



APPLICATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES FOR STOCK MARKET TRADING AND PREDICTION

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ABSTRACT

With the introduction of AI and ML, stock market trading is changing the game. These technologies can be used for sentiment analysis, automated decision making, quick data processing and forecasts. The objective of this paper is to review the application of AI and ML in stock market trading and prediction with special emphasis on AI trading performance, comparison with human-based trading, market volatility and sentiment-based market movements. The study team performed descriptive and comparative analyses by using secondary data collected from financial databases, stock market sources, regulatory documents, research initiatives and financial periodicals. The analysis considers data from 2015 to 2023, with year-to-date statistics for 2024 considered separately. It was advised that the analysis of the data should comprise descriptive statistics, comparison, correlation, regression and appropriate tests of significance. The percentage of AI-based trade increased from 14.3 percent in 2015 to 61.6 percent in 2023, according to the data supplied. In addition to the returns, the market volatility reduced from 9.4% to 7.6%, and the trading of AI-based trading beat the trading of humans. Sentiment study revealed that the market responded positively to positive news and negatively to negative sentiment. The study found that conventional artificial intelligence may considerably improve the efficiency of trading, market analysis and prediction. However, algorithmic risks, data constraints, transparency, ethical issues and regulatory challenges point to the need for adequate regulatory structures and competent human control.

KEYWORDS:-Artificial Intelligence, Machine Learning, Stock Market Prediction, Algorithmic Trading, Sentiment Analysis, Market Volatility, Trading Performance, Financial Markets etc.

INTRODUCTION

The stock market is an instrument for investment, capital development and economic growth in the modern financial system. Various factors influence stock prices, such as company performance, economic factors, investor behaviour, political events, market mood and worldwide changes. The difficulty of stock market analysis is due to the number and pace of financial data. Human decision-making, experience and manual analysis are the basis of traditional trading strategies, although these

might be constrained by the time and capacity to handle large data sets. AI and ML have brought new ways of analysing the stock market and making decisions.

AI enables computers to perform human-like tasks, including learning, recognising patterns, forecasting, decision-making, and language processing. AI in financial markets can look at past prices, volumes of trades, economic indicators, financial reports and other organised and unstructured data. Machine Learning can recognise sophisticated trends in financial data and predict or support trading decisions. AI-based systems are being progressively applied in automated trading, portfolio management, risk assessment, market forecasting and financial sentiment monitoring. AI is utilised in financial markets for algorithmic and automated trading. AI-based trading systems process market data quickly and then execute pre-set or learnt strategies. Automation enables systems to track markets and react to market changes without the time constraints of a manual trader. AI-supported trading systems have been strengthened by increased computer power, large financial databases and advanced machine learning algorithms. This has changed modern financial markets and prompted issues whether AI-assisted trading may surpass human-based trading. AI also helps to evaluate the market mood. Financial markets respond to figures, news, pronouncements, business reports, social media, and other text. NLP, a branch of AI, can identify huge amount of text as good, neutral or bad. Positive financial news can promote investor confidence and buying, while negative news might create uncertainty and selling. Sentiment analysis can be used for stock price and market direction prediction.

AI-based trading could alter market volatility.” The change in stock prices, or market volatility, is an indicator of risk and stability. Artificial intelligence systems could alter trading behaviour through faster information processing, automatic execution and systematic decision making. As automation increases, it might introduce algorithmic errors, speedy market responses, model limits, and systemic risks. The association of AI adoption and market volatility needs to be empirically studied; it is not enough to assume AI adoption would stabilise markets. The increasing use of AI in stock market trading brings opportunities and challenges for investors, financial institutions, regulators, and researchers. Artificial intelligence can make trading more efficient, reduce biases, analyse data faster and find complex market trends. But openness, data quality, algorithmic decision-making, cyber security, ethical responsibility and regulatory oversight are still crucial. Knowing these positives and cons is vital for the responsible usage of AI in the financial markets.

