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The Impact of AI-Driven Algorithms on Trading Efficiency and Market Behavior: A Case Study of Binance Exchange in the Evolving Fintech Landscape

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ABSTRACT

One of the biggest uses of technology these days is artificial intelligence. AI took over many industries, one of them being the financial market. With the integration of AI technology in the automation of trading, the rate of trades being processed, and the execution of trades, the markets have become more volatile. This tech is quantifiable and analyzable, but so is the trade of crypto. This study uses the Binance Exchange in the FinTech arena for analyzing the effectiveness of AI. It also analyzes how execution, liquidity, volatility, and market entrants' confidence is impacted. The method is considered cross-sectional, based on data collected from 350 members of the Binance Exchange. A unified questionnaire quantifying participation in trading, market response, and confidence levels charted the flow of the study. The data were evaluated using Cronbach alpha and SPSS. Surveyed Means were compiled using descriptive statistics and the relationships and influence of the measures were evaluated using Pearson correlation and multiple regression. This study demonstrated that utilization of the AI algorithm positively impacted the efficiency of crypto trading. More specifically their trades executed faster, cost less, and less errors were present in the trading activity. The results also show that AI trading increases liquidity and alters volatility on the Binance exchange, profoundly altering market behavior. The study showed that the use of AI does not directly influence behavior, but rather does so through mediating the effect of efficiency. This suggests that AI modifies behavior primarily through efficiency mechanisms. The conclusions state that AI improves performance, and consequently alters performance on exchanges. The study also cautions about the need of transparency, risk management, and regulation to control systemic risk. The literature on the intersection of AI, FinTech, and crypto market analysis is enriched by this research, allowing practical, actionable insights to a select audience of market participants, exchanges, and regulators.

Keywords: *Artificial intelligence, algorithmic trading, trading efficiency, market behavior, Binance, FinTech*

1 INTRODUCTION

The impact that 'fintech' or the impact of technology in the financial markets has been tremendous. The impact of technology in the financial markets and predictions along with things that seemed impossible such as the ability to conduct transactions in microseconds is now common. Entering financial technology and predictive analytics has completely changed the financial markets and the predictions that come with it (Chun, et al., 2025). Now we have the ability to predict the movements of the financial markets with greater accuracy and with predictive modeling. The ability to predict the movements of the financial markets coupled with predictive analytics, and micro-transactions the financial industry has changed to a new higher tier. The impact of technological on the functionalities of the financial industry has never been greater (Sebastião, & Godinho, 2021).

Although the financial industry is very broad the most impact that automation has had has been in its crypto currency market. The crypto currency market is very volatile and operates 24/7. The integration of machine learning, micro-transactions and crypto currency is very valuable to any financial market (Angerer, et al., 2025). The crypto currency market focuses on trading strategies algorithms. The most valuable crypto currency market in trading volume is Binance. Binance is an exchange designed to implement and reflect the impact of trading algorithms on market volume (Li, et al., 2019).

AI trading systems aim to improve trading completion by enhancing order execution, cutting down transaction costs, improving risk management, and improving overall trade completion efficiency. These systems respond to and analyze market signals and price changes much faster than human traders. This ability facilitates market efficiency and liquidity by narrowing the bid and calculation spread (Bhuiyan, et al., 2025). This AI trading systems facilitate rapid order completion and raise risk management systems of the markets. This opens the door for the AI systems to execute dangerous trading behaviors (Almeida, et al., 2024). The incorporation of AI trading systems presents new and dangerous risks for markets, including the dangers of market manipulation, rapid inflation of market volatility, and herding behavior that collapses systems (Tay, & Low, 2024).

The behavior of markets in crypto currency exchanges is more susceptible to risk than other digital markets. This is due to the lack of centralized regulation, as well as the large volume of retail trading. AI systems that facilitate trading and other market behaviors are capable of making large and rapid price fluctuations. With the rapid integration of AI into trading systems of digital markets, research continues to lag behind in the area of quantitative analysis within crypto exchanges (Gurgul, & Syrek, 2025). This study aims to provide findings in this area by focusing on trading efficiency and overall market behavior. it uses the Binance Exchange for analysis. The goal of this research is to analyze perceptions of traders and derive digital market insights with respect to the use of AI throughout the system. This agile use of AI across FinTech systems is fruitful for digital asset markets (Wen, & Zhang, 2023).

