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Utilization of Artificial Intelligence in Investment Decisions Under Market Volatility

Manager vs. Machine

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ABSTRACT:
The adoption of artificial intelligence (AI) in the financial sector has consistently increased, driven by the AI boom that began in 2015. However, the amount of prior study of AI-powered instruments is quite limited, especially in volatile market conditions. Furthermore, the number of empirical studies comparing the performance of AI portfolio managers to their human counterparts is notably scarce. Thus, the study aims to fill this gap in the existing literature and determine whether AI outperforms a traditional portfolio manager under volatile market conditions, considering the Ukrainian conflict and Silicon Valley Bank (SVB) collapse. The study divided the sample data into two categories: AI-managed funds and human-managed funds. The event study method was selected as the research approach, with the aim of identifying possible abnormal returns during the events. Abnormal returns were calculated for ±20 days around the event date. Additionally, cumulative and holding period returns for eight separate observation periods were determined. All returns were risk-adjusted using the S&P500 index. Furthermore, a systematic literature review was conducted to examine previous empirical studies. The purpose was to answer a specific research question about psychological and other factors that influence the investment decision-making process and its outcomes between AI and human.

The results indicate that neither management approach, AI nor a human portfolio manager, consistently outperformed the other. AI funds exhibited higher abnormal returns during the Ukrainian conflict, while human-managed funds had higher abnormal returns during the SVB collapse. Conversely, AI funds demonstrated higher long-term performance after both events. Furthermore, the findings imply that the selection of better management approach in the investment decision-making depends on specific circumstances. The results highlight that neither decision-making method—AI or human-driven—is mutually exclusive; instead, they serve different purposes, each with distinct strengths and weaknesses. A hybrid approach, combining the strengths of both AI and human portfolio managers, could optimize performance across various investment situations, results state.

Moreover, the study introduced two hypotheses: H0, the null hypothesis, assumed that the utilization of artificial intelligence has no impact on investment performance in volatile market conditions. Alternatively, H1, the alternative hypothesis, posited that the utilization of artificial intelligence does impact investment performance in volatile market conditions. Based on the results, the null hypothesis, H0, was rejected and while the results suggested strong support to the alternative hypothesis, H1. In addition, it should be noted that the sample size of this thesis could have been larger, but that would have been challenging due to the comprehensive research approach focusing on each individual fund. As a further research proposal, the number of samples and the observation period should be increased in order to create more significant results. Also, another proposal is to enhance this research by integrating AI algorithms into investment decisions at a practical level. However, the implementation can bring challenges due to companies' data encryption principles.

KEYWORDS: Event Study, Abnormal Return, Performance, Artificial Intelligence, Portfolio Manager, Exchange Traded Fund, Investment Decision-making

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1 Introduction

Investing is not as rational as many of us believe. People have a variety of biases that can affect investment decisions. Human investors are likely to make decisions based on emotions, biases, a lack of expertise, or patience, which can result in suboptimal investment returns. In a world where markets fluctuate and information is readily available, it is difficult to avoid panic sales and impulsive purchases. Considerable amount of finance literature is based on research which indicates biases in human judgment and decision-making to explain investor behaviour and market anomalies, such as studies by Daniel et al. (1998), De Bondt (1998) and Gärling et al. (2009) which states that investors do not act rationally what comes to investing.

According to the findings of an U.S. survey (McNair, 2021), 66 percent of investors have made a spontaneous or emotionally charged investing decision that they later regretted. 32 percent of investors have traded while drunk, survey states. Furthermore, consumers who manage their own portfolios have a more difficult time keeping emotions out of investing than those who use a financial advisor, the findings reveal.

Human limitations are one of the most serious issues in investing. Fortunately, there is a potential solution available. Artificial intelligence (AI) provides a systematical approach for addressing these issues. AI's primary function is to reduce exposure to psychological traits that can result in negative outcomes. AI can defeat many human limitations by analysing massive amounts of financial data, making objective investment decisions based on data-driven insights, and constantly learning and adapting to changing market circumstances.

New financial technology and innovations have transformed the finance industry by providing more value for investors' time and effort, as well as new ways for organizations to generate more returns. Technological advancements and the use of artificial intelligence are changing service delivery across multiple industries at the moment. Knowledge of how to apply AI and the ability to extract insights from available data will enable organizations in financial services and other industries to improve their competitiveness, which in turn will help the organizations to increase their revenues and market share.

Institutions in the financial industry face intense competition, which inevitably increases the operational and survival requirements of financial institutions. As a result, it is critical to understand about the possibilities of artificial intelligence, as it may be a determining factor in the company's performance in the future. Artificial intelligence has the potential to become a valuable tool in the investment decision-making process for institutional investors. In the future, the use of AI in the investment process may result in completely new and innovative ways of investing, thereby creating new opportunities and enhancing the financial sector's global development.

The financial markets have seen major transformations as a result of significant advances in computing power, data science, and telecommunications. In this new environment of financial markets, computers have the power to gather and analyse massive amounts of data while executing trades in milliseconds. All this autonomously and without human intervention. Even though, AI is still a relatively new phenomenon in human history and the use of artificial intelligence in investment decisions is even more recent. Pioneers in their field who have already begun to use artificial intelligence in financial decision-making have started to see positive results by now (OECD, 2021a). This technological revolution has resulted in a fundamental reorganization of financial markets. Therefore, it is important to examine the possibilities of the utilization of AI in investment process.

Artificial intelligence is considered as a key technology of the future. That is why it is critical to understand what AI is and how it can be applied to our needs. As artificial intelligence becomes more prevalent, it is vital to understand not only the benefits it provides, but also the disadvantages. When used correctly, artificial intelligence can provide new profit opportunities, ultimately leading to greater market share and a substantial advantage over competitors.

1.1 Purpose of the study

The purpose of this study is to examine the profitability and effectiveness of using artificial intelligence in investment decisions, particularly under volatile market conditions. This study conducts research into the performance of AI-powered funds in comparison to traditional human-managed funds. In this study, the research problem of comparing the performance of AI and humans is examined primarily by analysing the returns. Furthermore, the study extends to investigate the psychological and other elements that influence the outcomes. In general, is it possible to increase profits by engaging AI into investment decisions?

The research problem will be examined through the following research questions:

- How does AI perform under volatile market conditions, and how profitable are AI-powered funds during that time versus traditional funds managed by humans?
- What are the psychological factors and other elements that influence the investment decision-making process of an AI versus human?

The study examines AI-driven funds and traditional funds' performance in volatile market conditions using the event study method, which quantifies the financial impact of particular events on asset prices. Through the use of the event study method, this study intends to examine the impact of the Ukrainian conflict and the collapse of Silicon Valley Bank on the performance of both AI-driven and human-managed ETF funds.

First, the study focuses on the period of conflict in Ukraine, which began several months after the deployment of military bases near Ukraine's border (Zafra & McClure, 2023). After that, Russia invaded Ukraine on February 24, 2022. At the time, the S&P 500 index fell more than 10 percent from its recent high and the US stocks closed at their lowest level since June 2021 (Horner & Wursthorn, 2022). The ongoing military action raised concerns, especially over the loss of lives and destruction of property, but also about its potential impact on the global economy and the reactions of global financial markets.

Moreover, the study examines the period of Silicon Valley Bank (SVB) collapse. The story began in 2020, when SVB changed its strategy and transformed itself as an investment company. In response to the impact of the Covid-19 pandemic on interest rate decreases, SVB channeled its interest-free deposits into securities, while cash flows from the booming tech industry soared for its core customer, technology companies (Ivantsov, 2023). However, SVB's securities investments together with the Federal Reserve's decision to raise interest rates to combat inflation, resulted to a dramatic decrease in the investments (Ivantsov, 2023). Fears about SVB's solvency prompted a mass withdrawal of deposits, leading to SVB's collapse on March 10, 2023, marking the second-largest bank failure in US history after Washington Mutual during the 2007–2008 global financial crisis (Ivantsov, 2023). This crisis had far-reaching consequences, leading Swiss authorities to intervene in Credit Suisse just five days later. The collapse of SVB also significantly impacted Credit Suisse, a major global asset manager and systemically important bank, causing a rapid decline in its shares (Staff, 2023 which raised concerns about potential spillover effects on the global financial system.

To conclude, the aim of the study is to determine an answer to the research problem of whether AI outperforms a traditional portfolio manager under volatile market conditions, in the context of the Ukrainian conflict and the collapse of Silicon Valley Bank. In addition, the study attempts to identify the underlying causes for this potential outperformance in the decision-making process. Also, the goal is to provide a broad overview of artificial intelligence, offering the reader a thorough understanding of what AI is and how it operates.

1.2 Hypotheses

The efficient-market hypothesis (EMH), assumes that asset prices reflect all available information, suggesting an incapability to consistently generate excess returns in the markets (Fama 1970). The presumption of the study is that markets incorporate information efficiently. The hypotheses focus on examining the influence of artificial intelligence on investment decisions, particularly in volatile market scenarios. A direct comparison is made between AI and human capabilities, specifically during volatile market conditions. Based on

EMH, the null hypothesis states that the use of artificial intelligence has no effect on investment outcomes in such conditions:

H_0: *The utilization of artificial intelligence has no impact on investment performance in volatile market conditions.*

Considering cumulative data, the study evaluates the overall impact of events during the event windows. While AI excels at real-time data prediction and analysis, human competencies involve complex reasoning based on nuanced contextual knowledge and reliance on intuition in uncertain situations. Despite these differences, it is reasonable to presume that the use of AI influences investment decisions, potentially yielding either negative or positive effects. Consequently, the alternative hypothesis is expressed:

H_1: *The utilization of artificial intelligence does impact investment performance in volatile market conditions.*

The validity of the alternative hypothesis is contingent on the statistical significance of the impact observed in returns during events. This hypothesis aims to explore the potential influence of AI on investment performance under volatile market conditions.

1.3 Motivation

The urge for conducting this study arises from the growing significance and relevance of artificial intelligence (AI) as well as the prevailing AI boom. Furthermore, there is a critical need for further study of AI’s impact from a financial perspective.

The main motivation of this study is that there is a significant gap in scientific research when it comes to comparing the performance of artificial intelligence and human managers, especially under volatile market conditions. There are just few studies about comparing AI and human portfolio managers in general, but none regarding volatile market environment, to my knowledge.

Although, the motivation for research arises not only from the limited amount of previous literature, but also from the factors of the current global situation, such as the growing popularity of artificial intelligence. When OpenAI was released in 2015, the AI boom started to form, and its popularity has grown at an exponential rate ever since. At the moment, artificial intelligence is conquering the world and establishing its position globally at extremely rapid speed. It has entered every aspect of the people’s life and is expanding so quickly that no one can forecast its limits. Based on a report by Grand View Research (2023), AI's current market size of 200 billion dollars is predicted to increase to almost two trillion dollars by 2030, demonstrating the industry's rising tendency.

In addition, despite the fact that artificial intelligence is a relevant topic with almost limitless possibilities, the potential of AIs performance in a quantitative form that describes its financial capability versus humans, has received little attention in the field of scientific research as well as the aspect of AI in financial decision making.

1.4 Previous literature

The existing literature and articles in this field offer limited insights into the distinctions in investment decisions when comparing the financial performance of AI and humans. While many studies in the financial literature evaluate the performance of hedge fund managers in particular, just a few compare AI driven exchange traded funds (ETFs) against those managed by humans. For example, Harvey et al. (2017) investigated the performance differences between discretionary and systematic hedge funds (no daily intervention by humans) and discovered similar results in performance of both categories. In contrast, Grobys (2022) and Niang (2021) found that hedge funds with higher levels of automation outperform those with a higher level of human engagement. Furthermore, Chen et al. (2022) studied AI-powered mutual funds, revealing that they outperform funds managed by humans. Nevertheless, none of these studies compared the performance of AI to human managers under volatile market conditions or examined ETFs.

A closer look at Eugene Fama's (1970) Efficient Market Hypothesis (EMH) theory asserts that in efficient markets, prices include all available information. This fundamental theory is applied to quantify how certain events affect the value on securities. The financial impact of an event can be measured through event studies, a widely used statistical method in economics, and finance (Binder, 1998). The method was first introduced in the 1960s by Ball & Brown (1968) and Fama, Fisher, Jensen & Roll (1969), establishing the methodology in its current form. It has since been applied in various empirical studies to examine the influence of an important occurrence or contingent event on the value of a security.

The effect of specific events, such as war, geopolitical shocks, or bank failures in the securities market, have previously been studied in the empirical literature. The selection of these study's events was based on the assumption that increased market volatility often arises in response to certain occurrences such as geopolitical conflicts and banking crises. Like study by Bredin & Fountas (2018) asserts, conflicts, war, and banking crisis tend to increase economic uncertainty. Furthermore, prior literature supports the assumption that that higher economic uncertainty is positively related to increased market volatility (Antonakakis et al., 2013; Bansal et al., 2014; Tong et al., 2023;). In addition, Gray and Kucher (2000), investigated the effects of World War II on government bond prices, whereas studies on the 2008 global financial crisis examined the effects of financial crises and banking shocks on global financial markets, see, e.g., Grammatikos & Vermeulen (2012) and Bénétrix et al. (2015). This study contributes to the existing literature by examining the potential impacts of increased market volatility particularly on AI-based securities focusing on recent events, such as the collapse of Silicon Valley Bank and the conflict in Ukraine. However, while previous research has already examined at the effects of the Ukrainian conflict on the stock market (Boungou & Yatié, 2022; Izzeldin et al., 2023) and the effects of the SVB collapse (Martins, 2023; Pandey et al., 2023), none of these studies have focused on AI-based instruments, underlining the focus of this research.

In addition, the field of behavioural finance which examines financial psychology to analyse investors' actions, has been widely studied in the financial literature, and it owes much to the concept's primary founders, Amos Tversky, Daniel Kahneman, and Richard Thaler.

Despite being a widely researched field, it has very limited or hardly any research on the psychological differences between artificial intelligence and humans in the context of investing decisions. Most research on AI financial decision-making focuses entirely on the AI perspective, often disregarding direct comparisons with human decision-making. One of the early studies on the subject by Pomerol (1997) compared two aspects of AI and humans in decision-making: diagnosis and look-ahead, indicating AI's competence in diagnosis but a lack of attention on look-ahead thinking. Ren's study in 2021 highlighted the strategic relevance of implementing AI technology in finance, whereas Chen and Ren's study in 2022 presented an overview of AI and human behavioural elements with no specific focus on investment decision-making or in-depth analysis based on prior literature. In contrast, this study provides a broad overview for examining the psychological factors that influence investment decisions between AI and humans through prior literature.

To my knowledge, no empirical studies have assessed the impact of bank failures, conflicts, or volatile market conditions on general AI-driven investment performance. Additionally, there is a lack of empirical research comparing AI and human portfolio managers in volatile market conditions. Despite extensive study in behavioural finance, a notable gap exists in understanding psychological distinctions between AI and human managers in the context of investment decisions. This research aims to address these gaps in the current literature.

1.5 Structure of the study

The paper comprises seven chapters, each serving a distinct purpose. Chapter one introduces the study, outlining objectives, motivation, and hypotheses. Chapter two presents a comprehensive overview of artificial intelligence, including historical development. Chapter three observes traditional human-managed funds, focusing on investment decision-making and psychological factors. In contrast, chapter four delves into AI-powered funds, examining their functioning. Chapter five introduces the empirical part, presenting data and research methodology. Chapter six covers key findings and analysis of AI-powered and traditional funds. Finally, chapter seven presents' discussions, conclusions, and analyses the results' importance, reliability, and validity while addressing the study's contribution.

2 Artificial Intelligence

This chapter provides an overview of artificial intelligence and its history. Furthermore, how artificial intelligence is applied in the financial industry is discussed. The purpose is to provide a broad overview of artificial intelligence, and its applications in the financial sector.

