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| RESEARCH ARTICLE

AI-Induced Market Thinning: An Empirical Analysis of Trading Participation Using Volume, Trade Frequency, and Activity Metrics

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| ABSTRACT

Artificial Intelligence (AI) and algorithmic trading platforms have revolutionized today's financial markets through their growing levels of automation, predictive capacity, and speed. AI-driven trading helps the market run smoothly in normal times, but when these trades are coming from the same predictive signals, it can have unintended consequences of market participation and, in the short term, a liquidity contraction. This paper explores the issue of AI market thinning by conducting an empirical study on trading participation based on different metrics such as volume, frequency of trades, and active trading interval. It's a research that analyzes how market participation changes during periods of high activity, with AI signals, by examining the price movements, trading volume, transaction frequency, and activity indicators of historical intraday market data. Model-based threshold conditions, based on predictive trading indicators and probability-based classification techniques, are used to identify AI-generated buy and sell signals. The study compares periods of normal market activity with periods of strong market activity as signaled by artificial intelligence, and finds that there is no evidence of a depressing effect on market activity from synchronized algorithmic trading. Market thinning can be quantified by trading volume, number of transactions and active trading intervals. Initial estimates suggest there could be substantial contraction of participation, with fewer trades executed and shallower liquidity levels, due to concentrated AI-driven trading signals. The study also analyzes these results in the context of the market microstructure theory, which points to a higher degree of order flow diversity and a lower trading participation as evidence of thinner markets and greater liquidity fragility. This study is meaningful because it combines the advantages of AI signal analysis with empirical market participation data, providing insights into the impact of automated trading systems on financial market liquidity and stability. The results could help regulators, institutional investors and market analysts understand the risks of participation in a synchronized environment with AI-driven trading and enhance the tools they have to monitor liquidity for resilience in increasingly automated financial markets.

| KEYWORDS

Artificial Intelligence Trading, Market Thinning, Trading Volume, Trade Frequency, Market Microstructure and Algorithmic Trading

| ARTICLE INFORMATION

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I. Introduction

A. Background

In the modern era of finance, Artificial Intelligence (AI) technologies and high-frequency trading systems have revolutionized the financial landscape, bringing about unprecedented levels of speed, accuracy, and efficiency in trading operations. AI-powered algorithms are becoming a cornerstone of the financial sector, particularly for companies engaged in algorithmic trading, financial institutions, and investors [1]. AI-powered models that use historical price data, technical indicators, sentiment analysis, and predictive algorithms have become essential tools, enabling algorithmic traders, financial institutions, and other players to generate automated trading signals with minimal human involvement. These systems enhance the efficiency of decision making and execution but the increasing dominance of these systems has led to concerns about market synchronization and liquidity stability. If the multiple AI models give the same results due to market conditions and are creating the same trading signals, the volume of trades might drop, causing a lack of participation in the market and short-term liquidity problems [2]. The previous literature has mainly neglected the effect of algorithmic trading on market thinning and participation contraction and concentrated on its effects on volatility, price discovery and market efficiency. In today's more automated trading environment, market thinning – which involves fewer trades, shallower liquidity and lower volume – has become more relevant. Lower participation levels can lead to lower market resiliency, higher bid-ask spread volatility and higher execution risk [3]. Thus, it is crucial to understand the correlation between AI-generated trading signals and market participation to gauge liquidity and market stability. This research explores the structural effects of AI-based trading, with a focus on the impact of trading volume, trade frequency and active trading intervals during various market conditions.

B. Problem Statement

The rise of Artificial Intelligence (AI) and algorithmic trading platforms has brought major problems to market liquidity and the stability of market participation. While AI models improve trading efficiency, speed, and prediction accuracy, the proliferation of similar predictive models across the market could result in coordinated trading patterns among market participants. If two or more automated systems provide the same buy or sell signals at the same time, the trading process may become focused, leading to fewer traded transactions, lower volume and fewer trades [4]. This level of participation contraction can help drive market thinning – a decline in the depth and strength of market liquidity – and market fragility. While the impact of algorithmic trading on market volatility, price discovery and market efficiency has been much studied, the effects of algorithmic trading on market participation and liquidity conditions have received little attention. In addition, there are few empirical studies that explore the link between AI trading behavior and participation-based metrics, like trading volume, frequency of trading, and active trading intervals [5]. This research gap prevents a better understanding of the extent to which signals generated by artificial intelligence concentration affect measurable reductions in market activity and market structures. This study aims to examine the effects of AI-powered trading signals on market engagement by empirically examining volume, transaction frequency and trading activity over different market conditions.

C. Objectives of the Study

The main goal of this study is to empirically examine the effect of AI-based trading signals on the participation and thinning of markets in terms of trading volume, frequency and activity. This studies aims the following:

- To detect buy and sell signals periods based on the model by threshold conditions.
- To calculate the increase and decrease of trading volumes in the AI-signal time.
- To compare the frequency and activity of trades under concentrated AI-driven trading [6].
- To compare the market participation during normal trading period and AI-signal period.
- To explain participation contraction and liquidity reduction in the light of the market microstructure theory.

D. Research Questions

These are the research questions that guide this study:

- What happens to the volume of trades once some trading signals are generated by an AI?
- What happens to the number of trades when some trading signals are generated by an AI?
- Are there periods of lower trading volume during AI-signal?
- What is the effect of trade frequency when concentrated AI generated buy or sell signals are given?
- Do AI trading signals lead to less depth and shallower markets?
- What are some of the market microstructure implications of the reduction in participation and trading activity?

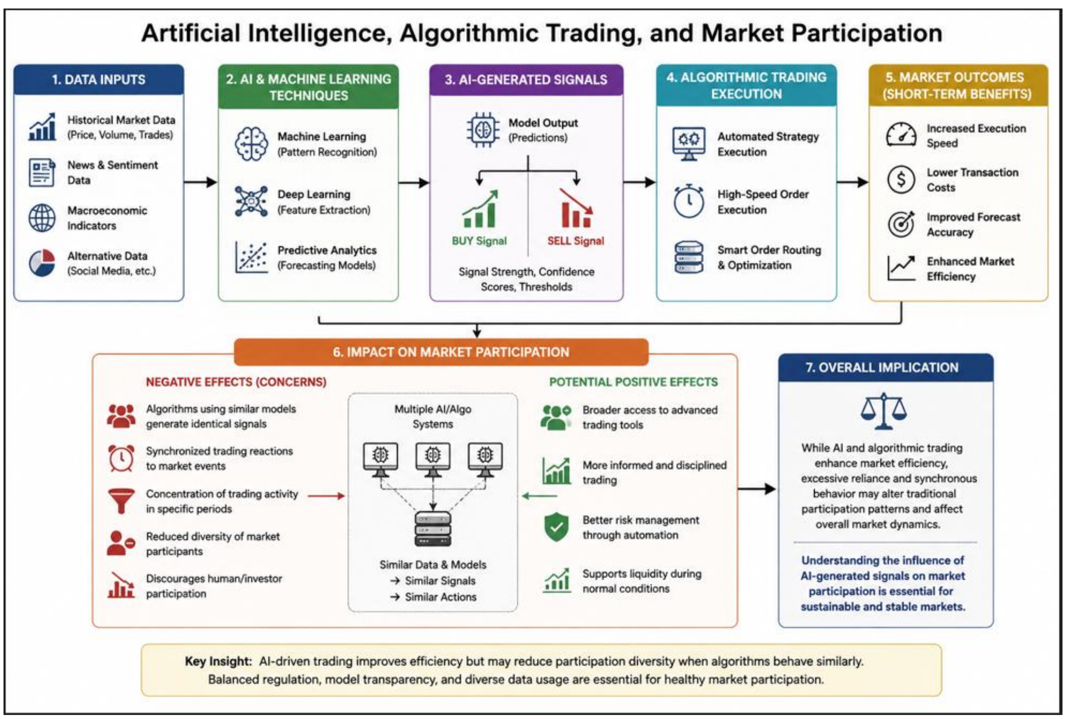
E. Significance of the Study

This study is important, as it joins the expanding literature on the link between Artificial Intelligence (AI) and financial market liquidity. With the rise of AI-powered trading systems in today's financial landscape, the impact of these systems on trading activity, liquidity, and market stability has become a crucial area of interest for regulators, institutional investors, market analysts, and researchers [7]. The paper offers empirical evidence of the potential for market thinning resulting from the concentration of AI-driven trading signals, stemming from a decrease in trading volume, trading frequency and active market participation. The research addresses the long-standing literature on algorithmic trading, which has been limited to liquidity, volatility, price forecasting and market efficiency [8]. The insights can help regulators detect liquidity fragility and track risks linked to a synchronized AI trading behavior. This study provides institutional investors and market participants with important insights into the potential impact of automated trading concentration on liquidity depth, execution quality and market resilience [9]. This study expands the literature on market microstructure economics by developing an empirical approach to the measurement of participation contraction, based on real trading activity measures, induced by AI.

