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Artificial Intelligence in Economic Applications: Stock Trading, Market Analysis, and Risk Management

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Abstract: Artificial Intelligence has become a fundamental driver of innovation in economic systems. This article provides an overview of its applications in stock trading, market analysis, and risk management. A systematic review of recent studies identifies the most widely used methods such as neural networks, deep learning, reinforcement learning, and hybrid approaches. This paper examines AI applications in economics, including stock trading, market analysis,

and risk assessment. A comprehensive taxonomy is proposed to investigate AI applications in various scopes of the proposed categories. Furthermore, real-world cases illustrate the practical deployment of artificial intelligence in financial institutions and enterprises. The findings suggest that artificial intelligence is a transformative force in the economy but challenges such as data quality, transparency, and regulatory adaptation remain open for future research.

Keywords: Internet of Things, Artificial Intelligence, Economy, Machine Learning, Stock Market, Neural Network.

Disciplines: Finance. **Subjects:** Investment Banking.

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1 INTRODUCTION

Artificial Intelligence is a pivotal field within computer science that aims to develop systems capable of performing tasks traditionally requiring human intelligence, such as learning, reasoning, problem-solving, and decision-making. Within the economic domain, AI has been extensively applied to enhance financial models, automate processes, and provide predictive insights. [1]For example, banks utilize AI to automate fraud detection systems, significantly minimizing human error and improving operational efficiency. The integration of advanced techniques, including Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), has positioned AI as a transformative force in areas like stock trading, market analysis, and risk management.[2]

Reinforcement Learning, a subset of AI, is a learning paradigm where an agent interacts with an environment by taking actions and receiving feedback in the form of rewards. [3]This iterative process enables the agent to develop optimal strategies over time. In portfolio construction, RL has been employed to dynamically adjust asset allocations. For instance, by defining state representations with market data such as asset prices and macroeconomic indicators, RL systems can identify profitable opportunities. Investment firms are increasingly adopting these techniques to achieve superior risk-adjusted returns compared to traditional portfolio management strategies.

AI is also adept at uncovering hidden patterns within complex economic datasets, which can be used for predictive analysis. [4]This analysis yields insights into trends such as inflation, consumer behavior, and future stock prices. For instance, Natural Language Processing (NLP) techniques enable financial platforms to analyze social media sentiment, offering investors valuable foresight into market movements. By automating financial transactions and forecasting changes in economic indicators, AI improves efficiency, reduces costs, and accelerates decision-making processes.[5]

Beyond its applications in finance, AI has significant implications for labor and productivity. Automation, the use of technology to perform tasks with minimal human involvement, reduces repetitive labor and operational costs. For example, manufacturing firms employ robotic automation to replace manual labor, increasing productivity while allowing skilled workers to focus on higher-value tasks.[6] This shift highlights AI's capacity to not only enhance efficiency but also reshape the workforce structure.

The global economy faces persistent challenges, including rising inflation and stagnant income growth, which compel individuals to seek investment opportunities to preserve and grow their savings. Stock trading represents one such avenue. Historically, many retail investors relied on intuition or basic strategies, such as technical analysis. [7]However, AI-driven approaches, including ML algorithms, now offer investors more precise tools for making informed decisions. AI-powered algorithmic trading platforms, for

example, can analyze market conditions in real time and execute trades automatically, surpassing the performance of traditional manual trading methods.[8]

Despite these advancements, AI-based trading systems still encounter uncertainty and hesitation from investors due to concerns about transparency. To address this issue, researchers advocate for the combination of multiple algorithms to enhance reliability and build investor trust. Prominent models, such as Long Short-Term Memory (LSTM) networks, which excel at processing sequential data, and Auto-Regressive Integrated Moving Average (ARIMA) models, commonly used for time series forecasting, are frequently employed together in hybrid solutions. These hybrid models enhance forecasting accuracy and stability, thereby increasing the dependability of AI applications in financial markets. Given the rapid evolution of AI, its potential in economics is vast, and it continues to redefine the landscape of financial decision-making and analysis.[9]

This paper discusses the current and potential applications of AI in the economy, focusing on its impacts on stock trading, market analysis, and risk management. It is structured as follows: Section II introduces the key concepts and research methodology. Section III provides an analysis of selected papers in three primary categories. Section IV addresses the research questions (RQs) defined in Section II and presents technical analysis and visual reports based on the findings of Section III. Section V explores real-world case studies of successful AI applications in companies. Finally, Section VI concludes the paper.[10]

