strict verification path for foundation models in the banking sector [20]. AIFIRM put forward a regulatory system for applying GenAI and LLMs in financial risk management under the EU AI Act [19]. Although the above studies have improved our knowledge of GenAI's abilities and identified some risk factors, there are still certain deficiencies in the current research. No research has systematically explored the entire chain of risks associated with the deployment of GenAI, from data collection and model operation to systemic market disruption, and an all-encompassing, multi-level governance system specifically for financial investment research has not been put forward.

1.3. Research content and significance

Given the above deficiency, this paper will use a systematic literature review method to study GenAI in financial investment research from three integrated dimensions. First, it introduces the technical changes in the development of generative models from traditional machine learning and identifies four main technical paths: Transformers, LLMs, GANs and pre-training; fine-tuning and prompting paradigms. Second, the three categories of GenAI applications in financial investment are investment research and analysis, risk assessment and forecasting, and customer interaction and advisory. Third, the four categories of risks in GenAI deployment are classified as data-related risks, model-related risks, application-level risks and systemic risks, and based on this division, a new

three-tier risk management system is proposed, consisting of a technical level, an application level and a governance level.

From a theoretical standpoint, this paper helps extend the academic system by adding an organised analytical system to connect technology-focused AI research with regulation-focused risk governance research, and offers a new type of framework for addressing GenAI-specific risks that is missing in the existing single-layer model. In practice, the above framework can help financial institutions develop generative AI responsibly, enable senior management to improve market efficiency and ensure regulatory compliance, and win the trust of the public in AI-driven financial services.

2. Theoretical foundation and research hypotheses

The first is the Technology Acceptance Model (TAM) by Davis in 2000. TAM thinks that a person's use of new technology is mainly determined by the two factors of perceived usefulness and perceived ease of use. TAM can be used to explore the reasons for and ways in which financial institutions have adopted GenAI tools to improve efficiency in report generation, sentiment analysis and portfolio advice for financial investment. Analysts and portfolio managers are beginning to believe that Generative AI can increase research efficiency and provide simple-to-use applications for users, so its application has gradually expanded [12, 21]. Generative artificial intelligence will thus be able to improve the efficiency of investment research.

The second is Risk Governance Theory; it proposes an organised, multi-level stakeholder system for identifying, evaluating and reducing risks throughout the organisation [19, 22]. The old risk governance model in finance is a rule-based system of determinism. GenAI is probabilistic and non-deterministic; therefore, the governance model must also be different. This theory suggests that a risk classification system should cover technical data problems and all sorts of other systemic market risks, and layered governance structures need to be built at all levels of risk management to clarify responsibilities [22].

The third is Socio-Technical Systems Theory, which holds that the performance of an organisation requires the joint optimisation of the social subsystem (human roles, institutional processes, regulatory norms) and the technical subsystem (algorithms, data infrastructure, model architecture) [20, 23]. Application of GenAI in finance: According to the above analysis, good technical ability is not sufficient. At the same time, it needs to establish a human-supervision system, institutional accountability mechanisms and regulatory compliance mechanisms. This view will directly guide the Design of the three-layer framework proposed here.

Based on the above theoretical foundations, the following hypotheses are proposed.

H1: Generative AI technologies, such as LLMs, GANs and multimodal models, can improve the efficiency and depth of financial investment research by automating text generation, pattern recognition and predictive analysis compared to traditional AI methods [5-8].

H2: The deployment of GenAI in financial investment introduces a full-chain risk structure of four types (data-related, model-related, application-level, and systemic risks) that are inadequately covered by the existing risk management frameworks designed for conventional AI [15, 16, 18].

H3: A three-tier risk management system that integrates the technical, application and governance dimensions can offer all-encompassing and effective risk control for generative AI compared with a single-tier or technology-only model [19, 20, 22].

H4: The proposed framework is in line with actual industry operations, as shown in the case studies of commercial banking, insurance and asset management [20, 24, 25].

3. Technological background and core techniques

3.1. From traditional AI to generative AI. technological evolution

There have been three generations of application for AI in financial investment. The first generation of research employed traditional machine learning algorithms, including K-nearest neighbours (KNN), support vector machines (SVM), logistic regression and time-series models such as ARIMA and GARCH, and these served as the initial tools for stock price prediction, credit risk classification and financial forecasting [2, 26, 27]. Although suitable for organised numerical data, the above methods performed poorly when handling unstructured text, failed to respond promptly to changes in the market environment, and were unable to capture complex non-linear relationships among all kinds of data [2, 28].

