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The Impact of Artificial Intelligence on Financial Markets

Improving Trading Strategies and Optimising Market Efficiency Through AI

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Abstract

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This thesis examines how financial markets are being transformed by artificial intelligence (AI) with particular reference to trading strategies and market efficiency. It employs a documentary research method to note how AI has transcended rule-based systems to machine learning, utilized in automating trades, enhancing price discovery, and minimizing costs.

The paper integrates financial theory, such as Efficient Market Hypothesis, with an appreciation for algorithmic trading through AI and concludes that AI enhances liquidity and trading speed at the price of "black-box" transparency, systemic risk, and ethical concerns over bias and anonymity.

The findings state that while AI supplements, robust risk management and regulatory oversight are required to address these matters. Suggestions are made for explainable AI models, standardized reporting, and integration into risk management frameworks of AI-specific measures to guide practitioners and policymakers.

Keywords: artificial intelligence, algorithmic trading, market efficiency, systemic risks

The originality of this thesis has been checked using Turnitin Originality Check service.

Contents

Glossary

AI	Artificial Intelligence
EMH	Efficient Market Hypothesis
HFT	High Frequency Trading
LSTM	Long Short-Term Memory
NLP	Natural Language Processing
RNN	Recurrent Neural Networks

1 Introduction

The financial markets evolved rapidly during the past decades, and technology has had a growing impact on market practices and outcomes. Among the most innovative technologies, artificial intelligence (AI) had its potential evolved from theoretical presumptions to practical, daily uses in trading, risk management, and market forecasting. This thesis explores the impact of AI on the financial markets and, more precisely, the effects of AI on trading strategies and market efficiency.

Defining the scope of the study: The subject of the study is the convergence of technology and finance. Use of AI in the financial markets spans areas of application from predictive analytics and algorithmic trading to risk management in real-time. This convergence is not only revolutionizing how trade intermediation is being performed at record velocity, but is also remaking the foundations of market functioning. In the context of the current high-stakes high-volatility financial scenario, the market participants and the regulators must understand the role of AI. Presently, knowledge is that while AI comes in the guise of increased efficiency in the form of added liquidity and faster price discovery, it also comes with its array of challenges in the guise of transparency, systemic risk, data bias and privacy concerns (Frankenfield, 2021; Van Roy, 2020).

Present Central and State Characteristics: It is in the present that deep learning and machine learning technologies are at the forefront of financial innovation. They have transformed traditional processes of trading by rationalizing decisions and high-speed actions of trading, which are able to carry out trades in the fraction of a millisecond blink of time. In the midst of the same, the industry is defined by a humongous imbalance in the rapid development of technology and the slow, measured progress of the normative frameworks and the ethos of the industry. Prior research has emphasized initially the potential of AI in lowering the cost of trades and increasing marketplace liquidity, but fewer detailed at length the risks, above all, of the "black-box" of AI models and system-wide consequences. This study continues the research effort of prior studies by synthesizing quantitative facts and qualitative knowledge to present a more nuanced analysis of the double-edged nature of AI in financial markets (Gibson, Krueger and Riand 2021; Khurana 2024).

Existing literature and Central questions: Central amongst these is the question: how is AI impacting trading strategies and the efficiency of the market? This stems from a need to build on existing literature that in the majority of instances addressed piecemeal areas—that is, predictive analytics or algorithmic trading—without including the systemic and ethical ramifications in a single work. In addition, there is a crucial need for longitudinal studies analyzing the dynamic implications of AI under different market conditions. Filling the gaps, this study seeks to address a critical knowledge gap in the existing literature and give practitioners and decision-makers useful insights.

Purpose and Structure of the study: The study aims to contribute to the advanced level of knowledge of how AI-innovations are affecting trading activity and market efficiency and, at the same time, delineate the risks and hazards of the same innovations. This thesis is summarised in some required chapters: It is preceded by a comprehensive literature review that plays the role of supporting theory and highlighting current trends and gaps in the literature in the given research field. This is followed by the chapter of theory and analysis framework, which condenses these findings in a conceptual bridge directly relating to AI adoption and market performance measures to each other. The method chapter expounds in detail the documentary method of study employed in the study, and the findings chapter is a synthesised analysis of secondary data in testing hypothesised assertions. The conclusions and recommendations chapter summarises the findings of the study and provides practical and policy-related advice to future studies and implementation.

Setting the stage for the chapters to follow, the introduction points not only to the revolutionary potential of AI in finance but to the imperative of examining both the opportunities and risks of AI in a cautious and timely manner. Its conclusions seek to contribute to the existing body of knowledge and establish a firm basis upon which further research and decision-making in the field will be conducted.

Study Organization: Following this chapter, the thesis is organized as follows:

Chapter 2: Review of the literature considers the continuous development, uses in the current period, and intrinsic controversies of the topic of AI in the financial markets.

Chapter 3: Theory and Analytical Framework constructs a conceptual framework that links AI-driven trading strategies and market efficiency results.

Chapter 4: Methods outlines the documentary research design and data collection processes applied.

Chapter 5: Presents the result of the systematic analysis of the secondary data.

Chapter 6: Conclusions and Recommendations provides a summary of the general findings and a guide to practice and future research.

Additional definitions and explanations, i.e., the definitions of "machine learning," "price discovery," and "algorithmic trading," are given in the thesis wherever necessary to build a more precise conception of the content.

2 Literature Review

In this chapter, we are defining the scope of the study through critical synthesis of existing literature on artificial intelligence (AI) in financial markets by combining existing literature and central questions on how such technologies develop, how they are used in trading techniques, and how they influence market efficiency. The chapter is also distinguishing the purpose and structure of the study through synthesis of different methods, models, and empirical studies in identifying key areas of research gaps to direct future chapters.

The evolution of AI in finance began in the earliest rule-based automated systems. Early work in symbolic reasoning and expert systems were the foundations of the developments that followed. Bresnahan and Trajtenberg (1995:27) traced the initial use of general purpose technologies upon the activity of economics, the same perceptions having since then been cross-applied to account for how the first AI tools began to have impact upon decision-making in finance. During the decades that followed, when computing power and large data sets became more and more readily available, more advanced methodologies developed, including the use of more advanced learning as well as, more recently, deep learning techniques. These developments not only had systems running on pre-programmed processes but also to learn and adapt utilizing past market activity, recognize trends, and even forecast future price level alterations. Frankenfield (2021) has examined how the developments led to a paradigm change in the manner in which financial markets react to information.

