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Review

Generative Artificial Intelligence in Finance: A Systematic Literature Review and a Research Agenda

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Abstract: This study presents a systematic literature review on the implications of the use of generative artificial intelligence (GAI) in finance. With the rapid advancement of GAI technologies and hybrid adversarial-variational frameworks, GAI's integration into the financial industry has gained significant importance. Despite the growing body of research, comprehensive analyses of GAI's potential applications, opportunities, and challenges in finance remain limited. The objective of our study is to synthesize the existing literature on the implications of GAI in finance and propose future research directions. The methodology involves a five-step systematic literature review process, including identification, selection, relevance and quality assessment, data extraction, and data synthesis of relevant articles published between 2020 and 2025. The evaluation based on 42 selected articles highlights several applications of GAI in finance, which include synthetic data-driven financial innovation, time-series forecasting and algorithmic trading, risk modeling and stress testing, as well as GAI-driven budgeting tools. Potential opportunities for GAI use in finance embrace enhanced operational efficiency, optimized customer service, innovation and sustainability capabilities, strengthened financial compliance, and improved data processing and analytical capabilities. Nevertheless, challenges such as technical risks, regulatory risks, ethics and moral concerns, market risks, operation and maintenance risks, and mental risks are also identified. Finally, we propose a research agenda focusing on both process-related and content-related recommendations to address these challenges and guide future research on the implications of GAI in finance.

Keywords: GAI-Alignment Risk; Generative Artificial Intelligence; Labor Displacement; Model Hallucination; Regulation

1. Introduction

Recent years have witnessed paradigmatic shifts in generative artificial intelligence (GAI), driven by advances in probabilistic deep learning architectures such as diffusion models, autoregressive transformers, and hybrid adversarial-variational frameworks [1–4]. Its deep integration into financial data analysis, intelligent marketing, and robo-advisory services is reshaping the global financial industry. GAI tools such as ChatGPT, DALL-E, and Deepseek, with their robust capabilities in content generation, data analysis, and pattern recognition, have demonstrated significant potential in financial risk management, customer service, investment decision-making, and market forecasting [5]. For instance, text mining-based financial market analysis techniques can rapidly identify signals of "bull" and "bear" markets, aiding investors in capturing market trends; the Synthetic Data Ecosystem (SynDEc) addresses the issues of data scarcity and privacy protection in financial services through incentive mechanisms and cross-institutional data sharing; deep learning models enhance the efficiency and accuracy of financial operations

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by automating report generation and optimizing trading strategies; and large language models (LLMs) streamline micro-tasks to boost research efficiency, excelling in six domains: creativity and feedback, writing, background research, data analysis, coding, and mathematical reasoning [6–9].

However, the widespread application of GAI has also given rise to a series of issues, including inadequate algorithmic transparency, data privacy risks, and ambiguous ethical responsibilities [10]. Moreover, it has exerted negative impacts on the short-term employment of freelancers in the online labor market [11].

The increasing complexity of GAI architectures has introduced systemic risks, posing dual challenges to technical governance and operational safety. Multimodal systems integrating Transformer-based reasoning with diffusion-synthesized data exhibit emergent behaviors that surpass traditional interpretability frameworks, creating "algorithmic black boxes" that obscure decision-making pathways in high-risk financial scenarios [12,13]. Qu et al. [14] identified two major types of machine "unlearning" techniques for large language models (LLMs): unlearning structured data and unlearning unstructured data. They also pointed out a series of challenges associated with these techniques, including over-unlearning, under-unlearning, and model integrity issues. Concurrently, trading agents based on reinforcement learning may experience unexpected crashes during stress tests, which further amplifies the risk of adversarial vulnerabilities.

The rapid deployment of GAI in finance has outpaced the formation of disciplinary consensus, resulting in methodological fragmentation and disordered regulatory frameworks. The Bank for International Settlements (BIS) analysis on fin-tech in 2023 observed that data-driven machine learning methods are increasingly adopted in quantitative finance, often at the expense of transparent integration with classical financial theories (https://www.bis.org/publ/arpdf/ar2024e.pdf). This epistemological disjunction results in the fact that large-scale LLMs' self-financing daily-rebalanced strategies can significantly predict future stock returns, yet exhibit a high rate of hallucination in small-scale derivative pricing tasks [15]. The absence of unified evaluation metrics has fostered methodological arbitrage, where institutions selectively report performance indicators favoring proprietary systems, thereby imposing conceptual and regulatory challenges on oversight bodies.

Given the nascent nature of GAI technology and its relatively recent entry into the financial sector, empirical case studies remain limited, leaving academic exploration of GAI in finance at an early stage. Existing studies predominantly focus on isolated aspects of GAI's impact, such as technical implementations (i.e., generative adversarial methods for asset pricing models) or business model innovations (i.e., AI-driven customized financial services), while lacking comprehensive analyses of technological opportunities, risks, and governance [16]. Additionally, the "black-box" nature of LLMs and their hallucination phenomena in financial applications hinder the interpretability of decision-making processes, posing challenges for financial governance teams in adopting AI solutions [10].

This study aims to conduct a systematic literature review to synthesize the potential implications of GAI in the financial industry and propose future research directions. In the successive sections, we first define the core characteristics of GAI and identify its typical application scenarios in finance. Subsequently, through rigorous information extraction, text integration, and quality assessment, we select highly relevant studies concerning the implications of the use of GAI in finance and extract key information. We then extract and integrate the research approaches and contents to construct a comprehensive analytical framework encompassing the potential opportunities, risks, and mitigation strategies for GAI use in finance. Finally, we create a research agenda for future studies in this field, providing a reference for researchers and financial practitioners.

2. Research Background

This section provides the necessary background concerning the key concepts of our study, including the definition of GAI (Section 2.1) and applications of GAI in finance (Section 2.2). The applications of GAI in the financial field include four aspects: synthetic data-driven financial innovation, time-series prediction and algorithmic trading, risk modeling and stress testing, as well as GAI-driven budgeting tools. Based on these introductions, a detailed analysis of the opportunities and challenges of GAI use in finance will be carried out in Section 4.3. **Figure 1** presents the main research context of this article. First, we clarify GAI's definition that it can output text, codes, and images. Secondly, we explore its specific applications in the financial field, and these preparations lead to the analysis of opportunities and challenges of GAI use in finance.

