Artificial Intelligence in Financial Risk Contagion: A Survey

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Abstract

This survey paper explores the transformative impact of artificial intelligence (AI) in managing financial risk contagion, highlighting its role in identifying, assessing, and mitigating risks within financial systems. By integrating machine learning (ML) techniques, AI enhances predictive accuracy and robustness, crucial for navigating volatile market conditions. Key advancements include the use of reinforcement learning and federated learning, which provide scalable and secure frameworks for decentralized data analysis while ensuring privacy and compliance with regulatory standards. The paper also emphasizes the importance of domain knowledge and causal reasoning in improving model interpretability and aligning predictions with expert insights. Despite challenges related to data quality, model transparency, and regulatory compliance, AI methodologies continue to evolve, offering more reliable and ethical solutions for financial risk management. This evolution is supported by innovative frameworks like the Domain Knowledge Infusion Method (DKIM) and the integration of fractional derivatives, which enhance the understanding of complex financial dynamics. The survey concludes that AI's role in financial risk management is pivotal, driving the sector towards greater efficiency, transparency, and inclusivity, and unlocking new opportunities for innovation and stability in financial markets.

1 Introduction

1.1 Significance of AI in Financial Systems

The integration of artificial intelligence (AI) into financial systems has fundamentally transformed the identification, assessment, and management of financial risks. Machine learning algorithms, in particular, have enhanced decision-making through predictive analytics and insights that were previously unattainable. Watson et al. [1] emphasize that AI's ability to clarify the predictions of opaque algorithms is critical in finance, where transparency and accountability are essential. This capability not only improves risk management but also fosters trust in AI-driven financial solutions.

AI's impact extends to operational optimization and innovation within financial systems. Weng [2] highlights that AI enhances efficiency by automating routine tasks and facilitating accurate, timely risk assessments, which is vital for maintaining stability in volatile markets. Furthermore, AI applications are broadening beyond risk assessment; federated AI frameworks, as proposed by Hoang et al. [3], integrate diverse data sources to enhance credit scoring accuracy and inclusivity, showcasing AI's potential to democratize financial services.

The regulatory landscape is evolving alongside AI advancements. Fenwick [4] discusses how regulators are increasingly adopting AI to stimulate economic growth while ensuring compliance with changing standards. This dual role of AI in transforming and regulating financial systems underscores its critical importance in modern finance.

Moreover, the need for explainability and interpretability in AI applications is paramount. Islam et al. [5] note that the 'black box' nature of many AI models necessitates interpretability mechanisms to