2.1 Definition and Overview of Artificial Intelligence

The ways AI and humans use to operate are entirely different, yet the goal is the same. Human-like intelligence is an empirical science related to psychology that includes experiments, human behaviour, and mental processes, whereas AI's rational approach incorporates a combination of mathematics, engineering, and statistics.

Artificial intelligence is a part of computer science that attempts to develop machines or computer systems capable of doing activities that would normally need human intelligence. The fundamental objective of AI is to create machines that can think, learn, reason, and adapt in the same way that humans do.

According to Russell and Norvig (2022), AI systems can be basically assembled into two categories: *Narrow AI systems* designed for narrow tasks, such as recommendation systems and online personal assistants, and *Artificial General Intelligence,* also known as *General AI (AGI)*, which refers to systems with human-like cognitive capabilities and can perform well in a number of areas. AGI systems can understand, learn, and gain knowledge in a way that is similar to human intellect, they continue. In contrast from Narrow AI, AGI is not limited to certain tasks and may adapt and succeed in several kind of tasks (Russell & Norvig, 2022). Moreover, aside from Narrow AI and AGI, there is a third hypothetical AI system category known as *Artificial Super Intelligence (ASI*). As stated by Russell & Norvig (2022) ASI is a theoretical artificial intelligence system that outperforms even the most talented humans in terms of cognitive capacity. They explain that because of the significant ethical and safety considerations surrounding its relationship with humanity, ASI is still purely speculative.

Artificial intelligence uses algorithms that allow it to learn, analyse data and make informed decisions. Lowe & Lawless (2021) assert that an algorithm is a procedure or set of rules that a computer must follow in calculations or other problem-solving operations. Basically, an algorithm is a set of instructions designed to accomplish a given task, they define. In practice, it might be described using a simple method like multiplication equations: computers only execute it in binary form, while humans use decimals (Lowe & Lawless, 2021). Figure 1. below depicts the general AI operation process by observing the AI process in action step by step.

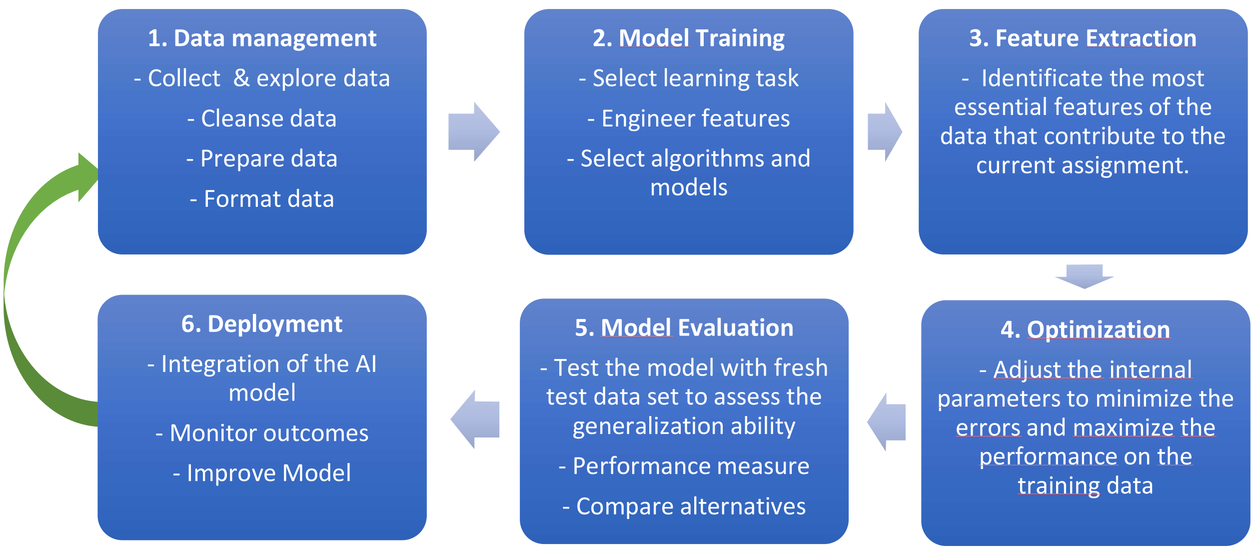


Figure 1. AI workflow.

This study concentrates on the most relevant AI algorithms within the subject of the study. The first technique observed is machine learning (ML), which is certainly among the most important AI techniques. Machine learning is a core AI technology and a subgroup of AI. As Ahmed et al. (2022) states, ML is an artificial intelligence technology that allows systems to learn patterns from data without being explicitly programmed for it. ML gains knowledge from experiences or data sets rather than from instructions alone. Ahmed et al. (2022) continues that, in general, machine learning focuses on explicitly identifying a problem that a computer is able to solve. The problem must be described mathematically, in a form that can be solved by an algorithm. ML models are frequently composed of a set of rules, procedures, or sophisticated "transfer functions" that can be applied to identify intriguing data patterns or predict behaviour. ML utilizes data to make predictions about uncertain events in the future, and incorporates methods from statistics, neural networks, operations research, and physics. It employs these methods to uncover hidden patterns in data without being specifically programmed for what to observe or discover (Ahmed et al., 2022)

Machine learning employs algorithms to create models. ML algorithm is a process that is executed on data to produce a ML model, so the ML Model is the result of a machine learning algorithm applied to the data (Ahmed et al.,2022). In addition, as asserted by Russell & Norvig (2022) machine learning means that it must learn to predict, classify, or find patterns based on certain data. In order for the machine to learn these skills, it has three different learning styles at its disposal. The three types of ML are supervised, unsupervised and reinforcement learning (Russell & Norvig, 2022).

Next, Russell & Norvig (2022) talk about different AI learning methods. *Supervised learning* is the process by which an artificial intelligence system is trained on pairs of input and output data to generate predictions or classifications. *Unsupervised Learning*, on the other hand, is the process through which an AI system identifies patterns, clusters, or correlations in data, without any explicit guidance, they explain. Moreover, *Reinforcement Learning* means as learning through interaction with an environment. In this method the AI agent receives feedback in the form of incentives or penalties in order to optimize its actions (Russell & Norvig, 2022). Figure 2. shows the learning process in its simplest form.

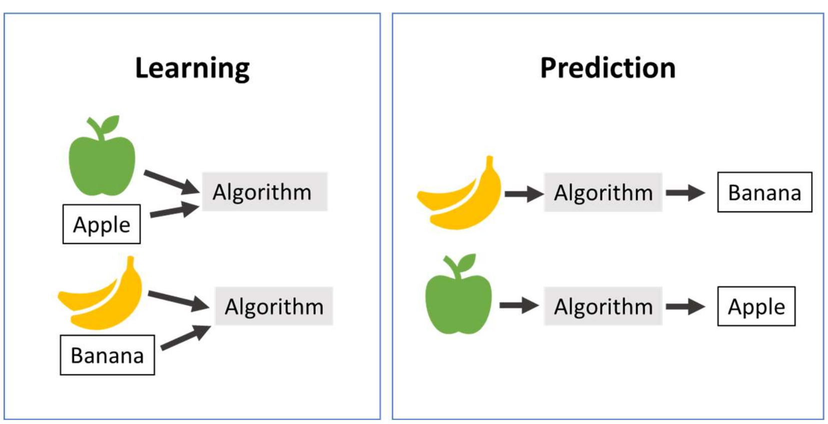


Figure 2. Example of machine learning prediction.

Deep Learning (DL) is one of the most essential AI techniques and a special subset of AI and ML, that teaches machines to make intelligent decisions on their own. According to Ahmed et al. (2022) and Lowe & Lawless (2021), deep learning is a class of algorithms, and it involves a higher level of automation than typical ML models. It is basically a three- or more-layered neural network. They state that, these neural networks seek to imitate human brain behaviour by learning from substantial amounts of data. Whereas a single-layer neural network is capable of producing approximations, additional hidden layers of deep learning can assist in accuracy optimization and improvement, they summarise.

Several AI products and services employ deep learning in order to improve automation and conduct analytic and physical activities without human involvement. Deep learning technology is at the core of everyday products and services like voice-controlled electronic devices and credit card fraud detection, as well as emerging technologies like self-driving vehicles (Alzubaidi et al., 2021; Russell & Norvig, 2022).

As explained by Ahmed et al. (2022), a *neural network* (NN) is a ML model and a subgroup of machine learning which serves as the foundation for deep learning algorithms. NN is a series of algorithms that uses interconnected neurons in a layered structure to communicate between each other and process information in response to external inputs, they add. Basically, it is a set of different techniques or algorithms that determine the relationship between several underlying factors and process the data in a similar way to the human brain, they explain. NN is ultimately a mathematical version based on the biological brain.

Furthermore, *Natural Language Processing* (NLP) is an element of AI that stands for the ability of a system or machine to learn, perceive, and understand human language as it is delivered (Ahmed et al.,2022). The majority of NLP methods use ML and DL-based techniques to obtain insights from human language and NLP enables machines to understand human speech (Ahmed et al.,2022). For example, speech recognition is one of the things that can be implemented with the help of natural language processing. According to Russell & Norvig (2022), NLP can detect fake news, spam, as well as provide responses. It is also used in applications like as language translation and chatbots (Russell & Norvig, 2022). Figure 3. visualizes how the AI and its subsets are positioned in relation to each other.

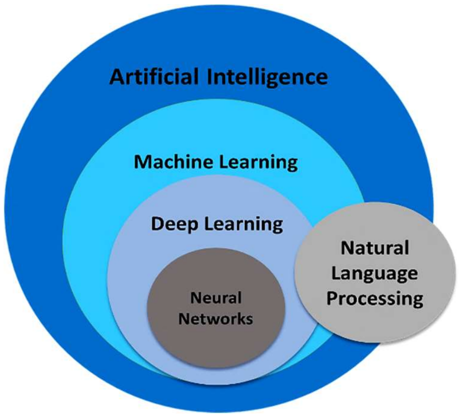


Figure 3. Positioning of Artificial Intelligence, Machine Learning, Deep Learning, Neural Networks and Natural Language Processing.

As Russell & Norvig (2022) explain, AI needs agents to achieve its goals in the best possible way. They define that, an artificial intelligence agent can be viewed using an example, in which the AI agent perceives and acts in the environment. The function of an agent specifies the action that the agent takes in response to any sequence of observations, they add. They also clarify that agent's goal is to observe its environment and act in accordance with it, in order to achieve its goals. The main purpose is to act as optimally as possible in relation to the environment in order to obtain the best result. An agent's adequate shape and structure are determined by its surrounding environment (Russell & Norvig (2022).

ML can be utilized to empower an AI agent or product to learn from experience, such as how to complete a task and achieve a goal. Given the information offered by the environment and knowledge built into the agent, a rational agent should take an action that is predicted to maximize its performance (Lowe and Lawless, 2021; Russell & Norvig, 2022). According to Russel and Norvig (2022) the performance measure assesses the agent's behaviour in a given environment. They continue that the aim of a rational agent is to maximize the expected value of a performance measure, and there is a high risk that the agent will optimize the wrong objective if the performance measurement cannot be performed or is difficult to define.

Additionally, there are also different types of agents which are roughly classified into different categories: first, model-based reflex agents attempt to track features of the world that are not visible in existing observations, whereas simple reflex agents respond directly to observations, as noted by Russell & Norvig (2022). Then again, goal-based agents looking for to achieve a specific goal, whereas utility-based agents seek to maximize their own “satisfaction”, they conclude.

2.2 Historical Overview of AI

It all began in 1943, when Warren McCulloch and Walter Pitts developed a computational model for neural networks (NNs), which served as the cornerstone for foundations of artificial intelligence (Lowe & Lawless, 2021). Then again, in 1950, Alan Turing published an article “Computer Machinery and Intelligence” in the academic journal Mind, in which he debated how to create intelligent machines and introduced a method how to test their intelligence. The procedure came to be known as the "Turing Test," and it was a form of experimentation to see if a computer could exceed a human (Cowell, 2019). In the experiment he utilized a human interrogator as part of his strategy to ask questions in order to find out whether the responses came from a computer or a human (Cowell, 2019). Turing's research was the most influential and significant contribution to artificial intelligence at the time, and the name "artificial intelligence" was adopted by the scientific community six years later (Lowe & Lawless, 2021).

Today, Alan Turing has been recognized as one of the great fathers of artificial intelligence and one of the prominent codebreakers of World War II, whose cryptology provided information that was considered to speed up the Allied victory, as asserted by Cowell (2019). He embraced the first visions of modern computing, and his intellect created revolutionary insights into what is today referred to as artificial intelligence (Cowell, 2019).

1951, Marvin Minsky envisioned a neural network simulator machine that evolved into stochastic neural analog amplification calculator, also known as SNARC and it is considered as the first neural network machine (Russell & Norvig, 2022). Later, in the summer in 1956, John McCarthy and Marvin Minsky hosted the first academic conference on artificial intelligence, “Dartmouth Summer Research Project on Artificial Intelligence” in New Hampshire, which had a significant impact of AI research over the next twenty years (Lowe & Lawless, 2021; Russell & Norvig, 2022). Artificial intelligence thrived from 1950s to early 1970s as computers could hold more data and got faster, cheaper, and more accessible (Rockwell, 2017). Machine learning algorithms developed as well, and people knew which algorithm to use for which task. Early experiments, such as General Problem Solver by Newell and Simon and Joseph Weizenbaum's ELIZA, one of the first chatterbots, were promising in the areas of problem solving and spoken language interpretation (Rockwell, 2017).

In 1973, as stated by Lowe & Lawless (2021) most funding resources were rejected from AI research, owing mostly to Sir James Lighthill's report on the state of artificial intelligence, where he underlined that traditional AI problems could be solved by other sciences and general artificial intelligence is impossible to accomplish. As a result, funding for AI research dropped and the years that followed were known as the "AI Winter," which lasted from 1974 to 1980, they continue. Gladly, it didn’t last forever. After the "AI Winter" in 1986, David Rumelhart and James McClelland published a book in which they developed ideas about parallel distributed processing and neural network models and created computer simulations to giving computer scientists the first testable neural processing models (Lowe & Lawless, 2021).

The 1980s similarly witnessed the rise of robots, with numerous scientists arguing that for AI to be useful, it must have a body, which resulted in the development of sensor-motor abilities (Lowe & Lawless, 2021). Likewise, Edward Feigenbaum pioneered expert systems that replicate the decision-making process of a human expert, and the program was designed to ask an expert in the subject how to act in a certain situation, and once the machine learnt the answers, non-experts could obtain guidance from that program (Lowe & Lawless, 2021; Rockwell, 2017). Afterwards, in the 1990s, a new paradigm known as "intelligent agents" gained widespread acceptance in the AI field (Rockwell, 2017). In addition, 1997 was a significant year for the development of AI when IBM's Deep Blue computer game system defeated human for the first time. The game was played between an IBM supercomputer and the reigning world chess champion Garry Kasparov (Rockwell, 2017).

The 2010s also saw a lot of development. In 2002, iRobot released the Roomba robot vacuum cleaner, which could navigate independently and also avoid obstacles, according to Lowe & Lawless (2021). In 2004, the United States Department of Defence Research Organization (DARPA) launched a challenge to develop vehicles capable of traveling more than 150 miles autonomously, they continue. Similarly, DARPA announced the Urban Challenge for Autonomous Vehicles initiative in 2007, and after that, Google constructed its first self-driving car, making its entry into the self-driving autonomous car market in 2009 (Lowe & Lawless (2021).

Between 2011 and 2014, Smartphone apps Siri, Google Now, and Microsoft Cortana were released, and they used natural language to answer questions, make recommendations, and conduct activities, as stated by Lowe & Lawless (2021). Moreover, SCHAFT Inc., a Google company, produced the HRP-2 robot in 2014, which was capable of driving a vehicle, walking over debris, climbing a ladder, removing debris, walking through doors, cutting through a wall, closing valves, and attaching a hose, they explain. Moreover, finally, in 2014, the Turing Test was passed when chatbot Eugene Goostman - a fake 13-year-old boy from Odessa, Ukraine, who didn't speak English fluently - tricked 33 percent of the jury into thinking he was a real child during a five-minute interview (Pulakkat, 2014).