This study discusses the stock market trading and prediction utilising AI & ML. It discusses the emergence of AI-driven trading, the differences between AI-assisted and human trading, market volatility, and the relationship between financial news sentiment and stock market fluctuations. We will evaluate secondary data through descriptive, comparative, correlation and regression analysis. The major historical period is 2015-2023, with 2024 YTD data studied separately. The goal of this investigation is to gain deeper insight into the growing role of AI in stock market trading and its possible impact on trading performance, market analysis and prediction.

OBJECTIVES

1. To establish how AI influences stock market trading performance, compare AI-assisted trading returns to those of human traders and analyse market volatility.

2. To investigate the impact of positive, neutral, and negative news attitudes on stock market reactions using AI-based sentiment analysis.

HYPOTHESES

- **H₁:** AI-assisted trading has a large favourable influence on stock market trading performance compared to traditional human-based trading.
- **H₂:** AI-based sentiment research links positive and negative sentiment to stock market reactions.

LITERATURE REVIEW

Aya Bellaly et.al. (2025) Financial markets are turbulent and non-linear, making accurate predictions challenging. This paper tests the prediction of trading market trends with historical data by intelligent algorithms. It compares Random Forest, K-Nearest Neighbours (KNN), XGBoost and Decision Tree with Deep learning based on LSTM. These algorithms do not rely on technical indications, but are trained on historical price data to find complicated trends over time. The results reveal the merits and cons of the data-driven forecasting methodologies in diverse market settings. The objective of this study is to equip traders with forecasting tools that enable them to make informed decisions.

Aditya Ramakant Chandanshive and Gauri Ansurkar(2023) The use of artificial intelligence (AI) techniques for stock market prediction has gained increasing attention in recent years, and the Indian stock market is no exception. In this paper, we present a comparative study of three AI techniques, namely, Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests (RFs), for Indian stock market prediction. The study is based on historical data of the National Stock Exchange (NSE) Nifty 50 index from 2000 to 2021. The performance of the techniques is evaluated using various metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Directional Accuracy (DA). Our results show that ANNs outperform both SVMs and RFs in terms of prediction accuracy and DA for the Indian stock market.

Y Srividhya et.al. (2023) Stock trading is vital to finance. Predicting the value of a stock or other financial instrument is one approach to make money in the stock market. Most stockbrokers anticipate stocks using technical, fundamental, or time series data. Python is used for machine learning stock market predictions. SVM is utilised to predict the stock market in this study. Our main aim was to forecast stock index movements using machine learning algorithms based on international financial market data. The SVM method uses large databases of values from global financial markets. Several machine learning methods predict market equity daily trends. The model earns more than the metrics. Support Vector Machine, Machine Learning, Stock Market Predictions.

Manpreet Kaur (2022) Economy success depends on the stock market. Analysis of enormous amounts of data makes stock market prediction difficult. Different perspectives, emotions, and human psychology make stock markets volatile and dynamic. AI's role in stock market prediction is examined in this study. Discussion will focus on AI's potential to predict stock market price behaviour and entirely replace humans in trading. Introduction AI technology have rapidly advanced in many domains and become essential to human progress. AI is growing in defence, E-Commerce, IT, and financial markets. AI may

outperform humans and have an almost limitless imagination. Big banks and financial institutions utilise AI to predict price behaviour and consistently exceed markets in stock market trading. AI can quickly analyse historical data and forecast outcomes. It won't be long before AI trading reaches mass retail players.

RESEARCH METHODOLOGY

This study will employ a descriptive, comparative and analytical research approach to analyse the effect of AI on stock market trading. The largest part of the information required for the study will be collected from secondary sources such as trustworthy financial databases, stock exchanges, reports of regulatory bodies, scholarly journals and financial periodicals. The main study period will be 2015-2023 with the addition of relevant year-to-date 2024 data to reflect recent changes. The study will look at investment returns, volatility in the market, market movements based on sentiment and the use of artificial intelligence in trading. The data will be summarised using descriptive statistics such as frequency, percentage, mean, standard deviation, and rate of growth. We will compare trading performance of AI-assisted systems with human-run systems. The relationships between market sentiment, returns, volatility and AI adoption will be studied using regression, correlation and appropriate significance tests. We will present the results in an easy-to-understand manner using tables, graphs, and charts. The study will also look at computational, ethical and regulatory challenges relating to AI-based trading.