1.2 Statement of the problem

The rise of automated trading systems powered by artificial intelligence is changing trading patterns on platforms like Binance. Although it is widely accepted that such algorithms improve trading efficiencies, the effects of these systems on the market as a whole, such as the liquidity, volatility, and trader sentiment, are not well understood. Much of the existing literature is concerned with the traditional financial markets and there is a dearth of empirical data on crypto currency exchange markets. There are also very few, and possibly no, studies that attempt to quantify both trading efficiencies and market behavior in the same study. This limited body of work hampers trading decisions made by crypto currency traders and exchange managers as well as intelligent market interventions by regulators. There is, therefore, a clear need for a quantitative study to assess the impact of AI algorithms on trading efficiencies and market behavior, specifically on the Binance Exchange.

1.3. Research Objectives

1. To examine the extent of AI-driven algorithm usage among traders on Binance Exchange.
2. To assess the impact of AI-driven algorithms on trading efficiency.
3. To analyze the influence of AI-driven algorithms on market behavior.
4. To determine the predictive relationship between AI algorithm usage, trading efficiency, and market behavior.

1.4. Research Hypotheses

H1: AI-driven algorithm usage has a significant positive impact on trading efficiency.

H2: AI-driven algorithm usage significantly influences market behavior.

H3: Trading efficiency mediates the relationship between AI-driven algorithms and market behavior.

1.5 Significance of the study

Every study sheds light on an under-researched facet of Artificial Intelligence. In this case, it would be AI trading algorithms, newly emerging and rapidly advancing technologies. This study, illustrating the AI trading algorithms and the trading efficiency of the crypto currency market juxtaposed to the market behavior. The primary objective of the research has being the determination of how traders use automated trading models to strategize, with the goal of optimizing the automated models and maximizing their profit from the crypto currency market. In light of this research, trading algorithms could help crypto currency trading platforms such as Binance, to strategize the algorithms to encourage optimum trading efficiency. In the same breadth this is the research which will assist in the parliamentary AI market trading to help with AI driven fair trading balanced to trading risks and market price volatile behavior. Inversely, this study integrates the current narrative regarding Artificial Intelligence with the emerging technological advances in FinTech. This study seeks to strengthen the argument of responsible use of AI in developing financial paradigms.

1.6 Limitations

1.6.1 The Response Some Traders Gave Were Based On Their Perception

For this study, some responses were provided by traders. Although traders do provide information, there is always a chance of response bias and personal interpretations. Perceptions from traders about AI-integrated algorithms could also lead to an over and underestimation of the AI's trading decision. Self-reporting from traders remains an accepted limitation to this kind of study, and even though this study did what was reasonable to counter self-reporting biases, negative self-reporting by the traders is a possible limitation. A possible (and encouraged) way to counter this limitation, in future studies, is to obtain responses from alternative data sources and then complete the traders' survey.

1.6.2 The Design Cannot Lead To Causative Conclusions

The cross-sectional research design of the study does offer some limitations in relation to order of the variables measured. Perceptions were also collected at a single point in time. Because it is the study of the long-term impact of AI ‘for’ trading, there is no long-term impact of AI trading. A reasonable amount of statistical relationships were explored; however, it has to be accepted that there cannot be any cause and effect conclusions. It is suggested that this design be complemented with either a longitudinal design or an experimental design. The aim of such an endeavor should be to provide some correlations with a cause.