Research also elaborated on the role of AI in specific trading strategies. Some of the papers have pointed out the method by which AI is being applied by the algorithmic trading systems to execute trades at high velocities not available by manual efforts. HFT systems, for instance, use the predictive models of the use of the RNN and the LSTM architectures that have turned out to be more effective in the context of forecasting the short-term fluctuations of asset price dynamics (Engelhardt, Ekkenga and Posch 2021: 45). It is shown in literature that by facilitating the work of trade execution in automation, AI not only makes the activity more efficient but also lowers the transaction cost by minimizing bid–ask spreads. Comparative studies explain the phenomenon in which high levels of algorithm activity in the market will lead to increased liquidity and the decline in operating frictions in markets (Van Roy, 2020).

In addition to execution trading, the implementation of AI in predictive analytics also gained a lot of attention. It is asserted in literature that the utilization of both quantitative methods and qualitative data of the kind of sentiment analysis by natural language processing (NLP) allows market models in AI systems to use more heterogeneous units of data. It supports high-speed price discovery, hence market efficiency. Empirical evidence underpins the argument that AI models can effectively combine news, social mood, and macro indicators into the models of forecasting, hence reducing market players' information asymmetry (Frankenfield, 2021). Such functionality has far-reaching implications not only in the production of profit from price changes, but also in stabilizing the markets by converting the asset prices rapidly to underlying fundamentals.

In these technological advancements, the literature is not oblivious to the risks of adopting AI. At the top of the list of concerns is the "black-box" nature of the majority of deep models, which will potentially obscure the decision-making process. Gibson et al. (2021) present the lack of transparency of the algorithms as causing complications in risk estimation and risk management. Such uncertainty is of greatest concern in the case of automated systems triggering algorithmic trading to produce system implications in a random fashion, including flash crashes or cascades of market collapse. Empirical studies indicate that the high-speed execution of trades by automated systems makes market volatility increase during crises, raising a question about the sustainability of AI systems in the long term. In addition, ethical concerns in the literature have also evolved. Huge databases needed to train high-order AI models are likely to carry and even intensify underlying historical prejudice, triggering discriminatory or inequity behaviors in market operations. According to Khurana (2024), the need to address data privacy and security concerns concurrently or in parallel with technology innovation, particularly when financial institutions increasingly utilize AI to support core decision processes, is discussed. Such ethical concerns are not mere hypotheses but are real in imposing on the development of policy and building of regulatory frameworks to achieve market integrity. Further, while many studies indicate the benefits of AI, there is less literature on the full perspective of its effects under different market conditions. Much of the literature considers the scenario of developed markets, and relatively fewer studies pay more attention to emerging markets where the institutional environment and technological infrastructures can significantly differ. Further, studies on the dynamic effect of AI in a period of time are scarce. Real-time studies covering more broadly and in the ability to study the evolving interaction of AI adoption, market efficiency, and system risk are also mentioned in literature.

2.1 Overview

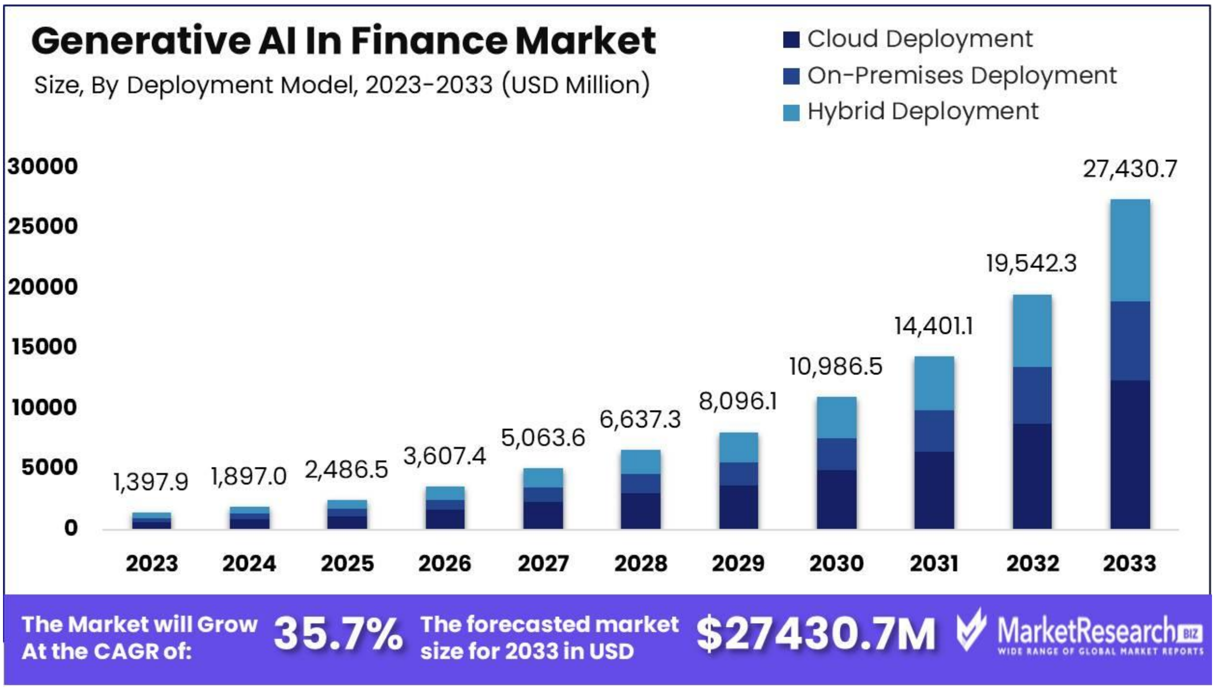

Figure 1. The forecasted market size of Generative AI (marketresearch.biz Vishwal, 2024)

Artificial intelligence started the twentieth century as a conceptual entity, initially characterized by symbolic and rule-based approaches to reasoning. Subsequent growth in statistical data, computer technology, and data accessibility led to the development of AI as a group of technologies-machine learning, deep learning, and natural language processing-whose capabilities include the faculty of learning, adaptation, and performing higher-order cognitive processes (Bresnahan and Trajtenberg 1995: 27; Frankenfield, 2021).