The second wave of research has applied deep-learning models to boost the accuracy of stock-trend forecasting and financial risk assessment, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks [27, 29]. These models were still mostly in a discriminative form. They can classify or predict based on the input data but cannot generate new content or reason over unstructured information sources [28].

The third generation that is the subject of this study is generative AI. The development of the Transformer architecture and self-attention mechanisms have allowed for parallel processing of sequential data and capture of long-range dependencies, thus expanding the application range of financial AI [5, 6]. A representative result was the release of BloombergGPT, a 50-billion-parameter large language model pre-trained on a combined dataset of general text and more than 363 billion tokens of financial data [30]. BloombergGPT showed that domain-specific LLMs can outperform general-purpose models in financial text comprehension, sentiment classification, named entity recognition and question answering tasks [5, 30]. This development is a change in mode from previous models of classification and prediction to new models that generate, reason about and create context-aware financial information [4].

3.2. Core generative AI technologies

3.2.1. Transformer architecture and large language models

The Self-Attention mechanism in a Transformer model can process sequential data in parallel and learn long-distance dependencies in financial text [5, 6]. GPT-4 is a general-purpose large language model that can perform tasks such as financial report generation, regulatory text analysis and multi-turn investment consultation [31]. Domain-specific variations have achieved even higher accuracy in the financial NLP benchmark [5, 30]. Fine-tune the above models on curated financial data to improve their relevance, factual basis and task-specific performance [18].

3.2.2. Generative adversarial networks (GANs)

GANs are used to address the problem of lack of data in finance. GANs generate synthetic financial time-series data to perform stress tests under extreme market conditions that have not been adequately covered by the training data [7]. Wasserstein GAN with gradient penalty (WGAN-GP) has shown good results in generating realistic credit default data and outperformed other oversampling methods, such as SMOTE [7].

3.2.3. Pre-training, fine-tuning and prompting paradigms

The dominant development mode for financial GenAI applications has become the pre-training, fine-tuning and prompting pipeline. First, a foundation model is trained on a large general-purpose corpus, and then it is fine-tuned with financial data for a specific purpose, such as earnings call analysis or risk report generation [18, 20]. Prompt engineering can also be used for zero-shot or few-shot learning to extract structured information from financial data without model fine-tuning [5-8].

4. Application categories of generative AI in finance

4.1. Investment research and analysis

GenAI is Changing Investment Research Through Three Interconnected Abilities. LLMs can handle both organised numerical data and unstructured text in financial reports, such as annual reports and earnings calls, for intelligent analysis and risk indicators [5, 8]. A Generative AI model can be trained to carry out all-encompassing financial analysis of a company using both quantitative data, such as the rate of increase in revenue and debt-to-asset ratio, and qualitative information provided by management's reports; it can also detect any inconsistencies between the two sources. In addition to analysis, GenAI can automatically generate an initial investment recommendation report by combining the main contents, thus shortening the turnaround time for analysts significantly [8, 9]. Multimodal models are used to analyse market data, news sentiment and macroeconomic indicators in market interpretation for risk assessment and investment decisions [9, 32]. The above models can collect data from all over the country to find new trends or risk connections in different industries that have not been known before. In research assistance, AI-agent systems that use retrieval-augmented generation (RAG) technology and knowledge graphs serve as institutional knowledge bases to help analysts access historical research reports, synthesize cross-sector insights, and generate draft investment theses [9, 33]. Recently, empirical studies have shown that RAG systems adapted for financial report analysis can accurately answer both quantitative and qualitative investor questions in practice by using high-quality embedding and retrieval components [33].

4.2. Risk assessment

Generative AI for Financial Analysis and Risk Assessment. Collect a large number of news articles, social media posts and analyst reports to analyse the public's mood about the company at various times. These models are better able to handle problems of context and change in investor confidence than the traditional keyword-based method [4, 5]. GenAI is also being used to improve the early-warning function of risk detection through pattern recognition, association and prediction. Based on the above attributes, the model can find potential risk factors and their corresponding reasons for the rise in risk [7, 29]. Generative AI can build a portfolio and perform scenario analysis according to historical and real-time data from all sides to assess the potential impact of tail-risk events, such as interest-rate shocks and geopolitical disruptions [14, 27].

