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The utilization of artificial intelligence in investment decisions

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ABSTRACT:
This thesis examines the role of artificial intelligence (AI) in portfolio optimization by focusing on how AI-based methods can enhance investment performance compared to traditional approaches such as Modern Portfolio Theory and Capital Asset Pricing Model. Behavioral finance research has shown that investors are prone to psychological factors which often lead to irrational decision-making. AI and particularly machine learning (ML) offers potential solutions to these cognitive limitations by enabling more objective and data-driven decision processes. This study evaluates the use of AI models in mitigating the impact of behavioral biases on the investment process.

The existing literature indicates that AI-based models offer potential tool alongside with traditional benchmarks. ML algorithms can identify complex and nonlinear patterns from vast amounts of financial data. However, broader implementation of AI models still faces challenges and limitations that needs to be addressed. Computational demands, interpretability problems and regulatory compliance slows down the wider adoption of these applications.

KEYWORDS: Portfolio optimization, Behavioral Finance, Artificial Intelligence, Machine Learning, Deep Learning, Reinforcement Learning, Natural Language Processing

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1 Introduction

In recent years the financial industry has witnessed a transformative shift with the arrival of advanced technologies, particularly artificial intelligence (AI). For decades, both classic and modern AI techniques have drawn interest, being applied to a growing number of areas within finance, economics and society (Longbing, 2023). As markets become increasingly volatile and data-driven the need for innovative approaches to portfolio management and risk assessment has emerged.

When it comes to investing, humans are not as rational as we think. People face variety of challenges in investing that undermine rational decision-making. Factors such as biases, emotions, lack of information, impatience, and attitudes can significantly corrupt their ability to make successful investment choices. Many financial studies such as (DeBondt, 1998) and (Kahneman & Tversky, 1979) have examined these shortcomings and all of them states that investors behave irrationally when it comes to investing.

Fortunately, artificial intelligence (AI) offers a powerful tool for these human limitations. AI algorithms are designed to act without biases allowing for more rational and objective decision-making processes. These algorithms can continuously learn and adapt based on new information and available data. This helps investors to make decisions that are data-driven rather than being influenced by emotions and biases. By reducing the influence of these factors, AI applications promote more consistent and rational financial behavior (Gu et al., 2020; Tao et al., 2021; Lim et al., 2022). Moreover, AI models are capable to adjust real-time changes in market conditions which makes them valuable in volatile environments (Alzaman, 2024).

In addition, one of the advantages of AI is the ability to analyze vast amounts of data accurately and quickly. As the study (Immenkötter, 2024) states, computer systems can process a considerable amount of information compared to human capabilities. This capability enables AI to identify different market patterns and trends that humans might not notice. Furthermore, the complexity of the available data makes it difficult for individual investors to analyze and process all relevant information efficiently and objectively. Various sources generate constantly changing high-dimensional and noisy datasets that require significant amount of resources and expertise to interpret (Bhuiyan et al., 2025).

Despite the advantages that AI models offer, the reliability of these systems depends on the quality of the input data and robustness of the algorithms. Inaccurate or biased data might lead to distorted results and poor decisions (Bhuiyan et al., 2025). Additionally, the lack of transparency makes it difficult to investors and regulators to understand how certain conclusions are achieved (Giudici & Raffinetti, 2023). These highlight that ensuring data integrity, improving interpretability and strengthening regulation are crucial for safe and functional utilization of AI applications.

Therefore, it is important to further research the benefits of using AI to support investment decision-making. The existing literature analyzes various methodologies, highlighting the potential of AI applications to enhance portfolio management. Using the above-mentioned literature along with others, this thesis aims to demonstrate the potential of artificial intelligence as an excellent tool for supporting financial decision-making. Ultimately offering significant advantages in portfolio optimization through improved profit maximation and risk management.

1.1 Purpose of the study

The purpose of this paper is to examine the use of artificial intelligence in investment decision-making, with a specific focus in portfolio optimization for better returns and risk management. I study how individual investors could benefit from different methods by accommodating AI with already known information and strategies. Existing literature sees artificial intelligence as a helpful tool, that promotes investors objectivity and limits the debilitating factors that we humans have as decision makers (Lim et al., 2022; Blohm et al., 2022; Darskuviene & Lisauskiene, 2021). According to Mahmood et al, (2024) traditional investment methods fail to take behavioral factors into account, leading to suboptimal investment decisions. Hence, the first hypothesis follows:

H1: The use of artificial intelligence applications can increase investment returns compared to traditional methods.