In the financial markets, the application of AI had initially been confined and was generally limited to rule-based portfolio allocation systems, but the explosion in computing power and data ubiquity in the 2000s and beyond propelled the trend towards the utilization of more sophisticated AI systems in trading processes. This development is captured in Figure 1, where the history of utilization of AI in financial systems is summarized —from the heuristic models of the early days to the high-frequency algorithms of the contemporary period. These developments also capture the financial markets' increasing reliance on data-driven decision-making (Van Roy, 2020).

Artificial intelligence impacts finance in the present day. Uses include asset direction of price forecasting and creating intricate algorithms for trading, as well as fraud prevention and real-time risk management. Increasingly, AI processes are being adopted to screen huge levels of market data faster and more accurately than classical manual processes. For instance, automated algorithms of machine learning can identify very minute deviants and trends in historical data, enabling the traders to accurately forecast the direction of the market and adjust strategies in real time (Frankenfield, 2021).

In addition, risk management is also a role of AI. Advanced algorithms are already analyzing real-time market data to detect potential risks or unusual trading activity, allowing companies to embrace a risk-controlling proactive stance and achieve market stability. In addition to efficiency maximization, AI also lowers the cost of trading by minimizing bid–ask spreads and enhancing liquidity, a quality that correlates directly to the efficacy of markets (Gibbon et al. 2021). These qualities render AI both a strategic trader's asset and a market process-improving innovation.

2.2 AI in Trading Strategies

One of the biggest applications of AI in markets is high-frequency trading (HFT) in the guise of algorithmic trading. Such algorithms driven by AI can trade in milliseconds, far faster than a human (Engelhardt et al. 2021: 45). HFT uses high levels of statistical analysis and pattern detection to exploit minor price differentials or bid-ask spreads, which serves to increase market liquidity and decrease transaction costs.

Figure 2 presents a data flowchart of the algorithmic trading system and defines the data capture and pre-processing steps in the form of decision-making and order execution automation. It is precisely this high-speed loop that lies at the foundation of the realization of a market edge in the new markets of finance.

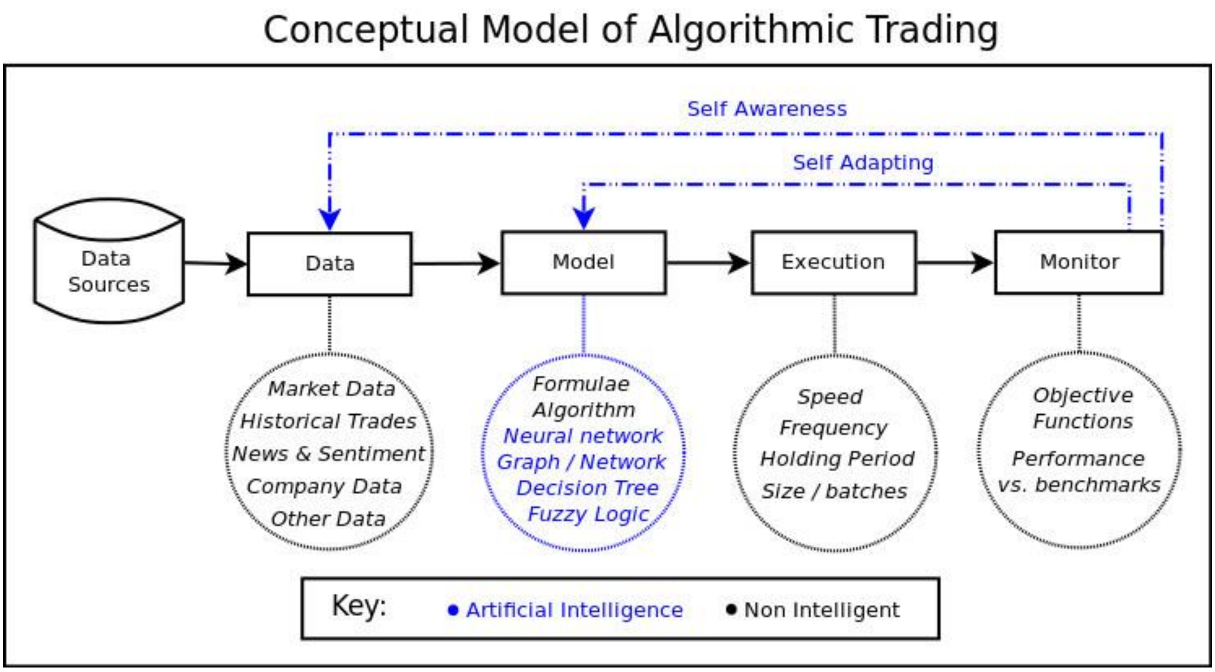

Figure 2. Conceptual Algorithmic Trading System (Asgari, 2017)

In addition to the execution of trades, AI plays a significant role in forecasting models and predictive analytics. Its use in time-series models of data, price movement forecasting, and market volatility forecasting uses techniques like recurrent neural networks (RNNs) and the LSTM networks. By using several of data sets, including historical price, macro data, and even investor sentiment expressed in social networks, the models can create advanced predictive outputs that it isn't always feasible to achieve using traditional econometrics (Frankenfield, 2021).

Empirical evidence indicates that AI forecasting models work better under stable situations compared to traditional models but fail under situations of unexpected regime change or external volatility in the market, implying the need to update them constantly (Gibson et al. 2021).

2.3 AI and Market Efficiency

Market efficiency also encompasses the manner, as well as the speed at which the data is transmitted and in which the asset prices change in response to it. AI seeks to accomplish the former by rapidly processing valuable data coming in through data streams and hence reducing the data asymmetry. AI trading systems increase and facilitate the market and the stocks or security's liquidity levels. Empirical evidence shows that more algorithmic trading in markets leads to the bid–ask spreads and volatility levels becoming tighter (Van Roy, 2020).

For instance, HFT and AI markets have been contrasted to traditional markets, and the traditional markets were found to have a greater number of transaction costs and more volatile price trends. These advantages of AI are also evident in Figure 3 in the shape of a graphical comparison of algo setups and traditional market setups in a plot of trading volume. Such graphs give a lot of insight regarding the systemic effect of AI in market functioning.

