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Generative Adversarial Networks: A Systematic Review of Characteristics, Applications, and Challenges in Financial Data Generation and Market Modeling: 2019-2024

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A B S T R A C T

Generative Adversarial Networks (GANs) have emerged as a promising solution for machine learning and artificial intelligence algorithms constrained by data availability and accessibility. Financial markets, alongside healthcare, present significant challenges due to data privacy and confidentiality concerns. GANs enable researchers to generate synthetic financial data that closely mirrors real-world datasets, facilitating advancements in market analysis and modeling. Despite their potential, a comprehensive evaluation of GAN-based financial data generation remains limited, necessitating a systematic assessment of existing methodologies and findings. This paper presents a systematic review of GAN architectures applied to financial data generation and market modeling. Our study is distinguished by its comprehensive exploration of various GAN variants and their specific applications within different facets of financial markets, including stock price prediction, algorithmic trading, portfolio optimization, risk management, and fraud detection. Leveraging thirty relevant papers from four major databases (IEEE Xplore, Web of Science, Scopus, and arXiv), we synthesized key findings, identify challenges, and highlight limitations in the application of GANs for financial data generation. Our findings reveal that while GANs enhance data privacy and accessibility, they also face limitations such as mode collapse, instability during training, and regulatory concerns in financial markets. This qualitative review provides valuable insights for researchers and stakeholders, offering a foundation for future studies and innovative applications of GANs in financial markets.

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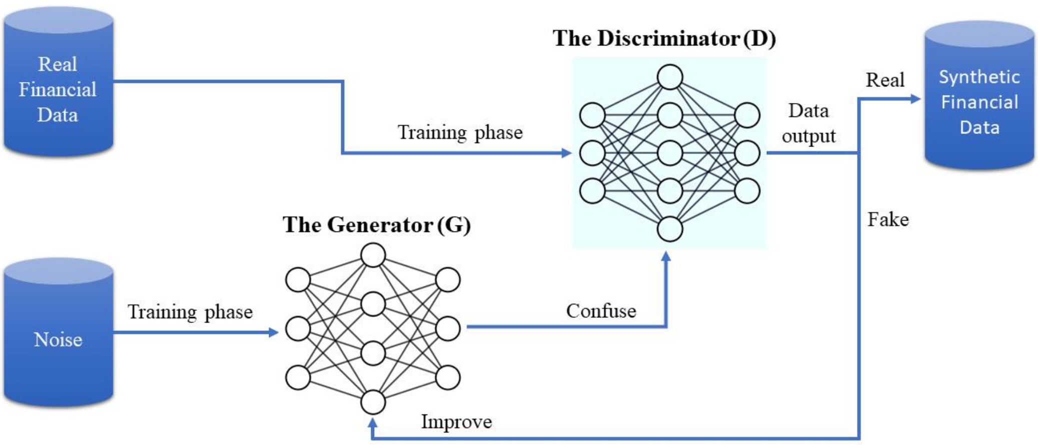
Graphical Abstract



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1. INTRODUCTION

In today's fast-paced world, technology has significantly transformed the way companies analyze the financial markets in which they operate. The volatile nature of financial markets requires businesses to remain constantly updated on market trends to stay competitive. However, obtaining high-quality, real financial data relevant to market simulations remains a persistent challenge. Whether it is to study market trends, manage risks, or conduct competitive analysis, access to essential financial data is often restricted due to privacy concerns, data sharing limitations, or the prohibitive cost of acquiring data.

As in many other domains such as healthcare (1, 2), facing data accessibility issues, deep learning has played a crucial role in advancing data generation techniques (3, 4). One of its most impactful contributions is the development of Generative Adversarial Networks (GANs). These networks stem from foundational deep learning architectures, particularly those designed for unsupervised learning, enabling machines to generate highly realistic synthetic data. GANs, first introduced by Goodfellow et al. (5), have emerged as a promising solution for generating synthetic financial data. GANs can produce artificial datasets that closely replicate the statistical distributions and properties of real-world financial data. These synthetic datasets not only preserve privacy and sensitive information but also provide a viable alternative for stakeholders such as researchers, companies, and policymakers. GANs' ability to generate high-fidelity financial data has opened new opportunities for predictive modeling, financial risk assessment, and market scenario simulations.

Since their introduction, numerous variants of GANs have been developed, each designed to address specific data generation challenges such as images generation (6–11), audio synthesis (12) , and tabular data generation (13,14), across different domains. Despite these advancements, a clear research gap remains in the application of GANs for financial data generation. While GANs have shown promise in generating realistic financial data, challenges persist in areas such as model stability, mode collapse, and ensuring that synthetic data maintains financial market dynamics while being useful for real-world applications. Additionally, few studies provide comprehensive evaluations comparing different GAN variants on financial datasets, making it difficult to determine best practices in this domain.

To address these gaps, this article presents a systematic review of the application of GANs for financial data generation, analyzing key scientific research papers published between 2019 and 2024. Our study follows a structured methodology to ensure comprehensive coverage of relevant work. Specifically, we:

- Collect research papers from four major academic databases.
- Define clear inclusion and exclusion criteria for selecting relevant studies.
- Analyze and compare different GAN architectures tailored for financial applications.
- Identify key findings, challenges, and future research directions in the field.

By structuring our review in this manner, we aimed to provide a well-rounded perspective on how GANs contribute to financial data generation, highlight the most effective architectures, and discuss remaining challenges for future research.

