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Original Article

Can Artificial Intelligence Improve Customer Acquisition in Digital Stock Broking Platforms?

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ABSTRACT: *Stock broking and other financial services are constantly being transformed by Artificial Intelligence (AI) with personalization, improved data analysis, consumer engagement, and smart decision-making. This study aims to investigate how customer acquisition can be improved by AI in stock broking, while focusing on its uses in sentiment analysis, predictive analytics, portfolio management, reinforcement learning, and risk analysis. This study uses a quantitative research design and collects secondary data from recent studies published in peer-reviewed journals, as well as from publications, stock exchanges, reports, official websites, and other credible sources. Customer acquisition can be supported by AI through personalized services, more relevant and faster information, better customer experiences, and more efficient services for digital stock broking platforms. AI models like Reinforcement Learning and Deep Learning are highly prevalent in financial trading research because they can identify complex patterns and adapt to market changes. The study also explores potential benefits for trading, investment profitability, portfolio management, and risk assessment. However, data quality, transaction costs, model bias, overfitting, cybersecurity issues, lack of interpretability and uncertain market conditions limit AI's potential. Therefore, AI's success in driving customer acquisition depends on transparency, responsible use, compliance, reliable data, and strong market knowledge.*

KEYWORDS: *Customer Acquisition, Artificial Intelligence, Stock Broking, Reinforcement Learning, Deep Learning, Portfolio Management.*

1. INTRODUCTION

The landscape of finance and business intelligence (BI) is rapidly being transformed by "Artificial Intelligence (AI) and machine learning (ML)" (Pallathadka et al., 2023; Bawack et al., 2022; Kalia, 2021). Organizations increasingly rely on these technologies to make better decisions, streamline data-driven operations, and improve the overall customer experience (Vanneschi et al., 2018; Pal, 2022). AI and ML are redefining the way organizations gather and analyze big data in finance. AI models continually strengthen traditional business platforms with predictive analytics, real-time tracking, and automated insight generation. AI tools continually improve prediction accuracy, provide actionable insights, and identify outliers and patterns (Giudici, 2018).

Organizations increasingly analyze unstructured data from images, videos, and social media using technologies such as computer vision and natural language processing (NLP) to gain deeper insight into consumer behavior and market trends (Ahmed et al., 2022; Song et al., 2019). Stock broking is central to AI-based financial analysis (Hilpisch, 2020; Areiqat et al., 2020). Financial institutions use these technologies for fraud detection, tailored financial services, model training, and risk management. AI models analyze historical data to predict future trends and detect fraud in real time, customizing strategies to match personalized risk profiles (Vanneschi et al., 2018). In addition, robo-advisors use AI to provide tailored, automated investment suggestions and improve access to wealth management and financial planning.

E-commerce has undergone rapid transformations with AI, improving aspects of the consumer experience such as personalized recommendations, inventory tracking, dynamic pricing, and customer service (Goodell et al., 2021; Garg et al., 2021). Recommendation engines analyze user preferences and behavior to drive consumer engagement and sales. AI-based virtual assistants and chatbots improve consumer service by resolving queries and providing instant responses (Ghimire et al., 2020; Areiqat et al., 2021). In addition, AI and ML continually optimize supply chain activities through demand forecasting, inventory management, improved customer satisfaction, and reduced delays. AI has added new applications and capabilities to stock broking. For instance, reinforcement learning can develop smarter trading models (Bharadiya, 2023; Bahrammirzaee, 2010).

Similarly, models can use pre-trained information using transfer learning for new roles to minimize the need for computation and data resources. The opacity of AI models can be addressed with explainable AI (XAI) to add interpretability and transparency in decision-making for building trust and regulatory compliance.

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1.1. BACKGROUND

Significant advances in technologies like big data and AI are transforming the finance sector. High-dimensional big data from various sources and channels pose major challenges in identifying, understanding, and effectively extracting useful knowledge. The high dynamics and complexity of behaviors, financial events, and systems increase concerns about modeling, optimizing, characterizing and managing their working systems and behaviors. With widely available financial data and computing power for processing and storage, the latest AI technologies have led to a rise in new tools and technologies (Challa, 2023).

Compared with traditional decision- and data-based applications, modern AI solutions are widely used in financial data analysis to improve understanding and insights through exploration and modeling beyond data management. Value investing is an effective, timeless strategy that gained popularity at the beginning of the 20th century and was later adopted as an AI-based arbitrage process. By the late 1990s, tech stocks were overrated, and the whole economic structure was transformed in the US, which led to a huge dip in the stock prices of tech companies when investing was known as a low-risk, passive, and low-return medium (Challa, 2023). Figure 1 illustrates the flow of client data for AI-driven wealth management.

