JOURNAL OF TECHNOLOGY MANAGEMENT AND BUSINESS
ISSN: 2289-7224 e-ISSN: 2600-7967

Vol. 12 No. 1 (2025) 15-32
https://publisher.uthm.edu.my/ojs/index.php/jtmb

JTMB

Artificial Intelligence in Investment: Analysing Variations, Functions and Impacts

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DOI: https://doi.org/10.30880/jtmb.2025.12.01.002

Article Info

Received: 21 Janury 2025
Accepted: 12 March 2025
Available online: 30 June 2025

Keywords

Investment decision, financial forecasting, algorithmic trading, stock screening, AI impact

Abstract

The integration of Artificial Intelligence (AI) in the investment domain has gained significant traction. Yet, the existing body of research remains fragmented, lacking a cohesive understanding of AI's varied forms, functions, and broader implications on the classical financial models and market dynamics. This study addresses this gap by systematically reviewing and consolidating scattered insights on AI applications in investment, organising them into a structured and comprehensive framework for better understanding. A systematic review methodology categorises 12 distinct AI variations based on their specific functions, including predictive analytics for market forecasting, automated trading systems, stock screening tools, and automated technical analyses. The impact of AI is deductively analysed based on a structured understanding of its capabilities, variations, and functional roles, revealing that while AI enhances trading performance through greater efficiency, accuracy, and liquidity, it also presents challenges such as increased market volatility and the potential marginalization of retail investors, often benefiting larger institutions. By synthesising fragmented literature into a cohesive framework, this study offers a clear and organised understanding of AI's diverse applications in investment and their broader implications for classical financial models and evolving market dynamics. It provides critical insights for scholars and practitioners, contributing to the discourse on equitable AI integration and sustainable financial development. This review not only serves as a valuable reference for understanding AI in investment but also establishes a foundation for future research, innovation, and policy exploration in the field.

1. Introduction

The field of investment trading has undergone a profound transformation in recent years, driven by the rapid emergence and integration of Artificial Intelligence (AI) (Azzutti, 2022; Chen & Ren, 2022; Fior et al., 2022; Hyun Baek & Kim, 2023). AI has emerged as a pivotal technology, offering sophisticated tools that enable the processing of vast datasets (Lei et al., 2022), the identification of complex patterns (Chen & Chen, 2019), and the generation of predictions with unprecedented accuracy (Loi et al., 2023; Serrano, 2022). These advancements have significantly enhanced the efficiency and effectiveness of trading strategies, thereby providing institutional and retail investors with a competitive edge in an increasingly dynamic and complex financial landscape. However, despite the growing adoption of AI, the existing body of research remains fragmented, with studies often focusing on isolated AI techniques or specific applications without providing a comprehensive overview of the field.

Traditionally, investment trading has been dominated by human expertise and relies on the intuition, experience, and judgment of seasoned traders (Oberg et al., 2018; Stein, 2023). However, the rise of AI technologies has ushered in a paradigm shift in which data-driven insights and automated processes are becoming central to decision-making. Cutting-edge AI technologies, including machine learning algorithms and deep learning models (Jang & Seong, 2023; Schmidhuber, 2015), have become integral to contemporary trading strategies. These technologies not only enhance decision-making processes but also optimize trading performance (Helms et al., 2022) by delivering real-time analytics (Schrettenbrunner, 2023; Wu & Duan, 2017) and executing transactions at speeds beyond human capability (Arumugam, 2023; Tudor & Sova, 2022).

The existing research on AI in investment trading spans a wide range of applications, reflecting the diversity and versatility of this field. AI technologies are employed in various investment activities, including forecasting market trends (Adcock & Gradojevic, 2019; Atsalakis et al., 2019; Kumar et al., 2021), automated trading operations (Helms et al., 2022; Horn & Oehler, 2020), and technical analyses (Bertsimas & Kallus, 2020; Deprez et al., 2021; Henríquez & Kristjanpoller, 2019). These applications leverage a variety of AI methods such as Gaussian Naive Bayes (Ampomah et al., 2021), decision trees (Höppner et al., 2020; Oyedele et al., 2023), neural networks (Schmidhuber, 2015; Serrano, 2022), and support vector machines (Chen & Hao, 2018; Nti et al., 2020). Each technique offers unique advantages tailored to specific trading functions and contributes to the optimization of investment strategies. However, current literature remains fragmented, with studies often focusing on individual AI techniques or specific applications in isolation. This fragmented approach has resulted in a scattered knowledge base, making it challenging for scholars and practitioners to gain a holistic understanding of how AI reshapes trading strategies and market dynamics. Furthermore, there is limited research that systematically consolidates these findings into a unified reference, hindering the ability to compare, contrast, and leverage the diverse applications of AI in investment trading. In addition, since AI can do much today, no studies have discovered its impact on current practices based on AI's defined capabilities.

This study seeks to address these gaps by systematically reviewing and consolidating AI's diverse applications in investment trading. Specifically, this study aimed to answer three key questions: What are the functions of AI in investment trading? Which AI techniques can be used to accomplish these specific functions? How do these AI variations and their defined capabilities impact the current market practices? By addressing these questions, this study provides a comprehensive understanding of how AI technologies are applied to investment activities and explores the broader implications of AI adoption. The significance of this study lies in its ability to synthesise fragmented knowledge into a cohesive framework. Although individual researchers have explored specific AI techniques, such as decision trees for predictive analytics or Neural Networks for automated trading, this study aims to compile and organise these diverse applications into a single, meaningful reference. It provides scholars and practitioners with a holistic understanding of AI's capabilities and limitations in investment trading, enabling them to navigate this complex and rapidly evolving field more effectively. Furthermore, this study addresses the urgent need for a unified reference that captures the diversity of AI applications in investment trading, thereby making an essential contribution to the field.

2. Methodology

The methodology section outlines the systematic approach adopted in this study, ensuring a rigorous and transparent review of the literature on AI applications in investment trading. This study adheres to the ROSES (Reporting Standards for Systematic Evidence Syntheses) framework (Haddaway et al., 2018), which provides a structured methodology tailored for interdisciplinary research. The process begins with the formulation of research questions using the PICO framework (Lockwood et al., 2015), followed by a systematic search strategy encompassing the identification, screening, and eligibility determination of relevant studies. The subsequent steps include a quality appraisal, data abstraction, and thematic analysis to categorise the AI functions and techniques. The following subsections detail each stage of the methodology and ensure clarity and replicability during the review process.