2. METHODOLOGY

The methodology adopted in this systematic review involves collecting, analyzing, and synthesizing insights from relevant scientific literature, including journal articles, conference proceedings, and book chapters, focusing on the application of Generative Adversarial Networks (GANs) for financial data generation. This approach aims to achieve two primary objectives: first, to highlight significant advancements in GAN architectures across domains addressing data accessibility challenges, and second, to identify those architectures specifically tailored for financial data generation.

In this section, we outline the systematic review process and provide an overview of the databases and sources included in this study.

2. 1. Systematic Review Approach Unlike bibliometric analysis (15), which focuses on the quantitative evolution of a research field, a systematic review emphasizes the qualitative aspects of a research field (16, 17). A systematic review is a research methodology aimed to synthesize knowledge from both empirical and theoretical studies to uncover hidden patterns or research trends across relevant papers. This methodology often follows the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which provides a minimal set of guidelines to help researchers rigorously report various systematic reviews and meta-analyses (18). Figure 1 shows the PRISMA framework flow chart.

Rooted in Western positivist traditions, the systematic review approach prioritizes academic knowledge (19). It involves gathering relevant research papers and qualitatively synthesizing their insights. Like other types of literature reviews, a systematic review follows a defined protocol. Khalid et al. (20) outlined five key steps for conducting a robust systematic review, which we can summarize as follows:

- **Framing a research question:** Establishing clear objectives and boundaries for the review.

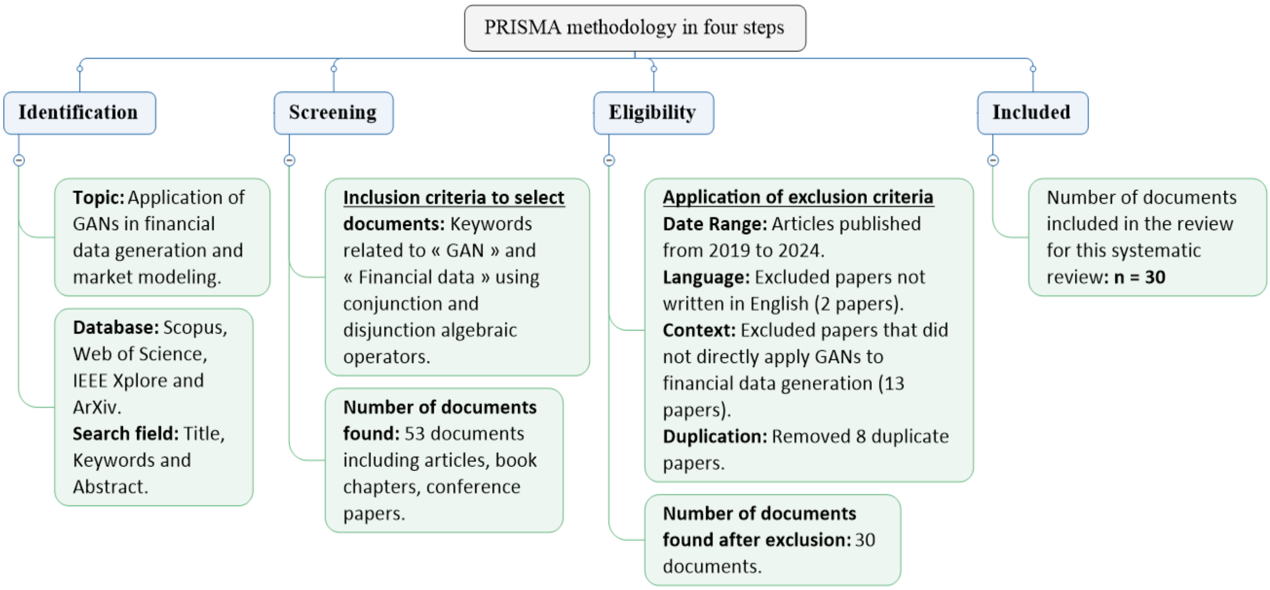

Figure 1. PRISMA framework flow chart

- **Identifying relevant publications:** Conducting a comprehensive search across databases and sources.
- **Assessing study quality:** Evaluating the methodological rigor and reliability of selected studies.
- **Summarizing the evidence:** Synthesizing findings from the included studies.
- **Interpreting the findings:** Drawing conclusions and identifying gaps or trends for future research.

Our systematic review includes both theoretical studies, which explore conceptual advancements and innovative architectures in the field of GANs, and empirical studies, which provide evidence of practical applications of GANs in financial data generation.

2. 2. Databases and Papers Collection Overview

In the scientific world of research, various databases are commonly used to collect historical papers for bibliometric analysis, systematic reviews, and other forms of literature review. These databases enable researchers to find papers across diverse fields. Among the most widely used are Scopus (developed by Elsevier in 2004) and Web of Science (originally developed by Eugene Garfield in 1997 and currently managed by Clarivate Analytics since 2016). These two databases are particularly academic in nature and are considered the most reliable for locating scientific papers (21). Additional databases include Google Scholar, SpringerLink, PubMed, ArXiv, Lens, and IEEE Xplore, among others. To ensure comprehensive coverage of relevant papers, we selected four distinct databases for this systematic review: Scopus, Web of Science, IEEE Xplore, and ArXiv. Many researchers, such as Fernández et al. (22) and Mongeon and Paul-Hus (23), recommend using multiple databases in systematic reviews to enhance the quality and breadth of the search. In particular, Scopus and Web of Science are considered complementary, as they collectively cover a wide range of academic papers.