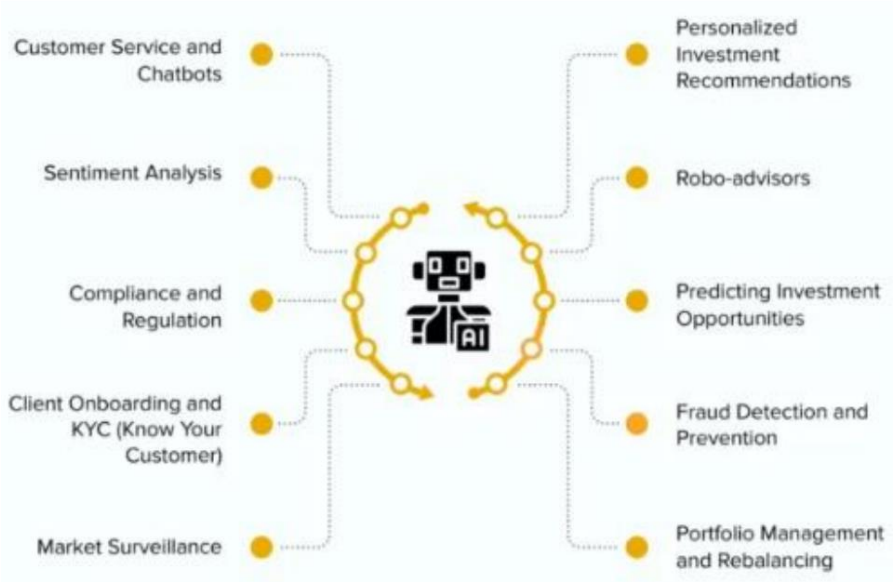


FIGURE 1 Flow of Client Data for Wealth Management

Source: *Challa (2022)*

Finance is an important infrastructure for sustainable economic and societal growth, enabling the exchange of information, wealth, and experience, ROI, risk management, and the valuation of capital flows and assets. Finance includes the flow of input, transfer, and output based on mutual identification of wealth, efficient data dissemination, confidence among people, and sustainable growth, where the initiator supplies wealth acquired through the process of capital flow. Several factors affect participants' trust in assurance and commitment, as well as their credit assessment, including event-based, industry, and general news; knowledge of events; relationships between news items; and the geographical location of messages (Ogundimu, 2025).

With the rising coverage of news online, financial analysts and investors find it challenging to accumulate news and track relevant items that may affect stock prices. It is vital to filter out relevant items automatically, as irrelevant ones would increase noise, time, and cost. News filtering and classification aim to identify snippets containing vital news to address this filtering problem (Ogundimu, 2025).

2. LITERATURE REVIEW

Rane et al. (2024) examined the transformative potential of AI and ML in finance, e-commerce, and business intelligence, drawing on recent technological advances. AI and ML have drastically improved business intelligence through more accurate data processing, predictive analytics, and stronger decision-making. AI models are redefining fraud detection, risk control, and tailored financial services, making financial systems more efficient and secure. The e-commerce sector is undergoing a major shift as AI improves the overall experience through dynamic pricing, chatbots, and tailored suggestions. It integrates big data analytics, AI, and the Internet of Things (IoT) to create a data-driven, interconnected business landscape. This study also discusses ethical concerns like biased models, data privacy, and the need for frameworks. In addition, it identifies key areas for future studies to improve trust and transparency while developing “explainable AI (XAI)” systems to support sustainable practices. It explains the transformative potential of AI and ML for finance and analytics, enabling researchers, policymakers, and practitioners to leverage these approaches for sustainable development.

Ogundimu (2025) reviewed case studies and existing techniques to show how AI can detect fraud, improve credit scoring, manage trading, and enhance portfolio management while maintaining regulatory compliance. This study also investigates the effect of AI automating daily banking operations and its importance in increasing customer interaction, managing tasks, and delivering investment advice. In addition, the journal focuses on major concerns like explainable models, cybersecurity, biased data, and regulations. Quantum computing and explainable AI are among the emerging trends experts are focusing on to understand how the finance landscape could be transformed. Policymakers, banks, and researchers in global finance have adopted several valuable rules.

Sabale (2025) investigated the transformative potential of AI in stock trading, while focusing on its effect on predictive analytics and decision-making. With natural language processing, cutting-edge ML models, and real-time analytics, AI tools have improved traditional strategies and redefined stock trading. They highlighted how AI has improved decision-making through accurate forecasts, portfolio optimization, and sentiment analysis, while discussing challenges such as ethical concerns and data quality. The study observed its effectiveness in case studies of hedge funds and AI platforms that improved profitability and trading efficiency. This study also discussed implications for AI to improve trading and investment in the stock market.