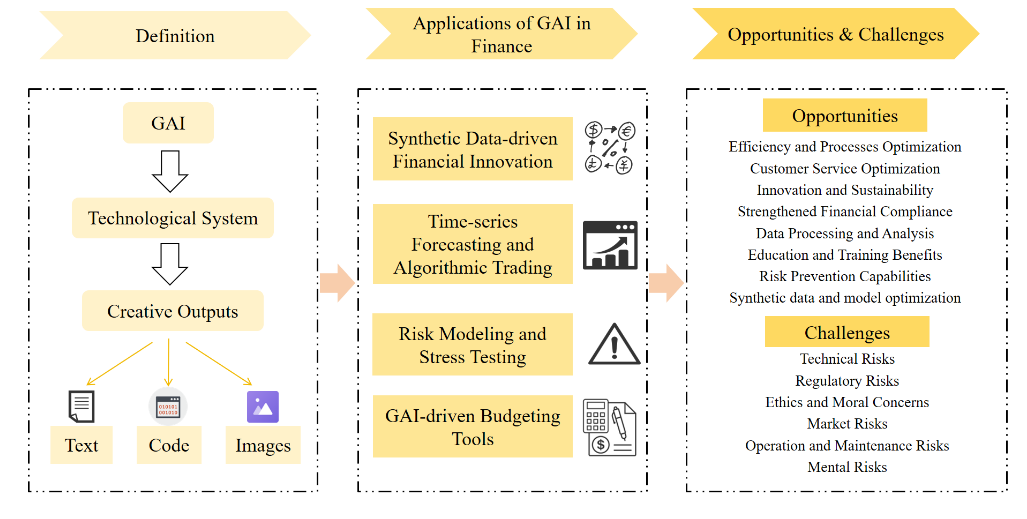

Figure 1. The Definition, Applications, Opportunities and Challenges of GAI Use in Finance.

2.1. Definition of GAI

As a cutting-edge branch of artificial intelligence, the definition of GAI continues to evolve with technological progress. The National Institute of Standards and Technology (NIST) defines GAI as a technological system that uses machine learning models to create outputs statistically similar to training data but with novelty. The European Union AI Act further emphasizes that such systems must autonomously generate non-deterministic outputs—text, code, images, etc.—based on a latent space model.

In digital content creation, GAI's core feature lies in its ability to generate novel content through deep learning architectures. Generative systems, composed of large-scale neural networks with billions of parameters, acquire generative potential through self-supervised learning. This capability manifests as creative outputs such as text generation, image synthesis, and cross-modal transformation.

In the digital governance industry, GAI is defined as algorithmic systems that analyze data distributions and autonomously generate novel, human-semantic-aligned content [17]. Technically, GAI encompasses generative adversarial networks, variational auto-encoders, and transformer architectures [2–4]. According to the World Intellectual Property Organization, such systems must generate non-repetitive innovative outputs, with core components including text tokenization, latent space mapping, and attention mechanisms [12,18,19].

In the financial context, GAI addresses privacy constraints through synthetic data generation and leverages sequence modeling for market predictions. The International Monetary Fund (IMF) working paper defines GAI as a technology suite that processes financial time-series data via autoregressive mechanisms to generate decision-support information with economic semantic value. Architecturally, temporal Transformers, federated learning frameworks, and interpretability modules are employed to ensure compliance [20,21].

Given the sensitivity of GAI applications in finance, the studies selected for this paper focus on literature in the fields of financial engineering, computational economics, and financial law, while excluding research on general-purpose content generation technologies.

2.2. Applications of GAI in Finance

2.2.1. Synthetic Data-Driven Financial Innovation

GAI addresses data scarcity through synthetic data generation, emerging as a novel tool for financial modeling. The potential application of synthetic data in nature and climate finance has been carefully investigated [22]. By emulating real-world data, synthetic data assists financial institutions in coping with environmental uncertainties, fluctuations in social and governance scenarios, and enhancing data availability. Besides, a credit scoring model based on conditional Generative Adversarial Networks (GANs) has been developed and found that the oversampling method based on Wasserstein GAN with Gradient Penalty (WGAN-GP) performs exceptionally well in multi-class credit score classification [23]. It effectively addresses the issue of data imbalance and significantly enhances the performance of the classification model. In the field of anti-money laundering (AML), federated learning frameworks have been employed to synthesize transaction data across institutions, thereby protecting customer privacy while enhancing the generalization capabilities of models. However, the Financial Stability Board (FSB) has cautioned that deviations between synthetic data and real economic laws may lead to systemic misjudgments, resulting in the risk of model hallucination. Recent studies have demonstrated that GANs, through their adversarial training mechanism, can more accurately simulate the distribution of normal data, thereby effectively reducing the false alarm rate. Nevertheless, the generation of adversarial verification graphs is necessary to enhance transaction security [24].

2.2.2. Time-Series Forecasting and Algorithmic Trading

In quantitative investing, GAI optimizes trading strategies by capturing nonlinear market features. A temporal fusion transformer model was constructed for multi-step time series forecasting [20], simultaneously predicting the 10th, 50th, and 90th percentiles to aid in optimizing decision-making and managing risks. Text mining techniques were utilized to train GAI models on futures market corpora [6], labeling "bull" and "bear" terms to provide real-time market trend advice for investors. Additionally, an AI-driven text summarization framework was presented for sentiment analysis of MD&A sections in 10-K filings, achieving an average annual return of 12.37% in buy-hold strategies [25]. Previous studies also developed and evaluated a Retrieval-Augmented Generation (RAG) system using the Design Science Research (DSR) approach [26], exploring the application of RAG models in financial report question-answering. Their work aimed to enhance the accuracy and reliability of Large Language Models (LLMs) in financial analysis, thereby providing investors with more accurate and relevant information.

2.2.3. Risk Modeling and Stress Testing

GAI enhances the resilience of the financial system by continuously simulating extreme events. Comparative studies have shown that GANs tend to generate smooth volatility curves in the simulation of liquidity crises, thereby underestimating the liquidity spiral effect and consequently exacerbating market volatility [27]. In contrast, the diffusion models have demonstrated remarkable performance in image generation tasks due to their probabilistic modeling advantages, achieving FID scores within 5% for the CIFAR10 and LSUN Bedroom large model datasets [1]. The IMF has recommended incorporating the technology of using variational auto-encoders to generate tail-risk scenarios and reduce the error rate of bank capital adequacy ratio calculations into the macro-prudential regulatory toolkit. It has also emphasized the establishment of a closed-loop control mechanism of "generation-validation-iteration".

2.2.4. GAI-Driven Budgeting Tools

The application of GAI tools in Fintech has become pervasive, particularly in the realm of corporate budget setting. GAI-driven budgeting tools leverage sophisticated technologies such as machine learning and data mining to transform financial planning. These tools process vast amounts of data swiftly, identifying intricate patterns and trends that inform more accurate budget forecasts. For instance, they can analyze historical financial data, market dynamics, and even external factors like economic indicators to predict future expenses and revenues with greater reliability. This enables businesses to formulate more realistic budgets, monitor spending with enhanced precision, and make timely adjustments. Evidence from numerous case studies indicates that companies utilizing GAI-driven budgeting have achieved substantial improvements in budget accuracy and overall financial performance [28,29].

3. Research Approach: Systematic Literature Review

This work implements a systematic literature review to retrieve relevant researches that target the implications of the use of GAI in finance. This approach aims to provide a rigorous and unbiased review that reflects the current state of the target research field and provides a basis for future research [30]. In the next sections, a five-step guideline is performed to help identify, select, and assess relevant studies [31]. It covers (1) identification of studies, (2) selection of studies, (3) study relevance and quality assessment, (4) data extraction and (5) data synthesis.