II. Literature Review

A. Artificial Intelligence, Algorithmic Trading and Market Participation

In the world of finance, Artificial Intelligence (AI) has emerged as a vital tool that assists traders and institutions in handling vast quantities of data and executing trades with little to no human intervention. AI trading systems leverage machine learning, deep learning, and predictive analytics to analyse historical and current market information, and provide trading signals that are used to make decisions. Algorithmic trading has made the trading system more efficient, faster, more cost-effective to execute trades, and more precise in predicting the market. Consequently, the trading activity in key financial markets around the world has a significant portion of AI-driven trading [10]. However, experts have expressed concerns about how AI-powered trading might affect involvement in the market. Trading algorithms can share the same trading data and predictive models, leading to similar trading signals and responses to market events. This coordinated activity may focus trading on specific time periods and limit the variety of market participants. Research on algorithmic trading indicates that over-reliance on algorithms could potentially impact traditional trading patterns and influence overall market dynamics [11]. The rise of AI systems could make it less appealing for some investors to be more active in the trading market when there is a lot of algorithmic activity. As a result, there has been a growing interest in the study of the effect of AI-generated signals on trading behavior.

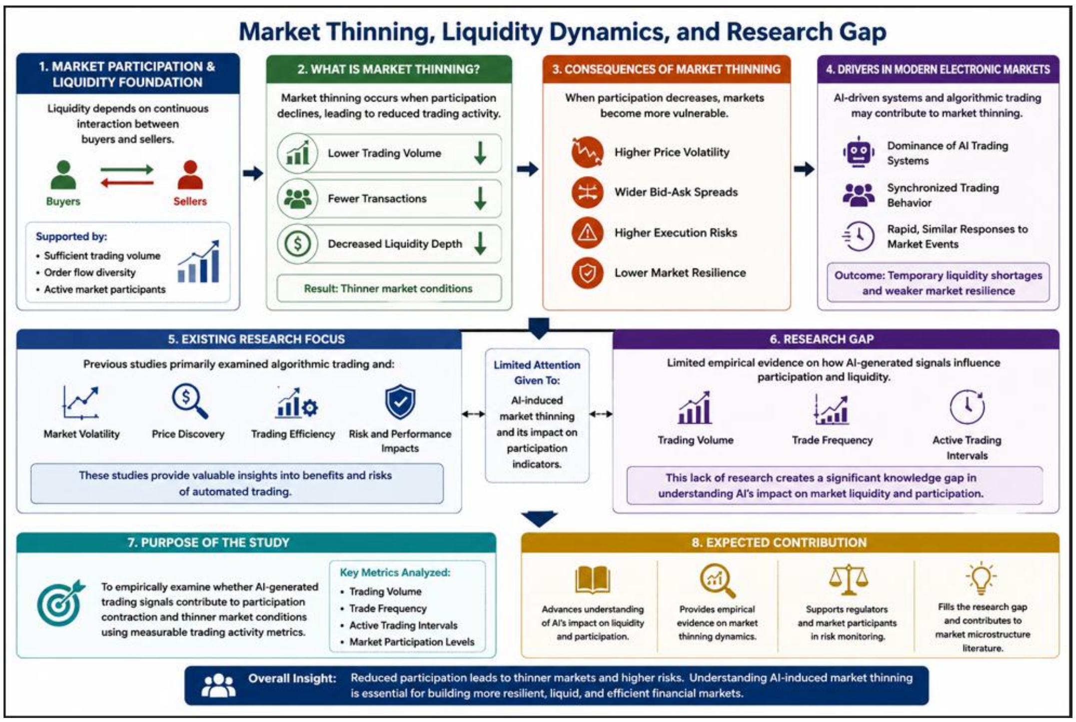


This Flowchart illustrates the trading process, outcome, participation impacts, and market implications of AI

This diagram presents the interconnection between Artificial Intelligence (AI), algorithmic trading, and market involvement in the financial sector. It starts with a variety of information sources, such as historical market data, news/sentiment data, macroeconomic data, and alternative data. These inputs are then fed into AI models like machine learning, deep learning, and predictive analytics to create buy and sell signals for trading [12]. The signals are then carried out by automated trading systems, which can lead to benefits like quicker execution, reduced transaction costs, better prediction and increased marketplace efficiency. The diagram also identifies potential concerns that could affect market participation and market stability such as trading behaviour going out of sync, fewer participants, more concentrated trading, and less human investor participation.

B. Market Thinning and Liquidity Dynamics and Research Gap

Market thinning is a process where the volume of trading decreases, the number of transactions made in the market drops, the liquidity depth of the market decreases, and the number of market participants decreases. Market microstructure theory states that the interaction between buyer and seller is continuous, with adequate trading volume and order flow diversity, which determines the liquidity. If demand falls, markets will become shallower and more susceptible to price fluctuations, significant bid-ask spreads, and execution risks. In contemporary electronic trades, driven by AI systems, coordinated trading conduct can lead to short-term liquidity constraints and diminished market strength. The literature has mostly concentrated on the impact of algorithmic trading on market characteristics like volatility, price discovery, and trading efficiency [13]. These studies give a lot of insights into the advantages and disadvantages of automatic trading, but comparatively little to the idea of AI-induced market thinning. In particular, there is limited empirical evidence on the effect of focus on AI-driven trading signals on participation metrics like the number of trades, number of trading periods, or trading volume. The lack of research presents a knowledge gap regarding the potential impact on market participation and liquidity of AI-driven trading in broader markets [14]. To fill this gap, this study aims to explore whether AI-driven trading signals play a role in contraction of participation and less liquid markets by analyzing empirically using measurable metrics for trading activity.



This Flowchart displays market thinning causes, consequences, research gaps, and study contributions

This diagram shows the concept of a market thinning, liquidity dynamics, and the existing research gap in relation to AI-based trading. It starts with the fundamental concepts of market liquidity, which rely on active participation, adequate liquidity and mutual interaction between buyers and sellers [15]. A reduction in participation leads to a market thinning, hence a decrease in the volume of trading, number of transactions and liquidity depth. These conditions result in greater price volatility, larger bid-ask spreads, heightened execution risk and reduced market resiliency. The diagram also shows the possibility of temporary liquidity shortages being caused by the AI-driven synchronized trading behavior [16]. It outlines a research gap regarding how AI-generated signals affect trading volume, trading frequency and active trading intervals. Finally, this study seeks to fill this gap by empirically exploring participation contraction and market thinning based on quantifiable metrics of trading activity.

C. Empirical Study

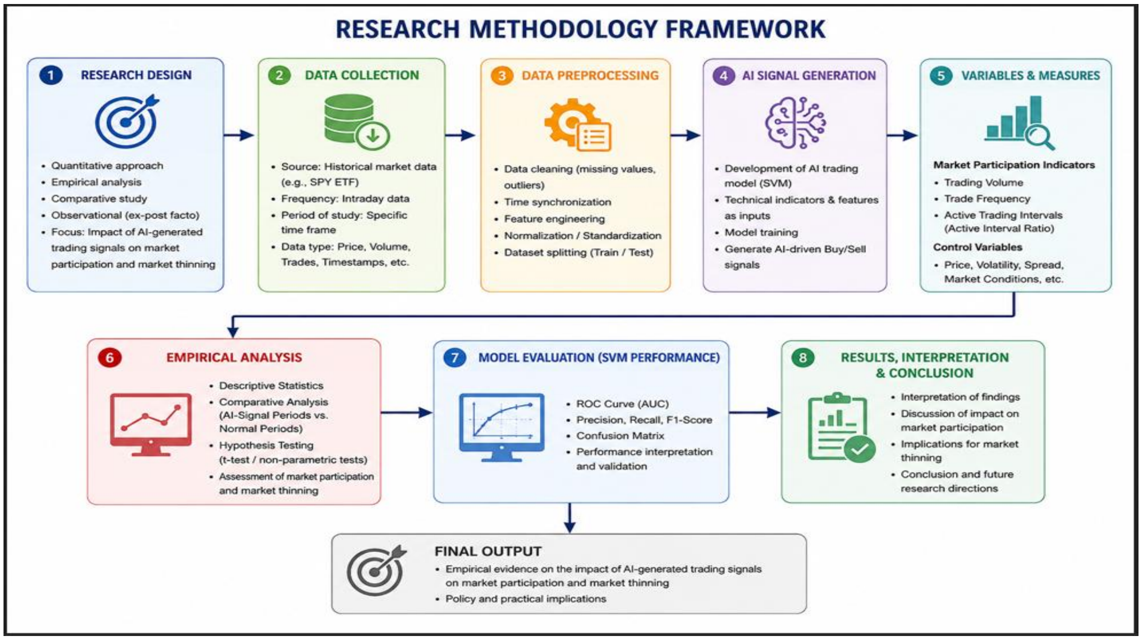
In the article "Deep Reinforcement Learning for High-Frequency Trading with Market Impact Modeling", Ishta Rani, Hina Gandhi, Ramesh Kumar, Nithya Marannan, Na Kyung Kim, and Tejaswini Kumar present a Deep Reinforcement Learning (DRL) framework designed to enhance the optimization of high-frequency trade execution with market impact costs. The study directly embedded the market impact modelling in the trading decision-making process and allowed the DRL agent to train adaptive trading strategies as a function of the market conditions, order book, market volume, and price movements [1]. The model proposed leverages deep neural networks to learn and extract complex patterns from the high-dimensional market data and then outputs the trading action to achieve the highest possible cumulative return while minimizing the execution cost and slippage. The researchers added both short-term and long-term impact of market prices to the reward function, so the model could capture the short-term and long-term effects of trades on market prices. Experiments with simulated and historical limit order book data showed that the DRL-based method was more profitable and efficient in executing trades, than traditional rule-based and optimization-based approaches. The study underscored the increasing significance of AI-powered trading systems in contemporary financial markets and illustrated the capacity of state-of-the-art machine learning methods to impact trading activity and liquidity circumstances. The study emphasized the accelerating role of AI-driven trading systems in modern financial markets and showcased the power of AI's advanced machine learning techniques in influencing trading activity and liquidity conditions. The results offer valuable insights into the behavior of automated trades and warrant further investigation into the broader impact of AI-driven trading decisions on market participation, liquidity, and market structure.