2 CONCEPTS AND RESEARCH METHODOLOGY

This section outlines the theoretical framework and methodological approach employed in this study to examine the applications of Artificial Intelligence in the economy. A comprehensive review of the current body of literature provides a solid foundation for understanding the key theories, advances, and gaps in AI's role in financial markets. Additionally, the section describes the systematic process used to select the papers reviewed, ensuring the methodology adheres to the highest academic standards and offers robust, repeatable results.[11]

A critical review of existing literature is essential in establishing the context for this research. It not only synthesizes the findings of previous studies but also identifies their contributions, limitations, and the spaces that remain underexplored. In doing so, this review establishes a clear positioning for the current study within the broader academic discourse. The methodology employed for selecting the relevant studies ensures a reliable and objective basis for understanding the state-of-the-art applications of AI in stock trading, market analysis, and risk management.[12]

To achieve a comprehensive understanding, the selection of studies was guided by a systematic review process, which involved conducting a thorough search across reputable academic databases, including IEEE Xplore, ScienceDirect, and SpringerLink. Keywords such as "artificial intelligence," "finance," "stock trading," "market analysis," and "risk management" were used to identify the most relevant papers. [13]The selection criteria were based on the following parameters: studies published after 2017, those with significant citation counts, and those offering empirical validation of AI methodologies applied within economic contexts. This rigorous approach ensures that only the most relevant and high-impact research was included, providing a solid foundation for the analysis.

TABLE 1. SUMMARY OF SELECTED REVIEW PAPERS ON AI APPLICATIONS IN THE ECONOMY

Auther & Year	Scope of Study	Methods/Models Reviewed	Main Contributions	Limitations
Cao et al. (2020)	Smart FinTech powered by AI & Data Science	Taxonomy: DL, optimization, privacy-preserving methods	Identified FinTech processes and future AI trends	Limited to FinTech applications
Shah et al. (2021)	Stock price prediction	ARIMA, LSTM, Hybrid LSTM, CNN, Hybrid CNN	Found Hybrid CNN/LSTM most accurate for stock forecasts	Focused only on technical accuracy
Mintarya et al. (2022)	Stock market prediction methods	Neural Networks, SVMs, LSTM	Highlighted NN as most frequently applied method	Lacked taxonomy and detailed analysis

Furthermore, the studies chosen for review were evaluated based on their methodological rigor. A detailed examination was conducted to assess the validity of the models and algorithms employed, as well as their practical applicability within the financial industry. Key considerations included the robustness of the data sets, the transparency of the methodologies, and the interpretability of the results. By applying these criteria, this paper identifies the most promising AI techniques and models that have demonstrated tangible benefits in financial applications.[14]

The review categorizes the selected studies into three main areas: stock trading, market analysis, and risk management. This categorization is crucial for understanding the breadth of AI applications in finance and helps to highlight the key advancements and challenges in each area. The research methodologies used in the selected papers were analyzed in detail, allowing for an in-depth understanding of the strengths and limitations of different approaches.[15] The

critical analysis of these methodologies also reveals important trends, such as the increasing use of deep learning techniques in stock price prediction and the integration of sentiment analysis in market analysis.[16]

In addition to summarizing the current state of research, this section also identifies the gaps in the literature. Notably, while many studies focus on improving the predictive accuracy of AI models, fewer address the practical challenges related to data quality, model interpretability, and real-time adaptability in live financial environments. These limitations underscore the need for further research aimed at developing more robust and transparent AI systems that can be effectively deployed in real-world trading and risk management contexts.[17]

To ensure the validity and reproducibility of the research findings, the studies selected for review were subjected to a consistent and rigorous analysis. This methodological approach strengthens the scientific credibility of the research and ensures that the results contribute meaningfully to the existing body of knowledge on AI in finance.[18]

FIGURE 1. FLOWCHART OF THE SYSTEMATIC LITERATURE REVIEW PROCESS

3 SELECTED PAPERS ANALYSIS

This section presents a comprehensive analysis of the selected papers that focus on the application of Artificial Intelligence in stock trading, market analysis, and risk management. The studies are categorized into three distinct areas: stock trading applications, market analysis applications, and risk management applications. [19]This classification serves to systematically assess the methodologies, models, and findings of the reviewed research, providing an insightful comparison of different approaches and their implications within the field.