3.1. Identification of Studies

In order to establish a clear criterion for judgment, we determine our literature review objectives to (1) identify and position previous research relative to the implications of GAI use to finance, (2) summarize research approaches adopted by other scholars to study the implications of GAI use in finance, (3) integrate valid conclusions and insights on GAI use in finance from other scholars. To achieve the first objective of our literature review, i.e., to identify and position previous research relative to the implications of GAI use in finance, we addressed the following questions in the literature selecting process:

1. What specific research background is focused on in the previous research on the topic of implications of GAI in finance?
2. What problems has the previous relevant research solved and what contributions has it made concerning the GAI use in finance?

With regard to the second objective, i.e., to summarize research approaches adopted by other scholars to study the implications of GAI use in finance, led to the following questions:

3. What specific research methods (e.g., qualitative analysis, quality analysis methods) have been used in existing relevant studies?
4. Have previous relevant studies addressing the implications of GAI use in finance proposed new research methods and approaches?

For the third objective, i.e., to integrate valid conclusions and insights of GAI use in finance from other scholars, led to the following questions:

5. What are the specific applications of GAI in finance?
6. What are the potential benefits and challenges of the use of GAI in finance?
7. What new developments are possible for GAI in finance in the future?

We select and identify studies relevant to the implications of the use of GAI in finance using the Web of Science, which is an important database for global academic information, including journals and literature from Elsevier, Springer, Wiley-Blackwell, Taylor & Francis, Sage, and other publishers. The identification and selection process was carried out in March 2025, and only covered papers published no later than March 22nd, 2025.

3.2. Selection of Studies

During the selection of studies, we defined the search terms (see **Table 1**) and the inclusion criteria. We limited the search results to journal articles and conference proceedings written in the English language and published in 2020-2025. The searches were limited to nine areas: computer science, engineering, business economics, social issues, communication, behavioral sciences, government law, information science library science and sociology. Areas such as mathematics, automation control systems, and mathematical computational biology were excluded because articles from these areas may be highly technical or irrelevant to our research topic.

Table 1. Search Terms Used for the Literature Review.

Databases	Search Terms in the Title/Keywords
Web of science	"finance" OR "economic" OR "capital market" OR "financial" OR "fintech" OR "labor" OR "investment" OR "employment" AND "generative AI" OR "GAI" OR "AIGC" OR "LLMs" OR "large language models"

We applied the search process in March 2025 using the following terms and obtained 854 results concerning the implications of GAI use in finance. After careful observation and discussion, it was found that most of the literature after the first 100 results only focused on either "generative AI" or "finance", or regarded GAI as a minor role, which did not comply with the criteria. In order to reflect the current state of GAI use in finance comprehensively, we included the first 150 results with the highest relevance (as assessed by the database).

3.3. Study Relevance and Quality Assessment

The third step of our study concerned the study relevance and assessment, which consisted of two sub-steps. First, we read the title and abstract to determine the relevance of the study using the following two criteria:

1. GAI use should play a substantial role in the study. Studies that regard GAI use as a minor or secondary research object were excluded in this phase.
2. Studies should focus on the application and implications of GAI in finance. If the study does not focus on the financial sector, it should be excluded in this phase.

The title and abstract of each paper were independently reviewed and agreed upon at least two authors. According to the criteria above, 81 studies were excluded and 69 studies remained.

Second, using the third and fourth criteria, we assessed the relevance and quality of the remaining studies by reading the complete contents.

3. At least one specific research method should be adopted in the study (e.g. literature review, case studies, document analysis, etc.). Studies that merely contain authors' opinions without providing any logical analyzing process should be excluded.
4. Studies should possess sufficient accuracy and consistency. The objectives of the study should be clearly stated, the research methods should be in line with the research objectives, and raised questions should be completely answered. Studies that failed to comply with these standards should be excluded.

After independent assessments and discussion, we excluded studies that did not meet any of the above quality criteria and limited publication from 2020 to 2025 to ensure the timeliness of the literature review. At this stage, we removed 27 studies and ended up obtaining 42 studies directly addressing GAI use in finance. **Figure 2** shows the process of literature identification, screening, eligibility and inclusion. In the identification stage, 704 results were excluded based on the research topic, leaving 150 results. During the screening stage, 81 studies were removed due to the low relevance of titles and abstracts, resulting in 69 remaining results. In the eligibility and inclusion stage, 27 studies were excluded after full-text review due to quality issues, leading to the final inclusion of 42 studies.

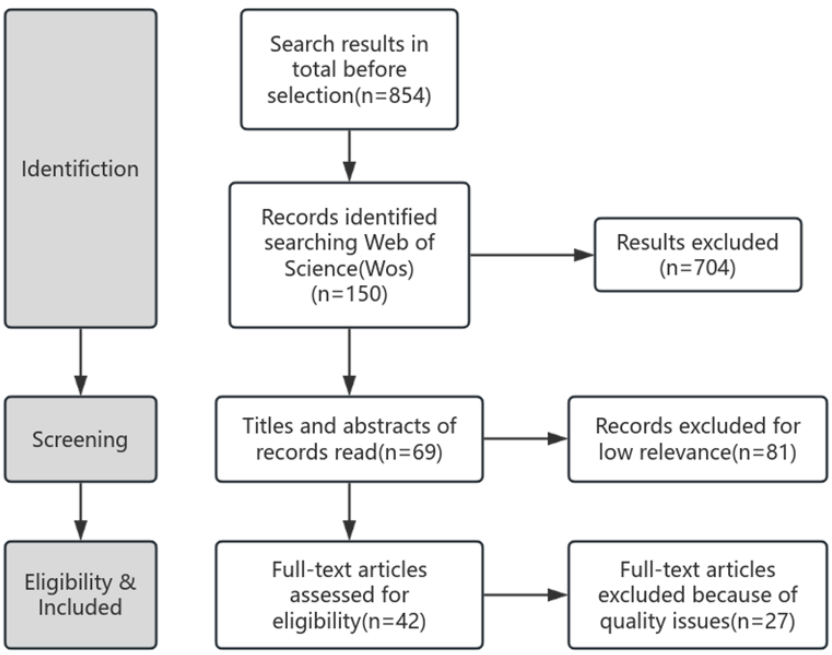

Figure 2. Study Selection, Assessment and Inclusion.

3.4. Data Extraction

After detailed reading and discussion, we decided to collect data from the 42 selected studies on four following aspects: descriptive information, approach-related information, quality information, GAI and finance information. **Table 2** provides a detailed description of the information we have collected.