Later, in 2016, Google's DeepMind AlphaGo supercomputer won world champion Lee Sedol in one of the world's most complex strategy games, and the AI learned the game in 30 hours using unsupervised learning (Lowe & Lawless, 2021). Similarly, AlphaGo Zero won the world's greatest chess computer program in 2017, and the AI taught itself to play chess in less than four hours (Lowe & Lawless, 2021).

In 2015, OpenAI, an artificial intelligence lab, was founded with the purpose of developing "artificial intelligence," or AGI, or software that is as intelligent as humans (Verma, 2023). After couple years, in 2020, OpenAI presented GPT-3 "the API" which was meant for answering inquiries in natural language but can also translate between languages and process writing (Verma, 2023). Then, in 2021, OpenAI introduced DALL-E, a deep learning model that could create graphics based on human instructions (Verma, 2023). Year later, OpenAI launched a free preview of ChatGPT, the latest AI chatbot built on GPT-3.5 (Kay, 2023). Ultimately, in 2023, OpenAI announced the fourth version of its multimodal language model, GPT-4, which is delivering safer and more reliable responses as well as solving challenging problems with improved accuracy (Kay, 2023).

The development of artificial intelligence has come a long way from the 1950s to today. AI development has accelerated in recent decades, owing to enhanced computers and increased computer capacity. Currently, the AI market includes a wide range of sectors, including technology, healthcare, finance, retail, manufacturing, transportation, marketing, education, agriculture, energy, entertainment, government, and so on. These sectors have been implementing and integrating AI into their operations for applications ranging from medical imaging and fraud detection to personalized learning experiences and self-driving automobiles. The adaptability of AI is driving continuous growth and innovative benefits, enhancing decision-making and productivity across many industries.

2.3 AI in Finance

One of the few heavily automated businesses is the financial sector. According to Bartoletti et al. (2020), computerized systems have automated all elements of financial service functions, resulting in massive volumes of data. AI has the potential to be widely used in finance, given the business is essentially focused on formulas, statistics, and strategies, they note. On a broad scale, AI is able to improve nearly all areas of the financial sector.

According to Bartoletti et al. (2020) AI has a significant impact in the financial sector. On practical level, AI can be utilized for example in lending, making payments and deposits, insurance, investments, and wealth management and it is already being used for credit scoring by banks and financial organisations, they explain. AI is a significant tool especially in the finance industry's customer service operations, and for example, AI can generate consumer enquiries and provide assistance, such as a chatbot or answering machine for a bank (Bartoletti et al., 2020). AI can also perform credit scoring: whereas the traditional method relies on static variables and historical data, artificial intelligence-based credit scoring evaluates a wide range of data points using machine learning algorithms (Bartoletti et al., 2020). Furthermore, artificial intelligence is employed as a tool in the identification of fraud by financial organisations, because it is capable of recognizing unusual patterns in activities such as credit card transactions (Hilpisch, 2020).

Likewise, portfolio managers can benefit considerably from AI techniques in portfolio management. AI can assist portfolio managers with data analysis, risk assessment, asset allocation and performance tracking, and among other things, it can even compose and rebalance portfolios (Hilpisch 2020). Furthermore, intelligent technology can assist with investing operations such as trade execution: for example, AI is capable of learn how to perform large-block deals while minimizing transaction costs, he continues. AI can even perform derivatives hedging, where AI is taught to optimally execute hedge transactions against specific derivative instruments or portfolios (Hilpisch 2020).

Table 1. Examples of AI applications in financial market activities (OECD 2021b).

<table>
<tr><td rowspan="7">Asset Management</td><td rowspan="7">Algorithm trading</td><td rowspan="7">Credit intermediation</td><td rowspan="7">Blockchain-based finance</td><th>Back Office</th><th>Middle Office</th><th>Front Office</th></tr>
<tr><td>Post-trade processing</td><td>Risk management</td><td>Asset allocation</td></tr>
<tr><td>Trading P&L, reconciliations</td><td>KYC checks</td><td>Robo-advisors, Chatbots</td></tr>
<tr><td>Reporting and record management</td><td>Compliance</td><td>Biometric authentication</td></tr>
<tr><td>Data analytics</td><td>Control functions / processes</td><td>Trade execution</td></tr>
<tr><td>Credit scoring / risk underwriting</td><td>AML / CFT</td><td>Personalised recommendations</td></tr>
<tr><td>IT / infrastructure</td><td>Anti-fraud</td><td>Customer service</td></tr>
</table>

Table 1. above presents real life examples of different AI applications in financial activities. There are several ways artificial intelligence can be employed in different functions of the financial sector, and the integration of artificial intelligence into financial operations has already spread to various financial functions.

3 Traditional Funds

3.1 Overview of traditional funds

An investment fund i.e., mutual fund, in general is an instrument that invests in various types of assets and is owned by investors who have purchased fund units, which are in fact shares of the fund. The fund's assets may consist of cash, stocks, loans, tangible or intangible assets, and most funds have been established to hold multiple types of assets. Basically, a fund means any combination of assets and broadly, almost any economic collection or pooling can be considered as a fund (Hudson, 2014; Kallunki et al., 2019). In general, the fund's revenue is based on the income generated by its investments, which include interest income, dividends and the increase or decrease in the value of the invested capital (Kallunki et al., 2019).

The assets of the fund are owned by the persons, entities and foundations who invested in it, in proportion to the size of their investment. One of the main features of a traditional fund is the presence of a professional fund manager who manages and advises the fund. Traditional funds select stocks and make investment decisions mainly through human judgment. Portfolio managers are responsible for managing funds' assets and deciding how to invest them. As asserted by Kallunki et al. (2019) and Hudson (2014) the fund may invest in multiple types of instruments in accordance with its approved investment policy. The capital of the fund varies according to the fluctuation in the value of its investments and how investors buy and sell fund shares, they continue. This affects the calculation of the value of the shares, as the value of each individual share is calculated based on the fund's worth (Hudson, 2014; Kallunki et al., 2019).

The price of a fund unit is always the same for both the new investor and the existing investor who sells the share, i.e., the value of the unit is the fair market value of the fund's investments divided by the number of fund shares currently in circulation (Kallunki et al., 2019). When fund units are subscribed or redeemed, the fund's capital increases or decreases, Kallunki et al. (2019) explains. Fund units are not typically traded on the stock exchange but exchange traded funds (ETF’s) are publicly listed funds whose fund units are traded on the stock exchange like a stock, and their price is determined according to supply and demand (Kallunki et al., 2019).

Kallunki et al. (2019) continues to explain about different types of funds. They state that there are many different types of funds with different characteristics. Short-term investments funds, for example, invest in short-term money market securities such as government bonds and corporate bonds. The Long-term investment funds, on the other hand, invest primarily in bonds and other interest instruments with loan terms of more than one year. There are also mixed funds, which invest in both bonds and stocks, they add. The weightings of bonds and stocks may vary between mixed funds. In contrast, equity funds invest principally in stocks, Kallunki et al. (2019) asserts.

In addition, as declared earlier, ETF investment funds are publicly listed funds that trade similarly to stocks. ETFs' investment policies are stated in the fund's policy, and investment policies between ETFs might differ significantly, Kallunki et al. (2019) says. Most ETF funds are index funds, and their return is equal to the target index's performance minus the fund's expenses. In its research, this paper focuses on exchange-traded funds.

Following, this thesis observes at the funds that serve as benchmarks for traditional funds for this paper. The funds are carefully chosen based on their characteristics.

The first traditional fund utilized in this research is Dimensional U.S. Core Equity 2 ETF. The following paragraph is based on data sourced from the fact sheet and fund prospectus provided by Dimensional Fund Advisors LP (2023). The fund is actively managed exchange-traded fund and trades under the ticker symbol DFAC on NYSE Arca. As confirmed by Dimensional Fund Advisors LP (2023.), the ETF seeks long-term capital appreciation while addressing the federal income tax implications of investing decisions. The DFAC is intended to invest in a wide and diverse range of securities of U.S. companies. Moreover, the portfolio invests in companies of different sizes, with a focus on companies with lower capitalization, lower relative price, and higher profitability than their competitors in the US Market. The fund Advisor, in the function of portfolio manager, makes investment decisions with specific characteristics when necessary. The ETF does not attempt to replicate the performance of a particular index and under normal conditions, DFAC will invest at least 80 percent of its net assets in securities of U.S. companies.

Another fund considered in this study is the Avantis U.S. Equity ETF, which trades under the ticker AVUS on Nyse Arca. The information in this paragraph is drawn from the fact sheet and fund prospectus supplied by American Century Proprietary Holdings (2023). The ETF is actively managed and incorporated in the United States. The fund does not seek to track the performance of a specific index. The main objective of the ETF is to seek long-term capital appreciation by primarily investing in a wide selection of US companies of all market capitalizations, sectors, and industries. The fund places a strong emphasis on small-cap companies that are expected to have higher returns, better profitability, and attractive value characteristics. In contrast, AVUS tends to reduce or exclude investments mainly in larger companies that are expected to have lower returns, profitability, and less attractive value characteristics. The fund's advisor is American Century Investment Management. Portfolio managers constantly analyze market and financial data to make buy and sell decisions with desired characteristics. In addition, they regularly evaluate the portfolio inclusion criteria. Under typical market conditions, the fund invests at least 80 percent of its assets in equity securities issued by US companies.

3.2 Investment decision-making process of human

Humans make nearly 35 000 decisions every day (Krockow, 2018). Decisions can range from small to huge, like what to wear today, what to eat for lunch, whether to buy a house from city or countryside, and so on. Decisions can be performed in many ways, with fast or in-depth consideration (Krockow, 2018). These choices can be minor or life changing.

Human decision-making is a complex and multidimensional phenomenon that has been researched from various fields such as psychology, neuroscience, economics, and behavioural science. While there is no single model that can generally describe every human-made decision, the Kahneman's ground-breaking theory (2011), based on the dual-process model by Posner & Snyder (1975) is a commonly accepted paradigm for understanding human decision-making. The Kahneman's model divides the decision-making process into two segments: *System 1*: fast, intuitive thinking, which happens automatically and with minimal effort (instincts, habits, past experiences) and *System 2*: slower analytical thinking which is conscious and logical (reflection, planning, and problem solving). The dual-process model theory works as a benchmark theory for behavioural and brain sciences that can be reformulated and adapted to fit to almost any human behavioural context.

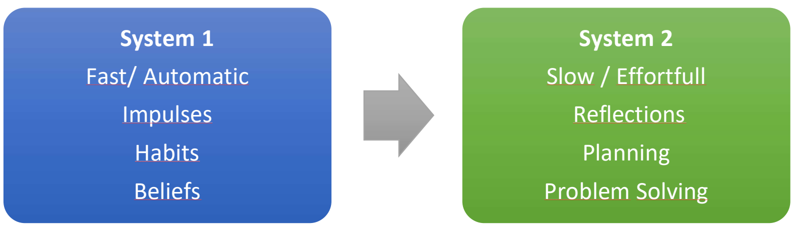


Figure 4. Dual Process Theory (Kahneman, 2011; Posner & Snyder; 1975).

In practice, Kahneman's theory (2011) could be described in the following way. Imagine you're a coffee enthusiast, and every morning you instinctively head to your favourite local coffee shop without much consideration. You know the barista by name and your normal order is nearly a natural instinct. It's a routine that requires minimal cognitive effort because it's become rooted in your daily life. However, one day you arrive at the coffee shop only to discover that it is closed for renovation. You're now facing an unexpected decision-making process and must consider your options: Should you try a new coffee shop close by? Is it worth driving a little further for your favourite brew? Maybe you could make your own coffee at home, but that would take more time. Consequently, in this scenario, the habitual decision (system 1) to go to your regular coffee shop is disrupted, prompting you to consider and evaluate alternative options (system 2).

In addition, Engel and Singer (2008) give explanation about advanced human abilities in the context of decision-making. Moral, ethical, and emotional understanding contribute to human decision-making, laying the groundwork for nuanced decisions, they state. These abilities with creativity, enable humans to generate innovative solutions to problems with efficiency, they add. Moreover, the basic human abilities like, self-awareness, intuition, and instinct, was well as the ability to read and interpret situations, contribute to the understanding of context required for making nuanced decisions (Engel & Singer, 2008). Furthermore, human decision-making extends to considering social and cultural factors, and the ability to consider the impact of decisions on others, based on Engel and Singer (2008).

3.2.1 The portfolio manager's decision-making framework and techniques

The role of a portfolio manager requires constant decision-making on many different areas. Portfolio management requires an in-depth knowledge of the strengths and weaknesses, opportunities, and risks of various investment instruments. A portfolio manager oversees all of the trades executed during the day by the investment fund or portfolio by making final decisions on the securities involved.

Moreover, portfolio management can be either passive or active. Passive management involves replicating the performance of a specific market index without active trading, while active management requires constant decision-making by the portfolio manager who actively buys and sells securities to often outperform a specific index, such as the S&P 500 (Bodie et al., 2023). This study focuses on active portfolio management approach.

The success of the fund depends on the fund manager's ability to make the right decisions, based on thorough market research, market forecasts and the manager's expertise. Portfolio managers are constantly tracking market trends, economic events, political movements, and corporate news, which guide the timing of trade execution decisions to profit from anomalies (Bodie et al., 2023). Furthermore, decision-making is required from several areas such as asset allocation and diversification, which are also critical elements of portfolio management.

First, asset *allocation* is a critical concept that involves making decisions regarding the combination of assets within a portfolio. Different asset classifications include stocks, bonds, cash equivalents, and derivatives (Kallunki et al., 2019). Recognizing that different asset classes exhibit varying degrees of volatility; managers strategically balance their portfolios based on their risk tolerance and financial targets (Kallunki et al., 2019). The asset allocation decision entails selecting from these general asset classes, whereas the security selection decision involves selecting which specific stocks to hold within each asset class (Bodie, et al., 2023). Second, *diversification* is a fundamental concept of portfolio management, which also demands constant decision-making by managers. Diversification is based on Modern portfolio theory (Markowitz, 1952) according to which owning a portfolio of different asset classes is less risky than owning a portfolio of similar assets. Portfolio managers seek to capture the total returns of various sectors over time while reducing volatility by creating a diversified portfolio of investments stretching across asset classes, industries, and geographical areas (Bodie et al., 2023).

Third, *rebalancing* involves regularly checking and adjusting the investment allocation of the portfolio to its initial target allocation, which helps to lower the risk and volatility in the portfolio, often leading to improved returns, as stated by Malkiel & Ellis (2020). The rebalancing process allows the manager to capture profits and enhance growth opportunities in sectors with favourable outlooks, all while staying within the original risk-return profile of the portfolio, Malkiel & Ellis (2020) continue. Fourth, *cost efficiency* is an important part of portfolio management that requires a comprehensive strategy involving a number of critical components and a significant amount of decision-making effort. Tax efficiency, minimizing transaction costs, optimizing operational processes, and involving diversification strategies, are all important (Malkiel & Ellis, 2020). The primary objective is to maximize returns while minimizing unnecessary costs, consequently increasing the overall performance of the investment portfolio.

Portfolio management also include making risk-related decisions. Managers determine the overall level of risk in the portfolio by allocating weights to various asset classes. The manager's decisions are subject to a range of risks, such as the selection of securities, allocation choices, and investing style, whether based on a value or growth, or small-cap versus large-cap investment method (Bodie et al., 2023). *Risk management* is an important part of the investment decision-making process. It includes identifying and evaluating the risks connected with an investment, followed by deciding whether to accept the identified risk in the context of the expected return (Malkiel & Ellis, 2020). For example, standard deviation, Sharpe ratio, beta, value at risk (VaR) and conditional value at risk (CVaR) are all common risk measurements (Bodie et al., 2023; Malkiel & Ellis, 2020), and portfolio managers make numerous financial decisions based on the outcomes of these measurements.