Additionally, behavioral factors expose investors to taking excessive risks which originates from insufficient knowledge, skills and lack of available resources (Darskuviene & Lisauskiene, 2021; Barber & Odean, 2001). This leads to the second hypothesis, which follows:

H2: Artificial intelligence reduces risk exposure more effectively than human decision-making alone.

These hypotheses are based on current literature, which mostly suggests that the utilization of artificial intelligence provides a potential tool to enhance investment decision-making in portfolio optimization alongside traditional methods.

1.2 Structure of the study

The first chapter introduces the topic, discusses the purpose of the study and presents hypotheses. Second chapter presents the theoretical framework which includes Modern Portfolio Theory, Capital Asset Pricing Model, Prospect Theory and Cognitive biases. The third and fourth chapters examine the existing literature in more detail, focusing on the behavior of individual investors and machine learning approaches in portfolio optimization. Chapter five presents the empirical results that covers benefits and limitations of AI-based models in investment decision-making. Finally, the conclusion chapter summarizes the key findings of the thesis. The reference list is added after the last chapter.

2 Theoretical framework

This section of the study presents the main theoretical foundation for investment decision-making and portfolio optimization. The section explains traditional financial theories like Modern Portfolio Theory and Capital Asset Pricing model and address their limitations regarding investors behavior. In addition, Prospect Theory and cognitive biases are introduced to clarify how psychological and emotional factors influence investors.

2.1 Modern Portfolio Theory

Modern Portfolio Theory (MPT) was developed in 1952 by Harry Markowitz. MPT suggests that it is possible to create a set of ideal investment portfolios that offers the highest expected return for a specific level of risk using mean-variance optimization. This is achieved through diversified portfolios where investments are spread across various assets to reduce risk exposure. Investors can reduce portfolio volatility without scarifying expected returns by calculating covariances and combining assets which have low or negative correlation (Salo et al., 2024).

A central concept in MPT is the efficient frontier, which represents the set of portfolios that offer the best possible expected return for the given level of risk. Portfolios that are below the efficient frontier line are considered suboptimal. These portfolios may give the same expected return as the optimal portfolio but involve a higher level of risk or provide the same level of risk but yield a lower expected return. Investors can select their optimal portfolio along the efficient frontier line based on their individual risk tolerance (Grasse et al., 2016).

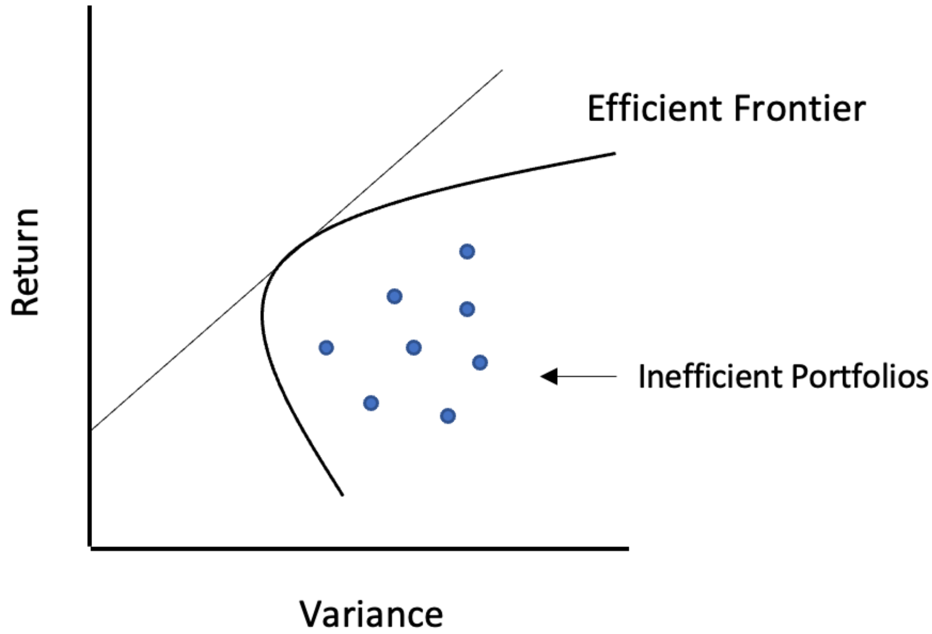

Figure 1. Illustration of Efficient Frontier (Grasse et al., 2016)

One of the shortcomings of MPT is that it assumes that investors behave rationally and avoid taking risks, meaning they prefer less risky portfolio for a given level of expected returns. However, behavioral finance studies recognize the fact that investors have many behavioral biases which influence the investment decisions, making them act irrationally (DeBondt, 1998; Hirshleifer, 2001).