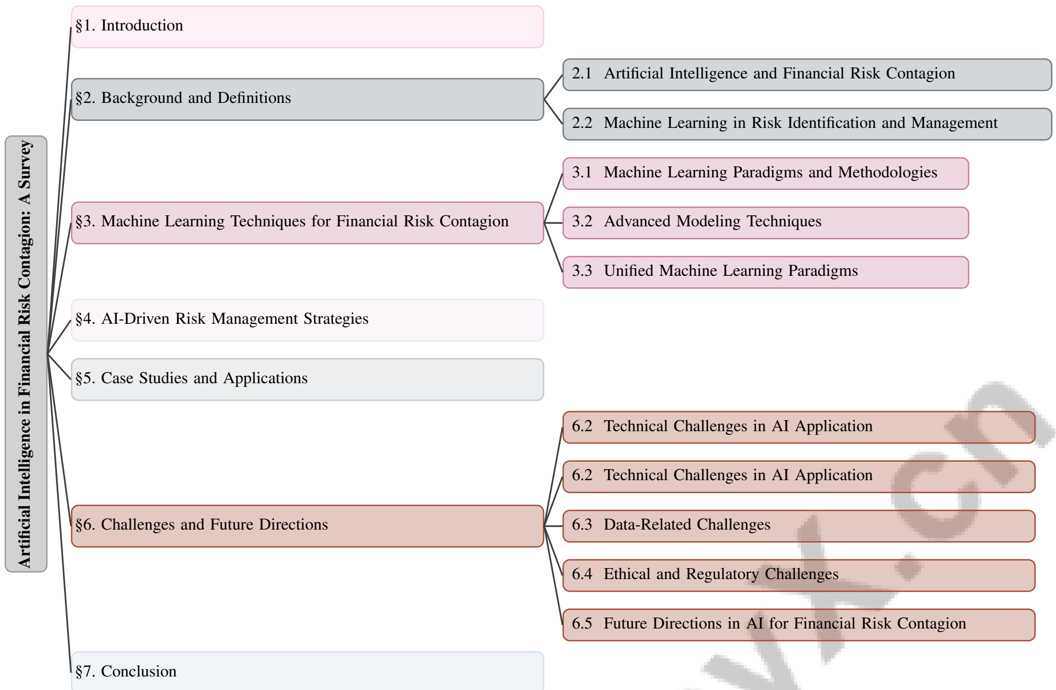

Figure 1: chapter structure

comply with regulatory requirements and maintain stakeholder trust, particularly in finance where decision-making transparency is crucial.

1.2 Structure of the Survey

This survey is organized to provide a comprehensive understanding of AI's role in financial risk contagion, aligning with broader analyses of AI's impact across various sectors, including finance, as discussed by Weng [2]. The paper begins with an introduction that highlights AI's significance in transforming financial systems and managing risks. The subsequent background and definitions section clarifies key concepts such as AI, financial risk contagion, and risk management, establishing a foundation for later discussions.

The survey explores machine learning techniques tailored for financial risk contagion, examining paradigms, methodologies, and advanced modeling techniques, while integrating unified machine learning approaches. This section aims to elucidate the strengths and limitations of various methods, providing nuanced insights into their applicability in financial contexts.

AI-driven risk management strategies are then analyzed, focusing on innovative frameworks like federated learning that enhance risk management and contribute to financial stability. Case studies, particularly the Domain Knowledge Infusion Method (DKIM) in bankruptcy prediction, illustrate practical implementations of AI and machine learning in managing financial risk contagion. DKIM enhances the interpretability of traditionally opaque models, such as artificial neural networks and support vector machines, by incorporating domain knowledge, which is crucial in finance where regulatory frameworks demand transparency. Research indicates that infusing domain knowledge improves model clarity and aligns with emerging regulatory requirements, marking a significant advancement in financial risk assessment [6, 1, 5, 7].

The survey also addresses challenges and future directions in AI applications for financial risk contagion, discussing technical, data-related, ethical, and regulatory issues, along with potential research opportunities. The concluding section synthesizes key findings, reiterating AI's critical role in enhancing financial risk management and stability. Through this structured approach, the survey aims to provide a holistic view of AI's transformative impact on financial risk contagion.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Artificial Intelligence and Financial Risk Contagion

Artificial Intelligence (AI) is integral to financial systems, particularly in mitigating financial risk contagion, which involves the spread of instability across interconnected institutions and markets [4, 2]. AI's capability to rapidly analyze extensive datasets enhances the detection and management of risks that may trigger such contagion. Machine learning (ML), a pivotal component of AI, utilizes adaptive algorithms to bolster predictive accuracy and robustness, essential in the volatile financial environment [8, 9].

Understanding the causal dynamics of risk propagation is crucial for effective contagion management. Incorporating causality analysis into AI models significantly improves their interpretability and effectiveness, offering insights into the intricate interactions within financial systems [10]. This understanding is vital for devising strategies to mitigate contagion effects and ensure financial stability.

AI's role in financial risk contagion extends to applications such as option pricing and credit risk assessment. AI models adeptly handle the complexities of pricing quanto options, which are sensitive to foreign exchange rate fluctuations. Federated AI frameworks enhance creditworthiness assessments by leveraging diverse data sources, improving accuracy and inclusivity for individuals with limited financial histories [3]. However, balancing accurate risk predictions with model interpretability remains challenging [6].

2.2 Machine Learning in Risk Identification and Management

Machine learning (ML) techniques are pivotal in identifying and managing financial risks, offering sophisticated methodologies for analyzing complex datasets and forecasting potential disruptions. Feature attribution and interpretability are critical for understanding model predictions and ensuring regulatory compliance. Rational Shapley values, combining traditional Shapley values with counterfactual explanations, integrate user-specific beliefs into risk management, enhancing interpretability [1].

Ensuring robustness in ML models is crucial in dynamic financial environments, where data bias and model complexity can impede generalization [8]. Tailored data strategies are necessary to navigate challenges related to data reliability and accessibility [9], addressing both legal and technical hurdles.