2.1 Review Protocol Process

This systematic review adheres to the ROSES framework, a structured methodology tailored to conduct comprehensive literature syntheses (Haddaway et al., 2018). The ROSES framework is particularly relevant for this study because it is designed for environmental and social science systematic reviews and offers a flexible and rigorous approach that aligns with the interdisciplinary nature of AI in investment trading, spanning finance, technology, and social implications. ROSES provides an adaptable structure for synthesizing diverse evidence, making it suitable for this study's focus on consolidating fragmented research across multiple domains. The research process began by formulating pivotal research queries, followed by a systematic search approach encompassing three key stages: identification, screening, and eligibility determination of relevant studies.

Subsequently, the quality of the selected articles was assessed, and data extraction, analysis, and validation were performed. The ROSES diagram in Figure 1 visually depicts the review workflow.

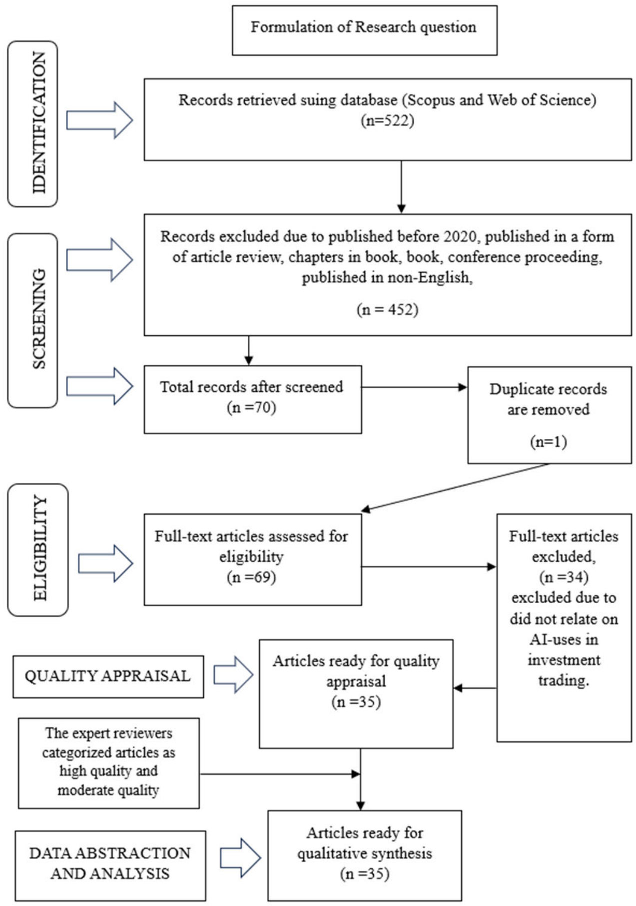

Fig. 1 *The flow diagram was adapted from Mohamed Shaffril et al. (2020)*

2.2 Formulation of Research Questions

The research questions were formulated using the PICO framework, a tool introduced by Lockwood et al. (2015), to assist in developing structured review questions based on three core elements: Population or Problem, Interest, and Context. This framework has been widely adopted in qualitative and mixed-methods systematic reviews across disciplines, such as healthcare, social sciences, and business research (Stern et al., 2020; Munn et al., 2018), making it a proven and reliable tool for exploring complex, interdisciplinary topics. For this study, the Population or Problem focuses on AI applications in investment trading. The interest lies in understanding the diverse functions and techniques of AI, and the context encompasses broader implications for market dynamics and trading practices. The PICO framework is particularly suitable for this study, as it ensures clarity, focus, and alignment with the research objectives, enabling a systematic exploration of fragmented literature while maintaining rigor and relevance for both scholars and practitioners. The research questions guided the development of search queries and the selection of relevant databases, thereby shaping the scope of the review.

2.3 Systematic Searching Strategies

The systematic search strategy consisted of three primary steps: identification, screening, and eligibility. A comprehensive search string was created based on these research questions (Table 1), targeting AI applications in stock trading and investment. The Scopus and Web of Science databases were selected for their relevance to AI and financial research. The categorization of AI functions and variations emerged from the thematic analysis conducted in the reviewed literature. The researchers examined selected articles and identified recurring patterns in applying AI to investment trading, which led to the classification of these variations into four key functional categories. Therefore, the theme of AI functions was identified based on common and predominant discussions in the existing literature, reflecting AI's most widely recognized applications in the domain. This process of categorization was an integral part of the data abstraction and analysis phase, ensuring that the identified AI variations and functions were systematically organised accordingly.

2.3.1 Identification

During the identification phase, the study utilized a comprehensive approach employing synonyms and variations of the primary keywords' artificial intelligence" and "investment trading" to broaden the search for relevant articles in the Scopus and Web of Science (WoS) databases. These terms were chosen because they encapsulate the core focus of AI applications in investment trading, ensuring that the search captured the most relevant and impactful studies in the field. This tailored approach ensures that the search strategy is both comprehensive and precise, capturing the breadth of AI applications in investment trading while minimising irrelevant results. Based on these terms, an extensive search string was constructed.

The selection of Scopus and WoS as primary databases for this study is justified by their reputation as leading multidisciplinary databases with extensive coverage of high-quality peer-reviewed literature. Both are recognized for rigorous indexing standards, advanced search functionalities, and comprehensive scope, making them ideal for systematic reviews in interdisciplinary fields, such as AI in investment trading. Scopus is known for its broad coverage of scientific, technical, and social science literature, while Web of Science is renowned for its emphasis on citation tracking and high-impact research. Together, these provide a robust foundation for identifying relevant studies and ensuring review comprehensiveness. Distinct search strings for Scopus and Web of Science are required because of their unique search syntax and indexing systems. Scopus employs TITLE-ABS-KEY to search within titles, abstracts, and keywords, whereas Web of Science utilizes Topic Search (TS). These variations ensure that search queries are optimized for the functionalities of each database, thereby maximizing the retrieval of relevant articles.

This methodology enhances the rigor and reliability of the review, ensuring that the findings are predicated on a robust and representative sample of extant research. The selected databases, renowned for their advanced search functionalities, comprehensive indexing, quality control measures, and multidisciplinary scope, facilitated the identification of 522 articles.