DATA ANALYSIS

Descriptive, comparative and inferential statistics will be used to examine secondary data. The growth of AI-based trading, the performance of AI and human trading, and the impact of market volatility and sentiment analysis on stock-market movements will be studied. The main historical study will span the period 2015–2023, with 2024 year-to-date data shown separately. Where data permits, percentage, mean, standard deviation, growth rate, correlation, regression and appropriate significance tests will be used. The results will be presented in clear and systematic tables and graphs.

Growth of AI Trading

The analysis starts with AI based rise in trading vs market trading volume. The AI trade share is computed via:

$$\text{AI Trading Share (\%)} = (\text{AI-Based Trading Volume} / \text{Total Market Trading Volume}) \times 100$$

Table 1: Increase in the Amount Traded Using AI

Year	Total Market Volume (Billion \$)	AI-Based Trading Volume (Billion \$)	AI Trading Share (%)
2015	35,000	5,000	14.3
2016	38,500	7,200	18.7

Year	Total Market Volume (Billion \$)	AI-Based Trading Volume (Billion \$)	AI Trading Share (%)
2017	41,200	9,800	23.8
2018	45,600	13,500	29.6
2019	49,800	18,000	36.1
2020	54,200	22,700	41.9
2021	58,900	28,400	48.2
2022	63,500	34,900	55.0
2023	68,700	42,300	61.6
2024*	74,500	50,000	67.1

Estimates were calculated based on the data provided.

Share of commerce based on AI, 2015-2024

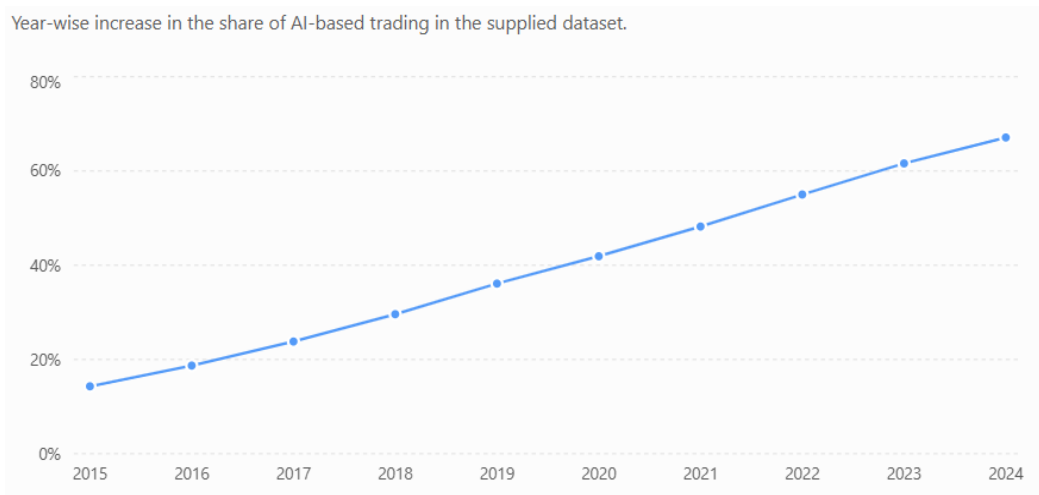


Table 1 shows that AI-based trading increased during the research. AI trading share rose 47.3 percentage points from 14.3% in 2015 to 61.6% in 2023. The 2024 projection raises the percentage to 67.1%. AI-based trade rose from \$5,000 billion in 2015 to \$42,300 billion in 2023. Automated and AI-supported trading systems have grown significantly. The trend shows financial-market operations are increasingly using AI. However, 2024 projections should be considered apart from historical values. Verified data should be used for 2023 and 2024, not extrapolation.