Reinforcement Learning (RL) offers promising avenues for developing automatic Financial Trading Systems (FTFs), addressing the limitations of traditional models in adapting to market volatility. RL algorithms learn optimal trading strategies through market interaction, enhancing system adaptability and resilience [11].

Integrating ML into existing business systems presents challenges, particularly in aligning these systems with business objectives and regulatory requirements [12]. A strategic approach to ML integration is essential for effective deployment within established infrastructures.

The gNTS process, as illustrated by Kim [13], exemplifies ML's application in financial risk management by modeling volatility characteristics for foreign asset returns and exchange rates. Such advanced modeling techniques are critical for accurately pricing complex financial instruments and managing associated risks.

Incorporating explainability into ML models is essential for fostering trust and ensuring compliance with financial regulations. The data-driven explainable case-based reasoning approach enhances transparency in ML predictions, enabling stakeholders to comprehend the rationale behind risk assessments and decisions [6].

In recent years, the application of machine learning (ML) techniques in the field of financial risk management has garnered significant attention. The evolution of these techniques is characterized by a complex interplay of various paradigms and methodologies that aim to improve the accuracy and reliability of risk predictions. As illustrated in Figure 2, this figure depicts the hierarchical structure of machine learning techniques for financial risk contagion, categorizing key paradigms and methodologies, advanced modeling techniques, and unified ML paradigms. It highlights the integration of diverse approaches to enhance model robustness, interpretability, and compliance, ultimately improving risk prediction and management in financial systems. Such a structured overview not only clarifies the relationships among different methodologies but also emphasizes the importance of a comprehensive approach in addressing the multifaceted nature of financial risks.

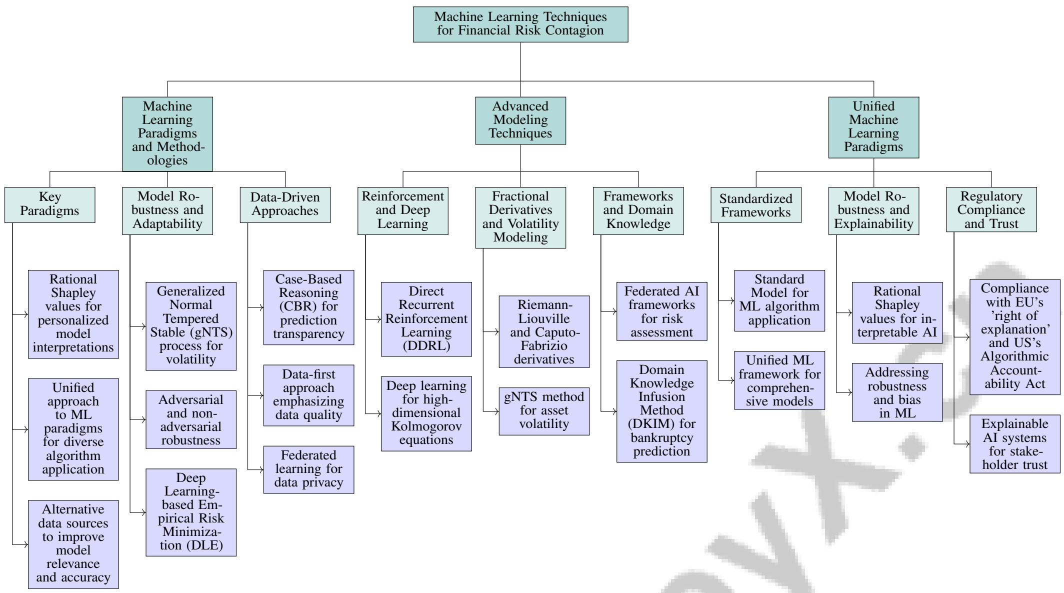

Figure 2: This figure illustrates the hierarchical structure of machine learning techniques for financial risk contagion, categorizing key paradigms and methodologies, advanced modeling techniques, and unified ML paradigms. It highlights the integration of diverse approaches to enhance model robustness, interpretability, and compliance, ultimately improving risk prediction and management in financial systems.