Our choice of these four databases was guided by the need to include a broad spectrum of academic papers related to the application of GANs in financial data generation. This approach enabled us to diversify the selection by incorporating both highly academic publications and general research articles published over the past five years. To avoid duplicate entries and minimize bias, articles were carefully selected based on their titles, abstracts, and content.

Once the databases were determined, we applied the PRISMA methodology mentioned earlier to identify relevant papers on GAN applications in financial data generation. In 2009, Moher (18) introduced the PRISMA framework simplifies the systematic review process into four key steps: identification, screening, eligibility assessment, and inclusion in the analysis (24). These steps ensure the rigorous and transparent selection of studies, as illustraed in Figure 1.

The paper collection process for this systematic review adhered to the PRISMA methodology. The objective was to collect a diverse range of scientific papers published over the past five years, sourced from the four databases mentioned earlier. The selection criteria included relevance based on titles, keywords, abstracts, and content. This review considered various types of publications, such as book chapters, journal articles, and conference proceedings, all related to Generative Adversarial Networks (GANs) and their applications in financial data generation.

To ensure comprehensive coverage, we employed logical algebra operators ("AND" and "OR") to construct keyword combinations targeting GANs and financial data generation. The search query used was: ("Generative Adversarial Networks" OR "GAN") AND ("financial data" OR "synthetic financial data" OR "market modeling") AND ("data generation" OR "synthetic data").

Initially, for the fours databases considered, this search yielded 53 papers, capturing a wide range of topics related to financial data and market modeling. After applying exclusion criteria to ensure relevance (see the Screening and Eligibility phases in Figure 1), 30 papers were ultimately included in this systematic review. These selected studies specifically address the application of GANs for financial data generation and their relevance to various market-related aspects.

3. LITERATURE REVIEW: OVERVIEW OF GAN VARIANTS

The concept of Generative Adversarial Networks (GANs) was first introduced by Goodfellow and his team (5, 25) in their seminal article "Generative Adversarial Networks". In this article, they presented an adversarial framework involving two models trained simultaneously in competition with each other: a generative model that learns and captures the real data distribution, and a discriminative model that estimates the probability of a sample being from the real training data versus the generative model.

The framework requires a considerable amount of real dataset as input for training. The primary objective is to produce a large set of synthetic data that closely resembles the real data distribution. During the training phase, the generative model aims to maximize the likelihood of the discriminative model making a mistake, while the discriminative model works to maximize its ability to distinguish between real and fake data generated by the generative model. This adversarial process can be illustraed in Figure 2 (26).

This foundational concept has since inspired the development of numerous GAN variants, each designed to address specific challenges or cater to particular applications. Table 1 summarized our systematic review, we present a comprehensive analysis of 16 cases as the most important GAN variants among those currently available. For each variant, we highlight its primary purpose and key characteristics, providing an in-depth overview of their unique contributions and applications.

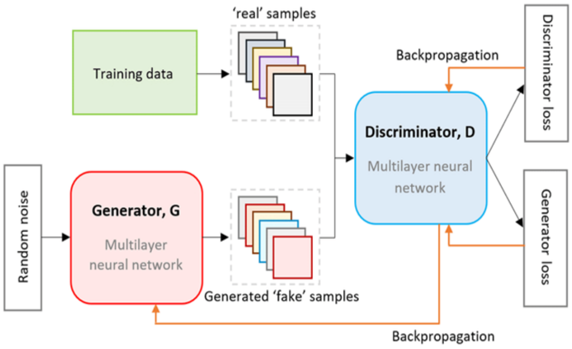

Figure 2. Example of GAN architecture

TABLE 1. Overview of GAN variants and their characteristics

No.	Authors	GAN variant	Purpose and characteristics
1	Goodfellow et al. (5)	Vanilla GAN	Vanilla GAN refers to the original GAN introduced by Goodfellow and his team (5) in the article titled "Generative Adversarial Nets."
2	Mirza & Osindero (12)	Conditional GAN (cGAN)	In the same year of 2014, Mirza & Osindero (12) presented cGAN. This variant of GAN extends the original GAN framework by incorporating conditional data (denoted as y), which is fed into both the generator and the discriminator. This allows the model to generate data based on specific conditions or labels. This variant of GAN is primarily used for text generation, audio synthesis, data augmentation, and video generation.
3	Radford et al. (7)	Deep Convolutional GAN (DCGAN)	This variant of GAN is widely known for generating high-quality images. In DCGAN, the discriminator is designed for image classification tasks, and the use of convolutional layers helps stabilize the training process, addressing challenges present in the original GAN.
4	Arjovsky et al. (27)	Wasserstein GAN (WGAN)	The original GAN struggles with vanishing gradients and mode collapse issues. Arjovsky et al. (27) presented WGAN, this GAN significantly addresses those issues by leveraging the Wasserstein distance, enhancing training stability and making the process more robust.
5	Kamthe et al. (13)	Copula flows for Synthetic Data Generation (CopulaGAN)	This variant of GAN is designed to generate synthetic tabular data while maintaining the relationships and dependencies between variables. It uses copula functions to model the joint distribution of the data, ensuring that the generated data accurately reflects the statistical properties of the original dataset.