3.5. Data Synthesis

The final step of our study concerned data synthesis. First, we systematically analyzed the raw data obtained from the above-mentioned studies, conducted descriptive analysis, research approach analysis and content analysis, and recorded our findings in Section 4. Second, based on the results of the systematic literature review, we put forward research suggestions for future research on GAI in finance. Each author first summarized and integrated the metadata of the included literature (see **Table 2**), and put forward suggestions from two aspects of the research approach and research content. After careful discussions among four authors, suggestions that did not meet the requirements of feasibility or relevance were excluded. Third, based on the analysis included in Section 4, we developed a research agenda on the implications of the use of GAI in finance in Section 5. Information from the 42 included studies were collected, discussed and integrated by two authors to create a draft framework, and the other two authors were responsible for reviewing and improving this agenda.

Table 2. Overview of Information Collected about each of the Selected Studies.

Category	Metadata	Description
Descriptive information	Complete reference	What is the complete reference to this source, including the author(s), the article's title and other information?
	Year of publication	In which year the study was published?
	Journal/conference	In which journal or conference proceedings was the study published?
	Digital object identifier (DOI)	What is the study's DOI? If no DOI is available, what alternative method can be employed to locate the study?
	Keywords	What are the keywords of the study?
Approach-related information	Study objective	What is the study objective /main question?
	Research method(s)	Which research method(s) is used in this study?
	Theory mentioned	What theory is mentioned in this study? What does this theory mean?
	Availability of research data	Does this study contain any specific data? If so, is the data available? What is the source(s) of these data?
Quality-related information	Research approach	Does the research approach in this literature align with the research objective? Is it logical and interpretable? For literature reviews: is the literature review timely? Does it align with the research objective? Is the citation process appropriate enough? For case studies: is the analysis process rigorous enough? Is there any logical gap in the process of reaching a conclusion? For empirical analysis: Are the models and variables carefully measured? Is the sample size big enough to draw a general conclusion?
	Accuracy of the theory	Does the theory employed in this study align with the study objective? Does the theory play a key role in the study?
GAI and finance related-information	Study's contribution	What contributions did this study make?
	Applications of GAI in finance	What are the specific applications of GAI in the financial field?
	Potential opportunities and benefits of GAI use in finance	What are the potential opportunities and benefits of using GAI in finance?
	Potential challenges and risks of GAI use in finance	What are the potential challenges and risks of using GAI in finance?
	Future research agenda	What potential developments might GAI bring about in the financial sector in the future? What is the research agenda?

4. Results from the Systematic Literature Review

This section describes the analysis results of the screened literature that mainly involves the risks and impacts of GAI on the financial sector. Below we will report the results of descriptive analysis, approach analysis and content analysis.

4.1. Descriptive Analysis

The first part involves descriptive information. We analyzed the research objectives of the screened literature and found that most of the studies were exploratory and constructed a framework by summarizing the current situation and challenges. Through a literature search on the Web of Science, a total of 854 articles were identified, but only 42 papers focusing on the risks and impacts of GAI in finance were ultimately screened and listed. Compared to research on GAI across the entire field, literature focusing on the impact of GAI on the financial sector is relatively limited.

The selected articles were all published within the past three years, with the majority of the literature published in journals (n = 35) and a small number included in conference proceedings (n = 7). Except for being included multiple times in journals such as *COMPUTER*, *OECONOMIA COPERNICANA*, *APPLIED SCIENCES-BASEL*, *Journal Article*, and *POLICY AND SOCIETY*, the literature included in this study comes from different journals, with most of them covering the fields of economics and finance, and a few journals related to data and management science.

4.2. Approach Analysis

This section discusses the research methods for screened literature, with the most important method being literature review (n = 32). Other methods include case studies, model system construction, official document report analysis, empirical analysis, data statistical analysis, thematic analysis, interview research, comparative analysis, and theoretical analysis (see **Figure 3**). Qualitative methods dominate research, with over 60% of the sample literature being qualitative studies (n = 27). In contrast, there are fewer studies using quantitative methods (n = 5) and a combination of both methods (n = 10) (see **Figure 4**).

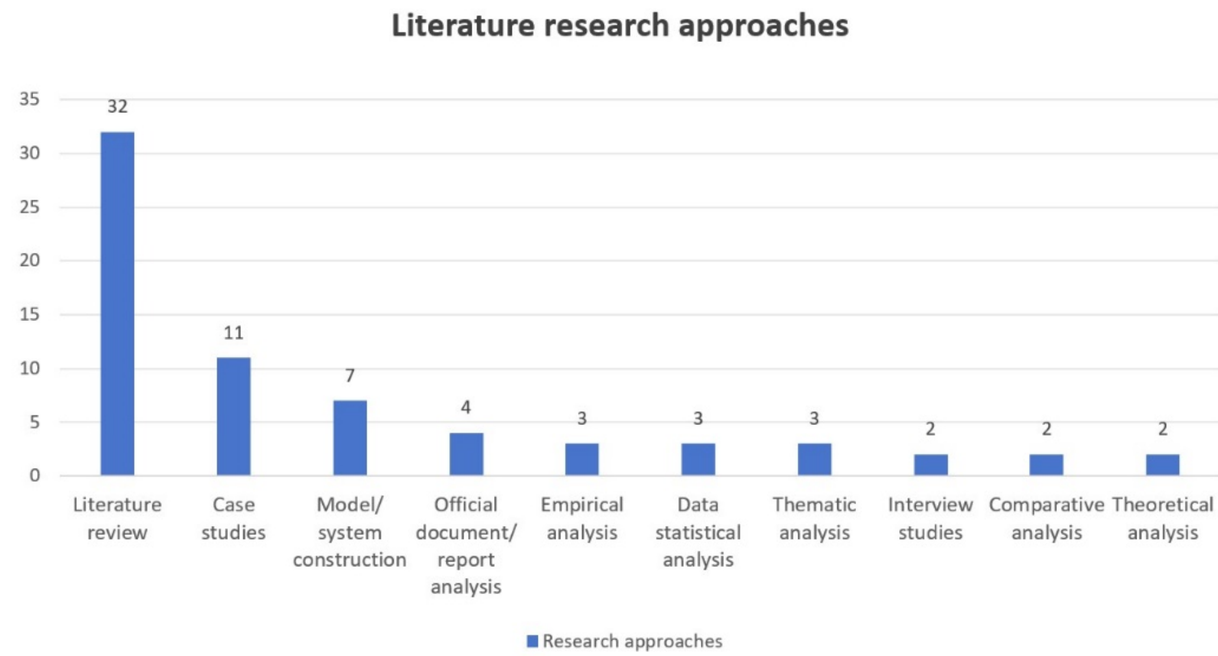

Figure 3. Research Methods Used by the Studies in our Review.

4.3. Content Analysis

This section conducts a content analysis of the selected literature, including the potential opportunities (Section 4.3.1) and challenges (Section 4.3.2) of GAI use in the financial field, as well as mitigation recommendations for the aforementioned challenges (Section 4.3.3). The following analysis is based on the author's own views and arguments, excluding references and other sources to avoid repetition and duplication.