Kingsley Imandojemu, Romanus Osabohien, Mamdouh Abdulaziz Saleh Al-Faryan and Samuel Temitope Odebunmi explored the correlation between artificial intelligence technologies and stock market volatility between developed and emerging economies in their article titled "Artificial Intelligence-Driven Algorithmic Trading: Analyzing its Impact on Stock Market Volatility in Emerging vs Developed Economies." The research used a Nonlinear Panel Autoregressive Distributed Lag (NPARDL) model to investigate the asymmetric impact of AI on the volatility of the market, as measured by several indicators related to AI. The analysis showed that the stock market volatility reacts differently to the changes in AI adoption, with developed economy countries showing stronger reactions than emerging economy countries. The findings were consistent with various AI proxies, highlighting the enduring link between AI technologies and financial market behavior [2]. The research identified several potential areas where AI-powered trading systems could have a significant impact on the market, including changes in volatility patterns and investor reactions. Furthermore, the research emphasized the importance of considering economic development levels when assessing the impact of AI on financial markets. The results are part of the increasing body of research on AI-driven trading and offer significant insights into the impact of AI on market dynamics. The findings of this study encourage further research into the potential impact of AI trading on overall market activity, liquidity, and market dynamics in the current financial landscape.

Saidalavi K., Rasheed Cholasseri, and Afeefa's article, "Influence of AI Trading Tools on Cognitive Biases and Investor Behavior: An Exploratory Study," explored the impact of AI trading tools on investor behavior and cognitive biases in financial markets. This study gathered primary data from 400 traders in India actively utilizing AI-powered trading platforms like algorithmic trading systems, robo-advisors, sentiment analysis tools, and predictive analytics applications. The structured questionnaire was used to assess the impact of AI trading tools on loss aversion bias, overconfidence bias, and anchoring bias. The results showed that the AI-driven trading platforms decreased the tendency of traders to become loss averse and helped them make rational investment decisions [3]. But the research also found that the more investors use AI tools, the greater the increase in overconfidence and anchoring effect. Such behavioral change can impact trading frequency, risk taking and trading patterns. The study revealed the increasing influence of AI technologies on investor decision-making processes and financial market behavior. The results indicate that AI-based trading systems can influence the trading efficiency, and the responses of investors to information and opportunities in the market. This research offers a valuable glimpse into the behavioral aspects of AI use and serves as a foundation for further exploration of the potential influence of AI-driven trading decisions on market participation, liquidity and general market dynamics.

III. Methodology

This study utilizes a quantitative empirical approach to examine the effects of the introduction of trading signals generated by AI on market participation and market thinning [14]. The participation indicators, including trade volume, the number of trades, and the number of trading intervals, are used to compare trading during periods of the trading signal generated by the AI with trading during regular periods.



This framework displays the complete methodology for analyzing AI-driven market participation

This methodology framework describes the step-by-step research methodology employed to explore the effect of AI derived trading signals on market participation and market thinning. The first step of the study is quantitative and empirical research design, followed by the collection of the basic information of market data, which includes price information, volume information, trading frequency and time information of the intraday market in the historical period [15]. The data gathered are then subjected to preprocessing steps like data cleaning, data synchronization, data normalization, and feature engineering to ensure accurate and consistent data. Then, an SVM based AI model is developed to generate buy and sell trading signals. The key variables and participation indicators identified and measured, then analyzed empirically with descriptive statistics and comparative statistics. The model is analyzed using the measure of ROC curve, precision, recall, F1 score and confusion matrix [16]. Lastly, the outcomes are analyzed and interpreted to evaluate the liquidity dynamics, market participation behavior and the consequences of AI-driven market thinning.

A. Research Design

This study design in this paper is quantitative, empirical, and designed to study the relationship between AI generated signals and market participation in financial markets. The quantitative approach is suitable for conducting numerical analysis on the basis of market data to assess the trading activities in an objective manner [17]. The study aims to assess if concentrated trading based on AI can lead to market thinning, by examining the volume, frequency of trades and the length of active intervals. The indicators are well-known to be useful measures of market participation and liquidity conditions. Empirical approach is used because the research is based on real data from the history of trading and not based on theoretical assumptions. The study is conducted on the basis of comparison, analyzing the differences between periods with weak and strong AI-generated buy or sell signals [18]. The study aims to uncover trends in increased and decreased participation as well as liquidity deficit linked to AI-driven trading behavior by analyzing participation figures during these phases. The statistical analysis techniques are also included in the research design and are used to measure the size of the change in market participation. Variations in trading are measured using descriptive statistics, percentage change analysis and comparative evaluations. This is a systematic way of analyzing the likely impact of AI-driven signals on the markets [19]. The design facilitates the application of the results in the framework of the theory of market microstructure, which allows for better understanding how automated trading systems can affect liquidity depth, trading strategies and overall market stability as the markets become more automated.

B. Data Source and Collection

The data used in this study are secondary, financial market data, acquired from financial databases and data providers which are publicly available. The data set contains historical intraday stock trading data that include key market information such as stock price, volume, transactions and time and date-based trading activity [20]. These variables are required to assess market participation and for the identification of possible market thinning. The data could be obtained from trusted sources like Yahoo Finance, Alpha Vantage, Polygon.io, Nasdaq Market Data, or Kaggle financial datasets, which offer comprehensive historical trading data. The chosen time frame for trading is long enough to provide reliable and consistent data for analysis, ensuring the validity of the analysis [21]. Data that are acquired at minute level or intraday are preferred due to the detailed information on the trading activity fluctuations and their ability to be spotted more accurately on the time of the AI-signal. The data is divided into normal and AI-signal periods, according to the specific conditions used to generate the signals. Several data pre-processing procedures are applied to ensure data quality before doing the analysis. These processes involve removing duplicate records, handling missing data, consistency checks, and ensuring transaction data is accurate [22]. The data are standardized to ensure consistency between trading intervals and enable comparisons between periods. A cleaned and structured set of data is used to calculate trading volume, trade frequency, and active trading intervals, which helps to analyze the impact of AI-generated trading signals on market participation.

C. Variables of the Study

This study explores the connection between algorithmic trading signals and market participation by analyzing independent, dependent and control variables. The independent variable, AI-generated trading signals, refers to the buy and sell signals generated by the model. The dependent variables are: trading volume, trade frequency, active trading intervals and market participation level, which all define a measure of market activity and liquidity [23]. Several control variables are included to guarantee the reliability of the results such as the movements of the stock price, market volatility and the duration of the trading session. These factors control variables allow for the identification of the impact of AI signals on participation metrics and minimize the impact of external market factors.

