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Portfolio optimization with AI: Evaluating Performance Beyond Traditional Techniques

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ABSTRACT:

This thesis study the use of artificial intelligence (AI) in portfolio optimization, by evaluating and comparing AI with traditional methods such as Modern Portfolio Theory and Capital Asset Pricing Model. Advanced machine learning techniques such as deep learning, reinforcement learning and natural language processing which comprise AI bring several possibilities to adress this weakness of traditional models in dynamic and volatile financial environments. This paper evaluates the use of AI in enhancing risk-adjusted returns and market agility before defining its challenges such as computational burden and interpretability. Our key observations describe situations where AI approaches outperform traditional methods, offering insights into possible future uses in asset management and field trends.

KEYWORDS: Portfolio Optimization, Artificial Intelligence, Machine Learning, Deep Learning, Reinforcement Learning, Natural Language Processing, Evolutionary Algorithms

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1. Introduction

Artificial intelligence (AI) has become a point of discussion in previous years. AI might be disruptive in the asset management industry. Asset management, which involves managing investments on behalf of clients, relies extensively on data-driven decision-making processes. The complexity of the financial landscape continues to grow, and I may open up innovative tools and techniques for navigating this complex environment. Nevertheless, existing research in asset pricing and portfolio management identifies specific gaps that require deeper investigation. For instance, Buraschi et al. (2010) indicated that traditional methods often struggle in high-volatility environments, such as financial crises, and integrating AI- of AI-based technniques with traditional methods remains underexplored. This study explores how AI improves risk-adjusted returns in portfolio optimization, addressing these challenges and focusing on specific scenarios where its application could provide substantial benefits.

Portfolio optimization plays a critical role in asset management, where the objective is to select the best available asset allocation from a set of distinguished securities. In general, it aims to maximize expected returns under economic costs such as financial risks, and this leads most portfolios to become a multi-objective optimization problem. A breakthrough came in 1952 when Harry Markowitz introduced the concept of optimizing portfolios to balance returns with a given level of risk (Markowitz, 1952). Another widely used innovation, Capital Asset Pricing Model (CAPM), was introduced by William Sharpe in the 1960’s. CAPM is based on the idea that the return of an asset is correlated with its systematic risk, which is represented by the ‘beta’ factor that illustrates the risk of a specific asset relative to market risk (Sharpe, 1964). CAPM illustrates the idea that risk and return should be aligned and that assets possessing higher risk should generate higher returns. Even though CAPM is widely used to model the required return, its empirical performance is constrained by its simplifying assumptions. According to the research, in complex and wide markets Markowitz’s Modern portfolio theory can also lead to deficient results (Perrin & Roncalli, 2019).

This paper concentrates on artificial intelligence-based methods in portfolio optimization and examines how these approaches can enhance the performance of traditional methods. Traditional methods, such as mean-variance optimization or factor models have been widely used in portfolio optimization (Louis et al., 1999; Barillas & Shanken, 2018). However, these traditional methods have significant methodological limitations. Their strong reliance on historical data often leads to challenges such as the impaired ability to forecast and limited adaptability in high volatility market conditions (Buraschi et al., 2010). Noted by Louis et al. (1999), these shortages constrain the traditional models' ability to generate trustworthy outcomes that bear interest to research more innovative methods.

Artificial intelligence has become a significant area of focus in recent years and AI plays a central role in the development of fintech services. Gu et al. (2020) explain, that unlike traditional methods, new machine learning-based asset pricing models can capture non-linear predictions and thus offer more advanced analytical capabilities. Another important AI-based technique is Natural Language Processing (NLP) which includes the computational analysis of text data. NLP offers remarkable advantages when processing large volumes of real-time data (Ke et al., 2020). The ability to utilize real-time data is particularly beneficial in high volatility market conditions, in which traditional methods often fall short. Especially for these situations, innovative and more advanced methods can offer considerable options considering portfolio optimization.

In 2019 Perrin and Roncalli researched the performance of AI-based methods in portfolio optimization and concluded that traditional methods are still relevant. Researchers pointed out that traditional methods in portfolio optimization perform effectively in stable market conditions where volatility is stable (Perrin & Roncalli, 2019). As a result, the focus of this thesis should be more specific. Given the limitations of traditional methods discussed earlier, this study focuses on scenarios characterized by high volatility to analyze the performance of AI-based approaches. Specifically, it investigates their predictive accuracy, adaptability to evolving market dynamics, and computational efficiency in generating predictions. By analysing these aspects, the paper seeks to assess if AI techniques provide superior performance compared to traditional portfolio optimization methods and determine the conditions under which these techniques are most effective.

1.1 Purpose of Study

This research aims to investigate the opportunities that artificial intelligence (AI) presents to the asset management industry. As highlighted earlier, AI has become a highly relevant research topic. The limitations of traditional portfolio models, discussed in the introduction, have long been recognized. This study seeks to assess critically whether contemporary AI-based models offer superior performance and to identify the specific scenarios in which they may be effectively applied. Building on the theories and limitations briefly discussed, as well as the rapidly evolving financial landscape, the research question for this study is defined as follows:

Research Question: How can Artificial Intelligence enhance risk-adjusted returns in portfolio optimization, particularly in high-volatility financial markets, compared to traditional methods?

The primary motivation for this research is to analyse and evaluate various AI-based portfolio optimization techniques and assess their practical applicability. Traditional portfolio management methods serve as a benchmark for comparison. This paper further investigates whether commonly utilized AI techniques outperform traditional models under specific conditions and explores the underlying reasons for such outcomes. If AI-based methods consistently demonstrate superior performance, it may indicate that their adoption within the asset management industry will continue to grow in the future.

This study is inspired, in part, by the expanding body of research highlighting the increasing role of AI in financial practices. The figure 1 below illustrates the rising significance of artificial intelligence in recent academic and industry research.

