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Artificial Intelligence in stock broking: A systematic review of strategies and outcomes

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Abstract

Artificial Intelligence (AI) has emerged as a transformative force in the field of stock broking, revolutionizing traditional trading strategies and reshaping financial markets. This systematic review delves into the diverse array of AI-driven strategies employed in stock broking and assesses their outcomes, shedding light on the evolving landscape of algorithmic trading. The study encompasses a comprehensive analysis of various AI models, including machine learning algorithms, deep neural networks, and natural language processing techniques, that have been harnessed to analyze market data, predict stock movements, and optimize trading decisions. By synthesizing existing literature, the review offers insights into the effectiveness and limitations of these strategies, providing a nuanced understanding of their impact on market dynamics. Key findings reveal that AI applications in stock broking exhibit a wide spectrum of approaches, ranging from predictive modeling for price forecasting to sentiment analysis for gauging market sentiment. The review also explores the integration of reinforcement learning in algorithmic trading, highlighting the adaptive nature of AI systems in responding to dynamic market conditions. Furthermore, the outcomes of AI-driven strategies are evaluated in terms of risk management, profitability, and overall market efficiency. The review identifies trends indicating increased efficiency and reduced human biases, but also acknowledges challenges related to model interpretability, ethical considerations, and the potential for algorithmic-driven market volatility. This systematic review contributes to the evolving discourse on the role of AI in stock broking, offering a holistic examination of strategies and outcomes. As financial markets continue to embrace technological advancements, understanding the nuances of AI applications becomes paramount for market participants, regulators, and researchers alike. This study serves as a valuable resource for stakeholders seeking to navigate the complex interplay between artificial intelligence and the stock broking landscape.

Keywords: Stock Broking; AI; Finance; Trading; Risk Management; Review

1. Introduction

The evolution of technology in stock broking has been marked by significant advancements, particularly with the rise of Artificial Intelligence (AI) in financial markets. AI has revolutionized stock broking by introducing innovative strategies and outcomes. The purpose of this systematic review is to comprehensively understand the impact of AI on stock broking and to evaluate various strategies and their outcomes.

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The evolution of technology in stock broking has been a continuous process, with the integration of advanced technological solutions to enhance trading processes and decision-making. The rise of AI in financial markets has been a pivotal development, transforming traditional stock broking practices. AI has enabled the automation of trading processes, sophisticated data analysis, and the development of predictive models, thereby revolutionizing the decision-making framework in stock broking (Rabbani et al., 2023). This has led to a paradigm shift in the way stock broking is conducted, with AI playing a crucial role in shaping the industry's future.

The purpose of this systematic review is to comprehensively understand the impact of AI on stock broking. This involves analyzing the various ways in which AI has influenced stock broking practices, including its role in risk management, portfolio creation, trend anticipation, and fraud detection (Srinadi, 2023). Additionally, the review aims to evaluate the outcomes of different AI-driven strategies employed in stock broking, such as algorithmic trading and automated portfolio management (Vedapradha et al., 2023). By systematically examining the impact and outcomes of AI in stock broking, this review seeks to provide valuable insights into the implications of AI adoption for the industry and its stakeholders.

In conclusion, the systematic review will contribute to a comprehensive understanding of the transformative impact of AI on stock broking, shedding light on the various strategies employed and their outcomes. By synthesizing the existing literature on this subject, the review will provide valuable insights for practitioners, researchers, and policymakers in the financial industry.

2. Stock Broking: Strategy and Outcomes

To develop effective stock broking strategies, it is crucial to consider various factors such as stock price behavior, management forecast precision, customer retention, and market volatility. Li & Zhang (2015) emphasize the importance of maintaining stock prices in strategic disclosure decisions, indicating that managers consider stock price behavior when making decisions (Li & Zhang, 2015). Additionally, Koh & Noor (2021) suggest that understanding the behavior of individual investors and encouraging their participation in the stock market is essential for developing effective marketing strategies in a competitive market (Koh & Noor, 2021). Furthermore, Agrawal & Mittal (2019) highlight the need for stock broking firms to integrate customer needs with their strategies, people, and business processes to measure customer relationship management (CRM) effectiveness (Agrawal & Mittal, 2019).