Table 1 *The search string*

Database	Search Strings
Scopus	TITLE-ABS-KEY ((artificial AND intelligence AND in AND stock AND trading AND investment))
Web of Science	TS ((artificial AND intelligence AND in AND stock AND trading AND investment))

2.3.2 Screening

The screening phase applied a set of inclusion and exclusion criteria to the 452 identified articles, as outlined in Table 2, to ensure methodological rigor and focus. The timeframe of 2020–2024 was selected to capture the most recent advancements in AI applications within investment trading, reflecting the significant growth in research activity during this period (Okoli, 2015). The review was limited to empirical journal articles published in English to maintain consistency and quality, as these articles underwent rigorous peer review and provided evidence-based insights. Conference proceedings, books, book chapters, and review articles were excluded to prioritize primary research. This process resulted in the exclusion of 452 articles and one duplicate, leaving 69 eligible articles.

The tailored search strings and unique indexing systems of Scopus and Web of WoS may have contributed to the retrieval of distinct sets of articles, thus minimising overlap. Additionally, applied filters, such as the restricted timeframe and exclusion of non-empirical studies, further narrowed the pool of articles. Although automated deduplication tools are often recommended for systematic reviews, the manual process used here, combined with subtle differences in article metadata, may have influenced the identification of duplicates. These criteria and processes were designed to enhance transparency, replicability, and alignment with the study objectives, ensuring a systematic and focused review.

Table 2 *The inclusion and exclusion criteria*

Criteria	Inclusion	Exclusion
Timeline	2020-2024	Before 2020
Document Type	Research article	Conference proceeding, book, book chapter, review article
Language	English	Non-English

2.3.3 Eligibility

The eligibility phase involved a thorough manual evaluation of the 69 remaining articles to ensure alignment with the study's inclusion criteria. Each article was carefully examined based on its title and abstract in order to determine its relevance to AI applications in investment trading. Articles were excluded if they primarily focused on unrelated areas, such as market testing or debt instruments, lacked empirical evidence, or employed undefined methodological approaches. This rigorous process led to the exclusion of 34 articles, resulting in the inclusion of 35 articles in the final review.

To ensure transparency and replicability, the eligibility criteria were strictly adhered to, and the reasons for exclusion were systematically documented. This approach minimizes the bias and ensures that the selection process is consistent and defensible. By focusing on articles that directly address AI deployment in investment trading and meet the methodological standards of the study, the review maintains a high level of rigor and relevance. This systematic approach not only strengthens the validity of the findings but also provides a clear framework for future research to replicate or build upon this study.

2.4 Quality Appraisal

To ensure the quality of article content, the remaining papers were evaluated by two subject matter experts using a comprehensive assessment process. Drawing on the guidance provided by Petticrew & Roberts (2008), experts categorised papers into one of three tiers: high, moderate, and low quality. Only articles deemed of high or moderate quality were retained for further review. The experts' evaluations focused on assessing the articles' level of interest and methodological rigor in order to determine their quality ranking. For an article to be included in the review, both authors reached a consensus that its quality was at least moderate. Any discrepancies were resolved through discussions between the authors before deciding which articles were to be included or excluded from the review. This process resulted in 29 articles being ranked as high quality and six as moderate quality, rendering all the remaining papers eligible for inclusion in the review.

2.5 Data Abstraction and Analysis

This study adopted an integrative literature review approach, encompassing a variety of research methodologies and employing qualitative data synthesis (Whittemore & Knafl, 2005). A comprehensive review of 35 relevant articles was conducted, with a focus on analysing the abstracts, results, and discussion sections. The extracted data pertaining to the research questions were compiled and organised in a tabular format.

Through systematic thematic analysis, this study classifies the diverse AI techniques found in the literature into four common primary functions: Predictive Analytics, Automated Trading, Screening Analysis, and Automated Technical Analysis. These functions were derived by comprehensively reviewing the existing fragmented literature and identifying recurring patterns that enabled the categorization of these four overarching functions, which encapsulate the majority of the research on AI applications in investment. Next, this study systematically categorises various AI techniques, including Decision Trees, Support Vector Machines, and Neural Networks, based on their primary applications in investment trading. Thematic analysis consolidated the fragmented findings into a comprehensive insight, which identified 12 distinct AI variations aligned with the study's four overarching functional areas.

The authors collaboratively validated the classification process to ensure consistency and accuracy and to resolve any discrepancies through discussion. This structured analytical approach enhanced the transparency and replicability of the methodology used in this study. Following a rigorous selection process, a systematic review of 35 articles spanned a diverse range of AI applications in investment trading. The methodology employed facilitated an in-depth analysis of primary AI functionalities and their respective variations or techniques. These analytical categories were derived from themes identified through a thematic coding approach that involved grouping the articles based on common AI functionalities.

3. Results and Findings

The Results section presents a comprehensive synthesis of AI's diverse functions and variations in investment based on extensive research. This includes four identified AI functions and twelve variations documented in the existing literature, as outlined in Table 3, which systematically organises the previously fragmented literature on AI in investment trading into a coherent framework, offering a valuable reference for its diverse applications. The next section, Impact on Market from the AI Variations and Functions, delves into how these AI functions and variations influence market dynamics and investment practices, particularly their implications for market volatility and investor equity positions, as informed by insights from the literature. This is followed by an Action-Based Recommendation section that provides practical strategies to address the impacts discussed.