Shanmuganathan (2020) focused on the possible implications of AI tools and technical glitches in behavioral finance. AI applications in behavioral finance have evolved rapidly in the past few years. This study highlighted recent advances in AI in financial advisory solutions. Using a theoretical framework, it evaluates performance to produce reliable portfolios aligned with investors' sentiments. Robo-advising has replaced traditional financial solutions over the years in wealth management because of recent developments and increased technical knowledge of clients who prefer active control over their investments while tracking data from various sources. Robo-advisors are currently identified as the most disruptive source for wealth and asset management. Robo-advisors are automated platforms that manage portfolios using quantitative models, and they are easy for consumers to access. This study adopts a longitudinal case study design based on the behavioral process of financial decision-making and investors' use of robo-advisors, as behavioral decisions are believed to be vital to executing consumers' financial portfolios.

Shaikh et al. (2024) investigated how AI has redefined stock trading, including its benefits, effects and applications. This study explores how natural language processing (NLP), predictive analytics, machine learning, etc., improve decision-making and trading processes. This study theoretically analyzes existing research on AI applications in stock trading and compares AI models with traditional approaches. It also discusses the regulatory, technical, and ethical challenges of using AI in stock trading. The study finds that AI makes trading more effective and accurate, giving users an edge by analyzing big data and responding to market shifts. However, the pace of AI trading can increase market volatility, so robust regulatory mechanisms are needed. The study examines market vulnerabilities and how AI helps both individual and institutional investors make rational decisions. AI is transforming stock trading games with faster, more accurate decisions. However, AI still faces challenges related to data quality, decision complexity, and ethical issues. It is recommended to balance these factors to use AI responsibly and support the growth of the broader financial world.

2.1. RESEARCH GAP

Recent studies have observed significant influence of AI on investors' sentiments in stock trading. They have investigated acceptance of robo-advisors, AI-based fintech, personalized suggestions, financial behavior and customer experience. They have identified financial knowledge, familiarity with AI, and innovative behavior of users as factors affecting adoption of fintech. Studies on robo-advising have examined perceived risk, trust, and preferences as factors affecting adoption. This study fills a major empirical gap. Existing studies focus mainly on behavioral intention and surveys rather than actual changes in consumer behavior. This study focuses on how AI can improve consumer acquisition in stock broking.

2.2. RESEARCH OBJECTIVES

- To investigate how AI is applied in stock broking to increase profitability for investors
- To assess transformation and growth in actual customer acquisition with the use of AI

3. METHODOLOGY

This study uses a quantitative research design that includes collecting secondary data and reviewing recent studies published in peer-reviewed journals. It also draws on information from credible online sources, including stock exchange data, regulatory publications, official websites, reports, and other databases. This study identifies key AI applications and customer-centric mechanisms by reviewing recent studies published from 2020 to 2026 on digital financial systems. Recent studies have focused mainly on Robo-advisors, adoption of AI-based fintech solutions, AI-based financial services, consumer financial behavior, personalized information availability and customer experience.

To understand the application of AI in business intelligence and stock broking, this study is based on an extensive review of recent studies across databases such as Scopus, IEEE Xplore and Google Scholar. Only studies relevant to the impact of AI in

stock broking and the finance sector will be included. The available data will then be critically analyzed to identify key trends and findings.

4. RESULTS AND DISCUSSION

4.1. AI AND CUSTOMER ACQUISITION

AI has been adopted more widely among millennials and Gen Z than among previous generations. This niche behavior is not limited to younger generations. The shift to AI-controlled search has been faster than the growth of social shopping and has now expanded to B2B markets. Marketers who see change as an update are already behind the curve. The growth of natural, conversational language enables context-based, long queries, creating a more tailored discovery experience for consumers. Similarly, those using traditional searches are depending mainly on AI-generated data instead of clicking links. Q&A, AI overview, and paid placements are overwhelming blue links in almost every area. Generative AI is trusted by almost half of online shoppers for comparisons and initial searches, though trust varies by age group and product category (Figure 2).