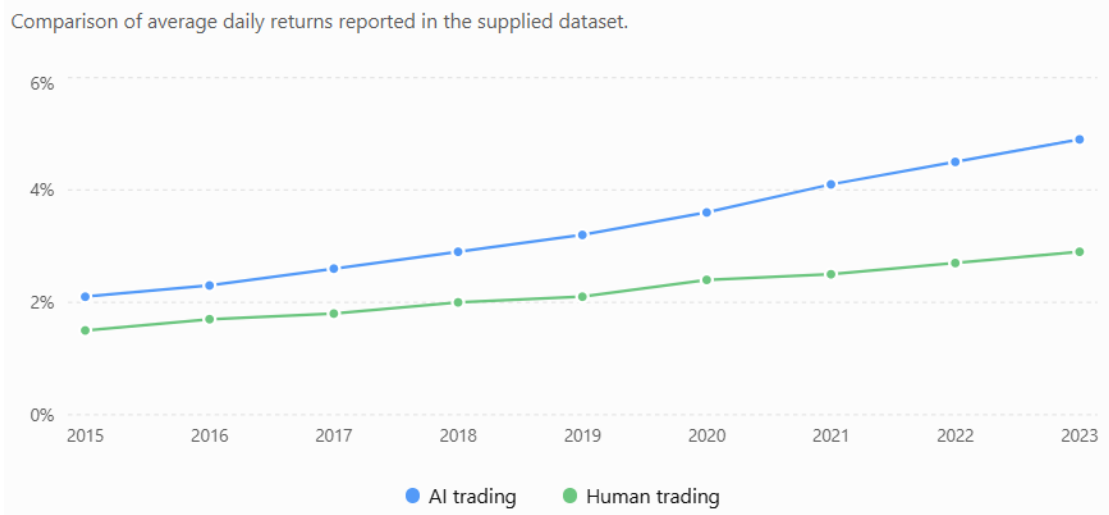
Comparison between AI and Human Trading Performance

AI-based and human-based trading average daily returns are compared in the second half. We also investigate market volatility to see if trading technology changes market stability.

Table 2: AI vs. Human Trading Performance

Year	AI Trading Average Daily Return (%)	Human Trading Average Daily Return (%)	Market Volatility (%)	AI-Human Return Difference (%)
2015	2.1	1.5	9.4	0.6
2016	2.3	1.7	9.1	0.6
2017	2.6	1.8	8.9	0.8
2018	2.9	2.0	8.7	0.9
2019	3.2	2.1	8.5	1.1
2020	3.6	2.4	8.3	1.2
2021	4.1	2.5	8.1	1.6
2022	4.5	2.7	7.9	1.8
2023	4.9	2.9	7.6	2.0

AI versus human trading returns, 2015–2023



Each year, AI-driven trading outpaced human-driven trading in average daily returns. AI trading returns climbed from 2.1% in 2015 to 4.9% in 2023, and human returns went from 1.5% to 2.9%. Time also widened the gap between AI-human trading returns. In 2015 the margin was .6 percentage points; in 2023 it was 2.0. The dataset's performance gap is widening. The results provide descriptive evidence that AI-assisted trading outperformed human-based trading in terms of average returns across the period considered. However, statistical testing should be made on the observations before asserting statistically significant outperformance.