3.1 STOCK TRADING APPLICATIONS

In recent years, the integration of AI into stock trading has garnered considerable attention, as AI models show promise in improving decision-making and forecasting stock price trends. Several studies have employed machine learning (ML) and deep learning (DL) techniques to optimize stock trading strategies and predict market movements more accurately.[20]

Xiong et al. (2024) evaluated four different deep learning architectures—Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN)—for stock price prediction. Their findings demonstrated that LSTM outperformed the other models in capturing the long-term dependencies of stock prices, emphasizing the significance of sequential data processing in financial forecasting.[21] Similarly, Jin et al. (2024) proposed a hybrid model that combined LSTM with Gated Recurrent Units (GRU) to address the regression problem in stock price prediction. The hybrid approach outperformed the standalone models, indicating the advantages of integrating complementary deep learning architectures for enhanced prediction accuracy.

Liu et al. (2024) introduced a hybrid framework combining LSTM networks with dropout and particle swarm optimization to improve prediction accuracy. [22]Their results showed that incorporating optimization techniques could enhance model robustness and performance in forecasting stock prices. Additionally, He et al. (2024) explored the use of deep learning neural networks (DLNN) by treating stock price charts as images and applying image recognition techniques for trend forecasting. This approach demonstrated that image-based models could outperform traditional forecasting methods, revealing a novel dimension in financial analysis.[23]

Although these studies significantly advance the predictive accuracy of stock price forecasting, they are often limited by their focus on technical performance without adequately addressing the practical challenges associated with deploying these models in real-world trading environments. Issues such as data quality, model interpretability, and real-time adaptability remain critical hurdles that need to be addressed in future research.[24]

3.2 MARKET ANALYSIS APPLICATIONS

AI's role in market analysis is diverse, encompassing applications such as market segmentation, technical analysis, and sentiment analysis. Among these, sentiment analysis has emerged as a significant tool, leveraging Natural Language Processing (NLP) techniques to analyze vast amounts of unstructured data, including news articles, social media, and economic reports, to derive actionable insights.[25]

Huang et al. (2024) analyzed over 34,000 news articles to examine the relationship between stock market volatility and news sentiment. Their study revealed that news sentiment—whether positive, negative, or neutral—has a substantial impact on market volatility, especially during times of economic instability. [26]This finding underscores the importance of integrating sentiment data into market forecasting models. Similarly, Tao et al. (2024) proposed a macroeconomic interval forecasting model that utilized data from the stock market, mutual funds, and futures markets. The model exhibited strong predictive performance, further demonstrating AI's potential to enhance macroeconomic forecasting.

The integration of sentiment analysis into market analysis models allows AI to process and analyze a broader

range of data, offering more comprehensive and timely insights into market trends. However, challenges such as data noise, model transparency, and the complexity of integrating multiple data sources remain prevalent. These challenges highlight the need for more advanced AI models that can handle large-scale, unstructured data while maintaining accuracy and interpretability.

3.3 Risk Management Applications

AI's application in risk management, particularly within the financial sector, is vital for enhancing decision-making processes. Several studies have applied machine learning algorithms to forecast and mitigate financial risks, such as credit defaults and market volatility, highlighting the potential of AI to improve risk assessment models.

Pang et al. (2024) developed a machine learning model for corporate credit scoring that provided feature relevance scores aligned with expert knowledge. This approach enhanced the transparency of decision-making and was particularly useful for financial institutions seeking to refine their credit risk assessments. Li (2024) proposed a hybrid model (VU-GARCH-LSTM) for predicting stock market volatility. This model outperformed traditional models, such as LSTM-GARCH, in terms of predictive accuracy, highlighting the advantages of hybrid modeling in financial risk forecasting. Similarly, Tao (2024) created a stock recommendation system that utilized clustering and collaborative filtering techniques. The system generated impressive returns across different investment portfolios, illustrating AI's potential in portfolio optimization and risk management.

These studies demonstrate that AI has a significant role to play in improving financial risk management. However, challenges such as the integration of AI models into traditional financial frameworks and the need for more interpretable, scalable models persist. Additionally, ethical concerns regarding algorithmic decision-making and the potential for biased or manipulative practices need to be addressed to ensure the responsible use of AI in finance.