4.3. Customer interaction and advisory

GenAI is fundamentally reshaping customer-facing financial services by moving beyond standardized responses toward personalized, explainable, and continuously available advisory services. In intelligent advisory, GenAI transforms complex financial information and investment decision logic into interactive and interpretable recommendations tailored to individual investors.

These systems can support client communication and demand identification, explain portfolio recommendations, generate personalized content such as risk alerts and behavioral guidance, and automate routine advisory tasks including periodic reports and portfolio updates [3, 10]. Platforms such as Wealthfront have demonstrated how AI-powered robo-advisors can deliver personalized asset management plans, although research suggests that excessive adjustments to advisory parameters may hinder long-term investment objectives [10]. More broadly, Feng et al. proposed a five-principle framework for responsible AI in financial planning based on fiduciary duty, adaptive personalization, technical robustness, ethical fairness, and auditability, highlighting the importance of balancing operational efficiency with consumer protection.

GenAI also enhances customer question-and-answer services through advanced natural language understanding and generation capabilities. By identifying customer needs and translating complex financial terminology and regulatory requirements into accessible explanations, these systems can improve communication quality while providing continuous and scalable support during periods of high service demand [6, 34]. In doing so, they help reduce information asymmetry between financial institutions and retail investors.

Despite these benefits, building trust in AI-generated financial advice remains a significant challenge. Existing evidence indicates that perceived accuracy, transparency, and the ability to explain recommendations strongly influence users' willingness to rely on GenAI-assisted advisory services [35, 36]. Consequently, the long-term success of GenAI in customer-facing financial services depends not only on technological performance but also on institutions' ability to ensure transparency, accountability, and consumer trust.

5. Risk classification of generative AI in finance

5.1. Data-related risks

The foundational level of risk is data risk, and GenAI models are highly dependent on the quality, organisation and distribution of the training data [13, 14]. Data bias is when AI systems learn and then spread the structural biases in the training data to make unfair or biased predictions. Given that the training data for a consumer lending model predominantly includes middle-aged professionals, it will likely have a higher error rate when evaluating younger borrowers and thus engage in systemic credit discrimination [37]. Privacy leakage is the risk that sensitive personal or organisational information is memorised, reconstructed or accidentally disclosed by the model during generation. AI in wealth management or health insurance may inadvertently disclose a client's health status, income level and transaction history, thus violating regulations such as GDPR and PIPEDA [19, 37]. Insufficient data representativeness refers to a lack of coverage for extreme events, new markets or structural regime changes in the training data, and thus model failure under abnormal conditions. Stock trading models trained only on extended bull market data may fail during a sudden market crash or liquidity crisis [7, 29].

5.2. Model-related risks

Bad data will result in a poor-performing model, and there are other risks of generative models. Model-related risks stem from the inherent structure, training and operation characteristics of generative models. High-quality data do not eliminate the risk of model complexity and opacity [18, 22]. The black-box problem refers to the highly complex internal decision logic of deep generative models, and as a result, their outputs are difficult for users, auditors and regulators to comprehend.

Banks that apply credit scoring or anti-money laundering models based on LLMs may face regulatory issues if they are unable to explain why a particular customer was denied credit or flagged as high-risk [19, 20]. Lack of explainability refers to the inability to provide verifiable, traceable reasoning paths at the level of output, rather than the black-box problem. An AI-generated portfolio recommendation that cannot explain the reasons for its risk or changes under different market conditions fails to meet the fiduciary duty in high-risk financial advisory [22]. Model drift is a decline in the model's performance over time due to changes in the environment or data distribution. Fraud detection models that have not been updated according to new patterns of fraud are gradually losing their accuracy, thus raising the proportion of false alarms and failed detections [18, 29].

5.3. Application-level risks

Besides the technology itself, applying Generative AI to finance in actual operations will also present new problems. Application-level risks occur when GenAI is integrated into the actual financial business process, due to inadequate design of human-AI interaction, misallocation of decision authority, and institutional deficiencies [15]. Mistakenly Advised Investments occur when AI provides investment advice based on erroneous reasoning, outdated information or incomplete assumptions that fail to meet the investor's best interests; examples include recommending delisted financial products, proposing leverage strategies inconsistent with the client's risk level, and generating portfolio allocations based on hallucinated market data. The results will be small amounts of money or damage to the reputation of the advising institution. Accountability is unclear after a loss caused by AI's recommendation. The problem of whether the fault lies with the developer of the AI, the financial institution or the end-user has not been determined legally or operationally in regions without specific liability regulations for artificial intelligence [22-37]. Over-automation is the excessive reliance by human decision-makers on AI output without independent judgment or reasonable verification. In a high-frequency environment, the demand for speed will lead to less critical acceptance of AI recommendations; as a result, the professional capabilities of human analysts will decline and institutional dependence on systems with unknown failure modes will gradually emerge [20].