6	Brock et al. (28)	BigGAN	The BigGAN model, introduced by Brock et al. (28), explores the challenges of scaling up GANs for complex datasets like ImageNet. The authors demonstrate that training GANs at a large scale, with significantly wider architectures and larger datasets, can produce high-fidelity images.
7	Jinsung et al. (29)	Time-series GAN (TGAN)	TGAN is optimized for generating synthetic time series, a critical area for applications such as financial forecasting and traffic analysis. Unlike traditional GANs, which may struggle with capturing temporal correlations, TGAN combines the flexibility of unsupervised generative models with the control of supervised training.
8	Karras et al. (30–32)	Style-Based Generator Architecture GAN (StyleGAN)	StyleGAN is a GAN architecture designed for intuitive, scale-specific image synthesis by separating high-level attributes from stochastic variations.
9	Jordon et al. (33)	Private Aggregation of Teacher Ensembles GAN (PATE-GAN)	When it's question of reproducing highly sensitive data (34), PATE-GAN (33) is a good choice. This variant of GAN is designed to generate synthetic data while preserving privacy through differential privacy guarantees. This model combines GANs with the PATE (Private Aggregation of Teacher Ensembles) mechanism, making it particularly suitable for applications requiring a high level of protection for sensitive data, such as financial data.
10	Rajabi & Garibay (35)	Fair Tabular Data GAN (TabFairGAN)	TabFairGAN is particularly suited for scenarios requiring synthetic tabular data that balances accuracy and fairness.
11	Xu et al. (14)	Conditional Tabular GAN (CTGAN)	Like TabFairGAN, CTGAN is designed to generate realistic synthetic tabular data, but this GAN modeling both discrete and continuous variable distributions, even in the presence of multimodal continuous columns or imbalanced discrete ones. Leveraging a conditional generative adversarial network (GAN), CTGAN addresses the unique challenges of tabular datasets, outperforming traditional statistical and deep learning methods.
12	Seyfi et al. (36)	COmmon Source CoordInated GAN (COSCI-GAN)	COSCI-GAN (36) was presented as a proceeding paper at the 36th Conference on Neural Information Processing Systems (NeurIPS). It is designed to generate multivariate time series data while preserving inter-channel and feature relationships. By generating data from a common latent point and using a central discriminator to maintain dynamic correlations, COSCI-GAN improves data quality for downstream tasks such as classification and prediction.
13	Zhang et al. (8, 9)	Realistic Image Synthesis with Stacked (StackGAN)	Generates high-resolution images from text descriptions in a two-stage process.
14	Choi et al. (2)	Medical GAN (MedGAN)	In the healthcare sector, medGAN (2) was presented to generate realistic synthetic electronic health records (EHRs), specifically by modeling high-dimensional discrete variables derived from real patient records.
15	Echchakoui (24)	Cycle-Consistent GAN (CycleGAN)	This GAN is a model designed for unpaired image-to-image translation. The goal of this variant of GAN is to learn a mapping between two domains (e.g., source domain X and target domain Y) without requiring paired training data.
16	Ni et al. (37)	Sig-Wasserstein GANs (SigWGAN)	Presented as a proceedings paper at the 2nd ACM International Conference on AI in Finance (ICAIF 2021), SigWGAN (37) is a time-series generator that integrates continuous-time stochastic models with the newly proposed signature W-1 metric. The model leverages Logsig-RNN, based on stochastic differential equations, to capture complex temporal dynamics.

4. APPLICATIONS OF GANS IN FINANCIAL DATA GENERATION AND MARKET MODELING

The primary objective of this systematic review is to provide a comprehensive overview of the application of GANs in generating financial and market modeling data. Our investigation has identified several related studies addressing this topic. For instance, Kannan (38) reviewed deep generative models for synthetic financial data generation, comparing them to traditional methods while examining their applications, challenges, and future directions. Similarly, Eckerli and Osterrieder (39) presented an overview of GANs in finance, testing three GAN variants on financial time series. Their goal was to showcase how these GANs function, their capabilities, and their current limitations in handling financial data.

While these papers address aspects of the subject, they fall short in exploring a wide range of GAN variants and identifying the GANs most suitable for generating financial data across various aspect of the market. These gaps underline the significance of our work. To the best of our knowledge, this systematic review is the first to highlight, through the analysis of 30 papers published across IEEE Xplore, Web of Science, Scopus, and ArXiv, the application of diverse GAN variants in financial data generation and market modeling.

In Table 2, we provide an overview of the application of GANs in synthetic financial data generation. Our qualitative analysis is based on 30 relevant papers selected, summarizing the key findings and the specific market aspects addressed.