Table 3 *The themes and sub-themes*

No	Author	Function				Technique											
		PF	TE	S	AT	G	B	D	M	BL	A	S	R	RN	C	DN	PS
1.	(Cheng & Wang, 2023)		/													/	
2.	(Zou & Xiao, 2024)	/			/												/
3.	(Aloud, 2021)		/	/									/				
4.	(Park et al., 2024)		/													/	
5.	(Nti et al., 2020)	/										/					
6.	(Reddy & Balamanigandan , 2023)	/								/							
7.	(Wang et al., 2021)			/				/									
8.	(Miranda García et al., 2023)	/				/	/										
9.	(H. Liu et al., 2022)		/						/					/	/		
10.	(Solares et al., 2022)			/							/						
11.	(J. Wang & Chen, 2024)		/		/				/			/					
12.	(Hung et al., 2024)		/									/					
13.	(Ampomah et al., 2021a)	/				/											
14.	(Dhafer et al., 2022)	/									/						
15.	(Mahjouby et al., 2024)	/								/						/	
16.	(Kirtac & Germano, 2024)	/				/	/	/		/							
17.	(H.-H. Liu et al., 2023)		/												/		
18.	(Huang et al., 2024)	/		/								/	/				
19.	(J. Wang et al., 2022)			/												/	
20.	(Ding & Qin, 2020)	/					/								/		
21.	(Serrano, 2022a)	/											/	/			
22.	(Ghosh & Chaudhuri, 2021)				/				/							/	
23.	(Wu et al., 2024)	/											/				
24.	(Ospina-Holguín & Padilla-Ospina, 2021)	/			/							/				/	
25.	(Jamous et al., 2021)	/	/											/	/		/
26.	(Quang, 2022)		/	/				/				/					
27.	(Aldhyani & Alzahrani, 2022)	/	/					/	/					/			
28.	(Lee & Moon, 2023)	/	/					/	/			/					
29.	(Buz & de Melo, 2024)				/				/								
30.	(Chang et al., 2021)	/														/	
31.	(Lin et al., 2021)				/										/	/	
32.	(Taguchi et al., 2022)	/												/	/	/	
33.	(Pattanayak et al., 2024)	/			/				/							/	
34.	(Jeong et al., 2023)		/					/	/								
35.	(Yang et al., 2022)		/													/	

Function

PF-Predictive/Forecast, TE-Trading Execution, S-Screening, AT-Automated Technical

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Technique
G-Gaussian Naive Bayes, B-Bayesian Classifier, D-Decision Tree, M- Multi-layer Perceptron, DN-Deep Neural Learning, BL-BiLSTM (Bi-Long Short-Term Memory), A-Artificial Neural Networks, S-Support Vector Machine, R-Random Forest, RN-Recurrent Neural Networks, C-Convolutional Neural Networks, PS-Particle Swarm Optimization

3.1 Functions of AI in Investment Trading

This review demonstrates that AI makes substantial contributions to various aspects of investment through four functional domains: Predictive Analytics, Automated Trading, Screening Analysis, and Automated Technical Analysis. These functions are associated with a range of AI techniques, which are frequently utilized in conjunction with traditional methods to enhance decision-making and performance, as illustrated in Figure 2 of Functions of AI in Investment Trading and Corresponding AI Variations. Predictive Analytics, for instance, is commonly associated with techniques such as Gaussian Naive Bayes (GNB), Bayesian Classifier, Decision Trees, and Bi-Long Short-Term Memory (BiLSTM), which are employed to identify market trends and forecast future movements. Similarly, Automated Trading has witnessed the adoption of approaches such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), and Random Forest to improve the efficiency of trade execution, often complementing human oversight. Screening Analysis benefits from methodologies such as Recurrent Neural Networks (RNNs) and Particle Swarm Optimization (PSO), which facilitate asset filtering, although these techniques are not necessarily applied in isolation. Finally, Automated Technical Analysis is frequently associated with tools such as multi-layer perceptron (MLPs), Convolutional Neural Networks (CNNs), and Deep Learning Networks to decode complex market patterns, typically operating in conjunction with traditional analysis methods. These AI techniques, while frequently referenced in the context of these functions, constitute a part of a broader toolkit that reflects the evolving role of AI in enhancing trading practices.

