Artificial Intelligence in Financial Portfolio Management

Archival Research based on Secondary Data in form of Relevant Publications.

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Description

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Abstract

Artificial intelligence (AI) has become an increasingly prominent tool in financial portfolio management, transforming how investment decisions are made. As the financial landscape grows more complex, AI offers opportunities to enhance efficiency and precision in portfolio optimization. This study investigates the historical evolution, current role, and future implications of AI in portfolio management. The research focuses on key AI techniques such as machine learning, deep learning, and predictive analytics, which enable portfolio managers to process vast amounts of data, identify patterns, and improve decision-making. An inductive approach, relying on secondary data, was applied, analyzing publications to gather insights into the current state of AI in this field. The findings reveal that while AI enhances portfolio management through real-time data analysis and dynamic strategy adjustment, limitations persist, particularly regarding transparency and model reliability. Despite these challenges, AI continues to revolutionize financial portfolio management, providing tools for more informed decision-making and better risk management. Future research could focus on real-time testing of AI models and further exploring ethical and regulatory concerns in the industry.

Keywords/tags (subjects)

Artificial intelligence, portfolio management, machine learning, financial decision-making, risk management, predictive analytics.

Miscellaneous (Confidential information)

No confidential information was disclosed in the thesis.

Contents

Figures and Table

1 Introduction

Significant ramifications for the finance industry have resulted from the revolution in investment decision-making brought about by the incorporation of artificial intelligence (AI) into financial portfolio management. The application of AI algorithms and methodologies has seen tremendous growth as the global financial environment becomes more data-driven and sophisticated, providing previously unheard-of opportunities for more effective and efficient portfolio management.

I'm interested in how artificial intelligence (AI) could change conventional methods of managing financial portfolios as a student and future finance professional. This thesis looks at how artificial intelligence (AI) has evolved historically in financial portfolio management, how it is used today, and what the ramifications of this quickly changing technology are.This thesis has three distinct research goals. In order to understand how AI has evolved in financial portfolio management, it is first necessary to examine its early uses and innovations. The second is to look at how AI is being used in financial portfolio management, including its uses, advantages, and drawbacks in the context of contemporary finance.

Lastly, to examine the effects of AI on financial portfolio management, including how it affects risk management, investment decision-making, and the field's prospects going forward.This study attempts to offer important insights into the historical evolution, present state, and potential future of artificial intelligence (AI) in financial portfolio management through a thorough review of pertinent literature, in-depth interviews with industry experts, and examination of real-world case studies. The results of this study will add to the corpus of literature already available on artificial intelligence in finance and offer useful insights for practitioners, scholars, and policymakers who are interested in the nexus between AI and finance.

This thesis aims to illuminate the development, function, and impact of AI in financial portfolio management, offering a comprehensive perspective on this fast-changing field. The research aspires to add value to the ongoing discussions and debates about AI's role in finance and to encourage additional exploration in this area.

1.1 Background, motivation, and purpose

As a second-year student studying international business, finance is a field that truly fascinates me. I am always keeping an eye on new trends and technologies that are shaping the future of this industry. One such trend that has particularly intrigued me is the integration of artificial intelligence (AI) in portfolio management, bringing together two of my interests: asset management and the use of AI as a predictive and automation tool (Zhang & Chen, 2017). Portfolio management, as I have learned so far, relies on human expertise and historical data analysis to make investment decisions. However, with the rapid evolution of technology, AI now offers new possibilities to push the boundaries of this traditional approach. By using sophisticated algorithms, AI can analyze massive amounts of real-time data from various sources such as financial data, news, economic trends, and even social media, to identify patterns and trends that would be impossible for a human alone to detect.

What motivates me the most is the promise of AI as a prediction tool. By combining the power of AI with human knowledge and experience, it is possible to obtain more accurate and reliable forecasts on the performance of financial assets, which can help portfolio managers make more informed decisions and optimize the performance of their portfolios (Liu et al., 2024). To complete my thesis on the role of artificial intelligence in financial portfolio management, I have also delved into the history of this complex relationship between AI and finance. By examining the evolution of AI techniques applied to portfolio management over time, I have gained an understanding of how these technologies have progressed to become increasingly sophisticated and have a significant impact on investment decisions (Liu et al., 2024).Understanding the key milestones in the history of AI in financial portfolio management has allowed me to better grasp the challenges, opportunities, and implications of this ever-evolving technology in today's financial world.Another major advancement of AI in portfolio management is the automation of processes. Through AI, routine and time-consuming tasks such as asset allocation, risk management, and implementation of investment strategies can be automated, allowing managers to focus on more strategic and value-added tasks (Bartram et al., 2020). As a future finance professional, I am convinced that AI will play an increasingly important role in portfolio management. However, it is important to note that AI is not a magic solution, and human expertise remains essential in making informed decisions and assessing potential risks.

The integration of artificial intelligence in portfolio management opens exciting new prospects for the future of the financial industry. As a passionate student of finance and emerging technologies, I am excited to closely follow the developments of AI in this field and learn more about how it can improve the management of financial assets and shape the future of the industry. I am also aware of the ethical, confidentiality, and regulatory challenges associated with the use of AI in finance, and I am committed to staying informed and addressing these concerns as I continue to explore this fascinating topic.

1.2 Research objectives, questions and approach

The research objectives of my thesis are to trace the historical development of AI in financial portfolio management and explore its current role in the field. Guided by key questions, my research will investigate the early applications of AI in finance, breakthroughs that have shaped its evolution, and the challenges and limitations faced. The research approach will involve a comprehensive review of relevant literature, in-depth interviews with industry experts, and analysis of real-world case studies. This investigation will shed light on the history and contemporary implications of AI in financial portfolio management.

Research Questions:

RQ1: What is the historical evolution of artificial intelligence in financial portfolio management?

RQ2: How is AI currently applied in financial portfolio management, and what are the main benefits and limitations associated with its use?

RQ3: How does AI impact investment decision-making and risk management in contemporary financial portfolio management practices?

RQ4: What are the future prospects and challenges for AI in financial portfolio management?

Research Objectives:

RO1: To trace the development of AI in financial portfolio management, identifying key milestones, breakthroughs, and early applications that have shaped the field through archival research and literature review.

RO2: To investigate the current role of AI in financial portfolio management by analyzing its practical applications, evaluating its advantages and disadvantages, and assessing its effectiveness in decision-making and risk management.

RO3: To assess the implications of AI on investment strategies, risk management, and portfolio optimization through case studies and interviews with industry experts, providing insights into how AI influences modern financial decisions.

RO4: To explore the future potential of AI in financial portfolio management by examining emerging trends, innovations, and the ethical, regulatory, and technical challenges that might shape its continued evolution in the field.

Research Approach:

- Literature Review: Review existing research studies on the use of artificial intelligence in portfolio management, highlighting key advancements and current research gaps.
- Historical Analysis: Review key developments in artificial intelligence in portfolio management over the past decades, identifying technological advancements, models, and methods used.
- Comparative Study: Compare the advantages and limitations of using artificial intelligence in portfolio management compared to traditional approaches, examining performance, risk management, asset diversification, and other relevant criteria.
- Analysis of Current Challenges: Identify the specific challenges that artificial intelligence approaches face in portfolio management, such as market volatility, data reliability, and model transparency, and examine proposed solutions to address them.

1.3 Thesis structure

In this thesis, the author begins by introducing the key concepts that are central to the discussion, such as artificial intelligence (AI) and financial portfolio management, through a literature review. This review not only defines these important concepts but also provides a historical context that allows the reader to understand the evolution of AI within the field of financial portfolio management. By laying this foundation, the author ensures that the reader is well-positioned to grasp the more complex discussions that follow.

In the second chapter, the author delves into current research on the use of AI in financial portfolio management, using a framework that highlights six key elements: knowledge discovery, higher dimensionality, adaptation and evolution, memory augmentation, integrated reasoning, and collective behavior. These elements are explored in detail to show how AI has been integrated into the processes and strategies of financial portfolio management today.

After these in-depth analyses, the next chapter addresses the limitations, reliability, and validity of AI in this context. The author examines the challenges and considerations that arise when applying AI in financial management, as well as how these issues impact the effectiveness of AI tools. Finally, the key findings of the research are presented, summarizing the main takeaways from the study.

2 Literature review

2.1 Financial Portfolio Management

Financial Portfolio Management: The process of managing a collection of financial assets, such as stocks, bonds, and other securities, with the goal of achieving specific financial objectives, such as maximizing returns and minimizing risks.

Effective financial portfolio management involves a variety of activities, including asset allocation, diversification, risk management, and performance measurement. These activities require careful analysis of market conditions, economic trends, and individual company performance.Financial portfolio management has evolved over time, with the integration of new technologies and innovative approaches. One such approach is the integration of artificial intelligence (AI) into portfolio management. As noted by (Bartram et al., 2020), " AI and statistical models are currently used by a significant number of asset management firms to operate trading and investing platforms. The increasing application of AI to many asset management activities necessitates a more systematic examination of the various techniques and applications involved, as well as the concomitant opportunities and challenges they bring to the sector." (p. 10).AI has the potential to revolutionize financial portfolio management by enabling more accurate and timely analysis of massive amounts of data. With the ability to analyze real-time data from various sources such as financial data, news, economic trends, and social media, AI can identify patterns and trends that would be impossible for humans to detect. This can help portfolio managers make more informed decisions and optimize the performance of their portfolios.However, it is important to note that AI is not a magic solution and does not replace the need for human expertise in financial portfolio management. As noted by (Liu et al., 2024), "Data quality and integrity are key issues in financial market data, often containing noise and missing values, directly affecting model accuracy and reliability." (p. 10).

Financial portfolio management is a complex process that requires a combination of expertise and technology to optimize investment returns while minimizing risks. The integration of AI into portfolio management offers exciting prospects for the future of the financial industry, but it also presents challenges and ethical considerations that must be carefully addressed.

Keywords:

Financial: Relating to or involving finance, money, or monetary matters.

Portfolio: A collection of financial assets, such as stocks, bonds, and other securities, held by an individual or an organization.

Management: Planning, organizing, directing, and managing resources (people, money, and assets) in order to accomplish particular goals and objectives.

Asset allocation: The act of spreading assets over several asset classes (such cash, bonds, and equities) in order to control risks and attain diversity.

Risk management: the procedure for determining, evaluating, and reducing the risks connected to investments in a portfolio in order to guard against possible losses.

Diversification: the practice of spreading risk and perhaps increasing profits by investing in a range of assets.

Investment strategy: The plan or approach used to guide investment decisions in a portfolio, taking into consideration factors such as risk tolerance, investment goals, and market conditions.

Portfolio optimization: The process of designing a portfolio to achieve the best possible balance between risk and return, based on mathematical models and statistical analysis.

Performance evaluation: The process of measuring and analyzing the performance of a portfolio to assess its effectiveness in achieving investment objectives.

Asset management: The professional management of a portfolio of assets on behalf of investors, typically carried out by investment managers or asset management firms.

2.2 Artificial Intelligence

Artificial intelligence (AI) is a term that has evolved over time and has been addressed by different authors and from various perspectives. Historically, AI was first mentioned in scientific literature in the 1950s when researchers began developing machines capable of simulating human intelligence. Since then, the concept of AI has evolved and has been interpreted in different ways by different authors and in different disciplines. Over the decades, many authors have studied and defined AI from various perspectives. Some have considered AI as a scientific discipline, while others have approached AI from a philosophical, ethical, or societal point of view. Definitions of AI have also evolved based on technological advancements, practical applications, and emerging ethical and social questions.

One of the early definitions of AI was proposed by Alan Turing in the 1950s, (Turing, 1950). According to Turing, AI can be defined as the ability of a machine to imitate human intelligence indistinguishably. This definition emphasizes the machine's ability to replicate human behaviors and thought processes. Over time, other definitions of AI have emerged. For example, Herbert A. Simon, an economist and psychologist, proposed a definition of AI as the ability of a system to perform tasks that would normally require human intelligence. This definition emphasizes the functional capabilities of AI, i.e., its ability to autonomously accomplish specific tasks.

Other authors have addressed AI from an ethical and societal perspective. For example, Wendell Wallach and Colin Allen, (Wallach & Allen, 2008), proposed a definition of AI as the ability of a system to make autonomous decisions based on predefined ethical principles. This definition emphasizes the ethical responsibility of AI systems in autonomous decision-making. As AI has developed and been applied in many fields, including healthcare, transportation, energy, and others, definitions of AI have continued to evolve. New perspectives have emerged, including transparency, accountability, governance, and social impact of AI.

Today, there is no universal and consensus definition of AI. Researchers, practitioners, and policymakers continue to debate and reflect on the definitions and implications of AI in society. Nevertheless, many international organizations, governments, and research organizations have proposed definitions and frameworks to guide the understanding and responsible application of AI in different contexts.

As technology continues to advance at an unprecedented pace, It seems obvious that artificial intelligence (AI) will become more and more significant in our daily lives. AI is already changing many facets of our society, from virtual assistants and autonomous vehicles to tailored suggestions and diagnosis in medicine. The potential uses of AI are numerous and are only growing as a result of continuous developments in robotics, machine learning, deep learning, and natural language processing.

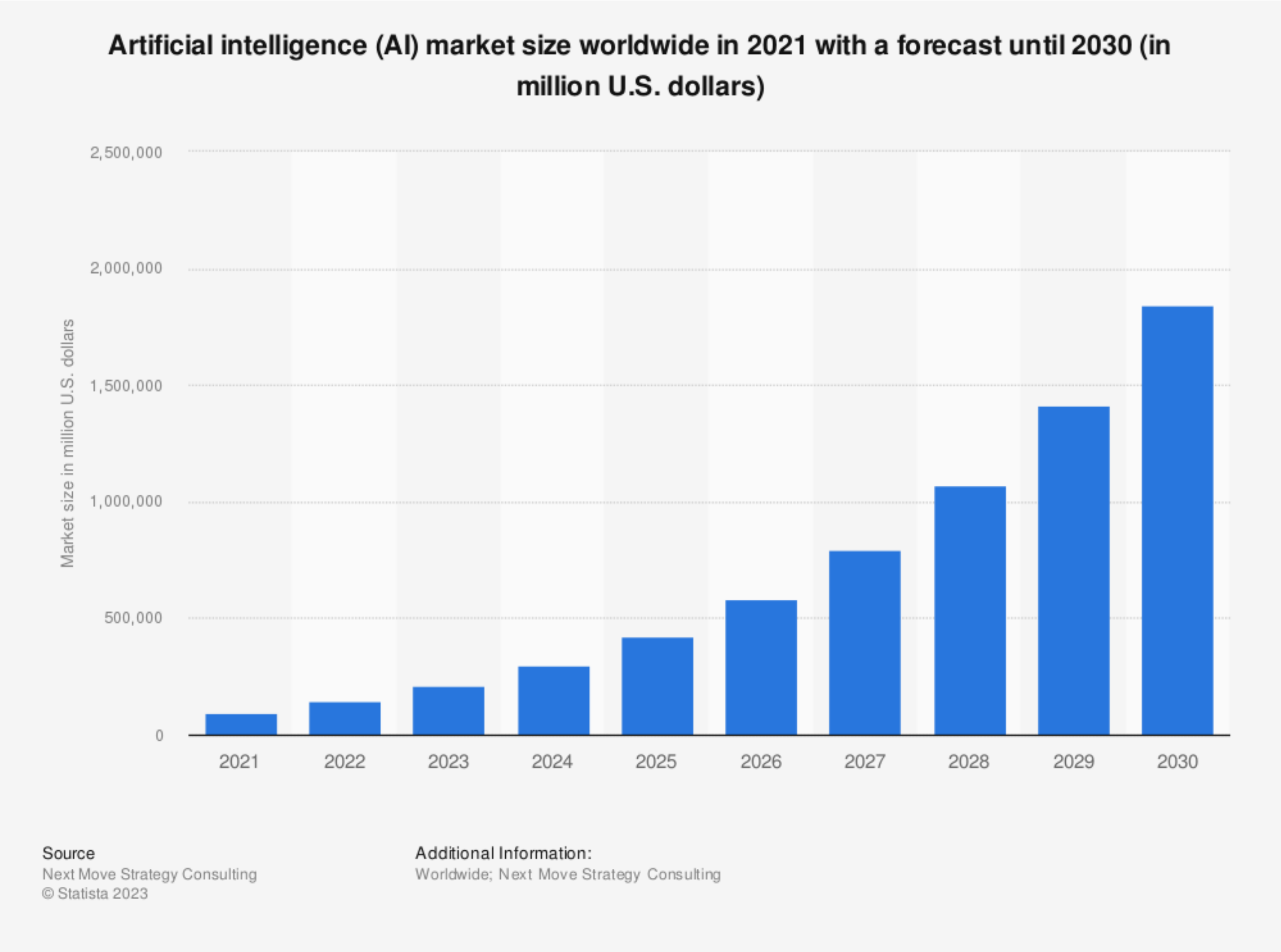


Figure 1. Global artificial intelligence market size 2021-2030,Published by Bergur Thormundsson, 2023, (Statista).

In the upcoming decades, the artificial intelligence (AI) market is anticipated to rise rapidly. By 2030, its current worth of around $100 billion is predicted to increase twentyfold to almost $2 trillion. There are many distinct industries covered by the AI market. AI will be incorporated into business structures in an assortment of areas, including supply chains, advertising, product creation, research, analysis, and more. The main themes advancing AI in the upcoming years are chatbots, image-generating AI, and mobile applications.

Artificial Intelligence (AI): The simulation of human intelligence in machines that are programmed to perform tasks and learn from experience.

Keyword:

Machine Learning: a branch of artificial intelligence that uses statistical models and algorithms to let machines learn and get better at tasks without the need for explicit programming.

Deep Learning: A type of machine learning that involves training neural networks with multiple layers to process complex data and make decisions.

Natural Language Processing (NLP): A branch of AI that focuses on enabling machines to understand, interpret, and generate human language.

2.3 Artificial Intelligence in portfolio management, historical context.

Artificial Intelligence in portfolio management is becoming increasingly well-known and widely used in the financial industry. As technology continues to advance, and data becomes more readily available, financial institutions and investment firms are increasingly leveraging AI and machine learning techniques to enhance their investment strategies. AI-powered portfolio management platforms and tools are gaining popularity due to their ability to process and analyze large volumes of data quickly and accurately, identify complex patterns and trends in financial markets, and make informed investment decisions in real-time. The use of AI in portfolio management is seen to improve investment outcomes, optimize portfolio performance, and enhance risk management strategies. As a result, the adoption of AI in portfolio management is expected to continue to grow as the financial industry seeks to leverage the potential of these advanced technologies to gain a competitive edge in the market.