Moreover, Bassey et al. (2013) stress the significance of effective customer service in retaining clients among stock broking firms, especially in a competitive market with homogenous services (Bassey et al., 2013). Understanding customer needs and satisfaction is crucial for long-term association with clients, as discussed by (Anappindi & Manohar, 2011). Additionally, it is important to consider market volatility, as changes over time can impact stock broking strategies. Guo & Wohar (2006) highlight the need to capture time variation in volatility by examining changes in macroeconomic and business factors to explain the change (Guo & Wohar, 2006).

In summary, effective stock broking strategies should consider maintaining stock prices, understanding investor behavior, integrating customer needs with business strategies, providing effective customer service, and adapting to market volatility. By considering these factors, stock broking firms can develop robust strategies to navigate the complexities of the stock market and enhance their overall performance.

2.1. Literature Review

The application of artificial intelligence (AI) in stock broking has seen significant advancements, particularly in the utilization of machine learning algorithms, deep neural networks, and natural language processing techniques. Machine learning algorithms have been widely employed in stock market prediction, with studies implementing deep autoencoders and sentiment analysis to develop cooperative deep learning models for stock market prediction (Ks & Mk, 2022). Additionally, deep learning models such as Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) have been utilized to predict stock prices (Muthukumar, 2021; Kasten et al., 2023). These AI techniques have enabled the identification of non-linear dependencies in stock market price sequences, showcasing the potential of machine learning in stock market trend prediction (Wen et al., 2019).

Furthermore, natural language processing techniques have been instrumental in analyzing the effect of news and public mood on stock movements (Li et al., 2014; Adeniyi et al., 2020). Studies have demonstrated the use of NLP in sentiment analysis and event extraction for stock forecasting, highlighting the importance of sentiment, semantic, and event-extraction-based approaches in stock forecasting (Sivri et al., 2021; Cheng et al., 2022). Moreover, the historical evolution of NLP has paved the way for its application in stock broking, enabling the extraction of valuable insights from textual data related to stock market trends (Nadkarni et al., 2011; Oti and Ayeni, 2013).

In the historical context of algorithmic trading, the emergence of high-frequency trading has been a significant development. Traditional trading methods have been revolutionized by algorithmic trading, with AI playing a pivotal role in this transformation. The use of AI and machine learning in algorithmic trading has enabled the development of robust predictive models for stock price prediction, leveraging deep learning and NLP to enhance forecasting accuracy (Mehtab & Sen, 2019; Mehta et al., 2021; Anamu et al., 2023). Additionally, the application of AI in analyzing structured events has empirically shown that stock price movement is predictable, further emphasizing the historical shift towards algorithmic trading driven by AI advancements (Ding et al., 2014).

In conclusion, the integration of AI, machine learning algorithms, deep neural networks, and natural language processing techniques has significantly impacted stock broking. These technologies have not only enhanced stock market prediction and trend analysis but have also transformed traditional trading methods into algorithmic trading, particularly with the emergence of high-frequency trading.

2.2. AI Strategies in Stock Broking

To develop effective AI strategies in stock broking, predictive modeling for price forecasting is crucial. Machine learning models have been employed for predicting stock movements, such as LSTM and CONV1D LSTM networks (Wang et al., 2021). These models have been evaluated for accuracy and reliability, leading to the development of more profitable automated trading strategies for investors and providing risk managers with more accurate forecasts (Mehtab & Sen, 2021). Additionally, a granular approach to stock price prediction in short-term time frames using machine learning and deep learning-based models has been proposed, emphasizing the importance of combining statistical and machine learning methods for stock price forecasting (Sen & Chaudhuri, 2021). These studies provide valuable insights into the application of AI in stock broking, emphasizing the significance of accuracy and reliability in predictive modeling.