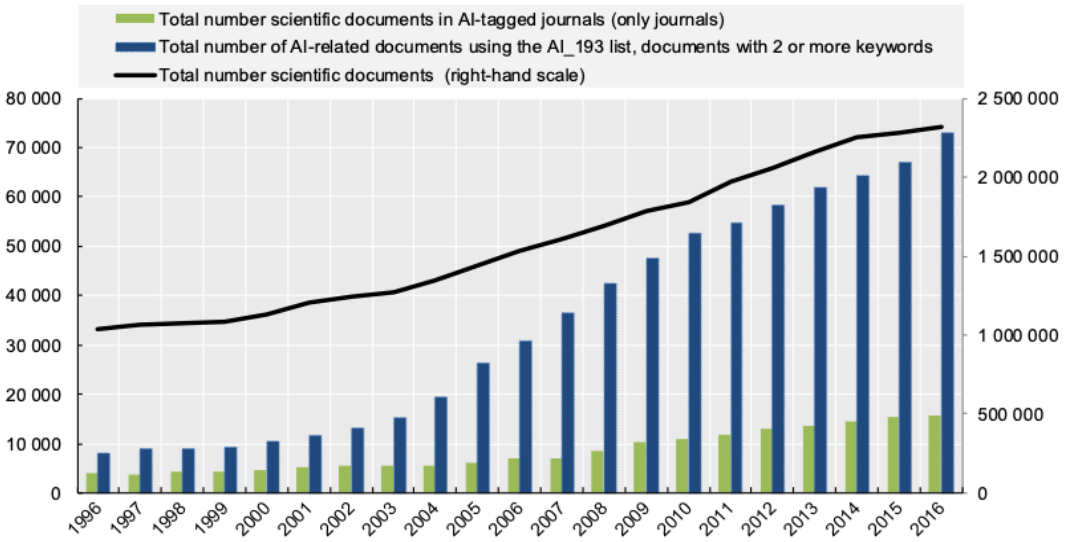

Figure 1. Growth of research on artificial intelligence 1996-2018 (OECD, 2020).

1.2 Structure of Study

The structure of this study is organized as follows: First, the theoretical framework of traditional portfolio optimization methods will be examined, emphasizing their foundational principles and inherent limitations. Subsequently, the theoretical foundation of AI approach methodologies will be explored, focusing on the role of advanced machine learning techniques, including deep learning, reinforcement learning, and natural language processing. The following sections detail an analysis of the applications and performance of AI-driven approaches, focusing on optimization algorithms and neural network frameworks for portfolio optimization. Finally, a thorough comparison and analysis of AI-based methods will be undertaken to conclude the main insights and implications for future research.

2. Theoretical framework

The following section of this study will provide a concise overview of the theoretical frameworks underpinning traditional linear models, which have historically been integral to portfolio optimization. Their inherent limitations will also be critically examined. The subsequent chapter will explore the methodological foundation of AI-based methods.

Portfolio optimization involves allocating assets to maximize returns for a given risk level or minimize risk for a targeted return (Rachev et al., 2008, p. 36). The goal is to construct a portfolio that aligns with an investor's risk tolerance, return objectives, and investment horizon. Introduced by Harry Markowitz in 1952, Modern Portfolio Theory (MPT) provides a framework for balancing risk and return through diversified portfolios. Using mean-variance optimization, the model calculates asset covariances to construct portfolios with the highest return for a specified risk level. MPT assumes investors are rational and risk-averse, preferring lower risk for the same expected return.

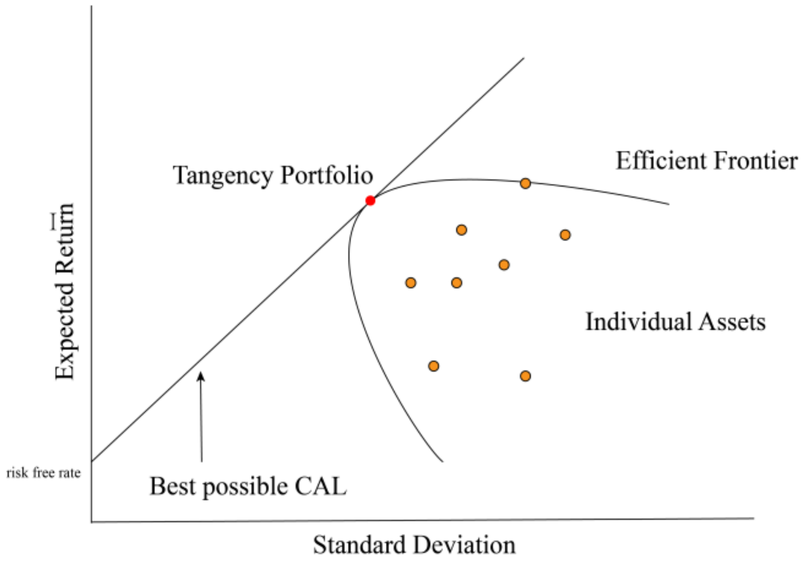

Figure 2. Illustration of Markowitz' Modern Portfolio Theory (Markowitz, 1954).

MPT illustrates risk with the standard deviation of the assets. Modern Portfolio Theory posits that diversification with assets exhibiting low or negative correlations can reduce overall portfolio risk without compromising returns. MPT's key assumptions—and inherent limitations—include the normal distribution of returns and static correlations between assets. However, during extreme market conditions, including periods of heightened volatility or financial crises, these assumptions often fail, rendering these models less reliable or inapplicable (Duchin & Levy, 2010; Pesaran & Timmermann, 1995).

Building on Modern Portfolio Theory (MPT), William Sharpe and other researchers introduced the Capital Asset Pricing Model (CAPM) in 1965. Fama and Kenneth (2004) explain that CAPM estimates an asset’s expected return based on its systematic risk, quantified by its sensitivity to market returns or beta. It is widely used to determine the required return on investments and to estimate the cost of capital (Fama & Kenneth, 2004). In 2018, researchers Barillas and Shanken conducted a study highlighting that CAPM continues to serve as a baseline model in asset pricing. However, they also critiqued CAPM for its simplicity and pointed out that it is frequently outperformed by multifactor models.

In the context of portfolio optimization, multifactor models are regularly used to asset pricing. Barillas and Shanken (2018) explain that these linear models can combine macroeconomic factors and firm-specific fundamentals to predict asset returns. One of the most important theoretical foundations for multifactor models is Arbitrage Pricing Theory (APT), introduced by Stephen Ross in 1976. APT enhances the principles of the CAPM by adding different factors to the linear model thereby predicting more accurate returns of assets (Ross, 1976). Models based on APT are often referred to as multifactor models. One of the most well-known multifactor models is the Nobel Prize awarded Fama-French three-factor model founded by Eugene Fama and Kenneth French in 1992. Three-factor model extends the single-factor CAPM by adding two factors – size and book to market value. Those supplemental factors, in addition to market returns, provide a more comprehensive explanation of asset pricing.