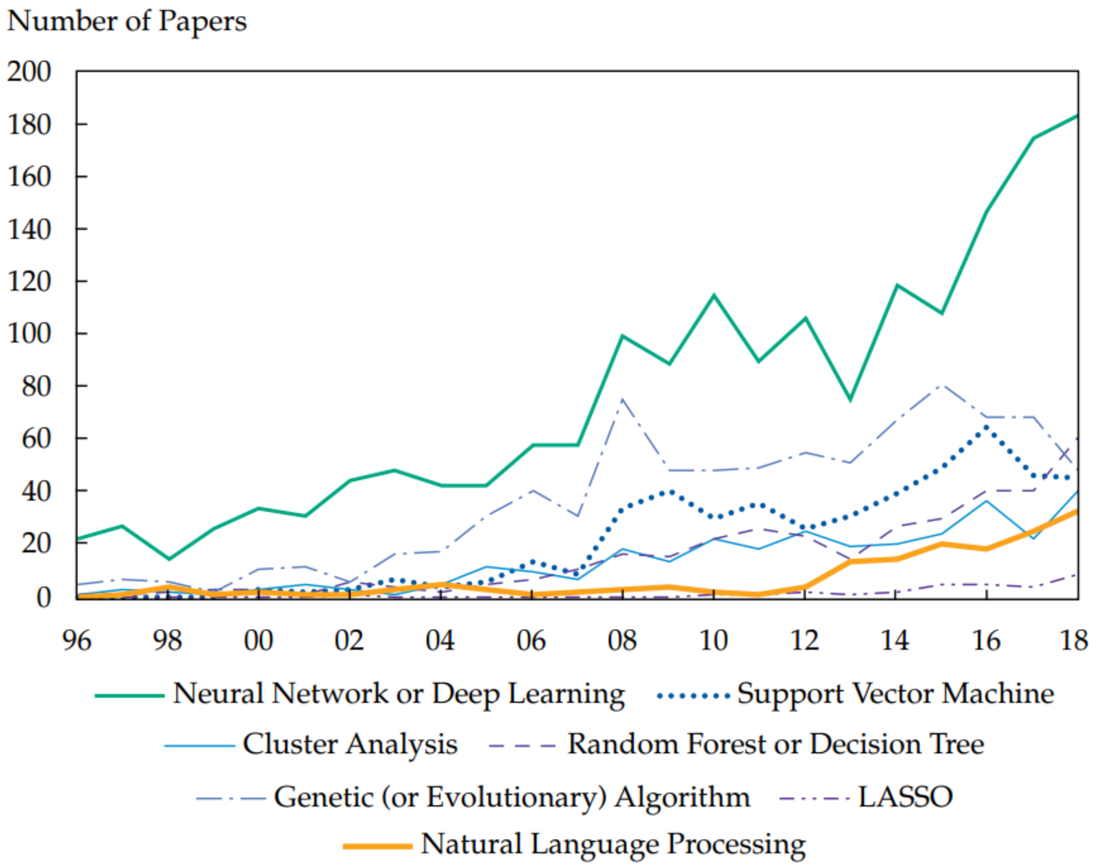


Figure 2. Number of Published Papers by AI Technique over Time, 1996–2018

Notes: The chart illustrates the annual count of published papers that include particular keywords. This data is drawn from the number of published papers cataloged in *Scopus*, spanning from 1996 to 2018. The selected papers contain the keywords "[finance]" and/or "[asset management]," in conjunction with at least one of the following terms: "[cluster analysis]," "[genetic algorithm]" or "[evolutionary algorithm]," "[lasso]," "[natural language processing]," "[neural network]" or "[deep learning]," "[random forest]" or "[decision tree]," and "[support vector machine]."

Fintech 1.0 (analog): Fintech 1.0 (analog) refers to the first wave of technological innovation in the financial services industry that occurred before the advent of digital technologies and the internet.

Fintech 1.0 was primarily focused on the use of analog and physical technologies to automate or enhance traditional financial processes such as financial transactions, account management, risk management, credit verification, etc.

Examples of Fintech 1.0 include automated teller machines (ATMs), credit card payment systems, paper-based checks, and other analog methods used to improve or streamline traditional financial services.

2) Fintech 2.0 (digitilisation): Fintech 2.0 (digitalization) refers to the second wave of technological innovation in the financial services industry that emerged with the widespread adoption of digital technologies and the internet. Fintech 2.0 is characterized by the use of digital technologies, data, and online platforms to transform and disrupt traditional financial services, creating new business models, products, and customer experiences.

Examples of Fintech 2.0 include online banking, mobile payment apps, peer-to-peer (P2P) lending platforms, robo-advisors, blockchain-based technologies, and other digital solutions that leverage advanced technologies to deliver financial services in more efficient, convenient, and innovative ways. Fintech 2.0 has significantly impacted the financial industry, changing the way financial services are delivered, consumed, and regulated.

3) Fintech 3.0 (startups): Fintech 3.0 (startups) refers to the third wave of technological innovation in the financial services industry that is characterized by the rise of innovative and agile startups leveraging advanced technologies to disrupt and transform traditional financial services. Fintech 3.0 is driven by entrepreneurial ventures that are challenging established financial institutions and business models by offering innovative, customer-centric, and technology-driven financial solutions.

Examples of Fintech 3.0 include emerging startups that focus on areas such as digital wallets, decentralized finance (DeFi), regtech (regulatory technology), insurtech (insurance technology), wealthtech (wealth management technology), and other disruptive technologies and business models that are reshaping the financial industry landscape.

Fintech 3.0 : businesses are renowned for their capacity to swiftly adjust and react to shifting market conditions, and they frequently place a high priority on user experience, simplicity, and accessibility. They frequently use cutting-edge technology like cloud computing, big data, machine learning, artificial intelligence (AI), and others to provide creative financial services and solutions that go beyond accepted financial conventions.

Smart Fintech: The Smart Fintech is a sector of financial technology that combines advancements in finance, such as blockchain and cryptocurrencies, with those in artificial intelligence, including quantum computing, deep learning, big data, and machine learning. It aims to integrate these cutting-edge technologies to offer innovative financial solutions and transform the way financial services are delivered and managed.

Keywords:

Blockchain: A blockchain is a distributed ledger, a database shared across a network of computers. Each block in the chain contains multiple transactions and is secured by a cryptographic hash of the previous block in the chain.

Cryptocurrencies: Cryptography is used by digital or virtual currencies to manage the production of new units, secure transactions, and confirm asset transfers. Cryptocurrencies are not governed or managed by a single organization; instead, they operate on decentralized networks like blockchain. Cryptocurrencies include, for example, Litecoin, Ethereum, and Bitcoin.

DeFi: An abbreviation for Decentralized Finance, which refers to a type of financial system that operates on blockchain networks and utilizes smart contracts to provide decentralized, transparent, and permissionless financial services.

Quantum Computing: Emerging field of computing that uses principles of quantum mechanics for computation, potentially revolutionizing fields such as cryptography, drug discovery, and optimization. Utilizes quantum bits (qubits) for increased processing power but faces significant technical challenges.

2.4 Integrated Reasoning

Integrated Reasoning for AI in Portfolio Management: Integrated Reasoning refers to the ability of AI systems to reason across different domains, integrate different types of information and knowledge, and make informed decisions. In portfolio management, integrated reasoning is crucial for making informed investment decisions based on a variety of factors, including market conditions, company performance, and economic trends.According to (Herrmann & Masawi, 2022), Integrated Reasoning can enhance the performance of AI-based portfolio management systems by integrating multiple sources of information and knowledge, such as financial data, news, social media, and economic trends. By analyzing and reasoning across these sources, AI systems can make more informed and accurate investment decisions.

In a study by (Bartram et al., 2020), an integrated reasoning approach was applied to portfolio management, which included the use of machine learning algorithms for feature selection, clustering, and classification. The approach was tested on a real-world dataset and demonstrated improved performance compared to traditional portfolio management methods.However, it is important to note that integrated reasoning AI systems require proper data management and human oversight to ensure that the algorithms are making informed and ethical decisions. As noted by (Ouyang, 2022), "Artificial intelligence, as a new data analysis and forecasting tool, has excellent processing capability for high-dimensional and serial data in the field of quantitative investment." (p.1).Integrated reasoning is an important component of AI-based portfolio management systems, and it has the potential to enhance investment decision-making and portfolio performance. However, it must be implemented with proper data management and human oversight to ensure the transparency, ethics, and accountability of AI-based portfolio management.

2.5 Adaptation and evolution

Adaptation and evolution for AI in portfolio management refers to the ability of AI systems to adapt to changing market conditions and evolve to improve their performance over time. As noted by (Pawar et al., 2024), "The performance of portfolio weights from the previous trading period is inserted into the networks. "(p. 2).To achieve adaptation and evolution, AI systems in portfolio management use machine learning algorithms that enable them to learn from past data and adjust their strategies accordingly. This allows the AI systems to continuously improve their performance and adapt to changing market conditions.

In a study by Garrido-Merchán et al. (2023) , an AI-based portfolio management system was developed using a learning algorithm. The system was tested on a real-world dataset and demonstrated superior performance compared to traditional portfolio management methods. The study also showed that the AI system was able to adapt to changing market conditions and improve its performance over time.Another approach to adaptation and evolution in AI-based portfolio management is the use of genetic algorithms. Genetic algorithms are a type of optimization algorithm that mimic the process of natural selection to find the optimal solution. In a study by (Gopikrishnan et al., 2001), a genetic algorithm was used to optimize portfolio selection based on historical financial data. The results showed that the genetic algorithm outperformed traditional portfolio optimization methods and was able to adapt to changing market conditions.However, it is important to note that the adaptation and evolution of AI-based portfolio management systems requires continuous monitoring and human oversight to ensure that the algorithms are making informed and ethical decisions. As noted by Vidler (2024) "We have already seen the evolving need for more robust and industrial-strength analysis platforms to understand, interpret, and evaluate AI decisions." (p. 7).

Adaptation and evolution are critical components of AI-based portfolio management systems, and they have the potential to enhance investment decision-making and portfolio performance. However, proper data management, continuous monitoring, and human oversight are necessary to ensure the transparency, ethics, and accountability of AI-based portfolio management.

2.6 Knowledge Discovery

Knowledge Discovery for AI in Portfolio Management: Knowledge discovery refers to the process of extracting useful knowledge and insights from data. In portfolio management, knowledge discovery involves the use of data mining and machine learning techniques to identify patterns and relationships in financial data, news, economic trends, and other sources of information.

According to Ayala et al. (2021), knowledge discovery can improve the performance of portfolio management by providing insights into market trends, company performance, and other factors that can affect investment decisions. By using machine learning algorithms to analyze and classify data, portfolio managers can identify hidden patterns and relationships that can inform their investment strategies. In a study by Zhang and Chen (2017), a knowledge discovery approach was applied to portfolio management, which included the use of machine learning algorithms for data classification and clustering. The approach was tested on a real-world dataset and demonstrated improved performance compared to traditional portfolio management methods.However, it is important to note that knowledge discovery techniques must be used with caution and human oversight to ensure that the algorithms are making informed and ethical decisions.Knowledge discovery is an important component of AI-based portfolio management systems, and it has the potential to enhance investment decision-making and portfolio performance. However, it must be implemented with proper data management and human oversight to ensure the transparency, ethics, and accountability of AI-based portfolio management.

2.7 Collective Behaviors

Collective behaviors refer to the coordination and collaboration of multiple autonomous agents to achieve a common goal. In portfolio management, collective behaviors can be used to optimize the performance of investment portfolios by leveraging the intelligence and decision-making capabilities of multiple AI agents.

One example of collective behaviors in portfolio management is swarm intelligence. Swarm intelligence involves the use of multiple autonomous agents, or "swarm members," that work together to find the optimal solution to a problem. In portfolio management, swarm intelligence can be used to optimize asset allocation and risk management by analyzing massive amounts of data and identifying patterns and trends that would be impossible for a single agent to detect.Another example of collective behaviors in portfolio management is multi-agent systems (MAS). MAS is a group of autonomous agents that interact with each other to achieve a common goal. In portfolio management, MAS can be used to manage complex portfolios and optimize performance by leveraging the intelligence and decision-making capabilities of multiple agents. Collective behaviors have shown great promise in portfolio management, as they can help portfolio managers make more informed decisions and optimize the performance of their portfolios. However, it is important to note that the implementation of collective behaviors requires proper coordination and management to ensure that the agents are working together effectively and efficiently.

2.8 Memory Augmentation

Memory Augmentation for AI in Portfolio Management: Memory augmentation refers to the use of external memory to improve the performance of AI systems in solving complex problems. In the context of portfolio management, memory augmentation can enhance the ability of AI systems to process and analyze large amounts of financial data and make informed investment decisions.

According to Ye et al. (2020), memory augmentation can be used to store and retrieve historical financial data, which can be used to inform investment decisions. This approach can improve the accuracy and effectiveness of AI-based portfolio management systems.In a study by Yang et al. (2020), a memory-augmented neural network (MANN) was proposed for stock prediction in portfolio management. The MANN used an external memory module to store and retrieve historical stock prices, which were used to inform stock prediction. The approach was tested on real-world datasets and demonstrated improved performance compared to traditional machine learning methods.However, it is important to note that memory augmentation also requires proper data management and human oversight to ensure that the algorithms are making informed and ethical decision.Memory augmentation is a promising approach to improving the performance of AI-based portfolio management systems. However, it must be implemented with proper data management and human oversight to ensure the transparency, ethics, and accountability of AI-based portfolio management.

Another system used by AI is the Memory AI plays it’s playing a significant role in optimizing financial portfolios through advanced methodologies like Long Short-Term Memory (LSTM) networks and reinforcement learning. These techniques enhance investment strategies by predicting asset returns and managing risks effectively. As (Yang, 2022) demonstrate, “LSTM adds a memory to each nerve in the hidden layer, so that the memory information in the time series is controllable." This indicates that LSTMs incorporate a memory mechanism that allows them to manage and utilize past information effectively, enhancing their predictive capabilities, Improved LSTM models have shown superior performance in investment portfolio design, outperforming traditional methods.

2.9 Higher dimensionality

Higher dimensionality refers to the use of complex and large-scale datasets in portfolio management, beyond traditional financial data, to analyze and identify investment opportunities. The integration of higher dimensionality in portfolio management is made possible by artificial intelligence (AI) algorithms that can process and analyze large amounts of data from various sources, including social media, news articles, and economic indicators.

The use of higher dimensionality in portfolio management has the potential to provide unique insights and opportunities that would be difficult or impossible to identify using traditional financial data. As noted (Magoč et al., 2009), "Computational intelligence techniques are very useful tools for solving problems that involve understanding, modeling, and analysis of large data sets. One of the numerous fields where computational intelligence has found an extremely important role is finance." (p. 2).Nevertheless, the use of higher dimensionality also comes with challenges, including the complexity and heterogeneity of the data, and the need for sophisticated AI algorithms to process and analyze the data. In addition, higher dimensionality may also increase the risk of overfitting, which can lead to inaccurate investment decisions. The integration of higher dimensionality in portfolio management has the potential to provide unique investment opportunities and insights. However, it requires sophisticated AI algorithms and careful consideration of the quality and relevance of the data used to avoid overfitting and inaccurate investment decisions.

2.10 Identified Research Gap

Some authors allowing in exploring the research gap and the research

- (Zhang & Chen, 2017) An Artificial Intelligence Application in Portfolio Management. The paper "An Artificial Intelligence Application in Portfolio Management" explores how AI is revolutionizing finance, particularly in portfolio management. It highlights that AI algorithms can significantly boost investment returns by optimizing portfolio selection. One of the key techniques discussed is spectral clustering (SC), which allows for a deeper analysis of stock relationships. This method enhances decision-making and leads to better-performing portfolios compared to traditional approaches.The study shows that portfolios built using AI, especially with the SC method, tend to outperform conventional strategies, offering a competitive edge in the financial markets. It also introduces the concept of network analysis in stock markets, revealing that investing in stocks that hold central positions in a complex network can yield higher returns.The paper reviews various AI techniques and applications in finance, emphasizing the value AI brings to portfolio management. This research illustrates how AI is becoming an essential tool for investors, transforming traditional investment approaches with advanced data analysis and decision-making capabilities.

- (Sutiene et al., 2024a) Enhancing portfolio management using artificial intelligence: literature review. It begins by discussing traditional performance metrics like the Sharpe ratio, Treynor ratio, and Jensen's Alpha, which have long been used to assess how well portfolios are performing, especially when adjusting for risk. The Sharpe ratio, for example, is highlighted as a vital tool for analyzing mutual fund performance, while Jensen's Alpha is useful for comparing how a portfolio measures up against market benchmarks, factoring in systematic risk.The paper then dives into the growing influence of AI in portfolio management, especially the use of tools like natural language processing (NLP) to analyze corporate reports and even social media sentiments. This helps investors make more informed decisions when it comes to asset allocation and managing risk. AI techniques like evolutionary algorithms and neural networks are also mentioned for their ability to solve complex problems in portfolio optimization, helping to balance multiple objectives at once.However, there are challenges. The paper emphasizes issues related to transparency and fairness in AI systems, as well as the need for explainable decisions. Investors and regulators need to understand how these AI-driven decisions are made, which has sparked discussions around creating more explainable AI models in the finance world. With new regulations emerging in Europe, these concerns are becoming increasingly important.Lastly, the paper looks at how performance attribution has evolved. Understanding where a portfolio's returns are really coming from—whether from skill or luck—has always been key. The paper discusses different ways to attribute returns, and how AI can enhance this process, offering deeper insights into what's driving portfolio performance.

- (Vidler, 2024), Recommender Systems in Financial Trading: Using machine-based conviction analysis in an explainable AI investment framework. The paper explores how Artificial Intelligence (AI), particularly through Recommender Systems (RS), is transforming portfolio management by replicating many traditional roles of human analysts. AI enhances the decision-making process for portfolio managers by providing data-driven insights and offering tools like collaborative filtering, content-based filtering, knowledge-based, and case-based systems, with knowledge-based systems being the most widely used in asset selection. These AI outputs can be integrated into decision support systems, helping portfolio managers correlate recommendations with macroeconomic factors for more informed decisions. Metadata plays a crucial role in enabling both the technical functionality of RS and further analysis by portfolio managers. Additionally, the concept of Explainable AI is emphasized to build trust by providing visualizations and transparency into AI's decision-making processes. The paper also highlights the evolving role of analysts, as AI-driven systems increasingly supplement or replace traditional methods, reflecting a broader trend towards automation and data-driven approaches in the finance industry. Overall, the paper demonstrates how AI and RS are boosting the efficiency and effectiveness of investment decisions, signaling a significant shift in the landscape of portfolio management.

-(Liu et al., 2024), ROBO-ADVISORS: REVOLUTIONIZING WEALTH MANAGEMENT THROUGH THE INTEGRATION OF BIG DATA AND ARTIFICIAL INTELLIGENCE IN ALGORITHMIC TRADING STRATEGIES. The paper explores how robo-advisors are revolutionizing wealth management by integrating big data and artificial intelligence (AI). It highlights how AI technologies, like machine learning and natural language processing, are used to sift through large datasets, helping identify market trends and optimize investment portfolios. This not only improves decision-making for financial services but also makes the process more efficient. AI-powered algorithmic trading strategies play a key role in this transformation, as they can quickly analyze vast amounts of data to predict market trends and make real-time trading decisions. However, the paper also points out some challenges, such as data quality, transparency of algorithms, and the need to meet regulatory standards. Ensuring accurate data is essential to avoid mistakes that could impact trading outcomes. Despite these challenges, the paper emphasizes the potential for AI to drive innovation in wealth management, helping financial services become even more effective. Looking to the future, it's clear that AI is not just a passing trend but a major shift that is reshaping the financial industry. The ability of AI to learn and adapt makes it an invaluable tool for investors and institutions alike. In short, the paper paints an optimistic picture of how robo-advisors and AI are changing the landscape of wealth management, while acknowledging the hurdles that need to be addressed along the way.

