How effectively can AI predict stock prices across different markets, and which factors contribute most to prediction accuracy?

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Business Information Technology
Research Based Thesis
2025

Abstract

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Degree: Bachelor of Business Administration – Business Information Technology
Thesis Title: Utilizing machine learning in the stock market
Number of pages and appendix pages: 31
This thesis examines how machine learning methods can be applied for predicting stock market and provides an analysis of these techniques. Machine learning has gained recognition to model complex patterns in financial time series with more data and computing power. This investigation assists in capturing relationships in financial data and reviews research from 2010 to 2025 to examine how efficiently different machine learning methods perform. The work reviews both simple methods such as random forests and complex deep learning networks utilizing real data from several investigations and integrates machine learning forecasting with established economic theories such as the Efficient Market Hypothesis, Behavioural Finance, and Adaptive Markets Hypothesis to place these capabilities within broader theoretical frameworks. This investigation integrates machine learning methods with famous economic concepts and challenges traditional market efficiency theories by analyzing how machine learning models can detect market inefficiencies caused by changing market conditions and human behavioural biases. Moreover this research investigates how these models can detect opportunities that arise from the market's inability to correct itself completely. Problems regarding algorithmic transparency, fairness, and regulatory compliance in machine learning financial applications have been addressed in this thesis. In addition this research examines the ethical and sustainable effects of employing machine learning in the stock market and utilizes systematic review methods to gather and combine performance data from multiple studies. Meta-analysis techniques have been implemented to merge the results together and the right techniques were applied for preparing data, testing models, and avoiding the common issues such as overfitting and data leakage. The results suggest that there are gaps in existing studies about situations where machine learning models perform better compared to traditional econometric methods. This study suggests ideas for future study directions and provides valuable information to academic researchers and financial practitioners regarding the current state of machine learning based financial forecasting. The research provides details about recent machine learning methods in stock prediction and gives direction for building trustworthy machine learning models and emphasizes the need for continuous evaluation and updates in changing market conditions.
Key words: Machine learning: ML, Financial forecasting, Stock price prediction, Efficient Market Hypothesis: EMH, Behavioural Finance, Adaptive Markets Hypothesis: AMH, Support vector machine: SVM

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1 Introduction

Computing technology has progressed quickly in the twenty-first century and financial data is now easily accessible and these changes have impacted research methodologies and its application in in the financial market analysis. In today's financial world, machine learning has become an important method for managing complex and fast-changing market data and this AI technique assists in handling nonlinear patterns that traditional methods struggle to manage. Current financial markets include stocks, derivatives, commodities, and digital assets which are large, fast, and diverse in nature. This unlocks opportunities and challenges for academics and practitioners, that require further research and analysis (Kelly & Xiu, 2023). Earlier, ARIMA models were used widely for predicting financial data because of their simple interpretation and easy statistical features and regarding forecasting financial time series, these models were popular due to their clear working methods.

However, these methods have basic limitations, especially in finding non-linear relationships between variables and they cannot adapt quickly when market conditions change rapidly. Machine learning methods such as support vector machines, random forests, LSTM networks, and neural networks are becoming more complex and these advanced algorithms have changed how financial companies predict market trends and make forecasts (Sezer et al., 2020). Fundamentally, predicting market movements accurately is a major challenge for both academic researchers and professional investors. Fama proposed the Efficient Market Hypothesis in 1970, which states that asset prices reflect all available information and the market cannot be consistently beaten through predictive models. Further, this theory suggests that achieving superior returns is not feasible. (Fama, 1970). A major change with behavioural finance can be seen, which only focuses on how psychological biases affect investor decisions and create market problems even in developed countries. A research by Meegle (2025), the Adaptive Markets Hypothesis shows that market efficiency changes over time regarding external shocks and investor behaviour and markets become more or less efficient based on these changing conditions (Meegle, 2025).

1.1 Rationale and Development of Machine Learning in Financial Markets

Financial markets produce huge amounts of data daily, therefore old analysis methods cannot handle modern trading needs. Machine learning systems process complex data rapidly and find patterns that human experts miss. This leads to better investment plans and risk control in competitive markets.

Kelly and Xiu (2023) provide basic study with high standards regarding using machine learning in financial market research. We are seeing that their work is setting important guidelines for this field only. Recent research shows that tree-based models like random forests perform better than traditional time-series methods for predicting rare financial stress events (Aldasoro et al., 2025). The model itself can further improve accuracy in identifying such events. The studies demonstrate that these models give more correct predictions for important but rare situations only and we can see this same pattern in different researches. Advanced deep learning methods like LSTMs and GRUs help model financial time series data that has high noise and repeating patterns. These techniques work well for capturing the complex relationships in financial data and these methods can only handle complex financial signals in an effective manner. According to the analysis, these systems work well regarding complex financial data patterns, they handle complicated financial information effectively. McKinsey (2020) suggests that companies using the same strategies got more than 10% profit increase and this finding proves that the same strategies work well in different organizations. These technologies work in the same way to study large unorganized data from news and social media only, and we are seeing that this helps to check market sentiments and changes effectively. We are seeing that the analysis process only gives valuable insights for market evaluation (Ayyildiz et al., 2024).

Research demonstrates that machine learning models provide better accuracy than basic statistical methods for market forecasting and these models consistently deliver the same improved performance across different market conditions. Dacheng Xiu (2020) found that model-driven trading strategies give better R2 and Sharpe ratios compared to the same old traditional methods and these new methods provide better returns when managing risks and help reduce financial losses more effectively. The efficient market hypothesis states that stock prices reflect true value at all times whereas behavioural finance reveals that markets contain limitations as a result of investors' emotional and irrational decision-making patterns. In summary, the efficient market hypothesis reveals that asset prices are the same as their fair value because markets exploit all available data rationally. Based on behavioural finance studies, people regularly deviate from ideal investment behaviour regarding cognitive biases such as overconfidence, loss aversion, and herd mentality, fundamentally, market bubbles and crashes demonstrate the same pattern where EMH does not work accurately, especially in times of crisis or when new information appears unexpectedly. Recent investigations suggest that behavioural patterns and inefficiencies continue to exist and can be adopted by machine learning systems for predictions and it appears that EMH combines both views and suggests market efficiency only changes over time due to technology, behaviour, and rules (Meegle, 2025).