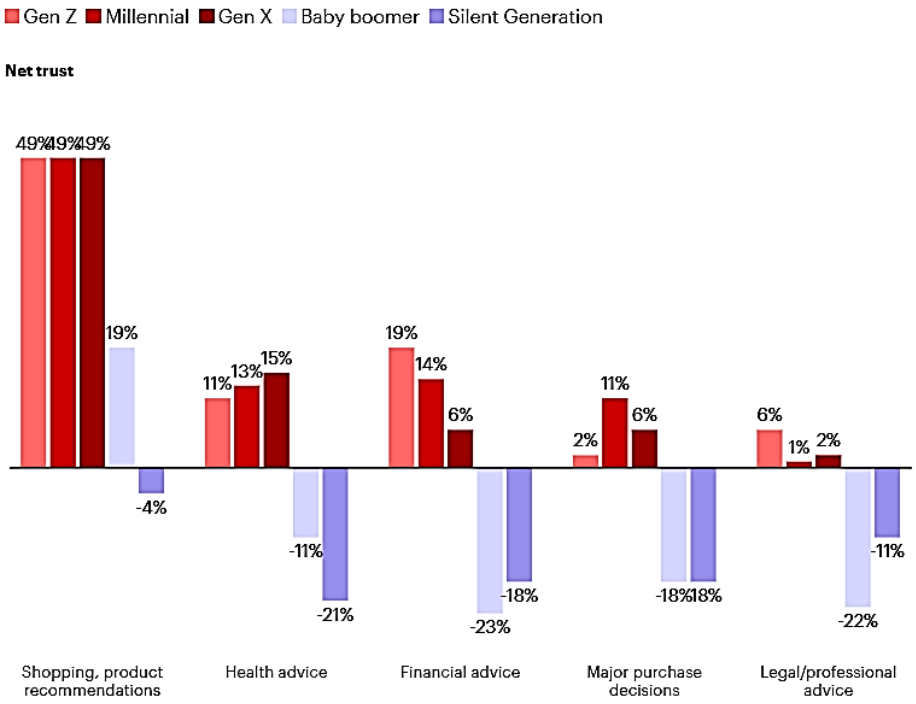


FIGURE 2 Generation of Consumers Trusting Gen AI for Common Activities

Source: *Sommerfeld et al. (2026)*

Many market leaders are rethinking how their operating model is organized for marketing. A silo of SEO in one lane, where advertisements and public relations (PR) exist in one lane and influencer marketing in another, cannot keep pace with the pace or with the consistency of change in demand. It can redesign ways of working across functions to adopt shared performance metrics, run rapid experiments across technical, owned, and earned teams, and unify governance. In practice, it has become more of a capability and less of a campaign. Marketing communication serves as both long-term components and temporary task forces (Sommerfeld et al., 2026).

4.2. AI IN STOCK BROKING

In stock broking, technology has advanced rapidly, especially with the rise of AI in financial markets. AI has redefined stock broking by enabling innovative outcomes and strategies. This section explores the impact of AI on stock broking and related strategies. Technology in stock broking has continually evolved, integrating advanced tools to improve decision-making and trading processes. In financial markets, AI has played a pivotal role in transforming traditional stock broking practices. AI has automated predictive model development, trading processes, and data analytics to revolutionize decision-making in stock broking (Rabbani et al., 2023). This has dramatically shifted how stock broking is conducted, and AI has shaped the industry's future.

To develop effective stock broking strategies, it is worth considering factors such as forecast precision, stock price behavior, market volatility, and customer retention. Li and Zhang (2015) focused on the importance of stock prices in intelligent disclosure decisions, suggesting that managers consider stock price behavior in decision-making. In addition, understanding investor behavior and increasing engagement in the stock market helps build effective market strategies (Koh and Noor, 2021).

In addition, stock broking firms are required to combine consumer needs with people, strategies, and corporate processes to evaluate the effectiveness of "customer relationship management (CRM)" (Agrawal and Mittal, 2019).

In addition, Bassey et al. (2013) focused on the benefits of efficient customer service for customer retention across stock broking firms by providing homogeneous services. Understanding customer satisfaction and the need for long-term client relationships is important (Anappindi and Manohar, 2011). In addition, it is worth considering market volatility, as changes can affect stock broking over time. Volatility captures time variation and helps identify business changes and macroeconomic factors that may require adjustments (Guo and Wohar, 2006). Overall, effective stock broking requires maintaining stock prices, integrating consumer needs into strategies, understanding investor behavior, adapting to market changes, and providing effective consumer service. Stock broking firms can build strategies to navigate stock market challenges and improve overall performance using these factors.

4.3. PORTFOLIO MANAGEMENT WITH AI

Portfolio creation is a long-term process that aligns with the investor's preferred risk and reward level and adjusts over time to increase returns. This process has three layers: planning, execution, and feedback (Figure 3) (Baker and Filbeck, 2013). The planning layer is the first layer in this process. An institutional client (asset owner), such as a wealth management firm or pension fund, requires an asset manager to manage the portfolio according to its investment policy. This mandate is defined by investment policy. It outlines the client's circumstances, limitations, and needs to achieve specific goals at the specified risk level.