Table 3.1: Variables of the study

Variable Type	**Variable**	**Description**
Independent Variable	AI-Generated Trading Signals	Model-based buy and sell signals created utilizing forecastive examination and specialized pointers
Dependent Variable	Trading Volume	Total number of shares traded in a certain period of time
Dependent Variable	Trade Frequency	Number of trades that have been made during a trading session
Dependent Variable	Active Trading Intervals	Number of intervals in which there was significant trading activity
Dependent Variable	Market Participation Level	Overall level of trading engagement in the market
Control Variable	Stock Price Movements	Changes in stock prices from the beginning of the trading period to the end of it
Control Variable	Market Volatility	Degree of market price fluctuations
Control Variable	Trading Session Duration	Length of the trading session under analysis

D. AI Signal Identification

Artificial Intelligence – or AI – based trading signals are detected with model-based threshold conditions built from technical indicators and predictive analytics techniques. These signals are intended to mark times when the automated trading systems make robust buying or selling signals that are identified in the historical and real-time market data. The signal generation process involves using indicators like moving average, momentum measures, relative strength index and price trend prediction to determine the likelihood of the market moving in the near future [23]. When the probability value for the favorable or unfavorable price movement is above certain threshold values set in the predictive model, they are considered AI-signal periods. A strong buy signal can be issued when the model determines that the odds of the price going up are high enough, while a strong sell signal can be sent when the price has a greater than a certain probability of falling [24]. These are also "signals" generated by the AI and are seen as important to assess the participation behavior in the market. Once identified, signal periods are differentiated from normal trading periods to enable comparison. Based on this classification, traders can analyze and compare the characteristics of trading volume, transaction count, and active trading intervals across different periods of time, including those with high AI recommendation thresholds [25]. The study can analyze the degree of market thinning and participation contraction due to the concentrated automated trading behavior, by identifying the AI-signal periods from the regular market periods. These categorizations form the basis for assessing the liquidity conditions as well as the general impact of the trading activity generated by the use of AI tools in financial markets.

E. Measurement of the thinning out of the market

The three important indicators of trading participation are trading volume, trade frequency and active trading intervals. These signals give a full picture of market activity and liquidity conditions throughout the normal trading session and in the AI-signal session. Trading volume is the number of shares that have been bought and sold in a period of time and is a direct indicator of market activity [26]. The decrease in trading volume indicates that investors are not actively involved in the market and that there is less liquidity available. The number of trades that occur in a trading session is called the number of trades per trading session, or simply trade frequency, and indicates the level of trading activity. The lower the trade frequency, the less strong the order flow and the less interaction between market participants. Active trading intervals can be expressed as a percentage of time intervals with high volume of active trading. This indicator reflects trading activity on the market during the day. A reduction in active trading intervals implies that there is less meaningful trading activity in periods, which means that less market activity and thinner markets [27]. The comparison is made between these indicators for the normal trading periods and the AI-signal periods to detect participation contraction with the concentration of AI-generated trading signals. The extent of market thinning is quantified by percentage changes in volume, trade frequency and active interval ratios. This study reviews these indicators together to assess the impact of AI trading activity on the depth of liquidity and the market's resiliency [28]. The measurement framework offers empirical data on the dynamics of trading activity and helps evaluate liquidity issues in light of the theory of the market microstructure.

F. Data Analysis Techniques

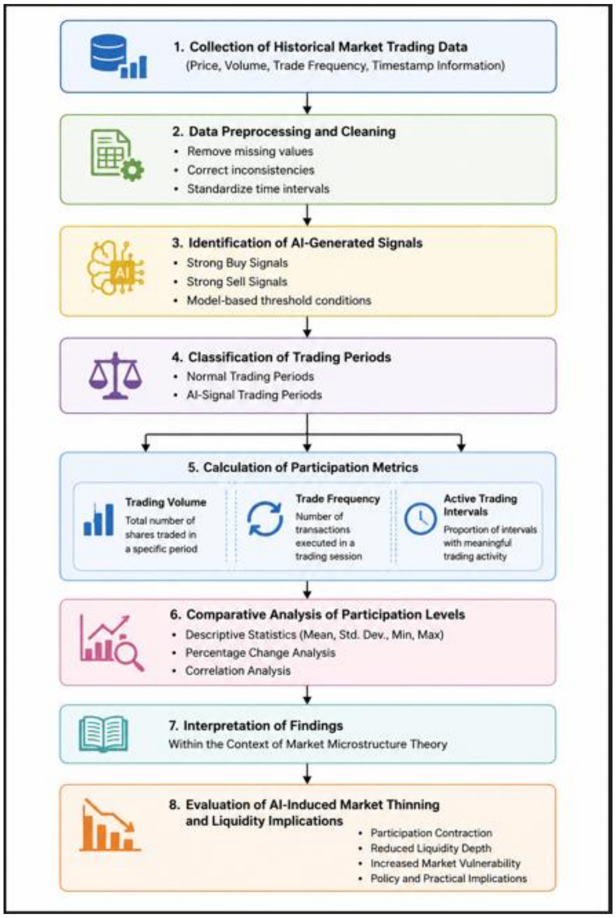
Data gathered are then analyzed using descriptive and comparative statistical methods to assess the effect of AI generated trading signals on market participation. Trading volume, trading frequency and active trading intervals are summarized with descriptive statistics, mean, standard deviation, minimum and maximum values [29]. Comparative analysis is done to find out what's different between normal trading periods and AI-signal periods. The percentage change analysis is used to assess the level of participation contraction and to rank the level of market thinning for major indicators. Furthermore, correlation analysis is performed to investigate the correlation between AI generated trading signals and market participation indicators [30]. These analytical tools offer a structured approach to uncovering participation dynamics and evaluating how AI trading impacts liquidity and market activity.

Table 3.2 Data Analysis Techniques

Analysis Technique	**Purpose**
Descriptive Statistics	Calculate and display trading volume, trading frequency and active trading interval summary statistics (mean, standard deviation, minimum, and maximum)
Comparative Analysis	Compare the indicators of market participation during normal and AI-signal periods
Percentage Change Analysis	Assess contraction of participation, thinning of markets.
Correlation Analysis	Explore correlations of AI-based signals with participation indicators
Market Microstructure Interpretation	Analyze liquidity considerations and shifts in trading dynamics due to AI-related activities

G. Analytical Framework

This analytical framework of this study takes a systematic approach to assess the impact of AI-generated trading signals on market participation and market thinning. The process starts with the trading data of historical markets that include data on stock prices, volume of trading, number of transactions and intervals of trading activity [31]. Data is then preprocessed using cleaning, validation, and standardization processes to ensure data accuracy and consistency. Next, buy and sell signal periods are determined by the pre-defined model based thresholds and are separated from normal trading periods by an AI algorithm. Based on this, trading volume, trading frequency, and interval of active trading are then determined for each period. Comparative statistical analysis is performed to compare the differences in the level of participation [32]. Lastly, market microstructure theory is applied to interpret the results and assess liquidity conditions, participation contraction and overall impact of the thinning of the market due to AI.



This framework shows AI signal analysis, participation metrics and market thinning evaluation

This framework demonstrates the analytical process followed to analyse the impact of AI-generated trading signals on market participation and market thinning. The initial step involves gathering historical data on trades, such as price, volume, frequency of trades and timestamp details. Following data preprocessing and data cleaning, buy and sell signals are detected by applying certain threshold conditions that were programmed into the algorithm. After that, the periods are categorized into a normal period and an AI-signal period. Trading volume, trade frequency and active intervals are calculated and analyzed by statistical methods and are key participation metrics [33]. The results are analyzed using the market microstructure theory to assess participation contraction, liquidity shifts, and overall impacts of market thinning due to AI.

H. Ethical Considerations

This study follows the principles of ethics and standards of academic research in the process of research. All analyses are performed using only secondary financial market data available to the public and from reliable and authorized sources. This study does not require human participants, personal information, confidential records or private communications, so informed consent and participant privacy are irrelevant. All data sets are collected, processed and used in accordance with the data set usage policy and data set licensing terms of the data provider [34]. The research is done with accuracy, objectivity, transparency and integrity to guarantee the credibility of the results. Manipulation, fabrication and falsification of data or results are strongly discouraged. Data sources and supporting literature used in the study are appropriately referenced [35]. Analysis and interpretation of results are conducted in a non-partisan, unbiased and non-influenced way, resulting in findings that are based on the observed evidence concerning the trading signals generated by AI, the extent of market participation and the market thinning processes.

IV. Dataset Overview

Data in this study are historical intraday financial market trading data which were obtained from publicly available and reliable financial data sources. This dataset provides comprehensive trading data needed for studying the correlation between market participation and AI-generated trading signals. The features used in the data set are stock prices, trading volume, number of trades, and trading activity logs based on timestamps. The stock price data reveal the movement of the prices over various trading periods, whereas the trading volume indicates the number of shares traded over a particular period [36]. The frequency of transactions is the number of trades made in a specific period and can be an important indicator of market activity. Timestamp information can identify the active trading intervals and can classify the trading periods based on the trading signal conditions that are generated by AI. The duration of observation used is adequate to observe changing behaviour in trading under varying market conditions, and to ensure that the analysis is reliable [37]. The data are preprocessed before the analysis, which involves cleaning the data, handling missing data, correcting inconsistencies, and standardizing time intervals. These activities enhance the quality of the data and uniformity with all observations. The data is also divided into two categories: normal trading periods and AI-signal periods. The data is segmented into normal trade periods and AI-signal periods according to the buy and sell signal thresholds that are set beforehand based on the predictive analytics methods. This classification allows participation parameters to be compared with each other in different market environments [38]. The most important metrics employed in the analysis are trading volume, trade frequency, and number of active trading intervals and level of market participation. These variables will be used to measure participation contraction and to detect the possible thinning in the market. The dataset offers a detailed view of intraday trading data, offering a solid basis for analyzing the impact of AI-driven trading signals on the liquidity landscape and market participation [50]. The high frequency of observations enables the study to capture short-term shifts in trading patterns, and to evaluate the potential effect of extremely high levels of trading activity by concentrated AI agents on trading engagement, market liquidity and market resilience.