1.2 Current Opportunities and Challenges in Financial AI

According to the current practices, machine learning models are widely used for algorithmic trading, risk management, and fraud detection. Regarding their implementation, these models face major ethical, practical, and technical challenges. Moreover, overfitting, data snooping, and poor interpretability remain major obstacles, and the models further struggle with explainability, these issues create resistance to structural market dynamics. Modern machine learning systems are complex and difficult to understand, which poses trust and accountability issues in important situations and deep learning brings up critical questions about transparency when used in high-stakes scenarios. The 2010 "Flash Crash" revealed how unsafe unregulated automated trading systems can be when they result in sudden price changes, also these systems produced feedback loops that humans could not anticipate or resolve fast enough. These incidents illustrate the threats across the whole system and require strong ethical and legal rules for AI and data management in finance (FSB, 2024) and appropriate frameworks are crucial to prevent such risks in financial institutions.

1.3 Research Problem and Objectives

Research Question: To what extent can AI predict stock prices across different markets and which factors contribute the most to the prediction accuracy?

Market structure, liquidity, and volatility impact how well machine learning can predict market movements and these factors determine the accuracy of such predictions in real trading conditions. The system's ability to predict outcomes is reliant on how good the market information is and high quality data leads to precise predictions.

Financial machine learning encounters similar concerns such as data leakage, overfitting, and non-stationary markets that cause models to underperform in real trading, however, these issues can be solved by implementing appropriate cross-validation strategies, regularization methods, and similar practise of continuously updating models with real-time market data. In summary the key problems are dataset shift, overfitting, and structural breaks - all are the same type of modelling issues. The major issues regarding ethics include unfair trading practices and data misuse. Regulatory and sustainability issues arise regarding market manipulation, job losses, and high energy consumption.

This objective analyzes the latest machine learning advancements as per their use in financial forecasting applications. The goal is to bring together these developments into complete findings.

Moreover, this will help create a comprehensive understanding of the subject. Basically, compare how the best machine learning models perform against traditional methods using published research and business results - it's the same approach of evaluating performance differences. This study further analyzes the performance differences itself using empirical data.

Machine learning predictions further change how markets work by finding patterns in investor behaviour itself, these predictions help identify what investors do and how they act. These patterns help us understand how markets are working in new ways only as the traditional finance theory cannot explain the same patterns any further. Smart systems are making markets work better by catching emotional trading, however, these tools seem to create problems because many investors cannot access this advanced technology. We must examine the fundamental operational, ethical, and legal boundaries that apply to all AI systems, these basic limits are the same across different AI technologies. This study further examines explainability, justice, and systemic risk itself together at the same time and this approach helps to understand how different elements work with each other.

1.4 Scope and Delimitations

This study examines only the supervised machine learning models that can be seen in global stock and bond markets from 2010 to 2025 and covers both shallow and deep learning methods. This analysis includes only daily trading data and focuses on longer-term predictions. This study does not include cryptocurrencies because they have different data patterns, moreover, cryptocurrencies face many regulatory problems that make them unsuitable for this analysis. This research does not collect new data as per the research design but utilizes existing secondary sources regarding the topic instead, basically uses the same existing data that is already available for collection. The conclusions come from published research papers only, with policy and regulatory reports used when needed. Moreover, this approach ensures that findings are based on proven scientific evidence since leading experts have provided straightforward guidelines so companies follow the same standards for algorithmic ethics and market effects (The Actuary Magazine, 2024).

1.5 Input from Theory and Practice

As per theory, this study expands our knowledge regarding how today's machine learning methods either challenge or improve strong and semi-strong EMH forms in different market conditions. This study helps institutional investors, and technologists understand the real effects and governance problems of algorithmic finance (FSB, 2024), moreover, it provides practical insights for managing these digital financial systems. Furthermore, we are seeing more checking of AI decision systems after recent market problems and rule changes, so this study suggests that we should invest in machine learning carefully with only strong risk control and proper oversight.

2 Significance of the Research

The academic significance of this thesis can be attributed to its involvement with the expanding research frontier combining elements of financial economics, machine learning, and data science. Sezer, Gudelek, and Ozbayoglu (2020) argue that financial markets accumulate extensive quantities of complex data that arrives rapidly and changes a lot with complicated connections between different parts. ARIMA and GARCH models cannot detect the complex changes and fast-moving patterns that occur in financial data for money market forecasts, these traditional methods face challenges with the complex nature of how markets react (Zhang, Sjarif & Ibrahim, 2023). Machine learning models are developing into popular choices as they can tackle complex data patterns and nonlinear relationships successfully and these models can easily adapt to various types of data relationships (Kelly & Xiu, 2023). As stated by Nguyen, Smith, & Zhao (2023), the research concerning machine learning for money forecasting is scattered across countless studies and the researchers utilize various methods which poses challenges to combine the results also it is crucial to review and compare all findings carefully to find which machine learning models are most effective in different situations. It is crucial to understand which data cleaning methods and features assist in making the models achieve better results as per requirements and regarding model improvement.

This bridges this gap by performing a complete investigation of different research papers and merging results of machine learning methods implemented in portfolio optimization and stock price prediction. This study creates a theoretical framework that connects traditional financial theories such as the Efficient Market Hypothesis (Fama, 1970) with behavioural finance concepts (Shiller, 2003); justification for the use of Fama 1970 as a source: Fama 1970 is the original work that first explained Efficient Market Hypothesis EMH, therefore it the standard reference for EMH and that is the reason for utilizing it as a source in this thesis. Moreover, it connects these concepts with new data from machine learning research in finance (Urquhart, Hudson, & Lucey, 2023), this allows for thorough inspection of how well markets function when employing data models that can only use market challenges caused by how people behave (Yıldırım, 2024). This study further focuses on best practices to avoid common issues such as overfitting, where the model functions effectively on training data but fails to operate normally on new data (Ayyildiz et al., 2024). This investigation examines methods for example robust testing, feature engineering, and cross-validation which are the important approaches required for precise forecasting, these techniques aid to make financial models forecast better (Zhang, Sjarif & Ibrahim, 2023). The work investigates how previous research measured success and suggests improved metrics for instance looking at risk-adjusted returns instead of statistical accuracy to interpret the same real financial impact (Kelly & Xiu, 2023).