Figure 3. Exchange-traded funds annual portfolio turnover ratio comparing other active EFTs and AI-driven EFTs (www.imf.org, n.d.)

Another of the more significant market drivers will be the processing of new data quickly and effectively. AI systems will likely achieve this by using natural language processing (NLP) and big data analysis. By having the ability to monitor and process up-to-the-minute news, social media, and announcements in real time, AI algorithms can create decision-quality insight that is directly converted into timely market response. This blend of quantitative and qualitative data facilitates more accurate price discovery and the rapid convergence of market prices back to their underlying fundamental values (Frankenfield, 2021).

In addition, AI computer programs have high proficiency in separating noise and useful signals. They assist investors in distilling data-driven conclusions about market movement and streamlining decision-making. Thus, AI is a prime catalyst in the elimination of lag in market reaction to news—and maximizing the efficiency of the entire system.

2.4 Risks, Challenges and Ethical Considerations

Despite of the numerous benefits, the application of AI in financial markets also comes along with enormous risks. Among the unsettled problems, there is the “black-box” nature of most AI algorithms. The models, and particularly those developed using deep learning methodologies, are opaque, and the decision-making process is difficult to understand (Gibson et al. 2021). Lack of transparency poses unintended system risks, where errors or misperceptions in the model have far-ranging consequences in regard to market stability.
The rapid execution of trades by AI systems also generates system risks. Concentration of like algorithms at and between institutions, say, can produce synchronized trading patterns that increase market volatility. Historical flash crashes have caused fears that automated trading at times generates sudden and explosive price misallocations (Engelhardt et al. 2021). The potential of market manipulation is also increased where AI systems are not supervised, and operators without ethics could use the volatility of the algorithms under their control to shape market outcomes.

The last, however, of the areas of concern is the ethical use of AI in finance. AI systems rely greatly on historical data, which can contain implicit prejudice and thereby systemically perpetuate algorithmic discrimination. Such prejudice might hurt specific market participants or reinforce existing inequalities (Khurana 2024). The large data collection that supports AI activity also generates fundamental questions regarding data security and privacy. Financial institutions must ensure that their AI activity complies with the demands of the law and ethics, respecting the privacy of the individual and supporting decision transparency.

2.5 Gaps in Literature and Future Research Directions

While there exists some literature on the benefits and drawbacks of AI in markets, the literature also leaves some gaps and those need to be addressed. Specifically, there are not many empirical articles formally estimating the effects of AI on market efficiency under different market conditions. Most articles are composed of single-case studies or theoretical models rather than time-series data of dynamic effects that change across time. Papers also do not compare the relative performances of AI-based trading strategies in emerging and developed markets, in which the context and structural market characteristics are considerably different (Gibson et al. 2021).

Literature Review Conclusion

Overall, the literature testifies that artificial intelligence completely reshaped the landscape of the financial market through enhanced trading models, forecasting, and market efficiency in general. Although AI technologies are of great utility—high data processing velocity, improved liquidity, and low cost of transaction—they also carry intrinsic risks, including systemic risk, obscurity of algorithms, and their ethics. Empirical studies are called for by the literature, specifically the comparison of the market dynamic under different environments of the economy, and the incorporation of the ethics of AI and trading models.

The results of the literature review directly address the study research question: how is AI affecting trading strategies and market efficiency? These are the building blocks upon which the chapters that follow elaborate by outlining the research methodology, presenting the empirical analysis, and lastly, the implications of the advent of AI in financial markets.

3 Theory and Analytical Framework

The research question of this study is: In What Ways is AI Impacting Trading Strategies and Market Efficiency? Following a wide-ranging literature review, the conceptual framework below seeks to integrate different theoretical pillars of examining the revolutionary role of AI in financial markets. Based on core financial theory, comprising the Efficient Market Hypothesis (EMH) and the economics of transaction costs, behavioural finance innovation, and technology in algorithmic trading, the conceptual framework concludes that the employment of AI in trading activity not only changes the execution and forecasting of trades, but also imposes detectable impacts on market liquidity, price discovery, and systemic resilience.

Theoretical Background: Classical finance theory, and more emphatically, the Efficient Market Hypothesis (Fama 1970), argue that asset prices are the sum of available data. Efficient processing by AI systems, however, is in contradiction to the static hypothesis. Dynamic and flexible notions of the theme are presented by the Adaptive Markets Hypothesis (Lo 2004), which argues that market efficiency is a market participant response to technological change. It is also informed by the theory of transaction cost economics, as conceived by Williamson (1981), upon which the argument that a decoupling of the frictional cost of exchange)—through high-speed, algorithmic processing)—has the potential to modify the market dynamic at a root level rests. These models, in a sense, present a starting point to think about the potential of AI to make a contribution to bid–ask spreads, transaction costs, and the speed of price discovery being eroded.

Synergy of Algorhythmical and Behavioral Knowledge: Conventional models base their assumption of rational market behaviour, whereas behavioural finance school of thought knowledge shuts the door on environmental pressures and mood of investors creating some marketplace inefficiency in the system. AI's ability to process high levels of data-including qualitative news feed tipping, social networks, and economics publications-allows more probing of market mood beyond the conventional analysis. Advanced machine learning models, including recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, identify nuanced, non-linear trends beyond the conventional analysis (Frankenfield, 2021). Such fusion of quantitative discipline and behavioural knowledge therefore represents a more advanced algorithmic trading type, in which AI systems evolve and update in real time to new market shapes.

Conceptual Model: Conceptual model defined in the current study synthesizes these threads of theory in a single model. In this model, the use of AI in trading strategies is the independent variable. This variable impacts a group of crucial dependent measures, i.e.:

Market liquidity: High-speed processing and real-time analysis by artificial intelligence decrease the bid–ask spreads and operating costs, enhancing liquidity.

Price Discovery: AI-driven predictive analytics fuel the alignment of the price of an asset and fundamental drivers by minimizing the lag of market events and price movements in available information.

System stability: In addition to efficiency, AI also threatens to produce system failures–such as flash crashes–when the same models react in concert to market stimuli, a risk that stems from the un transparent or “black-box” nature of the majority of deep learning systems (Gibson et al. 2021).