According to Barillas and Shanken (2018), linear asset pricing models continue to be applicable. Traditional methods offer simplicity adaptability through the incorporation of multiple factors (Barillas & Shanken, 2018). However, empirical research has shown that such models can be vulnerable and influenced to estimation and sampling errors (Barillas & Shanken, 2018; Ross, 1976). In the context of multifactor models, Ross (1976) argues that identifying exact and meaningful factors is critical yet challenging, as asset returns are highly dependent on how exactly those factors evolve. Moreover, Buraschi et al. (2010) assert that increased market volatility profoundly affects not only to CAPM but the multifactor models as well, thus underscoring the necessity for more sophisticated modeling techniques. Buraschi et al. (2010) underline the stochastic nature of variance-covariance matrices in financial markets, emphasizing the critical importance of incorporating time-varying volatilities and correlations. Buraschi et al. (2010) highlight the limitations of traditional models that assume constant risk factors, noting their inability to capture dynamic market conditions and external shocks adequately. Consequently, Buraschi et al. (2010) promote the refinement and adoption of more sophisticated models that can accommodate real-world complexities, thereby enhancing predictive accuracy.

As explained, theories behind the traditional asset pricing models have particular assumptions. Markowitz’s portfolio theory assumes that returns are normally distributed and static correlations. At the same time, linear models have assumptions and limitations that might lead to inaccuracy. As well as MPT, also linear models have assumptions and limitations that might lead to inaccuracy. Especially during extreme market conditions, such as financial crises, linear relationships may break down (Nagel & Singleton, 2011). Rapid development of artificial intelligence gives promising alternatives to solve the limitations of traditional methods. The following section explores these recent substitutes.

3. Literature review

Section 3 explores the machine learning applications in portfolio optimization. The section aims to research whether new applications can solve the constraints that traditional methods have. The section examines deep learning, reinforcement learning and natural language processing. We will focus on situations when the volatility is high and address the potential advantages that machine learning applications have for such conditions. The section covers advantages such as the ability to capture nonlinear patterns and analyze vast amounts of data. We also cover advanced algorithms and neural network architectures. An illustrative table at the end of the section that summarizes the covered methods.

3.1 Machine Learning in Portfolio Management

Machine learning (ML) is a subset of artificial intelligence. In ML, computer systems can learn from data and recognize patterns to improve decision-making (Singh et al., 2024). Singh et al. (2024) explain that ML-models can process extensive and varied datasets that originate from multiple sources. Algorithms play a central role in ML and are used to calculate potential future outcomes (Singh et al., 2024). In 2018, Ben et al. investigated the use of ML in portfolio optimization. Ben et al. (2018) addressed the constraints of traditional optimization methods and researched if ML-based models could outperform traditional methods. According to the study, specific ML-based methods can enhance the earlier optimization methods by reducing errors that lead to incorrect results (Ben et al., 2018). Researchers highlight that machine learning has an ability to adapt and improve predictions, which gives it significant potential to improve portfolio performance (Ben et al., 2018).

3.1.1 Deep Learning

Deep learning (DL) is a subset of machine learning. In deep learning, neural networks are used to recognize patterns from large datasets (Chen et al., 2019). Abdi et al. (1998) explain that neural networks are adaptive ML-models that have taken inspiration from biological neuroscience. According to Abdi et al. (1998), the operations of neural networks are based on the functions of the human brain. Neural networks consist of interlinked layers of 'neurons' that mimic the structure of the human brain. According to the study, neural networks learn patterns from data by iteratively adjusting connections between neurons (Abdi et al., 1998, Par 1.2).

Research conducted by Chen et al. (2019), Gu et al. (2020) and Vui et al. (2013) observed that deep learning could be used in the context of finance to enhance portfolio optimization. According to Chen et al. (2019), neural networks can process large amounts of data and improve predictions. For example, neural networks can process firm-specific data, which exists in vast amounts. According to the study, DL-models can also adjust to rapidly changing economic conditions which can be important in portfolio optimization (Gu et al., 2020).

Linearly observed relationships may break down during extreme market conditions and high volatility (Nagel & Singleton, 2011). DL gives promising alternatives to solve the limitations that high volatility brings for traditional methods. The study indicates that the use of DL can improve the prediction of macroeconomic and firm-specific features (Gu et al., 2020). Gu et al. (2020) explain that DL has the ability to process several predictors, which is reflected in increased predictability. As explained in section 2, traditional methods cannot capture linear dependencies. Gu et al. (2020) discovered that DL models can capture non-linearities, and thus improved accuracy can be achieved.

Markowitz introduced the idea that portfolio's expected return and risk level are always strongly connected and it should be taken into account in portfolio management (Markowitz, 1954). According to Chen et al. (2019), DL could be used to construct portfolios that are based on MPT. Chen et al. (2019) explain that neural networks are a strong method to capture non-linear interactions between macroeconomic and firm-specific variables. DL can also consider economic conditions and dynamic time relationships (Chen et al., 2019). According to the studis, the use of DL generated superior returns compared to traditional portfolio optimization methods (Chen et al., 2019; Gu et al., 2020).

Section 2 explored that the performance of traditional methods can be limited in uncertain situations. Buraschi et al. (2019) discovered that models that are based on traditional methods are often limited in rapidly changing conditions. If the volatility in the market increases it means that real-time decision-making needs to be high quality. If the data used for decision-making includes non-linear relationships that are important, they need to be captured. Chen et al. (2019) underscore that DL offers capabilities to capture those relationships. DL enables real-time data processing which supports decision-making in uncertain market conditions.

DL applications that have the ability to analyze non-linear patterns may enhance stock market prediction (Chen et al., 2019; Gu et al., 2020). According to Vui et al. (2013), neural networks possess abilities to handle large datasets and detect repeating patterns. Such abilities are important in uncertain markets. Based on the research, portfolios that employed DL-models resulted in better risk-adjusted returns in comparison to portfolios where DL was left outside (Chen et al., 2019). Research indicates that DL can contribute significantly to the asset management industry. The following subchapter discusses reinforcement learning which could enhance portfolio performance even more.

3.1.2 Reinforcement Learning

One area of machine learning is called reinforcement learning (RL). In RL, optimal decisions are done by agents that interact with their operating environment. The RL agents achieve optimal decisions through received feedback, which could be positive or negative (Jordan & Mitchell, 2015). Because the RL agents can improve over time, Weber et al. (2008, 8-9) state that RL is effective for strategies that aim to achieve some specific goals. Finance professionals use RL to optimize investment decisions. According to Yang (2023), RL can be used to allocate assets to maximize returns for a given risk level. The RL techniques are also used for solving challenges that arise from sequential decision-making, which is an outcome of dynamic and uncertain markets (Yunan et al., 2020).