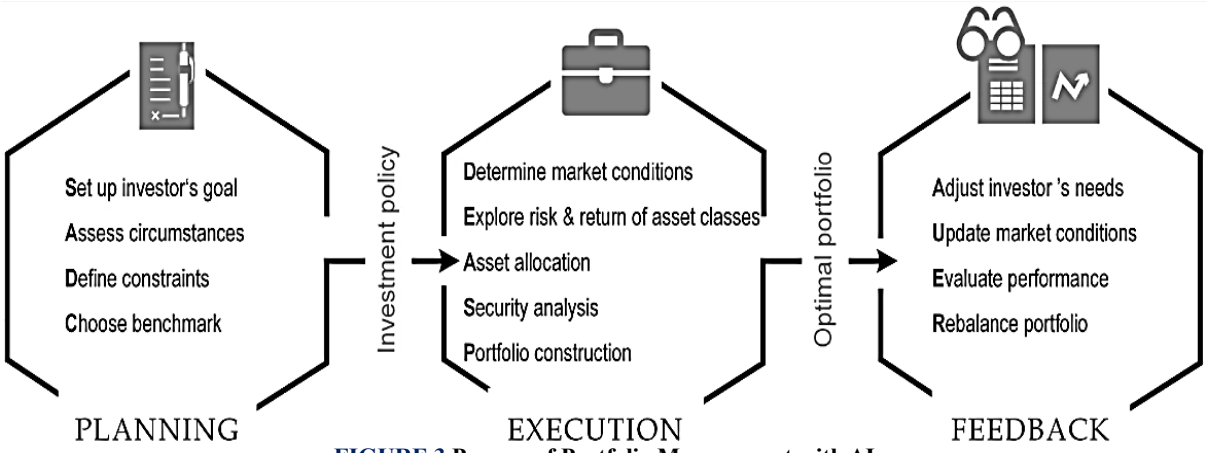


FIGURE 3 Process of Portfolio Management with AI

Source: *Baker and Filbeck (2013)*

This investment policy includes strategic asset allocation (SAA), which refers to lower and upper boundaries for allocating asset classes. It also requires defining risk capacity and tolerance. The execution layer is the second layer of portfolio management. The overall macroeconomic conditions are evaluated, with execution across different asset types and countries, exploring the risk-to-return ratio of assets. After changes in the portfolio's investment period, the feedback layer evaluates past performance alongside market conditions to determine whether the investment policy needs adjustment and the portfolio needs rebalancing (Horn and Oehler, 2020).

AI has disrupted most sectors over the years, including the financial sector. AI can support portfolio management in several ways, addressing limitations in traditional portfolio techniques and expanding options for generating additional alpha. For example, ML systems can learn from experience and predict asset prices. RL, or reinforcement learning, is one of the effective way to develop a dynamic, sequential theory of portfolio management. Sentiment analysis and text mining of fresh market news can enhance portfolio management. Dimensionality reduction in asset prices can detect a wide range of latent factors, improving the construction of a diverse portfolio. Deep learning can optimize an investment portfolio, or it can be used to build a portfolio that mimics an index with a small number of assets (Sutiene et al., 2024).

4.4. ADOPTING AI FOR CUSTOMER ACQUISITION IN STOCK BROKING

For effective AI adoption in stock broking, predictive modeling plays a vital role. ML models have been used for forecasting stock movements, such as COVID-LSTM and LSTM models (Wang et al., 2021). Researchers have evaluated these models for reliability and accuracy, developing more profitable automated trading strategies and providing more accurate results for investors and risk managers (Mehtab and Sen, 2020). In addition, deep learning and machine learning models can be used in the short term with a granular approach to predict stock prices, while emphasizing the need to combine ML and statistical models to predict stock prices (Sen and Chaudhuri, 2021).

4.4.1. SENTIMENT ANALYSIS

For market prediction, sentiment analysis can be conducted with "natural language processing (NLP)" techniques to measure market sentiments. Sentiment analysis can use NLP to classify market sentiment from online forums using "Long Short-Term Memory (LSTM)" (Wang and Yu, 2020). In addition, Brzeszczyński et al. (2015) extensively researched the effect of market sentiment on trading decisions and found that sentiment significantly impacts stock prices in emerging markets. In addition, Entrop et al. (2020) highlight the effect of social sentiment on price discovery in Bitcoin markets, further underscoring the importance of market sentiment. Overall, these studies highlight the importance of NLP for capturing market sentiment, understanding its effect on trading decisions, and integrating sentiment analysis into market forecasting.

4.4.2. REINFORCEMENT LEARNING

In algorithmic trading, reinforcement learning (RL) has great potential for adaptive strategies that can handle dynamic market conditions. In algorithmic trading, RL can optimize trading and build adaptive strategies. For instance, Buehler et al. (2019) used RL in algorithmic trading for "deep hedging" in trade execution. In addition, dynamic strategies are used for making stock decisions based on deep reinforcement learning to introduce an adaptive strategy for stock training based on deep RL by Yu et al. (2022), while focusing on "gated recurrent units (GRU)" for making adaptive decisions.

Case studies have explored the real-world applications of RL in model training, highlighting its efficiency in dynamic settings. These studies focused on optimizing and adapting RL models to address challenges in financial markets. In addition, Meng and Khushi (2019) examined the effect of transaction costs on the benefits of RL models compared with baseline models, offering valuable insight into the practical application of RL in trading. Overall, RL has shown its benefits in model training through adaptive strategies that address the market's dynamic needs. RL has been adopted successfully to develop adaptive strategies and optimize trading.