2.2.1. Sentiment analysis in market prediction

To integrate sentiment analysis into market prediction, natural language processing (NLP) applications have been utilized to gauge market sentiment. Wang & Yu (2020) employed sentiment analysis using the Long Short-Term Memory (LSTM) method to classify sentiment from online stock forums, demonstrating the application of NLP in capturing investor sentiment (Wang & Yu, 2020). Furthermore, the impact of market sentiment on trading decisions has been extensively studied. found that sentiment significantly influences stock prices in emerging markets, emphasizing the importance of sentiment as a key variable driving market movements (Brzeszczyński et al., 2015). Additionally, Entrop et al. (2020) highlighted the impact of social-based sentiment on price discovery in Bitcoin markets, further underlining the relevance of sentiment in market dynamics (Entrop et al., 2020). These studies collectively underscore the significance of NLP in capturing sentiment and the substantial impact of sentiment on trading decisions, providing valuable insights into the integration of sentiment analysis in market prediction.

2.2.2. Reinforcement learning in algorithmic trading

Reinforcement learning has gained attention for its potential in algorithmic trading, allowing for adaptive strategies in response to dynamic market conditions. The application of reinforcement learning algorithms in algorithmic trading has shown promising results, particularly in optimizing trade execution and developing adaptive trading strategies. For instance, "Deep Hedging" by Buehler et al. (2018) demonstrates the potential of reinforcement learning in algorithmic trading, specifically in the context of optimal trade execution (Buehler et al., 2018). Furthermore, "Dynamic stock-decision ensemble strategy based on deep reinforcement learning" by Yu et al. (2022) introduces an adaptive stock trading strategy based on deep reinforcement learning, emphasizing the use of gated recurrent units (GRU) to make adaptive trading decisions (Yu et al., 2022).

Case studies have illustrated the practical applications of reinforcement learning in algorithmic trading, showcasing its effectiveness in dynamic market environments. These studies have emphasized the adaptability and optimization capabilities of reinforcement learning algorithms in addressing the complexities of financial markets. Moreover, Meng & Khushi (2019) investigated the impact of transaction costs on the profitability of reinforcement learning algorithms compared with baseline algorithms, providing valuable insights into the practical considerations of implementing reinforcement learning in trading strategies (Meng & Khushi, 2019).

In summary, reinforcement learning has demonstrated its potential in algorithmic trading by enabling adaptive strategies to respond to dynamic market conditions. Case studies have showcased the successful application of reinforcement learning algorithms in optimizing trade execution and developing adaptive trading strategies, highlighting their effectiveness in addressing the challenges of financial markets.

2.3. Risk management in AI-driven strategies

The impact of AI starts with data collection and preparation for deploying AI-driven systems, which can lay the foundation for some effective infection control strategies.

This study contributes to the ongoing discussion on developing fair and unbiased AI systems by providing an overview of the sources, impacts, and mitigation strategies related to AI bias. A strategy for mitigating a particular type of bias can exacerbate another, leading to collateral damage and eroding its effectiveness. Overall, this work presents an in-depth examination of the integration of data-driven and AI technologies in the steel industry, highlighting their potential and future directions.

Risk management in AI-driven strategies involves the assessment of risk factors and the implementation of mitigation strategies. The impact of AI in addressing risk factors is evident in various domains. For instance, in the fight against antimicrobial resistance, AI-driven systems play a crucial role in data collection and preparation, laying the foundation for effective infection control strategies Tran et al. (2022). Additionally, the survey by provides insights into the sources, impacts, and mitigation strategies related to AI bias, contributing to the ongoing discussion on developing fair and unbiased AI systems (Ferrara, 2023). Furthermore, highlight the importance of human visual explanations in mitigating bias in AI-based assessment of surgeon skills, emphasizing the need for effective mitigation strategies to address bias in AI systems (Kiyasseh et al., 2023). Moreover, 's work presents an in-depth examination of the integration of data-driven and AI technologies in the steel industry, showcasing the potential of AI in accelerating material research and intelligent manufacturing technology, thereby contributing to risk management in the industry (Geng, 2023).