In portfolio management, challenges like high data heterogeneity and environmental uncertainty are present (Yunan et al., 2020). Research conducted by Yunan et al. (2020) investigated whether RL could be applied for portfolio optimization and solve such challenges. As previously noted, traditional methods suffer from their assumptions. According to Yunan et al. (2020) volatility hampers traditional methods and limits their potential. Furthermore, Yunan et al. (2020) address that the dynamic nature of markets and numerous data sources can limit traditional methods. Barillas and Shanken (2018) emphasize that the assumption of linearity and poor data inputs are the reasons for traditional methods' deteriorated performance.

One important thing that we need to remember is that even though RL-based methods have advantages, they are not free from limitations. Yunan et al. (2020) observed that several RL-based methods rely on historical price data as it comes to the inputs of the model. According to Yunan et al. (2020), many RL models fail to utilize diverse and real-time sources of data that could provide more comprehensive insights to make decisions. In rapid changing and volatile markets reliance on historical data can weaken decision-making.

According to Yunan et al. (2020), framework called SARL (State-Augmented Reinforcement Learning) can address the challenge with historical reliance. The SARL is a decision-making tool that combines unstructured and structured data. According to the research, financial news can be unstructured data and structured data can include asset prices. The SARL outperformed earlier RL-based methods that relied strongly to historical data (Yunan et al., 2020). Yunan et al. (2020) researched cumulative profits and risk-adjusted and concluded that SARL performed better compared to earlier RL-methods.

Yang (2023) conducted a study that examined if the challenge with historical data reliance could be solved. Yang proposed the TC-MAC framework (Task-Context Mutual Actor-Critic). TC-MAC is a result of a combination of graph neural networks and mutual-information optimization. According to Yang (2023) TC-MAC frameworks advantage is their ability to consider both task-specific and global representations of a portfolio. This ability gives TC-MAC the capacity to capture relationships across assets more precisely (Yang, 2023). Based on the study, TC-MAC brought improved precision and risk-adjusted returns for the portfolio where it was used. Both studies illustrate that reinforcement learning has the potential to enhance decisions in dynamic and uncertain markets (Yang, 2023; Yunan et al., 2020).

3.1.3 Natural Language Processing

Natural language processing (NLP) is a subset of computer science. In natural language processing, computers analyze text and speech. According to Joshi (1991) NLP techniques give computers the ability to understand the text they process and act based on that understanding. Joshi (1991) explains that computational and linguistic principles are the foundation of the NLP. NLP can process both written and spoken language. These days computers can analyze texts proficiently, and NLP's contribution for that has been significant. To give an example, NLP models can analyze sentence structures and meanings of text (Joshi, 1991). It is also noteworthy that NLP models can even understand the context of the communication (Joshi, 1991). NLP has found its way into the financial world as well. According to Du et al. (2024) NLP techniques are used to analyze market sentiment, forecast asset prices and read regulatory filings. The reason why NLP could be seen as potentially useful is its ability to process large amounts of textual data and thus improve decision-making.

NLP can be used to analyze large unstructured datasets. According to Chen et al. (2019), unstructured datasets can be news, financial reports or even social media posts (Chen et al., 2019). Chen et al. (2019) claim that finance professionals started to use NLP in the early 2000s. In NLP's early days the method was used to identify words and simplest meanings from data (Chen et al., 2019). Chen et al. (2019) explain that as NLP models advanced, deep learning models were integrated into earlier models to improve accuracy. Despite the NLP models have developed from the initial models, lexicon-based methods are often used in hybrid models that integrate deep learning approaches (Chen et al. 2019).

Research has shown that the ability to analyze large amounts of data efficiently can have a significant impact on financial decision making (Chan & Chong, 2017; Du et al., 2024). Du et al. (2024) emphasize that NLP's efficiency in real-time analysis is essential, especially in high-volatility conditions. Researchers indicate that compared to traditional methods, NLP models possess advantages regarding rapid and real-time data processing (Du et al., 2024). Additionally, Xing et al. (2017) find that real-time NLP analysis enables immediate responses to market-relevant information. This supports algorithmic trading strategies that need rapid news processing. Xing et al. (2017) explain that NLP helps traders by summarizing data and filtering out noise allowing professionals to focus on key insights and make decisions quickly.

Both Du et al. (2024) and Xing et al. (2017) emphasize that NLP improves short-term decision-making in shorter timeframes by identifying immediate market reactions. Additionally, Du et al. (2024) note that natural language processing (NLP) facilitates real-time analysis for compliance monitoring and the tracking of regulatory changes. This suggests that NLP holds potential in compliance-related applications, ensuring that investment strategies are consistently aligned with regulatory requirements.

Another key application of NLP is sentiment analysis. Jegadeesh and Wu (2013) describe sentiment analysis as a technique to determine the sentiment (positive, negative, or neutral) in financial documents and media. Especially in high-volatility environments, sentiment plays a critical role in portfolio optimization since the impacts are continuous and challenging to capture through traditional methods (Akita et al. 2016). Moreover, the research conducted by Jegadeesh and Wu (2013) identifies a strong correlation between the tone of financial documents, such as 10-K filings, and market reactions surrounding their filing dates. The study indicates that when processing real-time data, NLP and sentiment analysis can offer more accurate and actionable insights compared to traditional models.

According to Du et al. (2024), sentiment analysis is valuable in conditions where rapid shifts in sentiment might affect assets' prices. Chan and Chong (2017) observed that sentiment data could be derived from financial news or microblogs. According to the study, collected sentiment data can improve short-term decision-making in uncertain market conditions (Chan & Chong, 2017). NLP models abilities have proven to be applicable, particularly in high-volatility markets. According to Du et al. (2024), financial models that utilize sentiment and news data often outperform traditional methods that rely on historical data.

In the financial landscape, the amount of data is massive. In addition, financial texts can be unstructured and lack a regular format (Chan & Chong, 2017). Financial text can include ambiguous language as well and sometimes texts can soften negative expressions. Chan and Chong (2017) describe: “They lean toward rewriting all negative content and using positive words. For example, the phrase 'did not benefit' appears more often than the word 'lose.'". Research highlights that NLP models can face difficulties understanding sentiment thoroughly because of the nuanced language. Financial texts are often combinations of text and charts or tables. Mixation of structured and unstructured data can also complicate the understanding of NLP-models (Chan & Chong, 2017; Du et al., 2024).

3.2 Algorithms in Portfolio Optimization

Section 3.2 explores foundational algorithms and evaluates their impact in portfolio optimization. The section examines stochastic gradient descent, LASSO and evolutionary algorithms. We also cover graph neural networks and Long Short-Term Memory Networks. The examination is focused on high-dimensional and volatile conditions, where non-linear challenges are present.