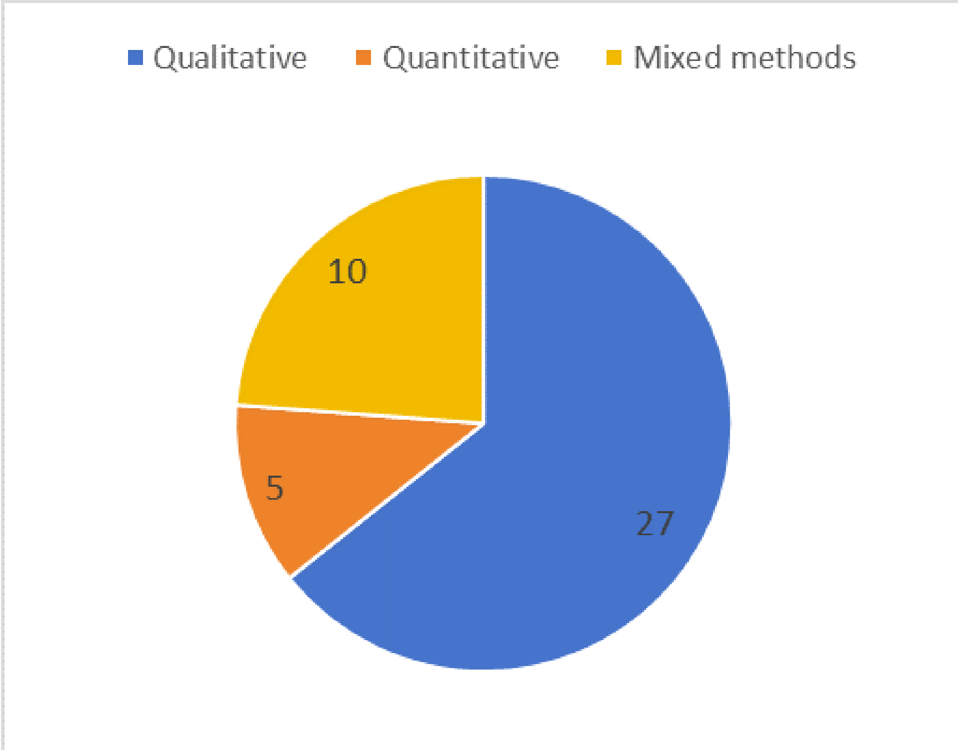

Figure 4. The Proportion of Qualitative, Quantitative, and Mixed Methods Used by the Studies in Our Review.

4.3.1. Potential Opportunities of GAI for the Financial Industry

In this section, we will discuss the potential opportunities of GAI in finance. By reviewing the screened literature, we identified opportunities in eight categories: (1) efficiency and processes optimization, (2) customer service optimization and experience improvement, (3) innovation and sustainability capabilities, (4) strengthened financial compliance and governance, (5) enhancement in data processing and analytical capabilities, (6) education and training benefits, (7) risk prevention capabilities, and (8) synthetic data and model optimization (see **Table 3**).

Table 3. Potential Opportunities of GAI Use in Finance.

Category	Detailed Opportunities and Articles
(1) Efficiency and processes optimization	Optimizing investment portfolios [32,33] Enhancing the speed and accuracy of decision-making [32] Automating a variety of tasks in the financial sector [34] Automating document generation and customer service [32] Automating audit processes [35] Accelerating data processing speed [25,36] Reducing labor costs [8,37] Optimizing resource allocation [8] Simplifying processes to improve accuracy and efficiency [32,38]
(2) Customer service optimization and experience improvement	Providing personalized financial advice to customers [8,36] Enhancing customer interaction to improve customer experience [32] Intelligent customer service and chatbots [32] Personalized marketing [39] Offering round-the-clock technical support to help customers quickly obtain the information they need [40] Generating user-friendly information to enhance market competitiveness [32]
(3) Innovation and sustainability capabilities	Promoting cooperation between financial institutions and other industries to explore new business areas and cooperation models [7] Creating new financial positions and bringing new employment opportunities to the industry [41,42] Facilitating financial institutions in serving vulnerable populations and customers in remote areas to enhance the inclusivity of financial services [7] Assessing the environmental risks of financial institutions, and formulating sustainable development strategies [7] Designing more innovative and competitive financial products according to market demand and customer preferences [22,42,43] Developing personalized financial products [44] Creating new types of financial instruments [9]

Table 3. *Cont.*

Category	Detailed Opportunities and Articles
(4) Strengthened financial compliance and governance	Generating compliant synthetic data [32] Compliance monitoring and early warning [34] Encrypting data and conducting anonymization operations [32] Financial institutions integrate data from different departments and channels through GAI to achieve data sharing and collaborative utilization [7] Anti-money laundering and counter-terrorist financing [45] Optimizing internal governance to improve operational efficiency and transparency [44] Interpreting and applying regulations appropriately [32] Compliance risk assessment and checks [32,46] Analyzing transaction data and customer behavior to identify and prevent financial fraud and money-laundering activities [47,48]
(5) Enhancement in data processing and analysis capabilities	Utilizing alternative data to assist in credit decisions, providing more accurate credit assessments for customers without traditional credit records [36] Generating more accurate credit scoring models based on historical data and user behavior patterns [39] Mining potential information and patterns in financial data [7] Integrating multi-source data to provide a more comprehensive analytical perspective [49] Data visualization [47] Cleaning, organizing, and validating data [47] Generating high-quality synthetic data to reduce financial institutions' dependence on real data [7] Identifying and correcting errors and anomalies in data to improve data quality [50] Real-time data interpretation [51]
(6) Education and training benefits	Simulating real-world financial scenarios for professional skills training [52] Popularizing financial knowledge [52]
(7) Risk prevention capabilities	Processing large amounts of non-traditional data such as social media data and transaction behavior data to more accurately predict default risks [50] Monitoring data access and usage behavior to promptly detect data leakage risks [7] Simulating different market scenarios and product performance to cope with the risks of complex financial products [7,43] Multi-dimensional risk analysis [6] Simulating extreme scenarios to test the resilience of financial systems and tools [49] Identifying potential risk factors that traditional methods may overlook [51]
(8) Synthetic data and model optimization	Generating code based on context to optimize legacy frameworks and review code to identify defects and inefficiencies [40] Training machine learning models to reduce hallucination phenomena [40] Generating synthetic data to replace real data for sharing and model training [7] Providing suggestions for building financial models and checking model logic and parameter settings [53]

First, by automating tasks and optimizing decision-making processes, GAI can significantly improve the operational efficiency of financial institutions. Based on extensive data training, GAI can analyze market dynamics in real time, optimize investment portfolios, and enhance risk management capabilities [32]. Automated tasks in the financial field and audit processes can reduce labor costs and accelerate data processing speed [8,25,34,35].

Second, GAI empowers financial institutions to provide smarter and more personalized services, enhancing customer loyalty. Intelligent customer service and chatbots can respond to customer needs at any time, improving customer engagement and experience [32]. Meanwhile, GAI can generate user-friendly market information, combined with user profiles to generate personalized investment plans, to enhance market competitiveness [8,32].