2.2 Capital Asset Pricing Model

Built on MPT, William Sharpe and John Lintner presented the Capital asset pricing model (CAPM) which is a pricing model used in finance to calculate the expected rate of return and to evaluate the cost of equity capital (Fama & French, 2004). According to Fama and French (2004), CAPM indicates the long-term average return that investors require from a security. The core concept of CAPM is systematic risk, which cannot be reduced by diversifying investments. The expected return is calculated as the sum of risk-free rate and the risk premium where the risk premium is determined by the investment's beta coefficient. The beta measures the sensitivity of a specific asset to market movements.

When the beta value is greater than one it means the investment is more volatile than the market, and beta value below one means that it is less volatile. CAPM can be presented by the following equation (Fama & French, 2004):

$$E(R_i) = R_f + \left[E(R_m) - R_f\right]\beta_i$$

Explanation of the formula:

$E(R_i)$	= Expected return of stock (i)
Rf	= Risk-free interest rate
E(Rm)	= Market portfolio's expected return
β_i	= Beta coefficient of stock (i)

Another key concept in CAPM is the Capital Market Line. Sharpe (1964) introduced the Capital Market Line (CML), which illustrates the risk-return tradeoff for efficient portfolios that combine risk-free asset with the market portfolio. Portfolios that are on the CML represent the best possible combinations of risk and return that investors can achieve through diversification. According to Sharpe (1964), every rational investor who aims for profit maximization wants to move left along the line to minimize risk and upwards to maximize return.

Although the CAPM provides a central theoretical framework for expected returns while taken risk into account, investors do not necessarily evaluate risk solely through volatility and beta. Emotions and irrational behavior can lead to deviations from the returns predicted by the model. (Apergis and Rehman, 2018). For instance, behavioral finance research argues that psychological factors such as overconfidence and herd behavior often influence how individuals perceive and react to risk (Shiller, 2003).

2.3 Prospect Theory

Prospect theory was introduced in 1979 by Kahneman and Tversky and is considered to be a fundamental theory in behavioral finance. The theory explains how people make decisions under risk and uncertainty. According to the study Kahneman and Tversky (1979), investors make decisions in two stages. First stage is the editing phase, where different choices are organized and simplified using heuristics to make the decision-making process easier. The second stage is the evaluating phase, in which investors assesses the potential gains and losses of these choices relative to specific reference points. Kahneman and Tversky (1979) explain that these reference points serve as a psychological benchmark against which outcomes are judged.

Unlike the previous benchmark theory for decision making under risk, prospect theory demonstrates that individuals make irrational decisions and value gains and losses asymmetrically (Kahneman & Tversky, 1979). According to Kahneman and Tversky, cognitive biases and emotions are guiding decisions rather than the highest expected utility. In addition, Prospect theory argues that people tend to misjudge probabilities, giving too much weight to unlikely events and not enough weight to more certain ones.

2.4 Cognitive biases

Cognitive biases are systematic patterns that deviate from rational judgment, leading individuals to make decisions that are not always logical or optimal. These mental shortcuts help people simplify complex situations but also distort perception and reasoning. Ultimately, causing inconsistent and irrational choices (Hirshleifer, 2001).

2.4.1 Overconfidence

One of the most widely recognized and researched cognitive bias in psychology is overconfidence. Overconfidence refers to systematic tendency of individuals to believe that their opinions are more reliable and accurate than they actually are (Jhonson & Fowler, 2011). Jhonson and Fowler (2011) highlights that overconfidence can have both positive and negative effects on individuals. It may improve the probability of success, but it can also lead to false conclusions and unrealistic expectations. Ehrlinger et al. (2016) explain that overconfidence originate from distorted self-assessment and selective attention to information that confirms ones' abilities while ignoring errors or limitations.

According to Moore and Healy (2008), overconfidence is defined in three different ways. These are overestimation of ones' actual performance, overplacement of ones' performance relative to others and overprecision in ones' beliefs. Moore and Healy (2008) further explain the overestimation by example where a student who took a quiz, believes that he answered more questions right than he actually did. This way the student overestimated his score. Overplacement take place when people think they are better than others in doing something. For instance, students may overplace their test score to be highest in the class when in reality they only got an average score compared to the rest of the class (Moore and Healy, 2008). Overprecision occurs when people have too much faith in the accuracy of their conclusions (Moore and Healy, 2008).