3 Machine Learning Techniques for Financial Risk Contagion

3.1 Machine Learning Paradigms and Methodologies

Method Name	Model Interpretability	Data Utilization	Robustness Strategies
RSV[1]	Rational Shapley Values	Sampling From Subspace	Robust Methods Estimating
gNTS[13]	Crealnvp Model	Empirical Market Data	Risk-neutral Measure
DLE[7]	-	-	-
CBR_E[6]	Explainable Cbr	Historical Case Data	Particle Swarm Optimization

Table 1: Table ef presents a comparative analysis of various machine learning methodologies applied in financial risk contagion. It examines key aspects such as model interpretability, data utilization, and robustness strategies, highlighting the diverse approaches and their potential contributions to enhancing predictive accuracy and model stability in volatile financial environments.

Machine learning (ML) paradigms and methodologies are crucial for innovating strategies in financial risk contagion, enhancing both predictive accuracy and model robustness. Table 1 provides a structured overview of selected machine learning paradigms, detailing their interpretability, data utilization, and robustness strategies, which are crucial for addressing the complexities of financial risk contagion. Watson et al. [1] highlight the integration of rational Shapley values, which combine feature attributions with counterfactuals to offer personalized explanations, underscoring the need for tailored model interpretations in finance. Hu [14] calls for a unified approach to ML paradigms, simplifying the application of diverse algorithms, which is essential given the intricate interactions among financial entities. Bilokon [9] emphasizes the importance of alternative data sources, suggesting that non-traditional data can uncover market dynamics missed by conventional methods, thereby improving ML model relevance and accuracy.

Kim's introduction of the generalized Normal Tempered Stable (gNTS) process [13] illustrates ML's adaptability in capturing distinct asset volatility characteristics, crucial for managing financial

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risk contagion. Braiek [8] categorizes research into adversarial and non-adversarial robustness, highlighting the necessity for stable models amid volatile markets. Berner [7] discusses Deep Learning-based Empirical Risk Minimization (DLE) to address traditional methods' limitations, utilizing deep neural networks for high-dimensional Kolmogorov equations, relevant for complex financial data. Li [6] proposes a data-driven Case-Based Reasoning (CBR) system to enhance ML prediction transparency, crucial for understanding risk assessments.

Lawrence [12] advocates for a data-first approach, stressing data quality's role in model design, vital in financial risk contagion where data integrity impacts ML model efficacy. The exploration of ML paradigms and methodologies reveals their contributions to mitigating financial risk contagion, particularly in enhancing model interpretability and robustness, addressing data privacy through federated learning, and integrating domain knowledge for improved explainability in sensitive applications like bankruptcy prediction [9, 5, 8, 15, 3]. Advanced techniques such as rational Shapley values, gNTS processes, and data-driven CBR systems, alongside robust data strategies and unified frameworks, significantly enhance financial risk detection, evaluation, and management.

3.2 Advanced Modeling Techniques

Advanced modeling techniques leverage machine learning to navigate financial market complexities. Li [11] proposes Direct Recurrent Reinforcement Learning (DDRL), enhancing trading strategy adaptability beyond traditional methods. Ryehan [16] explores fractional derivatives like Riemann-Liouville and Caputo-Fabrizio to uncover hidden chaotic dynamics in financial systems, offering deeper market insights. Kim's gNTS method [13] effectively models volatility characteristics, essential for accurate pricing amidst complex dependencies. Berner [7] demonstrates deep learning's potential in solving high-dimensional Kolmogorov equations, addressing computational limitations of traditional methods.

Hoang et al. [3] introduce federated AI frameworks, creating high-dimensional consumer representations to improve risk assessment. Islam's Domain Knowledge Infusion Method (DKIM) [5] enhances bankruptcy prediction models by integrating domain knowledge, emphasizing real-world applicability. Bilokon's survey [9] provides a framework for diverse data sources, crucial for developing advanced models in financial risk management. The integration of advanced techniques—such as reinforcement learning, deep learning, and fractional derivatives—signifies progress in financial risk management, enhancing predictive accuracy and decision-making [11, 7]. These models, employing sophisticated methodologies and diverse data, improve risk prediction, evaluation, and management, contributing to financial system stability.