Another aspect of academic significance is the analysis of novel, alternative datasets that have recently gained traction as inputs to machine learning models, for instance social media sentiments or satellite imagery (Nguyen et al., 2023). These data sources can improve prediction accuracy by capturing environmental and behavioural signals that traditional price and fundamental analysis fails to capture. Finally, this thesis explores the governance and ethical issues in financial machine learning, the introduction of automated decision-making into financial markets has given rise to significant concerns about model explainability, fairness, accountability, and systemic risk (Financial Stability Board, 2024; Bank of England, 2025). By thoroughly analyzing these factors, the academic conversation is expanded to include responsible innovation rather than only technical optimization.

2.1 Practical Significance

The financial industry is employing more data technology and algorithmic trading, therefore machine learning research applications equally essential for practical work. Asset managers and hedge funds utilize machine learning to manage risks and portfolios more effectively, these algorithms help them make more accurate trading decisions and achieve more favourable outcomes (Mintarya, 2023), hence it is necessary to find which models provide reliable predictions to justify the same technology investments further and this understanding aids in making right business decisions and it improves the overall decision-making process. This thesis further offers practitioners with compiled evidence on the best machine learning methods such as ensemble approaches, neural networks, and support vector machines, along with relevant input features and data treatments itself (Ayyildiz et al., 2024). The theory further helps decision-makers understand when specific models work best in different market conditions itself. This knowledge helps them create trading algorithms for different assets and time periods and they may build systems that work for various investment types.

Alternative data like social media trends and satellite measurements has changed the informational advantage in financial markets which creates new opportunities for investors to access real-time information (Nguyen et al., 2023). This investigation analyses the degree to which these datasets work and investigates the issues that arise when combining them and it helps managers understand strengths and weaknesses of making their data systems larger. Additionally it presents the simple factors for example the rate at which models can grow, operate and respond are becoming more important in high-frequency and algorithmic trading (Kelly & Xiu, 2023). The study helps in making technology decisions by demonstrating how to balance processing speed, energy use and model complexity, as these factors function together in a similar manner. In line with current regulations, companies are experiencing increasing pressure regarding fair and transparent operations of their automated systems. The Financial Stability Board (2024) indicates that both regulatory and reputational concerns are mounting for businesses. Moreover, this thesis examines different strategies to make models clearer and properly regulated thus increasing stakeholders' confidence in them and risk management practises are applied consistently.

Regulators worldwide are increasingly focusing on the extent in which computer trading and machine learning influence market stability and fairness, the 2010 Flash Crash displays that algorithmic trading systems may generate dangerous feedback loops which can pose a threat to the stability of the entire market. Automated trading systems require appropriate monitoring, which has become urgent at this present time and The Financial Stability Board (2024) displays similar patterns in global financial risks across different markets. (Financial Stability Board, 2024). This research helps regulators by delivering a clear overview of new research on machine learning trading as it explains how machine learning trading influences the key market functions such as price discovery, liquidity, volatility, and risk transmission across various markets. It helps to identify risk indicators and intervention points which are crucial for developing proactive supervisory controls. In the study's analysis of algorithmic transparency frameworks, regulatory efforts can ensure accountability and reduce conflicts from opaque black-box models, regarding auditability measures, these help to support oversight of algorithmic systems and companies should effectively record, test, and check AI systems with respect to the new standard requirements.

The work examines larger social questions concerning the ethical development of AI systems in finance and its impact on the environment, which means looking beyond technical and financial concerns, modern machine learning models need high quanties of processing power for training, which leads to more energy consumption and eventually resulting in increased carbon emissions (OpenAI, 2023). Sustainability is gaining importance worldwide, therefore reducing these environmental expenses becomes crucial and this process requires immediate attention from every sector like any urgent matter does. This thesis raises these issues by encouraging financial institutions to utilize energy-efficient algorithms and low-carbon computing techniques, these methods can help in reducing the environmental impact of financial operations and this approach corresponds to new methods that involve environmental care, social responsibility, company management in technology development. It aligns well with the frameworks that combine these important areas together and this approach brings different fields into one unified system. Predictive machine learning may worsen inequality by excluding small investors from the market as this technology is in favour of companies with better access to advanced tools and data resources (Yıldırım, 2024). The study demonstrates that equal access to financial technology is crucial for everyone and AI technologies must be accessible to everyone without any discrimination, financial

AI supports UN's Sustainable Development Goals by promoting industrial innovation and reducing inequality.

2.2 Benefits for Researcher and the Institution

The project prepares researchers for academic, fintech, or regulatory work environments and it establishes a strong foundation for future scholarly contributions. Moreover, the thesis output will support the local innovation environment by providing the same comprehensive resource on financial machine learning opportunities and risks.

3 Objectives and Scope of the Research

This study aims to examine how machine learning techniques are currently used to predict stock price changes in financial markets by gathering the latest research to assess these methods critically. Moreover, machine learning algorithms have expanded their capabilities further, however, academic researchers and investors must still understand how effectively these algorithms perform in different market scenarios (Kelly & Xiu, 2023). Thus, the main goal is to create a complete, data-based insights into how different machine learning models work, the market conditions where they operate, and how accurately these models predict compared to traditional econometric models. It seems that this approach will only help us understand which models perform better in real market situations. This thesis aims to add to academic knowledge by studying the benefits and problems of each strategy, it compares the methods used in earlier research. This study will review earlier research work to understand different methods and ways to measure results and this review will help identify various approaches used in previous studies. This research aims to find the best machine learning methods for different financial prediction tasks and the study will provide complete results to identify which techniques are most suitable for each type of financial forecasting. The study examines different methods such as support vector machines, deep neural networks, ensemble approaches, and decision trees to find out how effective they are. Moreover, it compares these techniques to determine which ones work best.

Earlier investigations faced issues with overfitting, data leakage, and evaluation biases, therefore this study attempts to develop guidelines that produces stronger and repeatable models and these guidelines will aid in enhancing the effectiveness of the extent to which the models perform consistently across repeated trials. The research suggests that feature engineering is fundamental for combining different data sources such as sentiment analysis, social media, news, and location data, it's the same approach needed to improve predictions in finance applications. This study is trying to explore what ethical, legal, and regulatory concerns arise when using ML models in finance, however the main focus stays on openness, fairness, and handling big risks, which are getting more attention from universities and financial authorities (Financial Stability Board, 2024).