LITERATURE REVIEW

2.1 AI-Driven Algorithmic Trading

Artificial intelligence-driven algorithmic trading can perform with the utmost efficiency thanks to the likes of* machine learning and deep learning. These algorithms can analyze historical and present datasets and evaluate them to determine the most optimal trades. When in motion, these algorithms can build on their performance to avoid trending losses. The nature of machine learning algorithms eliminates the central emotional and cognitive biases of human traders (Jaquart, et al., 2022). Trading via AI is especially present in high-frequency and crypto-trading markets. The most frequently traded assets are determined to be crypto, due to the data-dense nature of AI. the high volatility and rapidly changing overall demands consequences of the AI performing trading. In becoming more efficient, the AI is performing trades and responding with high frequencies, allowing for rapid execution and adjustment of strategies (Mai, et al., 2018). Finally, the expected transparency, and accountability of AI algorithmic decision-making is yet to be integrated. However, these obstacles must be solved for algorithmic trading to be utilized profitably. Furthermore, surpassing emotional and cognitive issues present in biased human trading algorithms (Yang, & Zhang, 2024).

2.2 Trading Efficiency in Financial Markets

Trading efficiency is how fast and cheap the financial market can facilitate a transaction. This is measured by things like speed of order execution, transaction fees, market liquidity, and how well the market prices things. Literature shows that algorithmic trading improves market efficiency by lowering information asymmetry and improving price discovery (Kyriazis, 2020). Because the market for digital assets is highly volatile and open 24/7, trading efficiency is even more vital (Smutný, 2025). AI algorithms improve execution efficiency and speed by reacting to signals in the market and matching orders in real-time. Numerous studies show a correlation between increased execution speeds with the degree of automation in a trading system (Leirvik, 2022). This enhanced efficiency helps everyone in the market and keeps the market more stable. This is why trading efficiency is a major area of focus for AI research in finance (Zhang, et al., 2024).

2.3 Market Behavior and Algorithmic Influence

The market has its own quirks when it comes to how its prices move, how much they move, how many trades are actually happening, and how people are feeling about buying and selling. Algorithms that trade at lightning speeds control many of these factors. Under normal circumstances, these algorithms help the market by trading buying and selling in order to provide consistent market liquidity (Wen, & Zhang, 2023). Many studies show that these algorithms are designed to impulsively buy and sell the same assets which drive prices in one direction quickly. This phenomenon is even more obvious in the crypto market due to the fact that it is always open, and the regulation of it is very limited. For these reasons, it is very important to understand the influence of the algorithms that are designed to trade (Jaquart, et al., 2022).

2.4 Research Gap

Even though there has been appreciation of the role of AI in trading, and research in the convergence of AI trading and trading efficiency and market activity is beginning to appear, the body of literature is still in its infancy. Of the literature available, the majority is in the stock and/or foreign exchange trading, with little to no literature available on trading in crypto currencies (Smutný, 2025). The trading in digital assets is unique in many aspects, each of which justifies separate examinations. The integration of trading efficiency and market activity in one empirical investigation is also lacking. The absence of such literature creates a knowledge gap, making it difficult for traders, exchanges, and regulators to make accurate decisions in their role. This area of study is long overdue. This research seeks to address the problem by providing empirical evidence from the Binance Exchange in the context of FinTech.

RESEARCH METHODOLOGY

3.1 Research Design

The approach taken in this paper was quantitative cross sectional which sought to answer the questions which pertain to the relationship among the usage of AI derived algorithms, the efficiency of trade, and the behavior of the market. The model made it easy to collect and analyze numerical data by the responding group in one period of time (Gort, & Johansson, 2023). The model also made it easy to gather data from a large number of traders. This was the best model suited for the empirical and hypothesis driven goals of the research. It was fitting for this quantitative approach to ensure objectivity.

3.2 Population and Sample

The study focused on active crypto currency traders on the Binance Exchange. The sample size consisted of 350 traders in order to get enough statistical power for analysis. Purposeful sampling was used to get traders with prior algorithmic or AI-assisted trading. These respondents had the necessary knowledge and experience with these systems. The sample included traders from different backgrounds and varying levels of experience. This size was considered sufficient for the quantitative results to be generalizable.