In Figure 3, advanced modeling techniques for financial risk contagion are exemplified. This figure illustrates the key categories of advanced modeling techniques in financial risk management, highlighting reinforcement learning, fractional derivatives, and deep learning as pivotal approaches for enhancing predictive accuracy and decision-making. The "Model Spaces and Experiences in Deep Learning: A Comprehensive Framework" explores model types and experiences in deep learning, emphasizing the standard equation's role in enhancing learning through feedback. The "3D Surface Plot with Contour Lines" visually represents data relationships, aiding in understanding complex structures for effective financial risk modeling. These examples highlight the sophistication and applicability of advanced modeling techniques in financial risk management [14, 13].

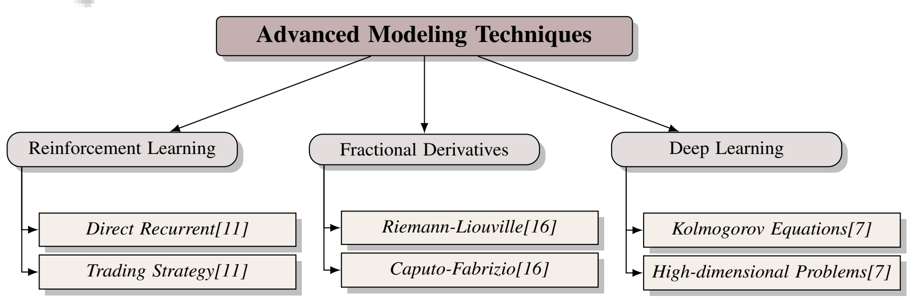

Figure 3: This figure illustrates the key categories of advanced modeling techniques in financial risk management, highlighting reinforcement learning, fractional derivatives, and deep learning as pivotal approaches for enhancing predictive accuracy and decision-making.

3.3 Unified Machine Learning Paradigms

Integrating diverse machine learning (ML) paradigms into a unified framework advances risk prediction and management in financial systems. Hu [14] discusses a standardized formalism akin to the Standard Model in physics, streamlining ML algorithm application and understanding to address financial risk contagion challenges. A unified ML framework synthesizes learning paradigms, developing comprehensive models that leverage each approach's strengths, crucial for robust and adaptable models in dynamic markets. This integration enhances predictive performance and risk assessment reliability, promoting standardization and composability of ML methodologies. It improves model robustness and explainability, addressing challenges in finance and healthcare. Incorporating domain knowledge and techniques like rational Shapley values ensures interpretable AI decision-making, fostering confidence in outputs [14, 1, 5, 8, 3].

A standardized ML framework enhances model interpretability and transparency, fostering stakeholder trust and compliance with regulatory requirements, such as the EU's "right of explanation" and the US's Algorithmic Accountability Act. By integrating various learning paradigms, this framework develops more explainable AI systems, addressing robustness needs in machine learning and mitigating bias and discrimination [14, 5, 8]. A cohesive structure for diverse ML methodologies enables models that perform well and offer clear insights into prediction drivers.

4 AI-Driven Risk Management Strategies

4.1 Federated Learning and Financial Risk Management

Federated Learning (FL) offers a transformative approach to managing financial risks by enabling collaborative model training across decentralized data sources while preserving data privacy. This approach mitigates data reliability and security concerns by keeping data localized, thus minimizing breach risks and ensuring compliance with privacy regulations [15]. The ability of FL to process decentralized data without compromising privacy is particularly crucial in financial contexts, where safeguarding sensitive information is essential [3].

FL's adaptability in providing personalized explanations, tailored to user-specific needs, enhances risk management strategies. Watson et al. [1] highlight the importance of such personalized insights for informed decision-making in financial risk management. By incorporating these tailored insights, FL frameworks offer nuanced risk assessments that address stakeholders' unique requirements.

Moreover, the dynamic regulatory and innovation ecosystems proposed by Fenwick [4] align with FL, fostering an environment conducive to responsible AI-driven innovation. This synergy allows financial institutions to utilize advanced AI techniques while adhering to evolving regulatory standards.

Implementing FL in financial risk management also addresses the 'data crisis' identified by Lawrence [12], emphasizing efficient data handling. By eliminating the need for centralized data aggregation, FL overcomes challenges posed by data silos, enhancing the scalability and efficiency of AI-driven risk management systems.