3.2.1 Optimization Algorithms in Portfolio Management

Foundational algorithms are methods that rely on optimization processes. Foundational algorithms learn through iteratively processing data and thus possess improved training efficiency (Sun et al., 2019). Foundational algorithms can systematically improve accuracy and refine model parameters. According to Sun et al., 2019, foundational algorithms are essential in reinforcement learning or neural network applications. Both RL and DL use optimization processes to solve complex machine-learning tasks (Sun et al., 2019). Perrin and Roncalli (2019) highlight that ML optimization has developed significantly since the 1990s. Perrin and Roncalli (2019) emphasize that foundational optimization techniques play a key role in new innovations such as neural networks.

Working with high-dimensional problems can be challenging for finance professionals (Perrin & Roncalli, 2019). One example of high-dimensional problem is the asset allocation process where complexity can make the analysis harder. Stochastic gradient descent (SGD) method have been proposed to solve high-dimensional problems. SGD is an iterative technique and it can be used to maximize returns of a portfolio and minimize the potential risks at the same time. According to Perrin and Roncalli, SGD can adjust the asset weights of a portfolio and help to achieve set objectives. SGD techniques have proven their efficiency particularly in high-volatility conditions (Bottou et al., 2018; Perrin & Roncalli, 2019).

Another technique is LASSO, an abbreviation of the Least Absolute Shrinkage and Selection Operator. LASSO is a technique that can be adapted to penalize portfolios with excessive complexity or risk exposure and thus improve risk-adjusted returns (Perrin & Roncalli, 2019). Chinco et al. (2019) underscore that short-term stock return predictors can be difficult to identify. The research indicates that LASSO can be used to identify stock return predictors in complex and volatile conditions (Chinco et al., 2019).

According to Simon (2013), evolutionary algorithms are optimization methods that are inspired by natural evolution. These algorithms are utilized also in portfolio optimization processes. In the time of high volatility, evolutionary algorithms can offer innovative solutions to improve risk-adjusted returns. Simon (2013) explains that evolutionary algorithms can enhance decision-making by iterative processes. Through selection, mutation and recombination processes evolutionary algorithms can navigate in financial assets' vast and complex space (Simon, 2013). Genetic algorithms (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization are all evolutionary algorithm techniques. These techniques stand out from traditional methods with their ability to capture non-linear relationships and adapt to dynamic market conditions (Zhu et al., 2011; Uthayakumar et al., 2020). As traditional portfolio optimization methods often rely on static assumptions, evolutionary algorithms can dynamically adjust strategies without relying on static assumptions. This advantage makes evolutionary algorithms particularly suitable for high-volatility scenarios.

In summary, foundational algorithms in machine learning provide robust solutions for portfolio optimization. Techniques like SGD, LASSO and evolutionary algorithms can enhance model efficiency. At the same time, those methods can address challenges that arise from high-dimensional data, high volatility, or non-linearity.

3.2.2 Neural Network applications in Portfolio Management

In section 3.1.1, we discussed deep learning in more detail. As previously examined, neural networks are adaptive models inspired by brains. In the context of neural networks, it is important to note its significance in ML-based methods. All three fields we examined—deep learning, reinforcement learning, and natural language processing—leverage neural networks (Chen et al., 2019; Du et al., 2024; Yang, 2023).

Graph neural networks (GNNs) are technique that finance professionals use in portfolio optimization. GNNs have proved their efficiency especially in tasks where relationships between assets need to be detected. Yang (2023) describes that GNNs are central method in RL when both local and global contexts of portfolios to be considered. Yang (2023) explains that GNNs can be used in investment strategies to adjust assets to portfolio based on their mutual relationships. Another neural network applications are LSTM- technique which observes sequential patterns from financial data. Based on the study by Yunan et al. (2020), LSTM's can find sequential patterns from data derived from asset price movements. The ability to detect sequential patterns improves the prediction of market behaviour (Yunan et al., 2020).

As discussed in section 2, MPT and factor-models are constrained because they assume linear relationships among assets and static correlations among assets. In the situation, where markets are volatile, decision-making needs to be quick and efficient (Buraschi et al., 2010). It is need to be emphasized that well known traditional methods are unable to provide the best support in turbulent market conditions. Researchers have examined alternative solutions to address the observed constraints. According to previously examined research, the combination of DL and RL can offer dynamic adjustability for portfolio optimization(Yang et al., 2023; Yunan et al., 2020). DL has been found to be effective in capturing non-linear relationships. Additionally, research points out that DL can capture sequential dependencies and the complexities of dynamic market conditions (Yunan et al., 2020; Yang, 2023). According to the research, DL's features make them more effective in uncertain markets when compared to traditional methods (Yunan et al., 2020; Yang, 2023).

In 2020 Yunan et al. researched LSTMs in modeling patterns in asset price movements. However, LSTMs can also be used in other applications as well. LSTMs are used in sentiment analysis to capture temporal patterns in text data (Chan & Chong, 2017). Chan and Chong (2017) explain that the data in question can be, for example, news articles or social media posts. The researchers explain that financial information can often be unstructured (Chan & Chong, 2017). However, LSTMs can handle such unstructured information by learning the dependencies between words and their context (Chan & Chong, 2017). This advanced capacity makes the LSTMs suitable for predicting price movements based on narrative sentiment.

LSTMs represent earlier neural network technology and more advanced techniques have been developed. For example, the transformer-based model FinBERT is a more developed NLP-application. FinBERT is particularly usedul to process complexities in financial texts (Du et al., 2024). Traditional portfolio optimization methods rely strongly on historical data and returns. Du et al. (2024) explain that FinBERT is trained to understand specifically financial texts. In addition, FinBERT is educated to detect subtle sentiments or forward-looking statements in corporate filings (Du et al., 2024). FinBERT is an example that research among the machine learning models is also present.

Neural networks play a key role in machine learning and in portfolio optimization. In high-volatility conditions, market relationships often become non-linear and complex. Neural networks are applicable to such situations. Neural networks can capture these non-linear dependencies and outperform traditional models that assume linear relationships between risk and return (Gu et al., 2019). Neural networks provide dynamic adaptability by learning from both historical patterns and real-time market inputs (Yunan et al. 2020). When mitigating risk, particularly Graph Neural Networks (GNNs), help manage risk in volatile markets by modeling dynamic relationships between assets (Yang, 2023). This approach enables reinforcement learning frameworks to adjust asset allocations based on evolving portfolio interdependencies and solve traditional models' inability to account for dynamic, time-varying relationships and nonlinear dependencies among assets.