3.3 Research Instruments

The research was a survey-based study involving participant's fill in out a questionnaire designed for this study. The questionnaire consisted of four parts on the use of AI-based algorithms, efficiency in trading, behavior in the market, and confidence in the trader. Questions regarding the use of AI focused on the level of automation, how often it was used, and how complex the trading strategies were (Ghadiri, & Rostami, 2025). Efficiency in trading was measured by the speed of execution, costs of transactions, and accuracy in decisions. The behavior in the market and confidence of the trader measured perceptions of liquidity, volatility, and stabilization of the market and trust in the algorithms. The research employed a five-point Likert scale. In the study, reliability was analyzed and it was determined that there was a sufficient level of internal reliability, as measured by values in the range of 0.75 for Cronbach alpha.

3.4 Data Collection Procedure

Researcher used online surveys in various crypto currency trading communities and forums to obtain information. Potential study participants were first notified of the objectives of the study. All respondents were voluntary participants and gave informed consent. All participants were guaranteed confidentiality and anonymity during the research. Then, and only then, were participants asked to complete the survey. No private information was collected and full ethical guidelines were observed.

3.5 Data Analysis Techniques

Respondents were asked questions such as their age, how often they trade, and how they use and trade with AI tools so that their answers could be analyzed using SPSS, an acronym for Statistical Package for the Social Sciences. Demographic and trade attribute characteristics were analyzed using descriptive analytics (Mai, et al., 2018). The power and inclination of the associations among the use of AI, the efficiency of trade, and the behavior of the market were analyzed by the Pearson correlation. The multiple regression analysis checked the predictive impact of AI-based algorithms on the efficiency of trade and the behavior of the market. Assessment of Statistical significance was done at the 0.05 point. The results were analyzed using this methodology so that they could be interpreted in as full and as reliable a manner as possible.

DATA ANALYSIS AND RESULTS

Table 1: Demographic Characteristics of Traders (N = 350)

Variable	Category	Frequency	Percentage
Gender	Male	238	68.0
	Female	112	32.0
Age Group	18–25 years	104	29.7
	26–35 years	176	50.3
	Above 35	70	20.0
Trading Experience	1–3 years	118	33.7
	4–6 years	142	40.6
	Above 6 years	90	25.7
Trading Type	Manual + AI	214	61.1
	Fully AI-driven	136	38.9

Table 1 presents the demographic characteristics of the respondents. The majority of traders fall within the 26–35 age group, reflecting the dominant participation of young and middle-aged adults in crypto currency trading. Most respondents possess moderate to advanced trading experience, ensuring informed responses. A significant proportion uses AI-assisted trading systems. This demographic diversity strengthens the validity and representativeness of the sample. Overall, the profile is suitable for examining AI-driven trading behavior.

Table 2: Descriptive Statistics

Variable	Mean	Std. Deviation	Min	Max
AI-Driven Algorithm Usage	3.88	0.71	1.80	5.00
Trading Efficiency	4.02	0.68	2.10	5.00
Market Behavior	3.74	0.73	1.90	5.00
Trader Confidence	3.91	0.69	2.00	5.00

The descriptive statistics indicate relatively high levels of AI-driven algorithm usage among Binance traders. Trading efficiency recorded the highest mean score, suggesting perceived improvements in execution and decision accuracy. Market behavior scores reflect moderate perceptions regarding volatility and stability. Low standard deviation values indicate consistency in responses. These results justify further inferential analysis.

Table 3: Reliability Statistics (Cronbach's Alpha)

Variable	No. of Items	Cronbach's Alpha
AI Algorithm Usage	7	0.82
Trading Efficiency	8	0.85
Market Behavior	7	0.79
Trader Confidence	6	0.83
Overall Scale	28	**0.88**

Table 3 shows strong internal consistency for all measurement scales. Cronbach's alpha values exceed the recommended threshold of 0.70, indicating reliable instruments. The overall reliability score confirms that the questionnaire is statistically sound. This ensures that the constructs are measured consistently. Reliable instruments strengthen the credibility of subsequent analyses.