2.11 Research Framework

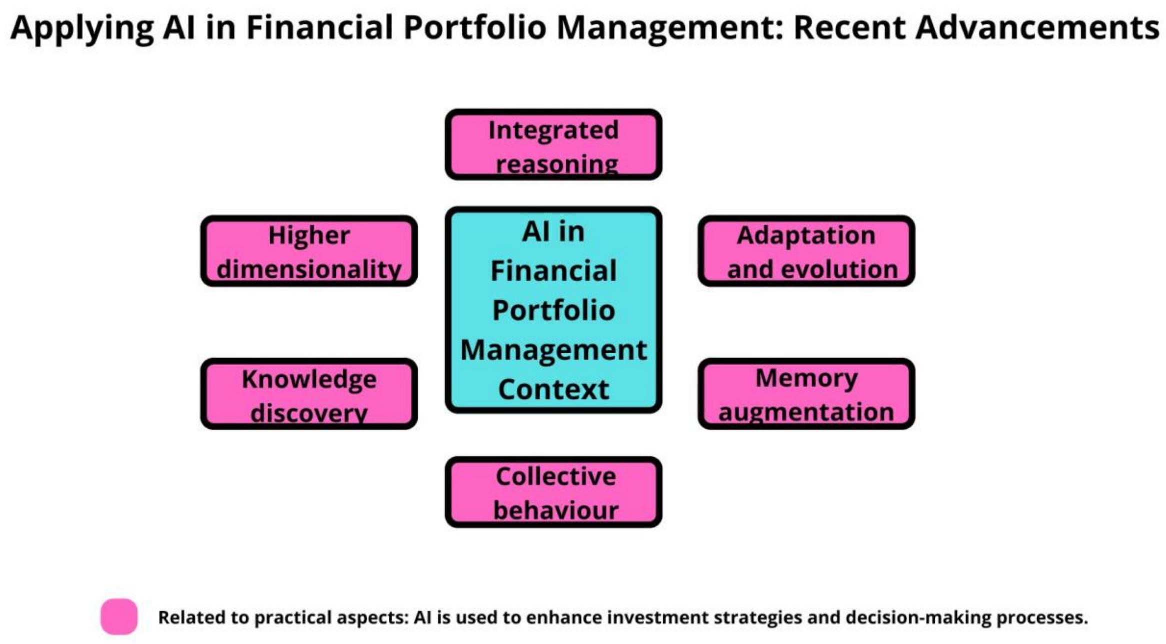


Figure 3. Darrigo, (2024). *Applying AI in Financial Portfolio Management: Recent Advancements*.

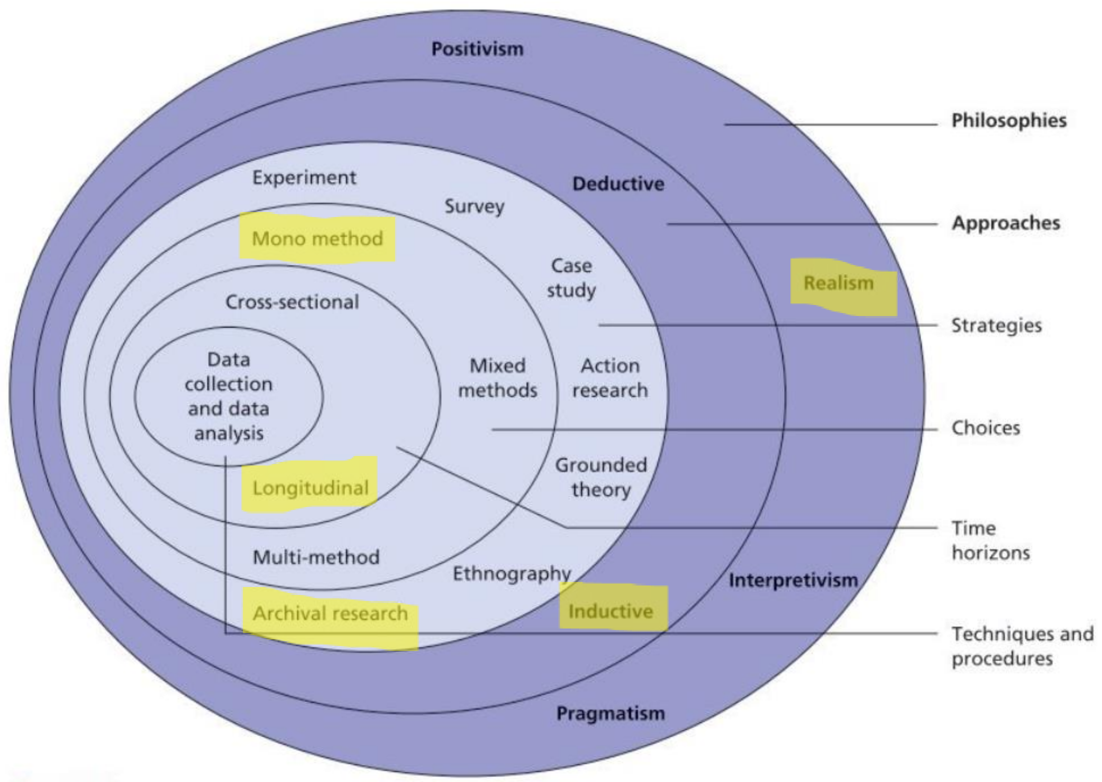
In this framework that I created, I explore how artificial intelligence (AI) is transforming the way we manage financial portfolios by making decision-making smarter and more efficient. The framework dives into how AI helps uncover new insights, handle large and complex data sets, and detect patterns in collective behavior that we couldn't identify before. What makes AI so powerful is its ability to adapt and evolve, learning from the data and improving continuously. It takes much of the guesswork out of investing, enabling portfolio managers to make better-informed decisions by optimizing processes that consider multiple factors at once. In short, AI isn't just another tool in financial management—it's a game changer that reshapes how we approach investing in today's fast-moving markets.

3 Research methods and implementation

3.1 Research context

As a student at Jamk, I am currently writing this thesis as part of my academic studies. My purpose is to develop my expertise in the field of artificial intelligence through financial portfolio management. The defense of this thesis is an essential step in my academic journey and will allow me to demonstrate my in-depth understanding of the subject. I am writing this thesis with enthusiasm and curiosity, as this subject truly interests me, and I hope that the knowledge I have acquired and developed during the writing of this thesis will be useful in my future jobs.

3.2 Research design



3.2.1 Research philosophy: Realism

As a philosophical stance, realism stresses the existence of an outside world that exists apart from the human mind. Adopting a realistic approach in your thesis on the use of AI in financial portfolio management entails taking into account the verifiable facts and data associated with the area. It entails admitting that there is an objective reality that can be investigated by observations and empirical investigation.Because it stresses the need of empirical evidence in comprehending the reality of artificial intelligence applications in financial portfolio management, realism is also consistent with a scientific and positivist approach to knowledge generation.

By improving the validity and dependability of your findings and further the field's understanding by firmly establishing your study in reality.Finally, by using a realistic approach in your thesis, you may analyze the state of the art of AI applications in financial portfolio management objectively and with proof. It gives your research a strong basis and guarantees a thorough and exacting analysis of the topic.

3.2.2 Research purpose: Descriptive

A descriptive approach allows for a thorough analysis of existing research in the field. Using a descriptive approach in my thesis on the state of the art of artificial intelligence applications in financial portfolio management can have a number of benefits. First, it allows for a clear and detailed understanding of the concepts, methods, techniques, and AI models used in the field. I can guarantee a comprehensive understanding for readers by providing in-depth explanations of how these approaches work, their objectives, advantages, limitations, and practical applications. You are able to thoroughly explain and evaluate the different strategies put forth by researchers, as well as the outcomes attained, the techniques utilized, and the information gathered. Your study gains validity and credibility from this thorough analysis, which strengthens and validates it.It makes it easier to communicate the results and conclusions of your research. You may successfully convey your findings to readers by accurately and clearly presenting your results, backed up by specific examples, figures, and graphs. This improves your argument and makes your thesis more compelling.Using a descriptive technique helps readers understand your point. You may make your research intelligible to a wider audience, including individuals who lack in-depth academic expertise of the subject, by using straightforward language, thorough explanations, and tangible examples. This encourages your study findings to be shared more widely and have a greater effect.A thorough, understandable, and approachable examination of the state of the art in the subject is provided by using a descriptive method in your thesis on AI applications in financial portfolio management. It makes your study a significant addition to the corpus of current knowledge by enhancing its impact, rigor, and trustworthiness.

3.2.3 Research approach: Inductive

Using specific observations or facts to make general conclusions is known as inductive reasoning. Using an inductive method in your thesis on the use of AI in financial portfolio management entails closely analyzing the particular research results, case studies, and empirical data associated with the subject.
You might examine the particular examples of artificial intelligence applications in financial portfolio management to make more generalizations and conclusions by using inductive reasoning in your thesis. A thorough grasp of the state of the art in this subject may be attained by using this method to find patterns, trends, and similarities within various research and data sets.The significance of empirical data and firsthand observations in forming research conclusions is also acknowledged by inductive reasoning. You may improve the validity and reliability of your study by carefully analyzing the particular facts and evidence that are accessible. This will allow you to draw conclusions and insights that are supported by real observations and data.Additionally, using an inductive method in your thesis can help you grasp the complexity of artificial intelligence applications in financial portfolio management in a nuanced and context-specific way. It enables you to think about the usefulness, constraints, and possible difficulties of applying and overseeing AI in actual financial contexts.

3.2.4 Research strategy/method: Archival research is based on relevant publications.

There are several benefits to basing my study on previous studies and relevant articles for my thesis on the application of AI in financial portfolio management.

I can perform archival research to provide your study a solid foundation. By building on previously authored works that have completed peer review and been published in reputable journals, you

can ensure that your study is grounded in acknowledged knowledge and expertise in the field. This increases the validity and reliability of your study by referencing the findings and observations of past researchers who have conducted in-depth research in the same topic. You may find reliable and authentic sources by conducting research using archives. The reliability of the data and conclusions is ensured by reputable publications with strict review and publication criteria, such as journals, conferences, and reliable websites. By citing these sources, you may demonstrate to your audience the validity of your research and the strength of your findings.
A thorough picture of the current state of the art in the topic may be obtained through archival research. You may obtain a comprehensive grasp of the state of research today, including the most recent developments, patterns, and difficulties in the use of artificial intelligence in financial portfolio management, by going over pertinent papers again.

This enables you to situate your study within the body of existing literature and pinpoint any gaps or areas that require more research, thus advancing the field's understanding. Furthermore, you may critically assess the approaches, models, and conclusions offered in earlier articles by focusing your research on archival research. You can analyze the advantages and disadvantages of various strategies, spot contradictions or gaps in the literature, and suggest fresh lines of inquiry or enhancements to current techniques. This critical evaluation enhances the validity of your own research findings and aids in the development of an educated and fair viewpoint on the state of the art.

3.2.5 Methodological choice: Mono-method in form of archival research

I have decided to use archival research as my mono-method approach for my thesis, which is on the use of artificial intelligence in financial portfolio management, for a number of strong reasons.

In my opinion, doing ro-bust research requires maintaining methodological rigor and consistency. I can make sure that my study is carried out using a consistent and repeatable technique by only employing archive material, such as published literature, reports, and historical data. Because other researchers may replicate my study using the same historical data, this strengthens the overall robustness of my research and increases the validity and trustworthiness of my findings. Through archival research, I may access a wealth of existing data that can be thoroughly examined and understood to learn more about the topic of financial portfolio management. Historical market data, financial reports, trade journals, and other pertinent sources that provide a rich and extensive dataset for research can all be considered archival data. I can now carry out in-depth research without having to gather primary data, which can take a lot of time and resources.I can perform longitudinal analyses and look at trends and patterns over time by using archive research. I can watch changes in investment strategies, examine the success of financial portfolios, and see how artificial intelligence applications are developing in this sector via historical data. My investigation gains depth and context from this longitudinal perspective, which also enables me to offer insightful thoughts on the field's historical evolution and current situation.

3.2.6 Time horizon: Longitudinal

Using a longitudinal approach, I will begin by focusing on the topic's historical elements in my thesis before looking at the field's current status.

Understanding the growth of artificial intelligence in financial portfolio management becomes easier by investigating the topic's historical elements. I can learn about the beginnings, development, and early uses of AI in this subject by looking into the historical background. This point of view provides a comprehensive picture of the development of AI by tracing the innovations, challenges, and trends that have influenced it throughout time. I can discover a lot about the past accomplishments of AI models, their limits, and how they affect investment strategies by looking at historical data and literature on AI in portfolio management. This review explains the achievements, setbacks, and lessons discovered from past AI deployments, which might inform present procedures and next advancements. Following the creation of this historical framework, I will use a longitudinal technique to investigate the state of artificial intelligence in financial portfolio management today. In order to find novel patterns, obstacles, and possibilities in the subject, this approach entails analyzing recent data and literature. I will assess the newest research, models, techniques, and applications, determining their usefulness, limits, and possible influence on the financial industry. Understanding the latest developments and difficulties in AI-driven portfolio management requires a comprehensive and current study of the area, which is made possible by the use of a longitudinal method. This approach provides an extensive viewpoint that may guide future studies, practices, and regulations in the field by bridging the gap between past events and the present situation.

3.3 Data collection

Secondary Qualitative Data in form of relevant publications

As I delve into my thesis on the topic of realism in artificial intelligence applications in financial portfolio management, I will be relying heavily on secondary qualitative data from relevant publications.

Secondary qualitative data, in the form of published literature and research articles, holds significant importance in my research. These publications are authored by experts in the field and draw on extensive research, empirical studies, and analysis. They provide valuable insights, findings, and interpretations that have undergone thorough review and validation by the scholarly community.

There are compelling reasons why I have chosen to base my research on this type of data. Firstly, utilizing secondary qualitative data from relevant publications allows me to access a diverse range of information from reputable sources such as journals, conference proceedings, and reports. This comprehensive approach enables me to gather up-to-date information on various aspects of artificial intelligence applications in financial portfolio management, enriching the breadth and depth of my research. Relying on relevant publications ensures that my research is grounded in established theories, concepts, and empirical evidence. These publications have undergone rigorous peer review processes, enhancing their credibility and reliability. By building on existing research, I can leverage the insights and findings from previous studies to strengthen the validity and robustness of my own research and provide a solid foundation for my argumentation on the topic of realism.

3.4 Data analysis

Quantitative data analysis

Quantitative data collection and analysis are beyond the scope of this thesis.

Qualitative data analysis (codebook)

This study is based on secondary data of in form of relevant publications analyzed with the help of NVivo software.

Table 1. Codebook for data analysis based on the research framework

Code	Definition	When to use	When not to use
Integrated reasoning	Integrated reasoning, in the context of AI and financial portfolio management, refers to the capability of an intelligent system to amalgamate and employ diverse information and knowledge from various sources to analyze complex financial data and make investment decisions. This involves integrating reasoning processes such as deduction, induction, and abduction with other cognitive abilities like perception, learning, and decision-making to form a comprehensive understanding of the financial market and optimize the composition and management of a portfolio. Integrated reasoning in this context enables the AI system to consider a wide range of factors, including market trends, risk assessment, historical data, and economic indicators, to make informed investment choices and maximize returns while managing associated risks.	Look for passages that discuss how integrated reasoning is suported by artificial intelligence in the context of financial portfolio management enables AI systems to incorporate multiple sources of information and knowledge, reason and learn from them, and make informed decisions	Do not use for passages of text from publications that refer to other things than the concept of Integrated reasoning suported by artificial intelligence in the context of financial porfolio management.
Adaptation and evolution	In the context of AI and financial portfolio management, adaptation and evolution are crucial concepts. Adaptation refers to an AI system's ability to adjust its investment strategies, risk tolerance, and asset allocation in response to changing market conditions, economic factors, or unexpected events. This adaptability allows the AI-driven portfolio management system to optimize its decisions and allocations in real-time, ensuring that the portfolio remains aligned with the investor's financial goals.	Use this code to identify evidence in a text that refers to the concept of adaptation and evolution in the context of artificial intelligence supporting financial portfolio management. This may include discussions of how AI systems are designed to	Do not use for passages of text from publications that refer to other things than the concept of adaptation and evolution in context of using IA in financial portfolio management. It's refer to an AI system's ability to adjust and develop to respond

		learn and improve over time through machine learning algorithms, natural language processing, and other techniques.	to changing conditions or new tasks.
Knowledge Discovery	In the context of AI and financial portfolio management, Knowledge Discovery takes on a specific significance. It refers to the systematic procedures and methodologies employed to extract valuable insights and actionable information from financial data. This process encompasses data collection, data preprocessing, the application of advanced data analysis techniques like machine learning and risk assessment models, and the validation and interpretation of the findings.	Use this code to identify the evidence in form/passage of text that refer to the concept of Knowledge Discovery in Databases (KDD) in the context of using artificial intelligence for investment analysis, portfolio management, or other financial decision-making processes.	Do not use for passages of text from publications that refer to other things than the concept of Knowledge Discovery in context of using IA in financial portfolio management. it's referring to the processes and techniques used to extract knowledge from data.
Collective Behaviour	In the context of AI and financial portfolio management, the concept of collective behavior takes on a specific application. Here, collective behavior refers to the analysis and modeling of market dynamics and the actions of various market participants, including individual and institutional investors. AI systems, through the use of machine learning and computational techniques, can simulate and study the collective behavior of these market actors.	Use this code to identify evidence in form/passage of text that refer to the concept of collective behavior in the context of the using of artificial intelligence in financial portfiolio management, such as the study of emergent behaviors in a group of AI agents or the application of swarm intelligence algorithms in AI systems.	Do not use for passages of text from publications that refer to other things than the concept of collective behavior in context of usin IA in financial portfolio management. It may refer to the study and simulation of group dynamics and emergent phenomena using machine learning.

Memory Augmentation	In the context of AI and financial portfolio management, memory augmentation takes on a specialized role. Memory augmentation here pertains to the enhancement of an AI-driven portfolio management system's capacity to store, retrieve, and leverage financial data and historical information. This process may encompass the creation of advanced algorithms and architectures that empower the AI system to learn from past market conditions and investment outcomes. Additionally, it can involve the integration of external memory systems like financial databases, market research reports, and knowledge graphs to expand the depth and breadth of available financial information.	Use this code to identify the evidence in a passage of text that refers to the concept of memory augmentation in the context of artificial intelligence using for financial porfolio management. This can include techniques and technologies aimed at improving the storage, retrieval, and use of information by AI systems.	Do not use for passages of text from publications that refer to other things than the concept of Memory augmentation in the context of AI used for the process of financial portfolio management. Enhancing an AI system's ability to store and retrieve information from memory.
Higher Dimensionality	In the context of AI and financial portfolio management, higher dimensionality takes on a specific relevance. Higher dimensionality here refers to dealing with financial data that contains a multitude of features or variables, which can complicate the analysis and modeling process using conventional techniques. Financial data is often represented as a high-dimensional vector, with each dimension corresponding to a specific financial metric, asset, or variable.	Use this code to identify the evidence in a form/passage of text that refers to the concept of higher dimensionality in the context of artificial intelligence used for financial portfolio managemenr. This may include discussions on the use of neural networks and other advanced algorithms to process high-dimensional data and solve complex problems that cannot be easily addressed through traditional methods.	Do not use for passages of text from publications that refer to other things than the concept of Higher dimensionality in the context of AI used for financial portfolio management.

3.5 Ethical considerations

This study is based on publicly available relevant secondary sources with no exposure to ethical issues related to security, confidentiality and privacy of the analyzed data and information.

A due care has been taken to give credit to the authors of the publications cited in this thesis.

4 Research Results

Through an analysis of its historical development, present function, and ensuing ramifications, my research investigates the growth of artificial intelligence (AI) in the area of financial portfolio management. Investigating the many facets of AI in the finance industry is my aim.The primary goals are to: (1) evaluate the overall effect of artificial intelligence (AI) on the financial portfolio management landscape; (2) pinpoint the elements influencing the financial portfolio management sector, with an emphasis on the AI era; and investigate the consequences of the growing incorporation of AI into financial portfolio management.

As explained in Appendix 1, I have decided to use NVivo 12 for data collection and analysis. I can methodically collect essential information from specialized publications using NVivo 12. To provide a thorough grasp of the development of AI in financial portfolio management, the data is then painstakingly coded into pertinent nodes, as shown in Appendix 2.My research attempts to answer important topics like:

What is the historical evolution of artificial intelligence in financial portfolio management?

How is AI currently applied in financial portfolio management, and what are the main benefits and limitations associated with its use?

How does AI impact investment decision-making and risk management in contemporary financial portfolio management practices?

What are the future prospects and challenges for AI in financial portfolio management?