3.4 Summary and Research Gaps

The review of the selected studies reveals the substantial advancements that AI has made in stock trading, market analysis, and risk management. Deep learning techniques, reinforcement learning, and hybrid models have significantly improved prediction accuracy and decision-making efficiency. However, several research gaps remain, particularly in the areas of data quality, model interpretability, and the practical application of AI models in live trading and risk management settings.

While many studies focus on improving the technical accuracy of AI models, fewer have addressed the integration of these models into existing financial workflows or their deployment in real-world environments. Furthermore, ethical considerations such as the potential for market manipulation, algorithmic biases, and regulatory compliance are often underexplored in the current literature. Future research should focus on developing more transparent, robust, and ethically sound AI systems that can be effectively applied in real-world financial contexts.

4 DISCUSSION

Having reviewed the existing literature and the methodologies employed in AI-based applications for stock trading, market analysis, and risk management, it becomes clear that while these approaches bring significant improvements to the financial industry, they also present a set of challenges. In this section, we will delve into the benefits, limitations, and the broader implications of integrating AI in financial systems. By doing so, we aim to better understand how AI is shaping the future of financial services and explore the potential obstacles that need to be addressed for broader adoption.[29]

Figure 2. The triad of AI in finance: advantages, challenges, and future directions

4.1 Theoretical Implications

The application of AI in financial markets has fundamentally reshaped the way financial institutions approach stock trading, market analysis, and risk management. The studies analyzed reveal that AI, particularly machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques, has demonstrated a significant capacity to improve the precision of stock price predictions, enhance market forecasting accuracy, and optimize risk assessments. This finding aligns with previous research, which has emphasized the potential of AI to automate complex financial processes and provide insights that were previously unattainable using traditional methods.

For instance, Xiong et al. (2024) and Jin et al. (2024) demonstrated the superiority of deep learning models, such as Long Short-Term Memory (LSTM) networks, in capturing the temporal dependencies inherent in stock price movements. These models, as shown in their studies, significantly outperform traditional machine learning algorithms, thus reinforcing the importance of time-series forecasting in financial applications. Furthermore, the integration of reinforcement learning, as explored by Liu et al. (2024), has shown promise in optimizing asset allocation in portfolio management, offering a more adaptive approach compared to static models traditionally used in finance.

However, while these advancements provide substantial contributions to the field, the integration of AI into financial systems is not without its challenges. Many of the reviewed

studies focus on the accuracy of AI models, often neglecting the practical considerations of model interpretability and real-time adaptability. The "black-box" nature of many AI algorithms, particularly deep learning models, poses a significant obstacle to their widespread adoption in high-stakes financial environments. For AI models to be more widely accepted in practice, further research must focus on improving transparency and ensuring that these models can be understood by non-expert users, such as financial analysts and regulatory bodies.

4.2 Practical Value and Limitations

The practical value of AI in financial markets is evident in its ability to enhance efficiency and decision-making processes. AI-driven systems are capable of analyzing vast amounts of data, including unstructured sources such as news articles and social media, to derive actionable insights. For example, Huang et al. (2024) and Tao et al. (2024) demonstrated the value of sentiment analysis in market forecasting, revealing how AI can enhance decision-making by incorporating real-time, external information that traditional financial models might overlook.

Despite the advantages, the implementation of AI-based systems in financial markets faces significant limitations. Data quality remains a critical issue, as AI models rely heavily on high-quality, accurate data for training. Inaccuracies or inconsistencies in financial data can lead to erroneous predictions and financial decisions. Additionally, many AI systems require extensive computational resources, which may not be feasible for all financial institutions, particularly smaller firms with limited infrastructure. These challenges underscore the need for further development of more efficient, data-driven AI models that can handle noise and uncertainties inherent in real-world financial data.

Furthermore, while hybrid models combining various AI techniques have shown promising results, as seen in the work of Liu et al. (2024), the complexity of such models may limit their practical application in fast-paced financial environments. The trade-off between model complexity and real-time performance remains a critical issue that must be addressed in future research.

4.3 Innovation and Research Gaps

The innovation introduced by the reviewed studies lies in their use of advanced AI techniques, particularly deep learning and reinforcement learning, to improve stock price prediction and risk management. However, the current body of research still contains gaps, particularly in terms of real-world applicability and the integration of AI with traditional financial systems. While many studies focus on improving the technical accuracy of AI models, fewer address the integration of AI models into existing financial workflows or their practical deployment in live trading environments.