2.4.2 Confirmation bias

Confirmation bias is another well documented bias that individuals have. Confirmation bias means that people give more value for information and ideas that support their personal beliefs and downplay everything that are against them. This bias enables individuals to convince themselves of what they want to believe and therefore limits the ability to expand their knowledge (Hernandez & Preston, 2013). In addition, Peters (2022) explains that confirmation bias makes individuals less receptive to constructive feedback which reinforce their existing beliefs.

According to Peters (2022), confirmation bias also affects more deeply to social interactions. The research highlights that confirmation bias help individuals to maintain social relationships and protect personal identity and collective belonging. However, confirmation bias may amplify contradictions between individuals, leading to more intense group polarization (Peters, 2022).

3 Literature review

The following section reviews existing literature related to investors behavior and AI applications in portfolio management. First, the section delves deeper into psychological, emotional and social factors that shape individuals' financial decisions. After this, the section covers artificial intelligence applications that recent research has examined to improve portfolio optimization and address these behavioral limitations.

3.1 Irrationality of investors

Traditional financial theories often assume that investors act rationally and make choices based on the available information. However behavioral finance acknowledges the fact that emotions, cognitive biases and social factors significantly shapes investors behavior (Kahneman & Tversky, 1979; Barber & Odean, 2001; De Bondt, 1998). Economists often believe that these biases cancel out in a large scale because they vary among individual investors. However, this is not the case, as it has been studied that people have a tendency to share similar heuristics (Hirshleifer, 2001).

Overconfidence is a well-known bias that significantly influences the behavior of investors. Overconfidence affects how investors review financial statements, pay attention to various rumors, and consider the opinions of professionals regarding specific companies. How this information is interpreted depends on the investor's skill level, which in turn affects their performance in the stock market (Costa et al., 2017). Overconfidence may further guide investors to trade more frequently which leads to irregular and poor returns. This happens because investors are too confident about their opinions and believe to know the winning stocks (Baker & Nofsinger, 2002). Additionally, overconfident investors underestimate potential risks, and hold riskier portfolios (Barber & Odean, 2001).

In addition to overconfidence, confirmation bias has significant impact on investors. Park et al. (2013) study reveals that when investors are influenced by confirmation bias, they become excessively confident and unrealistically optimistic about their initial assumptions. This might widen the gap between the returns they actually gain and what they expected to gain. According to Cheng (2019), confirmation bias makes investors to actively follow financial analyses that confirm their investment beliefs and ignore warnings and negative signals that might lead to significant losses. Moreover, Park et al. (2010) underscore that similar to overconfidence, confirmation bias can lead investors to trade excessively, leading to inferior performance.

Investors also tend to rely too heavily on the first piece of information that they receive when making decisions. In other words, they anchor themselves in this initial value leading their future judgements being biased towards the value, even if it was irrelevant or misleading. This cognitive bias where investors don't rely on objective and relevant information is called anchoring bias (Costa et al., 2017). For instance, investors might hold on to losing assets for too long because they believe that the price will return to original purchase price even if the signals suggest further decline. This causes the investors hold on the stock longer than is necessary, increasing the risk of grater losses (Baker & Nofsinger, 2002).

According to Grinblatt and Kelonharju (2001), investors have a very strong tendency to break even after losing money. This can be explained with one of the most observed biases in investor behavior, known as the disposition effect. Disposition effect refers to the habit of investors selling assets that have gained value while holding onto assets that have lost value (Dhar & Zhu, 2006). Shefrin and Statman (1985) analyze the disposition effect and how it emerges in prospect theory introduced by Kahneman and Tversky (1979). They illustrate this habit by example. An investor buys a stock, but later its price drops. When the investor notices this drop, they have two options. They can sell the stock right away and admit the loss or hold onto it and risk further losses or have the chance to break even. Prospect theory suggests that investors usually choose to keep the losing stock instead of selling it (Kahneman & Tversky, 1979).

Social factors have a considerable role in investors behavior alongside with psychological biases. Conversations and interactions with other people often affect investors' emotions and decisions (Baker & Nofsinger, 2002). The interactions between investors causes correlation in investment transactions. This occurrence is known as herding in behavioral finance (Chiang & Zheng, 2010). Nofsinger and Sias (1999) explains herding as investors who collectively trades in the same direction for certain period of time. Kuo et al. (2024) highlights that herding behavior narrows the possibilities to find winning opportunities and therefore weakens investment performance.

3.1.1 Emotional behavior

Emotions, along with these biases, can profoundly affect investors actions, often leading to decisions that deviate from logical information. Emotions can cloud judgment and perception, sometimes causing investors to overreact to market events or hesitate when opportunities arise. Ultimately affecting their investment results (Bird et al., 2025). Current studies have found many factors that influence people's feelings and emotional states (Goetzmann et al., 2015; Kamstra et al., 2003; Edmans et al., 2007).