This model also considers the market activity to be moderated by many factors, including the regulator control, the levels of technology maturity, and the use of ethics in data usage. For instance, ethics, or data privacy and data bias, guide the artificial intelligent models, and the outcomes of the market are moderated by it indirectly. This is one of the areas that future studies need to start working on as they develop ethical frameworks and standards that will address the negative effects of these factors.

In order to address the array of theoretical study, the conceptual framework emphasizes the two-edged sword of AI: while its innovations generate a huge added value in market and trading efficiency, in turn, they also generate complexities that require sufficient risk management and open-ended regulative strategies. In practical terms, it will mean that the deeper AI penetrates financial markets, traditional risk management practice will need to integrate new AI-specialized trackers. Such hybrid architectures that combine traditional risk measures and real-time AI back-testing cycles might potentially bring the solution in hand.

3.1 Theoretical Foundations

In line with market efficiency and risk management theory, Efficient Market Hypothesis (EMH) stipulates that the market uses the entire set of available data in asset prices (Fama 1970: 55). However, the speed of data processing by AI challenges traditional assumptions by being able to shorten the time lag between new data and incorporation of the data in market prices. In addition, the adaptive market hypothesis (Lo 2004: 210) anticipates that market players will learn in the longer term, while technological progress, including AI, can change the balance of competitive approaches in the direction of a point where the price adapts to shift in underlying value more efficiently. Its ability to enable lower transaction costs — anticipated by transaction cost theory — also supports the hypothesis that faster, data-driven decision-making will increase the efficiency of markets (Williamson 1981: 42). Placing procedures that are traditionally carried out by humans, AI system technology makes possible tighter bid–ask spreads, tighter latency, and better supply–demand balance. It is this benefit of enhanced processing and cost realization, however, which is evidence of the hypothesis that next-generation technologies like AI remain highly effective in enhancing measures of market performance.

3.2 Conceptual Model

The theoretical framework of the research is derived from the literature and encompasses three primary dimensions:

Trading Strategies: In uses of AI in trading strategies—in the guise of algorithmic trading, high-frequency trading (HFT), and predictive analytics—the novelty is in the manner in which the orders are executed, the price is forecast, and the risks of investment are hedged out. Deep learning-algorithms, for example, can deal more rapidly in real-time market data compared to humans. This use of AI is likely to bring improved execution efficiency and enhanced responsiveness towards market indicators (Engelhardt et al .2021: 45).

Market Efficiency: Financial market efficiency is fundamentally in the speed at which new information is disclosed and implemented in the asset price. AI's ability to work in real time—in processes utilizing the use of natural language processing (NLP) in perspective to processing text-based data and sentiment—is undoubtedly at the core of addressing the problem of the asymmetry of information. Consistent with the above, markets where the use of AI methodologies is dominant will always be characterized by improved liquidity, low transaction cost, and a faster price-discovery mechanism (Van Roy, 2020).

System Risk and Ethical Problems: Along with the benefits, risks are also associated with the use of AI. To begin with, the “black-box” character of the majority of the AI systems reduces the transparency and will result in the risk of system risks in the guise of market meltdown or flash crashes. Ethical concerns like data privacy and data bias in the data set also are part of the operating conditions. It thus mandates the consideration of the risks so that the benefits of AI outweigh the harm to the stability of the entire market (Gibson et al. 2021).

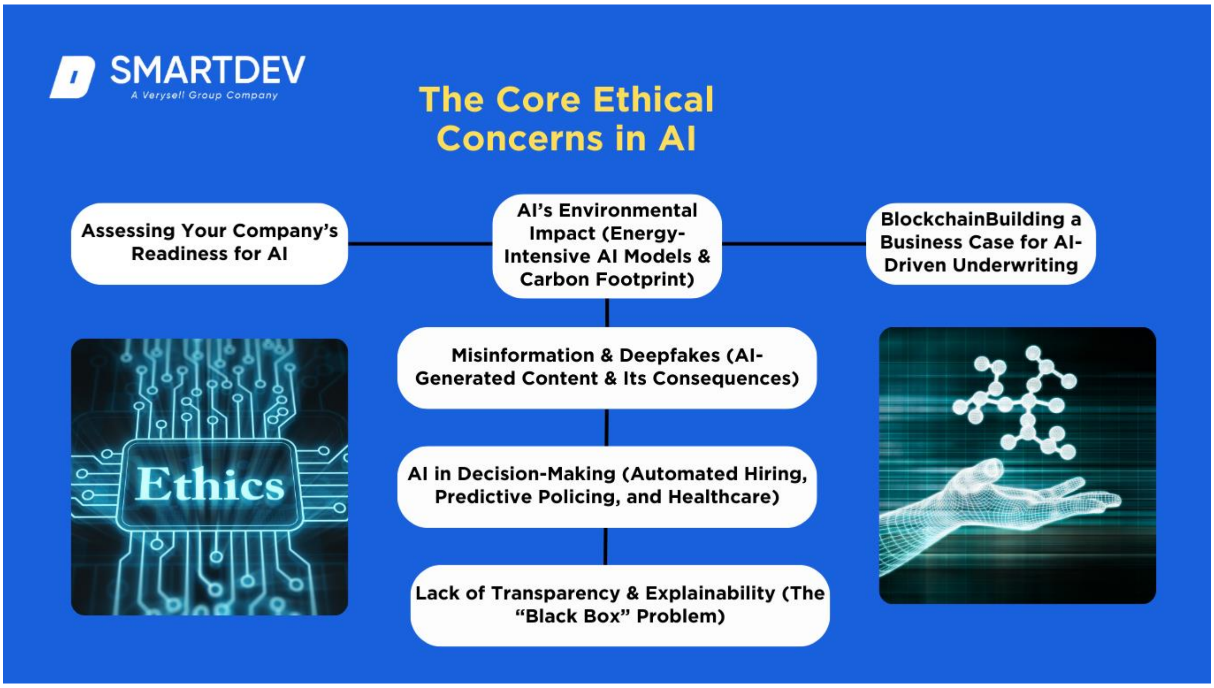

Figure 4. The Core Ethical Concerns in AI (Nguyen, 2025)

"AI technologies bring a host of ethical challenges. Business and policy leaders should understand the core AI ethics concerns in order to manage risk and build trustworthy AI systems." (Nguyen, 2025)

3.3 Methodological and Operational Considerations

Consistent with the theoretical and conceptual foundations, the study will adopt a mixed study design of quantitative empirical analysis and qualitative observation. Quantitatively, the primary market efficiency indicators (such as liquidity indicators, trading costs, and volatility measures) will be compared against the performances of AI-driven trading models. Sample data to be gathered and analyzed in order to establish statistical correlation include market trading algorithms, high-frequency trade data, and market liquidity indicators.