TABLE 2. Applications of GANs in synthetic financial data generation

No.	Authors	Market aspect addressed	Key findings and Discussion
1	Karst et al. (40)	Synthetic financial transaction data generation for banking applications.	Karst et al (40). provided a benchmark evaluation of various GAN models for generating synthetic financial transaction data in banking applications. According to the author, Conditional Tabular GAN (CTGAN) (14) balances fidelity, synthesis quality, efficiency, and privacy, making it suitable for general applications with moderate privacy concerns. DoppelGANger (DGAN) excels in privacy-sensitive tasks by minimizing re-identification risks, making it ideal for financial data sharing, though it struggles with data fidelity. Wasserstein GAN (WGAN) (27) ensures stable training and consistent data generation but has low column-wise fidelity, making it less suitable for precise data replication. Financial Diffusion (FinDiff) achieves the highest fidelity scores, preserving the original dataset's statistical distribution, making it ideal for tasks requiring high data replication accuracy. Tabular Variational AutoEncoder (TVAE) performs well in data augmentation and variability while maintaining structure but provides lower privacy protection than DGAN.
2	Naritomi & Adachi (41)	Stock price prediction and Financial time series augmentation.	In this paper, Naritomi & Adachi (41) proposed a data augmentation method using artificial market simulations based on Wasserstein GANs (WGANs) (27) to improve stock price prediction in high-frequency trading. The model was trained on trading data from the Tokyo Stock Exchange (FLEX Full) and successfully generated synthetic order events with realistic probability distributions. The results demonstrated that data augmentation using WGANs enhanced the accuracy of stock price movement prediction compared to models without augmentation.
3	Mohapatra et al. (42)	Synthetic financial transaction data.	In this paper, the authors demonstrate the effectiveness of using Conditional GANs (cGANs) (12) to generate synthetic financial transaction data for fraud detection while addressing data privacy concerns. To handle data imbalance, the approach incorporates edited nearest neighbor techniques, significantly enhancing the performance of machine learning models such as Support Vector Machines (SVM), Random Forest, and Logistic Regression. The method achieves notable improvements in precision, accuracy, and F1-score, proving robust against common fraud detection challenges, particularly data imbalance.
4	Mtetwa et al. (43)	Algorithmic trading optimization.	Mtetwa et al. (43) introduced the Visio-Temporal Conditional GAN (VTCGAN), which integrates image-based and multivariate time series GANs to generate realistic financial time series data and chart patterns. This synthetic data enhances the resilience and adaptability of algorithmic trading models, leading to improved decision-making and reduced risk exposure. Although empirical validation is pending at the time of this systematic review, VTCGAN demonstrates strong potential for optimizing trading performance and generalizability.
5	Kwon & Lee (44)	Financial market simulation & risk assessment.	This study investigates the ability of Generative Adversarial Networks (GANs) to simulate financial time series. The authors find that while GANs can capture key stylized facts, such as random walks, mean-reverting behavior, and time-varying volatility. Their performance in modeling multivariate dependencies remains limited. Specifically, GANs tend to generate correlated series that do not accurately reflect real market behavior. In this paper, the authors underscore that a naive application of GANs is insufficient and suggests that incorporating enhancements, such as attention mechanisms, could improve their ability to model financial time series more effectively.
6	Gu et al. (45)	Stock market prediction.	Gu et al. (45) proposed RAGIC, a novel Risk-Aware Generative Adversarial Network (GAN) framework for stock interval prediction. Unlike traditional point predictions, RAGIC generates multiple future price sequences while incorporating market randomness and risk awareness. It features a risk module (using volatility indices) and a temporal module (capturing historical trends). The study leverages Wasserstein GAN (WGAN) (27) to improve the quality of generated sequences. Experimental results show that RAGIC achieves 95% coverage with balanced interval width, outperforming traditional methods. The model is lightweight, computationally efficient, and provides useful insights for risk management and trading strategies.
7	Dogariu et al. (46)	Financial time series generation for stock market analysis.	The authors propose several Generative Adversarial Network (GAN)-based approaches to generate synthetic financial time series data with realistic statistical properties. The research addresses key challenges such as autocorrelation, volatility clustering, and central moment statistics, which are crucial for market modeling.
8	Park et al. (47)	Consumer credit data generation.	In this study, Park et al. (47) applied GANs to generate synthetic consumer credit data. The research evaluates data confidentiality, data Consistency, mutual information, and disclosure risk, demonstrating that GAN maintains consistency with real-world credit records while minimizing re-identification risks. The findings suggest that synthetic credit data can be a useful resource for financial big data training programs, with potential applications in risk assessment and credit scoring.
9	Ramirez et al. (48)	Asset allocation and portfolio optimization in public markets.	Ramirez et al. (48) proposed a novel portfolio optimization methodology that integrates a Markowitz-inspired framework with a Conditional-Value-at-Risk (CVaR) constraint. A key innovation is the use of synthetic data generated through a Modified Conditional Generative Adversarial Network (CTGAN) (14), which incorporates contextual information. This approach enhances portfolio performance, demonstrating the advantages of integrating contextual information over traditional historical data methods.