Third, GAI can promote cooperation between financial institutions and other industries, explore new business areas and cooperation models, and generate new products and models [7,9]. Through natural language processing and generation technology, financial institutions can provide services to vulnerable groups and customers in remote areas, improve the inclusiveness of financial services, and promote the sustainable development of inclusive finance[7].

Fourth, through compliance monitoring and early warning, GAI can identify and prevent financial fraud and money laundering activities, helping financial institutions cope with complex regulatory environments [34, 47]. Meanwhile, GAI can optimize internal governance to improve operational efficiency and process transparency and further enhance governance capabilities [44].

Fifth, based on historical data and user behavior-generated credit scoring models, GAI can mine potential information in financial data and generate high-quality synthetic data to reduce financial institutions' dependence on real data [7,39]. In terms of data analysis, GAI can integrate multiple sources of data and process and validate the data to improve quality and accuracy [47,49].

Sixth, GAI can simulate real-life financial scenarios for professional skill training, assist in disseminating financial knowledge, and cultivate practitioners' abilities in investment decision-making, crisis management, and other areas [52].

Seventh, by monitoring data access behavior and processing large amounts of non-traditional data such as transaction data, GAI can more accurately predict default risk [7,50]. By simulating extreme scenarios to test the resilience of financial systems and tools, GAI can identify potential risk factors that are easily overlooked by traditional methods, enhancing risk prevention capabilities [22,51].

Eighth, context-generated code can be reviewed by GAI to identify defects and inefficiencies. In practical application scenarios, GAI can reduce hallucinations, and check the logic and parameter settings of the model to provide suggestions for building financial models, further optimizing the model [40,53].

4.3.2. Potential Risks of GAI to the Financial Industry

In addition to potential opportunities, we also classified the potential risks mentioned in the screened literature. **Table 4** provides a comprehensive overview of the main challenges and proposes in six categories: (1) technical risks, (2) regulatory risks, (3) ethics and moral concerns, (4) market risks, (5) operation and maintenance risks, (6) mental risks. In response to these challenges, targeted mitigation strategies are explored in Section 4.3.3. **Figure 5** depicts the correspondence between primary risks and mitigation strategies. The left side lists the identified primary risks, while the right side shows multiple mitigation suggestions for each risk. Mitigation strategies for the same risk are placed in a rectangle and aligned horizontally with the corresponding risk for clear visualization.

Table 4. Challenges and Risks of GAI Use in Finance.

Primary Risks	Secondary Risks	Detailed Definition and Articles
(1) Technical risks	Model hallucination phenomenon	Hallucinations caused by biased training data, ambiguous prompts and inaccurate LLM parameters [34,54]
	Lack of interpretability ("black-box" issue)	Black-box nature of AI algorithms, challenges in transparency and accountability [10]
	Safety of intelligent system	Information hacked and accessed by detrimental parties [47]
(2) Regulatory risks	The complexity of regulatory mechanism	Challenges for regulators caused by the continuous evolution of GAI [55]
	Regulatory gaps	Legal gaps that arise from the implications of decisions made by autonomous GAIs [45]
(3) Ethics and moral concerns	GAI-Alignment risks	The development of AI should ensure the alignment with human values and morality [8]
	Bias and discrimination	Ethical biases rooted in the data that large language datasets trained on and historical or societal biases in the GAI such as racial or gender prejudices [8,56]
	Information security	Leakage of sensitive information and improper access to user-posted information [32,57]
	Privacy concerns	Concerns related to privacy and trust [40,54]
	Issues of intellectual property rights	Infringement on intellectual property rights [55,58]
	Misuse and overuse of data	Unauthorized disclosure or alteration of personal data [59]
	Data compliance risk	Compliance and legality of data used for the pre-training process [60]
(4) Market risks	Vulnerability caused by misleading information	Misleading predictions, instilling false impressions or prompting erroneous conclusions based on inaccurately generated data [61]
	Labor displacement issue	Substitution for knowledgeable workers, reducing their employment and earnings [11]
	Socioeconomic inequalities	Deepened socioeconomic inequalities if access to GAI technologies is uneven [41]
	Digital divide	Exacerbated digital divide impacting individuals and communities with different access and acceptance levels of GAI [59]
	Monopoly risk	Resource and power monopolization by large companies [59]
(5) Operation and maintenance risks	Cost of pre-training models	User cost of computational resources employed to pre-train models [9]
	Expense of updates and maintenance	Cost associated with maintaining and expanding the infrastructure [32]
	Environmental concerns	High levels of energy used and increased carbon footprint [55]
(6) Mental risks	Over-reliance on GAI	Risks of missing findings, misdiagnosing and misinterpreting data caused by over-reliance on GAI and atrophy of people's skills-deskilling [35]
	Risk of homogenization	Ideas economists work on will become more homogeneous and include fewer novel ideas [9]
	Decreased creativity and critical thinking	Impediment of critical thinking caused by over-reliance on GAI [59]

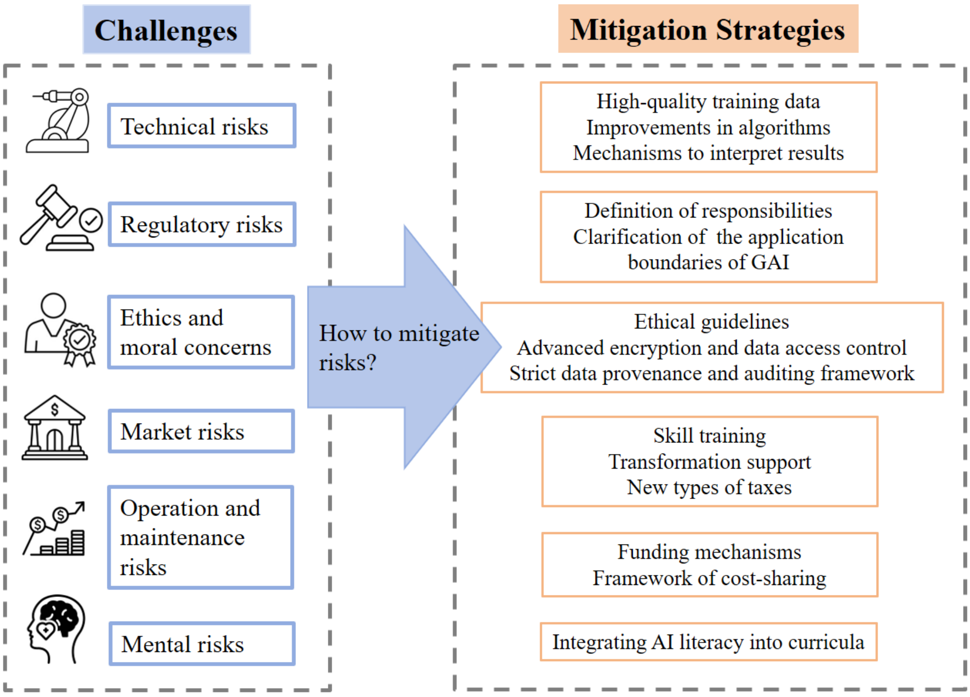

Figure 5. The Correspondence between Challenges and Mitigation Strategies.