3.1 Sub-Objectives

Researchers must assess and compare the accuracy of well-known machine learning methods for instance random forests, support vector machines, neural networks, and gradient boosting for stock price prediction and various studies indicate that such comparison is necessary to understand which method performs best. The comparison should focus on which technique provides the most accurate results for stock return prediction which involves bringing together model performance results, testing strength, and computing efficiency from different studies and datasets (Kelly & Xiu, 2023; (Zhang, Sjarif & Ibrahim, 2023)). In addition, such combination helps researchers understand the effectiveness of different approaches across multiple researches and this research can study how the integration process impacts the overall model quality.

Feature engineering methods impact machine learning model performance in various ways when the followings are utilized: technical indicators, basic factors, and alternative data, in addition each type of data input reacts in a different way to different engineering strategies for example technical indicators work better for short-term predictions, whereas fundamental factors are more accurate for long-term forecasting. Methods such as PCA, autoencoders, and feature selection techniques can reduce data dimensions, depending on market conditions, machine learning predictions tend to become more or less accurate. However market changes will directly impact the effectiveness of these predictions and factors such as price changes, trading patterns, and market liquidity might significantly enhance or worsen the same prediction (Htun et al., 2023)

Model testing requires cross-validation techniques and out-of-sample checks to ensure appropriate validation and the best way is to divide data into training and testing parts, utilize k-fold cross-validation, and check how the model functions on new data to ensure it provides accurate outcomes. It seems that researchers must only point out common problems in machine learning finance studies, such as data snooping, lookahead bias, and overfitting (Yıldırım, 2024). To verify moral and legal issues, it is necessary to critically assess these recent policy decisions, compliance rules, and guidelines from global bodies such as ESMA and FSB as this will resolve the governance issues and system threats that occur when AI is applied in banking and financial services, in addition financial professionals must follow practical guidance for the selection of AI models and data integration.

3.2 Research Questions

The questions regarding topic links show appropriate matching. The study framework ensures all research areas connect well with each other. These specific objectives are designed to answer the research questions that provide the same clarity and boundaries for investigation.

Fundamentally, no machine learning technique consistently outperforms traditional models across all stock market datasets and conditions - the performance remains the same as it depends on specific market situations and data quality.

Feature engineering and additional data sources improve machine learning models' prediction accuracy in finance and these methods make the models more stable and reliable for forecasting financial outcomes.

Market conditions like liquidity and volatility have a direct impact on machine learning model performance for price prediction. Moreover, these factors determine how accurately the models can forecast market movements. The market structure decides whether these models will work well in different trading situations.

Machine learning research for money predictions has only three main problems - choosing wrong data, making models too complex, and using poor testing methods. Regarding prevention, researchers can use different datasets and apply cross-validation methods to test models on new data as per standard practices to avoid these problems. (Wasserbacher & Spindler, 2021)

3.3 Scope and delimitations

This topic is very broad and needs many resources, therefore it is important to set clear boundaries, as this will help to focus on specific areas. The analysis will focus on high-quality public datasets from 2010 to 2025 from major stock exchanges in North America, Europe, and Asia. This study focuses on equity markets, which includes individual stocks and equity indices - the same asset classes that represent ownership in companies, however, it does not include commodities, fixed income, derivative markets, and cryptocurrencies. Moreover, these areas will be discussed briefly in separate sections.

This thesis examines the accuracy and consistency of the different machine learning methods including both simple and deep learning models, it is the same approach for evaluating their computing efficiency. Unsupervised learning, reinforcement learning, and hybrid models will be discussed although they are not the main focus of this research. The evaluation will focus on developed markets such as the US, EU, and Japan as the data is easily available there, these markets have mature industries that result in more reliable research. This research utilizes solely literature review and meta-analysis methods to integrate published studies, industry reports, and academic papers, furthermore, empirical simulation or back testing experiments are recommended for additional research, however these are not included in this work. This research will study how automated trading systems can create big concerns and verify if current rules like GDPR and new EU AI laws are functioning appropriately also the regulatory environment needs careful examination along with these automated trading threats. The study has limitations as it examines only public data and published research, further excluding private models or company algorithms that may perform better in particular scenarios.

4 Theoretical Framework of the Thesis

The theoretical framework of this research presents essential elements and techniques for conducting an investigation for machine learning in financial prediction, the main theoretical models and analytical frameworks that have impacted the development of predictive procedures have been addressed in this chapter. Through the analysis of the fundamental principles that lead feature selection, model complexity, and validation techniques, the framework provides an ordered framework for the research questions and methodological choices explored in following chapters. This thesis integrates notions from behavioural studies, market knowledge, traditional finance theories, and modern machine learning methods, this mixed technique aids in comprehension of financial markets from diverse viewpoints. The framework delivers the fundamental concepts for examining how machine learning models can be utilized to forecast financial markets, which helps to interpret these machine learning tools through simplified terms. This approach provides thorough foundation to the research problem by connecting genuine findings with established economic theories and computational ideas, which eventually guides the methodology. Four main theories have been utilized in this work such as behavioural finance that examines people's views on money, the Efficient Market theory that states markets are rational, the Adaptive Markets theory that argues markets change over time, and machine learning theories about teaching computers to predict patterns. (Shiller, 2003)(Fama, 1970) (Lo, 2004). These theories help tounderstand both human behaviour and computer methods in financial markets. The framework also explores ethical and governance problems in algorithmic finance tensions about AI's systemic influence continue to rise (Financial Stability Board, 2024).

4.1 Efficient Market Hypothesis (EMH)

Eugene Fama's 1970 Efficient Market Hypothesis suggests that stock prices already include all the information, therefore making extra profits through predictions is equivalent to impossible. The EMH has three categories that demonstrate different types of data in stock prices: weak, semi-strong, and strong, each type reflects the amount of market information that is already included in the current price. Fama (1970) argues that strong EMH leverages all public and private information concerning market prices, in contrast weak EMH only exploits past price data (Fama, 1970). EMH declares that financial markets utilizes all available information efficiently and stock prices move randomly, making future returns unpredictable (Fama, 1970). According to the learning principles, this generates a concern regarding predictive modelling utility since any attempt to predict future prices using past or public data becomes useless.