4.1 Adaptation and Evolution in AI-baised Portfolio Management

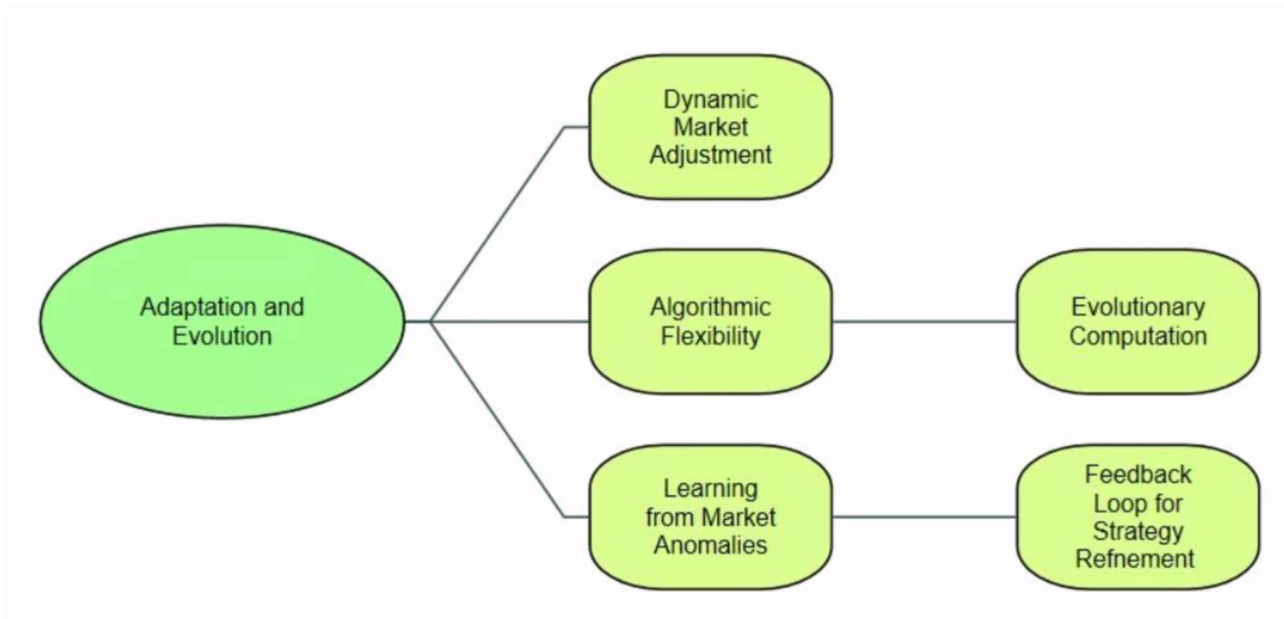


Figure 5. Mind map generated from NVivo 12 illustrating the key concepts of Adaptation and Evolution in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

The mind map above presents several critical factors related to the role of AI in adapting and evolving financial portfolio management strategies, based on relevant academic publications.

4.1.1 Dynamic Market Adjustment

Markets in the fast-paced world of finance constantly shift to accommodate a multitude of factors, such as changes in the economy, investor sentiment, and regulatory requirements. In order to remain ahead of the competition, portfolio management need to be agile and constantly modify their plans to safeguard and increase their investments. In today's unpredictable financial environment, the concept of dynamic market adjustment is crucial for success.

Readjusting assets on a regular basis is essential to portfolio management as the relationships between financial instruments change. According to Soleymani and Paquet, "Portfolio management continuously reallocates the assets which make up the portfolio in order to maximize return on investment while minimizing risk."" (Soleymani & Paquet, 2020, p. 1). It’s not just about picking the right assets but knowing when to change course—ensuring your portfolio is always positioned for growth while minimizing risk. **(Appendix 3.1)**

Thanks to advancements in deep learning and reinforcement learning, portfolio managers now have powerful tools to help them navigate these market changes in real-time. Liu et al. explain that by integrating " Our approach integrates key macroeconomic indicators and targeted news sentiment analysis into its framework, capturing a comprehensive picture of market dynamics" these models can provide a complete view of the factors driving market movements (Liu et al., 2024, p. 2). This allows for smarter, faster decisions that align with both short-term market shifts and long-term investment goals. **(Appendix 3.1)**

But it’s not just external factors like the economy that make dynamic adjustment so important. Market volatility—the wild ups and downs that investors sometimes face—can disrupt even the best-laid plans. As Ndikum and Ndikum highlight, markets often behave in unpredictable, "Markets often behave in unpredictable, 'non-stationary' ways, making adaptability crucial" ways, making adaptability crucial (Ndikum & Ndikum, 2024, p. 1). Being flexible in your strategy allows you to weather the storm and seize opportunities that arise, even in uncertain times. **(Appendix 3.1)**

Another interesting angle is the idea of evolutionary finance. According to Evstigneev and colleagues, stock markets naturally favor strategies that focus on long-term stability, stating that markets are " The evolutionary stability of portfolio rules ensures that rational, adaptive strategies dominate in the long run, while irrational strategies are eventually discarded." (Evstigneev et al., 2006, p. 6). While irrational market behavior can temporarily dominate, eventually rational strategies tend to prevail. It’s a balancing act—staying rational while adjusting quickly to market swings. **(Appendix 3.1)**

Dynamic market adjustment is about staying agile in a world where change is the only constant. By embracing advanced technologies like AI and reinforcement learning, portfolio managers can stay ahead of the curve, making real-time adjustments that ensure their portfolios remain strong and aligned with both market conditions and investor goals.

4.1.2 Algorithmic Flexibility

One of the key strengths of AI systems lies in their algorithmic flexibility, meaning their ability to incorporate new data in real-time. As Liu et al. (2024, p. 6) highlight: "Our study introduces a unique algorithmic approach that combines a non-stationary transformer with deep reinforcement learning to tackle market uncertainty." This approach allows for handling the non-stationarity of financial markets and responding to unexpected changes in real-time **(Appendix 3.2).**

Machine learning models integrated into portfolio management allow for the incorporation of various technical and macroeconomic indicators. Jiang et al. (2020, p. 7) specify: "The portfolio rebalance framework integrates machine learning models into mean-risk portfolios, allowing dynamic adjustment based on market trends." This integration of indicators enables the models to anticipate market movements and adjust decisions more reactively and accurately **(Appendix 3.2).**

The results of these approaches show increased flexibility in adjusting portfolio strategies. Soleymani and Paquet (2020, p. 4) explain: "Our framework demonstrates that algorithms can dynamically adapt to shifting macroeconomic indicators, enhancing long-term performance." This ability to quickly adjust investment decisions strengthens the resilience of portfolios against economic shocks **(Appendix 3.2).**

One of the great advantages of AI models lies in their ability to handle large state spaces and adapt in real-time, the ability to handle large state spaces and adapt in real-time is a key advantage of AI-driven portfolio management. This algorithmic flexibility offers optimized performance, even under uncertain and complex market conditions**.**

Evolutionary algorithms allow for the continuous improvement of AI strategies in portfolio management. As Liu et al. (2024, p. 6) explain: "Reinforcement learning algorithms are designed to evolve, continuously optimizing portfolio strategies by integrating performance data over time." This evolution capability enables strategies to adjust as new data becomes available **(Appendix 3.2).**

Furthermore, evolutionary strategies ensure the long-term stability of the market, as described by Evstigneev et al. (2006, p. 5): "The evolutionary stability of portfolio rules ensures that rational, adaptive strategies dominate in the long run, while irrational strategies are eventually discarded." This natural selection of the most effective strategies allows for more robust portfolio management**(Appendix 3.2).**

Evolutionary algorithms mimic the process of natural selection by adapting strategies to market conditions, as highlighted by Evstigneev et al. (2006, p. 7): "Evolutionary computation allows for dynamic adaptation, where agents improve their strategies through trial and error, mimicking natural selection." **(Appendix 3.2).**

4.1.3 Learning from Market Anomalies

Market anomalies, such as financial crises or unexpected events, provide learning opportunities for AI systems. Garrido-Merchán et al. (2023, p. 8) emphasize the importance of these anomalies in adjusting strategies: "Anomalies in financial markets provide opportunities for learning, where reinforcement learning can adjust and optimize portfolios based on historical data." AI leverages these events to improve its real-time decisions. **(Appendix 3.3).**

The gains or losses in capital allow the AI agent to receive continuous feedback for adjusting its decisions. Evstigneev et al. (2006, p. 5) state: "The endogenous wealth increase due to dividends and the capital gains or losses provides the agent with continuous feedback for learning and improvement." This feedback process enhances decision-making and strengthens resilience against market shocks. **(Appendix 3.3).**

Moreover, as Ayala et al. (2021, p. 7) explain, market movements, often unpredictable, are better analyzed by machine learning models that detect hidden patterns in these anomalies: "Market movements are often driven by unpredictable factors, but machine learning models are designed to identify hidden patterns in these anomalies." This learning capability is crucial for adjusting strategies in real-time. **(Appendix 3.3).**

The use of historical and external data such as financial news improves portfolio performance. Liu et al. (2024, p. 5) note: "Such models utilize historical price data and external information such as financial news, extracting features to guide portfolio rebalancing." This combined approach provides a better understanding of market fluctuations and helps adjust decisions accordingly. **(Appendix 3.3).**

The integration of feedback loops in AI systems allows for refining investment strategies based on obtained results. Jiang et al. (2020, p. 4) explain that: "The portfolio rebalancing strategy integrates feedback from market performance, allowing the agent to adjust risk and return preferences in real time." This continuous adjustment process is essential for improving decisions at each step. **(Appendix 3.3).**

Reinforcement learning systems incorporate these feedback loops in the decision-making process, as Liu et al. (2024, p. 7) state: "Deep reinforcement learning frameworks incorporate feedback loops where agents refine their actions based on historical returns and market conditions." This adaptability allows for better risk management in the face of financial market uncertainty. **(Appendix 3.3).**

The feedback based on portfolio performance helps refine risk and return management strategies. Ndikum and Ndikum (2024, p. 8) note: "Continuous feedback from portfolio performance enables the refinement of trading strategies, improving risk management and decision-making." **(Appendix 3.3).**

Evstigneev et al. (2006, p. 9) add that the market selection process naturally creates feedback loops that allow for the improvement of portfolio rules: "Market selection processes create natural feedback loops that allow for the improvement of portfolio rules through adaptive learning." This process fosters the evolution of investment strategies towards more rational and optimized decisions. **(Appendix 3.3).**

4.2 Integrated Reasoning

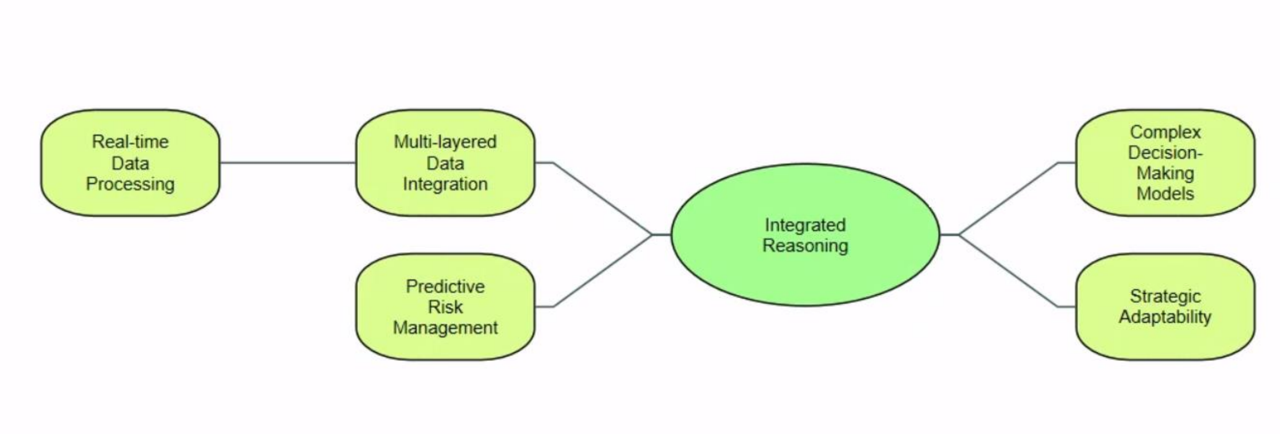


Figure 6. Mind map generated from NVivo 12 illustrating the key concepts of Integrated Reasoning in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

4.2.1 Multi-layered Data Integration

One of the key strengths of artificial intelligence (AI) in financial portfolio management is its ability to integrate data from multiple sources and process it in real-time. This multi-layered integration enables AI systems to react instantly to market fluctuations and adjust investment strategies accordingly. The Confidence Weighted Mean Reversion (CWMR) strategy is a great example of this, as it effectively exploits first- and second-order market information to optimize portfolios. *"The CWMR strategy is able to effectively exploit the power of mean reversion for on-line portfolio selection"* (Li et al., 2013, p. 434). **(Appendix 4.1).**

In real time, these algorithms dynamically adjust portfolio allocations based on immediate changes in asset prices. This not only captures short-term market trends but also allows for optimized investment decisions at every moment.

This real-time data processing is enhanced by continuous feedback loops, allowing AI agents to adjust risk and returns based on market performance. *"The portfolio rebalancing strategy integrates feedback from market performance, allowing the agent to adjust risk and return preferences in real time"* (Jiang et al., 2020, p. 4). The results of these dynamic adjustments often outperform static strategies. Li et al. explain, *"Through extensive numerical experiments on a variety of real testbeds, we show that the proposed CWMR algorithms significantly surpass a number of state-of-the-art strategies in terms of long-term compound return"* (Li et al., 2013, p. 435). **(Appendix 4.1).**

4.2.2 Complex Decision-Making Models

Financial decision-making is becoming increasingly complex as markets evolve rapidly. AI plays a crucial role in managing this complexity by using models capable of processing a large number of variables in real-time. Reinforcement Learning (RL) methods, for instance, allow AI agents to actively learn from market conditions by trying different trading actions and adjusting their strategies accordingly. As Park et al. (2019) explain, *"In RL methods, a learning agent can understand a complex financial environment by attempting various trading actions and revising its trading action policy"* (Park et al., 2019, p. 2). **(Appendix 4.2).**

Rather than simply trying to predict market winners, some AI strategies rely on statistical relationships between different stocks to exploit market variations and outperform the best-performing individual stocks. *"Our approach relies on predictable statistical relations between all pairs of stocks in the market"* (Borodin et al., 2004, p. 1). **(Appendix 4.2).**

AI systems also adapt their decisions based on changing market conditions, constantly evolving through dynamic rule bases. *"The trading rules adapt to changing market conditions, leading to an evolving rule-base that changes with time"* (Ghandar et al., 2009, p. 71). These models are often enhanced by hybrid systems, which combine artificial neural networks with other techniques to improve the accuracy of investment forecasts and decisions. **(Appendix 4.2).**

4.2.3 Predictive Risk Management

Risk management is one of the most critical challenges in portfolio management, and AI offers powerful tools to proactively anticipate and manage these risks. AI algorithms learn from past and present market conditions to establish rules that perform well even in dynamic market environments. *"The system learns to form rules that can perform well in dynamic market conditions"* (Ghandar et al., 2009, p. 71). **(Appendix 4.3).**

These algorithms often include evolutionary computation techniques, where strategies are tested, adjusted, and improved in real-time through a simulated process of natural selection. *"Evolutionary computation allows for dynamic adaptation, where agents improve their strategies through trial and error"* (Evstigneev et al., 2006, p. 7). **(Appendix 4.3).**

Moreover, the use of genetic algorithms enables efficient portfolio optimization while minimizing risks. *"The overall learning system incorporates a GA, a niching method, and several other components"* (Mahfoud & Mani, 1996, p. 545). Strategies such as constant portfolio rebalancing can also mitigate the risks associated with sudden market fluctuations. *"A constant rebalancing strategy can often take advantage of market fluctuations to achieve a return significantly greater than that of the best stock"* (Borodin et al., 2004, p. 2). **(Appendix 4.3).**

4.2.4 Strategic Adaptability

One of AI’s key advantages in financial portfolio management is its continuous adaptability to changing market conditions, allowing investors to adjust their strategies in real time to optimize returns. As Pan et al. (2006) note, "Intelligent finance represents a new direction [...] in the quest for absolute positive and nontrivial returns in investing and trading" (Pan et al., 2006, p. 1). **(Appendix 4.4).**

Strategic adaptability in AI relies on evolutionary learning algorithms that continuously refine investment strategies with each iteration. "The rules adapt to changing market conditions, leading to an evolving rule-base that changes with time" (Ghandar et al., 2009, p. 71). These algorithms allow AI systems to react quickly to market fluctuations while improving trading decisions over time. **(Appendix 4.4).**

The integration of machine learning into trading models allows for real-time adaptation, providing greater responsiveness to economic changes. "Learning agents can adapt their strategies using their observed experiences on each real trading day" (Park et al., 2019, p. 2). Ultimately, portfolios optimized through these systems benefit from continuous dynamic rebalancing to maximize returns while managing risks. *"The portfolio is constructed within a dynamic rebalance strategy to obtain high overall returns while keeping the risk under control"* (Jiang et al., 2020, p. 4). **(Appendix 4.4).**

4.3 Knowledge Discovery in Financial Portfolio Management with AI

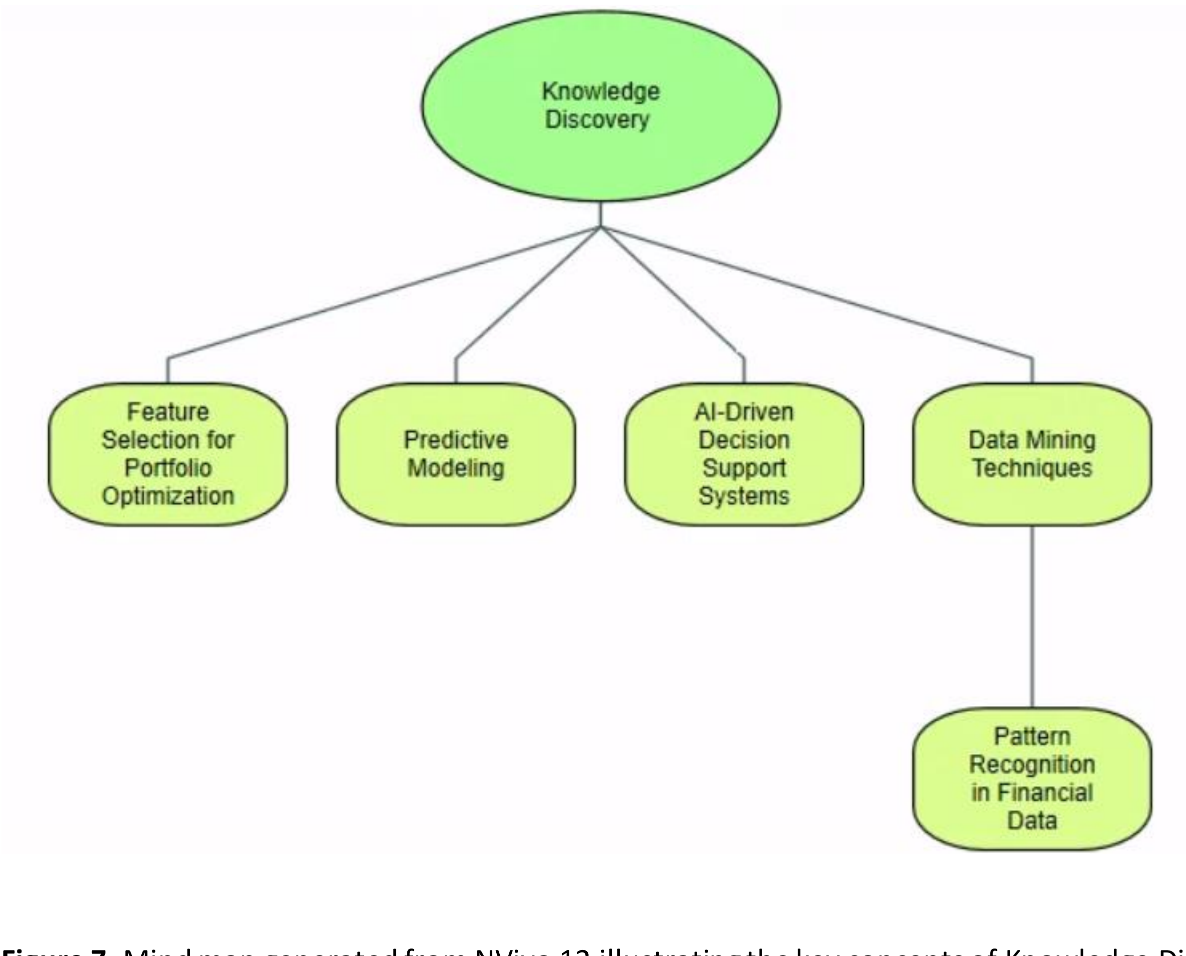


Figure 7. Mind map generated from NVivo 12 illustrating the key concepts of Knowledge Discovery in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

In the rapidly evolving world of finance, managing vast amounts of complex data has become essential. Modern portfolio management is no longer just about collecting this data, but about extracting actionable knowledge from it. Artificial Intelligence (AI) plays a crucial role in this process through approaches like *knowledge discovery*. This approach transforms raw data into valuable insights, helping portfolio managers make informed decisions. AI tools, such as data mining, feature selection, predictive modeling, and AI-driven decision support systems, are revolutionizing how portfolio managers optimize their strategies and mitigate risks.