First, inaccurate or misleading pre-training data may lead to erroneous conclusions and create false or synthetic data, causing model hallucination phenomenon [32,61]. It has been proved that GAI often outputs inaccurate or unsupported content when explaining financial concepts and recognizing alleviating behaviors [62]. Due to the opacity of the algorithm decision-making process, the complex interpretation process makes it difficult for users to intuitively understand the relationship between model inputs and outputs, which can easily lead to algorithmic black-box problems [10, 52]. Besides, information may be hacked and accessed by detrimental parties illegally, raising concerns about the safety of intelligent systems [47].

Second, when it comes to regulatory risks, the continuous evolution of GAI brings obstacles for regulators for it enhances the complexity of regulatory mechanism [55]. At the same time, legal gaps are also found in monitoring the use of GAI [45].

Third, ethics concerns are widely mentioned among selected studies. The narrowness of training data that GAI relies on can easily lead to algorithmic discrimination in AI applications [9]. The biased outputs generated by GAI may be toxic and not in line with human values and morality, thus raising GAI alignment concerns [8]. Moreover, GAI has issues such as violating customer privacy, violating regulatory guidelines, and infringing intellectual property rights, which have led to numerous legal risks and challenges in compliance with regulation and data privacy [35,59].

Fourth, the automation process may lead to unemployment risks and job loss, exacerbating wage and wealth inequality [47, 63]. If data and resources are overly concentrated in large technology enterprises, there may be a risk of algorithmic technology monopoly [41]. Meanwhile, the dissemination of misinformation by GAI may disrupt the job market, and the role of human creativity has also been questioned [45,64].

Fifth, GAI requires regular updates, and the cost of maintaining and expanding infrastructure is high [32]. The computation of model pre-training also consumes a lot of resources, resulting in increased costs in operation and maintenance [9]. High levels of energy used for training may raise environmental concerns such as an increase in carbon footprint [55].

Sixth, excessive reliance on GAI leads to the risk of missing or misreading data, resulting in the degradation of human skills [35]. Meanwhile, excessive reliance on large language models may lead to homogenization risks [9], which is not conducive to comprehensive analysis and innovative development in the financial sector.

4.3.3. Mitigation Strategies for the above Challenges

To address the issue of model interpretability, improvements in training algorithms and an increase in high-quality training data are proposed to enhance the model's understanding and processing capabilities of financial data to reduce the probability of "illusions" and other problems, as well as ensure its ability to provide reasonable and reliable recommendations in financial decision-making [61]. Studies pointed out that financial institutions must implement mechanisms to interpret the results generated by GAI and provide reasonable explanations for decisions [10].

With the continuous expansion of the application of GAI in finance, regulatory policies also need to follow up in a timely manner. It is necessary to clarify the definition of responsibilities in GAI applications, carefully evaluate the decision-making results of models [61], and reduce legal risks. Besides, relevant regulations should be formulated by governments and regulatory agencies to clarify the application boundaries of GAI in the financial field, while strengthening supervision of fin-tech companies to ensure their compliant use of GAI technology [44].

The security and privacy of financial data determine the trust of users, ensuring the secure flow of financial data in GAI applications. By using advanced encryption technology, data access control, and other means, data leakage and abuse are prevented, and the immutability of blockchain technology is utilized to enhance data integrity. With regard to the risk of bias and discrimination, the development of standards, ethical guidelines and code of conduct need urgent attention to ensure the appropriate use of GAI in computer science [57]. Strict data provenance and auditing frameworks needs to be established, requiring developers to document data sources, obtain proper consent and adhere to privacy laws.

Society and enterprises should jointly cope with the employment structure impact brought by GAI. Enterprises need to provide skill training and transformation support for employees, help them improve their digital skills, and adapt to new job demands. Relevant policies should be introduced to encourage the development of emerging employment opportunities, promote the optimization and transformation of employment structure, and promote the sustainable development of the financial industry and society. Additionally, it is necessary for governments to explore new types of taxes on AI-generated wealth to ensure that the welfare brought by GAI is broadly shared by the whole society [57].

Financial industry practitioners need to possess certain professional knowledge and skills to prevent violations and unethical behavior from occurring. Through training, education, and other means, financial and auditing professionals can understand the principles and applications of GAI, be able to apply this technology reasonably in their work, and effectively identify and prevent its risks [35]. At the same time, professionals need to remain highly vigilant about data security and privacy risks, avoid excessive reliance on new technological tools, and prevent them from weakening their critical thinking abilities [52].

Finally, to mitigate the high expenses of pre-training and maintenance, funding mechanisms such as public-private partnerships or subsidies can be established by governments or stakeholders to support smaller organizations. Additionally, standardized frameworks for cost-sharing can promote efficiency in model development. Regarding the over-reliance issue, policymakers should prioritize educational reforms that emphasize critical thinking and creativity alongside technical skills. Integrating AI literacy into curricula can help individuals understand the limitations of GAI and foster human-AI collaboration.

5. A Research Agenda on the Implications of the Use of GAI in Finance

Various research agendas centered around GAI use in finance have already been developed [52, 61, 65, 66]. For example, a critical agenda for further research in robo-advisors was presented [65], emphasizing robot design, customer features, service encounter characteristics, laws, ethics and regulations and research methods, and it is necessary to strengthen the evaluation and validation of GAI models [52]. The research agenda by Lee et al. [61] is not only focused on the model, but it lays much emphasis on clarifying the definition of responsibilities in GAI applications and requires more regulatory policies. In addition, the research agenda by Chatterjee [66] focuses on the security and privacy of financial data. It suggests to use of advanced encryption technology, data access control, and other means to prevent data leakage and abuse. Our research agenda complements these existing agendas by focusing specifically on the implications of the use of GAI in finance. The research agenda has been developed based on our systematic literature review and analysis of articles included in this special issue. It comprises four process-related recommendations (Section 6.1) and four content-related recommendations (Section 6.2) for researchers that examine the implications of GAI use in finance.