Goetzmann et al, (2015) examined how weather affects investor's mood and stock returns. The researchers found out that investor's mood tends to be more positive in sunnier days which further correlates to higher market returns (Goetzmann et al., 2015). In addition, Sariannidis et al. (2016) underline that high humidity level influences stock returns positively. On the contrary cloudier weather conditions makes people experience negative emotions, leading them to more likely avoid risks and make more cautious decisions (Goetzmann et al., 2015). Sariannidis et al., (2015) also provides evidence that windy conditions are associated with lower market returns.

Kamstra et al. (2003) introduced Seasonal Affective Disorder (SAD) which takes seasonal changes into consideration. The study demonstrated that seasonal mood variations caused by reduced daylight during Fall and Winter can systematically affect investors' risk preferences and market performance. According to the findings, investors experience lower mood levels as daylight decreases which leads investors to avoid risk and therefore cause market returns to decline (Kamstra et al., 2003). Conversely, increasing daylight improves investors' mood and raise risk tolerance which results in higher returns. Kamastra et al. (2003) suggest that these seasonal changes can generate predictable cycles in asset prices.

In a study done by Edmans et al. (2007), researchers investigated how results of sport matches effects to investor sentiment on asset prices. According to the research, national soccer teams' loss in an international competition often leads to strong decrease in stock prices in the following day. Edmans et al. (2007) noticed similar but less prominent loss effect in international cricket, rugby and basketball games. In more recent study Edmans et al. (2022) provided evidence of how music can influence investor behavior and market outcomes. Authors found that positive music sentiment is associated with higher stock market returns and negative sentiment predicted lower returns.

3.2 Portfolio management with machine learning

Machine learning (ML) is a subfield of artificial intelligence in which computer systems learn to recognize different patterns and make predictions from data. It is based on algorithms that are improving their performance through experience and new information (Jordan et al., 2015). Gu et al. (2020) and Pinelis & Ruppert (2020) studies shows that the use of ML in portfolio management provides clear benefits for optimizing both risks and returns and possibly achieving performance that is up to twice as high as the most prominent strategies. However, Pinelis & Ruppert (2020) states that ML's predictive power depends on the data quality. Implying Incomplete and poor datasets could distort forecasts and lead to misleading decisions.

ML algorithms are also capable of handling and analyzing data from various sources without being affected by the cognitive limitations that humans face. Furthermore, being mostly unbiased, these algorithms can take all available information into account and make less misjudgments in the process (Blohm et al., 2022). Despite these advantages, ML algorithms are still exposed to influence of biases. Lee et al. (2024) points out that these models can inherit biases from training data and replicate them, underlining the importance of evaluating the outcomes afterwards. According to Lee et al. (2024), ML algorithms has the potential to solve many challenges in modern portfolio management.

3.2.1 Deep learning

Deep learning (DL) is a subset of machine learning which is developed to handle more complex structures and data. Deep learning uses artificial neural networks that are an abstraction that mimics the complex neural connections of the human brain (Alzaman, 2024). Schmidhuber (2015) explain that these neural networks consist of numerous connected processors called neurons that enable computers to learn patterns from vast amounts of data.

Utilizing deep learning has been studied in the context of portfolio optimization. Alzaman (2024), Gu et al. (2020) and Ma et al. (2021) all examined the possibilities of deep learning to improve investment process. The results of the studies shows that deep learning can identify complex and nonlinear patterns from financial data and improve predictions in portfolio allocation. Gu et al. (2020) demonstrate that DL-models can improve risk-adjusted performance and adapt changing economic conditions. While illustrating several benefits, all three studies acknowledge the fact that DL models require substantial computational power and are challenging to calibrate effectively.

Traditional portfolio models often overlook the impact of investor sentiment and emotions on asset prices (Ma et al., 2021). Addressing these limitations, Ma et al. (2021) applied deep learning techniques into stock price prediction, improving the ability to capture market behaviors. Alzaman (2024) explains that investors irrationality is making markets prone to patterns and inefficiencies that are hard to capture with traditional models. Although DL’s ability to adapt to changing investor psychology is not yet fully proven, Alzaman (2024) emphasizes the ability of deep learning and especially neural networks to handle nonlinear behaviors.