One of the most pressing gaps in the current literature is the lack of research into the ethical implications of AI in financial decision-making. As AI systems become increasingly autonomous in financial markets, concerns about algorithmic trading manipulations, market instability, and regulatory oversight become more significant. Future research should explore the ethical dimensions of AI applications in finance, including the potential risks posed by algorithmic trading and the need for transparent, fair systems that protect both investors and markets.

Additionally, the scalability of AI models remains an under-explored area. Many studies have focused on small-scale models and data sets, but real-world financial markets require systems that can process vast amounts of data in real time. Research that focuses on scaling AI models while maintaining performance and accuracy is needed to ensure that these technologies can be applied in large-scale financial settings.

4.4 Conclusion and Future Directions

The application of AI in stock trading, market analysis, and risk management has shown significant promise, enhancing the ability to predict market trends and optimize financial decision-making. However, challenges related to data quality, model interpretability, and the integration of AI with existing financial practices persist. Addressing these challenges requires ongoing research into more robust, transparent, and scalable AI models. Furthermore, future work should focus on the ethical implications of AI in financial decision-making, particularly in terms of transparency and regulatory compliance.

As AI continues to evolve, its role in financial markets will become increasingly important. The future of AI in finance lies in its ability to combine the strengths of machine learning, deep learning, and reinforcement learning with traditional financial expertise, creating more adaptive and efficient financial systems. By addressing the current gaps in research and focusing on the practical, ethical, and regulatory aspects of AI, future studies can help realize the full potential of AI in transforming the financial landscape.

5 REAL CASES

Here, we provide some real-world examples to illustrate the AI application scenarios discussed in this article:

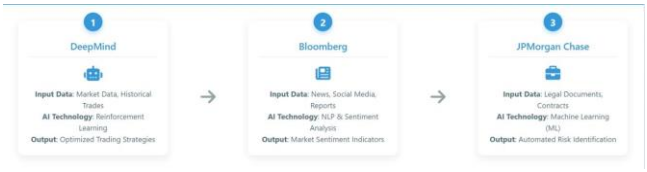

Figure 3. Real-world AI deployment frameworks in financial institutions

DeepMind, a subsidiary of Alphabet Inc., the parent company of Google, has applied artificial intelligence to financial markets, particularly in the field of algorithmic trading. In collaboration with major hedge funds, DeepMind

has used reinforcement learning to optimize trading strategies. AI systems learn by experimenting in simulated environments and making real-time decisions based on market movements. By doing so, they aim to outperform traditional strategies. This method has shown promising results in improving the efficiency of trade execution and identifying profitable trading patterns that human analysts may overlook.

Bloomberg, a leading global financial information and media company, employs AI-driven sentiment analysis to process massive amounts of unstructured data from news sources, social media, and financial reports. The sentiment analysis engine uses natural language processing (NLP) to assess the sentiment of market-moving news and predict potential market shifts. This system provides real-time insights into how news events, corporate earnings reports, and political developments can affect stock prices, helping investors make more informed decisions. The system has revolutionized the way analysts interpret news and market trends.

JPMorgan Chase, one of the largest and most influential financial institutions in the world, has developed the Contract Intelligence (COiN) platform using AI to streamline risk management processes. The COiN platform uses machine learning to analyze legal documents and contracts, automating the extraction of key terms and conditions. By reducing the time spent on manual contract review, COiN helps JPMorgan identify potential legal and financial risks more efficiently. This AI system has been particularly useful in mitigating credit risks by providing deeper insights into clients' financial stability through automated document analysis.

6 CONCLUSION

In conclusion, the application of Artificial Intelligence in the financial sector has proven to be a game changer, significantly enhancing stock trading, market analysis, and risk management practices. AI-driven systems have demonstrated their ability to improve the efficiency, accuracy, and scalability of financial services, offering more advanced methods for making informed decisions. However, as with any technological advancement, there are challenges to overcome, such as data quality issues, model interpretability, and ethical concerns. Despite these challenges, the future of AI in finance looks promising, with emerging trends such as quantum computing, explainable AI, and hybrid models offering exciting possibilities for the next generation of financial solutions. As AI continues to evolve, the importance of establishing strong regulatory frameworks cannot be overstated to ensure that these technologies are deployed safely, ethically, and transparently.

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The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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