5.1. Process-Related Research Recommendations

1. Avoid a generic focus on GAI and technology abuse. Firstly, it is necessary to clearly define the technical boundaries of "generative artificial intelligence", and avoid including other AI technologies, such as traditional machine learning, in the research scope. Secondly, be wary of the "technology hype" of GAI in the capital market scenarios. Researchers are recommended to conduct risk analysis in combination with specific cases (e.g., automated report generation, the spread of false information, algorithmic trading strategies) [32]. Therefore, researchers should avoid abstract discussions that are divorced from reality.
2. Strengthen the integration of interdisciplinary methodologies. As an overwhelming majority of research about AI use in finance adopted the framework of "technology-finance-law", we identified a need to strengthen the integration of interdisciplinary methodologies. At the technical level, exploring the algorithmic transparency, data dependency, and vulnerability to adversarial attacks of generative models is urgently required [52]. At the financial level, researchers are advised to analyze the impact mechanisms of generated content on market fluctuations, investors' behaviors, and asset pricing. At the legal level, formulating compliance standards for GAI, such as the authenticity of information disclosure and the attribution of algorithmic responsibilities is also suggested [61]. Meanwhile, encouraging mixed research methods, such as simulation, using natural language processing to analyze investors' sentiment, and combining case backtracking with empirical testing, is beneficial to break through the limitations of single-theory deduction.
3. Increase empirical research on the implications of GAI use in finance. Although considerable attention has been paid to GAI, it is not common in GAI research today to contribute to empirical testing. As confirmed by our research, most of the studies in our sample concerned literature reviews. The slow pace of empirical research on the finance industry implications of GAI use in the capital market, contrasted with the expedited drive in practical implementations, may lead to increased biases in government decisions, enabling investors to arbitrage or manipulate the market, rising levels of inequality, or the generation of interventions that are neither fair nor responsive to public needs, with potentially problematic ethical implications for societies and governance [59]. Thus, future research should extend beyond the conceptual and speculative levels and contribute to empirically testing the implications of GAI use in finance.
4. Promote open collaboration and enhance transparency. Financial institutions and academia are encouraged to share a database of GAI risk cases (e.g., market flash crashes caused by algorithmic failures) to break down industry data barriers and to boost research concerning GAI in finance. Core parameters and training logic of the models in studies (on the premise of not revealing confidential information) should become standard practice.

5.2. Content-Related Research Recommendations

1. Prioritize high-impact applications with weak mitigation strategies. Future research should focus on identifying and prioritizing the applications of GAI in finance that have the highest potential influence, while also considering the areas where current mitigation strategies are weak. For instance, despite GAI-driven synthetic data's significant potential for financial innovation, substantial risks related to data integrity and model hallucination are also posed. Similarly, GAI's role in risk modeling and stress testing is crucial, but current mitigation strategies for potential systematic risks are limited. Studies should aim to develop more effective risk mitigation frameworks to address these challenges while maximizing the benefits of GAI in these areas.
2. Analyze pathways for global collaborative governance. Although some studies have analyzed the risks of GAI in capital markets, it is not common to analyze the transmission mechanisms of the risks of GAI in transnational capital markets, such as the cross-border spread of false information and regulatory arbitrage [32]. Moreover, we identified a need to promote the mutual recognition of international standards (e.g., the localization adaptation of the OECD's "Guidance on the Governance of Artificial Intelligence Systems for Risk Management" in the financial sector), and establish a multilateral emergency response mechanism.
3. Investigate best practices in managing the risks of GAI use in finance. The selected articles revealed many risks for the use of GAI in finance (see Section 4.3.2). These include dealing with the risk of data misuse and manip-

ulation and the usage of automated risk assessment tools in ways that counteract the rudimentary values of transparency for replicability [53,55]. In the context of cross-sectoral collaboration around GAI, it is necessary to clarify the definition of responsibilities in GAI applications and strengthen the evaluation and validation of GAI models [52,61]. Our literature review revealed a lack of research into best practices in managing GAI use risks in finance. In research efforts related to risk management for GAI use in finance, scholarship should not neglect critical, ethical issues related to capital markets implications of GAI use, including fairness, explainability, transparency, accountability, bias, privacy, safety, security, and societal impact.

4. Protect the privacy of investors and maintain market fairness. Previous research in our literature has found the issue of exacerbated information asymmetry caused by GAI [7]. Institutional investors take advantage of generative models to gain an information edge, while retail investors face "algorithmic discrimination" [59]. At the same time, personalized investment advice assisted by GAI may induce irrational trading behaviors [9]. Therefore, it is necessary to construct an investor education framework to enhance the public's awareness of and defense capabilities against the potential risks of GAI.

6. Conclusions

To lay the foundation for the special issue that this article introduces, we (1) present a systematic review of existing literature on the implications of the use of GAI in finance and (2) develop a research agenda. We select and identify studies relevant to the implications of the use of GAI in finance using Web of Science, including journals and literature from Elsevier, Springer, Wiley-Blackwell, Taylor & Francis, Sage and other publishers. We limited publication from 2020 to 2025 to ensure the timeliness of the literature review and ended up obtaining 42 studies. The majority of the studies in our sample concerned literature reviews, model analysis, and policy document and report analysis.

In our qualitative analysis, we identified potential opportunities for GAI use in finance in eight categories: (1) efficiency and process optimization, (2) customer service optimization and experience improvement, (3) innovation and sustainability capabilities, (4) strengthened financial compliance and governance, (5) enhancement in data processing and analysis capabilities, (6) education and training benefits, (7) risk prevention capabilities, (8) synthetic data and model optimization. Challenges of AI use in finance were identified in six categories: (1) technical risks, (2) regulatory risks, (3) ethics and moral concerns, (4) market risks, (5) operation and maintenance risks, and (6) mental risks. Most of the examined studies apply a broad and inclusive use of the term GAI and discuss its impact. While these studies also discussed financial risks, they were more about the risks that are common to GAI.

Based on both the literature review and the analysis of articles included in this special issue, we propose a research agenda concerning the implications of GAI use in finance. The research agenda contains both process-related and content-related recommendations. Process-wise, future research on the implications of the use of GAI in finance should move towards more capital-market-sector-focused, empirical, multidisciplinary, and focus more on specific forms of GAI rather than GAI in general. It also recommends that researchers in the area of the implications of GAI use in finance should share the database to promote open collaboration. Content-wise, our research agenda calls for prioritizing high-impact applications with weak mitigation strategies (i.e., GAI-driven synthetic data, and GAI use in modeling and stress testing), as well as investigations of effective implementation, engagement, and global collaborative governance on GAI use in finance. Furthermore, the research agenda appeals research to construct an education framework in order to protect the privacy of investors and maintain market fairness.

The search criteria we used in our literature review intentionally excluded mathematics, automation control systems and mathematical computational biology, as areas from these areas may be highly technical or irrelevant to our research topic. In addition, we applied the search process in March 2025 concerning the implications of GAI use in finance. In order to reflect the current state of GAI use in finance comprehensively, we included the first 150 results with the highest relevance in Web of Science. However, other GAI-related systems that are not included in the database of Web of Science or do not use English as the writing language would not have appeared in our search. We may consider incorporating additional databases to further enrich our literature review and ensure a more comprehensive understanding of the topic in future research.

Today, a large portion of the research concerning GAI in finance is in the embryonic stage, and there is an urgent need for forward-looking theoretical research to guide the development of GAI in a direction that is in line with broad interests. Future research should utilize methods such as empirical research to continue exploring these issues.

Author Contributions

Conceptualization, S.Y. and Y.C.; methodology, Y.C.; writing—original draft preparation, Y.C., Y.J., J.L. and X.J.; writing—review and editing, S.Y., Y.C., Y.J. and X.J.; visualization, Y.C. and X.J.; supervision, S.Y. and Y.C.; project administration, S.Y. and Y.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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