Furthermore, portfolio managers employ a wide range of tools to assist them in making difficult investment decisions. Financial analysis software is essential for assessing individual securities, industries, and markets through the analysis of financial statements, in addition to previous performance (Maham, 2023). Usual analysis types include, for instance, ratio analysis, which calculates financial ratios for assessing a company's performance; trend analysis, delving into historical financial data to discern patterns; and common-size analysis, displaying financial information as a percentage of total sales (Maham, 2023). Access to comprehensive market research reports is critical when analysing trends, economic indicators, and industry-specific data (Maham, 2023). Additionally, conventional risk management models, such as standard deviation and beta, enable the evaluation and mitigation of various investment risks (Bodie et al., 2023; Malkiel & Ellis, 2020). Meanwhile, quantitative, and qualitative models, often based on mathematical algorithms, assist in the analysis of potential investments and the forecasting of market movements (Hayes, 2023). Asset allocation tools are critical for improving asset allocation in accordance with investor objectives, risk tolerance, and market conditions. All these different kinds of tools have a substantial impact on the decision-making process of the portfolio manager.

To enhance the competence of their investment decisions, portfolio managers can leverage various software precisely made for effective portfolio management. Prominent software options include Bloomberg Terminal, providing real-time financial information; FactSet, offering financial analytics and portfolio management; and Morningstar Direct, facilitating investment analysis, while Refinitiv Eikon provides financial information and analytics (Olumofe, 2023). Comprehensive systems like Charles River IMS and BlackRock's Aladdin incorporate all aspects of investment management, including portfolio and risk management (Whyte, 2019). Furthermore, MSCI RiskManager and RiskMetrics function as risk management and portfolio analysis tools (Whyte, 2019). Several programs seamlessly integrate financial analysis, risk assessment, and market research, providing portfolio managers with access to real-time data and comprehensive insights to support informed decisions. In the end, for human portfolio managers, the entire portfolio management is based on the manager's own decisions, which are made within the framework of human limitations.

3.2.2 Psychological factors and investment decision-making process

In the field of asset management, we often narrow our focus to evaluating the performance of investments, while the broader context in which investment decisions are made receives little attention. As a result, the importance of psychology in financial decisions is understated. Behavioural finance investigates investor behaviour to understand how people make decisions. Psychology is often defined as the study of mind or mental behaviour. Mental behaviour includes the area of thinking, and thinking contains actions like making decisions.

As a pseudonymous writer of Money Game, Adam Smith (1968, p.25–26) once said:

> *It sounds simplistic to say the first thing you have to know is yourself, and of course you are not necessarily out to become a professional money manager. But if you stop to think about it, here is one authority saying there are not formulas which can be automatically applied. If you are not automatically applying a mechanical formula, then you are operating in this area of intuition, and if you are going to operate with intuition- or judgement- then it follows that the first thing you have to know is yourself. You are- face it - a bunch of emotions, prejudices, and twitches, and this is all very well as long as you know it. Successful speculators do not necessarily have a complete portrait of themselves, warts and all, in their own minds, but they do have the ability to stop abruptly when their own intuition and what is happening Out There are suddenly out of kilter. A couple of mistakes crop up, and they say, simply, "This is not my kind or market," or "I don't know what the hell's going on, do you?" and return to established lines of defense. A series of market decisions does add up, believe it or not, to a kind of personality portrait. It is, in one small way, a method of finding out who you are, but it can be very expensive. That is one of the cryptogram which are my own, and this is the first Irregular Rule: If you don't know who you are, this is an expensive place to find out.*

To make sensible decisions and judgements about holding, selling, or acquiring assets, portfolio managers must predict the ups and downs of the financial market dynamics. Profitability is dependent on their capacity to identify securities positioned for future price increases and decreases. Accurate forecasts can result in substantial gains, highlighting the critical necessity of estimating future market movements in portfolio managers' decision-making process.

The area of financial decision-making has already been examined, with one example being the study by Cesarini et al. (2010), which investigates whether genetic variation can explain some of the individual differences in investment decisions, which is studied through observing how individuals differ in building their investment portfolios. The study examines the heritability of risk-taking in financial markets and real-life situations, highlighting the significant role of genetic variation in explaining individual differences. According to the study, genetic variation determines approximately 25 percent of individual variation in portfolio risk. The study states that genetic factors have a far greater impact on risk-taking behaviour than what is previously observed in studies on portfolio selection. Also, the results indicate that specific genetic factors could potentially offer insights into why people have varying levels of willingness to take risks. (Cesarini et al., 2010).

Personality psychology is an area of psychology that studies the impact of individual personality characteristics on behaviour. Personality traits have a huge impact on the decision-making process. The paper by Gambetti and Giusberti (2019) discusses the complex relationships between personality traits, decision-making styles, and investments. The research observes into control variables like gender, income, and experience, finding that these factors consistently predict investment perceptions and decisions. Additionally, the study reveals that men tend to select riskier investment strategies compared to women, and individuals with more investment experience tend to embrace higher-risk portfolios, underlining the role of experience in investment decisions (Gambetti & Giusberti, 2019).

The previous studies have indicated that anxious individuals avoid investing or saving money and prefer low-risk options like interest-bearing accounts, while those with high self-control and a solution-oriented mindset are more open to various asset classes (Gambetti & Giusberti, 2012; Oehler et al., 2017; Van Winden et al., 2011). These studies highlight a positive link between high self-control and long-term asset investments. Additionally, extroversion and independence are associated with a willingness to invest in stocks, especially the aspect of extroversion known as liveliness, which motivates individuals to take on financial risks (Dewberry et al., 2013; Gambetti & Giusberti, 2019).

Furthermore, persons with practical, solution-oriented thinking tend to better manage stock trend fluctuations through self-management, and those with high self-control have the highest skill on predicting stock trends. Conversely, individuals exhibiting traits such as impatience, distrust, introversion, unsociability, and traditionalism often perceive higher risks in investment decisions. In opposition, calm, and relaxed individuals with competitive, strategic thinking and low tendencies for guilt or self-doubt tend to earn higher returns. Additionally, individuals with high levels of extroversion, independence, and self-control typically adopt a rational, careful approach when evaluating investment options and are motivated to engage in investment activities, while highly anxious individuals tend to save money and refrain from making investments due to their perception of high risks, low control and returns (Bensi & Giusberti, 2007; Dewberry et al., 2013; Gambetti & Giusberti, 2019; Maner et al., 2007).

Financial decisions are often made under uncertain and complex settings, causing the decision maker to rely on intuition, which plays a major role in most judgments with diverse psychological biases. The intuitive decision-making procedure is called heuristics. Using heuristics, as demonstrated by Tversky and Kahneman (1974), can lead to numerous cognitive biases and particular fallacies. People are subjected to various "irrationalities" when making decisions, and these irrationalities can be categorized into two general group: First, *Information processing* - investors often fail to process information accurately, resulting in incorrect estimations of future probabilities of potential events and related rates of return (Bodie et al., 2023). Second, *behavioural biases* – people frequently make decisions that are inconsistent or systematically inefficient, even when they have information about a probability distribution of returns (Bodie et al., 2023; Slovic, 1972). The potential biases, as well as the two stages of decision-making (system 1 and 2) and heuristics, emphasise the degree of complexity and nuance involved in making decisions (Tversky & Kahneman, 1974).

Moreover, there are five main types of errors in information processing. For example, *Limited attention, under- and overreaction* results from the limited capacity of human attention and time, which prevents individuals from effectively processing all available information during decision-making, leading to reliance on intuition (Hirshleifer & Teoh, 2005). This can cause overreactions to important news and underreactions to less notable information. According to Daniel et al. (1998) and De Bondt & Thaler (1995), *Overconfidence* occurs when investors overestimate their own abilities and beliefs about forecasts, whereas *Confirmation bias* is the tendency to interpret new information in a way that reinforces or endorses our previous beliefs (Wason, 1960). C*onservatism bias*, on the other hand, results in slow adjustments to new information, resulting in underreaction to new information (Kahneman et al., 1982). Lastly, r*epresentativeness bias* occurs when investors draw too quick conclusions about trends or patterns (Barberis et al., 1998).

Even with flawless information processing, people will make decisions that aren´t entirely rational. The behavioural biases significantly impact how investors approach the balance between risk and return. *Framing, t*he concept by the pioneers in psychological literature, for instance*,* shows in which way the decision is presented, can influence choices (Tversky & Kahneman, 1974). For example, framing a decision as an obligation rather than an option can result in different outcomes (Tversky and Kahneman, 1979). *Mental accounting,* as described by Thaler (1985), reveals how we give different values to things, like money, based on mental categories. This means that decisions can never be completely neutral (Thaler, 1985). *Regret avoidance*, in contrast, explains why investors avoid admitting bad investment choices and often make emotional decisions instead of logical ones to prevent regret. This behaviour is driven by a desire to prevent regret from buying the investment in the first place (Bell, 1982; Loomes & Sugden, 1982).

Relatedly, *Affect and feelings* refer to the personal feelings that an investor may have about a particular instrument or company, which may impact investment decisions (Gilovich et al., 2004; Mellers et al., 1997; Schwarz & Clore, 1988). Lastly, *loss aversion* is a vital concept in prospect theory, developed by Kahneman & Tversky (1979) and is a descriptive model of risky decision-making. According to the theory, investors value gains and losses differently, preferring perceived gains over perceived losses. The psychological pain of losing is almost twice as intense as the pleasure of gaining. And when given two equal options, an investor will choose the one in term of potential gains, so whether the uncertainty of returns is framed as risky losses or risky gains, matters (Kahneman and Tversky 1979).

Also, a study conducted by Lerner et al. (2015) studies the impact of emotions on decision-making. According to the findings, emotions have a powerful and constant influence on decision-making, and interestingly, certain emotions, such as sadness, can even lead to more systematic and deliberate ways of thinking. In addition, Love (2010) found that major life events such as divorce, widowhood, and changes in family composition can significantly impact optimal portfolio allocations. Divorce and widowhood have a high impact on allocation, with variations based on gender, number of children, and age. Widowhood particularly reduces stock holdings, while divorce leads to divergent portfolio adjustments, with men favouring riskier investments and women opting for safer ones (Love, 2010).

Generally speaking, the broad spectrum of behavioural, psychological, and personality-related biases inherent in human decision-making has a significant impact on humans' investment decisions. It is fairly probable that these biases also influence the decisions made by portfolio managers, thereby affecting their performance. The complicated quality of human biases emphasises the difficulties in attaining optimal investment performance from the viewpoint of a human portfolio manager.

4 AI-powered funds

4.1 Overview of AI-powered funds

In todays around the clock global market environment, with an extensive range of unique and exotic financial instruments, artificial intelligence offers abilities that are rapidly surpassing traditional algorithms in finance and trading. In addition, trading systems powered by AI can play a significant role in helping traders to make sensible investment decisions based on huge amount of available real-time data.

In financial industry, AI plays a significant role by enabling advanced form of algorithmic trading, which involves the use of automated algorithms to manage various features of the trading process (ESMA, 2023). Advances in quantitative finance and machine learning have allowed computers to undertake financial analysis with greater speed and effectiveness than humans. In contrast, the complicated nature of financial markets, combined with the emergence of new financial products, has made real-time trading decisions difficult for humans (ESMA, 2023). While algorithmic trading is often used to enhance and automate order submissions and executions, it is typically applied only after a portfolio selection has been made (Hendershott et al.,2011; Lo et al., 2000). AI, on the other hand, takes a different strategy, making decisions early in the portfolio selection process, from the pre-trade to the post-trade stage (Abis, 2020).

Several AI-powered funds are in the form of ETFs. As artificial intelligence continues to demonstrate its growing capabilities, ETFs have started to harness the power of machine learning (ML) and natural language processing (NLP), states Zhang et al. (2023). The utilization of AI technologies enables these ETFs to create investment portfolios with superior features based on AI technology. AI-powered ETFs are intended to use ML algorithms to recognize market patterns and trends in order to make investment decisions, Zhang et al. (2023) explain. These algorithms are often trained on massive amounts of historical financial data, allowing for faster and more accurate data processing than human capabilities, they summarize. Next, this research discusses AI-based ETFs that are relevant to the study and are used in the comparison together with traditional funds.

The origins of the first AI-based fund can be traced back to a discussion of three experienced professionals in a business school class, each of them looking for a means to turn their résumé accomplishments into a thriving business (Field, 2022). Among them were Fidelity Investments vice presidents Art Amador, Intel's director of engineering Chida Khatua, and Apple's investment portfolio manager Chris Natividad, who came up with the idea for the world's first ETF managed entirely by artificial intelligence (Field, 2022).

Afterwards, AIEQ debuted in October 2017, and it was the world's first AI-managed public equity ETF, to fully utilize artificial intelligence machine learning techniques as a method for stock selection. AIEQ became soon one of the most popular funds in 2017, raising over 70 million dollars in just a few weeks (ETF Managers Trust, 2023a).

The AIEQ is actively managed ETF which is listed on NYSE Arca and it employs an investment strategy that focuses on equity securities listed on U.S. exchanges (ETF Managers Trust, 2023a). The strategy relies on the EquBot Model, developed by EquBot Inc, and the EquBot utilizes IBM's Watson AI platform to conduct a comprehensive analysis of U.S. common stocks, including SPACs (Special Purpose Acquisitions Corporations) and REITs (Real Estate Investment Trusts), using up to ten years of historical data in combination with recent economic and news data (ETF Managers Trust, 2023b). The Fund's investment advisor and subadviser rely on EquBot Model recommendations to determine which securities to buy and sell. The AIEQ ETF's primary investment strategy revolves around AI-driven analysis to optimize its portfolio composition and performance (ETF Managers Trust, 2023a; 2023b).

Alongside AIEQ, this research investigates another AI-powered fund listed on Nyse Arca. The fund is commonly known by its ticker QRFT, but its full name is QRAFT AI Enhanced U.S. Large Cap ETF. It operates as an actively managed exchange-traded fund with a primary focus on large-cap stocks traded on U.S. exchanges (QRAFT Technologies, 2023b). QRFT aims to achieve long-term capital appreciation by shifting its investments across five factors:

quality, size, value, momentum, and low volatility. The fund allocates its assets into equity securities, including common stock, American Depositary Receipts (ADR), and Global Depository Receipts (GDR) (QRAFT Technologies, 2023a). The ETF applies an artificial intelligence system called the QRAFT AI Quantitative Investment System (QRAFT AI) to select which stocks to include in the portfolio. While the primary stock selection process heavily relies on AI, the fund's automated framework incorporates human intuition and oversight in combination with the capabilities of AI (QRAFT Technologies, 2023a). The investment decisions for QRFT are ultimately entrusted to its advisor company which has full discretion over investment decisions for the fund (QRAFT Technologies, 2023a; 2023b.)

4.2 Investment decision-making process of AI

Traditional investment strategies rely on predefined rules or criteria, such as sector, size, or quality, to manage a portfolio. This approach can be limiting because it doesn't fully tackle the diverse elements of the global market landscape. The critical advantage of AI-powered ETFs is their ability to adapt their investment strategies and make decisions based on real-time market data. For instance, according to ESMA (2023) and Funds Europe (n.d.)., in times of increased market volatility, an AI-powered ETF can adjust by allocating more resources to assets expected to perform well under volatile market conditions. Similarly, when a new investment opportunity emerges, an AI-powered ETF can swiftly analyse relevant data to determine its potential as an investment target, they state.

Next, the research will observe how the processes of the AI-powered fund really operate. The section begins by introducing the AIEQ operating model, which Chris Natividad and Chida Khatua, the founders of AIEQ, present in an article written by Field (2022).