4.2 Innovative AI Frameworks

Innovative AI frameworks are crucial in refining risk management strategies, introducing enhanced adaptability and efficiency within financial systems. Hu's 'standard equation' [14] provides a cohesive framework for integrating diverse machine learning algorithms, facilitating the development of robust risk prediction methods in complex financial markets.

Federated Learning (FL) complements these frameworks by enabling collaborative model training across decentralized data sources while maintaining data privacy and security [15]. The architectures and methodologies within FL address inherent security challenges in financial applications, ensuring sensitive information remains protected during comprehensive risk assessments. This capability is vital for financial institutions seeking to leverage AI-driven insights without compromising data integrity or breaching regulatory standards.

Incorporating these innovative frameworks into existing risk management strategies enhances their efficacy by offering scalable, secure, and adaptable solutions. Hu's unifying ML framework streamlines the integration of advanced algorithms into risk management systems, improving predictive accuracy

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and operational efficiency. Concurrently, the federated learning methodologies discussed by Mammen [15] ensure these advancements comply with stringent data privacy and security requirements.

5 Case Studies and Applications

5.1 Domain Knowledge Infusion Method (DKIM) in Bankruptcy Prediction

The Domain Knowledge Infusion Method (DKIM) represents a significant advancement in leveraging artificial intelligence for bankruptcy prediction by integrating domain-specific insights to enhance model performance and interpretability. By incorporating expert knowledge into the feature selection process, DKIM enhances the accuracy and relevance of predictive models, as demonstrated using the Freddie Mac dataset, which includes loan-level credit performance data [5].

DKIM's primary advantage lies in its ability to embed domain knowledge into AI models while maintaining computational efficiency. This is achieved through the integration of expert insights directly into the model architecture, allowing for a nuanced understanding of bankruptcy risk factors. This approach not only improves predictive accuracy but also enhances interpretability, enabling stakeholders to understand the rationale behind model predictions. Transparency is crucial in high-stakes sectors like finance and healthcare, where regulations such as the EU's "right of explanation" and the proposed "Algorithmic Accountability Act" in the US require clarity in algorithmic decision-making. By addressing the limitations of traditional "black box" models, DKIM aligns with evolving standards for accountability and bias assessment in AI systems, fostering greater trust in AI-driven predictions in sensitive contexts like bankruptcy prediction [4, 1, 5].

Comparative analyses highlight DKIM's superiority over traditional statistical methods in terms of computational efficiency and interpretability. Liang [10] illustrates that causal AI methods, which underpin DKIM, outperform conventional techniques by elucidating causal relationships within financial data. This capability is crucial for developing robust bankruptcy prediction models that can adapt to the dynamic financial landscape.

DKIM's implementation underscores the importance of integrating domain knowledge into AI models to enhance practical utility and stakeholder acceptance. By combining expert insights with model predictions, DKIM not only improves bankruptcy forecast precision but also satisfies regulatory demands for interpretability in AI-driven financial decision-making, thereby fostering greater trust among stakeholders [1, 5, 6, 3, 7].

6 Challenges and Future Directions

In light of the complexities associated with the integration of artificial intelligence (AI) in financial risk contagion, it is imperative to examine the specific challenges that arise in its application. This exploration begins with an analysis of the technical challenges inherent in deploying AI models within this domain, which not only impact their efficacy but also raise critical concerns regarding transparency and reliability. Understanding these technical hurdles is essential for developing effective strategies that can enhance the overall performance of AI in managing financial risks.

6.1 Technical Challenges in AI Application

6.2 Technical Challenges in AI Application

The application of artificial intelligence (AI) to financial risk contagion is fraught with numerous technical challenges that impede its full potential. A significant issue is the 'black box' nature of many AI models, which obscures the decision-making process and raises ethical and regulatory concerns [5]. This opacity is particularly problematic in financial contexts, where understanding the intricate dependencies between features is crucial for accurate risk assessment [1].

Data-related challenges further complicate AI applications in financial risk contagion. The variability in data quality and accessibility can undermine the robustness of AI models, leading to overfitting and reduced generalizability [9]. The cultural shift towards a data-first approach is often underestimated, creating barriers to the seamless integration of AI into existing financial systems [12].