3.2.2 Reinforcement learning

Reinforcement learning (RL) is another area of machine learning where agents learn to make optimal decisions by interacting with their environment and observing the results (Hambly et al., 2023). The agents can gradually improve their strategy through experience and develop behavior to achieve specific goals (Hambly et al., 2023). According to Lim et al. (2022) RL methods are used in investment decision making and portfolio optimization.

Behavioral finance research shows that investors differ in their risk preferences which could affect portfolio returns. Some investors are risk-averse and avoid losses while others can tolerate more uncertainty for potential gains (Lim et al., 2022). These tendencies and adversity can impact asset prices and overall market volatility (Lim et al., 2022). In the study (Lim et al. 2022) researchers underscore the potential of RL techniques to overcome such irrational behavior by gradual portfolio rebalancing with neural network model on price prediction. While RL models demonstrate adaptability, Hambly et al. (2023) observe that market shocks and unknown changes can still deceive these systems.

Another problem with traditional methods in portfolio optimization is their inability to adapt to dynamic markets (Jang & Seong, 2023). Study done by Jang & Seong (2023) examined if RL could be utilized for portfolio management under such conditions by combining reinforcement learning with modern portfolio theory. The results demonstrated that RL-based strategies can enhance risk-adjusted returns and adapt more effectively to volatile markets over existing models (Jang & Seong, 2023). Even though the results showed potential, they failed to consider transaction costs and liquidity constraints that might diminish the observed advantages. Nevertheless, Jang and Seong (2023) underlined RL's potential to address limitations of traditional approaches and to provide investors with more flexible and resilient portfolio management tools.

3.2.3 Natural language processing

Natural language processing (NLP) is a part of computer science that is closely linked to artificial intelligence. NLP focuses on enabling communication between humans and computer through natural language (Fisher et al., 2016). According to Fisher et al. (2016), NLP is a set of computational techniques that allow computers to understand, process and generate language for various applications. Fisher et al. (2016) explains that the benefits of natural language processing has also been studied in the field of finance. For instance, some studies have incorporated NLP techniques to detect relationships between financial news and stock price movements (Fisher et al., 2016).

Investors irrationality and market inefficiencies make predicting the markets extremely challenging, if not impossible. In the study Du et al. (2025), researchers emphasize NLP's ability to analyze large volumes of real time data. By interpreting news and social media, NLP algorithms improve decision-making and enhance investors' ability to react to rapid market movements (Du et al., 2025). On the other hand, Hung et al. (2024) stress that the reliance of textual information introduces potential challenges. Unverified online content can distort NLP's outputs which leads to misleading conclusions.

NLP is often used in sentiment analysis which refers to detecting and retrieving subjective information from various sources (Hung et al., 2024). Du et al. (2025) explains that stock prices and market fluctuations are considerably influenced by investor sentiment, or in other words, investors' beliefs about the future outcomes. The findings of the study Hung et al. (2024) shows that NLP and sentiment analysis can capture investor behavior and market expectations better than traditional models that rely heavily on fundamental information and historical prices. Furthermore, Du et al. (2025) states that models that integrate public sentiment has been shown better results than equal-weighted strategies.

3.2.4 Robo-advisors

One of the most visible applications of artificial intelligence in investment decision-making and portfolio management is robo-advisors. Robo-advisors are digital platforms that utilize automated machine learning algorithms to offer financial advice and portfolio management services to investors (Tao et al., 2021). With minimal human intervention, they provide an accessible and cost-efficient alternative to traditional asset management practices (Tao et al., 2021). Robo-advisors lower the threshold of individual investors to enter investing and portfolio management, allowing even smaller investors to get more deeply engaged with strategies and guidelines (D'Acunto et al., 2019). Furthermore, the study D'Acunto et al. (2019) explains that these platforms act as an effective tool to investors to diversify their portfolios more effectively.

Besides being conventional and affordable, robo-advisor helps investors to be more objective and rational with the decisions (Darskuviene & Lisauskiene, 2021). Because the decisions are driven by algorithms, the influence of cognitive biases and emotional factors are decreased. For instance, Darskuviene and Lisauskiene (2021) emphasize that robo-advisors prevent investors from making impulsive decisions based on rapid market fluctuations.

Robo-advisors, despite growing utilization, raise questions about ethical responsibility and the quality of financial recommendations. Tao et al. (2021) note that investors' biases may still influence the advice that robo-advisors provide to investors. Additionally, D'Acunto. (2019) argue that while robo-advisors facilitate access to investing, they may also encourage overconfidence among individuals who underestimate financial risks.

4 Assessing AI applications in portfolio management

First part of this section examines how AI techniques and applications have been applied to portfolio optimization, highlighting the impressive performance reported in the recent studies. The second part shifts the focus to weaknesses of these methods and regulatory limitations that arise when integrating AI into financial decision-making.