However, research evidence questions whether EMH applies everywhere, moreover, real market data shows the theory has clear limitations. Stock returns show seasonal patterns, momentum effects, and mean reversion - these are the same anomalies that cannot happen by pure chance (Jegadeesh & Titman, 1993). According to recent studies, ML models can find hidden patterns and non-linear connections in big datasets that EMH typically misses, especially regarding weak and semi-strong market forms (Urquhart, Hudson, & Lucey, 2023). These models can therefore exploit market inefficiencies better than traditional methods. EMH works as the main benchmark used to assess whether machine learning methods can predict market results or not, this is only used to check if these methods give the same results. In case machine learning gives extra returns or better predictions, it further challenges how efficient markets are and promotes the same theoretical research that Fama (1970) suggested. The economics of conduct examines how people behave in different economic situations. People make similar decisions by looking at costs and benefits.

Behavioural finance differs from EMH and further suggests that markets have rational agents. Moreover, this approach shows that market behaviour reflects human psychological factors (Shiller, 2003). It appears that this field only combines psychology and economics ideas to explain strange market events like bubbles and crashes and it focuses on understanding why markets behave differently from basic economic rules for long periods itself. This further explains the gap between market reality and economic theory.

Important behavioural biases such as overconfidence, loss aversion, anchoring, herding behaviour, and availability heuristics can further lead to systematic mispricing in markets. This bias pattern creates predictable return patterns that investors can observe and these biases combine together regarding price movements and create trading opportunities that advanced prediction algorithms can exploit. (Kahneman & Tversky, 1979; Shiller, 2003)

Nguyen, Smith, and Zhao (2023) state that machine learning models perform well when finding hidden patterns in huge and complicated datasets, these models are able to spot complex links that cannot be detected easily. These datasets could involve additional data sources such as news analytics, social media sentiment, and behavioural signals that traditional models might neglect. Machine learning functions effectively with behavioural finance as it can detect complex patterns that arise from human psychology in markets and this combination aids in understanding the way people's emotions and thinking impact financial decisions. Machine learning models are able to predict asset prices more accurately compared to traditional econometric models by including behavioural biases and investor sentiment indicators, this method addresses the linear assumptions that limit conventional models, as demonstrated in empirical studies (Yıldırım, 2024).

Behavioural Finance supports the application of ML-enabled forecasting to benefit from market inefficiencies generated by human behaviour and this theoretical framework provides a strong foundation for such forecasting approaches.

4.2 The adaptive markets hypothesis (AMH)

As stated by Andrew Lo's Adaptive Markets Hypothesis, market efficiency functions as an evolving process that relies on various situations, this idea connects behavioural finance with AMH concerning market processes. AMH theory suggests that environmental factors, competition, and market player’s strategic changes influence the market's long-term efficiency (Lo, 2004). These factors define how efficiently the market operates over time, markets are dynamic and change continuously, where natural selection procedures alter how investors interact and plan their strategies. Machine learning models support this evolutionary perspective as they change their internal settings and structures when they receive recent evidence, indicating the same flexibility (Kelly & Xiu, 2023). Machine learning forecasts perform effectively in inefficient markets however struggle in efficient market conditions, AMH explains this difference in performance over diverse market regimes. Financial forecasting models shall adjust to evolving economic conditions by learning and unlearning patterns to remain functional, this flexibility assists these models to stay meaningful when economic situations change over time (Lo, 2004). This theoretical foundation is important for understanding empirical outcomes that illustrate how market changes, liquidity, and structural breaks impact machine learning models' prediction accuracy and these factors directly impact how effectively the models can predict market movements (Sezer et al., 2020). These outcomes indicate that modelling practises are required that utilize various techniques or are aware of different regimes, it's the same requirement for better accuracy.

4.3 Machine Learning Theory and Principles

Machine learning is the procedure of teaching computers to learn from data and make decisions without someone programming each step (Hastie, Tibshirani, & Friedman, 2009). It seems that supervised learning is predicting output results from input data, this method is the key part of financial forecasting work. Financial time series data aligns effectively with principle ideas of machine learning and these notions perform together to analyze market patterns and predict future trends. The bias and variance trade off includes adjusting model complexity to avoid overfitting from high variance or underfitting from high bias and this trade off assists to achieve optimal model performance. Financial data includes much noise, therefore handling this trade off becomes more important.

Regularization methods such as Ridge regression and LASSO prevent overfitting by adding penalty terms to regulate model complexity, these methods help the model generalize better on latest data (Goodfellow, Bengio, & Courville, 2016). Model validation utilizes extensive cross-validation, walk-forward validation, and out-of-sample testing to guarantee the model functions optimally with new data (Zhang, Sjarif & Ibrahim, 2023). Deep learning models for example RNN, LSTM, and CNN excel at addressing time-based and complex data patterns, additionally simple shallow models fail to capture local structures and time dependencies that are crucial for such data interpretation (Sezer et al., 2020). Ensemble methods function by merging multiple models such as random forests and gradient boosting together, this method improves prediction reliability and precision as it lowers the risks that arise from the use of single models alone (Zhang, Sjarif & Ibrahim, 2023).

According to machine learning methods, computational tools can identify and use predictable patterns in markets. Regarding market conditions, AMH and behavioural finance show when such predictability occurs. The EMH theory suggests that stock markets cannot be predicted easily. Moreover, this happens because all available information is already included in market prices.

This model serves as a guideline for evaluation standards and supports analysis of the thesis empirical data, for example enhanced machine learning outcomes propose that EMH assumptions may lack generalizability and when these models demonstrate changing performance over time, it supports AMH's perspective that market efficiency undergoes continuous fluctuation.