Federated learning, a promising approach for managing decentralized financial data, faces its own set of challenges, including communication overhead during training, data and system heterogeneity, and security threats from malicious participants [15]. Moreover, the computational complexity of training reinforcement learning models can be resource-intensive and time-consuming, further complicating their deployment in financial systems [11].

The necessity to balance regulation with innovation presents another hurdle, as regulatory frameworks must evolve to ensure the ethical use of AI while fostering technological advancement [4]. Limitations in data access and model interpretability exacerbate these regulatory challenges, necessitating frameworks that can guide the ethical application of AI in financial contexts [2].

Additionally, the computational time required for certain advanced modeling techniques, such as those involving complex optimization algorithms, can hinder the efficiency of AI applications in financial risk management [6]. Addressing these technical challenges is essential for the successful integration of AI into financial risk contagion strategies, ensuring that models are not only accurate and reliable but also interpretable and compliant with regulatory standards.

6.3 Data-Related Challenges

The efficacy of artificial intelligence (AI) applications in financial risk contagion is significantly influenced by data-related challenges that encompass data quality, sources, and reliability. A critical limitation identified in AI-driven models, such as those used for credit scoring, is their dependence on the quality of input data. Inadequate data can severely undermine the accuracy and reliability of these models, leading to suboptimal risk assessments and decision-making processes [3].

Data quality issues frequently arise from various factors, including inconsistencies, inaccuracies, and incompleteness within the datasets utilized for training AI models. These issues can undermine the robustness and trustworthiness of machine learning systems, as they impact the models' ability to perform reliably across diverse and unforeseen conditions. Addressing these data quality challenges is essential for ensuring the ethical application of AI technologies and enhancing their effectiveness in critical domains such as healthcare, finance, and social media. [17, 9, 1, 8]. These issues can be exacerbated by the heterogeneous nature of financial data, which is sourced from diverse origins with varying levels of reliability. The integration of such disparate data into a cohesive analytical framework poses significant challenges, as it requires sophisticated preprocessing and validation techniques to ensure data integrity.

The ever-evolving landscape of financial markets demands the continuous processing and analysis of real-time data, which not only intensifies the complexities of data management but also highlights the critical need for advanced AI technologies and dynamic regulatory frameworks to effectively navigate these challenges. [2, 9, 4]. The ability of AI models to adapt to rapidly changing data inputs is crucial for maintaining their relevance and accuracy in predicting financial risks. However, the volatility and unpredictability of financial data can lead to model drift, where the predictive performance of AI systems deteriorates over time due to shifts in data patterns.

The use of federated learning frameworks, which enable collaborative model training across decentralized data sources while safeguarding user privacy, adds layers of complexity related to maintaining data synchronization and ensuring consistency among various nodes within the network. This challenge is particularly significant in sensitive fields such as healthcare and finance, where the secure handling of private data is paramount, and necessitates sophisticated strategies to address potential vulnerabilities and operational inefficiencies. [15, 9]. Ensuring that data remains consistent and up-to-date across all participating entities is vital for the effective functioning of federated AI models, yet it remains a formidable challenge in practice.

Addressing these data-related challenges is essential for enhancing the robustness and reliability of AI applications in financial risk contagion. To effectively harness the potential of artificial intelligence and machine learning, it is essential to implement sophisticated data management strategies that not only emphasize high data quality but also enable the seamless integration of various data sources across multiple applications, such as finance, healthcare, and social media. Additionally, these strategies must ensure that AI models remain adaptable to the continually evolving data landscapes, thereby facilitating their practical deployment and ethical application in real-world scenarios. [17, 12, 9]

6.4 Ethical and Regulatory Challenges

The integration of artificial intelligence (AI) in financial systems presents significant ethical and regulatory challenges that must be addressed to ensure responsible and transparent deployment. As AI technologies, particularly machine learning (ML) techniques, become increasingly prevalent, the importance of ethical considerations in their design and implementation has grown substantially [17]. The primary issue lies in bridging the gap between the abstract ethical principles that guide AI ethics—the 'what'—and the practical methodologies required to apply these principles effectively in ML development—the 'how' [17].