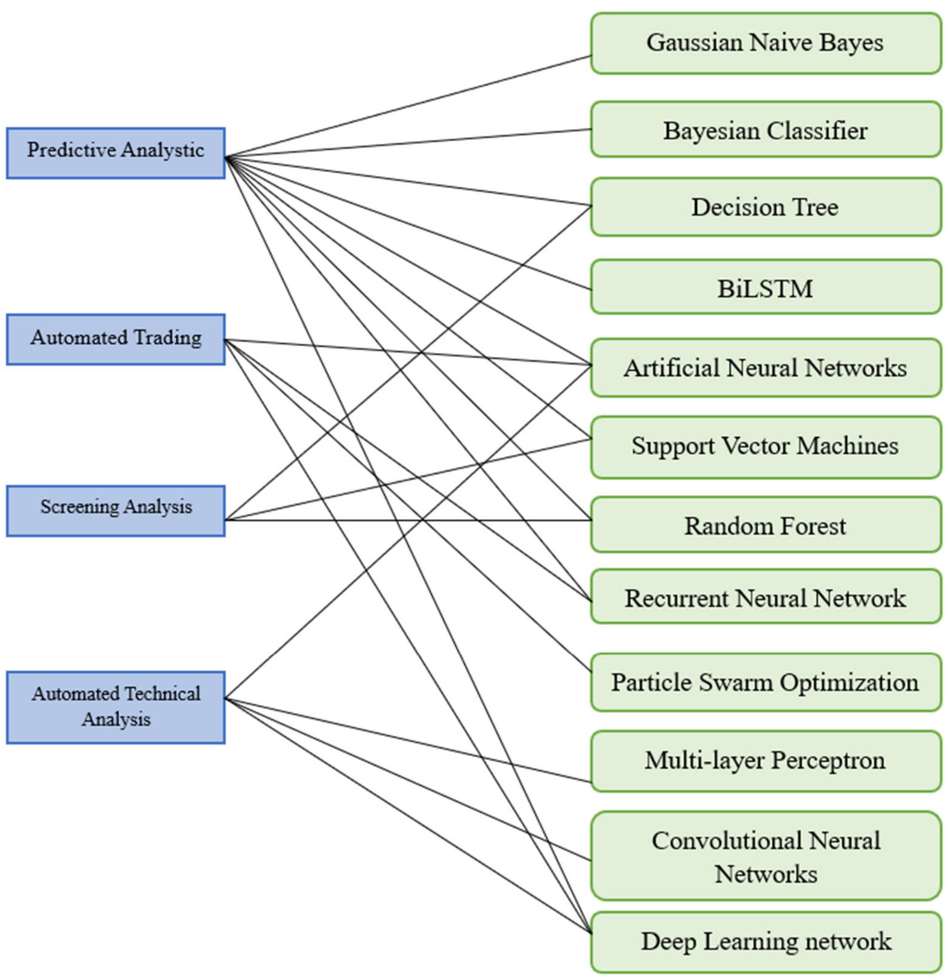

Fig. 2 *Functions of AI in investment trading and corresponding AI variations*

3.1.1 Predictive Analytics

The application of AI in investment serves as predictive analytics, which aims to forecast future stock prices (Reddy & Balamanigandan, 2023) and market trends (Lin et al., 2021) by analysing historical and real-time data (Nti et al., 2020). This approach leverages various data sources, including historical price data, financial statements, economic indicators, and news sentiment, to identify patterns and relationships that can predict future market movements (Ampomah et al., 2021; Mahjouby et al., 2024). Predictive analytics employs various AI techniques, such as GNB, Bayesian Classifiers, Decision Trees, BiLSTM, ANNs, SVMs, Random Forests, and RNNs, to analyse the complex interactions within these diverse datasets and generate forecasts of future stock prices and market trends (Ampomah et al., 2021b; Kirtac & Germano, 2024; García et al., 2023). The application of AI, particularly in the form of predictive analytics, demonstrates a transformative impact on strategic decision-making in investment trading, as evidenced by the existing literature. By analysing diverse data sources and employing advanced predictive models, AI enhances the understanding of market dynamics, enabling more accurate forecasts and reducing uncertainty. This capability supports the formulation of long-term investment strategies and the development of adaptive trading approaches, as highlighted in studies such as Ding and Qin (2020). The literature consistently underscores those predictive analytics provides traders with a competitive edge by identifying emerging market trends and facilitating data-driven decisions. Furthermore, the analysis revealed that AI-driven frameworks excel in uncovering the opportunities and risks that traditional methods often miss, thereby improving risk management and optimizing investment outcomes. This evidence-based perspective confirms that AI, functioning as a predictive analytical tool, significantly enhances the strategic decision-making process in investment trading, as derived from a comprehensive review of the literature.

3.1.2 Automated Trading

The use of AI in investments serves as an automated trading function, also known as algorithmic trading (Lee & Moon, 2023). This involves the application of AI to execute trades based on predefined strategies without direct human intervention. AI enhances trading efficiency and mitigates emotional biases that affect traders. Techniques such as PSO, ANNs, and RNNs are commonly employed for this function (Hung et al., 2024; Wang & Chen, 2024). Research has highlighted the role of deep reinforcement learning in decision support systems for financial disclosures, which can be integrated into automated trading strategies to optimize trading decisions. These methods continuously analyse market conditions and optimally execute trade to maximize profits (Aloud, 2021). An analysis of the existing literature confirms that the application of AI in automated trading is not only theoretically sound but also practically viable and widely applicable in real-world investment scenarios. By definition, automated trading systems rely on AI's ability to process vast amounts of data, execute trades at unparalleled speeds, and operate with precision, all of which align with the core capabilities of AI technology. Empirical evidence (Deng et al., 2023; Nimalendran et al., 2024) demonstrates that these systems are already being deployed effectively in financial markets, enabling high-frequency trading, reducing latency, and optimizing trade execution. The literature further supports that AI's capabilities in pattern recognition, real-time decision-making, and algorithmic consistency make it uniquely suited to automated trading. This alignment between AI's technical strengths of AI and the demands of modern trading environments underscores its practical relevance and potential in the investment domain. Thus, based on an analysis of existing research, it is evident that AI can function effectively as automated trading in real-world applications.

3.1.3 Screening Analysis

AI has also been used in stock screening analyses (Solares et al., 2022; Wang et al., 2021). This involves employing AI techniques such as Decision Trees, SVMs, and Random Forests to efficiently sift through large volumes of financial data and identify promising investment opportunities (Huang et al., 2024; Quang, 2022). The goal is to streamline the stock selection process and reduce the time and effort required by human analysts. Research has demonstrated the efficacy of applying machine-learning models, including decision trees, to design autonomous trading strategies that effectively screen and select stocks based on historical data and predictive analytics. The function of AI as a tool for screening analysis in investments is well supported by the literature, demonstrating its practical applicability and effectiveness in filtering and evaluating market data. AI-driven stock screening methods utilize specific criteria and filters, such as financial ratios, historical performance metrics, and other relevant indicators, to systematically analyse vast datasets. This capability allows traders to efficiently narrow investment options and focus on the most promising stocks, as highlighted by Quang (2022). The literature emphasises that this approach provides several key advantages, including increased accuracy in identifying high-potential investments, enhanced decision-making through data-driven insights, and a more structured and objective framework for investment analysis. By automating the screening process, AI reduces the time and effort required for manual analysis while minimising human bias. Furthermore, studies show that AI-powered screening tools enable traders to uncover undervalued stocks and capitalize on favorable market conditions more effectively than traditional methods. Evidence from existing research (Li et al., 2022) confirms that AI's analytical precision, scalability, and adaptability make it an indispensable tool for screening analysis in modern investment practices. Thus, based on an analysis of the literature, AI's role in this function is both real and transformative, offering tangible benefits to traders and investors alike.

3.1.4 Automated Technical Analysis

The application of AI in investment finance serves as an automated technical analysis that automates the analysis of technical indicators and chart patterns to provide real-time signals and notifications regarding market conditions and potential price movements (Buz & de Melo, 2024; Lin et al., 2021; Pattanayak et al., 2024). This approach relies primarily on technical indicators and chart patterns derived from historical price data and focuses on identifying trends, support, resistance levels, and other technical signals. Automated technical analysis utilises multilayer perceptron, ANNs, and CNNs to process and interpret technical indicators and chart patterns (Ospina-Holguín & Padilla-Ospina, 2021). For instance, research has explored combining predictive models with optimization approaches to enhance technical analysis. AI systems in this function are designed to notify traders of specific signals, such as potential trend reversals or breakout points, without making long-term predictions. This tool is used by traders who rely on technical signals to make quick trading decisions, as it helps identify entry and exit points, trend reversals, and potential breakouts or breakdowns in stock prices. The function of AI in automated technical analysis, although less extensively studied compared to other AI applications in investment, is supported by emerging evidence suggesting its feasibility and potential. Although limited, some studies and practical implementations have demonstrated that AI can effectively automate technical analysis by integrating data from various sources and applying advanced algorithms to interpret market trends. Automated technical analysis enhances efficiency by eliminating the need for manual analysis, reducing human errors, and enabling simultaneous evaluation of multiple technical indicators. This capability allows traders to react swiftly to market changes and execute trades based on reliable AI-generated signals, as Zou and Xiao (2024) note. By automating repetitive and time-consuming tasks, AI ensures consistency, objectivity, and precision in trading strategies, which are often compromised by manual processes. Furthermore, AI enables real-time analysis, providing traders with timely signals and notifications that support quick decision-making. While the literature on this function is still evolving, the convergence of insights from various resources indicates that automated technical analysis is not only possible but also increasingly adopted in practice. This suggests that AI has the potential to transform technical analysis by making it more efficient, scalable, and accessible to traders. Thus, based on the available evidence, AI's role in automated technical analysis, although not yet fully explored, holds significant promise for the future of investment trading.