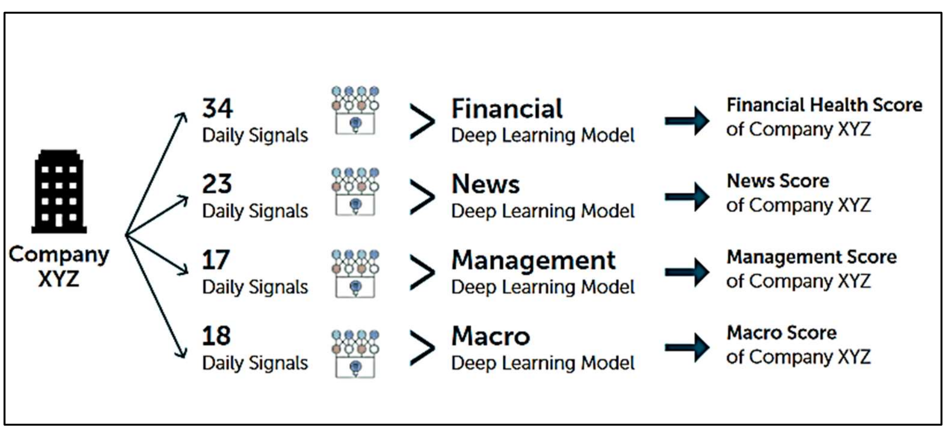
AIEQ is managed by EquBot. The article explains that EquBot is the primary operator of AIEQ, and the fund is dependent on EquBot's tens of thousands proprietary models. Every day, the EquBot platform collects and analyses data on the around 6,000 US companies that AIEQ tracks, Field (2022) writes. This data contains millions of data points from news, social media, industry and analyst reports, financial statements, technical, macro, and market data, among other things, as well as structured data from third-party data suppliers (Field, 2022). The EquBot Model also ranks companies, based on their potential to benefit from current economic conditions, trends, and world events, selecting approximately 30 to 200 companies with the greatest potential for appreciation over the next twelve months (ETF Managers Trust, 2023a). These selected companies are assigned corresponding weights, with the aim of achieving maximum risk-adjusted returns compared to the broader U.S. equity market (ETF Managers Trust, 2023a).

In addition, EquBot applies IBM Watson to support monitoring AI models, assist in its investment decision-making procedures for selecting securities, and extract insights from data, Field (2022) asserts. IBM's Watson AI is a powerful computing platform that can provide responses to presented questions, and it achieves this by connecting extensive data sets, encompassing both structured data and unstructured data, states Field (2022). It learns via structured data, such as financial statements, growth, expenditure on R&D, and market movements, he adds. However, he notes that it also obtains insights from unstructured data, such as news stories, blogs, social media, and company announcements. The IBM Watson platform utilizes machine learning, sentiment analysis and natural language processing in its processes, according to Rothney (2021). Watson AI constantly learns and improves from each analysis it performs, such as recognizing patterns, thereby enhancing the accuracy of its responses with each subsequent inquiry, she continues. IBM Watson monitors over 80,000 AI models, which is far too numerous group for humans to monitor (Field, 2022). After all, the platform operates like an equal army of 1,000 research analysts, traders, and quantitative analysts operating around the clock (ETF Managers Trust, 2023a).

Moreover, as specified by Field (2022), the AIEQ’s AI models are trained on five to 30 years of historical data, with more emphasis placed on recent data. The models are trained on a cost function, which implies that the model forecasts the expected return for each historical data point, such as an older news story from 2001, he explains. Likewise, he says that the models incorporate trust points to differentiate data sources, e.g., the models assign different weights to a New York Times article compared to a blog post. All this data is then integrated into knowledge graphs by EquBot, whose serve as important educational tools for AIEQ, he summarizes.

Whereas the system depends on a substantial group of 80,000 models, three of these models play a particularly significant role in shaping its decisions. Field (2022) talks about these models in his article. The key AI models are: *Financial Model*, which evaluates a company's financial state and performance over different time horizons, primarily using earnings and spending data. *Quality Model,* which utilizes around 170-line items, such as innovation ranking, to assess a company's current quality. And lastly, *Sentiment Analysis Model*, which applies IBM Watson's natural language processing tools to extract metadata and analyse the sentiments of over a million content pieces daily. In addition, EquBot employs a combination of internal tools and IBM Watson's OpenScale tool to continuously monitor 10 key metrics for each model (Field, 2022). These metrics help to flag any potential bias or deviations in the models' behaviour, while they track the decision-making processes of each model using decision trees, Field continues. Besides, two people monitor the actions of potentially biased metrics full-time, while the individual owners of each AI model check for any red flags and warnings daily to ensure responsible AI-driven decision-making (Field, 2022).

The figure 5. shows the AIEQ's investment process. AIEQ builds four DL prediction models for each analysed company, which are: finance, news and information, management, and macro. These all have multiple underlying signals (ETF Managers Trust, 2023b).



Picture 1. AIEQ's investment process (ETF Managers Trust, 2023b).

In addition to AIEQ, QRFT ETF uses an AI-based decision-making platform called QRAFT AI in its investment processes. The QRFT ETF selects assets using a unique AI algorithm that discovers patterns, signals, and connections through analysing data (QRAFT Technologies Inc., 2023a). QRAFT AI employs machine learning and deep learning technologies in its operations (QRAFT Technologies Inc., 2023b).

According to the fund prospectus sheet by QRAFT Technologies (2023a) the QRAFT AI evaluates, and filters information from the database based on defined criteria, to support the fund's defined investment thesis. The prospectus defines also that QRAFT AI selects and weights NYSE and NASDAQ-listed US companies by defined factors in order to provide broad exposure to a range of market factors affecting the US market. These factors are Quality (company's profitability), Size (market capitalization), Value (the company's market value compared to its book value), Momentum (the security's recent price return versus to the overall market over time), and Volatility (security's systemic risk versus the overall market as a whole). This collection of data is called the "Database of Large US Companies" (QRAFT Technologies Inc., 2023a; 2023b).

Moreover, the fund prospectus describes the investment process of QRAFT AI (QRAFT Technologies Inc., 2023a). At first, QRAFT AI evaluates each stock's relative price appreciation potential in comparison to other companies over the next four weeks, and this evaluation involves utilizing deep learning methods, which include handling massive amounts of data. Then, the system examines the distribution of each stock's relative potential for price appreciation during this period, using complex deep learning structures like Bayesian neural networks to estimate the level of uncertainty in its forecasts. Next, based on this analysis, QRAFT AI selects the top 300 to 350 stocks from the database by averaging the distribution of their relative potential for price appreciation. QRAFT AI also compresses this data and assesses how each individual factor may evolve and impact a company over time. This process identifies companies with the highest potential to outperform their U.S. large-cap peers in the upcoming four-week period. The equities in the database are then weighted according to a methodology designed to optimize risk-adjusted returns when compared to other companies. Afterwards, the final portfolios are provided to the U.S. Large Cap

Database for use by the Adviser's financial experts. QRAFT AI repeats these procedures every four weeks, and the financial experts at the Fund's Adviser make or adjust investments in the fund based on the newly generated information (QRAFT Technologies Inc., 2023a).

All in all, artificial intelligence finds functions in trading through two key opportunities. First, it offers trading strategy recommendations, and secondly, it runs automated trading systems that not only make predictions but also determine the appropriate actions and even execute trades. AI-powered trading systems can autonomously identify and execute trades, functioning independently without human involvement (OECD, 2021a).

4.2.1 AI techniques and models for investment decision-making

Artificial intelligence technologies and models for making investment decisions are based on machine learning, which is the fundamental technology of artificial intelligence. Several major proprietary trading firms have incorporated ML models into their trading strategies and ML is already largely employed in trading activities including liquid assets, such as equities, futures, and foreign exchange, due to the multitude of real-time data for these instruments (BoE & FCA, 2019; ESMA, 2023). Generally, different ML approaches and models can accomplish different things, and each one tends to succeed at specific functions, making them suitable for different purposes (BoE & FCA, 2019). Often, the best results come from combining predictions and opinions from various AI techniques, known as ensemble methods, which have been proven to generate more accurate results than any single method alone (BoE & FCA, 2019).

For instance, machine learning approaches such as LASSO regressions, elastic nets, and artificial neural networks (ANNs) have natural mechanisms for selecting the most important components from data set, increasing the reliability of predictions. According to research like Feng et al. (2020) and Freyberger et al. (2020), LASSO regression can automatically find the most relevant parameters for predicting future returns from a large pool of return-predictive signals. Furthermore, the LASSO technique can be used to find lead-lag correlations between various asset classes or markets, allowing for evaluation of which industry or market returns act the most crucial role in predicting returns compared to all other markets or industries, they confirm. In addition, advanced versions of LASSO regression, known as "elastic nets," offer a balanced approach by ensuring that estimated coefficients do not become excessively large, which reduces the chance of the model "overfitting" and reduces spurious coefficient estimates to zero, considerably improving the model's performance (Bartram et al., 2021; BoE & FCA, 2019; Feng et al., 2020; Freyberger et al., 2020).

Then again, ML approaches such as artificial neural networks, support vector machines, and tree-based models are successful at detecting non-linear patterns, such as how input variables interact (BoE & FCA, 2019). This ability increases the creation of single and multi-factor signals by collecting more complicated correlations and intricate details in the input data (Bartram et al., 2021; Bartram et al., 2020).

As mentioned in the paragraph introducing the working models of AI, Artificial Neural Networks (ANNs) are computer algorithms that imitate the neural network structure of the human brain. They learn by adjusting connection weights to minimize errors between predicted and desired data labels, making them valuable for tasks such as stock price predictions (Weng, 2022). They are also competent at pattern recognition, capable of identifying complex patterns in data (Montesinos et al., 2022). Moreover, Bayesian neural networks, a variant of ANNs, employ Bayesian reasoning to better understand the probability distribution associated with various neural network configurations. Bayesian networks can be used to anticipate execution shortfall as a measure of transaction costs (Pan et al., 2021; Wu, 2021). This method is especially beneficial when data is missing as it may generate the most likely result based on the existing data (Ticknor, 2013). The approach prevents overfitting, facilitates learning from limited data, and offers a measure of confidence in predictions. Essentially, Bayesian neural networks incorporate probabilistic reasoning to enhance the robustness and informativeness of their predictions (Ticknor, 2013).

In contrast, tree-based models are an example of one of the most common of ML trading strategies. A simplest form is a decision tree, which is used for classification and regression tasks (Kumar & Ravi, 2007). Buschjager and Morik (2018) express that it features a hierarchical tree structure with a root node that doesn't have any incoming branches, internal nodes (decision nodes), and leaf nodes. They add that both root and decision nodes evaluate and partition the data into more comparable subsets, which are represented by the leaf nodes or terminal nodes. The leaf nodes symbolize all the potential outcomes inside the data set (Buschjäger & Morik, 2018). Figure 5. Presents the decision tree algorithm.

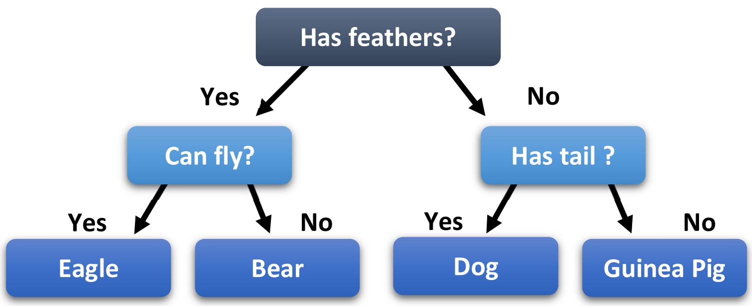


Figure 5. Example of decision tree algorithm.

Equally, according to Buschjager & Morik (2018) and Ho (1995) random forest is an advanced model that is made up of several decision trees to produce a single outcome. Unlike traditional decision trees, each individual decision tree makes its own predictions, which are then combined using an averaging process to form the random forest's predictions, they continue. This algorithm is useful for solving regression or classification problems. Both methods, decision trees and random forest, are proven to be quite successful in predicting outcomes in traditional financial data analysis scenarios, such as forecasting stock prices and identify patterns in market data (BoE & FCA, 2019). They can also be utilized to determine whether to buy or sell a stock, based on factors such as current price, trading volume, and market trends (BoE & FCA, 2019). The basic theory is that several decision tree models, each with a unique perspective, produce more accurate forecasts than a single decision tree (Buschjäger & Morik, 2018)

Likewise, Support Vector Machines (SVM) are supervised algorithms that have applications in both classification and regression. According to Hao et al. (2013), they are also known for their resistance to overfitting, which ensures reliable learning from training data. SVMs are effective in learning boundaries that separate feature spaces into distinct classes, allowing new data points to be classified, they state. However, that the computational requirements of SVM make the model unsuitable for large data sets, they add. SVMs are powerful in pattern recognition, data analysis, and finding insights and relationships from data set (Hao et al., 2013). Basically, they operate by taking inputs and providing valuable results, allowing them to find hidden patterns in the data, Hao et al. (2013) summarises. SVM can also be used for portfolio selection, by using a model based on the predictions it generates (Hao et al., 2013).

Conversely, Natural language processing (NLP) tools can be applied in ML to build factors based on textual input from sources such as corporate annual reports and news articles. in the words of Qian et al. (2022) NLP models are useful for sentiment analysis because they are effective at analysing unstructured textual data and can derive relevant information from it. Equally, sentiment analysis is a technique for analysing the relationship between market movements and financial news. For example, news about a company and general stock market can have a substantial effect on stock movement: thus, sentiment analysis aids in assessing market sentiment and making informed investment decisions, Qian et al. (2022) affirm. It is also an excellent tool for examining unstructured content about a specific company in order to identify inconsistencies and anomalies (Landauer et al., 2023).

Modern Portfolio Theory (MPT), also known as Mean-Variance Optimization Model (MVO), presented by Markowitz in 1952, and the Capital Asset Pricing Model (CAPM) an extension of MPT, developed by Sharpe in 1964, are foundational theories of the relationship between risk and return in investment decisions. Based on Lin & Liu (2008), traditional portfolio optimization strategies, such as Markowitz MVO Model (1952), have limitations due to their rigid structure and the difficulties in precisely calculating expected returns and variance-covariance inputs. ML technologies can solve these restrictions by providing more accurate estimates of expected returns as well as replacing the variance-covariance matrix with more reliable alternatives, they assert. Additionally, genetic algorithms, rooted in Darwin's and Matthew's (1859) theory of natural selection, are valuable in portfolio optimization by considering additional constraints that are not easily solved by traditional closed-form methods, as Lin & Liu (2008) note. Their operation starts with a randomly generated initial set of potential solutions, and as it repeats, it creates new solutions by combining information about solutions that work better in the population, they explain. These new solutions replace inferior solutions, resulting in a gradual improvement in the quality of the solutions over time. Genetic algorithms are flexible as they don't require a precise mathematical formulation of the problem or make assumptions about the objective function's characteristics, Lin & Liu (2008) confirm. Therefore, they are well-suited for complex problems where other optimization algorithms may fall short (Lin & Liu, 2008).

Moreover, reinforcement learning (RL), which incorporates genetic algorithms, may be utilized to directly generate portfolios (Calvo-Pardo et al., 2020; Chapados & Bengio, 2001; Hu & Lin, 2019). These algorithms take historical market data as input and autonomously learn to either effectively replicate a specific market index or maximize the Sharpe ratio of the portfolio (Calvo-Pardo et al., 2020; Du, 2022). In addition, neural networks, particularly as elements within deep learning, may be utilized to construct portfolios and perform asset allocation, in which they are applied in two main ways: as predictive models, often in combination with methods like mean-variance allocation, to guide investment decisions, and secondly, to determine asset allocation recommendations (Branke et al., 2009; Chapados & Bengio, 2001; Du, 2022; Hu & Lin, 2019).