One of the main challenges is the lack of actionable tools and methods for developers to integrate ethics into the ML development process [17]. This deficiency can lead to AI systems that inadvertently perpetuate biases, lack transparency, or fail to adhere to established ethical standards. In financial contexts, where decisions can have profound impacts on individuals and institutions, ensuring that AI systems operate ethically is paramount.

"Regulatory frameworks must adapt to effectively address the growing ethical concerns surrounding artificial intelligence while simultaneously promoting innovation through strategies such as dynamic regulation and the development of innovation ecosystems, which can enhance investment and foster responsible AI integration across various industries." [17, 2, 4]. This involves developing comprehensive guidelines that not only outline ethical principles but also provide practical tools and methods for their implementation. Such frameworks must balance the need for innovation with the imperative to protect stakeholders from potential harms associated with AI deployment in financial systems.

Moreover, the opacity of many AI models, often referred to as the 'black box' problem, poses additional regulatory challenges. To maintain stakeholder trust and ensure compliance with evolving regulatory standards, it is essential to develop AI systems that are both interpretable and transparent. This is particularly critical in high-stakes sectors like finance and healthcare, where the use of complex "black box" models raises ethical concerns and regulatory challenges. Recent developments, such as the European Union's "right of explanation" and the proposed U.S. "Algorithmic Accountability Act," highlight the need for clear explanations of algorithmic decisions and the assessment of AI systems for bias and discrimination. By integrating domain knowledge and employing advanced explainable AI techniques, such as rational Shapley values, organizations can enhance the interpretability of their AI models, thereby fostering greater accountability and trust among stakeholders. [17, 4, 1, 5]. This necessitates the development of models that offer clear insights into their decision-making processes, allowing stakeholders to understand and verify the rationale behind AI-driven financial decisions.

6.5 Future Directions in AI for Financial Risk Contagion

Future research in AI for financial risk contagion should prioritize the development of robust data governance frameworks, ensuring that data quality and accessibility are maintained across decentralized sources. This involves exploring automated data cleaning techniques and establishing standards for model deployment in financial risk management, as suggested by Lawrence [12]. Additionally, the integration of ethical AI use and the investigation of socio-economic impacts of AI across various sectors are crucial for fostering responsible innovation [2].

Enhancing the security and efficiency of Federated Learning (FL) frameworks is another critical area for research. Mammen [15] highlights the potential of integrating blockchain technology to improve security and developing incentive mechanisms to encourage device cooperation. These advancements would ensure that FL can effectively manage decentralized data while maintaining privacy and compliance with regulatory standards.

The exploration of alternative combinations of fractional derivatives to improve the understanding of chaotic dynamics in financial systems is essential for advancing computational capabilities, as noted by Ryehan [16]. This research could lead to improved models that capture the complex and nonlinear behaviors of financial markets, thereby enhancing risk prediction and management.

The Domain Knowledge Infusion Method (DKIM) should be validated across multiple datasets to enhance its generality and applicability. By incorporating additional domain knowledge concepts, DKIM can provide more robust and interpretable models for financial risk management [5]. Furthermore, expanding the applicability of causal AI methods to a broader range of scientific problems, as

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Liang [10] suggests, will facilitate the integration of causal reasoning into machine learning models, improving their interpretability and effectiveness.

Future research should also focus on developing more efficient optimization algorithms for Case-Based Reasoning (CBR) systems, as proposed by Li [6]. Extending the application of CBR systems to other decision-support systems beyond financial risk detection could enhance their utility and adaptability in various contexts.

7 Conclusion

This survey illustrates the profound influence of artificial intelligence (AI) on the landscape of financial risk management, emphasizing its pivotal role in the identification and mitigation of systemic risks. The integration of AI, particularly through machine learning (ML) techniques, has significantly enhanced the precision and resilience of risk prediction and mitigation strategies in dynamic market environments. Techniques such as reinforcement learning and federated learning have enabled scalable and secure decentralized data processing, ensuring both privacy and regulatory compliance.

Incorporating domain knowledge and causal reasoning into AI frameworks further improves model transparency and ensures that predictions are consistent with expert insights, thereby bolstering AI's effectiveness in addressing financial risk contagion. Despite ongoing challenges related to data integrity, model transparency, and regulatory adherence, the continuous advancement of AI methodologies offers promising solutions to these issues, paving the way for more dependable and ethically sound AI-driven financial systems.

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