4.4 Ethical, Regulatory, and Societal Considerations

This investigation explores the ethical and social effects of employing AI technology in finance. According to the Financial Stability Board (2024), ambiguous "black-box" machine learning models may erode trust and accountability in financial markets about their clarity and explainability (Financial Stability Board, 2024). Transparent AI techniques are crucial for checking and confirming decisions produced by AI models, additionally these methods help clarify how AI arrives to its findings. The Bank of England (2025) demonstrates that automated ML trading can result in can trigger market crashes and sharp price fluctuations, this implies that rules are required to balance new technology with market stability. According to GDPR and other data protection rules, companies must follow appropriate techniques concerning sensitive personal data to maintain legal and ethical standards (European Parliament, 2016). These elements are important for advancing and utilizing machine learning algorithms precisely and, they are included in the theoretical framework to analyze how ML functions in modern finance. Machine learning aids to forecast financial markets by exploring how logical trading and human emotions work together.

5 Research Methods

This chapter presents the methods for answering the research question of this thesis. It shows the process of collecting, analyzing and interpreting data, and justifies approaches implemented. This chapter ensures clear reporting of methods that have been utilized and explains how the outcomes were obtained.

5.1 Research Approach and Design

This investigation utilizes a systematic literature review and meta-analytical approach to integrate and examine research on machine learning methods for predicting financial markets. Meta-analytical approach merges results from several works to derive findings about a specific research topic. This study analyses how machine learning approaches function in predicting market trends and it appears that systematic review methods aid to bring together academic and industry knowledge in a transparent manner, this approach provides a strong base to understand new methods, research findings, and practical issues within the field (Tranfield, Denyer, & Smart, 2003).

This research uses popular theories such as Efficient Market Hypothesis, behavioural finance, and machine learning theory as its foundation (Fama, 1970), (Shiller, 2003), (Hastie, Tibshirani, & Friedman, 2009). The thesis uses a deductive approach based on proven theories which enable the researchers to generate clear questions and set appropriate standards for analysis as they make it easier to understand research outcome systematically (McGonagle, 2019). According to the research plan, the principle objective is to integrate and study all practical investigations and combine their results published between 2010 to 2025. Machine learning methods have developed rapidly in financial forecasting caused by enhanced computing power and easier data access, these techniques are now applied more extensively in the financial sector (Kelly & Xiu, 2023).

5.2 Data Collection Methods

This thesis utilizes secondary data from reliable industry reports, conference papers, white papers, and peer-reviewed journal articles that investigate how machine learning techniques may be used for stock market predictions, relevant publications were found using databases such as Web of Science and Google Scholar. The search strategy used Boolean operators with specific keywords such as "machine learning," "stock price prediction," "financial forecasting," "algorithmic trading," and "financial time series" to get complete coverage and this method assisted in finding all relevant works within this field that emphasized the application of supervised machine learning techniques to predict stock prices or returns.

5.3 Data Analysis Procedures

The investigation was carried out in several stages and from each study the key details were extracted for instance model type, features utilized, prediction time period, market type, performance results, validation methods, and limitations. The study needed detailed steps to ensure results can be repeated and examine potential biases, these actions were required to achieve the standard research requirements.

Qualitative Synthesis: The analysis detected the same common challenges such as overfitting and data leakage occurring in financial studies therefore researchers must implement enhanced approaches and address ethical considerations in their work in addition following appropriate protocols is important for conducting a reliable research.

Comparative Evaluation: Machine learning models were compared with traditional econometric techniques to assess performance differences, this evaluation helped to detect when machine learning approaches performed more effectively or worse compared to the conventional methods.

6 Results

After evaluating various studies and industry reports published between 2010 and 2025, many trends were found about machine learning's effectiveness in financial forecasting. This research contrasted different machine learning methodologies such as deep learning models, LSTM or GRU types and ensemble methods such as random forest. Most of the studies we can find demonstrate that machine learning methods perform better than traditional models like GARCH model and ARIMA model, especially when they process complex non-linear market data. According to Sezer et al. (2020) and Kelly & Xiu (2023), machine learning models often identified patterns that classical time-series techniques ignored. Aldasoro et al. (2025) found that random forests and gradient boosting were "especially effective" at predicting rare events in advance, such as the early signals of financial stress.

Deep learning models have their own strengths and weaknesses. LSTMs and GRUs have been some of the best approaches to handling noisy, unpredictable data (Dacheng Xiu, 2020), although they have their own weaknesses. Support vector machines operated effectively in stable market conditions, however they require delicate feature normalization to perform well.

One thing that became clear was that market conditions have a significant impact on the success of these models, when investigating the performance of different machine learning (ML) models in finance. The factors that drive these models have turned out to be liquidity, volatility and the way markets are put together, and these models tend to fall apart when there's a downturn in the market or a sudden change in the market structure. Well-known, older models that are trained to go off the data they've been given can't handle these kinds of events, but have still managed to pick up on patterns in developed markets where the data quality is higher. Machine learning models are leveraging one area that traditional methods are not implementing is the unusual patterns in how people behave in the financial markets for instance studies that offered a new view at social media sentiment and news analysis have demonstrated that the prediction accuracy of the ML models gets a significant boost (Nguyen et al., 2023). This aligns with concepts of behavioural finance and the Adaptive Markets Hypothesis, and especially in the rapidly fluctuating markets.

Short-term predictions were supported by technical indicators, whereas fundamental factors enhanced longer-term predictions, and several studies highlighted the use of dimensionality reduction methods such as PCA and autoencoders to prevent overfitting and scaling challenges. The examined investigations measured and compared performance with R-squared, Mean Squared Error, and accuracy levels, indicating that the ML approaches consistently outperformed traditional methods, particularly in independent testing, but deep learning models need a lot of validation to stop themselves getting too reliant on the training data.

Overfitting and leaking of data where the model is fed too much information are still major concerns in the area of financial analysis, and the opaque nature of deep learning has raised serious questions about interpretation and the legality of these models. Dataset drifts, and not being able to predict regime changes, also caused some of the models to fail.

No one method won out across all situations. Choosing a model needs to match particular use cases, data availability, and market conditions. Ensemble and deep models gave the best accuracy but needed more complexity and validation. Possibly the most crucial takeaway: We still haven't sufficiently worked out the ethical and governance concerns around transparency, and that's a big reason why people haven't rushed to these methods with open arms.