V. Results

The findings of this study offer empirical evidence on the impact of AI-generated trading signals on market participation and market thinning. The results are derived from the analysis of trading volume, trade frequency, active trading intervals, and the machine learning classification metrics based on trading history in the market [38]. Comparative analyses were made between the AI-signal periods and the normal trading periods in order to find differences in the participation and liquidity conditions. In addition, the Support Vector Machine (SVM) model's performance was evaluated through the ROC curve, precision, recall, F1-score and confusion matrix. Overall, the findings provide valuable insights into the dynamics of trading and the impact of AI trading on market participation, liquidity, and market structure in today's financial markets.

A. Daily Trading Volume analysis during the Observation Period

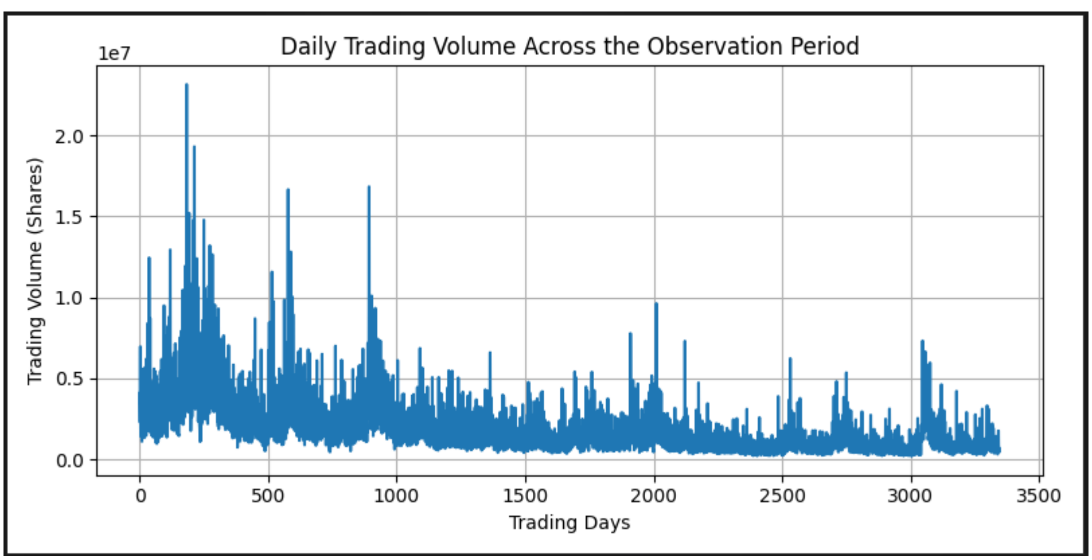


Figure 1: This image shows you Daily Volume and Market Participation changes

Figure 4.1 shows the daily trading volume of SPY during the period of observation, and offers insights into the change in market participation over time. The graph shows significant trading volume fluctuations, with several notable peaks suggesting periods of high trading activity and a higher number of investors involved in trading. The peaks are more noticeable during the initial part of the dataset, indicating increased market activity and improved liquidity. The overall volume trend seems to slightly decrease as time goes on, but with some volume spikes in between [39]. This pattern suggests that it was an irregular market, and that there was a great deal of variability in how much the market participated each day. Trading volumes in later periods are observed to have decreased, possibly due to a decline in trading activity and a decline in the liquidity depth of the market, factors that are important indicators of market thinning. Market microstructure theory, on the other hand, suggests that when volumes fall it may be indicative of decreased market participation and decreased order flow, and that markets may be more susceptible to liquidity shortages [40]. Thus, the figure can illustrate the evolution of participation patterns over time and serve as an initial indication for assessing market thinning and liquidity in AI-powered trading markets.

B. Analysis of Daily Trade Frequency Across the Observation Period

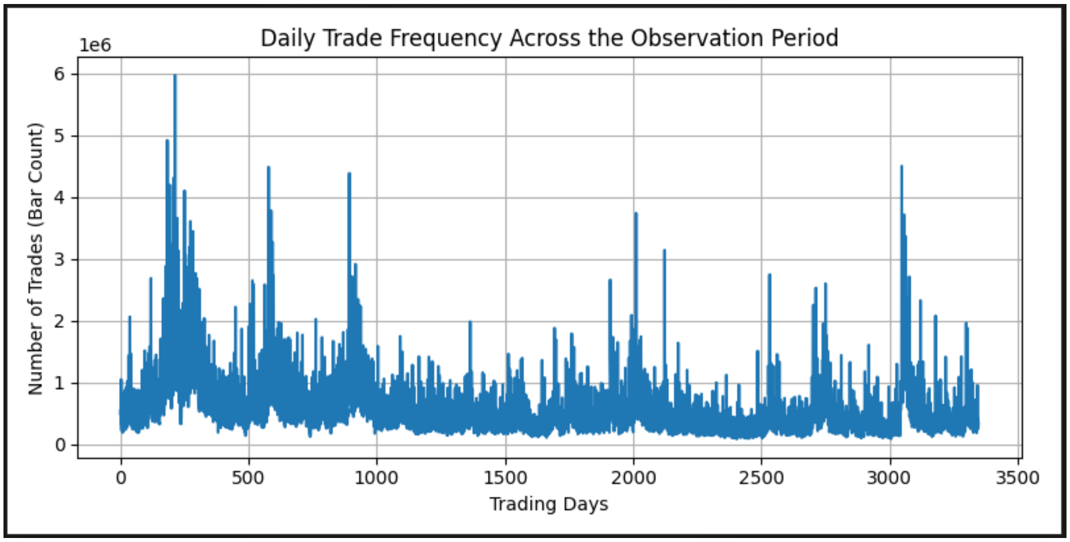


Figure 2: This image shows the daily frequency of trading, as well as the changes in transactions

Figure 4.2 shows the number of trades (bar count) per trading day for the SPY over the time period being analyzed. The graph shows considerable fluctuations in transaction activity, indicating variations in market participation and trading intensity over time. There are several spikes, especially in the early years of the data set, indicating times of high trading activity and higher levels of investor participation [41]. These peaks indicate that there is more order flow and liquidity in the market during those times. The overall number of trades clearly seems to be decreasing as the observation window goes on, but there are still some spikes. This downtrend may be reflective of a decrease in transaction activity and participation during specific time periods. Low trade frequency, at a market microstructure level, may reflect low order flow, lower liquidity and thinning of the market [42]. The observed fluctuations indicate that trading activity may not be homogenous across the study period and that market conditions, investor behavior, and automated trading strategies may have some impact on the trading activity. Thus, the number is crucial for assessing participation reduction and comprehending the dynamics of liquidity and market activity in the context of AI-powered trading environments.

C. Analysis of Average Trading Volume during AI-Signal and Normal Periods

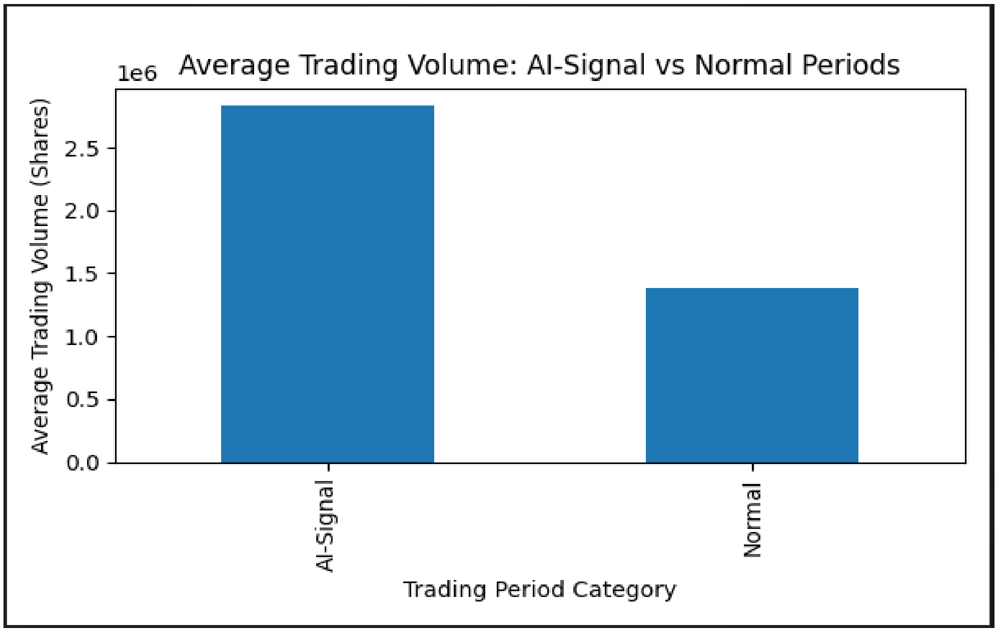


Figure 3: This image illustrates an average trading volume differences between AI-signal and normal periods