4.4.3. RISK MANAGEMENT

AI is deployed for data collection and preparation for some effective control mechanisms. In AI models, risk management involves identifying risk factors and implementing mitigation models. When it comes to addressing risk factors, the effect of AI is evident in different areas. For example, AI models play a vital role in data preparation and collection, laying the foundation for effective strategies (Tran et al., 2022). Ferrara (2023) reviewed the effects, sources, and mitigation techniques of AI bias and discussed the development of unbiased and fair AI models.

In addition, human visual explanations are important for mitigating bias in AI assessment and for effective bias mitigation (Kiyasseh et al., 2023). In addition, Geng (2023) examined AI and data-driven technologies, highlighting AI's benefits for smart manufacturing and materials research to improve risk management. Overall, these studies highlight the importance of AI in risk management, including implementing and assessing risk factors across different areas.

4.4.4. MARKET EFFICIENCY AND PROFITABILITY

AI strategies have been found to increase profitability in stock broking platforms. Wang et al. (2021) proposed an AI model based on DNN and FCM to increase returns on investment (ROI) and prediction accuracy. They highlighted the benefits of RL in profit generation and trade execution. However, some studies show that AI can beat the market consistently. Song and Jain (2022) discuss whether AI can outperform the stock market in the long term. Transaction costs can also affect the profitability of AI models.

Model training and AI have mixed effects on market efficiency. AI-based strategies can incorporate more trading and information to improve market efficiency. According to Chow et al. (2016), market liberalization can improve efficiency in some developing industries. AI may not result in efficient markets in other studies. The stock market in China has remained inefficient even after the emergence of AI trading (Gramatovici & Mortici, 2018). Market efficiency takes various forms, and AI may not affect all of them (Füss, 2005).

Questions remain about its potential to perform better and its effect on overall market efficiency. Further research is required to improve knowledge of AI's role in market dynamics and profitability in stock broking. Attention is needed to realize AI's full potential in this area, considering practical constraints, biases and transaction costs.

4.4.5. ETHICAL CONSIDERATIONS

In stock broking, there are several ethical challenges and considerations related to the use of AI, covering different aspects like potential for AI-based volatility and interoperability in the model. These considerations are important to ensure ethical and responsible AI use. Interpretability is a major concern in stock broking. AI models can interpret and understand decisions to ensure trust, accountability and transparency. Mittelstadt (2019) recommended embedding ethical considerations in governance and technological design, highlighting their importance in developing AI.

In the same way, an "embedded ethics" approach is recommended by McLennan et al. (2022), supporting the adoption of robust considerations to develop AI, highlighting how developers address ethical issues. It highlights the need for transparency and ethical codes in developing AI, especially in stock broking. In addition, the authors raise ethical concerns about model-driven volatility and market fairness and stability. AI is widely used in trading to impact market stability and dynamics.

Wang et al. (2023) discussed ethical considerations in using and developing AI, highlighting the ethical reflection and transparency needed to address AI-related challenges (Wang et al., 2023). In addition, Huriye (2023) discusses AI's impact on market change and assesses the effects of AI-based predictions on market stability and dynamics. In stock broking, ethical challenges and considerations include the need for transparency, accountability, and interpretability, along with the potential effects of AI trading on market stability and volatility. These considerations are needed to promote ethical and responsible AI in stock broking for transparency and fairness.

4.5. AI IN STOCK BROKING PLATFORMS

Financial markets are non-stationary, time-changing, non-linear and very complex. They are highly vulnerable and sensitive to factors such as political events, geopolitical influence, and financial news (Leles et al., 2019). With technological advances, AI models have been widely used in financial markets, transforming how financial services security can be improved and how financial transactions are managed. FinTech (financial technology) represents a new prospect in finance, using technology to respond to long-standing issues in investments, risk management, insurance and trading (Gai et al., 2018).

AI has been useful in areas like risk assessment, process automation, and developing customer services in the financial sector. Natural Language Processing (NLP), analytics, task automation and risk management can use AI models to personalize services and analyze large datasets. AI also helps in banking through fraud detection, personalization, and access to banking services, especially in low-income regions. AI is redefining the insurance and investment sectors by enabling tailored programs, risk management, and market prediction (Ferreira et al., 2021). Despite these improvements, challenges remain in integrating AI, including processing high-frequency data, ensuring data quality, and handling the dynamic, noisy nature of economic data. In addition, in multivariate financial markets, even small changes can significantly affect outcomes and trading choices (Dang, 2019).

AI-based trading impacts financial markets by mining critical data to deliver tools that are accessible and cost-effective for everyone. AI-driven decisions can be reliable, unbiased, and accurate, unlike those made by highly emotive people. AI is the next stage of trading models that learn from records of many past experiences. ML models can identify patterns to make predictions. As a result, AI model trading offers several benefits over traditional trading methods (Li et al., 2020).