4.3.1 Data Mining Techniques

Data mining techniques are a cornerstone of knowledge discovery in financial portfolio management, allowing AI to identify patterns within vast datasets. These techniques enable the recognition of trends and anomalies that would otherwise remain hidden. Pattern recognition in financial data is critical for making accurate predictions and enhancing portfolio strategies.

For instance, data mining allows analysts to detect patterns in stock prices, which is crucial for managing volatility. These techniques are vital for forecasting and managing the risks associated with stock price fluctuations.

Another key aspect of pattern recognition is identifying trends that may indicate future market movements. AI systems can analyze large datasets to detect these trends. "Pattern recognition in stock prices and volumes plays an important role in forecasting asset performance and market trends" (Sutiene et al., 2024, p. 3). By identifying these trends, AI models can make more informed decisions on portfolio allocation and risk management. **(Appendix 5.1)**

Data mining and pattern recognition also help in analyzing large volumes of text-based financial data. As mentioned, "AI-driven text mining techniques have been effectively used for recognizing patterns within firm financial reports, offering insights into stock performance" (Pan et al., 2006, p. 2). This highlights the importance of combining structured and unstructured data for deeper analysis. **(Appendix 5.1)**

Furthermore, pattern recognition through AI enhances the accuracy of predictions, improving both short-term and long-term portfolio performance. "Advanced AI techniques, particularly in data mining and pattern recognition, have shown improved predictive accuracy in financial markets, contributing to better portfolio management decisions" (Bouteïna, 2021). These patterns are often based on historical trends that help forecast market volatility and investment risks. **(Appendix 5.1)**

Incorporating these techniques into financial analysis enables the detection of crucial signals that inform decisions. "Pattern recognition algorithms are increasingly being used to detect anomalies and trends in large financial datasets, providing early warnings of market shifts" (Liu et al., 2022, p. 5). By recognizing these signals early, portfolio managers can take preemptive actions to mitigate potential risks. **(Appendix 5.1)**

4.3.2 Feature Selection for Portfolio Optimization

In portfolio management, identifying the most important factors influencing portfolio performance is crucial. AI helps in this task through feature selection techniques, which reduce the noise from irrelevant data and focus on the most impactful elements. This approach allows for the construction of more efficient portfolios and enhances the accuracy of AI models in managing investments.

AI-based feature selection helps identify the key variables that impact asset management, improving portfolio performance. For example, "Deep learning can optimize an investment portfolio directly or establish a portfolio that mimics an index with a small set of assets" (Sutiene et al., 2024, p. 2). This demonstrates how reducing features can simplify portfolio management while maintaining effectiveness. **(Appendix 5.2)**

Optimizing portfolio management also involves dimensionality reduction, which prevents redundancy and helps detect latent factors in asset prices. "Dimensionality reduction methods can detect latent factors of a broad range of asset prices, which improves the construction of a well-diversified portfolio" (Sutiene et al., 2024, p. 2). These techniques lead to better-diversified portfolios by considering hidden information that may not be immediately apparent. **(Appendix 5.2)**

Feature selection not only improves performance but also enhances the generation of additional alpha by improving prediction accuracy. "AI techniques can contribute to portfolio management in many ways, improving the shortcomings of classical portfolio construction techniques and extending the opportunities to generate additional alpha" (Sutiene et al., 2024, p. 1). **(Appendix 5.2)**

By focusing on the most relevant variables, portfolio managers can enhance out-of-sample performance, outperforming traditional approaches. *"AI can produce better asset return and risk estimates and solve portfolio optimization problems under complex constraints, resulting in better out-of-sample AI-based portfolio performance than traditional approaches"* (Sutiene et al., 2024, p. 2). **(Appendix 5.2)**

4.3.3 Predictive Modeling

Predictive models allow portfolio managers to anticipate market movements by using historical data. AI excels in this area by creating models that learn from past data to forecast future trends. These predictions are crucial for adjusting investment strategies in response to changing market conditions.

Predictive modeling techniques are widely used across various financial domains, including customer credit risk evaluation and stock market trends. "ML techniques have been predominantly used for risk evaluation of customer credit scores and risks along with loan and insurance underwriting" (Fan et al., 2006, p. 8). This highlights the versatile application of these techniques in risk management. **(Appendix 5.3)**

AI uses predictive models to analyze past data and make forecasts about future asset behavior. "Researchers in recent years have sought to improve prediction by analyzing unstructured text from firm financial reports, such as companies' annual reports" (Pan et al., 2006, p. 1). Unstructured information, such as company annual reports, provides a rich source of data for analysis. The Artificial intelligence is able to determine the impact of words and decide is is good or not for a share for example. **(Appendix 5.3)**

With AI, portfolio managers can make more informed decisions by detecting market signals before they become visible to others. "ML-based algorithmic trading models monitor and analyze real-time data to detect patterns, thereby giving traders a distinct advantage over the market average" (Fischer & Krauss, 2018, p. 2). This ability to detect trends early offers a significant competitive advantage. This capacity allow AI to react very quickly but sometime the system share information's and doesn't really understand the meaning of a sentence, so in certain case this could be inefficient. **(Appendix 5.3)**

And last but not least, predictive models improve the accuracy of overall economic forecasts, very important skill in portfolio management. "Predictive analytics has been widely employed in exchange rate forecasts, in stock markets, while macroeconomic predictions and forecasts are key in portfolio management" (Fischer & Krauss, 2018, p. 5). **(Appendix 5.3)**

4.3.4 AI-Driven Decision Support Systems

AI-driven decision support systems are transforming how decisions are made by automating the exploration of financial data. These systems can analyze massive amounts of data in real time, providing portfolio managers with actionable insights when they are most needed.

One of the key plus of these systems is that they make AI models more transparent and understandable. *"La nature même de l'intelligence artificielle rend les décisions plus transparentes et mieux comprises par les utilisateurs finaux grâce à des systèmes explicatifs"* (Bouteïna et al., 2021,

p. 3). Sometimes we don't really understand why AI act like that, but this helps build trust in the decisions generated by automated systems, it's bring important value to this. **(Appendix 5.4)**

These systems also offer clear explanations for the decisions made, which is crucial in a field where decisions must be justified clearly. "We define an explanation as an information in a semantically complete format, which is self-sufficient and chosen according to the target audience regarding its knowledge" (Bouteïna et al., 2021, p. 5). **(Appendix 5.4)**

(Bouteïna, 2021) explore various Explainable Artificial Intelligence (XAI) approaches, emphasizing the need for transparency in AI systems. Key techniques include model-agnostic methods like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), which enhance interpretability across different models, as told (Wang, 2024), “"Explainable Artificial Intelligence (XAI) has become essential as AI systems increasingly influence critical domains, demanding transparency for trust and validation." This quote highlights the necessity of transparency in AI, especially when these systems impact significant areas of society above all in Finance market and portfolio management.

By automating the processing of financial data, AI-driven decision support systems make it easier to discover relevant insights quickly. "Recent XAI objectives have been defined in the state-of-the-art, for which specific approaches have been proposed" (Bouteïna et al., 2021, p.1). This accelerates decision-making processes in fast-changing financial environments. Thanks to that the AI can be also more comprehensive with itself and take better decisions. It's a win-win situation. **(Appendix 5.4)**

These systems also make portfolio management processes more transparent by drawing on lessons from knowledge discovery and representation learning domains. "In order to make black-boxes more transparent, XAI approaches should be more inspired and take advantage of past and recent works in Knowledge and Representation Learning domains" (Bouteïna et al., 2021, p.2). **(Appendix 5.4)**

4.4 Collective Behaviour related to the use of AI in financial portfolio management

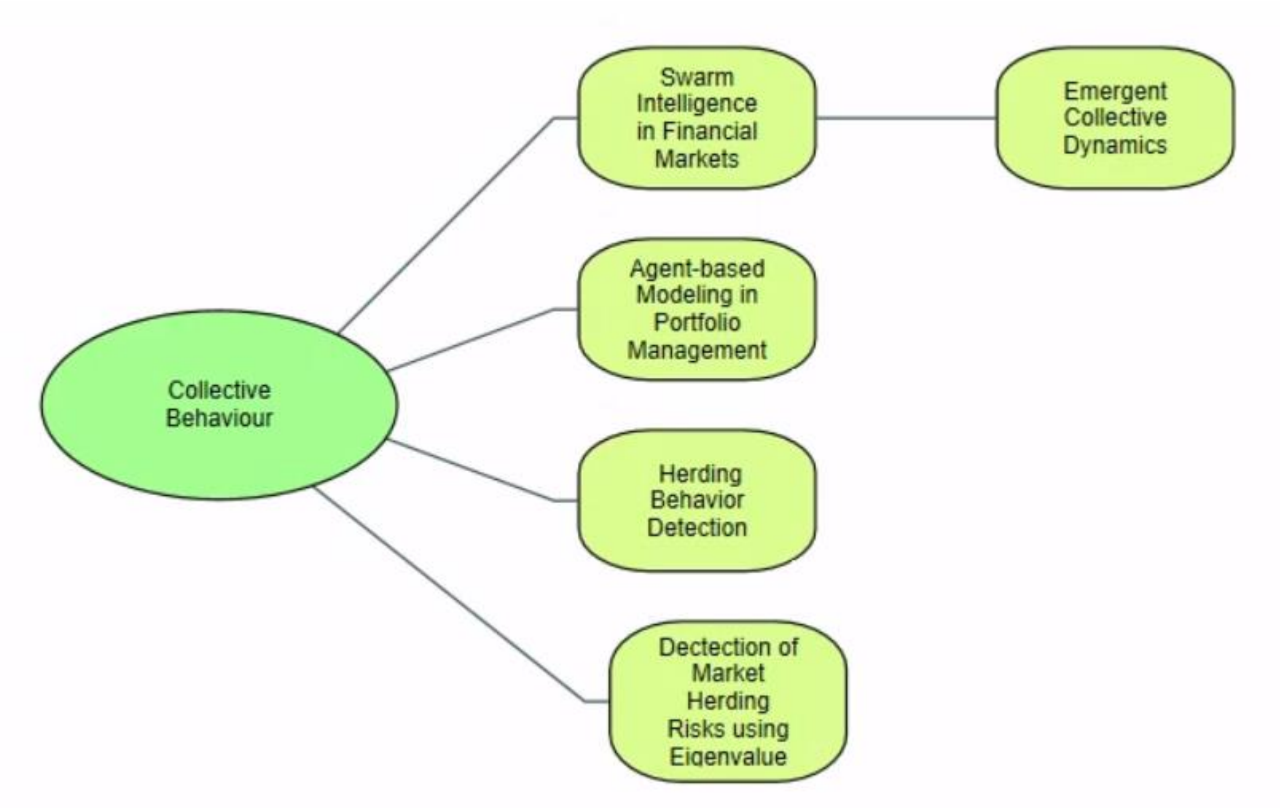


Figure 8. Mind map generated from NVivo 12 illustrating the key concepts of Collective Behaviour in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

4.4.1 Swarm Intelligence in Financial Markets

The concept of *swarm intelligence* is borrowed from nature, where collective behavior in groups such as swarms of ants or schools of fish leads to optimized decision-making. This concept is applied to financial markets to explain how the investment decisions of many actors (individuals and group) interact to create market trends. AI can harness this collective intelligence to adjust portfolios in real-time, especially during when it high volatility 's periods like Covid or mor recently USA election.

Financial markets often follow collective dynamics where simultaneous movements by many investors. "The collective dynamics of human society can exhibit emergent behaviors, which are often unpredictable from the standpoint of individual actions" (Bianconi et al., 2008, p. 4). This phenomenon is observed during market panics, where many actors adopt similar behaviors in response to the same events, it could create one big sell for financial title. **(Appendix 6.1)**

Modeling this type of behavior is essential to better anticipate market trends. "Market participants, acting independently, often create patterns of behavior that resemble swarm intelligence, influencing asset prices collectively" (Bianconi et al., 2008, p. 5). This collective behavior directly impact asset prices and should be considered in portfolio management in purpose to avoid taking the wave to late, the objective of that is to have advance on what's going on. **(Appendix 6.1)**

These emergent behaviors in financial markets highlight the importance of modeling collective decision-making in complex environments. "Swarm intelligence models have been increasingly applied in financial markets to simulate collective behavior during periods of high volatility" (Bianconi et al., 2008, p. 6). These models allow portfolio managers to adjust their strategies based on real-time market behavior. **(Appendix 6.1)**

One of the advantages of modeling collective behavior with AI is its ability to better understand the interconnections between investors and their actions. "systems are capable of capturing the emergent collective behavior in financial markets, helping to predict future market trends" (Bianconi et al., 2008). This ability to capture complex collective behaviors offers a significant advantage for portfolio managers looking to optimize their investment strategies. As (Niyazli, 2023) illustrate "This amalgamation enables the identification of collective irrational behavior, commonly known as herding in behavioral finance." This quote points to the phenomenon of herding, which is very important for understanding how collective behavior can have a impact in investment decisions and portfolio management. **(Appendix 6.1)**

Collective dynamics are not only observed during crises but also during sustained market growth, where investors follow similar trends. "Emergent collective dynamics can drive both bullish and bearish market trends, as investors mimic the behavior of others in response to perceived market movements" (Castellano et al., 2009, p. 4). Understanding these collective dynamics, in both bullish and bearish markets, is crucial for effective portfolio management. **(Appendix 6.1)**

4.4.2 Agent-based Modeling in Portfolio Management

The use of Agent-Based Modeling (ABM) in portfolio management has become indispensable for testing complex market behaviors and optimizing asset management. ABM allows for the creation of autonomous agents that interact in a virtual environment, executing various investment strategies, anticipating market trends, and managing risks. These agents are multifunctional and often equipped with learning mechanisms, such as Reinforcement Learning, to adapt their strategies to real-time market changes.

One particularly interesting system proposed by Huang & Tanaka in 2022 is the MSPM (Modularized and Scalable Multi-agent Reinforcement Learning-based System for Financial Portfolio Management), which is based on two types of agents. "MSPM involves two types of asynchronously-updated modules: Evolving Agent Module (EAM) and Strategic Agent Module (SAM)" (Huang & Tanaka, 2022). In this system, each EAM is dedicated to a specific asset, analyzing heterogeneous data such as financial news and historical prices using Deep Q-Networks (DQN). "An EAM takes heterogeneous data and utilizes a DQN-based agent to produce signal-comprised information" (Huang & Tanaka, 2022). The SAM, on the other hand, integrates this information to reallocate the assets within a portfolio. Thanks to this versatility, agents can adapt and be reused as needed, allowing for flexible and scalable portfolio management. **(Appendix 6.2)**

In a more advanced version, the Adaptive Predictive Portfolio Management Agent proposed by Kolonin et al. (2023) extends ABM's progress by introducing experiential learning. "The agent executes multiple strategies virtually and selects only a few for real execution" (Kolonin et al., 2023). This approach enables agents to test different strategies in a virtual environment before applying them in real-world settings. By leveraging both historical data and social media trends, these agents can predict market price movements, thereby optimizing the financial performance of the portfolio. **(Appendix 6.2)**

Systems like MSPM leverage Reinforcement Learning mechanisms to maximize long-term returns by continuously adjusting decisions based on market feedback. "The agent in EAM observes state vt, which consists of the designated asset's recent n-day historical prices st and sentiment scores ρt" (Z. Huang & Tanaka, 2022). These agents make decisions regarding the buying or selling of financial assets based on the received signals. This process enhances accumulated returns and dynamically adjusts decisions according to market fluctuations (Huang & Tanaka, 2022). **(Appendix 6.2)**

Kolonin et al. (2023) also introduced a multi-strategy analysis, where agents simultaneously test various strategies in a virtual environment to identify those that yield the best returns. "The multi-strategy adaptive portfolio management agent experiments with multiple strategies concurrently in a virtual environment" (Kolonin et al., 2023). This ability to dynamically adjust asset allocation based on market conditions optimizes portfolio management while minimizing risks associated with price fluctuations. **(Appendix 6.2)**

4.4.3 Herding Behavior Detection

Herding Behavior, a phenomenon where investors imitate the actions of a larger group, is reproducible in portfolio management. It can lead to irrational market movements, often driven by emotional reactions now rather than fundamental analysis. Detecting and understanding herding behavior is an essential step for portfolio managers who seek to mitigate its effects and improve decision-making. Today, artificial intelligence plays a central role in automating the detection of herding behavior, enabling faster and more precise analysis of these sudden market movements.

Herding behavior is particularly visible in financial markets, where it causes "significant price distortions," as noted by Howard (n.d). In his study, Behavioral Portfolio Management (BPM), he suggests that crowds follow each other, driven by fear of losses and/or social validation, influencing and dominating market movements. "Emotional investors make their decisions based on what Daniel Kahneman refers to as System 1 thinking: automatic, loss-avoiding, and quick" (Howard, n.d.). With advancements in AI, it has recently become possible to automatically model these behaviors through algorithms that capture emotional buying or selling patterns, allowing for the prevention of herding waves before they become too significant. **(Appendix 6.3)**

An effective method for detecting herding behavior involves analyzing the correlations and fluctuations in stock prices. According to Bury (2014), "a maximum entropy approach can describe the complex structure of financial systems and detect collective behaviors such as herding." He further explains that "pairwise maximum entropy models" are particularly useful for modeling simultaneous movements and collective trends in financial markets (Bury, 2014). Artificial intelligence can automate this analysis in real-time, continuously monitoring market movements to detect abnormal trends, doing so at a speed and scale that traditional methods cannot match. **(Appendix 6.3)**

Howard (n.d) discusses how general emotion can significantly distort market prices. He argues that price distortions are measurable and persistent, driven by "emotional reactions of investors to market events," which are not always based on rational analysis (Howard, n.d). AI algorithms, such as those based on machine learning, can capture these distortions by analyzing vast amounts of data, including market sentiments extracted from social media, discussion forums, and news. This enables the rapid identification of extreme distortion periods caused by collective emotional reactions.