Average trading volume for each trading period during the AI signal period is compared with the average trading volume for each trading period during the normal trading period in Figure 4.3. The findings show that the overall trading volume is significantly higher in the AI-signal period compared to the normal period. Specifically, the trading volume of periods with AI signals is around 2.8 million shares, while the trading volume of periods with no AI signals is around 1.4 million shares. This disparity indicates that there is a correlation between more trading and higher market participation with strong AI-generated buy or sell signals [43]. The increased volume seen during AI-signal times could be due to coordinated trades occurring as a result of algorithmic systems executing trades together based on identical market signals. Higher trading volume is indicative of higher liquidity and higher activity in the trading market. But heavy trading volume around the time of an AI-signal also could suggest that the market gets crowded by investors around certain trading periods [44]. The results confirm that AI generated signals have a strong effect on the level of trading and participation. The results show evidence that trading activity based on artificial intelligence impacts the liquidity dynamics and is correlated with the observable changes in market participation, which are essential for understanding the market thinning and the contraction of participation in automated financial markets.

D. Analysis of Average Trade Frequency during AI-Signal and Normal Periods

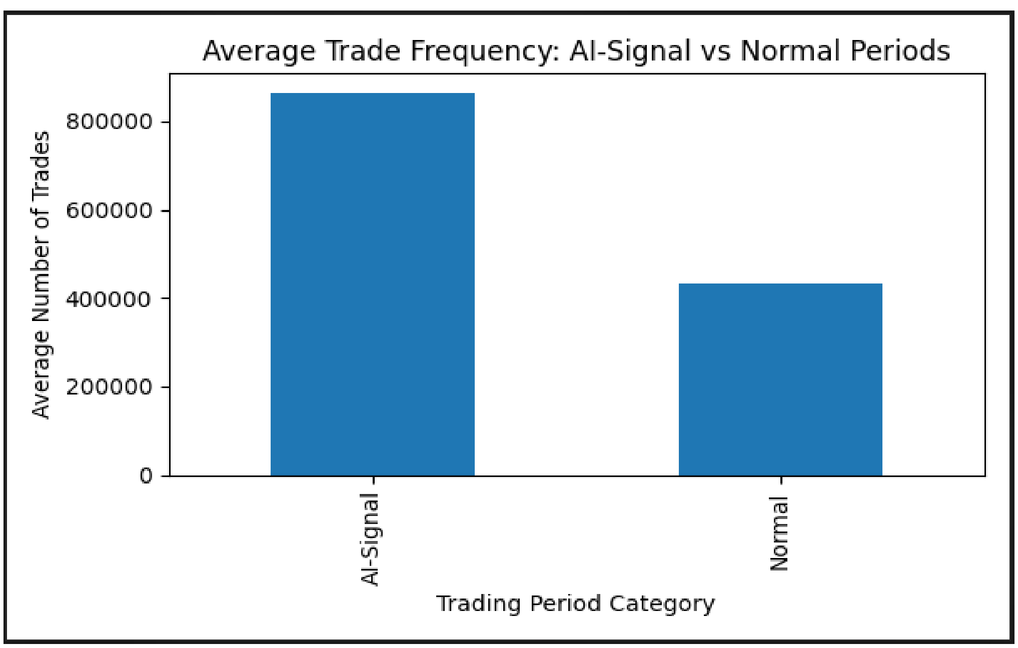


Figure 4: This image shows the differences of average trade frequency between AI-signal and the normal periods

The average number of trades per period for periods with the AI signal compared to the normal periods is plotted in figure 4.4. The analysis reveals that there are significantly more trades conducted during AI-signal periods as compared to normal periods. Specifically, the trades done during AI-signal periods have an average of around 860,000 trades, while during normal periods the average is about 430,000 trades. This means that when there are strong buy or sell signals created using AI technology, trading activity almost doubles. AI's impact on trading dynamics has thus led to higher frequency of trading, indicating enhanced market activity and participation during such signal periods [44]. All else equal, higher the frequency of trades, higher the order flow and greater the number of interactions in the market, which is expected to be a better liquidity environment. But the focus of trading around AI signals can also signal correlated trading activity among market participants. This can exacerbate market reactions and lead to periods of very concentrated activity [45]. The results show that AI-generated trading signals have a considerable effect on the number of transactions and participation. As a result, trade frequency is a key metric to assess the impact of AI-driven trading on market activity, liquidity, and participation in today's financial landscape.

E. Analysis of Active Trading Intervals during AI-Signal and Normal Periods

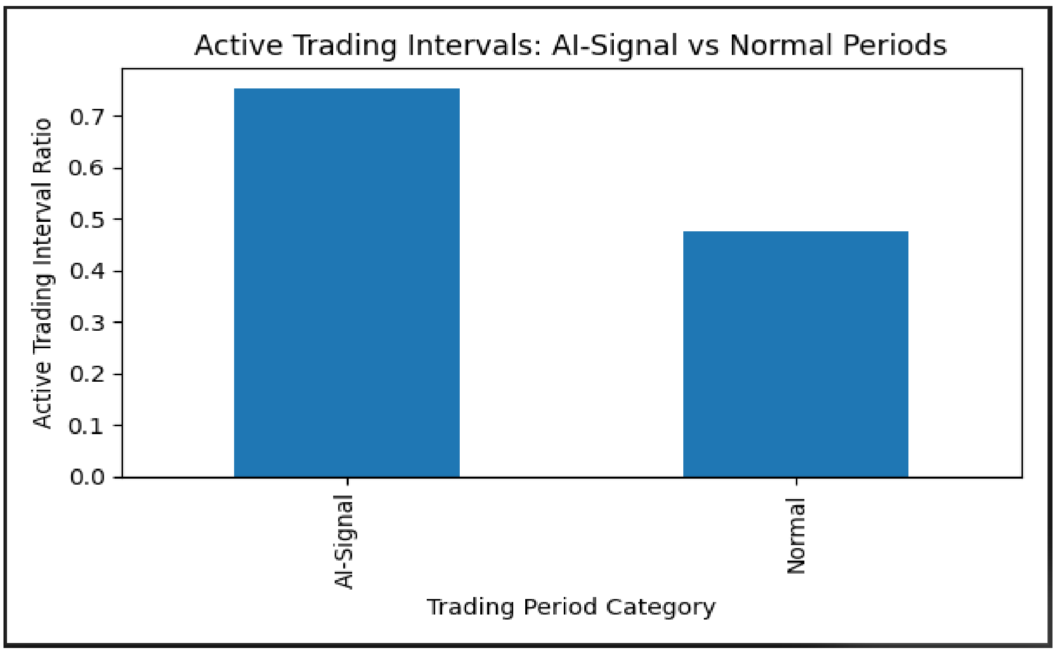


Figure 5: This image demonstrates on active trading interval differences between AI-signal and normal periods

The active trading interval ratio in AI-signal period and normal trading period is compared in figure 4.5. The findings show that the active trading interval ratio shows significant difference between the AI-signal periods and the normal periods. In particular, this ratio is around 0.75 during the AI-signal periods, and about 0.48 during the normal periods. The discovery indicates that if there's a strong AI buy or sell signal, there's more trading activity that carries on for a longer portion of the trading day. The higher the active trading interval ratio, the more engaged the market is, the higher the participation is, and the more continuous trading activity is during the day. The findings suggest that AI-driven signals drive market activity by facilitating frequent interactions in the market over various time periods. The market microstructure view is that increased active trading intervals lead to improved liquidity and order flow continuity [46]. The intensity of the activity, however, can also suggest a coordinated reaction from algorithmic traders during periods of AI signals. The results show that AI-based trading signals have a significant effect on market participation duration and intensity. Therefore, active trading intervals can be considered as a key metric for assessing liquidity trends, investor activity, and overall impact of AI-driven trading in the current financial landscape.