Qualitatively, the interviews of the finance professionals and the ethics assessors of AI will shed light on the perceived transparency of and the ethics and bias of AI use. Qualitative findings complement the quantitative findings by adding contextual explanations to account for quantitative trends emergent and thus including ethical and regulative considerations in the analysis.

Operationally, the research will draw on a variety of data resources, including financial databases, market data warehouses, and published articles about the use of AI in finance. Triangulation of data will give us robust measurement and analysis of the constructs of our conceptual framework. In particular, advanced statistical analysis, including regression analysis and time-series models, will examine the impact of AI use, controlling for the effects of external variables, including market volatility or macro-economic events.

3.4 Integration of Theory with Research Objectives

The research is directly informed by the theoretical framework. Keeping in mind the study question, the research attempts:

Determine if trading techniques focused on artificial intelligence are associated with measurable improvement in market efficiency outcomes (like lowering transaction costs and enhancing liquidity).

Predictive analytics, when performed through the use of AI algorithms, assist in the realization of enhanced price discovery and price forecast.

Consider the extent to which risks and ethical concerns at the system level will mitigate the positive effect of AI use on market efficiency.

Create policy recommendations and risk mitigation strategies based on the incorporation of AI in the financial markets

The goals naturally follow the conceptual framework and the findings of the literature. They are the roadmap to the study of the ways in which the potential of AI transformation is restricted by the unseen boundaries set by it upon itself. In the blending of the qualitative and the quantitative, the research aims to give the full picture of the role of AI in the remaking of market behaviour and trade politics.

3.5 Summary of Theoretical Contributions

In general, the theoretical and conceptual framework of this study follows the classical theory of finance and applied theory of artificial intelligence. This is a two-fold framework of the implications of AI: first, facilitating efficiency by virtue of high-speed processing and advanced models of trading, and, second, posing system, ethical, and operational problems. This two-fold framework not only rationalizes the research question, but also the methodological choices and interpretations of empirical findings.

In the present analysis, the above propositions will be tested empirically. We will base the analysis framework on classical theory and more contemporary technology-driven knowledge in order to properly capture the role of artificial intelligence in trading strategies and market efficiency in the present increasingly dynamic financial landscape.

4 Methods

This study uses the secondary research method, relying completely on published material and data in the form available in authentic and reliable publications, viz., systematic book material, research articles, business reports, and internet databases. Synthesizing the above material, the study provides conceptual and empirical analysis of artificial intelligence in financial markets, i.e., the role of AI in trading strategies and market efficiency.

4.1 Research Design

The design type applied is documentary in nature. As compared to the gathering of primary data using interviews or questionnaires, the study uses in-depth analysis of secondary data. The foundation of the design is to achieve insight into historical and current trends in the use of AI in the financial markets. In-depth analysis encompasses academic literature, business reports, official reports, and internet-based data that are applicable in the context of the problem being investigated. This method was applied on the assumption that it allows one to draw from a wide reservoir of evidence and viewpoints, and provides a solid base on which the effects of AI on market efficiency and trading are examined.

This approach is especially suitable to address the research question of "How is AI affecting Trading Strategies and Market Efficiency?" in the sense that it integrates evidence at multiple levels and by different approaches, and hence provides a wide angle view of technological innovation and its empirical manifestation in finance.

4.2 Data Collection

Research findings data were also gathered by carrying out extensive web-based searching in databases and electronic libraries including Google Scholar, JSTOR, ProQuest, and company sites. Use of specific terminologies including "artificial intelligence in finance," "algorithmic trading," "high-frequency trading," "market efficiency," and "price discovery" characterized the research activity. In addition, published books and company reports found available on the subjects were accessed through academic catalogs and institutional website listings.

The inclusion criteria in the choice of the sources were:

Peer-reviewed articles, academic publishing organizations, and reports of prestigious business associations were initially given priority

Relevance: Content that is pertinent to the subject of the use of AI in financial markets, trading, or market efficiency

Recency: Because computers and AI technologies advanced so quickly, more up-to-date articles published in the last ten years were favored to give more timely applicability.

Every paper previously selected was read in a systematic manner and its major findings, methodology, and conclusions were entered onto a master database. Data extraction involved the recording of quotable material, conceptual framework overview, recording of statistical findings, and the reporting of case studies or examples of the use of AI in the financial markets.

This was supported by reference management software like Mendeley or EndNote in the structuring of bibliographic details and cross-references, where it was easy to monitor every source and cite it accordingly using the Harvard system of referencing.

4.3 Data Analysis Techniques

The major analysis technique applied in this study is the systematic review of the literature, and this includes:

Across the selected sources, the general subjects of algorithmic trading, predictive analytics, market efficiency, risk, and ethics were recurring.

Literature evidence was mapped conceptually against the conceptual framework in the theory chapter, which links AI's technical capabilities to measures of market performance.

Comparative Analysis: Several studies were compared and similarities and differences in their findings regarding the effects of AI were analyzed. This helped to bring out areas in which the literature presents consistent evidence and areas of content that require more studies.

While the paper is not presenting quantitative results, it presents a quantitative comparison of primary market metrics surveyed in the literature, including bid–ask differential spreads, trade velocities, and measures of volatility. Report summaries are utilised in order to present the statistical correlation of the rate of AI integration and market efficiency measures. Graphs and plots of the secondary data, where applicable, have been reproduced (with appropriate citation) in order to present these relations in a graphical format.

Synthesizing the qualitative and quantitative data gathered through the literature, the study uses the opposing argument and statistical facts to infer a balanced view of the effect of AI on the processes of trading as per the findings of the market in general. Mixed synthesis allows the study to tackle the question of study on both sides of the argument without having to gather primary data.