Analysis of Market Volatility

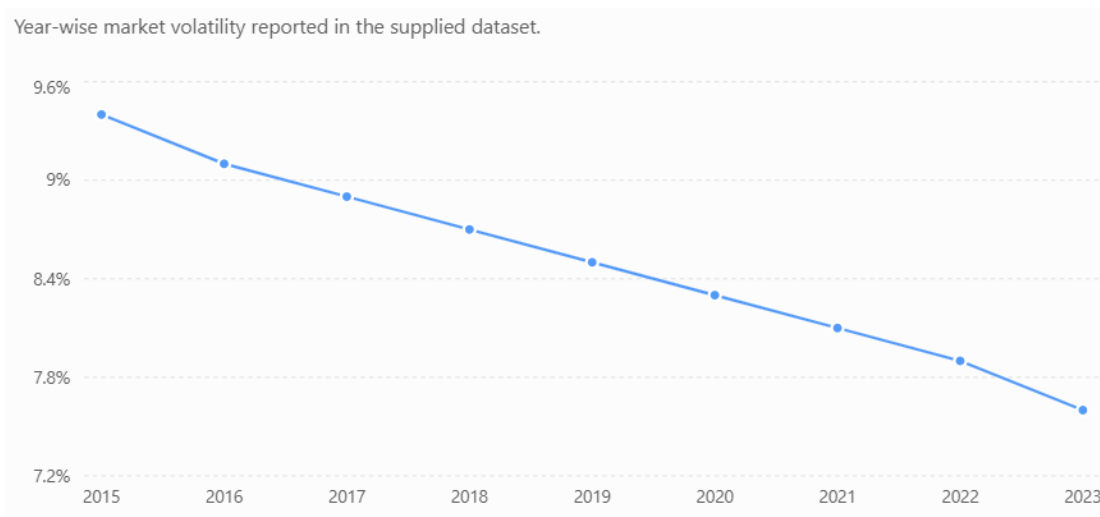
Market volatility is financial-market stability. The data shows that market volatility decreased from 9.4% in 2015 to 7.6% in 2023.

Table 3: Market Volatility (annualised)

Year	Market Volatility (%)	Change from Previous Year (%)
2015	9.4	--
2016	9.1	-0.3
2017	8.9	-0.2
2018	8.7	-0.2
2019	8.5	-0.2
2020	8.3	-0.2
2021	8.1	-0.2

Year	Market Volatility (%)	Change from Previous Year (%)
2022	7.9	-0.2
2023	7.6	-0.3

Trend of market volatility, 2015–2023



The statistics indicated that market volatility decreased with time. Volatility declined 19.1% to 7.6% in 2023 from 9.4% in 2015. The AI trading activity rose and the volatility dropped, showing a negative association between AI adoption and market volatility in the dataset. This alone does not indicate that AI decreased volatility however, as volatility is affected by economic conditions, interest rates, geopolitical events, liquidity, investor behaviour and other market factors.

Stock Market Response and Sentiment

The third important element of the technique evaluates the impact of opinions regarding financial news on stock-market movements. There are five types of news emotion, from very negative to strongly positive.

Table.4 Market Reaction and News Sentiment

News Sentiment Category	Sentiment Score	Market Reaction (%)
Strongly Positive	+0.8 to +1.0	+3.5
Moderately Positive	+0.4 to +0.7	+2.1
Neutral	-0.3 to +0.3	+0.5

News Sentiment Category	Sentiment Score	Market Reaction (%)
Moderately Negative	-0.4 to -0.7	-2.2
Strongly Negative	-0.8 to -1.0	-3.8