10	Kumar et al. (49)	Stock price movement prediction.	The paper proposes a novel method using Phase-space Reconstruction (PSR) and a Generative Adversarial Network (GAN) that leverages Long Short-Term Memory (LSTM) as the generator and Convolutional Neural Network (CNN) as the discriminator. This approach improves stock price direction prediction accuracy by 4.35%, reduces RMSE by 0.029, and decreases processing time by 78 seconds compared to existing models, achieving an RMSE of 0.0585 and directional accuracy of 61.45%.
11	Allen et al. (50)	Risk Management and Value at Risk (var) Estimation.	In this paper, Allen et al. (50) applied Wasserstein GANs (27) to generate synthetic financial data based on S&P 500 (Standard & Poor's 500) and FTSE 100 (Financial Times Stock Exchange 100 Index) index values. The research evaluates how closely the generated data mimics real financial time series using various statistical metrics, including regression analysis, moments, characteristic functions, and Random Forest models. A key application in this paper is the use of synthetic data to compute Value at Risk (VaR), demonstrating its potential for financial risk assessment.
12	Wiese et al. (51)	Equity option market data.	The study leverages GANs, including recurrent and temporal convolutional architectures, to simulate multivariate financial time series for option prices. GAN-based simulators outperform classical methods in generating realistic synthetic option market data, preserving key distributional properties and enhancing the training of option trading strategies with larger datasets.
13	Pires et al. (52)	Financial data privacy and integrity in transaction approval processes.	This study addresses data integrity and privacy challenges in financial transactions, focusing on the approval process for money withdrawals from FGTS, a Brazilian government fund. To overcome privacy regulations and data imbalances in financial datasets, Pires et al. (52) proposed a Hybrid Quantum-Classical Generative Adversarial Network (HQGAN), where a quantum circuit functions as the generator and a classical neural network as the discriminator. Although quantum-inspired methods show promise, HQGAN falls short in effectively capturing complex financial data patterns, emphasizing the need for further advancements in hybrid quantum-classical architectures.
14	Sana et al. (53)	Customer churn prediction in the telecommunications industry.	The authors proposed a privacy-preserving customer churn prediction (PPCCP) model using Generative Adversarial Networks (GANs) to generate synthetic data combined with adaptive Weight-of-Evidence (aWOE) transformation. This approach ensures data privacy while improving prediction performance. Experiments using eight machine learning classifiers on three public telecom datasets show that the GANs-aWOE method enhances accuracy by up to 28.9% and F-measure by 27.9% compared to previous models. The method protects customer data from privacy attacks while maintaining high prediction accuracy, making it a significant contribution to privacy-preserving in telecom.
15	Chen (54)	Financial risk management.	Chen (54) explored Feature-Enriched Generative Adversarial Networks (FE-GAN) for financial risk management, focusing on Value at Risk (VaR) and Expected Shortfall (ES) estimation. By integrating historical data, Geometric Brownian Motion (GBM) models, and time series analysis, FE-GAN enhances traditional GANs for financial time series modeling. The approach significantly improves model convergence speed, reduces estimation errors, and outperforms standard GANs in both VaR and ES estimation. Additionally, combining time series components (trend and seasonality) with GBM-derived volatility modeling further enhances VaR estimation, showcasing the complementary strengths of these techniques.
16	Xia et al. (55)	Financial market simulation.	This paper, presented as a proceedings paper at the 38th AAAI Conference on Artificial Intelligence (2024), introduces Market-GAN, a novel architecture designed to generate high-fidelity financial market data with semantic context control. The authors address key challenges, including the absence of context labels and the difficulty of producing precise, context-aligned data in non-stationary, noisy financial environments. Market-GAN incorporates market dynamics, stock tickers, and historical states, leveraging a two-stage training scheme to enhance data fidelity and contextual relevance.
17	Yoo et al. (56)	Stock market data simulation and machine learning-based trading strategies.	Yoo et al. (56) proposed a GAN-based stock market data simulation to address data scarcity in financial market analysis and trading system development. Their approach approximates real stock return distributions, overcoming limitations of traditional models like geometric Brownian motion. By training a machine learning model on both real and GAN-generated data, they develop a trading strategy and evaluate its performance. Experimental results show that incorporating synthetic data enhances trading performance and risk management, demonstrating the potential of GANs in financial market simulations.
18	Boursin et al. (57)	Commodity markets (electricity, gas, coal, fuel): commodity price simulation and deep hedging of options.	Boursin et al. (57) compared state of the art generative models for commodity price time series and evaluate their application in deep hedging of commodity options. CEGEN (Conditional Euler Generator) is identified as the best-performing GAN, excelling in replicating marginals, correlations, and consistency across datasets, while TGAN (Time Series Generative Adversarial Network) (29) offers more generality.
19	Efimov et al. (58)	Credit and fraud risk management operations.	In this research paper, Efimov et al. (58) demonstrated that a novel GAN architecture, combining conditional GAN (12) and DRAGAN (Discriminator Regularized Generative Adversarial Network), can generate synthetic financial datasets with high fidelity, closely approximating original data distributions. While models trained on synthetic data show slightly lower performance compared to those trained on original data, the generated data still serves as a reliable benchmark for financial applications.