Portfolio execution and rebalancing often require the development of models that account for transaction costs, notably market impact costs, and the formulation of strategies to minimize these costs. Nonparametric machine learning approaches, such as artificial neural networks and random forests, perform well in recognizing nonlinear and complex patterns in trade data and quotes (BoE & FCA, 2019; Ha & Hai, 2020). In contrast, parametric machine learning methods, such as LASSO regressions, provide valuable information about the elements influencing market impact, as Bartram et al. (2021) notes. Likewise, unsupervised ML algorithms, such as cluster analysis, can be utilized for categorizing assets and leveraging information from similar assets to estimate liquidity and market impact more effectively, they note. They further explain that cluster analysis is a classification method that splits data into groups with similar features, and that the model can be used to categorize new data after the clusters have been identified and named. It is primarily used for asset classification, but it can also be used for detecting anomalies, analysing data, and making execution recommendations (Bartram et al., 2020).

In addition, a talented group of machine learning tools revolves around reinforcement learning. RL is designed to make a series of decisions, such as trades, over a period of time, with the ultimate goal of achieving a specific goal, like maximizing the Sharpe ratio (Aloud & Alkhamees, 2021). Unfortunately, The RL approach has high computational requirements compared to other ML methods, but this barrier is expected to decrease as quantum computing technology advances. Another interesting area in trade execution is optimal execution. Researchers are applying a data-driven method, in which algorithms determine the ideal execution strategy based on how inputs change over time (Hendricks & Wilcox, 2014). RL methods are proven prominent in this field. Deep RL techniques, which include RL algorithms that leverage deep neural networks for function approximation, have also been successfully employed to optimal execution (Schnaubelt, 2022). Therefore, RL is primarily used to create optimal execution strategies, but it has demonstrated the ability to automate all aspects of portfolio management, including signal generation, optimization, transaction cost analysis, and execution (Hendricks & Wilcox, 2014; Jin & El-Saawy, 2016).

4.2.2 Absence of psychological factors

Artificial intelligence, when compared to human intelligence, is impressive, but it comes with evident limitations. These limitations arise from the fundamental differences between machines and humans.

AI process information in a statistical, objective, and abstract manner. In contrast, the human brain doesn't operate on abstract way. Instead, humans engage directly with their environment, viewing things comprehensively rather than as mere sets of numbers or data. Humans, for example, see the dog as a whole, not as a number matrix that depicts the image of the dog (Wichmann & Geirhos, 2023). Unlike computers, human brains aren't blank information processors. Instead, they have evolved over time to adjust to their surroundings, something that computer-based AI can't replicate (Buckmann et al., 2021).

According to Stojnić et al. (2023), AI systems, including ML models, lack true common sense and a deep understanding of the world. Humans have a natural ability to understand common sense concepts and make context-based decisions, whereas AI frequently struggles with nuance and context. Similarly, Picard et al. (2001) noted in relation to emotional intelligence that much work needs to be done before AI emotion interpretation may occur at the level of human skills. Emotional intelligence, which assists us in identifying, understanding, and managing emotions in ourselves and others, is a part of human intelligence. Because AI lacks feelings and emotional understanding, it is unsuitable for activities requiring empathy and emotional connection (Russell & Norvig, 2022).

Additionally, artificial intelligence is incapable of imagination and creativity, as noted by Buckmann et al. (2021). Humans are capable of being creative, thinking theoretically, and imagining new ideas. AI, on the other hand, is limited in its potential to develop truly unique ideas since it relies on patterns and data that it has been educated on, Buckmann et al. (2021) adds. Furthermore, while AI can be trained to perform certain tasks, it lacks the adaptability and versatility of the human mind. A human can learn and apply knowledge in many different domains and adapt to new situations without extensive reprogramming, as stated by Elliott & Kiel (2021). Likewise, humans hold the capability to establish long-term goals, plan for the future, and consider the comprehensive consequences of their actions (Buckmann et al., 2021). Artificial intelligence, on the other hand, tends to concentrate on short-term objectives and lacks a genuine understanding of long-term planning as well as the complexities of causal relationships (Buckmann et al., 2021).

When it comes to reasoning, humans are also quite good at filling in knowledge gaps and drawing reasonable conclusions, whereas AI systems often struggle with tasks that demand common sense or implicit knowledge (Russell & Norvig, 2022). Additionally, people can learn unguided, uncovering patterns and insights without needing explicit guidance or labelled information. In contrast, AI typically relies heavily on large amounts of labelled data and training (Buckmann et al., 2021; Russell & Norvig, 2022).

AI is morally and ethically deficient. Humans have a strong sense of morality and can form ethical decisions based on values, whereas AI systems follow the rules they have been programmed with or the information they have been instructed to follow (Buckmann et al., 2021). AI has no moral compass and is capable of acting in unethical ways (Buckmann et al., 2021; Russell & Norvig, 2022). While AI excels at certain activities, particularly those involving massive amounts of data and calculation, it falls short in many areas where human intelligence is successful.

Ultimately, we must evaluate the potential biases associated with decision-making of AI. In the developing field of AI applications, concerns have been raised about the incorporation of human biases into AI systems. The IBM Data and AI team (2023) has identified the most common human-based biases in AI, which are explained below.

To begin, the skewed or flawed information in training data may result in incorrect prejudices and outcomes within the AI system. Moreover, an algorithmic bias can occur due to the use of inaccurate training data, leading to errors or reinforcing biases. This kind of bias may add a layer of inaccuracy to the AI model, which could compromise its reliability.

Cognitive bias, on the other hand, is caused by programming faults and may introduce prejudice into algorithms if developers prioritize aspects based on their conscious or unconscious prejudices. In addition, human biases arising from previous experiences and preferences may mistakenly enter AI systems via data selection or weighting. For instance, a software engineer's preference for U.S. stocks over EU stocks could unconsciously influence the AI system's recommendations or decisions.

5 Data and Methodology

This chapter will present the selection method, the specifications, and the collection process of data utilized in this research. Similarly, the formulas utilized are presented.

5.1 Data description

The requirements were defined for the data set, and they included actively managed Equity ETFs with a geographic focus in the U.S., on the time period between 2021 – 2023. All ETFs seek long-term capital appreciation and are listed on Nyse Arca. In addition, the study utilized the S&P 500 index as a benchmark for the market return, which is generally considered the best single indicator of the U.S. stock market. The S&P 500 index tracks the largest companies across all sectors in the United States and captures approximately 80 percent coverage of available market capitalization (Bloomberg, 2023; S&P Dow Jones Indices, 2023).

The data was collected from Bloomberg Terminal. The statistics include cross-sectional time series data in the form of historical daily prices from four ETFs and the S&P 500 index from time period between June 14, 2021, to November 6, 2023. Daily prices of ETFs and S&P 500 index were closing prices for the recent day. The data did not include weekends or bank holidays. The number of observations was 626, as expressed in table 2.

Table 2. Descriptive Statistics.

	Descriptive Statistics				
	AIEQ	*QRFT*	*DFAC*	*AVUS*	*SPX Index*
Mean	34,28	39,91	26,15	72,90	4235,04
Standard Error	0,20	0,13	0,06	0,16	11,13
Median	32,41	39,49	26,32	73,27	4273,66
Mode	41,51	43,72	26,88	74,01	4352,34
Standard Deviation	5,01	3,16	1,52	4,01	278,47
Sample Variance	25,12	9,99	2,31	16,08	77544,23
Kurtosis	-0,98	-0,69	-0,54	-0,47	-0,83
Skewness	0,61	0,28	-0,24	-0,26	-0,19
Range	18,02	13,42	6,97	18,68	1219,53
N observations	626,00	626,0	626,00	626,00	626,00

5.2 Methodology

The event research methodology, first introduced by Fama, Fisher, Jensen, and Roll in 1969, is a widely used empirical tool for analysing the impact of new information on securities, as outlined in the introduction section of this study. Originally, the purpose of the event study approach was to determine how rapidly the market incorporated new information in stock prices, with the aim of evaluating market efficiency (Elton et al. 2014). The efficient market hypothesis (EMH) asserts that consistently outperforming the market is challenging, if not impossible (Fama, 1970). However, numerous empirical studies have tried to either confirm or disprove the Efficient Market Hypothesis. Substantial evidence from prior research indicates a lack of strong from of market efficiency. It has been demonstrated that investors can surpass market returns, achieving excess returns (De Bondt & Thaler, 1985; Grossman & Stiglitz, 1980; Shiller, 2003). Consequently, one could conclude that while real capital markets might exhibit some efficiency, the complete reliability of EMH is questionable.

Event studies employ abnormal returns to quantify the economic impact of an event by measuring deviations from expected market returns surrounding the event. This study used the event study method to investigate the possibility of abnormal returns under the Efficient Market Hypothesis (EMH) during particular events. The presence of abnormal returns could pose a challenge to EMH, implying delayed market pricing of information. If abnormal returns are discovered, for example, on behalf of AI funds, it would mean that integrating AI into investment decisions could result in additional gains, suggesting potential outperformance of regular market returns. Thus, if AI, for example, shows abnormal returns, it will highlight AI's capabilities, offering investors a chance to profit from excess returns and market inefficiencies by utilizing AI in investment decisions.

This thesis examined the effect of recent global events on the value of AI- and human-managed ETFs. The study examined the overall impact of the events to these funds, while another aim was to determine if markets incorporated information efficiently. The focus of this study was on a time period of volatile market conditions caused by conflict in Ukraine and collapse of SVB. The events chosen for this study were selected under the assumption that heightened uncertainty in the markets often leads to increased market volatility, which typically results from specific incidents, including geopolitical conflicts and banking crises (Antonakakis et al., 2013; Bredin & Fountas, 2018; Tong et al., 2023). These kind of events may have an impact not only on the financial industry, but also on the overall stock market. Such occurrences may have consequences for the global financial system, such as creating disruptions affecting multiple financial institutions (Allen & Gale, 2000; Chen et al., 1986).

In addition, as there was little or no information available on the performance of AI-based funds focusing on volatile market conditions, the research and return calculations concentrated on the event window of the Ukrainian war and the aftermath of the collapse of Silicon Valley Bank (SVB).

The previous literature on the psychology of investment decision-making (under chapters 3. and 4.) was also undertaken as part of the research methodology to obtain answer to the research question, focusing particularly the question about psychological factors and other elements influencing the investment decision-making process between AI- and human portfolio managers.

5.2.1 Return calculations

The event-study was applied to measure the magnitude of the effect of the specific events on the behaviour of AI-driven and human managed ETF funds. To determine whether these events had an impact on the AI managed and human managed ETFs, Average Abnormal Returns (AAR), Cumulative Average Abnormal Returns (CAAR) and Buy-and-Hold Average Abnormal Returns (BHAAR) were measured and tested for statistical significance. These methods were applied for computing daily, cumulative and holding period abnormal returns for the event window as well as multiple subsequent observation periods. All returns were risk-adjusted by S&P 500 index as a benchmark for the market return.

The event study had an estimation period which consisted of 150 working days from June 15, 2021, to January 14, 2022, assuming that the events had no effect on returns during the estimate period preceding the events and that the window represents a "normal" period.

In addition, the event window occurred symmetrically +20/-20 days around the event date. The total event window was 41 days. The event date was March 10, 2023, related to the SVB crisis and February 22, 2022, to the conflict in Ukraine. Furthermore, there were multiple distinct observation periods for presenting the results of CAAR and BHAAR. Both events were examined using the same estimation period. Figure 6. below illustrates the timeline utilized in this event study.

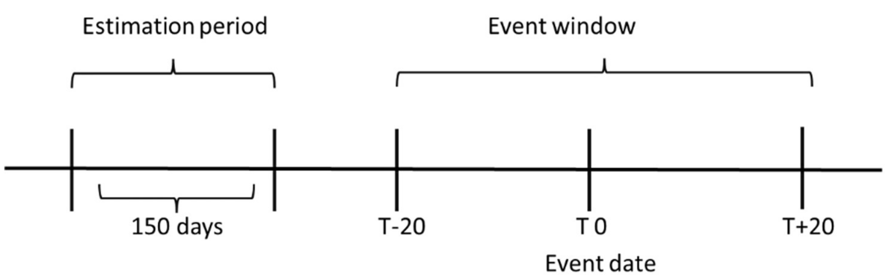


Figure 6. The timeline of the event study.

Following, the models employed to determine the returns are presented. The statistical OLS Market Model by Dyckman et al. (1984) was first utilized to estimate expected returns:

$$E[R_{it}] = \alpha_i + \beta_i R_{m_t} \tag{1}$$

where $E[R_{it}]$ represents the normal or expected returns of i (ETF), while R_{mt} represents the market returns of the benchmark S&P 500, on day t. The average returns are derived using the day's closing price. Next, to estimate the abnormal returns the following formula was applied:

$$AR_{it} = R_{it} - [\alpha_i + \beta_i R_{mt}] \tag{2}$$

where AR_{it} is the abnormal return of i (ETF) on day t. R_{it} is the return of i on day t, α is the intercept term of i (alpha), coefficient β_i is a measure of the sensitivity of R_{it} on the reference market (beta). R_{mt} is interpreted the same manner as in the previous formula.

Then the study assessed the AARs and CAARs for each category and utilized statistical analysis to test the significance of the data. First, the average abnormal returns (AARs) were calculated to quantify the overall impact of the event of all ETFs in the same category, like AI-driven or human-managed. The AAR formula calculates the average abnormal return at time t by combining the abnormal returns of all N ETFs.

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{3}$$

Afterwards, the AARs were used to calculate the cumulative average abnormal returns (CAARs) over the event window. The CAAR formula is valuable as it allows to examine the cumulative effect of the abnormal returns, which is particularly useful if the event's effects during the event window is not limited to the event day itself. In this method, the CAAR is calculated by summing all of the AARs over the T days in the event window:

$$CAAR_T = \sum_{t=1}^{T} AAR_t \tag{4}$$

Furthermore, the study applied different holding period return methods to increase robustness. Buy-and-Hold Abnormal Returns (BHAR) model by Ritter (1991), which serves as an alternative measure to cumulative abnormal returns. The major distinction is that *CAR* formula measures an *arithmetic* mean whereas *BHAR* is forming a *geometric* mean.
As an outcome, the BHAR was determined as follows:

$$R_{iT} = \prod_{T=1}^{T} (1 + r_{it}) - 1 \tag{5}$$

Where T is the number of months and as previously stated, r_{it} is the return on fund i on day t. BHAR takes advantage of investors' long-term investment perspective by generating long-term buy and hold returns by combining short-term returns (Kooli & Suret, 2004). The model assumes that that investors hold the securities during the specific time window without adjusting their holdings. The holding period return on the benchmark during the similar time for fund i, was also calculated in the same approach:

$$BHAR_{iT} = [\prod_{t=1}^{T}(1 + r_{it}) - 1] - [\prod_{t=1}^{T}(1 + r_{mt}) - 1] \tag{6}$$

Correspondingly, Buy-and-Hold Average Abnormal Buy-and-Hold Return (BHAAR) is the arithmetic mean abnormal holding period return on all ETFs in sample of size n. To simplify, BHAAR was employed to calculate average returns of BHAR, and so BHAAR was computed in the following method:

$$BHAAR_t = \frac{1}{N}\sum_{i=1}^{N} BHAR_{i,t}, \tag{7}$$

When examining one instrument, the share price fluctuations on that day (AR) or during the preceding period (CAR and BHAR) can be evaluated. If the study includes multiple instruments, the average of these changes (AAR, CAAR or BHAAR) is assessed to see if anything significant occurred on a group-wide level.

Furthermore, statistical significance of total AARs of the event windows as well as daily AAR values was measured using t-statistics equation:

$$t_{AAR} = \frac{AAR_{i,t}}{s_{AAR_i}} \tag{9}$$

Where t_{AAR} denotes t-value of AAR and s_{AAR_i} is the standard deviation of the estimation window. The Z-test, on the other hand, was performed to determine whether there was a difference between the mean value at a certain CAAR and BHAAR points and the mean and standard deviation observed during the estimating periods.

$$Z = (\bar{x} - \mu O) / \left(\sigma\sqrt{n}\right) \tag{10}$$

Where Z denotes z-value, $\bar{x}$ is the sample mean, μO is the population mean, and the sample standard deviation is denoted with σ whereas n is the number of observations.