These studies collectively underscore the significance of AI in risk management, emphasizing the assessment of risk factors and the implementation of effective mitigation strategies across diverse domains.

2.3.1. Profitability and market efficiency of AI in stock broking

Based on the studies provided, the following key points regarding the profitability and market efficiency of AI in stock broking can be highlighted; Several studies have found that AI-driven strategies can generate significant profits in stock markets. Study by Wang et al. (2021) developed an AI model based on FCM and DNN algorithms that achieved good prediction accuracy and investment returns. The study demonstrated the potential of reinforcement learning in optimizing trade execution and generating profits. However, some studies caution that the ability of AI to consistently "beat the market" is debated. Study by Song & Jain (2022) discusses whether AI can outperform the stock market in the long run, given the efficient market hypothesis. Transaction costs can also impact the profitability of AI algorithms.

The impact of AI and algorithmic trading on market efficiency is mixed. Some studies found that AI-driven strategies can improve market efficiency by incorporating more information and trading more efficiently. Study by Chow et al. (2016) found that market liberalization improved efficiency in some emerging markets. However, other studies note that AI may not necessarily lead to more efficient markets. Gramatovici & MORTICI (2018) found that China's stock market remained weakly efficient even after the rise of AI trading. Füss (2005) also notes that different forms of market efficiency exist, and AI may not impact all of them.

In summary, while some evidence suggests AI can generate profits in stock markets, questions remain regarding its ability to consistently outperform and its impact on overall market efficiency. Further research is needed to better understand the role of AI in stock broking profitability and market dynamics. Transaction costs, biases, and other practical considerations also require attention to realize AI's full potential in this domain.

2.3.2. Ethical considerations and challenges of AI in stock broking

Ethical considerations and challenges of AI in stock broking encompass various aspects, including model interpretability and the potential for algorithmic-driven market volatility. These considerations are crucial in ensuring the responsible and ethical deployment of AI in stock broking.

Model interpretability is a key ethical concern in AI-driven stock broking. The ability to understand and interpret the decisions made by AI models is essential for ensuring transparency, accountability, and trust. (Mittelstadt, 2019) emphasizes the need to embed normative considerations in technology design and governance, highlighting the importance of ethical principles in AI development (Mittelstadt, 2019). Similarly, Mclennan et al. (2022) propose an 'embedded ethics' approach, advocating for the integration of robust ethical considerations into the practical development of AI, emphasizing the collaborative addressing of ethical issues by ethicists and developers from the outset of development (McLennan et al., 2022). These Studies underscore the significance of ethical principles and transparency in AI development, particularly in the context of stock broking.

Furthermore, the potential for algorithmic-driven market volatility raises ethical concerns regarding market stability and fairness. The use of AI in trading algorithms has the potential to impact market dynamics and stability. Wang et al. (2023) provide insights into the ethical considerations surrounding the development and use of AI, emphasizing the need for transparency and ethical reflection on the challenges posed by AI (Wang et al., 2023). Additionally, Huriye (2023) discusses the impact of AI on market volatility, highlighting the need to carefully assess the implications of AI-driven predictions on market dynamics and stability (Huriye, 2023).

In summary, ethical considerations and challenges of AI in stock broking encompass the need for model interpretability, transparency, and accountability, as well as the potential impact of AI-driven trading on market volatility and stability. These ethical considerations are essential for promoting responsible and ethical AI deployment in stock broking, ensuring fairness, transparency, and market integrity.

2.4. Future Outlook and Emerging Trends of AI in Stock Broking

The future outlook of AI in stock broking is shaped by emerging trends that are poised to transform the industry. These trends encompass various domains, from technological advancements to market dynamics, and are expected to significantly influence the landscape of stock broking.