For instance, AI can respond to market conditions and predict based on market sentiment by finding hidden patterns that are not visible to humans because of big data. In addition, AI can work 24x7 and offers speed, accuracy, and cost efficiency with powerful computers. It also lacks human emotions, which is another major benefit. Fear is the main motivation for humans to take risks and lose. Emotions like jealousy, fear, or rage can harm their actions. Meanwhile, AI model training relies on confident, statistical conclusions drawn from previous data and different market conditions.

Although AI is widely used in financial markets, studies have identified several issues. Data is among the major challenges, including the very high frequency of data generated, data quality, and the constant addition of new sources, including financial news and mainstream media. In addition, financial indices are noisy, dynamic, multivariate and highly challenging to analyze (Mourelatos et al., 2018). Model behavior is another challenge, as financial markets consist of many variables, and a small change can snowball into market-wide effects. Therefore, making trading decisions requires substantial practical knowledge (Deng et al., 2017).

AI techniques are important for advancing and addressing existing challenges in the financial trading sector related to portfolio management, market changes, and risk management. Despite the rapid adoption and emergence of technology in the financial sector, a major gap remains in understanding AI in stock broking. Some charting approaches include candlestick, bar, and line charts. Candlesticks are basically the most popular charts. They are Japanese charts established around a century before bar and line charts. Investor sentiment strongly affects market conditions, as Homma observed in the 1700s, when demand, supply, and rice prices were highly relevant (Northcott, 2009). Candlesticks show sentiment, volume and price changes through different colors. Traders can analyze market behavior with candlestick charting.

The Japanese candlestick pattern displays the entire price movement over a period of time. Red and green are two important colors that define the price path. Green represents an upward (bullish) trend, and red represents a downward (bearish) trend. The shadow and body are key features of a candlestick, and opening, closing, lowest, and highest prices are four key price points. The body reflects the price range between the opening and closing prices over a period of time.

If the closing price is below the opening one, a bearish trend is displayed in black or red. If the closing price is above the opening one, the candle displays a bullish trend in an empty or green color. Figure 3 illustrates the difference between bullish and bearish candlesticks to define the key aspects of a candle. Candlesticks change over time, i.e., 1 minute, 5 minutes, 30 minutes, 1 hour, and so on.

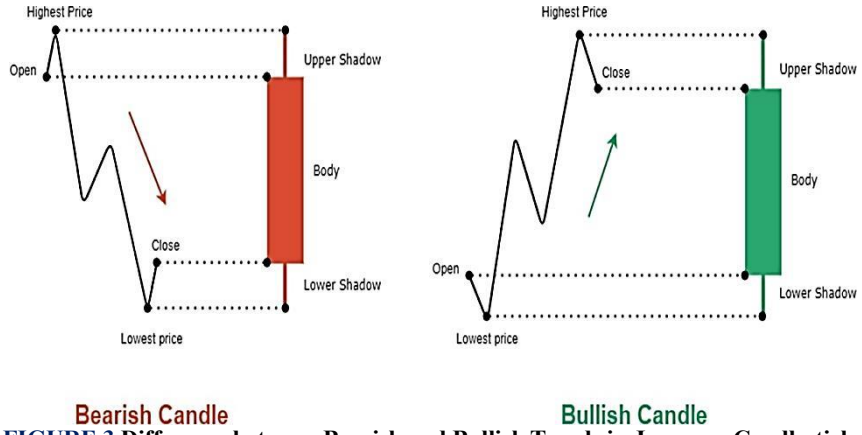


FIGURE 3 Difference between Bearish and Bullish Trends in Japanese Candlesticks

Source: *Dakalbab et al. (2024)*

Traders use several trading analyses to predict patterns and moves in the market. Usually, traders one or a blend of these techniques to match their trading style. Figure 4 illustrates these categories (Leles et al., 2019).