6 Results and analysis

The study divided the result data into two categories (AI and human): AI funds represented by AIEQ and QRTF, and human-driven funds represented by AVUS and DFAC. The separation was performed with the main purpose of the comparative analysis.

The hypotheses were tested by determining if the AI-driven funds outperformed human peers in the presence of the events. The performance was analysed utilizing the daily statistics of average abnormal returns. In addition to daily AARs, this study observed cumulative statistics, CAARs and BHAARs. Statistical analysis was applied to test the significance of the daily and cumulative results. In addition, the distinctions in the decision-making process between the AI and human was evaluated based on prior literature and a comparable analysis was conducted.

6.1 Returns and performance

The results determined whether AI-managed funds performed better than human-managed funds during the events. This answer to was achieved by analysing the AARs, CAARs and BHAARs and their statistical significance. After that, the hypotheses were tested.

6.1.1 Ukrainian Conflict

The event date for Ukrainian Conflict was February 24, 2022, and the event window occurred between 26.1.2022 – 24.2.2022. Table 3. illustrates the average abnormal returns, cumulative abnormal returns and buy-and-hold average abnormal returns of both groups 20 days before and after (T-20 to T+20) the beginning of the Ukrainian conflict.

At the event date (T=0), the AARs for AI funds were positive and statistically significant, while AARs for human-managed funds stayed positive but insignificant. Prior to the event (T-20 to T-1), the AARs of both groups were mostly insignificant, with roughly half of the days having negative returns and the other half showing positive returns for both groups. However, the negative AAR periods were brief, indicating that the negative effect of the conflict on both groups was short-term and temporary. Then again, AI funds showed statistically significant AARs on days T-19, T-17, and T=0, with T-17 exhibiting notably high significance levels. Conversely, human-managed funds displayed significant trends on T-18, T-14, and T-8. Furthermore, after the event date (T+1 to T+20), AARs varied widely across AI-managed and human-managed funds. In most cases, both groups generated positive but insignificant returns. Nevertheless, that the daily statistics of AARs show occasional statistical significance, the overall AAR values in the event window were insignificant for both groups, indicating that there was no significant market reaction to the conflict in Ukraine, suggesting strong form of market efficiency. Moreover, the difference in AARs between groups was insignificant, indicating that both groups performed similarly during the beginning period of the Ukrainian conflict.

Furthermore, the CAAR values and their significance varied between the groups in the event window, as demonstrated in Table 3. Prior to the event date (T-20 to T-1), the CAARs of AI funds were mostly positive, but also statistically significant from T-20 to T-18, with T-18 exhibiting high significance. In contrast, the CAARs of human-managed funds were negative and insignificant from T-20 to T-10, but turned positive between T-9 and T0, and the values were highly significant between T-8 and T+20. On the event day, both groups exhibited negative but insignificant CAARs. Similarly, after the event day (T+1 to T-20) returns were positive for both groups, but also significant for human-managed funds. Furthermore, the findings of BHAAR values within the event window were largely identical with the CAAR results, with human-managed funds having more occurrences of statistically significant values, whereas AI funds had higher returns in the event window period.

The CAARs and BHAARs daily returns and in total were significant for both groups, as their overall p-values were under 0.01 in the event window. The return difference between the groups was also major, and AI funds outperformed human-managed peers in terms of overall return performance. The results indicate that there was a significant market reaction to the conflict in Ukraine, suggesting weak form of market efficiency. In addition, AI-driven funds showed more consistent and positive performance during the event window compared to human-managed funds.

Table 3. AARs, CAARs and BHAARs in the Ukrainian conflict event window.

	AAR				CAAR				BHAAR			
T	AI	t-value	Human	t-value	AI	z-value	Human	z-value	AI	z-value	Human	z-value
-20	-0,35 %	-0,693	-0,39 %	-1,478	-0,35 %	*-1,920	-0,39 %	0,835	-0,35 %	*-1,859	-0,39 %	0,885
-19	-0,96 %	*-1,883	-0,01 %	-0,024	-1,31 %	**-2,350	-0,39 %	0,826	-1,31 %	**-2,276	-0,39 %	0,876
-18	0,49 %	0,954	-0,53 %	**-2,044	-0,83 %	**-2,132	-0,93 %	0,040	-0,84 %	**-2,069	-0,92 %	0,081
-17	1,45 %	***2,837	-0,09 %	-0,361	0,62 %	-1,484	-1,02 %	-0,099	0,60 %	-1,446	-1,02 %	-0,059
-16	0,36 %	0,702	0,24 %	0,925	0,98 %	-1,323	-0,78 %	0,257	0,96 %	-1,289	-0,78 %	0,299
-15	-0,40 %	-0,790	-0,35 %	-1,340	0,57 %	-1,504	-1,13 %	-0,259	0,55 %	-1,466	-1,13 %	-0,220
-14	0,48 %	0,946	0,57 %	**2,177	1,06 %	-1,288	-0,56 %	0,579	1,04 %	-1,255	-0,56 %	0,620
-13	-0,15 %	-0,300	-0,14 %	-0,547	0,90 %	-1,356	-0,70 %	0,368	0,88 %	-1,323	-0,71 %	0,408
-12	0,03 %	0,054	0,29 %	1,113	0,93 %	-1,344	-0,41 %	0,797	0,91 %	-1,311	-0,42 %	0,839
-11	0,38 %	0,738	0,29 %	1,120	1,31 %	-1,175	-0,12 %	1,228	1,29 %	-1,146	-0,13 %	1,274
-10	0,91 %	1,776	-0,02 %	-0,068	2,21 %	-0,769	-0,14 %	1,201	2,21 %	-0,746	-0,14 %	1,248
-9	0,20 %	0,393	0,29 %	1,123	2,41 %	-0,680	0,16 %	1,634	2,41 %	-0,657	0,15 %	1,686
-8	-0,47 %	-0,917	0,46 %	*1,764	1,95 %	-0,889	0,62 %	**2,312	1,93 %	-0,868	0,61 %	**2,375
-7	-0,36 %	-0,705	-0,07 %	-0,251	1,59 %	-1,050	0,55 %	**2,216	1,56 %	-1,028	0,55 %	**2,277
-6	0,42 %	0,822	0,21 %	0,810	2,01 %	-0,862	0,76 %	**2,528	1,99 %	-0,842	0,76 %	***2,595
-5	0,08 %	0,158	0,11 %	0,433	2,09 %	-0,826	0,88 %	**2,694	2,07 %	-0,805	0,87 %	***2,765
-4	-0,27 %	-0,523	0,10 %	0,376	1,82 %	-0,946	0,97 %	***2,839	1,79 %	-0,926	0,97 %	***2,913
-3	-0,59 %	-1,161	0,20 %	0,748	1,23 %	-1,211	1,17 %	***3,127	1,20 %	-1,185	1,17 %	***3,208
-2	0,67 %	1,313	-0,17 %	-0,658	1,90 %	-0,911	1,00 %	***2,874	1,86 %	-0,896	0,99 %	***2,948
-1	0,15 %	0,291	0,28 %	1,076	2,05 %	-0,845	1,28 %	***3,288	2,01 %	-0,830	1,28 %	***3,372
0	1,21 %	**2,379	-0,21 %	-0,791	3,26 %	-0,301	1,07 %	***2,983	3,26 %	-0,289	1,07 %	***3,059
+1	-0,29 %	-0,560	0,10 %	0,371	2,97 %	-0,429	1,17 %	***3,125	2,96 %	-0,417	1,17 %	***3,205
+2	0,19 %	0,371	0,21 %	0,792	3,16 %	-0,344	1,38 %	***3,431	3,16 %	-0,330	1,38 %	***3,518
+3	0,16 %	0,313	-0,24 %	-0,924	3,32 %	-0,273	1,13 %	***3,075	3,31 %	-0,265	1,13 %	***3,152
+4	0,14 %	0,275	0,37 %	1,411	3,46 %	-0,210	1,50 %	***3,618	3,46 %	-0,201	1,50 %	***3,710
+5	-0,52 %	-1,029	0,04 %	0,149	2,94 %	-0,445	1,54 %	***3,675	2,91 %	-0,438	1,54 %	***3,769
+6	-0,24 %	-0,474	-0,25 %	-0,947	2,70 %	-0,553	1,30 %	***3,311	2,66 %	-0,549	1,29 %	***3,393
+7	-0,07 %	-0,140	0,05 %	0,195	2,62 %	-0,585	1,35 %	***3,386	2,59 %	-0,581	1,34 %	***3,471
+8	0,33 %	0,648	0,38 %	1,460	2,95 %	-0,437	1,73 %	***3,948	2,93 %	-0,432	1,73 %	***4,048
+9	-0,33 %	-0,638	-0,20 %	-0,782	2,63 %	-0,583	1,52 %	***3,647	2,59 %	-0,578	1,52 %	***3,737
+10	0,28 %	0,542	0,33 %	1,253	2,91 %	-0,459	1,85 %	***4,129	2,88 %	-0,454	1,86 %	***4,234
+11	0,04 %	0,071	0,19 %	0,730	2,94 %	-0,443	2,04 %	***4,410	2,92 %	-0,438	2,05 %	***4,524
+12	0,07 %	0,133	0,05 %	0,207	3,01 %	-0,412	2,09 %	***4,489	2,98 %	-0,408	2,10 %	***4,606
+13	-0,07 %	-0,143	-0,42 %	-1,627	2,94 %	-0,445	1,67 %	***3,864	2,91 %	-0,441	1,67 %	***3,958
+14	0,62 %	1,224	0,06 %	0,213	3,56 %	-0,165	1,73 %	***3,946	3,56 %	-0,160	1,73 %	***4,042
+15	0,14 %	0,284	-0,05 %	-0,198	3,71 %	-0,100	1,67 %	***3,869	3,71 %	-0,093	1,67 %	***3,963
+16	0,39 %	0,766	-0,18 %	-0,684	4,10 %	0,075	1,50 %	***3,606	4,11 %	0,082	1,49 %	***3,692
+17	-0,43 %	-0,853	-0,05 %	-0,178	3,66 %	-0,120	1,45 %	***3,538	3,66 %	-0,114	1,45 %	***3,622
+18	0,04 %	0,082	-0,48 %	*-1,821	3,70 %	-0,102	0,97 %	***2,837	3,70 %	-0,095	0,96 %	***2,901
+19	-0,18 %	-0,363	-0,05 %	-0,186	3,52 %	-0,184	0,92 %	***2,766	3,51 %	-0,178	0,91 %	***2,823
+20	-0,23 %	-0,453	-0,23 %	-0,871	3,29 %	-0,288	0,70 %	**2,431	3,27 %	-0,282	0,68 %	**2,485

*In the CAAR and BHAAR calculation, the holding period is assumed to start at the beginning of the event window (− 20 days).

* * * value < 0.01, * * value < 0.05, * value < 0.1 show the level of significance.

When the cumulative statistics were examined further, it was clear that AI funds outperformed human-managed peers, with about 4,5 times more cumulative and holding period return than their human-managed peers, at the end of the event window (t+20), and the overperformance persisted across multiple observation periods, as table 4. Illustrates.

Table 4. Comparison of CAARs and BHAARs during and after the Ukrainian conflict.

	BHAAR		CAAR	
Date	**AI**	**Human**	**AI**	**Human**
24.03.2022	3,27 %	0,68 %	3,29 %	0,70 %
31.03.2022	3,33 %	0,27 %	3,35 %	0,29 %
29.04.2022	5,72 %	2,11 %	5,63 %	2,11 %
31.05.2022	8,11 %	3,84 %	7,88 %	3,79 %
30.06.2022	7,29 %	3,29 %	7,16 %	3,28 %
29.07.2022	8,37 %	3,25 %	8,09 %	3,25 %
31.08.2022	13,05 %	4,96 %	12,35 %	4,89 %
30.09.2022	13,01 %	5,79 %	12,52 %	5,69 %

Moreover, figure 7. graphs the AARs in the event window. There appears to be no overall pattern in the data, but AI funds fluctuated more than human-managed funds during the event window. The most noticeable positive trend for AI funds was at the T-19 to T-17 and during the event day T=0, whereas the peaks for human-managed funds were from T-14 to T-15 and on T-8. Considering of AI funds, the AARs increased considerably in the event date. Thus, can be stated that the conflict had a positive impact on the AI-funds AARs on the event date, but the strong impact did not persist longer.

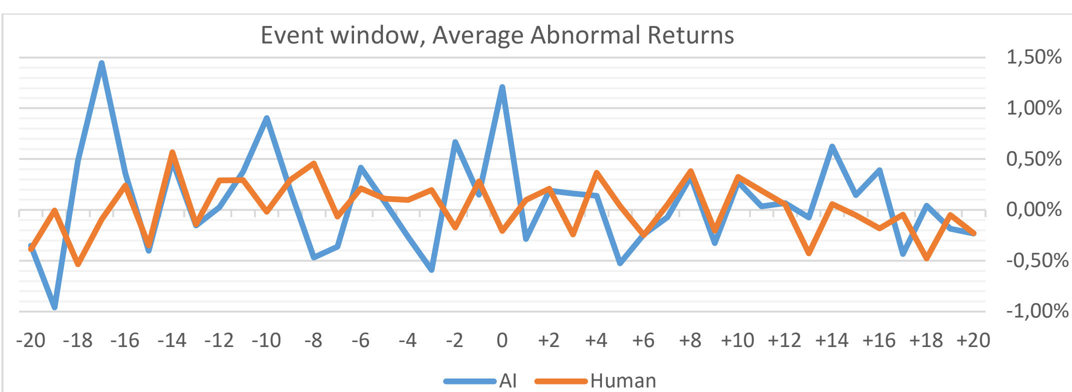


Figure 7. AARs in the Ukrainian conflict event window.

In conclusion, the overall values of AARs and the difference between the AARs, within the event window of Ukrainian conflict was insignificant for both groups, indicating similar performance between AI- and human-managed funds and the strong form of market efficiency. However, when considering CAARs and BHAARs, both groups exhibited overall statistical significance in the event window. In addition, there were significant difference between AI's and human-managed funds in the terms of CAARs and BHAARs in favor to AI, suggesting overperformance of AI funds in the context of cumulative and holding period returns within the event window. The total impact of CAARs and BHAARs was considered significant, affirming that the Ukrainian conflict did have major impact on both AI- and human-managed funds' abnormal returns. This implies weaknesses in market efficiency and support the effectiveness of the alternative hypothesis.

6.1.2 Silicon Valley Bank (SVB) collapse

The collapse of Silicon Valley Bank occurred on March 10, 2023, and the event window covered the period from February 9, 2023, to April 10, 2023. The AARs, CAARs and BHAARs of both groups 20 days before and after the collapse of SVB are depicted in Table 5.

Across the complete event window, the AARs for both groups exhibited a mix of negative and positive values, largely lacking statistical significance. In particular, AI funds demonstrated statistical significance on days T-17 and T+18. On the other hand, human-managed funds displayed a greater number of significant days, occurring at T-7, T-4, T+1, T+3, T+9, and T+17. The negative AAR observed on day T+1 for human-managed funds was the only highly significant value within the event window for both groups. Despite occasional instances of statistical significance in daily AARs, overall AAR values for the entire event window remained insignificant in both groups. This indicates that there was no notable daily market reaction to the collapse of SVB, implying a strong level of market efficiency. In addition, the lack of significance of the difference between the AAR values of the two groups indicates similar performance in the early stages of SVB collapse.