20	Jiang et al. (59)	Financial market supervision and risk prediction through data balancing.	The study leverages GANs to generate synthetic data that addresses data imbalance in financial market supervision, improving the prediction accuracy of high-risk events such as market manipulation and systemic risk. Experimental results show that GAN significantly enhances model performance, outperforming traditional oversampling and undersampling techniques. This approach provides a feasible solution for regulatory bodies to better detect and mitigate financial risks.
21.	Tovar (60)	Financial time series prediction, particularly for stock market trend forecasting in highly dynamic and volatile environments.	Tovar (60) proposed a novel hybrid deep learning model using Bi-LSTM as the generator and CNN as the discriminator in a GAN framework (Bi-LSTM-CNN GAN). This model outperforms existing Machine Learning and GAN-based approaches by effectively generating synthetic financial data that retains critical market features, improving the reliability of predictions, especially under high volatility scenarios like intraday trading.
22.	Lu & Yi (61)	Portfolio allocation diversification.	In this paper, Lu & Yi (61) proposed Autoencoding Conditional GAN (ACGAN), which integrates an encoder-decoder structure into CGAN to retain key features while generating financial time series. This approach enhances trend prediction and market uncertainty modeling, leading to better Sharpe ratios and portfolio returns compared to traditional Markowitz and CGAN models.
23	Gu et al. (62)	Stock market prediction.	Gu et al. (62) addressed the stock market prediction domain, specifically focusing on broad-index movements (e.g., Dow30 and S&P 500). They introduce IndexGAN, a Wasserstein Generative Adversarial Network (WGAN) designed for multi-step stock movement prediction. The novelty lies in incorporating domain knowledge, including news context learning and market volatility, to improve robustness and accuracy. Compared to existing GAN-based methods, IndexGAN mitigates mode collapse, leverages seq2seq learning, and employs a rolling strategy to adapt to market uncertainties. Experimental results demonstrate superior performance, achieving over 60% accuracy, surpassing prior state-of-the-art models.
24	Wiese et al. (63)	Financial time series modeling	Wiese et al. (63) proposed Quant GANs, a novel GAN-based approach leveraging temporal convolutional networks (TCNs) to model financial time series. The Stochastic Volatility Neural Networks (SVNNs) architecture within Quant GANs captures long-range dependencies, volatility clusters, and heavy tails in asset price data. The results demonstrate superior performance over traditional models like GARCH, especially in matching distributional and dependence properties.
25	Lu & Ding (64)	Portfolio analysis and allocation.	In this paper, Lu & Ding (64) proposed HybridCGAN and HybridACGAN, which integrate conditional GAN (CGAN) (12) and deep neural regression to enhance future trend prediction while preserving internal market structures. Unlike traditional CGAN/ACGAN, which emphasize data generation over prediction, this hybrid approach improves portfolio allocation efficiency across various industries in US and European markets.
26	Fu et al. (65)	Financial time series simulation for training and evaluating trading strategies.	Fu et al. (65) proposed two novel GAN architectures: Temporal Attention GAN (TAGAN) and Temporal Transformer GAN (TTGAN), which leverage attention mechanisms to improve the modeling of long-range dependencies in financial data. These models outperform QuantGAN (42) by producing more realistic autocorrelation and cross-correlation structures, improving the no-arbitrage condition for option surfaces, and reducing overfitting in time series simulations.
27	Bezzina & Vella (66)	Portfolio construction and risk management.	The authors propose a GAN-assisted portfolio construction technique that integrates correlation-aware synthetic data into traditional risk-based management. A holistic evaluation confirms its similarity to real market data. Empirical results demonstrate that incorporating synthetic data improves portfolio performance, leading to an 18.12% increase in the Sharpe Ratio compared to a benchmark portfolio based solely on historical data.

5. CHALLENGES AND OPEN RESEARCH DIRECTIONS

Although Generative Adversarial Networks (GANs) were first introduced in 2014, their application to financial data generation and market modeling only gained traction around 2019. In this systematic review we have highlighted how GANs have been employed in various aspects of financial markets, such as portfolio analysis, stock price prediction, and market simulation. However, several challenges and limitations remain in generating financial data using GANs. In this section we outline key challenges and potential future research directions.

5. 1. Challenges In Applying GANs To Financial Data: Data Limitations and Quality Issues

While financial markets generate vast amounts of data, high-quality, clean, and sufficiently granular datasets remain scarce. GANs require extensive training data, and noisy or incomplete datasets can significantly impact their performance. Additionally, financial datasets often suffer from structural breaks, non-stationarity, and regulatory-driven changes, making it difficult to maintain consistent data quality over time.

Limited stability in training GANs: Many articles using for this systematic review highlighted the difficulty of stabilizing GAN training when modeling complex financial time series. Convergence issues often arise due to the adversarial nature of GANs, making it challenging to achieve consistent results, particularly when dealing with volatile market data. Furthermore, mode collapse remains a persistent problem, where the generator produces a limited set of repetitive outputs instead of capturing the full distribution of financial patterns. To mitigate this, techniques such as Wasserstein GANs (WGANs) (27), gradient penalty regularization, and improved loss functions need to be explored further.

Model evaluation and benchmarking: At the time of this systematic review, there is no universally accepted evaluation metric for assessing GAN-generated financial data. The variants of GANs covered in this study rely on distributional metrics or dependence measures, but a unified approach that incorporates financial risk, market efficiency, and predictive performance is still lacking.

Capturing market dynamics and competitive aspects: While those GANs have been effective in modeling asset prices and volatility, they rarely account for competitive market dynamics such as interactions between market participants, market microstructure, and strategic competition. Incorporating these elements remains an open challenge.

Model training complexity and stability: Advanced models such as transformer-based GANs (e.g., TTGAN) require extensive computational resources, hyperparameter tuning, and large datasets. Training instabilities, such as mode collapse, make it challenging to generate diverse market scenarios. Moreover, overfitting can occur when GANs memorize specific patterns in historical financial data rather than learning generalizable features, particularly in small or highly correlated datasets. Regularization techniques and differential privacy methods could be useful to address this issue.

Long-range dependencies and market regimes: Financial markets are highly non-linear and subject to sudden regime shifts (e.g., market crashes, economic policy changes). While attention-based GANs (TAGAN, TTGAN) improve the modeling of long-range dependencies, they still struggle with capturing regime changes and extreme market events. One potential approach to addressing this limitation is integrating GANs with regime-switching models, such as Hidden Markov Models (HMMs) or recurrent neural networks (RNNs) with state transitions, to detect and adapt to sudden shifts in market. Additionally, developing hybrid models that incorporate time-varying risk factors and sentiment analysis could enhance the adaptability of GANs to real-world financial conditions.