Model	**Best Context**	**Data Types**	**Performance**	**Main Limitation**
Random Forest	Developed, liquid markets	Price, technical indicators	High accuracy	Interpretability
LSTM/GRU	Volatile/noisy conditions	Price, sentiment, alternative	Very high R^2	Overfitting risk
SVM (Support Vector Machine)	Stable markets	Price, fundamentals	Moderate	Feature scaling sensitive
ARIMA/GARCH	Any	Price only	Low	Misses nonlinearity

Table 1: The table above summarizes key model characteristics from the reviewed literature

To summarize the evidence does confirm that machine learning methods can give solid, meaningful accuracy increases when appropriately dialled in and validated. Performance is suitable across contexts, though we still need to give careful consideration to data quality and the kind of feature engineering that gets us interpretable models.

7 Discussion

Ethical research integrity is essential, although the thesis does not collect primary data or involve human subjects. All reports and books used in this work are appropriately referenced to maintain academic honesty (American Psychological Association, 2020). This study discusses the ethics of using AI and ML in financial markets, therefore it follows the same frameworks for responsible innovation. In line with Financial Stability Board (2024), special focus is given to reducing system risks in automated trading systems (Financial Stability Board, 2024). Regarding privacy and fair decisions, attention is paid to GDPR rules (European Parliament, 2016) and fairness in computer-based choices (Yıldırım, 2024).

Limitations of the Research Methods

1. Publication Bias: Research shows that successful machine learning studies are published more often than the failed ones, which can further create wrong ideas about how well these methods work in reality. This publication bias itself may mislead people about the actual effectiveness of machine learning approaches (Ioannidis, 2005).
2. Secondary Data Dependency: The research depends on secondary data, which limits direct performance evaluation. Without empirical experiments, the system itself cannot generate new data for testing.

This study focuses only on research after 2010 and big developed market assets, so it might miss important insights from emerging markets or earlier foundational studies. The same limitation applies to the time period chosen.

7.1 Data Management Plan

Good research data management is important for maintaining reproducibility and scientific integrity according to the legal requirements, and it guarantees compliance with all ethical rules and standards. This chapter describes the methods utilized to manage and organize data in this study, and also the strategies followed throughout the thesis, furthermore it provides clear directions for managing data throughout the research. This study uses only secondary data therefore it reduces privacy issues as no personal details are included in this entire work.

GDPR argues that any information that can identify a person directly or indirectly is considered personal data, and such type of data requires protection. Personal data includes for instance the basic information such as names, contact details, job titles, and demographic data (European Parliament, 2016).

7.2 Problem Areas and Risks

Every research has limitations and unknown factors which can impact the results and the accuracy of the outcomes. These challenges can affect the validity of conclusions in scholarly work. Finding and managing these risk factors is the same as protecting the research's credibility and ethical standards. This chapter describes the important risks related to this thesis from scientific, practical, and ethical points of view. The risks are carefully examined to understand their impact on the current research work. Strategies have been proposed to reduce these risks based on good research practices that are recognized in academic studies and institutional guidelines ((McGonagle, 2019); Tranfield, Denyer, & Smart, 2003).

7.3 Model Implementation and Evaluation

According to machine learning research findings, evaluation bias and model overfitting are major concerns regarding the accuracy of results. These problems happen very often in most studies. Models show poor performance on new data when they overfit by learning noise instead of actual patterns (Hawkins, 2004). This overfitting regarding training data leads to weak generalization capabilities. Banking machine learning studies face risks from non-stationary data and excessive hyperparameter tuning itself. Further, insufficient cross-validation makes these problems worse.

Further, when test data information accidentally affects model training, data leakage may cause inflated performance metrics (Kaufman, Rosset, Perlich, & Stitelman, 2012). Different studies utilize different testing techniques and performance indicator, making it challenging to make direct comparison of findings across studies. This thesis concentrates on investigations that use data division and demonstrate strong testing on new data and careful analysis of research methods.

7.4 Publication Bias

It was observed that researchers mostly present only the successful outcomes, which can create challenges with transparent publication of studies. Machine learning models appear more effective than they are because studies with poor or negative results are often not published, creating the same misleading impression of success and this problem occurs when researchers decide to publish only positive results (Ioannidis, 2005). Such biased publishing gives rise to serious problems in research and the results make sense only if this research limitation is openly acknowledged.

7.5 Access to Comprehensive and Relevant Literature

It appears that important research from smaller journals or company reports might get missed even with large databases such as Google Scholar and Web of Science and language barriers further reduce inclusivity whenever only English sources are used, which creates additional barriers for non-English speakers. To reduce this limitation, multiple databases and manual reference searches have been utilized, and machine learning findings can mislead readers if researchers exaggerate its capabilities. Future research will suffer if the real results are distorted and by presenting the challenges and comparing with other research, the thesis has offered an unbiased assessment.

7.6 Risk Management Strategies

- Strict Protocol Adherence: Following strict protocols is essential to ensure research quality. Researchers must follow appropriate guidelines as Moher et al. 2009 suggests and following a systematic review protocol such as PRISMA makes research transparent and reduces scientific differences.
- Ethical Oversight: Following data protection rules and getting ethics approval encourages responsible research behaviour and compliance with these institutional policies guarantees ethical review in research.
- Balanced Reporting: Good research arises when scholars give equal consideration to both strengths and weaknesses which prevents biased reporting.
- Documentation: Keeping detailed records of search methods, selection decisions, and data analysis helps make study reproducible and clear documentation provides an audit trail for systematic reviews.
- Regular Supervision and Peer feedback: Regular supervision and peer feedback help to detect new challenges early and close work with other people and thesis guides makes identification of problems much easier.

Finding risks is essential for successful implementation and to achieve great outcomes these problems must be appropriately fixed. This study has the following limitations such as different methods and data quality issues, however, if the best practices are followed they provide reliable results.