Unlike emotional crowds, Behavioral Data Investors (BDIs) rely on "thorough and extensive analysis of available data," using what Kahneman refers to as System 2 thinking: "effortful, high-concentration, and complex" (Howard, n.d). BDIs are better positioned to detect and exploit inefficiencies caused by herding behavior, as they focus on long-term, data-driven strategies rather than short-term emotional responses. By integrating AI into these analyses, BDIs can automate the decision-making process, relying on predictive models that anticipate crowd reactions before they lead to irrational market movements. These systems are among the most advanced in analyzing collective thinking, as they combine short- and long-term analyses. With AI and deep learning, they learn and reflect on how a collective thinks and reacts, allowing them to stay one step ahead and anticipate market movements. **(Appendix 6.3)**

4.4.4 AI-Driven Detection and Management of Market Herding Risks Using Eigenvalue Analysis

In financial portfolio management, the detection and mitigation of collective market risks, such as herding behavior, is crucial for minimizing systemic risk and improving investment strategies. Herding behavior, where a large group of investors mimics the actions of others, can lead to sudden market fluctuations and irrational price movements. By applying Artificial Intelligence (AI) to eigenvalue analysis in cross-correlation matrices, it becomes possible to detect these patterns early and mitigate their impact on portfolios. This approach draws on concepts such as Random Matrix Theory (RMT) and Wavelet Multiscaling, providing a powerful framework for identifying genuine correlations while filtering out noise from financial data.

A core method for understanding collective behavior in financial markets is the analysis of cross-correlation matrices. These matrices capture the relationships between different assets and reveal the extent to which they move together. In moments of market distress, such as crashes or periods of high volatility, the correlations between assets often increase significantly, leading to higher systemic risks.According to Conlon (n.d), Random Matrix Theory (RMT) plays a crucial role in filtering out the noise in these correlation matrices to focus on meaningful patterns: "The RMT filtered correlation matrix is shown to improve the risk-return profile of a portfolio of Hedge Funds". AI can be employed to automate this filtering process, enabling the real-time monitoring of market conditions. Through eigenvalue analysis, AI models can identify when the largest eigenvalues deviate significantly from their expected distribution, signaling heightened correlation between assets and potential herding behavior.**(Appendix 6.4)**

One of the key challenges in detecting herding behavior is distinguishing between normal market movements and those driven by irrational collective behavior. AI algorithms, particularly those leveraging machine learning (ML), can analyze large datasets in real time, identifying when asset prices move together more frequently than expected. As highlighted by Kumar (n.d), bio-inspired algorithms such as Ant Colony Optimization (ACO), "Ants were able to make shorter feasible tours. Their simulations demonstrated that ACO can give good paths for both symmetric and asymmetric instances of TSP. This algorithm outperformed simulated annealing and demonstrated that ACO can give good paths for both symmetric and asymmetric instances of TSP." can be adapted to track asset price movements and identify the best moments for portfolio rebalancing. In a similar way, AI algorithms can continuously monitor eigenvalue dynamics in cross-correlation matrices to detect synchronized market behavior. This is particularly effective when applied to high-frequency trading data, where changes in eigenvalue distributions can provide early warning signals of collective market risks. **(Appendix 6.4)**

In addition to RMT, the use of Wavelet Multiscaling techniques can further enhance the detection of collective behaviors by analyzing correlations across different time scales. Conlon's research shows that scaling properties of correlations are essential for risk management: "The scaled correlation matrices are then used as inputs to a portfolio optimization, to judge the effect of time granularity on Risk Management".**(Appendix 6.4)**

By applying AI-driven wavelet transforms to financial time series data, portfolio managers can assess the correlation dynamics at various frequencies (e.g., daily, weekly, intraday). This multi-scale analysis helps identify periods when correlations between assets are abnormally high at certain time scales, indicating increased collective behavior. AI systems can then automatically adjust portfolio allocations to mitigate risks during these periods, enhancing both the short-term and long-term stability of the portfolio.

One of the most valuable applications of AI in eigenvalue analysis is its potential for early detection of market crashes. As noted by Conlon (n.d), large eigenvalues often correspond to collective behaviors that precede significant market downturns: "The relationship between index returns and relative eigenvalue size is examined, to provide insight on the collective behavior of traders" .AI can continuously monitor the largest eigenvalues in a portfolio's correlation matrix. When these eigenvalues grow disproportionately large, it signals that many assets are moving in unison, which can indicate that herding behavior is pushing the market toward a crash. In this context, AI-based systems can issue warnings to portfolio managers, allowing them to reallocate assets to reduce exposure to systemic risk. **(Appendix 6.4)**

By integrating AI with eigenvalue analysis and wavelet multiscaling, portfolio managers can implement dynamic strategies to mitigate collective market risks. For example, AI algorithms can trigger automatic rebalancing of portfolios when certain thresholds in eigenvalue dynamics are crossed. This ensures that portfolios remain diversified and less exposed to the adverse effects of herding behavior.

4.5 Memory Augmentation in AI-baised Portfolio Management

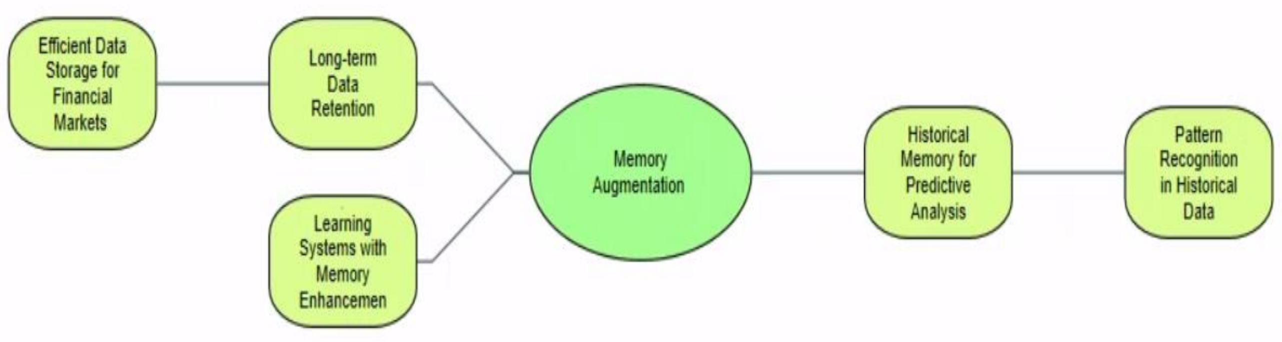


Figure 9. Mind map generated from NVivo 12 illustrating the key concepts of Memory Augmentation in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

4.5.1 Long-term Data Retention

In financial portfolio management, long-term data retention is crucial for allowing AI models to track the evolution of market trends over time. Through memory augmentation, AI can store large volumes of data over extended periods, helping to adjust decisions based on historical performance. This capability enhances the robustness of predictions and investment strategies.

As Amagai et al. mention, *"In asset management businesses, it is common to operate in the medium to long term due to the increase in operational burden and transaction costs. However, to compose a longer-term model, the number of usable learning data decreases due to the larger observation interval of the data; hence, the model performance declines"* (Amagai et al., p. 1). To address this decline in performance over the long term, AI systems use data augmentation techniques to combine information across different time scales. This allows them to maintain a high level of generalization ability. *"To solve this problem, a data augmentation was conducted by the combined use of data of multiple time scales, confirming its effectiveness to maintain a better generalization ability of trained models, even if the target task of machine-learning methods is longer term"* (Amagai et al., p. 1). **(Appendix 7.1)**

Thus, memory augmentation strengthens portfolio management by using not only short-term data to rebalance portfolios but also longer-term data. *"Data augmentation was applied for portfolio management, using both main timescale data for rebalancing the portfolio and shorter timescale data to enlarge the number of learning data"* (Amagai et al., p. 2). This approach makes models more efficient in contexts where data is limited or fragmented. **(Appendix 7.1)**

Furthermore, memory augmentation allows AI systems to retain data over longer periods, improving the models' ability to generalize their predictions. *"By utilizing memory augmentation, AI models can retain data over longer periods, allowing systems to improve the generalization ability of trained models"* (Amagai et al., p. 2). **(Appendix 7.1)**

In financial markets, where data is massive and complex, having efficient memory structures is crucial. These structures not only store large amounts of data but also ensure rapid access to it. As Munkhdalai et al. mention, *"Efficient memory structures should be able to scale gracefully with the quantity of information stored, especially in financial markets where large amounts of data must* *be rapidly retrieved"* (Munkhdalai et al., p. 1). This ensures that relevant information is available without delays, a critical feature for portfolio management. **(Appendix 7.1)**

Memory-augmented neural networks, or MANNs, play a key role in this process by supporting efficient data storage and retrieval. *"Memory-augmented neural networks (MANNs) support efficient data storage and retrieval operations, ensuring that relevant financial information can be accessed without delays"* (Munkhdalai et al., p. 3). This efficiency enhances the speed of decisions in an environment where every second counts. **(Appendix 7.1)**

4.5.2 Historical Memory for Predictive Analysis

The use of historical memory in AI systems strengthens predictive capabilities. By retaining historical data, AI can identify trends and anticipate future market movements, which is crucial for optimizing financial portfolios.

Memory augmentation enhances predictive analysis by allowing AI to store key financial data across different time scales, leading to more accurate forecasts. *"Memory augmentation supports better predictive analysis by allowing AI systems to retain key financial data across different time scales, leading to more accurate forecasts"* (Yang et al., p. 4). This approach enables the integration of historical data into predictive algorithms. **(Appendix 7.2)**

In particular, MEMGAN systems, which include memory augmentation, can decode historical financial data to identify interpretable patterns, aiding in forecasting market trends. *"The memory units within MEMGAN models decode historical financial data into interpretable patterns, which aids in forecasting market trends"* (Yang et al., p. 5). This allows a deeper understanding of market evolution through past data. **(Appendix 7.2)**

AI models can thus identify future anomalies by integrating historical data into predictive algorithms, thanks to memory augmentation. *"By leveraging augmented memory, AI can integrate historical data into predictive algorithms, making it possible to identify future anomalies"* (Yang et al., p. 6). This process improves risk management for portfolio managers. **(Appendix 7.2)**

Pattern recognition in historical data is a key component of memory augmentation in AI systems. This allows AI to detect subtle trends that may not be immediately evident in traditional financial analyses. *"Patterns from historical data are extracted by neural memory systems, which enable better detection of trends and predictive performance in portfolio management"* (Amagai et al., p. 3). This pattern recognition ability is crucial for optimizing portfolio management. **(Appendix 7.2)**

Neural memory models are capable of identifying subtle market patterns that would otherwise go unnoticed by traditional analysis methods. *"Neural memory models help in recognizing subtle market patterns, which might otherwise go unnoticed in traditional financial analysis"* (Yang et al., p. 5). With this technology, portfolio managers can anticipate future market trends more effectively. **(Appendix 7.2)**

4.5.3 Adaptive Learning Systems with Memory Enhancement

Adaptive learning systems augmented with memory allow AI to continuously adjust investment strategies based on past performances and current market conditions. By retaining information from previous decisions, these systems improve their ability to quickly react to market fluctuations.

Recurrent neural networks augmented with memory facilitate adaptive learning by retaining past knowledge and applying it to new financial data. *"Recurrent neural networks with augmented memory mechanisms enable adaptive learning by retaining previous knowledge and applying it to evolving financial data"* (Munkhdalai et al., p. 2). This allows models to better adapt to constant changes in financial markets. **(Appendix 7.3)**

Additionally, these memory-augmented models rapidly adapt to market changes by incrementally learning from past portfolio decisions. *"Memory-augmented models rapidly adapt to changes in financial markets by incrementally learning from past portfolio decisions"* (Munkhdalai et al., p. 4). This process enables more agile and responsive portfolio management. **(Appendix 7.3)**

Writing to memory allows systems to store information about past financial conditions, helping them dynamically adjust investment strategies. *"Writing to memory enables the system to store information about past financial conditions, which helps adjust investment strategies dynamically"* (Yang et al., p. 6). This flexibility enhances portfolio management based on new market data. **(Appendix 7.3)**

Finally, incremental learning within memory-augmented models is essential for managing portfolios, as it allows AI to adapt to new market conditions while retaining critical information from previous periods. *"Incremental learning within memory-augmented models is essential for managing portfolios, as it allows AI to adapt to new market conditions while retaining critical past information"* (Munkhdalai et al., p. 6). This continuous learning capability strengthens financial portfolio management. **(Appendix 7.3)**

4.6 Higher Dimensionality in Financial Portfolio Management with AI

Figure 10. Mind map generated from NVivo 12 illustrating the key concepts of Higher Dimensionality in AI-driven Financial Portfolio Management - Computer-Assisted Qualitative Data Analysis Tool

4.6.1 Feature Selection in High-Dimensional Data

In the realm of portfolio management, the analysis of high-dimensional data has become indispensable, especially with the increasing volume of available data. AI leverages sophisticated techniques to select the most relevant variables from a large number of dimensions, thereby improving the accuracy of predictive models. The importance of these techniques is highlighted by Fan and Li: *"Technological innovations have revolutionized the process of scientific research and knowledge discovery. The availability of massive data and challenges from frontiers of research and development have reshaped statistical thinking"* (Fan & Li, 2006, p. 1).

In many cases, the focus of researchers and financial analysts is not on individual parameters but on the overall impact of the selected data. *"In high-dimensional data mining, it is helpful to distinguish two types of statistical endeavors. In many machine learning problems, the interests often center around the classification errors, or returns and risks of selected portfolios rather than the accuracy of estimated parameters"* (Fan & Li, 2006, p. 2). Therefore, AI allows filtering and selecting the most impactful features, facilitating the optimization of investment decisions.

Dimensionality reduction and feature extraction are essential in all high-dimensional mathematical problems, particularly in financial applications. *"Dimensionality reduction and feature extraction play pivotal roles in all high-dimensional mathematical problems. The intensive computation inherent in these problems has altered the course of methodological development"* (Fan & Li, 2006, p. 3). Efficient management of these data allows better use of AI algorithms.

Finally, these challenges arise across various fields, including financial engineering and risk management: *"The challenges of high-dimensionality arise in diverse fields of sciences and the humanities, ranging from computational biology and health studies to financial engineering and risk management"* (Fan & Li, 2006, p. 4).

Principal Component Analysis (PCA) is a widely used method for reducing dimensionality in complex datasets. *"Principal Component Analysis (PCA) is widely used in dimensionality reduction to tackle high-dimensional data and reduce the feature space, thus improving model performance and simplifying portfolio selection"* (Gyamerah et al., 2023, p. 12). PCA helps AI models focus on the most important features, improving decision-making.

One of the main advantages of PCA is that it reduces the computational burden of machine learning models, which is essential when working with large financial datasets. *"PCA significantly decreases the computational burden of machine learning models by extracting the most relevant features from the dataset, which makes it a popular method in high-dimensional financial data"* (Gyamerah et al., 2023, p. 15). This allows models to optimize their performance without compromising the quality of predictions.

Moreover, PCA reduces the risks of overfitting, a common issue with high-dimensional data: *"High-dimensional data often leads to overfitting, and PCA helps to mitigate this issue by focusing on key components rather than the entire dataset"* (Gyamerah et al., 2023, p. 17). This ensures that AI models remain robust in the face of market changes.

4.6.2 Handling High-Dimensional Data for Portfolio Optimization

In financial portfolio management, handling large amounts of high-dimensional data is crucial for optimizing investment strategies. Data must be processed quickly and efficiently to allow managers to make informed decisions. As Lu et al. point out, *"Many financial analyses require timely data to support time-critical decision making. In this paper, we develop a novel indexing method to reduce latency of querying high-dimensional data, improving its efficiency in portfolio management"* (Lu & al., n.d., p. 2).

Optimizing financial portfolios often relies on the ability to query and analyze large datasets in real-time. *"We focus on the latency issue and develop a novel method to improve the query processing speed for high-dimensional financial data in relational databases"* (Lu & al., n.d., p. 2). This significantly reduces the time needed to extract key insights from complex data.

Efficient algorithms and models are essential for managing these massive datasets, allowing portfolio managers to act quickly in a constantly changing market environment. *"Handling high-dimensional data in financial portfolio management requires efficient algorithms and models capable of processing vast amounts of variables in real-time"* (Lu & al., n.d., p. 4). This improves the accuracy and efficiency of investment decisions.

Additionally, the PL-tree indexing method developed by Lu and colleagues offers significant improvement in the processing speed of high-dimensional data. *"Our novel PL-tree indexing technique significantly improves the timeliness and performance of high-dimensional data in financial applications, especially for time-critical decisions"* (Lu & al., n.d., p. 5).

4.6.3 Risk Management Using High-Dimensional Data

Risk management in financial markets increasingly requires the use of high-dimensional data. These large datasets allow better assessment of risks and the identification of hidden patterns. As Fan and Li note, *"The challenges of high-dimensionality in financial engineering often involve assessing risks across large, complex datasets, which requires both innovative algorithms and robust statistical models"* (Fan & Li, 2006, p. 1).

AI plays a fundamental role in extracting relevant features from these complex datasets, thereby improving the assessment and management of financial risks. *"Using machine learning, AI systems can extract relevant features from high-dimensional data to assess and mitigate financial risks"* (Becker, 2015, p. 12). By processing massive amounts of data, AI systems can detect subtle patterns and anomalies that may have gone unnoticed.

The importance of methods based on massive data is becoming increasingly evident, with AI systems able to identify patterns and anomalies in these complex datasets. *"The availability of massive amounts of data in finance necessitates methods like machine learning to process and identify patterns in high-dimensional data for risk management"* (Becker, 2015, p. 25). This ability to detect hidden risks helps prevent potential financial crises.

By leveraging these high-dimensional datasets, AI systems can significantly enhance financial risk assessments and identify potential anomalies or risks hidden within complex datasets. *"By leveraging high-dimensional data, AI systems can significantly enhance financial risk assessments, identifying potential anomalies or risks hidden in complex datasets"* (Becker, 2015, p. 30).

Detecting anomalies in complex datasets is essential for preventing crises or unforeseen events in financial markets. AI-driven techniques such as Local Outlier Factor (LOF) and Isolation Forest are crucial for identifying these anomalies in high-dimensional data environments. *"AI-driven anomaly detection techniques, such as Local Outlier Factor (LOF) and Isolation Forest, are essential for detecting anomalies in high-dimensional financial data, improving risk management"* (Agrawal, n.d., p. 3).

These algorithms take into account complex relationships between data points, elements often overlooked by traditional techniques. *"Anomaly detection algorithms, particularly in high-dimensional spaces, must account for complex relationships between data points that traditional techniques often overlook"* (Agrawal, n.d., p. 4). This allows for better risk monitoring in volatile market conditions.

By integrating anomaly detection into predictive analytics, financial firms can identify and respond to risks in real-time, reducing the likelihood of major market disruptions. *"By integrating anomaly detection with predictive analytics, financial firms can identify and respond to risks in real-time, reducing the likelihood of significant market disruptions"* (Agrawal, n.d., p. 6).

Model-based anomaly detection approaches, such as Support Vector Machines (SVM) and Random Cut Forest, are particularly effective in high-dimensional datasets for identifying deviations from expected market behavior. *"Model-based anomaly detection approaches, such as Support Vector Machines and Random Cut Forest, are particularly effective in high-dimensional datasets for identifying deviations from expected market behavior"* (Agrawal, n.d., p. 8).

4.6.4 Machine learning Models for hight-dimensional Data

In the world of financial portfolio management, technological advancements have paved the way for machine learning models capable of processing vast and complex datasets. These innovations are transforming how we predict and analyze financial markets in an increasingly dynamic environment. As Fan and Li emphasize, "Technological innovations have had a deep impact on society and scientific research. They allow us to collect massive amounts of data at relatively low cost" (Fan & Li, 2006, p. 1)(0602133v1). The availability of large datasets presents enormous opportunities in portfolio management but also introduces challenges related to dimensionality and data complexity.