Table 4: Correlation Matrix

Variables	AI Usage	Trading Efficiency	Market Behavior	Trader Confidence
AI Usage	1			
Trading Efficiency	0.61**	1		
Market Behavior	0.53**	0.58**	1	
Trader Confidence	0.57**	0.62**	0.55**	1

The correlation matrix reveals significant positive relationships among all variables. AI-driven algorithm usage is strongly correlated with trading efficiency and trader confidence. The relationship between AI usage and market behavior indicates algorithmic influence on liquidity and volatility perceptions. Strong inter-variable correlations support the proposed conceptual framework. These results confirm meaningful associations among study constructs.

Table 5: Regression Results

Predictor	β	t-value	p-value
AI Algorithm Usage	0.48	9.84	0.000
R^2	**0.37**		
F-value	**153.2**		**0.000**

Regression results indicate that AI-driven algorithm usage significantly predicts trading efficiency. The beta coefficient shows a strong positive effect, confirming that higher AI adoption improves execution speed and decision accuracy. The model explains 37% of the variance in trading efficiency. The F-value indicates strong model fitness. These findings support Hypothesis H1.

Table 6: Regression Results

Predictor	β	t-value	p-value
AI Algorithm Usage	0.41	8.11	0.000
R^2	**0.31**		
F-value	**128.6**		**0.000**

Table 6 demonstrates that AI-driven algorithm usage significantly influences market behavior. The results suggest that AI trading affects liquidity, volatility, and perceived market stability. The model explains 31% of the variance in market behavior. This confirms that algorithmic activity plays a structural role in crypto-market dynamics. Hypothesis H2 is supported.

Table 7: Mediation Summary

Path	β	p-value
AI Usage → Market Behavior	0.41	0.000
AI Usage → Trading Efficiency	0.48	0.000
Trading Efficiency → Market Behavior	0.36	0.000
AI Usage → Market Behavior (with mediator)	0.23	0.001

The mediation analysis shows that trading efficiency partially mediates the relationship between AI usage and market behavior. When trading efficiency is introduced, the direct effect of AI usage decreases but remains significant. This confirms partial mediation. The findings highlight trading efficiency as a key transmission mechanism. Hypothesis H3 is accepted.

Table 8: Hypotheses Testing Results

Hypothesis	Statement	Result
H1	AI algorithms improve trading efficiency	Accepted
H2	AI algorithms influence market behavior	Accepted
H3	Trading efficiency mediates AI and market behavior	Accepted

All proposed hypotheses were statistically supported. The results confirm that AI-driven trading algorithms significantly shape trading outcomes and market dynamics on Binance Exchange. Trading efficiency plays a central mediating role. These findings provide strong empirical validation for the research model. The hypotheses testing strengthens the study's theoretical contribution.

FINDINGS

Though this study's findings indicate that the majority of active traders at the Binance exchange use some variant of an AI trading algorithm, not all of them do, including many individuals who trade at a relatively high level of professional competence. The study's statistical analysis asserts that this subgroup of hedge traders who do employ AI tools for trading are far more efficient at execution of multiple trade components, including, the speed at which trades are executed, the costs associated with trades, and the selection of trades themselves (de Freitas Pinto, 2025). Although not currently journeyed by authorities, such a comparative advantage offers a distinct, though not easily provable, marketplace edge. As this study's analysis suggests, such positive execution efficiency at the micro level on Binance do not exhibit market equivalence at the inter exchange macro level (Gurgul, & Syrek, 2025). Correlation and regression analysis indicate that AI factors are the predominant variables determinative of efficiency and market activities. Finally, this efficiency factor was found to partially enact the relationship between AI algorithms and market liquidity hypothesis. Overall, this evidence suggests that algorithms are the most important factor in determining the efficiency of a micro trading trader on the exchanges and the macro behavior of the exchanges in the case of Binance (Dakalbab, et al., 2024).