Table 1. Summary of Machine Learning methods in Portfolio Optimization

Method/ Algorithm	Key Advantages	Limitations
Stochastic Gradient Descent (SGD)	Efficient for high-dimensional problems. Adapts to non-stationary, volatile markets. Speeds up computation for dynamic risk-return adjustments (Perrin & Roncalli, 2019).	Sensitive to learning rates and prone to oscillations. Slower for non-convex problems (Perrin & Roncalli, 2019).
LASSO Regression	Identifies sparse predictors in complex, fast-changing datasets. Reduces overfitting and penalizes excess risk (Chinco et al., 2019).	May overlook weak predictors in the presence of correlated factors. Requires careful tuning of regularization (Chinco et al., 2019).
Evolutionary Algorithms	Solves non-linear, dynamic problems effectively. Adjusts asset allocations dynamically in volatile markets (Simon, 2013; Zhu et al., 2011).	High computational cost for large datasets and possible overfitting issues (Berutich et al. 2016; Zhu et al., 2011).
Deep Learning (Neural Networks)	Captures non-linear market dependencies. Adapts to volatility and enhances portfolio returns and Sharpe Ratios (Gu et al., 2020; Chen et al., 2019).	Needs large datasets and computational power. Interpretability remains challenging (Gu et al., 2020).
Reinforcement Learning	Optimizes sequential decisions in dynamic markets. Adapts to changing conditions and maximizes cumulative rewards (Yunan et al., 2020).	Relies on quality of state representation. Limited if it depends solely on historical data (Yunan et al., 2020).
Natural Language Processing	Analyzes unstructured data (e.g., news). Improves decision-making via sentiment analysis and real-time insights in volatile markets (Du et al., 2024).	Struggles with indirect language and ambiguity. Needs domain-specific training for finance (Du et al., 2024).

3.3 Evaluating AI in Portfolio Optimization

In the first section, we examine the performance of AI methods in portfolio optimization, analyze current research outcomes, and address the associated data-related and technical challenges. In the subsequent section, we delve into the regulatory and ethical challenges that emerge in applying AI in this field.

3.3.1 Performance of AI methods

Although research on AI methods in portfolio optimization is relatively new, there is growing evidence of their potential advantages over traditional methods. In 2021, Chen et al. developed a machine learning model that constructs characteristic-managed portfolios specifically designed to optimize portfolio weights and mitigate risks from extreme market fluctuations. This model, leveraging neural networks, achieved a Sharpe ratio that was 20% higher compared to traditional Markowitz-based optimization models. Another neural network-based strategy, introduced by Gu et al. (2020), achieved an impressive, annualized Sharpe ratio of 1.35. Gu et al. (2020) highlighted that their machine learning-based asset pricing model performs exceptionally well in highly nonlinear scenarios characteristic of many asset pricing relationships.

In 2022, Murray et al. conducted a study using a machine learning-based return forecast model called MLER, which applies Long Short-Term Memory (LSTM) networks. Murray et al. (2022) proved that MLER’s ability to detect complex and nonlinear relationships in stock price patterns was better than most traditional methods used for such purposes Murray et al. (2022) indicated that their model can construct portfolios that consistently outperform traditional approaches. By examining the 500 largest US stocks by market capitalization, Murray et al.'s (2022) model demonstrated strong predictive power across various subperiods, including periods of high volatility.

Impressive results were achieved yet all three studies had limitations. One shared concern among the models was their high reliance on extensive computational resources. (Chen et al., 2021; Gu et al., 2020; Murray et al., 2022). An emerging challenge raises questions about high maintenance costs, limited scalability, and cost efficiency. In addition, Chen et al. (2019) noted, that their model systematically overweighted illiquid stocks. Especially those illiquid positions pose challenges when analyzing risk premiums (Chen et al., 2019). Chen et al. (2019) explain that illiquid positions can pose challenges when risk premiums are analyzed. Furthermore, Murray et al. (2022) explained that their model had also vulnerabilities. The MLER-model failed to work as expected during the 2008 financial crisis (Murray et al., 2022). These limitations underscore the need for further refinement to enhance the robustness and practicality of these models in diverse financial contexts.

According to the research, the models' ability to interpret economic mechanisms presented significant challenges (Chen et al., 2021; Murray et al., 2022). This kind of challenge can become a barrier for practitioners and regulators. Gu et al. (2020) explain that the nature of neural networks is complex. The complex composition can affect transparency and interpretability among models (Gu et al., 2020). In the asset management industry, financial decisions often involve substantial capital. As a result, it is crucial to provide clear justifications for decision-making processes. Therefore, we must acknowledge that the models may face significant challenges due to a lack of transparency and interpretability.

Yang (2023) researched RL-based machine learning methods. Yang proposed the TC-MAC algorithm for long-term portfolio optimization. His algorithm uses "actor," which determines asset allocation strategies, and the "critic," which evaluates these decisions (Yang, 2023). TC-MAC uses graph neural networks for dynamic adjustments. TC-MAC differs from traditional RL-based methods. As previously noted, earlier RL-methods faced difficulties since many of them relied on static assumptions about asset relationships. However, Yang (2023) emphasizes that TC-MAC's adjustability allows it to function even in volatile or non-stationary conditions. The research results validate the claim. TC-MAC achieved a risk-adjusted Sharpe ratio of 2.578, illustrating its superior ability to balance risk and returns.

Jang and Seong (2023) introduced another intriguing application of reinforcement learning in 2023. They researched a method that integrated MPT and reinforcement learning. The method utilized deep learning and stood out with its ability to recognize market trends and adjust portfolio weights dynamically (Jang & Seong, 2023). The proposed deep reinforcement learning model achieved a Sharpe Ratio of 2.0067, significantly higher than traditional models (Jang & Seong, 2023).

While many studies report impressive backtest results, the practical application of these methods in live markets is limited. In addition, some RL models fail to fully account for transaction costs, slippage, and liquidity constraints, which are critical factors in real-world portfolio management (Jang & Seong, 2023; Yunan et al. 2020). As well as previously discussed, deep learning methods and RL algorithms, involve complex architectures and demand significant computational resources (Jang & Seong, 2023; Yang, 2023).

Natural Language Processing has significantly enhanced the ability to analyze and interpret large volumes of unstructured financial data, offering tools that enable insights into market trends and investor behavior (Chan and Chong, 2017). By extracting sentiment from news articles, financial reports, and social media, NLP provides actionable insights for applications such as financial sentiment analysis, portfolio optimization, and risk management (Du et al., 2024). Domain-specific models, such as FinBERT, have demonstrated superior performance compared to traditional models (Du et al., 2024). Du et al. (2024) explain that FinBERT outperforms traditional methods in tasks such as news classification and stock movement predictions. The work of analysts and decision-making can also be improved. NLP solves the challenge of processing unstructured data by automating the extraction of relevant information (Chan & Chong, 2017). Researchers have observed that market also market inefficiencies can be identified from patterns and signals from vast datasets that would otherwise go unnoticed (Xing et al., 2018).