4.4 Limitations

Based on secondary data alone, the research is limited by the quality, timeliness, and volume of data available in published items. It is also likely that the trends or proprietary data have not been published. Inconsistency in the research also arises in the variation in the organisations' methodologies and data definitions. Despite the above, the systematic method applied helps overcome the weaknesses by the use of the best and available appropriate data sources.

No direct contact is necessary with the subjects as the study is conducted on published work and available public information. Ethically, the study is oriented towards correct citation of the work and respects intellectual property rights. Correct acknowledgement of the sources is provided in the manner of the Harvard system of referencing and openness and accountability in the study is ensured.

4.5 Methods Summary

Lastly, the study adopts the documentary study design in the collection of different secondary data held in academic, business, and internet databases. Systematic literature reviewing and thematic and quantitative analysis feed the analysis. Although the study did not use primary data collection techniques such as interviews, the mere reviewing of published studies provides valid results of the impacts of AI on trading functions and market efficiency. Methodology provides a wide and authentic study of the study issue.

5 Results

This chapter presents a concise overview of the systematic review and secondary data analysis conducted in the present work of research. It provides a summary of the findings under general headings of the effects of AI on trading strategies, AI's contribution towards market efficiency, and the systemic risk and ethical concerns therein. These sections cross-reference the findings of the literature study and the analysis framework in turn to address the research question in a concise manner.

5.1 AI’s Impact on Trading Strategies

There is also literature in support of the role of trading strategies being transformed by the use of AI. Evidence indicates that the use of algorithmic trading systems driven by AI methodologies supports the processing of trades in milliseconds. One of the drivers of HFT is high-speed execution. It is, for instance, observed by Engelhardt, Ekkenga, and Posch (2021: 45) that systems driven by AI have the ability to decrease the cost of trading by minimizing bid–ask spreads and enhancing the timing of execution in favor of relatively favored traders.

The systematic review illustrates the way in which artificial intelligence predictive analytics, the long short-term memory and recurrent neural networks architectures provide the precision of short-term price forecasting. This forecastability allows market players to balance dynamically their trading strategies in a bid to capture fleeting market opportunities. Other comparative studies between markets also illustrate that institutions utilizing the technology have a history of increased liquidity and fewer operations frictions. Syntheses of both academic studies and industry reports quantitatively show that AI-driven trading not just earns more money through arbitraging micro inefficiencies, but also facilitates smoother execution flows. These studies illustrate the role of AI in revolutionizing trading protocols and trade execution efficiency.

5.2 AI’s Contribution to Market Efficiency

There have also existed numerous studies in the literature that examine the contribution of AI to market efficiency. One of the indicators of efficiency being targeted is price discovery. It's possible that algorithms of AI will immediately aggregate and process snippets of news, social, and market data feeds and utilize it in its role of informing price. In accelerating the aggregation of the data, functionality manifests in a better representation of the underlying stock price fundamentals (Frankenfield, 2021). For example, results of studies in the literature indicate that the utilization of high-quality AI algorithms in markets manifests in lowering the bid–ask spread and improved liquidity (Van Roy, 2020). Such effects also result due to continuous and real-time supply and demand matching by algorithmic trading systems (Engelhardt et al. 2021).

In addition, quantitative evidence in a series of secondary data supports the same picture: in markets controlled by AI-strategy, liquidity ratios are improved and volatility, in the more enduring stable situations, is smaller compared to more typical market conditions. Graphical representations provided by reports published by market analytics provide the visual evidence that, as the injection of AI intensifies, time elapsed prior to disclosure of the data and market reaction diminishes exponentially. This is a correct observation in line with the theory which says that AI-enhanced trading speeds up the price discovery.

5.3 Systemic Risks and Ethical Challenges

While the benefits of embracing AI are evident, research also indicates significant challenges in existence. Among the problems in existence is the "black-box" character of the majority of AI algorithms. Several studies mention the inability of deep-learning models to provide openness as a factor that makes it hard to detect and correct errors whenever they are present (Gibson et al. 2021). Lack of openness in decision outcomes makes it difficult to assess risk in its totality whenever the market experiences volatility.

Empirical evidence in literature also supports the fact that the speed and autonomy of AI-driven trading in some situations are likely to cause market volatility. Examples of events in the context of the flash crash events attribute synchronized algorithmic activity to the development of rapid and abrupt distortions in price (Engelhardt et al. 2021: 45). Certain studies also note that while liquidity is increased by AI, the same systems in the instance of risk signal misinterpretation or unexpected change in the market environment cause cascading failure.

There are also ethical considerations in the issue. Cases of the AI algorithms, while learned on representative or biased data, replicating current inequalities or punishing certain market segments disproportionately by default appear in current literature. Traditional data privacy concerns also emerge, as large data gathering will need to happen in order to feed the advanced predictive models (Khurana 2024). It is in this way that literature generates a paradox: AI optimizes market efficiency and trading performances, and also generates risk, which will need to be addressed with caution.

5.4 Integrated Findings and Discussion

Synthesizing the respective evidence across the different strands, the findings are that AI use in financial markets is accompanied by considerable benefits, but also by not-inconsiderable risks. On the benefits side, AI-based trading practices have brought calibrated improvements in execution time, transaction cost, and liquidity, and these are drivers of market efficiency. These improvements are best seen in the context of high-frequency and algorithmic trading, where high-quality forecasting models and automatized trading procedures have narrowed bid–ask spreads and enhanced the velocity of price discovery (Van Roy, 2020; Frankenfield, 2021).

In the meantime, the debate also acknowledges the benefits of the same come at the cost of systematic risk and ethical concerns. The “black-box” problem is a serious one, so serious that the inability to fully explain AI decisional processes risks creating loopholes in the market's stability—and mainly in areas of high volatility and revolutionary change (Gibson et al. 2021). Ethical concerns of prejudice and data privacy serve to further highlight the necessity of robust regulating frameworks to guide the use of AI technologies.

Cumulatively, they support the view that while AI, by enhancing trading processes and market efficiency, also needs to be regulated and controlled, the findings of this study follow the theoretical framework developed in this study previously, whereby the functioning of AI was theorised to have a dual character, one enhancing efficiency and performance on the one side and generating problems on the other side.

5.5 Summary of Results

Overall, the results of the secondary research are that:

Trading Strategies: AI-powered trading platforms, and more so in high frequency in particular, optimize execution efficiency and reduce transactional cost. AI-driven predictive analytics create value by maximizing predictive precision.