4.1 Research evidence on the benefits of AI in portfolio optimization

Pinelis and Ruppert (2022) introduced a machine learning framework for portfolio allocation. Their approach divided investments between the market index and risk-free asset based on return and risk predictions. The empirical results of the study demonstrated Sharpe ratio that was 28 % higher than traditional buy-and-hold strategy. In 2020, Gu et al. compared multiple ML algorithms against traditional linear models to forecast asset risk premiums. With neural network forecast model, Gu et al., (2020) achieved performance that is over twice as high as the leading regression-based strategy with annualized Sharpe ratio of 1,35. Both studies (Pinelis & Ruppert, 2022) and (Gu et al., 2020) emphasized that their ML-based models are highly valuable in dynamic and uncertain market conditions and enhance risk-adjusted returns.

Alzaman (2024) applied deep learning model called Deep RankNet to stock portfolio selection and prediction of financial assets and compared the results against standard market benchmarks. The DL-based portfolio showed promising results getting 20 % higher returns than the general market by reaching Sharpe ratio of 1,59. In addition, the deep learning models performed even better when tested in highly volatile market conditions, demonstrating DL algorithm’s ability to capture nonlinear behaviors (Alzaman, 2024). Alzaman (2024) notes that the superior returns come at the cost of higher computational complexity which investors should consider when assessing practical implementation.

In 2023, Yang and Seong presented an approach that combines modern portfolio theory and reinforcement learning. They used RL framework together with DL algorithms to optimize stock portfolios. The proposed method showed exceptional Sharpe ratio of 2,01 outperforming traditional strategies as well as other state-of-art algorithms. Moreover, the method constructed by Yang and Seong (2023) adapts dynamically to market trends making it suitable for changing markets. Their findings suggest that reinforcement learning offers enhanced adaptability and mitigates risk without compromising returns.

Another study conducted by Yang (2023) examined reinforcement learning model for portfolio management called TC-MAC. The model integrates learning from individual asset features with overall portfolio context and improves investment strategies through a combination of actor–critic and mutual information loss functions. Yang (2023) tested the model on stock market and ETF data. TC-MAC achieved 2,58 Sharpe ratio, showing its superior competence to provide risk-adjusted returns under different market conditions (Yang, 2023).

Ma et al. (2024) proposed a method for portfolio optimization that utilize NLP with deep learning components. They presented multi-task learning model with a heterogeneous graph attention network (HGA-MT) that combines risk and return together with related stock information. HGA-MT model with Sharpe ratio of 2,03 exceeded other baselines used in the study, leading to increased and more consistent returns (Ma et al., 2024). The study highlights HGA-MT models' ability to reduce risk exposure.

Similarly, Hung et al. (2024) investigated natural language processing with deep learning to create Black-Litterman model. This model combined textual analysis with three different deep learning models to incorporate news sentiment to portfolio management. The best performing combination of Black-Litterman and gated recurrent unit (GRU) delivered Sharpe ratio of 1,30 (Hung et al., 2024). For example, the model outperformed Markowitz portfolio and S&P 500 stock market index. Hung et al. (2024) underline Black-

Litterman and GRU model's predictive ability to capture trends and asset prices in volatile markets.

Study done by Tao et al. (2021) explored risk-adjusted performance of robo-advisors comparing them to conventional funds in three-year period. The results showed that robo-advisors consistently outperformed investment funds and stock indices in returns and risk-adjusted performance. Robo-advisors demonstrated Sharpe ratios ranging from 0,81 to 2,18 (Tao et al., 2021). Tao et al. (2021) underline that the results were contributed by algorithmic trading, automatic rebalancing, and efficient tax features. More importantly robo-advisors maintained their performance in volatile market conditions, indicating their competence compared to human-managed portfolios (Tao et al., 2021).

4.2 Shortcomings and limitations of AI models

Despite many studies are showing promising results and superior performance of ML algorithms over traditional methods, they still face some challenges and limitations that needs to be addressed. Financial markets are generating massive amounts of information that is challenging to interpret even with ML models (Bhuiyan et al., 2025). Financial data contains extensive volumes of noise that these models might identify as false patterns, leading to low-quality predictions. According to Bhuiyan et al. (2025), DL models often capture noise in financial data which increases the risk of overfitting.