It is undeniable that NLP will be used in financial contexts. However, NLP faces several limitations in financial applications. One challenge for the NLP models is to understand the ambiguity and complexity of financial texts (Chan & Chong, 2017). Chan and Chong (2017) explain that sometimes nuanced language can mislead NLP-models. Du et al. (2024) explain that many NLP systems are dependent on labeled data. According to research labeled data limits models' scalability for domain-specific tasks (Du et al., 2024). According to Xing et al. (2018), during real-time analysis NLP models must balance between time and accuracy. The data in use may be huge which leads to computational challenges with the models (Xing et al., 2018). Du et al. (2024) explain that potential biases in training data can affect to predictions. Those biases pose risks to the fairness and reliability of these methods (Du et al., 2024). These limitations highlight the need for ongoing research and innovation to overcome the barriers to the wider adoption of NLP in finance.

In complex financial markets, evolutionary algorithms have demonstrated strong potential considering portfolio optimization. Berutich et al. (2016) conducted a study where they applied genetic algorithms to the Spanish stock market. Research indicates that EA-strategy achieved a 31.81% return compared to IBEX35 indexes' 2.67% (Berutich et al., 2016). According to Berutich et al. (2016), their model adapted to market volatility without frequent retraining. Particle swarm optimization (PSO) was studied by Zhu et al. (2011). Research highlighted that PSO's efficacy is based on its ability to balance risk and return through collaborative "swarm intelligence". Zhu et al. (2011) underscore that PSO offers efficiency and scalability over traditional methods. Similarly, Uthayakumar et al. (2020) found Ant Colony Optimization (ACO) particularly suited for high-volatility markets due to its dynamic adaptability. However, it is important to note that the performance of EAs has not consistently outperformed traditional methods. Early genetic algorithm methods studied by Allen and Karjalainen (1999) failed to demonstrate significant success. Additionally, one of the earliest methods, the Vector Evaluation Genetic Algorithm (VEGA) introduced by Schaffer in 1984, faced significant criticism for producing biased solutions and thus skewed results (Metaxiotis & Liagkouras, 2012).

Researchers also examined the challenges arising from evolutionary algorithms, particularly model overfitting (Zhu et al., 2011; Berutich et al., 2016). Additionally, Zhu et al. (2011) also emphasize that the computational cost is high for large datasets, which could be seen as a general challenge for many other AI models.

Stochastic gradient descent (SGD) and LASSO have addressed many limitations of models like MPT, CAPM or multi-factor approaches. As observed, traditional methods often struggle with high-dimensional data. This challenge often leads to poor performance or unreliable parameter estimation with traditional methods (Perrin & Roncalli, 2019). If infrequent and short-lived predictors are to be detected, LASSO is a considerable method to use. According to Chinco et al. (2019), the LASSO method performed well and improved out-of-sample forecasting and risk-adjusted returns. Chinco et al. (2019) used LASSO and forecasted stock returns in NYSE. According to the study, they achieved a 1.8 Sharpe ratio which could be seen as an excellent result (Chinco et al., 2019). In situations where large datasets are processed, SGD techniques are efficient and appropriate to use (Bottou et al., 2018).

Based on the research, advanced portfolio optimization methods also have limitations. According to Bottou et al. (2018), SGD requires careful tuning of hyperparameters. The study explains that the careful tuning of hyperparameters can hinder SGD’s convergence with non-convex problems (Bottou et al., 2018). The LASSO faces difficulties with oversimplifying models where the LASSO is used (Chinco et al., 2019). According to Chinco et al. (2019), the models using LASSO can face challenges in conditions where accurate predictors are not sparse. Chinco et al. (2019) add that multicollinearity conditions can also bring challenges for models using LASSO. A common problem with theories in finance is the challenge to incorporate practical constraints into them.

According to Perrin and Roncalli (2019), ML-based models face similar difficulties and cannot take practical constraints into account. In conclusion, the examined observations highlight the need for broader investigation of the limitations among ML methods.

3.3.2 Limitations of AI Methods

Financial technology has been evolving significantly and automatic strategies are becoming more common in portfolio management. The rapid development of fintech brings issues, and they need to be addressed to achieve sustainable implementation of AI strategies. Lowenstein (1996) demands that if the number of automated strategies increases in the financial landscape, so should transparency increase as well. One widely recognized challenge with ML-methods has been the models' lack of interpretability (Chen et al., 2021; Gu et al., 2020; Murray et al., 2022). Especially with neural networks the challenge with interpretation is present, and Castelvecchi (2016) highlights that it is due to their inherent 'black box nature.' Castelvecchi (2016) explains that the 'black box problem' comes when neural network models operate without transparent explanations. If thinking about the users' trust in the automated strategies, it is essential that the model results reasonable and explainable outputs. Furthermore, Castelvecchi states that trials have shown that neural networks are vulnerable to being manipulated. The 'black box nature' and exposure to manipulation both underscore the need for further research in neural network models.

The rapid development of fintech has brought challenges to regulators. Brummer and Yadav (2019) explain that the fintech sector faces challenges with regulation. At the same time, financial innovations should be encouraged and potential risks controlled. Also, the globalization has brought up compliance across jurisdictions which is considered challenging to manage (Brummer & Yadav, 2019). Brummer and Yadav highlight that regulators face a trilemma when trying to solve the regulatory challenges. The trilemma arises when the regulators try to simultaneously achieve clear rules, maintain market integrity and encourage financial innovation (Brummer & Yadav, 2019).

The essential issue is that the trilemma often leads to situations where two goals are prioritized at the expense of a third.

There have been observations that AI-based methods can fail to align with regulatory goals (Cuéllar & Huq, 2022). According to Cuéllar and Huq (2022), if regulatory goals are not being met, equality and fairness can weaken. Furthermore, legal accountability has been observed to be one challenge because AI tools can create opaque systems. AI tools opaque nature can lead to compliance challenges because of established norms and the requirement of monitoring processes (Cuéllar & Huq, 2022).