3.2 Variations of AI Techniques and Their Applications in Investment Trading

The analysis of the reviewed articles, as depicted in Figure 2 of Functions of AI in Investment Trading and Corresponding AI Variations, reveals the prominence of twelve AI techniques in investment trading applications. These include GNBs, Bayesian Classifiers, Decision Trees, BiLSTM, ANNs, SVMs, Random Forest, RNNs, PSO, Multi-layer Perceptrons, CNNs, and DLNs. The widespread adoption of these techniques across various investment approaches and research domains underscores their adaptability and significance, as tabulated in Table 4 of the AI Technique Variation And its Application in Investment Trading. By systematically categorizing these AI variations, researchers can gain a more nuanced understanding of their roles and potential in investment trading, thereby providing a crucial framework for examining the influence of AI on financial decision-making strategies.

Table 4 *AI technique variation and its application in investment trading*

AI Technique	Function and capabilities	Rationale for Application in Investment Trading
1. Gaussian Naive Bayes (GNB)	Predictive Analytics	Handles high-dimensional financial data efficiently, assuming independent features, making it useful for quick stock classification and trend prediction (Ampomah et al., 2021; Miranda García et al., 2023).
2. Bayesian Classifier	Predictive Analytics	Continuously updates probability estimations based on new information, making it ideal for dynamic markets where price movements fluctuate with incoming data (Ding & Qin, 2020; Kirtac & Germano, 2024).
3. Decision Tree	Predictive Analytics, Stock Screening	Provides structured decision-making by splitting data into branches, making it useful for stock screening based on financial metrics like P/E ratio and revenue growth (Quang, 2022).

4.	Bidirectional Long Short-Term Memory (BiLSTM)	Predictive Analytics	Processes historical price movements in both directions, improving stock price forecasting by identifying long-term market trends and dependencies (Mahjouby et al., 2024; Reddy & R, 2023).
5.	Artificial Neural Networks (ANNs)	Automated Trading	Identifies hidden patterns in large datasets, making it effective for automated decision-making in high-frequency trading with minimal human intervention (Dhafer et al., 2022; Solares et al., 2022).
6.	Support Vector Machine (SVM)	Predictive Analytics, Stock Screening	Optimally classifies stocks based on historical patterns, making it useful for technical analysis and identifying buy/sell opportunities (Hung et al., 2024; Nti et al., 2020).
7.	Random Forest	Predictive Analytics, Stock Screening	Uses multiple decision trees to improve prediction accuracy and reduce overfitting, ensuring robust investment screening (Aloud, 2021; Serrano, 2022).
8.	Recurrent Neural Networks (RNNs)	Predictive Analytics, Algorithmic Trading	Captures sequential dependencies in stock price movements, making it suitable for algorithmic trading and market trend analysis (Jamous et al., 2021; Serrano, 2022).
9.	Particle Swarm Optimization (PSO)	Automated Trading	Optimizes trading strategies by adjusting parameters dynamically, allowing for adaptive decision-making in algorithmic trading (Zou & Xiao, 2024).
10.	Multilayer Perceptron (MLP)	Predictive Analytics, Algorithmic Trading, Technical Analysis	Captures nonlinear stock market relationships, making it effective in pattern recognition and market forecasting (Buz & de Melo, 2024; Lee & Moon, 2023; Ranaldi et al., 2022).
11.	Convolutional Neural Networks (CNNs)	Technical Analysis	Recognizes complex patterns in stock charts and candlestick formations, assisting traders in visual pattern-based decision-making (Ding & Qin, 2020; Jamous et al., 2021).
12.	Deep Neural Learning (DNL)	Predictive Analytics, Algorithmic Trading, Technical Analysis	Integrates deep learning and reinforcement learning to continuously refine trading strategies based on market responses (Cheng & Wang, 2023; Stevenson et al., 2021).

AI reshapes the investment facet and offers powerful tools for analysing data, predicting trends, and automating decisions. This systematic review identified twelve key AI techniques that enhance the functions and capabilities of AI in trading: predictive analytics, automated trading, stock screening, and automated technical analysis. Each AI model contributed uniquely. GNB and Bayesian Classifiers use statistical probability to forecast price movements, making them essential for predictive analytics (Ampomah et al., 2021; Ding & Qin, 2020). For stock selection, Decision Trees and Random Forests categorise stocks based on financial performance, while SVMs refine the classification for more accurate screening (Nti et al., 2020; Aloud, 2021; Hung et al., 2024). These techniques streamline stock screening analysis, helping investors efficiently filter high-potential stocks. To analyse market trends over time, RNNs and BiLSTM detect sequential dependencies, improving predictive analytics and automated trading (Pattanayak et al., 2024; Reddy & Balamanigandan, 2023). Their ability to process past and future market behavior enhances price forecasting and algorithmic trade execution. ANNs and MLPs learn from vast datasets, mimicking human decision-making in automated trading (Ospina-Holguín & Padilla-Ospina, 2021). Combined with PSO, these techniques dynamically adjust trading strategies for high-frequency trading (Jamous et al., 2021). For automated technical analysis, CNNs detect chart patterns and market signals and DNL refines strategies through reinforcement learning (Liu et al., 2022; Aldhyani & Alzahrani, 2022). These AI models automate pattern recognition and enhance traders' ability to interpret market conditions accurately.

AI techniques applied in investment trading exhibit diverse operational characteristics that influence their strategic deployment across different market scenarios. Some models are optimized for speed, enabling the rapid classification and filtering of large volumes of financial data, an essential capability in high-frequency trading environments where decisions must be made within milliseconds (Chen & Hao, 2021). Other techniques are favored for their interpretability, making them suitable in contexts where transparent, explainable logic is required, such as institutional portfolio screening or in compliance-based settings, such as Shariah-compliant fund management (Zhang et al., 2021; Aloud, 2021). Additionally, certain models emphasize adaptability, allowing them to learn from real-time feedback and dynamically adjust trading strategies in response to evolving market conditions, which is advantageous in volatile automated trading systems (Li et al., 2022; Pattanayak et al., 2024).