The evolution of microprocessor architectures and their integration with AI is set to revolutionize stock broking. As highlighted by (Khan et al., 2021), upcoming trends in microprocessor architectures are expected to further propel the assimilation of AI in daily stock broking operations. This integration is likely to enhance processing capabilities, enabling more sophisticated AI-driven trading strategies and analytics. The integration of blockchain with AI presents new opportunities and challenges for stock broking. Salah et al. (2019) identified emerging trends in AI applications, such as explainable AI and automated machine learning, which are expected to shape the future of stock broking. The use of blockchain for AI, as outlined by , introduces new dimensions of transparency and security, addressing ethical considerations and enhancing trust in AI-driven stock broking systems. The convergence of wearable electronics, photonics, AI, and the Internet of Things (IoT) is anticipated to usher in an era of intelligent wearable systems in the AI/IoT era (Shi et al., 2020). This trend holds the potential to introduce innovative data collection methods and real-time analytics, providing traders with valuable insights and enhancing decision-making processes in stock broking.

The application of AI in predictive analytics for stock market forecasting is a burgeoning trend. Studies such as "Forecasting Korean Stock Returns with Machine Learning" Noh et al. (2023) demonstrate the potential of AI in enhancing predictive capabilities, offering valuable insights for traders and investors.

The ethical considerations surrounding AI in stock broking are gaining prominence. Responsible AI governance, as discussed by (Wamba & Queiroz, 2021), is becoming a critical trend, emphasizing the need for ethical and transparent AI deployment in stock broking. This trend is expected to shape regulatory frameworks and industry practices, ensuring the responsible and ethical use of AI in stock broking.

In conclusion, the future outlook and emerging trends of AI in stock broking are characterized by technological advancements, ethical considerations, and the convergence of AI with other domains such as microprocessor architecture, blockchain, and wearable electronics. These trends are poised to reshape stock broking practices, enhance decision-making processes, and introduce new ethical and governance considerations, ultimately shaping the future of the industry.

2.5. Recommendation and Conclusion

It is imperative for stakeholders in the financial industry to prioritize the integration of ethical guidelines into AI-driven strategies. This includes ensuring transparency, fairness, and accountability in algorithmic decision-making processes. Regulators should collaborate with industry participants to establish and enforce ethical standards to maintain market integrity.

Future research and development efforts should focus on improving the interpretability of AI models used in stock broking. Establishing methodologies for understanding and explaining the decisions made by these algorithms will not only increase trust among market participants but also assist regulators in monitoring and validating the compliance of

AI systems. As AI models evolve and adapt to changing market conditions, there is a need for continuous refinement of risk management strategies. Researchers and practitioners should explore ways to enhance the adaptive capabilities of AI-driven systems to respond effectively to unforeseen events, minimizing potential financial risks. Collaboration between experts in finance, computer science, and ethics should be encouraged to foster a holistic understanding of the impact of AI in stock broking. Interdisciplinary research teams can bring diverse perspectives to address complex challenges and promote the development of more robust and well-rounded AI solutions.

3. Conclusion

In conclusion, the systematic review provides a comprehensive analysis of the current landscape of Artificial Intelligence in Stock Broking. Key findings indicate a significant transformation in trading strategies, marked by the increasing role of machine learning, deep neural networks, and natural language processing. While AI-driven strategies show promise in enhancing efficiency and reducing biases, challenges such as interpretability and ethical considerations remain.

The future of research in AI and stock broking should address these challenges by focusing on interdisciplinary collaboration, continuous refinement of risk management strategies, and the establishment of ethical guidelines. Additionally, the field would benefit from further exploration of novel AI applications, such as the integration of emerging technologies and the development of hybrid models combining human expertise with machine intelligence. As financial markets continue to evolve, ongoing research and innovation will be essential to harness the full potential of AI in stock broking while mitigating risks and ensuring the stability and integrity of the global financial system.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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