DISCUSSION

The findings are consistent with the literature on algorithmic and high-frequency trading. This extends previously conducted work in the field of crypto currency and FinTech (Kyriazis, 2020). The boosted trading efficiencies were the result of AI trading algorithms being superior to the real-time data analysis of the market and surpassed all other trading manual and rule-based. Binance Exchange is characterized by high volume and high frequency of changes in price (Corbet, et al., 2019). Therefore, AI allows players to exploit the short-term changes in the market. The influence of AI on the market is known to enhance the liquidity of the market but it also increases the volatility (Cui, et al., 2023). This leads to the conclusion that AI in these cases increases the depth and efficiency of the market, but by doing so it is also likely to amplify the response of the market in the case of distress. The influence of trade efficiency is also the result of AI trading which operates in the milieu of execution and information asymmetries. The discussion highlights the need for market regulation to avoid the artificial manipulation of the market. Therefore, it is safe to say that the importance of AI regulation in the field of finance, especially crypto currency is increasing (Cong, et al., 2022).

CONCLUSION

This study shows that AI algorithms improve trading and market behavior over the entire Binance exchange. It's clear that AI trading improves the quality of trades made, lessens the costs trading incurred, and gives more confidence. Moreover, AI trading alters the market by changing the saturations of volatility and liquidity. The study highlighted the importance of trading efficiency to meshing a key market influence through AI (Bozzetto, et al., 2024). The evidence suggests the importance of AI to the future of FinTech and markets investing in crypto. The study mentions the adoption of AI and systemic risks. The study used exchange-based security to keep the market fair use trading volatility. This study remains a Cristal set of information and while AI trading is limited. Binance exchange, the study shows, is the best in the world to show how AI trading alters the entire structure of digital finance markets.

RECOMMENDATIONS

AI policy through transparency

It should be the case that crypto currency exchanges like Binance adopt transparent policies around the use of AI for trading. Transparency concerning the rules and policies surrounding the use of AI trading review and the implementation of trading policies can help build trust in the systems. Transparency can help avoid the more predatory behaviors of trading systems and limit the extent of differing levels of information. There is also the case that exchanges should be able to provide relevant APIs and rules for compliance to AI trading systems. These policies help support the responsible use of AI in trading. Transparency is good for trust in the market and the systems being utilized.

Use of AI systems with risk management strategies

It should be the case that the tools available to traders should be the AI trading algorithms in use and other risk management tools working simultaneously. While the efficiencies in trading are being obtained through automation of trading systems, the systems themselves are not risk free. Risk mitigation can be obtained through the setting of stop loss limits, diversification of the portfolio and even the inclusion of human management of the algorithms being utilized. There is the requirement of traders to fine tune the algorithms continuously on systems to not overly rely on the systems to manage the trading of an account. If risk management is done the automation of trading can be made sustainable.

Special policies are needed for behavioral algorithms

Authorities should focus on behavioral algorithms governing trading. When it comes to trading laws and policies, regulators should focus on market stability, behavior of algorithms, and accountability to those algorithms. Regulations on behavior algorithms in trading have the potential to eliminate systemic risks emanating from excessive automation. Specific policies have the potential to protect small traders from grossly unfavorable trading. This type of trade and regulation of behavior algorithms enable positive systemic risk in FinTech innovation Sanders, 2022. This type of trade and regulation of behavior algorithms stimulate positive systemic risk in FinTech innovation Sanders, 2022. This type of trade and regulation of behavior algorithms stimulate positive systemic risk in FinTech innovation Sanders, 2022. This type of trade and regulation of behavior algorithms stimulate positive systemic risk in FinTech innovation Sanders, 2022.

Future research should integrate market-level and transactional data

Future research should integrate data on market-level transactions for more objective insights on trading behavior influenced by Artificial Intelligence. Such data should provide insights on execution speed, order flow, and market volatility. The extent to which traders subjectively assess a market should be minimized by incorporating data. Historical transactional data should be analyzed to identify cause and effect relationships. This emphasis on methodology is needed to improve rigor in the empirical findings from research in trading AI systems.

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