One of the first hurdles in dealing with large datasets, especially in finance, is normalization, which ensures that the data is free from systematic biases. As highlighted by Fan and Li, "In the analysis of microarray data, one of the first statistical challenges is to remove systematic biases, which is collectively referred to as normalization in the literature" (Fan & Li, 2006, p. 4). This step is critical to ensure that financial models produce reliable forecasts, particularly when dealing with large, diverse datasets. **(Appendix 8.4)**

Among the many tools available for managing complex, high-dimensional financial data, Support Vector Machines (SVMs) stand out. As Rubio Adeva notes, these models "optimize a line that is furthest from two data classes, which helps manage the complexity of high-dimensional datasets" (Rubio Adeva, 2023, p. 22). This ability to separate data points effectively is incredibly valuable in portfolio management, where distinguishing between meaningful financial signals and random market noise is key to making sound investment decisions. **(Appendix 8.4)**

Furthermore, the integration of **artificial intelligence (AI)** into financial portfolio management adds significant value, particularly in terms of security and predictive accuracy. As Agrawal explains, "AI systems can quickly identify suspicious activities that deviate from the norm by training machine learning algorithms on large datasets of normal and malicious behavior" (Agrawal, n.d., p. 3). In portfolio management, these AI-driven systems can help mitigate risks by flagging anomalies in transactions or unexpected market fluctuations. **(Appendix 8.4)**

The use of **neural networks** in financial data analysis is also gaining traction. As Rubio Adeva points out, "The neural network achieved both the best AUC-ROC (0.889) and the best average precision (0.192), indicating its superior performance in dealing with high-dimensional data" (Rubio Adeva, n.d., p. 3). This high level of performance makes neural networks particularly valuable in portfolio management, where accurate predictions of returns are crucial for optimizing asset allocation and managing risks. **(Appendix 8.4)**

Finally, techniques like **Principal Component Analysis (PCA)** are often used to reduce dimensionality and enhance model performance. Agrawal notes, "Dimensionality reduction methods such as Principal Component Analysis (PCA) or Autoencoders may be used to reduce the number of dimensions, helping to alleviate the curse of dimensionality" (Agrawal, n.d., p. 3). This is especially relevant in portfolio management, where many financial variables interact in complex ways, and reducing the data to its most essential components can improve efficiency and decision-making. **(Appendix 8.4)**

5 Discussion

5.1 Limitations, reliability and validity

The use of artificial intelligence (AI) for financial portfolio analysis and management has expanded rapidly in recent years. However, while algorithms have been developed to assist professionals in analyzing massive amounts of data, the application of advanced techniques such as deep learning, integrated reasoning, and memory augmentation remains relatively recent in this field. Despite numerous tests and promising results, these AI systems remain largely limited to **robo-advisor** roles. They are not yet capable of fully autonomously managing a financial portfolio, particularly for large-scale commercial purposes. AI systems developed in recent years, such as **MEMAPM**, are primarily used for research purposes and have been tested on historical data rather than in real-time market scenarios. This limited application makes it challenging to claim with certainty that these systems will operate at 100% efficiency in dynamic, real-world conditions.

In terms of **reliability**, the approaches employed in this thesis rely on **secondary data**, primarily derived from academic publications and industry reports. These sources were carefully selected, prioritizing the most recent and relevant publications to ensure consistency in the data collection and analysis process. The sources used were verified for credibility, and the consistency of the findings was validated through a systematic approach to selecting relevant publications.

To ensure the **validity** of this research, the methodologies used for selecting publications and conducting the analysis were designed with rigor. The goal was to ensure that the conclusions regarding AI's impact on financial portfolio management are based on solid, transparent foundations.

Furthermore, all sources used in this study have been properly cited to avoid any issues of plagiarism and to maintain the academic integrity of the work. While limitations do exist, this study provides a comprehensive overview of the evolution and use of AI in financial portfolio management, highlighting both technological advances and future challenges.

5.2 Answering the research questions

Throughout this research, these main questions were asked by the author:

RQ1: What is the historical evolution of artificial intelligence in financial portfolio management?

RQ2: How is AI currently applied in financial portfolio management, and what are the main benefits and limitations associated with its use?

RQ3: How does AI impact investment decision-making and risk management in contemporary financial portfolio management practices?

RQ4: What are the future prospects and challenges for AI in financial portfolio management?

The integration of artificial intelligence (AI) into financial portfolio management has progressively expanded over several decades. Initially limited to simple rule-based models and algorithms, AI started gaining momentum with increased computational power and the ability to process large amounts of data. In the early 2000s, the first AI applications in portfolio management were mainly focused on predictive analysis, using tools like neural networks. The true transformation occurred with the advent of machine learning and deep learning, which significantly enhanced the accuracy of forecasts and the automation of decision-making processes. These innovations have paved the way for more extensive AI usage in the financial sector, marking key milestones in its evolution, as AI continues to evolve rapidly today

Today, AI is widely used in portfolio management through automation tools, real-time data analysis, and risk management systems. AI-powered portfolio platforms allow managers to process vast volumes of data from various sources, such as economic trends, financial news, and even social media sentiment. These systems offer significant advantages in terms of speed, accuracy, and the ability to identify complex patterns in market data. However, there are limitations, mainly due to the reliance on historical data used to train AI models, which may restrict these systems' ability to predict unprecedented or extreme events. Additionally, while AI can automate many tasks, it cannot fully replace human expertise, particularly in complex decision-making processes

AI has transformed investment decision-making by providing portfolio managers with real-time data analysis tools to make informed decisions. Predictive AI models can detect emerging trends and market anomalies, enabling managers to anticipate market movements and react proactively. In risk management, AI continuously monitors market conditions, allowing portfolios to be adjusted in real-time to maintain an optimal risk level. However, while AI enhances risk management capabilities, it also introduces specific risks, such as model risk, where assumptions underlying the models may not accurately reflect real market conditions

The future of AI in financial portfolio management looks promising, with numerous innovations underway. Advances in fields such as deep learning and reinforcement learning are poised to make portfolio management systems even more autonomous and efficient. The integration of new data sources, including non-financial information like ESG (environmental, social, and governance) data, is expected to further enhance AI's capabilities in portfolio optimization. However, AI faces significant challenges, particularly in terms of regulation, ethics, and model transparency. Additionally, ensuring that AI systems continue to be overseen by human experts will be crucial to avoid potentially risky or biased automated decisions

5.3 Dialogue between key results and knowledge base

Zhang and Chen (2017) highlight the use of artificial intelligence (AI) algorithms to optimize portfolio selection, particularly through the "spectral clustering" (SC) method. I acknowledge that this method offers advantages in analyzing stock relationships and can improve decision-making. However, it is important to note that, despite these advances, AI algorithms in portfolio management are not yet fully autonomous. As I found in my own research, these systems mainly function as

"Robo-Advisors" rather than fully independent portfolio managers. Their effectiveness relies heavily on the use of historical data, and their real-time application remains limited. Thus, while the AI described by Zhang and Chen enhances portfolio performance, it does not yet fully replace human managers in real-time commercial contexts. Sutiene et al. (2024) examine traditional risk management methods, such as the Sharpe ratio, and introduce sentiment analysis through AI tools. My research confirms that these tools play a crucial role in real-time decision-making. However, as I highlighted in my analysis, the transparency of decisions made by these algorithms remains a challenge. The importance of "explainable AI," as emphasized by Sutiene et al., is paramount. Investors and regulators need to understand how these decisions are made, especially when large volumes of data are analyzed. I also observed that this lack of transparency limits the widespread adoption of AI systems in portfolio management.

Vidler (2024) explores the use of AI-based recommender systems to enhance portfolio management. While these systems are effective in providing data-driven recommendations, I found that they do not yet rival human decision-making when it comes to integrating complex macroeconomic factors or unexpected market events. Recommender systems still need to adapt to the intricacies of financial markets, particularly regarding volatility and collective behavior. However, I agree with Vidler on the growing importance of knowledge-based systems, though significant challenges remain in making these systems more robust and explainable. Liu et al. (2024) focus on the impact of Robo-Advisors and algorithmic trading strategies in wealth management. Their study highlights the advantages of AI in analyzing large datasets to optimize decision-making. However, based on my research, although Robo-Advisors are useful, they are still mainly focused on optimizing strategies based on historical data rather than real-time information. These systems are still primarily used in a research context, and their real-time effectiveness has yet to be fully demonstrated. Additionally, issues related to data quality and algorithm transparency remain significant challenges before these systems can be fully autonomous in commercial environments. While Liu et al. foresee a promising future for these technologies, I believe substantial adjustments will be needed before they can be widely adopted.

5.4 Compliance with research ethics guidelines

This research examined the application of artificial intelligence in financial portfolio management using secondary data from relevant publications. Throughout this study, I took care to ensure that the research adhered to ethical guidelines. Since this study relied on secondary data analysis, the primary ethical considerations focused on data privacy and confidentiality.

Firstly, the data used was sourced from reliable sources, including academic literature, governmental reports, and news articles. All sources were properly referenced to ensure compliance with copyright regulations. Moreover, I would like to emphasize that no copyrighted or intellectual property-protected information was incorporated into this work.

Secondly, I took care to minimize any potential risks arising from the use of sensitive information, particularly concerning personal data. To reduce these risks, only widely available and published data was used, and no human data was involved. I made sure not to employ any statistics linked to individual identities or specific groups to ensure complete risk mitigation.

Thirdly, I took measures to maintain data confidentiality by storing all information in a secure location with limited access. I did not share any data with third parties without the appropriate permissions, and I ensured that any data that could be traced back to individuals or organizations was anonymized.

Finally, being aware of the potential limitations and challenges of using secondary data, I mitigated these risks by cross-checking data from different sources and analyzing the data with a critical and unbiased approach.

6 Conclusions

6.1 Key Findings

The key findings of my study highlight several significant developments in the integration of artificial intelligence (AI) into financial portfolio management. These findings demonstrate both the potential and limitations of AI as a transformative force in this sector.

- **Dynamic Market Adjustment**: One of the critical findings is that AI-driven systems enable portfolios to adapt dynamically to market changes. By leveraging algorithms designed to adjust continuously in response to market fluctuations, these systems can maintain an optimized balance between returns and risks. This dynamic adjustment allows portfolio managers to react quickly to unforeseen events in the financial markets, enhancing the flexibility and resilience of portfolios.

- **Algorithmic Flexibility**: AI systems also provide a high degree of algorithmic flexibility. This adaptability ensures that portfolio strategies can evolve as new data becomes available. These algorithms continuously learn from historical patterns and market anomalies, allowing them to refine their decision-making processes. However, the challenge remains in ensuring the transparency and explainability of these AI-driven decisions, particularly for investors and regulators.

- **Predictive Risk Management**: AI's ability to predict risks more accurately is another key outcome. By analyzing large datasets and identifying potential market risks, AI can help portfolio managers preemptively adjust their strategies to mitigate exposure. This capability is especially relevant in managing high-volatility environments where timely decision-making is critical.

- **Integrated Reasoning and Complex Decision-Making**: AI systems are increasingly adept at integrating multiple layers of financial data to support complex decision-making. By synthesizing information from diverse sources, including market reports and macroeconomic data, AI tools facilitate more informed investment decisions. This integration allows for better portfolio optimization by considering various factors simultaneously.

- **Higher Dimensionality and Data Management**: The study highlights the growing importance of managing high-dimensional financial data. AI excels in processing vast amounts of data that contain numerous variables, making it particularly valuable in financial modeling and portfolio optimization. However, the challenge lies in managing this complexity without losing sight of the essential features that drive portfolio performance.

- **Knowledge Discovery**: AI has revolutionized knowledge discovery in portfolio management by employing techniques like data mining and predictive modeling. These tools help uncover hidden patterns in financial data that can inform better investment decisions. This discovery process enhances portfolio optimization by identifying opportunities and risks that would otherwise go unnoticed using traditional methods.

6.2 Managerial implications

The findings of this study have significant implications for portfolio managers, especially as artificial intelligence (AI) becomes more integrated into financial portfolio management. Based on the key insights from this research, the following recommendations are offered:

AI has proven its ability to enhance portfolio management processes, particularly in optimizing asset allocation and portfolio selection. Managers should invest in AI technologies, such as machine learning models and neural networks, which allow for the analysis of vast datasets and enable faster, more informed decision-making. Integrating AI will lead to overall improved portfolio performance while helping to mitigate risks.

Leveraging AI in risk management is crucial for increasing both precision and efficiency. Portfolio managers should use AI models to monitor markets in real-time and adjust strategies accordingly. This real-time adaptability enhances risk management in volatile and uncertain environments. In particular, machine learning algorithms help anticipate market anomalies and allow managers to adjust portfolios proactively.

One of the key challenges identified in this study is the transparency of AI-driven decisions. It's essential for portfolio managers to adopt explainable AI models to ensure that decisions are not only understandable to themselves but also to regulators and clients. This will build trust in AI systems and encourage broader adoption of these technologies.

Managers should ensure that their AI systems utilize a wide range of relevant data sources, including macroeconomic indicators, social trends, and social media sentiment. AI excels at analyzing these non-financial data points, enabling more optimized decision-making and uncovering new or overlooked investment opportunities.

Lastly, the study emphasizes the importance of establishing strong governance to oversee the use of AI in portfolio management. Managers must ensure that AI systems are used ethically, keeping in mind the risks associated with algorithmic biases and automated decision-making. This ethical oversight will help avoid potential pitfalls in the increasing reliance on AI.

6.3 Recommendations for future research

Based on the findings of this study, there are several areas where further research could significantly enhance our understanding of the role and potential of artificial intelligence (AI) in financial portfolio management. These recommendations aim to build upon existing knowledge while opening new doors for exploration.

First, conducting longitudinal studies to examine the long-term impact of AI on portfolio management strategies would be invaluable. While this research sheds light on the current applications of AI, it would be interesting to see how these tools evolve over time, especially as market conditions change. Such studies could focus on comparing the long-term performance of AI-driven portfolios against human-managed ones, revealing the growing capabilities of AI in real-world financial scenarios.

Another important avenue for future research involves exploring the ethical considerations and governance around AI in portfolio management. As AI becomes more autonomous in decision-making, questions around transparency and accountability become more pressing. Research into the development of "explainable AI" models—ones that offer clear reasons behind their investment choices—could address current concerns about the opacity of AI systems. Furthermore, understanding how evolving regulatory frameworks are shaping AI's role in finance would provide valuable insights into its future potential.

Exploring AI's ability to handle financial market anomalies and rare events is also an area that warrants further investigation. While current AI models are excellent at detecting patterns in large datasets, their ability to adapt during unpredictable market conditions, such as financial crises, remains uncertain. Future research could focus on creating AI models that are resilient and capable of responding effectively to unexpected market shifts.

Additionally, there is significant potential in investigating the integration of emerging AI technologies like reinforcement learning and quantum computing into portfolio management. Reinforcement learning, with its ability to continuously adapt to changing market conditions, could play a critical role in optimizing dynamic investment strategies. Similarly, quantum computing, which can solve complex optimization problems at an unparalleled scale, holds the promise of revolutionizing how AI processes large financial datasets. Future studies should explore the practical applications of these technologies and their impact on portfolio performance.

Lastly, AI's ability to incorporate non-traditional data sources—such as social media sentiment or environmental, social, and governance (ESG) factors—into portfolio management is another promising area for future research. As ESG criteria become increasingly important to investors, understanding how AI can analyze and integrate these diverse datasets could give portfolio managers a distinct advantage. Research in this area could also contribute to the growing field of sustainable investing.

By focusing on these areas, future research can contribute to a more comprehensive understanding of AI’s expanding role in financial portfolio management, ultimately leading to more efficient, responsible, and informed decision-making in the industry.

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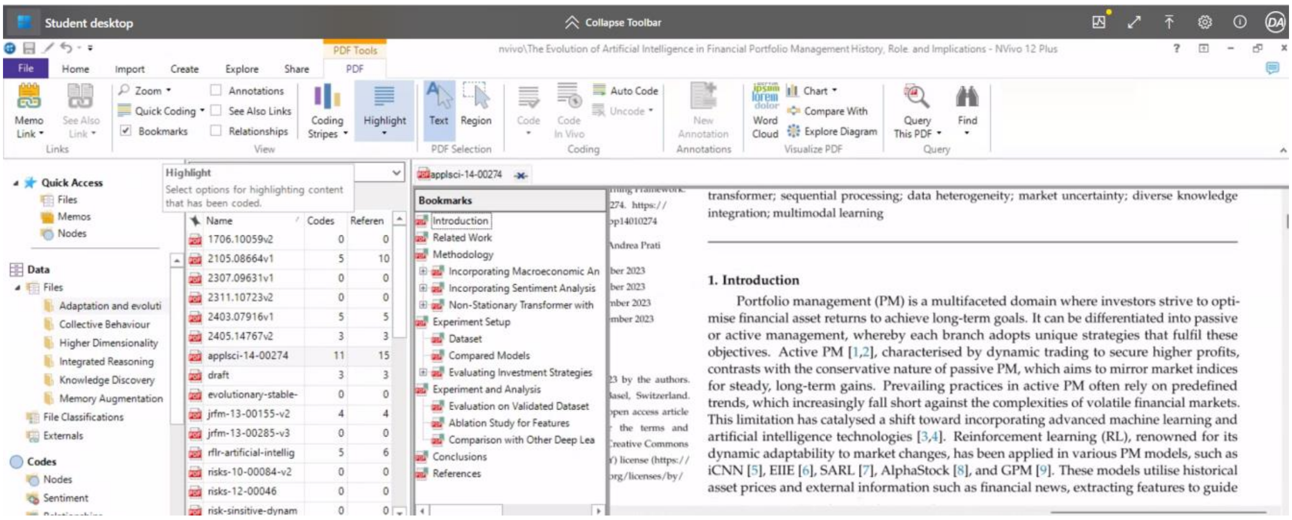
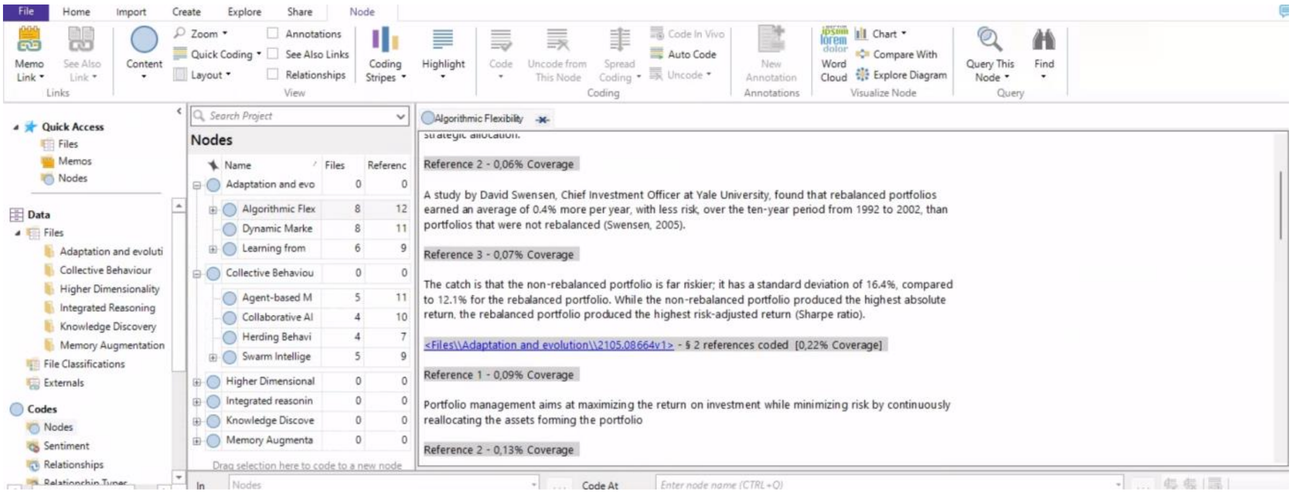
Appendices

Appendix 1. A screenshot showing the publications uploaded as secondary data from the NVivo 12 program.



Appendix 2. A screenshot showing the nodes created during data analysing phase (from NVivo 12 program).