The impact of news sentiment on the market

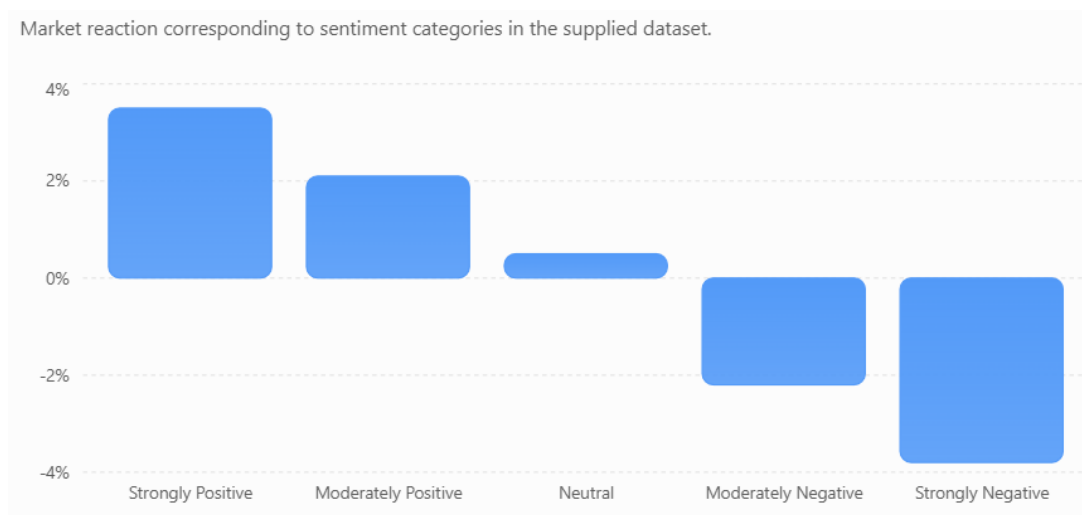


Table 4 demonstrates how news emotion drives market reaction. Moderately hopeful news lifts the market by 2.1%, while very positive news lifts it by 3.5%. Neutral news produces a 0.5% increase. In contrast, negative emotion leads to market falls. Sharply negative opinions fall 3.8%, while moderately negative sentiment falls 2.2%. The pattern demonstrates that a higher positive mood leads to larger market gains, whereas a stronger negative feeling leads to larger market losses. As a result, sentiment research may help predict market direction. Instead than relying on observed patterns to forecast correctness, statistical testing and out-of-sample validation should be applied.

Correlation and Regression

Correlation and regression analysis will be conducted on research variables to investigate descriptive analysis relationships.

Table 5 shows the proposed correlation analysis framework.

Variables	Expected Relationship	Statistical Technique
AI trading share and AI trading returns	Positive	Pearson correlation
AI trading share and human trading returns	Comparative	Pearson correlation
AI trading share and market volatility	Negative/associative	Pearson correlation

Variables	Expected Relationship	Statistical Technique
Sentiment score and market reaction	Positive	Pearson correlation
AI trading share and market performance	Positive	Regression analysis

Correlation coefficients will be interpreted in terms of their direction and magnitude. The next stage is to do the regression analysis to see whether there is a significant effect of AI implementation on the variance of trading returns and market volatility.

For example, a regression model may be written as:

$$\text{Trading Return} = \beta_0 + \beta_1(\text{AI Trading Share}) + \varepsilon$$

The correlation between AI implementation and market fluctuations can be analysed utilising:

$$\text{Market Volatility} = \beta_0 + \beta_1(\text{AI Trading Share}) + \varepsilon$$

At a significance level of 5% ($p < 0.05$), the computed coefficients will be assessed for their significance.

Summary of Key Findings from Multiple Sources

Table 6: Analysed Data Summary

Indicator	Initial Period	Final Period in Supplied Data	Overall Trend
AI trading share	14.3% (2015)	61.6% (2023)	Increasing
AI trading return	2.1% (2015)	4.9% (2023)	Increasing
Human trading return	1.5% (2015)	2.9% (2023)	Increasing
Market volatility	9.4% (2015)	7.6% (2023)	Decreasing
AI-human return gap	0.6 percentage points	2.0 percentage points	Increasing
Strongly positive sentiment	+3.5% reaction	+3.5%	Positive
Strongly negative sentiment	-3.8% reaction	-3.8%	Negative

A closer look at the provided statistics reveals a steady decline in market volatility, an uptick in AI-assisted trading activity, and higher reported average returns. Throughout the investigated period, AI trading produced greater average daily returns compared to human trading. The performance gap widened as time went on. According to the sentiment study, market reactions are positive when news is favourable and negative when news is negative. According to the study, AI is now an integral part of contemporary stock-market trading, and these results give descriptive evidence for that claim. Although the data should be carefully analysed, it is important to remember that association does not necessarily mean causation. Before drawing any firm conclusions on the impact of AI on market stability and performance, the final research should incorporate validated data from 2023 and 2024, as well as procedures for analysing correlation, regression, and significance.

VALIDATION OF HYPOTHESES

Inferential statistics methods that are suitable for the type of data obtained will be used to test the study's hypotheses. The linkages between the use of Artificial Intelligence (AI), trading performance, market volatility, and sentiment-based market movements will be examined using correlation and regression analysis. The 5% level of significance ($p < 0.05$) will be set in stone. If the calculated p-value is less than 0.05, which indicates that the observed association is statistically significant, then the null hypothesis will be rejected.