Although these techniques may support similar investment functions, such as predictive analytics, stock screening, or automated decision-making, they are not structurally identical. For example, Gaussian Naive Bayes (GNB) and Bayesian classifiers rely on probabilistic reasoning and perform well in scenarios requiring fast, low-complexity classification; however, their assumption of feature independence may limit performance in high-dimensional, interrelated datasets (Ampomah et al., 2021; Ding & Qin, 2020). Decision Trees provide clear decision rules that are easy to interpret, yet they can be prone to overfitting unless supported by ensemble techniques such as Random Forest, which aggregates multiple trees to enhance predictive robustness (Zhang et al., 2021). In contrast, RNNs and BiLSTM are designed to handle sequential dependencies, making them more suitable for time-series forecasting, where temporal patterns in stock price data are essential (Pattanayak et al., 2024; Reddy & Balamanigandan, 2023). These distinctions underscore that although multiple AI models may serve the same functional category, their practical roles differ according to the structure of financial data, need for interpretability, speed of execution, and adaptability to market dynamics. This synthesis underscores the need to understand the diverse AI techniques in connection with their functional purposes while acknowledging that their practical application varies according to financial data structures, interpretability requirements, execution speed, and adaptability in dynamic market environments.

4. The Impact of AI Based on Variations and Functions Exploration

AI has emerged as a revolutionary force in investment trading, fundamentally reshaping decision-making processes, enhancing operational efficiency, and introducing unprecedented adaptability and accuracy. This section builds explicitly upon prior systematic literature reviews, synthesizing scattered insights on AI variations and their practical functions. The distinctiveness of this analysis lies in its rigorous deductive approach, providing novel clarity by directly connecting these AI techniques and functions to tangible impacts in the investment facet while explicitly identifying how these practical market phenomena challenge and necessitate the reconsideration of classical financial theories. Table 5 clearly captures these innovative connections, integrating practical market impacts, the core assumptions of classical financial theories, and how these theories are influenced by AI.

Table 5 *AI's impact on investment market and influence on classical financial models*

Impact Area	Practical Implications	Classical Model & Core Assumptions	Influence of AI
Trading Speed	AI-driven systems execute transactions rapidly, improving liquidity but significantly raising market instability risks (Schrettenbrunner, 2023).	Efficient Market Hypothesis (EMH): Markets fully reflect all available information (Nti et al., 2020)	AI algorithms uncover and exploit hidden inefficiencies, challenging EMH's assumption of complete market efficiency (Arumugam, 2023)
Competitive Disparities (Institutional vs. Retail Investors)	Institutional investors using advanced AI tools significantly outperform retail investors, increasing market inequality (Grobys et al., 2022)	Capital Asset Pricing Model (CAPM): Expected returns are based on static systematic risk and rational investor behavior (Sharpe, 1964)	AI enables dynamic, adaptive risk management, shifting CAPM from static risk-return paradigms to real-time decision-making(Gu et al., 2020)
Market Volatility & Liquidity Risks	Algorithmic trading strategies cause synchronized market actions, exacerbating volatility and liquidity vulnerabilities (Jacob-Leal & Hanaki, 2024)	Modern Portfolio Theory (MPT): Portfolio decisions rely on historical diversification and risk-return optimization (Quang, 2022)	AI-driven predictive analytics replaces historical correlations, fundamentally reshaping portfolio management strategies (Wang et al., 2021)

Automation & Decision-Making Risks	Complex AI techniques pose transparency and interpretability challenges, leading to increased risks in market decisions (Kim et al., 2023)	Behavioral Finance: Market trends are influenced by cognitive biases and emotional decision-making (Shanmuganathan, 2020)	AI introduces new algorithmic-driven behavioral patterns, reducing human biases but creating new complexities for theoretical models (Shanmuganathan, 2020)

The increased trading speeds enabled by ANNs and Random Forest significantly enhance market liquidity but also create substantial risks that challenge the fundamental assumptions of classical theories, such as EMH. Empirical findings from (Jacob-Leal & Hanaki, 2024) and (Filiz et al., 2022)) reveal how rapid algorithmic trade disrupts market stability. Such practical evidence explicitly calls for a theoretical reassessment of EMH's assumption of market efficiency, as further validated by (Nti et al., 2020). Similarly, competitive disparities between institutional and retail investors, accentuated by the use of sophisticated AI methods such as RNNs and Random Forests, empirically validate the practical implications highlighted by (Aloud, 2021)). This scenario directly challenges CAPM's foundational assumption of static risk-return frameworks, emphasizing the need for dynamic, real-time adaptive risk management strategies supported by (von Walter et al., 2022).

Additionally, AI-induced volatility and liquidity risks driven by synchronized trading decisions through Decision Trees and ANNs underline the practical vulnerabilities in market dynamics documented by (Jamous et al., 2021). This empirical reality necessitates significant theoretical shifts in Modern Portfolio Theory, transitioning from reliance on historical data toward dynamic predictive analytics, a change empirically validated by (Casarin et al., 2023). Finally, the risks associated with automated decisions and complex AI models such as CNNs and DNNs highlight transparency and accountability challenges, as empirically demonstrated by (Wang et al., 2021). These practical considerations demand theoretical revisions in Behavioral Finance to adequately capture the emerging complexities introduced by AI-driven trading patterns, as discussed (Shanmuganathan, 2020). The insights provided herein serve as a foundation for the actionable recommendations presented in the subsequent section aimed at managing and leveraging these AI-driven market dynamics.