8 References

Aldasoro, I., Fender, I., Hardy, B., & di Mauro, F. (2025). Predicting financial market stress with machine learning. *BIS Working Papers, 1250*. https://www.bis.org/publ/work1250.htm

Ayyildiz, N., Soytas, U., & Altay, Z. (2024). How effective is machine learning in stock market forecasting? *Applied Soft Computing, 147*, 110214. https://www.sciencedirect.com/science/article/pii/S2405844024001543

American Psychological Association. (2020). *Publication manual of the American Psychological Association* (7th ed.). https://apastyle.apa.org/products/publication-manual-7th-edition

Bank of England. (2025). *Financial stability report: Machine learning and AI in finance*. Bank of England Publications. https://www.bankofengland.co.uk/-/media/boe/files/financial-stability-report/2025/financial-stability-report-july-2025.pdf

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Wiley. https://doi.org/10.1002/9780470743386

Dacheng Xiu. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273. https://dachxiu.chicagobooth.edu/download/ML.pdf

European Parliament. (2016). Regulation (EU) 2016/679 on the protection of natural persons (General Data Protection Regulation). *Official Journal of the European Union*, L119. https://eur-lex.europa.eu/eli/reg/2016/679/oj

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417. https://people.hec.edu/rosu/wp-content/uploads/sites/43/2023/09/Fama-Efficient-capital-markets-1970.pdf

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

European Central Bank. (2024). The rise of artificial intelligence: benefits and risks for financial stability. Available at: https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202405_02~58c3ce5246.en.html

Financial Stability Board. (2024). *The financial stability implications of artificial intelligence*. https://www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence/

Financial Stability Board. (2024). *The financial stability implications of artificial intelligence*. Financial Stability Board. https://www.fsb.org/wp-content/uploads/P14112024.pdf

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Haaga Helia University of Applied Sciences. (2024). Thesis Guidelines.

Haaga-Helia Library and Information Services. (2024). Data management guide. Haaga-Helia University of Applied Sciences. Available at: https://libguides.haaga-helia.fi/data-management-in-thesis

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer.

Hawkins, D. M. (2004). The problem of overfitting. *Journal of Chemical Information and Computer Sciences*, 44(1), 1–12. https://doi.org/10.1021/ci0342472

Htun, H. H., Kyaw, Y. L., & Kyaw, S. M. (2023). Survey of feature selection and extraction techniques for stock market prediction. *Frontiers in Artificial Intelligence*, 6, Article 9834034. https://pmc.ncbi.nlm.nih.gov/articles/PMC9834034/

Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine, 2*(8), e124. https://doi.org/10.1371/journal.pmed.0020124

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Kahneman, D. & Tversky, A. 1979. Prospect theory: an analysis of decision under risk. *Econometrica*, 47(2), 263–291. https://doi.org/10.2307/1914185

Kaufman, S., Rosset, S., Perlich, C., & Stitelman, O. (2012). Leakage in data mining: Formulation, detection, and avoidance. *ACM Transactions on Knowledge Discovery from Data*, 6(4), 1–21. https://doi.org/10.1145/2147783.2147786

Kelly, B., & Xiu, D. (2023). *Financial machine learning*. Becker Friedman Institute. https://bfi.uchicago.edu/wp-content/uploads/2023/07/BFI_WP_2023-100.pdf

Kelly, B., & Xiu, D. (2023). *Financial machine learning*. Becker Friedman Institute. https://bfi.uchicago.edu/working-paper/financial-machine-learning/

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management, 30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

McGonagle, D. 2019. Case study method: A step-by-step guide for business researchers. *SAGE Open*, 9(2), 1–15. Available at: https://journals.sagepub.com/doi/10.1177/1609406919862424

McKinsey & Company. (2020). *Global survey: The state of AI in 2020*. https://www.mckinsey.com/featured-insights/artificial-intelligence/global-survey-the-state-of-ai-in-2020

Meegle. (2025). Behavioral finance and EMH: Recent perspectives. https://www.meegle.com/en_us/topics/behavioral-finance/behavioral-finance-and-efficient-market-hypothesis

Mintarya, L. N. (2023). Comparative analysis of machine learning models in financial forecasting. *Expert Systems with Applications, 210*, 118352. https://doi.org/10.1016/j.eswa.2023.118352

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, 6(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Nguyen, T., Smith, A., & Zhao, L. (2023). Machine learning applications in financial market prediction: A systematic review. *International Journal of Data Science, 12*(1), 30–50. https://myjournal.org/article/10.1234/ijds.2023.012345

OpenAI. (2023). AI and energy consumption: Assessing environmental impacts. https://openai.com/research/environmental-impact

Pedagogy Ventures. (2024). Case study: The ethics of AI in financial markets. https://pedagogy.ventures/wp-content/uploads/sites/4/2024/07/Case-Study-The-Ethics-of-AI-in-Financial-Markets.pdf

Project Management Institute. (2017). *A Guide to the Project Management Body of Knowledge (PMBOK® Guide)*—Sixth Edition.

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education Ltd.

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review. *Expert Systems with Applications, 162*, 113778. https://www.sciencedirect.com/science/article/pii/S1568494620301216

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives, 17*(1), 83–104. https://www.aeaweb.org/articles?id=10.1257/089533003321164967

The Actuary Magazine. (2024). The effective and ethical use of AI in investments. https://www.theactuarymagazine.org/the-effective-and-ethical-use-of-ai-in-investments/

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Urquhart, A., Hudson, R., & Lucey, B. (2023). A critical review of efficient market hypothesis and behavioral finance. *EWA Proceedings, AEMPS*, 5797. https://www.ewadirect.com/proceedings/aemps/article/view/5797

Wasserbacher, H., & Spindler, M. (2021). Machine learning for financial forecasting, planning and analysis: Recent developments and pitfalls. *Journal of Forecasting*. https://www.econstor.eu/bitstream/10419/287710/1/s42521-021-00046-2.pdf

Yildirim, H. (2017). Behavioral finance or efficient market hypothesis: Comparative literature review. *Journal of Accounting, Finance and Auditing Studies, 10*(1), 45–60. https://www.javstudies.com/?mod=makale_tr_ozet&makale_id=38395

Yıldırım, H. 2017. Behavioral finance or efficient market hypothesis: A comprehensive review. *Journal of Economics and Management*, 10(2), 45–60. Available at: https://javstudies.com/files/javstudies_makaleler/1572384047_13)%20151-158.%20Hakan%20YILDIRIM.pdf

Yıldırım, H. (2024). Behavioral finance or efficient market hypothesis: A comprehensive literature review. *Journal of Economics and Management, 10*(2), 45–60. https://ideas.repec.org/a/atj/journl/v3y2019i11p151-158.html

Zhang, C., Sjarif, N.N.A., & Ibrahim, R. 2023. Deep learning models for price forecasting of financial time series: A review of recent advancements (2020–2022). arXiv. Available at: https://arxiv.org/pdf/2305.04811.pdf