Appendix 3. Quotes from relevant publications to highlight the evidence

Adaptation and Evolution in AI-driven Financial Portfolio Management	
Appendix 3.1: Dynamic Market Adjustment	"Portfolio management aims at maximizing the return on investment while minimizing risk by continuously reallocating the assets forming the portfolio" (Soleymani & Paquet, 2021, p. 1). "Our approach integrates key macroeconomic indicators and targeted news sentiment analysis into its framework, capturing a comprehensive

	picture of market dynamics" (Liu et al., 2024, p. 2). "Markets often behave in unpredictable, 'non-stationary' ways, making adaptability crucial" (Ndikum & Ndikum, 2024, p. 1). "Markets are evolutionary stable if and only if stocks are evaluated by expected relative dividends" (Evstigneev et al., 2006, p. 450). "AI can produce better asset return and risk estimates and solve portfolio optimization problems with complex constraints" (Bartram et al., 2020, p. 3).
Appendix 3.2: Algorithmic Flexibility	"Our study introduces a unique algorithmic approach that combines a non-stationary transformer with deep reinforcement learning to tackle market uncertainty." (Liu et al. 2024, p. 6) "The portfolio rebalance framework integrates machine learning models into mean-risk portfolios, allowing dynamic adjustment based on market trends." (Jiang et al. 2020, p. 7) "Our framework demonstrates that algorithms can dynamically adapt to shifting macroeconomic indicators, enhancing long-term performance." (Soleymani et Paquet 2021, p. 4) "Reinforcement learning algorithms are designed to evolve, continuously optimizing portfolio strategies by integrating performance data over time." (Liu et al. 2024, p. 6) "The evolutionary stability of portfolio rules ensures that rational, adaptive strategies dominate in the long run, while irrational strategies are eventually discarded." (Evstigneev et al. 2006, p. 5)
Appendix 3.3: Learning from Market Anomalies	"Anomalies in financial markets provide opportunities for learning, where reinforcement learning can adjust and optimize portfolios based on

	historical data." (Garrido-Merchán et al. 2023, p. 8) "The endogenous wealth increase due to dividends and the capital gains or losses provides the agent with continuous feedback for learning and improvement." (Evstigneev et al. 2006, p. 5) "Market movements are often driven by unpredictable factors, but machine learning models are designed to identify hidden patterns in these anomalies." (Ayala et al. 2024, p. 7) "Such models utilize historical price data and external information such as financial news, extracting features to guide portfolio rebalancing." (Liu et al. 2024, p. 5) "The portfolio rebalancing strategy integrates feedback from market performance, allowing the agent to adjust risk and return preferences in real time." (Jiang et al. 2020, p. 4) "Deep reinforcement learning frameworks incorporate feedback loops where agents refine their actions based on historical returns and market conditions." (Liu et al. 2024, p. 7) "Continuous feedback from portfolio performance enables the refinement of trading strategies, improving risk management and decision-making." (Ndikum et Ndikum 2024, p. 8) "Market selection processes create natural feedback loops that allow for the improvement of portfolio rules through adaptive learning." (Evstigneev et al. 2006, p. 9)

Appendix 4. Quotes from relevant publications to highlight the evidence of Figure 6

Integrated Reasoning in AI-driven Financial Portfolio Management	

Appendix 4.1: Multi-layered Data Integration	"The CWMR strategy is able to effectively exploit the power of mean reversion for on-line portfolio selection" (Li et al. 2011, p. 434). "On-line portfolio selection aims to determine a practical strategy for investing wealth among a set of assets to achieve some financial objectives in the long run" (Li et al. 2013, p. 434). "The portfolio rebalancing strategy integrates feedback from market performance, allowing the agent to adjust risk and return preferences in real time" (Jiang et al. 2020, p. 4). "Through extensive numerical experiments on a variety of real testbeds, we show that the proposed CWMR algorithms significantly surpass a number of state-of-the-art strategies in terms of long-term compound return" (Li et al. 2011, p. 435).
Appendix 4.2: Complex Decision-Making Models	"In RL methods, a learning agent can understand a complex financial environment by attempting various trading actions and revising its trading action policy" (Park et al. 2019, p. 2). "Our approach relies on predictable statistical relations between all pairs of stocks in the market" (Borodin et al. 2003, p. 1). "The trading rules adapt to changing market conditions, leading to an evolving rule-base that changes with time" (Ghandar et al. 2009, p. 71).
Appendix 4.3: Predictive Risk Management	"The system learns to form rules that can perform well in dynamic market conditions" (Ghandar et al. 2009, p. 71). "Evolutionary computation allows for dynamic adaptation, where agents improve their strategies through trial and error" (Evstigneev et al. 2006, p. 7). "The overall learning system incorporates a GA, a niching method, and several other components" (Mahfoud et Mani 1996, p. 545). "A constant rebalancing strategy can often take advantage of market fluctuations to achieve a

	return significantly greater than that of the best stock" (Borodin et al. 2003, p. 2).
Appendix 4.4: Strategic Adaptability	"Intelligent finance represents a new direction [...] in the quest for absolute positive and non-trivial returns in investing and trading" (Pan et al. 2006, p. 1). "The rules adapt to changing market conditions, leading to an evolving rule-base that changes with time" (Ghandar et al. 2009, p. 71). "Learning agents can adapt their strategies using their observed experiences on each real trading day" (Park et al. 2019, p. 2). "The portfolio is constructed within a dynamic rebalance strategy to obtain high overall returns while keeping the risk under control" (Jiang et al. 2020, p. 4).

Appendix 5. Quotes from relevant publications to highlight the evidence of Figure 7

Knowledge Discovery in Financial Portfolio Management with AI	
Appendix 5.1: Data Mining Techniques	"Machine learning approaches, particularly text mining techniques, have been implemented to predict stock return volatility, thus taking advantage of the availability of large amounts of unstructured data such as firm financial reports" (Fan et al. 2022, p. 1). "Most existing studies develop simple but effective models to analyze text, such as dictionary-based matching algorithms that use a set of manually constructed keywords" (Fan et al. 2022, p. 1).

	"In fact, researchers and practitioners have been exerting tremendous effort to predict volatility using various types of data" (Fan et al. 2022, p. 1). "Predicting stock return volatility is the key to investment and risk management" (Fan et al. 2022, p. 1). "Pattern recognition in stock prices and volumes plays an important role in forecasting asset performance and market trends" (Sutiene et al. 2024, p. 3). "AI-driven text mining techniques have been effectively used for recognizing patterns within firm financial reports, offering insights into stock performance" (Fan et al. 2022, p. 2). "Advanced AI techniques, particularly in data mining and pattern recognition, have shown improved predictive accuracy in financial markets, contributing to better portfolio management decisions" (Bouteïna et al., 2021, p.2). "Pattern recognition algorithms are increasingly being used to detect anomalies and trends in large financial datasets, providing early warnings of market shifts" (Liu et al. 2022, p. 5).
Appendix 5.2: Feature Selection for Portfolio Optimization	"Deep learning can optimize an investment portfolio directly or establish a portfolio that mimics an index with a small set of assets" (Sutiene et al. 2024, p. 2). "Dimensionality reduction methods can detect latent factors of a broad range of asset prices, which improves the construction of a well-diversified portfolio" (Sutiene et al. 2024, p. 2). "AI techniques can contribute to portfolio management in many ways, improving the shortcomings of classical portfolio construction techniques and extending the opportunities to generate additional alpha" (Sutiene et al. 2024, p. 1).

	"AI can produce better asset return and risk estimates and solve portfolio optimization problems under complex constraints, resulting in better out-of-sample AI-based portfolio performance than traditional approaches" (Sutiene et al. 2024, p. 2).
Appendix 5.3: Predictive Modeling	"ML techniques have been predominantly used for risk evaluation of customer credit scores and risks along with loan and insurance underwriting" (Fan et al. 2006, p. 8). "Researchers in recent years have sought to improve prediction by analyzing unstructured text from firm financial reports, such as companies' annual reports" (Fan et al. 2022, p. 1). "ML-based algorithmic trading models monitor and analyze real-time data to detect patterns, thereby giving traders a distinct advantage over the market average" (Fischer & Krauss, 2018, p. 2). "Predictive analytics has been widely employed in exchange rate forecasts, in stock markets, while macroeconomic predictions and forecasts are key in portfolio management" (Fischer & Krauss, 2018, p. 8).
Appendix 5.4: AI-Driven Decision Support Systems	"La nature même de l'intelligence artificielle rend les décisions plus transparentes et mieux comprises par les utilisateurs finaux grâce à des systèmes explicatifs" (Bouteïna, 2021). "We define an explanation as an information in a semantically complete format, which is self-sufficient and chosen according to the target audience regarding its knowledge" (Bouteïna, 2021). "Recent XAI objectives have been defined in the state-of-the-art, for which specific approaches have been proposed" (Bouteïna, 2021). "In order to make black-boxes more transparent, XAI approaches should be more inspired and take advantage of past and recent works in

	Knowledge and Representation Learning domains" (Bouteïna, 2021).

Appendix 6. Quotes from relevant publications to highlight the evidence of Figure 8

Collective Behaviour in Financial Portfolio Management with AI	
Appendix 6.1: Swarm Intelligence in Financial Markets	"The collective dynamics of human society can exhibit emergent behaviors, which are often unpredictable from the standpoint of individual actions" (Bianconi et al. 2023, p. 4). "Market participants, acting independently, often create patterns of behavior that resemble swarm intelligence, influencing asset prices collectively" (Bianconi et al. 2023, p. 5). "Swarm intelligence models have been increasingly applied in financial markets to simulate collective behavior during periods of high volatility" (Bianconi et al. 2023, p. 6). "AI systems are capable of capturing the emergent collective behavior in financial markets, helping to predict future market trends" (Bianconi et al. 2023, p. 7). "Emergent collective dynamics can drive both bullish and bearish market trends, as investors mimic the behavior of others in response to perceived market movements" (Castellano et al. 2009, p. 4)
Appendix 6.2: Agent-based Modeling in Portfolio Management	"MSPM involves two types of asynchronously-updated modules: Evolving Agent Module (EAM) and Strategic Agent Module (SAM)" (Z. Huang & Tanaka, 2022,p. 1) "An EAM takes heterogeneous data and utilizes a DQN-based agent to produce signal-

	comprised information" (Z. Huang & Tanaka, 2022, p. 2). "The agent executes multiple strategies virtually and selects only a few for real execution" (Kolonin et al., 2023, p. 1) "The agent in EAM observes state vt, which consists of the designated asset's recent n-day historical prices st and sentiment scores ρt" (Z. Huang & Tanaka, 2022, p. 5). "The multi-strategy adaptive portfolio management agent experiments with multiple strategies concurrently in a virtual environment" (Kolonin et al., 2023, p. 8).
Appendix 6.3: Herding Behavior Detection	""Emotional investors make their decisions based on what Daniel Kahneman refers to as System 1 thinking: automatic, loss-avoiding, and quick"(Howard, n.d.) p.5. "a maximum entropy approach can describe the complex structure of financial systems and detect collective behaviors such as herding."(Bury, 2014)p.113. " Emotional investors make their decisions based on what Daniel Kahneman (Thinking, Fast and Slow, 2012) refers to as System 1 thinking: automatic, loss-avoiding and quick, with little or no effort and no sense of voluntary control. On the other hand, BDIs make their decisions using thorough and extensive analysis of available data. BDIs use what Kahneman refers to as System 2 thinking: effortful, high-concentration and complex. "(Howard, n.d.)p.5.
Appendix 6.4: AI-Driven Detection and Management of Market Herding Risks Using Eigenvalue Analysis	"The RMT filtered correlation matrix is shown to improve the risk-return profile of a portfolio of Hedge Funds". (Conlon, n.d.)p.46 "Ants were able to make shorter feasible tours. Their simulations demonstrated that ACO can give good paths for both symmetric and asymmetric instances of TSP. This algorithm outperformed simulated annealing and demonstrated

	that ACO can give good paths for both symmetric and asymmetric instances of TSP."(Kumar, n.d.)p.19. "The scaled correlation matrices are then used as inputs to a portfolio optimization, to judge the effect of time granularity on Risk Management"(Conlon, n.d.) p.5. "The relationship between index returns and relative eigenvalue size is examined, to provide insight on the collective behavior of traders"(Conlon, n.d.) p.6

Appendix 7. Quotes from relevant publications to highlight the evidence of Figure 9

Memory Augmentation in Financial Portfolio Management with AI	
Appendix 7.1: Long-term Data Retention	In asset management businesses, it is common to operate in the medium to long term due to the increase in operational burden and transaction costs." (Amagai et al. 2023, p. 1) "To solve this problem, a data augmentation was conducted by the combined use of data of multiple time scales, confirming its effectiveness to maintain a better generalization ability of trained models." (Amagai et al. 2023, p. 1) "Data augmentation was applied for portfolio management, using both main timescale data for rebalancing the portfolio and shorter timescale data to enlarge the number of learning data." (Amagai et al. 2023, p. 2) "By utilizing memory augmentation, AI models can retain data over longer periods, allowing systems to improve the generalization ability of trained models." (Amagai et al. 2023, p. 2) "Efficient memory structures should be able to scale gracefully with the quantity of information stored, especially in financial markets where large amounts of data must be rapidly retrieved." (Munkhdalai et al. 2006, p. 1) "Memory-augmented neural networks (MANNs) support efficient data storage and retrieval operations, ensuring that relevant financial information can be accessed without delays." (Munkhdalai et al. 2006, p. 3) "The augmentation of neural networks with external memory improves data retrieval processes, which are critical for managing large-scale financial portfolios." (Munkhdalai et al. 2006, p. 4)
Appendix 7.2: Historical Memory for Predictive Analysis	"Memory augmentation supports better predictive analysis by allowing AI systems to retain key financial data across different time scales,

	leading to more accurate forecasts." (Yang et al. 2023, p. 4) "The memory units within MEMGAN models decode historical financial data into interpreta-ble patterns, which aids in forecasting market trends." (Yang et al. 2023, p. 5) "By leveraging augmented memory, AI can in-tegrate historical data into predictive algo-rithms, making it possible to identify future anomalies." (Yang et al. 2023, p. 6) "Memory-augmented neural networks facilitate learning from past financial data, allowing for more accurate market predictions." (Munkhda-lai et al. 2006, p. 7) "Patterns from historical data are extracted by neural memory systems, which enable better detection of trends and predictive performance in portfolio management." (Amagai et al. 2023, p. 3) "Neural memory models help in recognizing subtle market patterns, which might otherwise go unnoticed in traditional financial analysis." (Yang et al. 2023, p. 5) "AI systems using augmented memory excel at recognizing long-term patterns in financial da-tasets, improving the prediction of future mar-ket behavior." (Munkhdalai et al. 2006, p. 6)
Appendix 7.3: Adaptive Learning Systems with Memory Enhancement	"Recurrent neural networks with augmented memory mechanisms enable adaptive learning by retaining previous knowledge and applying it to evolving financial data." (Munkhdalai et al. 2006, p. 2) "Memory-augmented models rapidly adapt to changes in financial markets by incrementally learning from past portfolio decisions." (Munkhdalai et al. 2006, p. 4) "Writing to memory enables the system to store information about past financial conditions, which helps adjust investment strategies dy-namically." (Yang et al. 2023, p. 6)

	"Incremental learning within memory-augmented models is essential for managing portfolios, as it allows AI to adapt to new market conditions while retaining critical past information." (Munkhdalai et al. 2006, p. 6)

Appendix 8. Quotes from relevant publications to highlight the evidence of Figure 10

Higher Dimensionality in Financial Portfolio Management with AI	
Appendix 8.1: Feature Selection in High-Dimensional Data	"Technological innovations have revolutionized the process of scientific research and knowledge discovery. The availability of massive data and challenges from frontiers of research and development have reshaped statistical thinking" (Fan and Li 2006, p. 1). "In high-dimensional data mining, it is helpful to distinguish two types of statistical endeavors. In many machine learning problems, the interests often center around the classification errors, or returns and risks of selected portfolios rather than the accuracy of estimated parameters" (Fan and Li 2006, p. 2). "Dimensionality reduction and feature extraction play pivotal roles in all high-dimensional mathematical problems. The intensive computation inherent in these problems has altered the course of methodological development" (Fan and Li 2006, p. 3). "The challenges of high-dimensionality arise in diverse fields of sciences and the humanities, ranging from computational biology and health studies to financial engineering and risk management" (Fan and Li 2006, p. 4). "Principal Component Analysis (PCA) is widely used in dimensionality reduction to tackle high-dimensional data and reduce the

	feature space, thus improving model performance and simplifying portfolio selection" (Gyamerah et al. 2023, p. 12). "PCA significantly decreases the computational burden of machine learning models by extracting the most relevant features from the dataset, which makes it a popular method in high-dimensional financial data" (Gyamerah et al. 2023, p. 15). "High-dimensional data often leads to overfitting, and PCA helps to mitigate this issue by focusing on key components rather than the entire dataset" (Gyamerah et al. 2023, p. 17).
Appendix 8.2: Handling High-Dimensional Data for Portfolio Optimization	"Many financial analyses require timely data to support time-critical decision making. In this paper, we develop a novel indexing method to reduce latency of querying high-dimensional data, improving its efficiency in portfolio management" (Lu et al. 2014, p. 2). "We focus on the latency issue and develop a novel method to improve the query processing speed for high-dimensional financial data in relational databases" (Lu et al. 2014, p. 2). "Handling high-dimensional data in financial portfolio management requires efficient algorithms and models capable of processing vast amounts of variables in real-time" (Lu et al. 2014, p. 4). "Our novel PL-tree indexing technique significantly improves the timeliness and performance of high-dimensional data in financial applications, especially for time-critical decisions" (Lu et al. 2014, p. 5).
Appendix 8.3: Risk Management Using High-Dimensional Data	"The challenges of high-dimensionality in financial engineering often involve assessing risks across large, complex datasets, which requires both innovative algorithms and robust statistical models" (Fan and Li 2006, p. 1). "Using machine learning, AI systems can extract relevant features from high-dimensional

	data to assess and mitigate financial risks" (Becker 2015, p. 12). "The availability of massive amounts of data in finance necessitates methods like machine learning to process and identify patterns in high-dimensional data for risk management" (Becker 2015, p. 25). "By leveraging high-dimensional data, AI systems can significantly enhance financial risk assessments, identifying potential anomalies or risks hidden in complex datasets" (Becker 2015, p. 30). "AI-driven anomaly detection techniques, such as Local Outlier Factor (LOF) and Isolation Forest, are essential for detecting anomalies in high-dimensional financial data, improving risk management" (Agrawal 2023, p. 3). "Anomaly detection algorithms, particularly in high-dimensional spaces, must account for complex relationships between data points that traditional techniques often overlook" (Agrawal 2023, p. 4). "By integrating anomaly detection with predictive analytics, financial firms can identify and respond to risks in real-time, reducing the likelihood of significant market disruptions" (Agrawal 2023, p. 6). "Model-based anomaly detection approaches, such as Support Vector Machines and Random Cut Forest, are particularly effective in high-dimensional datasets for identifying deviations from expected market behavior" (Agrawal 2023, p. 8).
Appendix 8.4: Machine learning Models for hight-dimensional Data	"Technological innovations have had a deep impact on society and scientific research. They allow us to collect assive amounts of data at relatively low cost" (Fan & Li, 2006, p. 1) "In the analysis of microarray data, one of the first statistical challenges is to remove systematic biases, which is collectively referred to as

	normalization in the literature" (Fan & Li, 2006, p. 4) "Support Vector Machines (SVMs), introduced by Boser, Guyon, and Vapnik, optimize a line that is furthest from two data classes, which helps manage the complexity of high-dimensional datasets" (Rubio Adeva, 2023, p. 22) "AI systems can quickly identify suspicious activities that deviate from the norm by training machine learning algorithms on large datasets of normal and malicious behavior" (Agrawal, 2023, p. 3) "The neural network achieved both the best AUC-ROC (0.889) and the best average precision (0.192), indicating its superior performance in dealing with high-dimensional data" (Rubio Adeva, 2023, p. 3) "Dimensionality reduction methods such as Principal Component Analysis (PCA) or Autoencoders may be used to reduce the number of dimensions, helping to alleviate the curse of dimensionality" (Agrawal, 2023, p. 3)