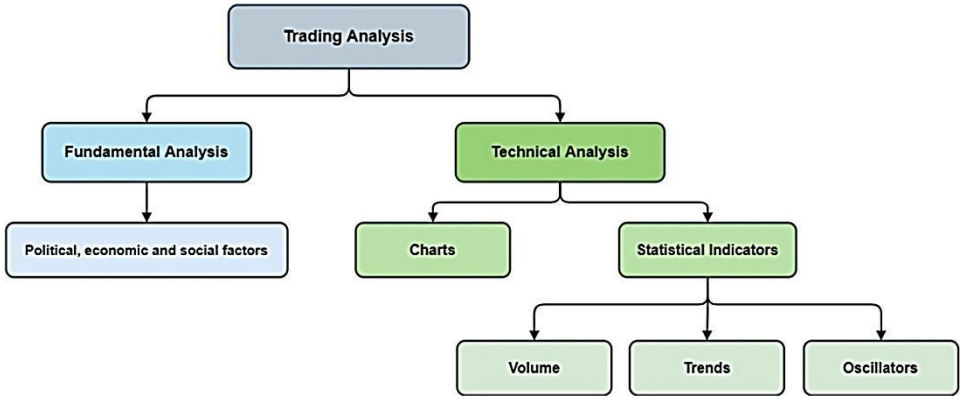


FIGURE 4 Categories of Trading Analysis

Source: *Dakalbab et al. (2024)*

- Fundamental Analysis: This approach analyzes how financial news and economic conditions affect market conditions to determine the inherent value of financial securities for trading (Ta et al., 2018). In this market, a calendar helps track major events and financial data that affect the market. It defines the relevance of events in global markets. These calendars help traders manage risk and stay positioned to plan.
- Technical Analysis: It relies on charts and statistical models that depict price movement over time, where each point represents the closing price for each day. Technical analysts find market trends and patterns in financial markets that can be exploited. This analysis can identify non-linear patterns that inform strategies by analyzing price series to capture major movements while filtering out random changes.

Table 1 compares these categories. Technical analysis predicts price movements using statistical indicators (such as relative strength, moving averages, convergence, etc.), price charts, and oscillators. Meanwhile, economic analysis is part of fundamental analysis, which requires thorough investigation and financial statements based on market sentiment.

TABLE 1 Difference between Technical and Fundamental Analysis

Particulars	Fundamental Analysis	Technical Analysis
Concept	Follows market sentiments and economics	Investigates price behavior to predict future price movements using statistical indicators.
Purpose	Market value is evaluated in case of overvalued and undervalued assets	Evaluates the ideal trading time to sell/exit or enter/buy in the market
Depends on	Economy, financial news, and statements	Charts like candlesticks and uses technical signs.

Uses in	Investigating current and past data	Consists of historical information
Works in	Investment and trading	Trading
Timeframe	Long-term	Short-term

5. DISCUSSION

AI is widely used in algorithmic trading, where complex models automate trading. It is often categorized by reasoning, learning, and decision-making (Treleaven et al., 2013). As computing improves, algorithmic trading has become more popular. It uses the power of existing computers, unlike human brokers. They are known for accurate, fast operations that improve accuracy and reduce trading costs (Mathur et al., 2021). In addition, backtesting is the process traders use to track the performance of a model or strategy using past data. Traders can use this technique to improve and fine-tune their techniques and models.

Algorithmic trading uses algorithms that follow specified strategies. These models use proven, basic techniques like setting stop-loss and profit targets based on the previous day's range and the current price. In addition, complex, robust models can be developed with AI. These models follow an approach that has been properly backtested across different market conditions. This involves testing and validating ML models to reduce overfitting risk and fine-tune their weights. Simulated trading uses backtesting with real-time information. If it is efficient, the model can be deployed widely and monitored to determine its viability. The system adapts and redeploys when performance declines, progressively updating and optimizing until it takes optimal actions (Li and Peng, 2019).

Five major types of AI models used in stock broking are deep learning, regression, classification, deep reinforcement learning and reinforcement learning. Classification categorizes data into specified classes. It can classify potential trades into “sell” or “buy” groups based on their ability to predict an asset's price movement. Regression models can predict continuous outcomes, such as a stock's future price. Regression analysis can provide needed insights into fluctuations and price patterns in the market, despite lower adoption. Deep learning is the most widely used strategy for processing large amounts of unstructured data, making it useful for identifying complex patterns, analyzing sentiment, and predicting price movements.

This technique trains models through trial and error to find the best course of action to maximize total reward. These models can optimize trading for long-term benefits by changing strategies dynamically to respond to market conditions. Deep reinforcement learning combines reinforcement learning's decision-making with deep learning's pattern-recognition capabilities. Hence, it can create autonomous systems that adapt to changing market conditions. Reinforcement learning, deep learning, and their combinations outperform regression and classification approaches. These approaches are preferred because of the complexity of financial markets. AI models should be sophisticated enough to adjust to changing market conditions and comprehend them.

6. CONCLUSION

In conclusion, AI integrates technological excellence with data-driven financial decisions to improve customer acquisition in stock broking. This study highlights AI's potential to improve sentiment analysis, predictive analysis, risk assessment, portfolio management, customer service, and automated trading. AI can provide quick information, automated support, investment solutions, and tailored suggestions to improve the overall consumer experience to reflect individual needs. Hence, these findings suggest that AI can enable customer engagement and acquisition in a highly competitive financial sector.

AI can improve investor profitability and trading efficiency. Previous studies have used deep reinforcement learning, reinforcement learning, and deep learning as some of the most common AI models. Meanwhile, evidence on long-term market efficiency and profitability remains mixed, especially because of market conditions, transaction costs, model efficiency, and data limitations. This study also highlights major implementation challenges, such as market volatility, algorithmic bias, data quality, cybersecurity, and overfitting.

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