5.4. Systemic risks

Systemic risks are large-scale threats that occur when data, models and applications work together in a large, cross-institutional environment [16]. Hallucination refers to the generation of plausible but factually incorrect information by generative models, such as fabricated regulatory provisions, non-existent financial data or erroneous product yield rates; this may lead to a chain of misinformation in the interconnected financial system [5]. Multi-model interaction risks arise from the interdependence of multiple institutional models; for example, an error in one model, such as a pricing issue, can be amplified by another, such as a risk control failure, thus triggering market resonance or a flash crash [16]. A cascade effect of financial system shocks occurs when a local technical or trust shock spreads through an interconnected financial network and threatens the stability of the entire financial system; for instance, failures in the payment system have led to a loss of consumer confidence and triggered a bank run [16].

6. Three-layer risk management framework

6.1. Technical layer

The Technical Layer will ensure the stability, reliability and accuracy of the GenAI system to address data and model risks. At this time, the selection of the model's architecture should meet the requirements of the financial application. LLMs are relatively suitable for tasks requiring the generation and understanding of financial text, and GANs can be used to generate synthetic data for stress testing and rare-event modelling. Multimodal Transformer models are more suitable for financial decisions that require the integration of text, numbers and pictures [5, 7, 32].

The other is a lower-level form of technical risk management. Generation quality can be evaluated using the above standard indicators: BERTScore, ROUGE and perplexity; additionally, domain-specific indicators such as fact-checking against verified financial databases [20] will be applied. Continue to observe continuously. Hallucination rate, factual accuracy, output stability and response delay are all indicators of the current performance and reliability of the model in a fluctuating market environment [8-18].

6.2. Application layer

In investment research and analysis, risk management includes verifying the accuracy of content by cross-referencing generated output with authoritative data sources, such as regulatory filings and verified financial databases, and adds a human-AI collaborative review process where senior analysts validate AI-generated research before release [9, 33]. To address the problem of non-representative data in risk assessment and forecasting, the framework uses GAN-generated synthetic crisis scenarios to stress-test predictive models for tail-risk events, and multiple independent data sources are employed to verify the output of sentiment analysis before raising a risk alert [7, 29]. The centre of responsibility for risk management in customer communication and guidance is designated. A clear system of responsibility specifies when to have a person override an AI's recommendation, such as when changing a portfolio risk too much. Transparency mechanisms can help clients understand the reasons behind AI-generated advice and challenge it, thus reducing the risks of over-automation and accountability gaps mentioned in [3, 15, 22].

6.3. Governance layer

Good governance starts with data governance; at all times during the life cycle of a model, diversity, representation and privacy protection of data must be ensured, bias audit procedures carried out, and regulations such as GDPR and PIPEDA complied with [19, 37]. The governance system will also use interpretability tools and documentation standards that meet the demands of regulatory disclosure to support model explanation [19, 20].

A person is still required. Clear rules should be established to determine the level of review, the chain of escalation and responsibility for decision-making of AI-generated output that will be used in high-stakes financial decisions [20-23]. Feng and others have proposed the following ideas to offer a basic system for responsible AI governance: fiduciary duty, adaptive personalisation and auditability. Finally, the governance system will add a regulatory compliance process and an independent audit mechanism for external model validation and bias testing, periodic governance reviews, etc., to ensure long-term accountability and institutional resilience [19-22].

The three levels are intended to work together and not operate independently as governance mechanisms. The Technical Layer will ensure the quality, reliability and performance of the model; the Application Layer will manage the risks of integrating GenAI into financial workflows; and the Governance Layer will provide institutional and regulatory support for continuous monitoring. Together, these layers form an all-encompassing governance system for the risks of GenAI deployment in financial investment across the entire lifecycle.