Overfitting is one of the challenges that comes up constantly with the machine learning models (Pinelis & Ruppert, 2024; Gu et al., 2020). Overfitting occurs when a model performs well on the training set but fails to generalize the learning to unfamiliar data (Bhuiyan et al., 2025). Gu et al. (2020) explains that while the high-dimensional nature of ML methods makes them highly flexible and efficient to interpret random noise in the data, it also increases their sensitivity to errors. This implies that the results of ML methods may appear to perform better in testing than in practical environments (Gu et al., 2020).

Gu et al. (2020) and Alzaman (2024) emphasize that ML models are computationally intensive and require substantial resources. Bhuiyan et al. (2025) argues that the technical expertise required to implement and maintain AI-based models limits their accessibility. In addition, training deep models is costly and takes significant effort and time to ensure it works properly (Bhuiyan et al., 2025). The researchers further mention that the energy consumption of large neural networks is significant and raise sustainability concerns. For these reasons, many of these models are beyond the reach of individual investors or even small firms (Alzaman, 2024).

One of the most mentioned problems of utilizing ML in financial applications is the lack of interpretability (Gu et al., 2020; Lee et al.,2023; Bhuiyan et al., 2025). The complexity of ML algorithms makes it difficult to understand or explain the process of specific predictions (Lee et al., 2023). Furthermore, Bhuiyan et al. (2025) explains that the inherent 'black box nature' of deep neural networks makes them particularly hard to interpret. This lack of transparency constitutes a significant obstacle for wider implementation in portfolio management, where trust and explainability are crucial for investors and regulators (Bhuiyan et al., 2025).

The growing adoption of artificial intelligence and machine learning in finance has raised notable concerns about regulations considering AI. Giudici and Raffinetti (2023) point out that the black-box nature of ML methods makes them difficult to validate in regulated industries where transparency is necessary. While ML delivers impressive results and high predictive accuracy, regulators also demand fairness, sustainability and explainability (Giudici & Raffinetti, 2023). The researchers underline the urgent need for framework of measures that evaluate compliance of the requirements over time. Future research should focus on developing explainable and resource-efficient AI models that can bridge the gap between the impressive potential of these models in testing and practical usability for investors in financial markets.

5 Conclusions

This study explores how artificial intelligence can be applied to investment decisions, with a particular focus on portfolio optimization. This issue is examined in more detail from the perspective of behavioral finance. As previous research has shown, investors are prone to various cognitive biases that traditional portfolio optimization models often fail to capture. The thesis reviews the most common biases that have an impact on investors decisions in financial markets and analyze how these biases affect to market fluctuations. Furthermore, the study investigates different machine learning methods that can be utilized in portfolio management and considers how these are able to reduce the impact of biases.

Traditional portfolio optimization models, such as CAPM and MPT, relies on the assumption that investors act rationally and without emotions. However, Prospect theory has demonstrated that individuals behave irrationally and evaluate risks differently. This irrational behavior influence significantly to market dynamics, increasing volatility and making market movements more challenging to predict. Artificial intelligence and more specifically machine learning, offers a potential solution to this problem and has demonstrated superior results in dynamic and uncertain market conditions against traditional benchmarks. ML methods like deep learning and reinforcement learning algorithms are capable of processing vast amounts of data, capturing complex nonlinear relationships, and adapting portfolio to rapidly changing market environments without the influence of cognitive biases.

Although the growing evidence is showing exceptional results with artificial intelligence in portfolio optimization, the practical exploitation still faces notable challenges. AI models are prone to overfitting which may give the impression of better performance in testing than in practice. They are also expensive and require considerable computational resources. Moreover, the interpretability problems and the lack of transparency remains a critical obstacle for larger adoption of AI models in portfolio management.

Future research should focus on improving AI models’ robustness, interpretability and applications in practice. To address overfitting and adaptability, new approaches should be developed to handle dynamic market regimes and non-linear financial data. Future studies should incorporate realistic trading conditions by accounting transaction costs, liquidity and implementation constraints to ensure that AI models remain effective in real market environment. Additionally, stronger attention should be placed on explainability by integrating tools that clarify how and why models make such predictions.

This study supports the view that artificial intelligence, and particularly machine learning methods, have significant potential to enhance investment decision-making. The current literature on ML applications supports the hypothesis of this study, which states that AI-based methods can increase investment returns and reduce risk exposure more effectively than human decision-making alone. ML-based techniques’ ability to handle large unistructural datasets and provide objective insights, especially in volatile and nonlinear situations, makes them valuable tool alongside traditional models. However, the advantages of AI can be fully realized when regulatory frameworks, practical limitations and safety standards are sufficiently improved and reinforced to ensure effectiveness, reliability and safety of these applications.

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