Based on the functional characteristics and structural designs of the AI techniques analysed in this review, important behavioral and ethical implications emerge, particularly in relation to transparency, bias, and unintended market effects. Black-box models, such as DNNs, RNNs, and PSO, which are effective in adaptive and high-frequency trading, operate with limited interpretability, making it difficult to trace how investment decisions are generated (Jamous et al., 2021). From a Behavioral Finance perspective, although AI can minimize individual decision biases, it also introduces new systemic concerns. For example, if models are trained on data that reflect historical market distortions or skewed investor behavior, they may reproduce and reinforce these biases in automated decisions (Helms et al., 2022; Horn & Oehler, 2020). Moreover, the ability of AI techniques such as ANNs and DNNs to detect patterns and execute trades at scale can lead to algorithmic clustering, where simultaneous reactions to similar signals generate market volatility, illustrated by events such as flash crashes (Tsai et al., 2024). These issues are not external to the technical performance of AI models but are embedded within their data dependencies, design limitations, and behavioral influence. As such, the findings of this study reveal that the impact of AI on investment markets includes not only improvements in speed and accuracy but also the amplification of risks related to explainability, fairness, and market stability, which are traceable to the operational logic of specific AI techniques.

5. Action-based Recommendations for the AI Practice in the Investment

The systematic organisation of AI functions and variations in investment trading provides a comprehensive understanding of AI's role of AI in financial markets. The findings indicate that large financial institutions disproportionately benefit from AI technologies because of their superior access to advanced machine learning models, computational resources, and automated trading systems. This disparity contributes to increased market volatility because AI-driven trading strategies often lead to rapid market shifts and complex risk environments, making it increasingly difficult for smaller investors to compete. Unequal access to AI-powered financial tools further exacerbates wealth inequality, widening the competitive gap between institutional and retail investors. To address these challenges, the following sector-specific AI adoption strategies are recommended, as shown in Table 6.

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Table 6 *Recommendations for AI practice in the investment facet*

Recommendation Area	Proposed Strategy	Implementation Measures
Enhancing Equitable Access to AI Technologies	Develop scalable, cloud-based AI platforms to bridge the accessibility gap between institutional and retail investors.	1. Subscription-based access to AI-powered tools (automated trading, predictive analytics, sentiment analysis). 2. Ensure affordability and accessibility to enable retail investors to leverage AI-driven decision-making. 3. Reduce the competitive disadvantage of smaller investors by democratizing AI tools.
Regulatory Safeguards for AI-Driven Market Stability	Introduce regulatory safeguards to monitor and constrain AI-driven automated trading, preserving market stability and investor protection.	1. Circuit breakers to prevent sudden AI-induced market crashes. 2. AI-driven liquidity-maintaining mechanisms to counterbalance rapid selloffs. 3. Transparent AI governance frameworks require institutions to disclose AI-driven trading mechanisms.

The disparity in AI access between large institutions and retail investors is a growing concern. The development of scalable, cloud-based AI platforms can democratize access to advanced tools, enabling retail investors to utilize automated trading algorithms, predictive analytics, and real-time market sentiment analysis. Such platforms can bridge this gap by allowing smaller investors to compete more effectively in the market. This approach aligns with the perspective that AI can empower individual investors by providing tools that were previously exclusive to larger firms. The rapid adoption of AI in trading requires robust regulatory frameworks to maintain market stability. Implementing safeguards, such as circuit breakers, can prevent sudden market crashes, while algorithms designed to maintain liquidity can counteract rapid selloffs. The U.S. Securities and Exchange Commission (2020) emphasises the need for regulatory approaches to AI in financial markets to address potential risks and ensure market integrity.

By implementing scalable AI platforms, tailored risk management systems, and regulatory safeguards, this study proposed a balanced framework for AI adoption in financial markets. These recommendations aim to reduce AI-driven disparities, protect market participants, and enhance the overall efficiency of AI-driven investment ecosystems. Ensuring equitable access, risk resilience, and market stability is essential to fostering an inclusive AI-powered financial environment that benefits both institutional and retail investors.

6. Conclusion and Recommendation for Future Study

This systematic review has successfully organised a wide and fragmented body of academic literature into a structured understanding of how AI is applied across the investment landscape. Guided by the ROSES framework, the study categorises twelve distinct AI techniques according to their specific functional roles, including predictive analytics, automated trading, stock screening, and technical analysis. This functional mapping not only clarifies how these models operate within investment processes but also provides analytical insights into how various techniques complement or contrast with one another in real-world applications. Drawing from a broad base of empirical studies, the review deductively explores the impact of AI on market dynamics, highlighting its influence on trading efficiency, volatility, transparency, and institutional-retail disparities. These developments are critically linked to foundational financial theories such as EMH, CAPM, MPT, and Behavioral Finance, illustrating how AI adoption is challenging and reshaping classical assumptions. The review also addresses concerns related to AI ethics, bias, and explainability while engaging in discussions on governance and responsible implementation. As a review in nature, it also delivers relevant insights into performance-related characteristics such as efficiency, adaptability, and interpretability across techniques where applicable. Overall, this study offers a timely and well-supported contribution to both academic and practical conversations, providing structured clarity and forward direction in a rapidly evolving field.

These findings highlight areas needing further academic investigation. First, a comparative analysis of AI models is necessary to understand techniques for optimizing performance under varying market conditions, such as neural networks, support vector machines, and decision trees. This focus arises from this study's observation that AI models function differently depending on whether the market is bullish, bearish, or highly volatile. Given market variability, it is crucial to identify which models yield robust results, especially for retail investors lacking advanced tools available to institutional counterparts. Understanding these dynamics could lead to more targeted AI applications, enhancing decision-making across diverse market conditions. Second, as AI's role in financial markets grows, regulatory concerns have emerged. This study reveals that AI-driven trading systems, while improving efficiency, could lead to market manipulation or exacerbate inequalities, benefiting larger institutions more. Future research should explore necessary regulatory frameworks to address issues like market transparency, algorithmic accountability, and ethical AI deployment. This research is vital for ensuring AI technologies are effective, fair, and sustainable long-term, safeguarding the financial system's integrity. These areas represent essential steps for academic inquiry and practical application in AI-driven trading.

Acknowledgement

This study was conducted independently and was not funded by any organisation, institution, or external grant. The author is grateful to the reviewers for their valuable input.

Conflict of Interest

This work has not been published previously and is not currently under review by any other publication. All authors have approved the submission of this manuscript and declared no competing interests.

Author Contribution

The authors confirm contribution to the paper as follows: ***draft manuscript preparation:*** Anuar, A. A*;* ***analysis and interpretation of results:*** Anuar, A. A*;* ***manuscript revision:*** *Sulaiman, A.A.,* Mohamad*, M.T. All authors reviewed the results and approved the final version of the manuscript.*

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