7. Discussion

7.1. Framework alignment with industry cases

To test the actual effect of the three-tier structure put forward in this paper, it is suitable to select three representative cases from different industries for analysis at the Technical, Application and Governance levels.

Commercial banks have used fine-tuned LLMs in GenAI for credit approval to improve the efficiency of automated credit risk assessment. The Selection Framework for the algorithm is at the technical level. LLMs are used for unstructured text analysis of loan application narratives and financial statements, and a model evaluation protocol is proposed to assess prediction accuracy and bias rate. At the Application Layer, the content verification mechanism will cross-reference the AI-generated credit decision with regulatory databases and have it approved by a human credit officer before being implemented. At the Governance Layer, the framework will address the problems of bias in historical lending data and regulatory requirements for explainability under fair lending laws [20] by introducing bias audit and model explainability governance.

GenAI in insurance claims processing helps automate the analysis of documents and detect fraud in an intelligent claims system. Eling and others have systemically investigated the effects of artificial intelligence (AI) at all links of the insurance value chain, and although AI can achieve cost reduction and more accurate risk prediction in underwriting and claims handling, problems such as the "black box" nature of models, data privacy issues, and changes in the risk environment have also emerged. The three levels of the new framework are as follows: Monitoring the Hallucination Rate and Performance Benchmarks of the Technical Layer for Target Model Reliability in Claims Adjudication. The Application Layer's stress-testing protocols fail to cover the data-representativeness gap for low-frequency catastrophic events. The third-party audit and regulatory compliance system in the Governance Layer provides external supervision for the industry and meets the requirements of the strict solvency regulations [19, 22, 25].

GenAI-powered platforms in asset management investment research have shown the ability to generate all-encompassing investment reports by integrating financial data, news sentiment and macro-economic indicators through multi-agent collaboration frameworks [9, 33]. The framework is in line with the good operation at all levels. The Technical Layer's algorithm selection will determine whether an LLM or a multimodal model is used for narrative generation and cross-asset analysis, respectively. The Application Layer's human-AI cooperative review process will be used to verify the accuracy of the client's content. The Accountability Protocol in the Governance Layer clarifies the division of responsibility for AI-generated analysis and human investment decisions [23, 24].

7.2. Hypothesis evaluation

Based on the systematic literature review and case studies, the four research hypotheses have been verified. Many studies have demonstrated the superior performance of GenAI in financial text generation, pattern recognition and predictive analysis compared to traditional methods; therefore, H1 has been verified. H2 is supported by the identification of twelve types of risk under the four proposed categories, and the existing single-category risk system is thus found to be inadequate. H3 is supported by the framework's shown capability to manage risks at all levels in a supporting manner, and it is not redundant, as shown in the case alignment analysis. H4 is partially verified. Although the framework is in line with the actual circumstances of banking, insurance and asset management, as shown in the documentation, there are no main empirical data from controlled implementation studies to support this verification.

8. Conclusions

Systematically explored the applications, risks and governance problems of generative AI in financial investment research in this paper. Based on an all-encompassing study of thirty-six academic and industrial materials, this paper has traced the development of technology from traditional machine learning to generative models, categorised GenAI applications into three areas of finance (investment research, risk management and customer service), and proposed a new four-type risk classification that covers data risk, model risk, application risk and systemic risk. The three levels of the new risk management system are technical quality control, application-specific risk management and institutional governance. The three industry cases of commercial banking, insurance and asset management were selected for alignment analysis in the framework validation. Academically, this paper extends the research on risks and governance for generative artificial intelligence systems, offers a structured analytical framework for subsequent studies, and integrates both technology-oriented and regulation-oriented perspectives. The system can help reduce the risks to the financial system, boost people's confidence in AI-driven financial services, and offer a reference for building an open and fair regulatory system for financial innovation. Provide a practical path for the financial industry to develop responsible GenAI.

The following are some deficiencies. Only secondary data from the systematic literature review in this study have been collected; primary empirical verification by financial institutions has not yet been carried out. Given the rapid progress in the field of generative artificial intelligence, some of the above technical attributes and risks may change substantially in the near future. Three Directions for Future Research. First, carry out a cross-market transferability study to explore the application of this framework in the development of financial markets and related industries, such as the technology industry. Second, release open-source companion tools for application of the framework in risk assessment at financial institutions. Third, study how the above framework can be extended to the entire industry for compliance and support the construction of a GenAI-specific risk management regulatory body.

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