Market Efficiency: High-adoption markets achieve greater price discovery, improved liquidity, and tighter bid-ask spreads, in line with the view that AI accelerates the integration of information in asset prices.

System Risk and Ethical Concerns: AI also subjects us to system risks, ranging from risk of vulnerability to market meltdown through algorithm synchronization to ethical concerns on the transparency, bias, and data privacy fronts.

These findings directly address the research question and provide a general response in the form of synthesised published evidence. They set the stage for the next section of conclusions and discussion in which the study's future implications to both research and practice will more completely be addressed.

6 Conclusions and Recommendations

The study focused on the impacts of artificial intelligence (AI) on market efficiency and trading practices. In line with a wide-ranging literature review and systematic analysis of the secondary data, the study found that the use of AI in the financial markets is a double-edge sword since, while the AI systems accelerate execution, reduce the costs of a transaction, bring more liquidity, and result in better price formation, the intrinsic problems of the secrecy of the majority of the AI models, the system risks, and data secrecy raise serious threats that need to be addressed by the market players.

6.1 Conclusions

The findings of this study are that artificial intelligence in trading systems has revolutionized the present financial markets in numerous significant ways:

Enhanced Trading Efficiency: Quantitative data in the academic papers and industry reports indicate that artificial-intelligence-driven trading systems, and more so high-frequency and algorithm-driven systems, enhanced trading latency considerably. Bid–ask spreads consequently narrowed, and fee per trade fell (Engelhardt et al. 2021: 45; Van Roy, 2020). Meanwhile, predictive analytics due to the use of machine-learning and deep-learning processes enhanced the accuracy of the asset price forecasts and, in turn, enhanced aligned market foundations and stock prices (Frankenfield, 2021).

Improved Efficiency in the Market: Machine AI can simultaneously process more than one feed of data, including news feeds, financial reports, and social feeds, in real time, thereby accelerating the price-discovery process. Such rapid integration results in improved market liquidity and stability. Graphical representation of secondary data always presents the fact that the more market incorporation of AI, the lesser the volatility under stability, and the assumption that AI makes market processes efficient in this regard holds true.
System Risks and Ethical Concerns: Although the benefits are high, the research observes that the speed and potential of AI systems also create system risks. "Black-

box" issues, where the specificities of the algorithms are unknown, contribute to the risk of controlling and regulating risks. Flash crashes and cascade failures are the worst-case scenarios as numerous algorithms in lockstep react to unexpected market stimuli (Gibson et al. 2021). Other risks include ethical concerns when AI systems, typically learned from the past, embed inadvertent prejudice or violate data privacy. These risks highlight the need to balance robust ethical and regulative frameworks and the practicability of the use of AI in finance (Khurana 2024).

Cumulatively, the evidence supports the twofold thesis that AI considerably boosts operating efficiency in trading and, in the process, generates new risk and complexity levels, and these need to be effectively managed.

6.2 Recommendations for Action and Future Research

The following implications regarding practices and research are the outcome of the findings of the present study:

Transparency of AI Models: Second and more critically, the other feature of disclosure is the lack of explainability in the majority of the AI systems. Banks and financial institutions have been proposed to examine and develop more transparent and explainable models of AI. This can be met by the use of techniques in AI models like explainable AI (XAI) and utilization of model audit tools, which will facilitate the identification of the algorithmic trade decision-making by the regulators and the users in a simpler way. These are needed to facilitate the identification of risk at the earliest available time, and also to prevent systemic instabilities.

Enhanced Regulatory Oversight: Regulators should have systems in place where it is compulsory to report the components of the AI systems, the trading algorithms being included. Constant checks and standard reporting systems will ensure the risks are contained and supervised in the correct manner. Efficient regulating systems will prevent circumstances where the rapid, automated execution of positions causes market volatility, thereby ensuring the stability of the financial system as a whole.

Banks and financial institutions should integrate AI trading alongside traditional risk management practices, it is proposed. It is feasible to get a more precise assessment of systemic risk by using a blend of traditional risk measures and AI measures in a hybrid system. This will require keeping a constant eye on forces in the market, stress-testing the AI models under different conditions, and having a backup set of measures ready in the event of potential flash crashes. Ethical and Bias Mitigation Practices: In view of the ethical issues encountered in the literature, organizations need to adopt proactive practices of identifying and mitigating the biases in the AI models. It can include the continuous monitoring of the data fed to the models to train, the use of fairness-aware techniques, and integration of diverse data sets so that the decisions to trade are not data-driven but also fair. Data security and privacy policies need to be defined and must be strictly followed so that the financial data of a sensitive nature do not get leaked out.

Future empirical studies: While this study provides a rigorous foundation in secondary studies, the use of primary data gathering techniques—i.e., interviews of experts in the field or case studies of specific trading exchanges—to test and build on these conclusions will strengthen future studies. Longitudinal studies, in particular, will be useful in being able to observe evolution of the effects of AI in a wide array of market conditions as they evolve in real time. Comparative studies in geographical markets or under conditions of different degrees of regulation will also provide insight into the role of context in the evolution of AI's potential and areas of risk.

Cross-Disciplinary Cooperation: Finally, due to the technological innovation of using AI in finance, the regulators, the technologists, and the researchers must constantly interact and collaborate. This would facilitate the development of best practices and innovative solutions to the technical, ethics, and regulatory problems of this research.

6.3 Limitations

Even though the study in question is one of a kind, caution needs to be applied. Secondary data limit the findings of the study to the quality and type of available literature. Methodological and definitional differences across studies also introduce a certain degree of inconsistency in reported findings. Finally, due to the rapid rate of AI technology development, some of the findings will become outdated and obsolete as new models and techniques emerge. These concerns will be addressed by successive research using primary data collection and advanced analysis techniques.

Summary

Briefly, the thesis illustrates how the use of AI in the financial markets led to the significant improvement of market efficiency and trading practices, including the reductions in transaction cost, improvements in price discovery, and improved liquidity. Such benefits are, however, moderated by systemic risk, ambiguity of AI models, and new ethical concerns. By facilitating increased transparency, increased regulator oversight, effective ethical controls, and further empirical analysis, the study provides a path forward to the regulators as well as the practitioners in leveraging the benefits of AI while keeping its risks at bay.

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