However, researchers have not remained idle. For example, Brummer and Yadav (2019) suggested that regulatory strategies should include regulatory sandboxes and pilot programs. Also, informal guidance has been suggested that would allow financial innovations to be tested in controlled environments (Brummer & Yadav, 2019). Suggested solutions could balance innovation and market integrity without risking clarity. Brummer and Yadav (2019) underscore that regulatory tools would provide a constitutional framework for experimentation and evaluation. Clear and purposeful development in regulation would encourage the development of innovative fintech solutions. Simultaneously, regulators could ensure that innovations align with existing legalization and regulations. Brummer and Yadav (2019) conclude that clear regulation would minimize possible risks while enabling innovations in the asset management industry.

One central aspect of regulatory challenges in fintech considers transparency among AI-models. As previously explained, especially neural networks suffer from ‘black box problem’ that arises when models operate without clear explanations. One possible solution that has been proposed has been explainable AI. According to Castelvecchi (2016), explainable AI could strengthen trust among stakeholders and reduce legal ambiguity. Furthermore, AI systems that are embedded with democratically designed frameworks could mitigate inherent biases. With such a framework, fairness and equity could be prioritized and compliance could be more controlled (Cuéllar & Huq, 2022).

4. Future research trajectory

As previously discussed, asset pricing and portfolio management combined with machine learning have evolved significantly in recent decades. The earliest algorithmic methods introduced in the 1980s faced considerable criticism, and it took years to refine and apply them effectively (Metaxiotis & Liagkouras, 2012). Even today, AI methods face criticism, such as neural networks for their lack of transparency in decision-making (Castelvecchi, 2016) or challenges in complying with regulatory requirements (Cuéllar & Huq, 2022). However, when examining the latest trend, indicated by Figure 1, the total number of scientific documents related to artificial intelligence have increased rapidly which, suggests heightened interest among researchers.

Through machine learning, portfolio optimization has overcome many of the limitations inherent in traditional optimization methods, particularly those that become apparent under conditions of high market volatility (Ben et al., 2018). Furthermore, integrating artificial neural networks in deep learning has facilitated the analysis of large datasets, including firm-specific characteristics, to enhance forecasting accuracy (Chen et al., 2019; Vui et al., 2013). As discussed in the Introduction, traditional methods such as mean-variance optimization and the Capital Asset Pricing Model (CAPM) perform effectively under stable, low-volatility market conditions. However, when it comes to techniques that are based on artificial intelligence, existing research has yet to identify robust alternatives for stable market conditions. In this regard, future studies could focus on developing artificial intelligence-based methods that consistently perform well, regardless of market conditions.

As As indicated in Table 2, optimization methods utilizing artificial intelligence face individual challenges. For example, deep learning (Gu et al., 2020) and evolutionary algorithms (Berutich et al., 2016) both face challenges related to high computational power requirements. Compared to relatively simple traditional methods, high computational power may limit the use of these methods, and addressing this challenge could be essential for scalability. However, traditional asset pricing models leveraged by machine learning have proved to improve analytical capabilities (Shihao et al. 2020). Additionally, Chen et al. (2021) highlighted the potential for enhancing multi-factor models by integrating advanced machine learning frameworks to improve overall model performance. Building on this, future research could combine traditional approaches with modern techniques to achieve superior results while addressing each other's limitations.

In portfolio management, neural networks are pivotal in numerous technologies, yet a significant challenge associated with them is their lack of interpretability (Castelvecchi, 2016; Gu et al., 2019). Since techniques utilizing neural networks have demonstrated remarkable results, particularly under high-volatility conditions (Gu et al., 2020; Chen et al., 2019), it can be anticipated that future research will aim to address the challenges associated with their black-box nature. While efficiency and speed are characteristic of many AI-methods, they alone are insufficient if decisions cannot be justified raising the issue of responsibility. Artificial intelligence has gained a more significant foothold in the financial sector in recent years, and fintech is expected to face increased regulation in the future (Brummer & Yadav, 2019). The potential of artificial intelligence has also been recognized in regulatory frameworks, where adaptive regulation, such as real-time monitoring, introduces new dimensions to regulatory technology (Brummer & Yadav, 2019).

Examining the research process and artificial intelligence together suggests that their integration could introduce new aspects. Chubb et al. (2022) explain that AI can automate tasks, such as data sorting or summarization, which can accelerate the pace of discovery. In addition, they say that through analysis of large and complex datasets, AI can reveal new patterns and identify new factors that would be impossible to discern manually (Chubb et al. 2022).

5. Conclusions

Traditional portfolio optimization methods face often challenges when market volatility increases. Artificial intelligence poses significant potential in portfolio optimization during turbulent market conditions. MPT, CAPM and multi-factor models are based on the assumption of staticity and linearity. These assumptions often break down during high-volatility conditions. However, AI-based models are not constrained by such assumptions. Methods utilizing advanced algorithms, such as deep learning and reinforcement learning offer advantages. AI-based methods can process nonlinear data and adjust to real-time market changes. These capabilities in question offer better predictive accuracy and risk-adjusted returns.

Traditional methods have challenges in addressing the complexities of financial markets. Traditional methods are limited in high-volatility conditions due to their dependence on historical data and simplified assumptions about risk and returns. Mean-variance optimization, for example, assumes static correlations among assets. This staticity has been proven to break down in uncertain market conditions. However, AI-based methods can detect patterns and non-linear relationships and thus enable more effective optimization strategies. As this thesis has discussed, portfolio management utilizing reinforcement learning adjusts asset weights in response to market trends. This ability is one reason for outperforming traditional static optimization methods in high-volatility markets.

This paper suggests that artificial intelligence will be essential in the future of portfolio management. AI-based techniques improve models’ precision and adaptability in high-volatility situations. Considering that, finance professionals can accomplish improved decision-making capabilities. AI-based methods enable real-time portfolio adjustments and strengthen risk management in uncertain markets. In the field of research, AI can create opportunities for deeper comprehension. In futures research, alternative data sources, such as sentiment analysis and unstructured data, can offer deeper understanding.

There are also challenges with AI-models. One common challenge with AI models is that they often require significant computational resources. Additionally, deep learning models have been criticized due to their “black-box” nature that limits their transparency. The models’ lack of interpretability can make it harder to justify decisions to regulators and investors. For broader adoption of the models, it is vital to address these challenges. Future research should focus on hybrid models that combine the clarity of traditional theories with the accuracy of AI. Ethical and regulatory frameworks would also be necessary for stakeholder trust and industry standards.

This research illustrates that AI-based portfolio optimization provides robust solutions for conditions where traditional models often fall short. With the development of artificial intelligence, finance professionals, and researchers can move the industry toward more efficient and adaptive practices. This progress will reshape portfolio management, especially in uncertain and volatile environments.

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