Economic aspect of the market in general: Most studies focus on applying GANs to financial markets, such as asset price modeling, stock market prediction, and risk management. However, broader macroeconomic dynamics remain largely unexplored. There is a lack of research using GANs to model global economic phenomena such as, inflation, business cycles, and the impact of monetary and fiscal policies. Expanding GAN applications to these areas could provide valuable insights into complex economic systems and policy-making.

5. 2. Open Research Directions: Incorporating Market Competition and Strategic Interactions

Future research can explore GANs that model competitive market environments with multiple agents employing diverse trading strategies. Game-theoretic could be used to simulate strategic interactions in trading, regulatory impacts, and competitive behaviors.

Improving Tail Modeling and Extreme Event Simulation: Financial markets exhibit heavy tails and extreme events, yet existing GAN models often fail to capture these accurately. While some studies use the Lambert W transformation to address heavy tails, further improvements are needed to enhance GANs' ability to simulate rare financial events such as market crashes. A promising direction would be the development of GAN architectures incorporating extreme value theory (EVT) or tail-risk-aware loss functions to better model financial anomalies.

Integration with Real-Time Data for Continuous Market Analysis: Developing GAN models that can be continuously updated with incoming market data could enable real-time market monitoring and adaptive strategies. This could involve using streaming GANs or online learning techniques, allowing models to evolve with changing market conditions while avoiding overfitting to outdated patterns.

Combining GANs with Reinforcement Learning for Market Simulation: Hybrid models that integrate GANs with reinforcement learning could enable dynamic market simulations where agents adapt their strategies over time, leading to more realistic and robust market models.

6. CONCLUSION

This systematic review has explored the application of Generative Adversarial Networks (GANs) in the generation of financial data and market modeling. Our qualitative analysis was based on 30 relevant research papers published across four databases: Web of Science, Scopus, IEEE Xplore, and ArXiv. To the best of our knowledge, this review is the first to explore not only the various GAN models since their inception in 2014 but also to highlight their application specifically within financial markets.

Our analysis highlights key market aspects addressed by GAN applications, including portfolio analysis, risk management, market simulation, and stock market analysis (see Table 2). Our findings highlight that while

GANs have demonstrated strong capabilities in generating high-fidelity financial data, certain market aspects, such as market competition, strategic interactions, long-range dependencies, and market regimes remain underexplored. Furthermore, we identified key challenges in applying GANs to financial data generation, including issues related to mode collapse, data biases, and evaluation metrics. Future research could integrate GANs with Reinforcement Learning for market simulation and develop GAN models that better address competitive market dynamics.

Despite the robust findings of this review, the keywords used for data collection may have influenced the scope of the selected studies. Hence, future research could benefit from employing alternative keyword strategies to enrich the breadth of analyzed literature.

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Persian Abstract

چکیده

شبکه‌های متخاصم مولد (GAN)به عنوان یک راه‌حل امیدوارکننده برای الگوریتم‌های یادگیری ماشین و هوش مصنوعی با محدودیت در دسترس بودن و دسترسی به داده‌ها ظهور کرده‌اند. بازارهای مالی، در کنار مراقبت های بهداشتی، به دلیل نگرانی های مربوط به حفظ حریم خصوصی و محرمانه بودن داده ها، چالش های مهمی را ارائه می دهند. GAN ها محققان را قادر می سازند تا داده های مالی مصنوعی را تولید کنند که از نزدیک منعکس کننده مجموعه داده های دنیای واقعی است و پیشرفت در تحلیل و مدل سازی بازار را تسهیل می کند. علیرغم پتانسیل آنها، یک ارزیابی جامع از تولید داده های مالی مبتنی بر GAN محدود است و نیاز به ارزیابی سیستماتیک روش ها و یافته های موجود دارد. این مقاله مروری سیستماتیک از معماری‌های GAN اعمال شده برای تولید داده‌های مالی و مدل‌سازی بازار ارائه می‌کند. مطالعه ما با کاوش جامع انواع مختلف GAN و کاربردهای خاص آنها در جنبه‌های مختلف بازارهای مالی، از جمله پیش‌بینی قیمت سهام، معاملات الگوریتمی، بهینه‌سازی پورتفولیو، مدیریت ریسک، و کشف تقلب متمایز می‌شود. با استفاده از سی مقاله مرتبط از چهار پایگاه داده اصلی (IEEE Xplore، Web of Science، Scopus و ، arXiv)، یافته‌های کلیدی را ترکیب کردیم، چالش‌ها را شناسایی کردیم و محدودیت‌ها را در کاربرد GAN برای تولید داده‌های مالی برجسته کردیم. یافته‌های ما نشان می‌دهد که در حالی که GANها حریم خصوصی و دسترسی داده‌ها را افزایش می‌دهند، با محدودیت‌هایی مانند فروپاشی حالت، بی‌ثباتی در طول آموزش، و نگرانی‌های نظارتی در بازارهای مالی نیز مواجه هستند. این بررسی کیفی بینش‌های ارزشمندی را برای محققان و ذینفعان فراهم می‌کند و پایه‌ای برای مطالعات آینده و کاربردهای نوآورانه GANs در بازارهای مالی ارائه می‌دهد.