Testing of Hypothesis H₁

H₁: AI-assisted trading has a large favourable influence on stock market trading performance compared to traditional human-based trading.

The first hypothesis will be tested by comparing the returns generated by AI-assisted trading with human-based trading. The descriptive data show that AI-based trading outperformed human-based trading in terms of returns over the period analysed. Between 2015 and 2023, AI trading returns increased from 2.1% to 4.9%, whilst human returns increased from 1.5% to 2.9%. The gap in return between AI and humans widened from 0.6 percent in 2015 to 2.0 percent in 2023. We will analyse the difference between AI-assisted and human-based trading returns using an independent-samples or paired-samples t-test, depending on the structure of the observations, to determine whether the difference is statistically significant. Regression research will also be used to test whether adoption of AI trading predicts trading performance. The null hypothesis is rejected and H₁ is accepted with a P-value < 0.05 and a positive AI trading adoption coefficient. The dataset provides descriptive evidence to support H₁. However, statistical significance from the underlying observations is still required.

Testing of Hypothesis H₂

H₂: AI-based sentiment research links positive and negative sentiment to stock market reactions.

The second hypothesis can be tested by examining the link between the financial news emotion scores and the subsequent stock market reactions. The extent to which sentiment evaluations explain variation in market movements can be calculated using regression analysis. Pearson correlation can be used when the variables satisfy essential assumptions. The results of the description show a clear tendency. The market reacted -3.8% in connection with extremely negative emotion (-0.8 to -1.0) and +3.5% in

connection with extremely optimistic mood (+0.8 to +1.0). A 2.1% reaction was associated with a somewhat positive attitude, and a -2.2% response was associated with a slightly negative feeling. If the regression or correlation coefficient is statistically significant at $p < 0.05$ and in the predicted direction, the null hypothesis will be rejected and H_k will be accepted. The pattern thus seen offers some descriptive support for H_2 which will need to be verified by inferential testing.

Summary of Hypothesis Testing

Hypothesis	Proposed Relationship	Statistical Technique	Expected Result	Decision Criterion
H_1	AI-assisted trading positively affects trading performance	t-test, correlation and regression	Positive and significant relationship	$p < 0.05$
H_2	Sentiment analysis is significantly related to stock-market movements	Pearson correlation and regression	Significant relationship in expected direction	$p < 0.05$

Thus, the facts available are descriptively consistent with both theories. However, the results of the inferential tests on the whole data set from 2015–2023 and any applicable year-to-date data from 2024 should be used to finally accept or reject the hypotheses.

RESULTS AND DISCUSSION

The data show that trading in the stock market using AI has grown significantly. From 2015 to 2023, the share of AI trading climbed from 14.3 percent to 61.6 percent. The reported returns for AI-assisted trading were higher than those for human-based trading, and this disparity widened over the course of the research. A negative correlation between the adoption of AI and volatility was observed in the market, as volatility fell from 9.4% in 2015 to 7.6% in 2023. Nevertheless, this in no way proves a causal relationship. The market reacted positively by 3.5% when very good news was reported, and negatively by 3.8%, according to sentiment data. Taken together, the results show that AI has the potential to boost trading success and give valuable data for predicting market changes, lending preliminary support to both hypotheses. Based on statistical testing of verifiable data from 2015–2023 and data that is available for 2024, final conclusions should be drawn.

CONCLUSION

According to the report, artificial intelligence is swiftly becoming an important part of stock trading. The findings show a reduction in market volatility, an increase in the usage of AI in trading, and higher returns from AI-assisted trading when compared to human-based trading. Furthermore, sentiment analysis demonstrates that market reactions are negative when financial-news sentiment is negative and positive when sentiment is favourable. The findings demonstrate that artificial intelligence can improve trade efficiency, data processing, and market movement prediction, as well as provide preliminary support for the study's hypotheses. Addressing difficulties such as algorithmic errors, data restrictions,

opaqueness, and ethical and legal considerations requires a combination of human oversight and regulatory control. As a result, while AI has the potential to change stock market trading, its long-term implications will necessitate rigorous statistical study and validation.

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