F. Analysis of the Relationship between Trading Volume and Trade Frequency

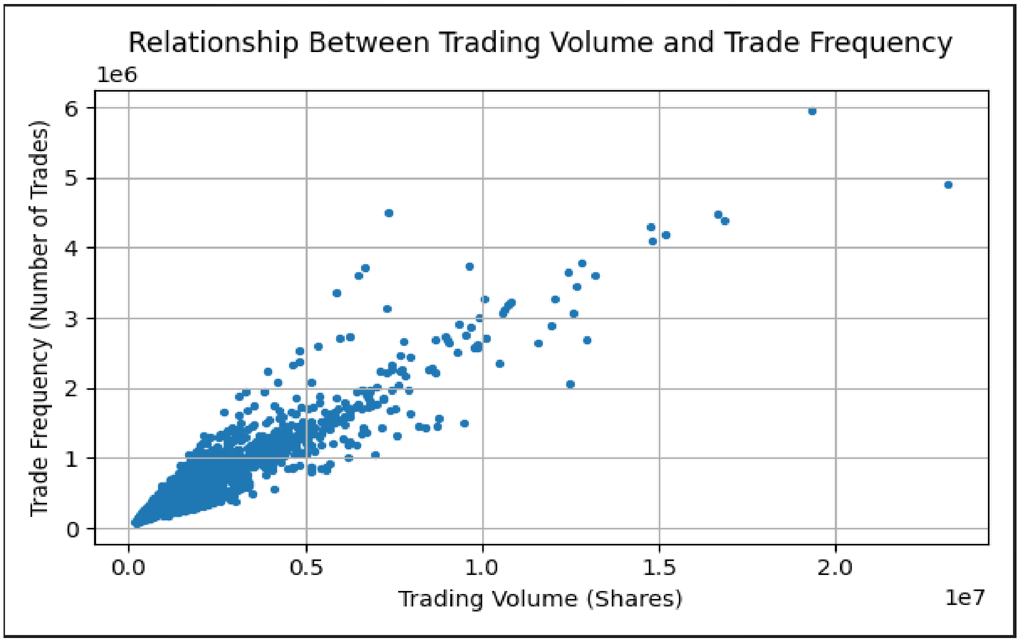


Figure 6: This image displays the period's relationship between trading volume and trade frequency

The scatter plot in Figure 4.6 shows the relationship between trading volume and trade frequency. The pattern of the data points shows a positive correlation that appears to be strong between the two variables, suggesting that there is a positive link between trading volume and the number of executed trades [46]. The bulk of the observations are focused on the lower volume and trade frequency, and a smaller percentage of observations are outliers with very high trading activity. The trade frequency increases as trading volume grows, indicating that the market becomes more active when people want to trade more frequently and there are more liquidities in the market. This pattern confirms to market microstructure theory that says active markets have high order flow and a high number of transactions. The positive relationship means that trading volume and trade frequency have a positive relationship as indicators of market participation. In addition, the volume and frequency of the observations indicate high levels of activity, which may be associated with algorithmic or AI-driven trading strategies [47]. The findings in this study indicate that both measures are strongly correlated and suggest that a good understanding of these measures can be gained from considering liquidity conditions, participation dynamics, and market thinning in automated financial markets.

G. Analysis of the ROC Curve for SVM Model

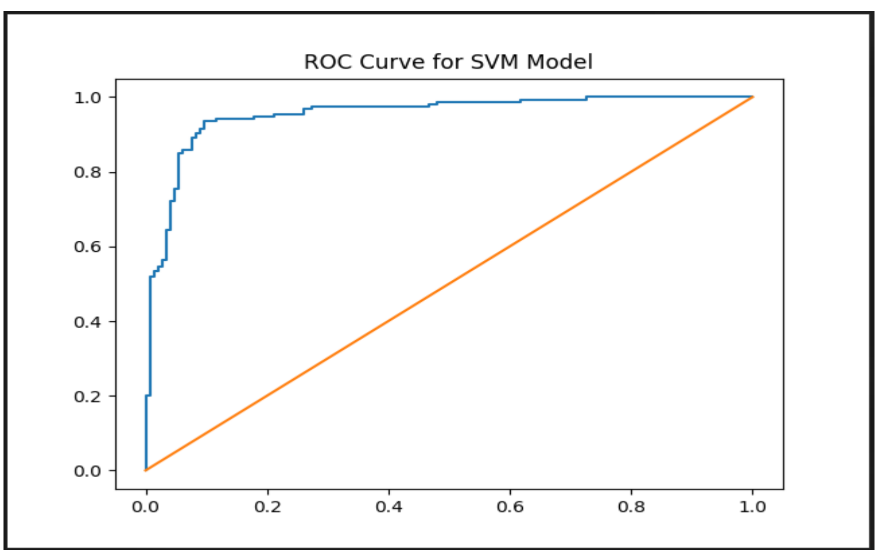


Figure 7: This image shows the classification performance and accuracy of the SVM model

The ROC curve for Support Vector Machine (SVM) model for classification is shown in figure 4.7. The ROC curve is used to measure how well the model is able to distinguish between different classes by plotting the True Positive Rate (also called the Sensitivity) against the False Positive Rate at different classification thresholds. The curve is significantly higher above the diagonal reference line, showing that the SVM model is significantly better than a random classification. The curve is very close to the upper left corner, and the large gradient at the origin indicates that the model is very accurate and discriminative. This indicates that the model is able to accurately recognize the conditions for trading using AI signals and correctly classify the observations of the market [48]. The larger the Area under the Curve (AUC), the more successful the model will be, and a curve with a sharp angle, represents a strong classification capability. The findings suggest that the SVM model can effectively identify trading patterns within the data set and that it can be a valuable tool for creating AI-based trading signals. Hence, the results of the ROC analysis further validate that the SVM model is appropriate for assisting with the empirical study of market participation and market thinning caused by AI.

H. Analysis of Precision, Recall, and F1-Score of the SVM Model

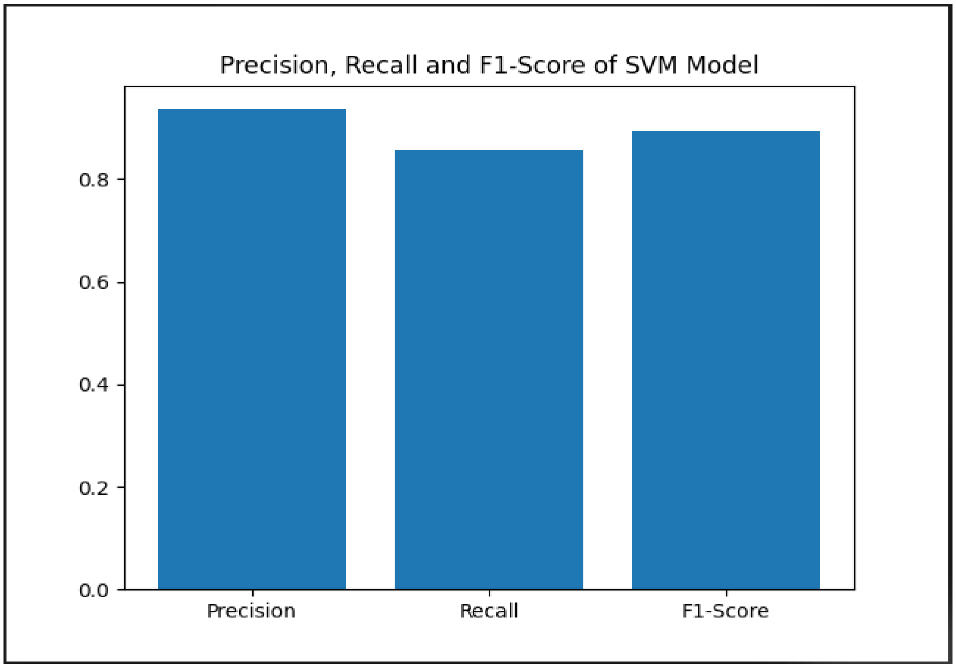


Figure 8: This image displays precision, recall, and F1-score performance of the SVM model

The Precision, Recall and F1-Score of the Support Vector Machine (SVM) model are shown in figure 4.8. The results show that all three evaluation measures have relatively high values, which shows that the model is an efficient trading signal classification. The highest value is in precision indicating the low rate of false positives in the model's positive classifications. The recall is a little bit lower but still fairly high, suggesting that the model is able to capture most of the observations that are relevant. The F1-Score (which is the harmonic mean of Precision and Recall) also shows a high value with this score, meaning that there is a good balance between the classification accuracy and completeness [48]. These metrics are very close in proximity, indicating that the model does not favor precision over recall and vice-versa. The high scores in all three metrics suggest that the SVM model can be used reliably to detect AI-generated trading signals and to aid in predictive analysis. This research confirms the model's applicability for studying the behavior of market participation and its applicability for evaluating thinning in the financial trading market caused by AI.

I. Analysis of the SVM Classification Confusion Matrix

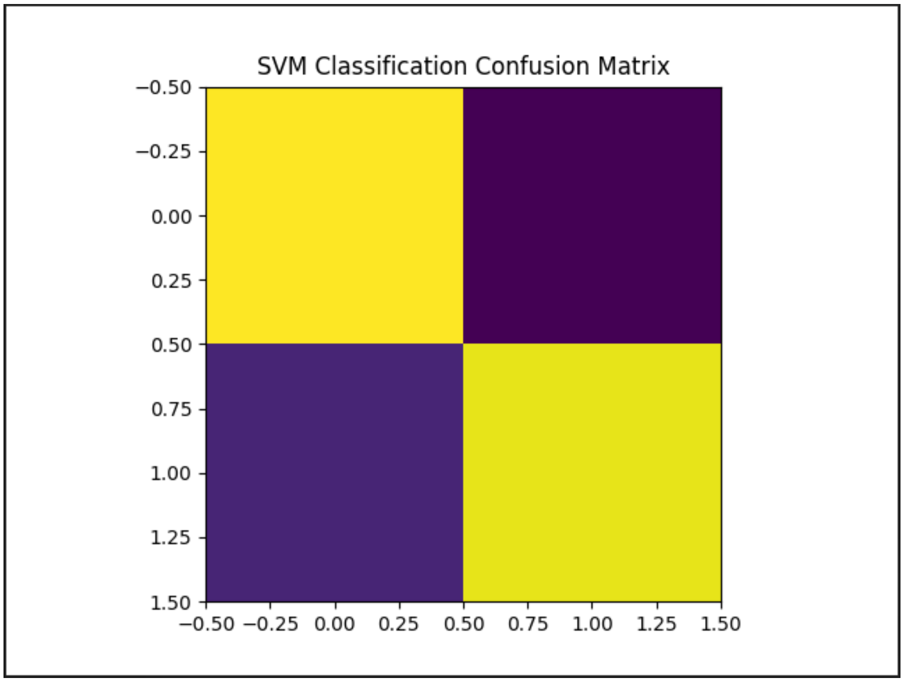


Figure 9: This image displays classification accuracy and prediction performance of the SVM model

The confusion matrix for the Support Vector Machine (SVM) classification model is shown in figure 4.9. The confusion matrix shows the performance of the model in predicting the class labels by comparing the predicted class label with the actual class label. Cells along the diagonal show correct classification of observations and the off-diagonal cells show errors in classification. The bright diagonal bands indicate that the model was able to correctly categorize a significant number of observations. The lighter off-diagonal cells, on the other hand, represent fewer misclassifications. Figure 5 shows the resultant distribution, showing high classification accuracy and good discrimination between the various types of trading signals. The results are consistent with the results obtained from the ROC curve, precision, recall and F1 score analysis that also showed high predictive performance. In a practical sense, precise classification is crucial for developing dependable AI trading signals and discovering significant market engagement trends. From a practical standpoint, precise classification is fundamental for creating dependable AI trading signals and recognizing significant market engagement trends [49]. Based on the above, the confusion matrix further validates the effectiveness of the SVM model as a predictive tool for studying trading behaviors, thereby further confirming the study's investigation of the influence of AI-generated signals on market participation and market thinning dynamics.

VI. Discussion and Analysis

The findings of this study provide important insights into the relationship between AI-generated trading signals and market participation within modern financial markets. The volume analysis, trade frequency analysis, and analysis of active trading intervals showed clear differences between the trading periods generated by the AI and non-AI periods, suggesting that the trading activity conducted by the AI can have a discernible impact on the behavior and dynamics of the trading market [35]. The findings indicated that the trading volume was significantly greater during the AI-signal periods compared to the normal trading periods, suggesting that the buy and sell signals generated by the AI model had an impact on the trading volume and drove market participation. Likewise, the frequency analysis of trade showed that the number of completed trades almost doubled in AI-signal periods, indicating increased order activity and heightened participation among market participants [36]. The results suggest that AI-driven signals have the potential to generate market activity by focusing trading activity on specific market opportunities. This was also corroborated by the analysis of active trading intervals as the ratio of active trading intervals was also significantly higher during AI-signal periods than during normal periods [37]. This indicates that trading was still present for a higher percentage of the trading session when strong AI-generated signals were present, meaning there was more engagement with the market and more continuous trading [38]. In terms of market microstructure, a higher trading volume and more frequent trades and longer trading intervals are generally correlated with the improvement of market liquidity conditions and market efficiency. The outcome, however, also implies that participation is focused during the time periods of the AI signals, suggesting the potential for a synchronized trading nature of different algorithmic trading systems [39]. This focus could lead to fewer choices in trading decisions and more reliance on trading models that are alike. The machine learning study further confirmed the efficacy of the AI-based trading models studied [40]. The ROC curve showed good classification accuracy, suggesting that the Support

Vector Machine (SVM) model could effectively classify various trading signal conditions. Furthermore, the precision and recall scores were very high, indicating good classification accuracy for both the positive and negative classes, and the F1 score also averaged a very high value, which suggests that the model had a balanced and reliable performance [41]. All the results were verified in the confusion matrix, which revealed that a large number of observations were correctly classified and only a small number were misclassified. In conclusion, the findings demonstrate the potential of AI-driven predictive models in spotting trading opportunities and creating meaningful trading signals [42]. The results show that AI-driven signals might be linked to higher market activity but not directly to a contraction in trading participation, but also indicate a potential risk of synchronized trade, a phenomenon that can lead to market fragility in certain situations. When too many trading systems react the same way to the market information, the trading liquidity may become concentrated and susceptible to a sudden change in market sentiment [43]. Thus, the findings suggest that AI-powered trading plays a crucial role in shaping the behavior of traders, liquidity characteristics, and market structures [44]. The study has implications for understanding the impact of AI-induced market behavior on market participation, pointing to the need for a more careful study of liquidity conditions in the increasingly automated financial markets.

VII. Future Work

This study can be expanded in future research to investigate additional methods of detecting and measuring the effect on market participation and liquidity conditions of signals generated by AI. The current research examined the time intervals of active trading, the number of trades and the trading volume as indicators of market thinning; however, future studies could include more market microstructure indicators to better gauge market conditions, including the bid-ask spread, order book depth, market impact costs and liquidity resilience indicators [45]. They can also study how AI-powered trading happens in various asset markets, such as stocks, foreign exchange markets, commodities, and crypto currencies and derivatives, to see if there are any differences in market thinning behavior across these different asset types [46]. In addition, the frequency of data used and access to real-time trading data may help to more accurately identify participation changes and liquidity shifts related to automated trading activity. Future studies will involve comparing the performance of various machine learning and deep learning models with the Support Vector Machine (SVM) model used in this research, including Random Forest, XGBoost, Long Short-Term Memory (LSTM) and Transformer-based models. These comparisons may offer more insights into the performance of different AI methods for creating trading signals and forecasting market participation trends. Future studies could also explore the impact of investor sentiment, news analytics, and social media information as additional variables for AI-powered trading models to gain a deeper insight into the influence of information spread on participation dynamics [47]. The other direction of research that shows promise is the regulatory and policy impacts of aggregated AI behaviour in trading, focusing on issues of market fairness, liquidity stability, and systemic risk management [48]. The interaction between institutional investors, retail traders, and algorithmic trading systems could be studied to assess various participant groups' contribution to market thinning under various market conditions. Longitudinal studies on a few market cycles and significant economic events could also provide more insights into the impact of AI trading on market participation during market stress and stability. But more studies that span several market cycles and major economic events could provide further insights into how AI-driven trading affects market participation in times of financial stress and stability [49]. Future research could explore the creation of frameworks for real-time monitoring and early-warning mechanisms that can identify contraction of participation and deterioration of market liquidity before significant market disruptions are realized. These developments would help to make financial markets more resilient by assisting regulators, exchanges and market participants in coping with the risks that come with increasingly automated and AI-driven trading markets.

VIII. Conclusion

This study analyzed the effect of AI trading signals on trading activity and market thinning by examining trading volume, trading frequency, and active trading intervals. The study was conducted in response to the growing use of Artificial Intelligence and algorithmic trading systems in financial markets, and worries about their effect on liquidity conditions and market stability. The study employed historical intraday trading data to examine the trading activity in the market during normal trading periods and AI-signal periods, assessing if the trading activity is concentrated during the AI-signal trading period and whether it has an impact on trading participation. The results indicated that the trading volume, number of trades and active trading interval ratios were significantly higher for AI-signal periods than for the normal periods. The findings suggest that AI-generated trading signals have a significant impact on trading behavior and the level of market participation, fostering increased market activity and liquidity. The machine learning analysis also showed that the Support Vector Machine (SVM) model is able to detect the trading signal with high precision, recall and F1-score values, which correspond to high ROC performance and good classification result on the confusion matrix, respectively. The market micro-structure results indicate that the use of AI in trading can influence liquidity dynamics and trading behaviour, and that there is also the potential for synchronized trading activity between different AI trading systems. The study was unable to detect severe participation contraction during AI-signal periods but the clustering of trading activity around AI-generated signals could lead to a greater vulnerability of the market under certain conditions. The study builds on the current body of knowledge by offering an empirical approach to the study of market behavior through measurable indicators of participation and predictive analysis methods for investigating the impact of AI. Moreover, the study provides insights to regulators, institutional investors, market analysts, and researchers interested in the changing landscape of artificial intelligence, liquidity dynamics, and market structure, highlighting the necessity of tracking AI-related trading activity and its impact on market participation, liquidity strength, and the sustainability of increasingly automated markets.

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