Conversely, the CAARs of the event window were significant for both groups. On the event day, The CAARs of both groups decreased by nearly half the previous day, however the difference was not statistically significant for either of them. Oppositely, AI funds showed statistical significance in the period from T-16 to T-3, with only the values on days T-10 and T-4 being statistically insignificant. Besides, AI funds showed negative CAARs on most days during this period, forming a consistently negative trend from T-4 to T+20. On the contrary, CAARs for human-managed funds were positive on approximately half of the days and negative on the other half of the event window. Remarkably, the returns turned negative and highly significant just one day after the event, starting at T+1 and lasting through T+20, suggesting that the collapse of SVB influenced the shift to negative returns of human-managed funds. The CAARs for the entire event window discovered a negative pattern for both groups, although AI funds had highly lower CAARs than human-managed funds during the event window.

BHAAR results closely aligned with CAAR findings for both groups. Regarding AI funds, statistical significance mirrored the period of CAAR results but started a day earlier at T-17. Likewise, a consistent negative trend was observed in the event window, marked by a negative return from T-4 to T+20. Similarly, the BHAAR results were in line with the CAAR results, as human-managed funds were positive before the event date from T-19 to T0 but turned negative after T+1 and remained negative until the end of the event window. Significant values for human-managed funds were observed in the time intervals T-15 to T-1, T+9 to T+10, and T+17 to T+20. In addition, the human managed funds outperformed AI funds in the context of event window BHAARs, as they did in the case of CAARs. To conclude, the CAAR and BHAAR results were consistent with each other, indicating that the collapse of SVB had a negative impact on holding time and cumulative abnormal returns in both groups, implying deficiencies in market efficiency.

Table 5. AARs, CAARs and BHAARs in the SVB collapse event window.

	AAR				CAAR				BHAAR			
T	AI	t-value	Human	t-value	AI	z-value	Human	z-value	AI	z-value	Human	z-value
-20	-0,72 %	-1,419	-0,05 %	-0,203	-0,72 %	1,437	-0,72 %	**-2,470	-0,72 %	1,484	-0,05 %	0,921
-19	-0,62 %	-1,220	0,24 %	0,925	-1,35 %	1,158	0,19 %	-1,126	-1,33 %	1,201	0,19 %	1,231
-18	0,02 %	0,036	-0,03 %	-0,128	-1,33 %	1,167	0,16 %	-1,175	-1,32 %	1,209	0,15 %	1,188
-17	0,99 %	*1,950	0,04 %	0,141	-0,33 %	1,612	0,19 %	-1,121	-0,35 %	*1,657	0,19 %	1,235
-16	0,21 %	0,402	0,09 %	0,331	-0,13 %	*1,704	0,28 %	-0,994	-0,15 %	*1,751	0,28 %	1,347
-15	0,59 %	1,163	0,34 %	1,301	0,47 %	**1,97	0,62 %	-0,493	0,45 %	**2,025	0,62 %	*1,785
-14	-0,22 %	-0,435	-0,03 %	-0,122	0,24 %	*1,871	0,59 %	-0,540	0,22 %	**1,922	0,59 %	*2,785
-13	-0,26 %	-0,512	-0,05 %	-0,203	-0,02 %	*1,754	0,53 %	-0,618	-0,04 %	*1,802	0,53 %	*1,675
-12	0,49 %	0,959	0,17 %	0,647	0,47 %	**1,973	0,70 %	-0,369	0,45 %	**2,026	0,70 %	*1,893
-11	-0,60 %	-1,179	-0,12 %	-0,476	-0,13 %	*1,703	0,58 %	-0,552	-0,15 %	*1,747	0,58 %	*1,732
-10	-0,30 %	-0,596	0,37 %	1,427	-0,43 %	1,567	0,95 %	-0,003	-0,45 %	1,610	0,95 %	**2,214
-9	0,21 %	0,419	-0,02 %	-0,081	-0,22 %	*1,663	0,93 %	-0,034	-0,24 %	*1,706	0,93 %	**2,187
-8	0,79 %	1,554	0,10 %	0,394	0,57 %	**2,018	1,03 %	0,117	0,54 %	**2,068	1,04 %	**2,312
-7	-0,39 %	-0,771	0,47 %	*1,789	0,18 %	*1,842	1,50 %	0,806	0,15 %	*1,887	1,51 %	***2,926
-6	0,13 %	0,259	-0,19 %	-0,718	0,31 %	*1,901	1,31 %	0,529	0,28 %	*1,947	1,32 %	***2,682
-5	-0,24 %	-0,475	-0,19 %	-0,746	0,07 %	*1,792	1,12 %	0,242	0,03 %	*1,833	1,12 %	**2,428
-4	-0,78 %	-1,534	-0,46 %	*-1,766	-0,71 %	1,442	0,66 %	-0,437	-0,74 %	1,474	0,65 %	*1,829
-3	0,49 %	0,962	0,19 %	0,736	-0,22 %	*1,661	0,85 %	-0,154	-0,26 %	*1,697	0,85 %	**2,078
-2	-0,17 %	-0,330	-0,03 %	-0,114	-0,39 %	1,586	0,82 %	-0,197	-0,43 %	1,622	0,82 %	**2,039
-1	-0,12 %	-0,230	-0,22 %	-0,838	-0,51 %	1,533	0,60 %	-0,520	-0,53 %	1,572	0,60 %	*1,756
0	-0,67 %	-1,311	-0,30 %	-1,138	-1,18 %	1,234	0,30 %	-0,957	-1,19 %	1,269	0,30 %	1,372
+1	0,11 %	0,218	-0,99 %	***3,794	-1,07 %	1,284	-0,69 %	**-2,417	-1,08 %	1,320	-0,70 %	0,095
+2	-0,54 %	-1,062	-0,07 %	-0,262	-1,61 %	1,041	-0,76 %	**-2,518	-1,61 %	1,075	-0,76 %	0,008
+3	-0,59 %	-1,152	-0,67 %	**-2,550	-2,19 %	0,778	-1,42 %	***-3,499	-2,18 %	0,809	-1,42 %	-0,841
+4	0,20 %	0,394	-0,13 %	-0,512	-1,99 %	0,868	-1,56 %	***-3,696	-1,99 %	0,898	-1,56 %	-1,011
+5	0,09 %	0,168	-0,42 %	-1,609	-1,91 %	0,906	-1,98 %	***-4,315	-1,90 %	0,937	-1,97 %	-1,542
+6	-0,17 %	-0,333	0,22 %	0,827	-2,08 %	0,830	-1,76 %	***-3,997	-2,06 %	0,864	-1,76 %	-1,270
+7	0,27 %	0,532	0,18 %	0,681	-1,81 %	0,951	-1,58 %	***-3,735	-1,81 %	0,980	-1,58 %	-1,046
+8	-0,18 %	-0,350	-0,19 %	-0,735	-1,99 %	0,871	-1,77 %	***-4,018	-1,97 %	0,906	-1,77 %	-1,289
+9	0,15 %	0,298	-0,53 %	**-2,023	-1,83 %	0,939	-2,30 %	***-4,796	-1,83 %	0,971	-2,29 %	**-1,956
+10	-0,53 %	-1,038	-0,10 %	-0,392	-2,36 %	0,702	-2,41 %	***-4,947	-2,35 %	0,733	-2,39 %	**-2,084
+11	-0,50 %	-0,990	0,49 %	*1,867	-2,87 %	0,476	-1,92 %	***-4,229	-2,81 %	0,517	-1,92 %	-1,474
+12	-0,33 %	-0,653	0,23 %	0,862	-3,20 %	0,327	-1,69 %	***-3,898	-3,13 %	0,372	-1,70 %	-1,190
+13	0,19 %	0,365	-0,20 %	-0,758	-3,01 %	0,411	-1,89 %	***-4,189	-2,95 %	0,453	-1,89 %	-1,440
+14	-0,11 %	-0,216	-0,18 %	-0,684	-3,12 %	0,361	-2,07 %	***-4,453	-3,05 %	0,405	-2,07 %	*-1,665
+15	0,51 %	0,996	0,00 %	-0,011	-2,62 %	0,589	-2,07 %	***-4,457	-2,59 %	0,620	-2,07 %	*-1,669
+16	0,19 %	0,366	0,06 %	0,225	-2,43 %	0,672	-2,01 %	***-4,37	-2,41 %	0,702	-2,01 %	-1,595
+17	-0,84 %	-1,639	-0,54 %	**-2,071	-3,27 %	0,298	-2,56 %	***-5,167	-3,22 %	0,331	-2,54 %	**-2,276
+18	-0,87 %	*-1,701	-0,06 %	-0,240	-4,13 %	-0,091	-2,62 %	***-5,259	-4,03 %	-0,044	-2,60 %	**-2,354
+19	-0,21 %	-0,420	-0,22 %	-0,840	-4,35 %	-0,187	-2,84 %	***-5,582	-4,24 %	-0,143	-2,82 %	***-2,629
+20	0,80 %	1,566	0,43 %	1,642	-3,55 %	0,171	-2,41 %	***-4,951	-3,49 %	0,203	-2,40 %	**-2,093

*In the CAAR and BHAAR calculation, the holding period is assumed to start at the beginning of the event window (− 20 days).

* * * value < 0.01, * * value < 0.05, * value < 0.1 show the level of significance.

A closer look at the cumulative data revealed that human-managed funds outperformed AI funds during the event window (10.4.2023). This overperformance lasted until May, when table 6 showed a reversal, with AI funds outperforming human-managed funds.

Table 6. Comparison of CAARs and BHAARs during and after the SVB collapse.

	BHAAR		CAAR	
Date	**AI**	**Human**	**AI**	**Human**
10.04.2023	-3,49 %	-2,40 %	-3,55 %	-2,41 %
28.04.2023	-5,43 %	-2,70 %	-5,68 %	-2,71 %
31.05.2023	-1,29 %	-3,83 %	-1,10 %	-3,88 %
30.06.2023	-0,37 %	-3,14 %	-0,14 %	-3,15 %
31.07.2023	2,26 %	-1,93 %	2,49 %	-1,90 %
31.08.2023	1,75 %	-1,93 %	2,02 %	-1,90 %
29.09.2023	3,07 %	-1,23 %	3,32 %	-1,18 %
31.10.2023	3,01 %	-1,78 %	3,29 %	-1,73 %

Moreover, Figure 8 illustrates the AARs trend throughout the event window. AI funds experienced notable volatility, with major peaks occurring during specific periods: T-20 to T-16, T-10 to T-8, T-4 to T-2, and T+17 to T+18. In contrast, human-managed funds presented a more moderate fluctuation, although significant peaks were observed between T-9 to T-7, T-4 to T-3, T+1 to T+3, T+9 to T+11, and on T+17. Despite the fact that there was no consistent trend in the event window, returns did exhibit volatility. As can be observed, the event had varying impacts on the funds, as AI funds yielded a positive return one day after the event, whereas human-managed funds experienced a notable decline on T+1.

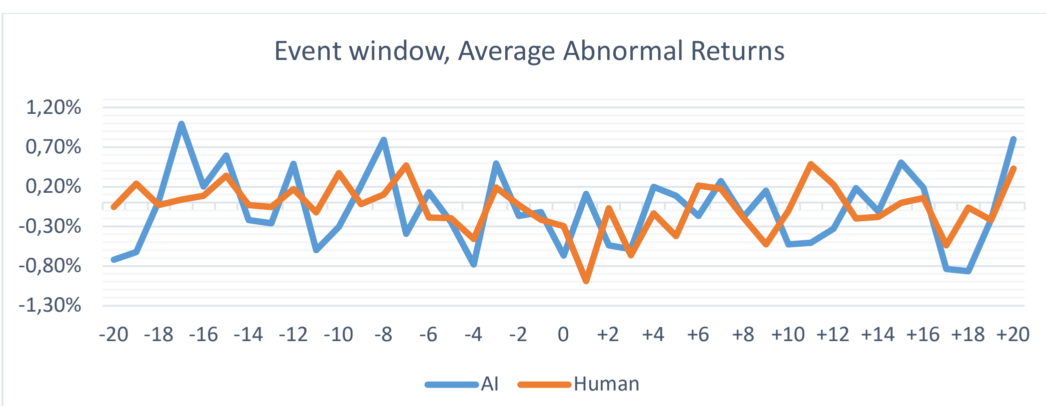


Figure 8. AARs in the SVB collapse event window.

The intention was to determine whether AI funds outperformed human-managed funds during the Silicon Valley Bank collapse from February 9 to April 10, 2023. Daily abnormal returns (AARs) indicated market efficiency with mixed, mostly non-significant values throughout the event window, suggesting no significant daily market reaction to SVB's collapse. However, cumulative abnormal returns (CAARs) were significant for both groups, with AI funds displaying statistical significance before the event, and human-managed funds after the event, with a negative trend starting one day after the event day. The overall CAAR pattern revealed a significant and negative impact on both groups. Also, BHAAR results aligned with CAAR findings, showing statistical significance for both groups. AI funds had a continuous negative trend from T-4 to T+20, mirroring human-managed funds whose CAARs turned significantly negative onT+1 again. The consistent pattern suggested a negative effect on the event for both groups, indicating market inefficiency.

In conclusion, whereas daily AARs exhibited market efficiency with no significant responses to the SVB collapse, cumulative approaches (CAAR and BHAAR) provided significant findings, revealing that both groups were negatively affected by the SVB collapse. This suggests deficiencies in market efficiency and lends support to the validity of the alternative hypothesis. Essentially, human-managed funds outperformed AI funds in both CAARs and BHAARs during the event window of SVB collapse.

6.1.3 Summary of returns and performance results

In summary, the purpose of the study was to compare the performance of AI-managed funds and human-managed funds during the conflict in Ukraine and the collapse of Silicon Valley Bank. Daily AARs showed no significant values for either event, suggesting market efficiency. However, both CAARs and BHAARs were statistically significant for both the Ukraine conflict and SVB collapse. In the context of the Ukrainian conflict, AI funds demonstrated superior performance over human-managed funds in terms of both CAARs and BHAARs. Conversely, during the SVB collapse, human-managed funds outperformed AI funds in both cumulative and holding period returns. The impact of the events on CAAR and BHAAR returns underlined the important impact of both the Ukraine conflict and SVB collapse, revealing vulnerabilities in market efficiency. In addition, the events had distinct effects on AI and human-managed funds, with the Ukrainian conflict yielding positive CAARs and BHAARs for both groups, while the SVB collapse resulted in negative CAARs and BHAARs for both.

In conclusion, the study suggests that AI funds performed better during the Ukraine conflict, while human-managed funds exhibited better performance during the SVB collapse, supporting the alternative hypothesis. Looking beyond the event window, AI funds presented higher returns in the longer term. The findings also suggest that the markets may not fully adhere to the efficient market hypothesis, as AI demonstrated the potential to achieve abnormal returns by exploiting market inefficiencies during the Ukrainian conflict, and particularly over the longer term in both events, as shown in tables 6 and 8. These findings support the alternative hypothesis and indicate deviations from the efficient market hypothesis.

6.2 Decision-making process between human and AI

Again, the study classified the data again into two groups focusing on decision-making and conducting a comparison analysis between AI and humans. The results emphasized the substantial differences in decision-making processes between humans and machines.

The results demonstrated that psychological factors and various other elements that influence the decision-making process created significant differences between humans and AI systems. Although both humans and AI contribute to decision-making, the fundamental mechanisms and methods employed diverged considerably. The summary of the weaknesses and strengths are presented in table 7 and 8, which summarized the differences based on the findings obtained from the literature review in Chapters 3 and 4.

Table 7. Weaknesses in decision-making processes between human and AI.

Human	AI
Weaknesses	
1. Dual-Process Model: System 1 may lead to impulsive decisions based on emotions, habits, and biases. System 2 requires conscious effort, making it susceptible to decision fatigue and possible errors under cognitive load.	**1. Context and Nuances:** Artificial intelligence systems have difficulty understanding contextual information and nuanced situations, leading to misinterpretation of complex scenarios.
2. Heuristics: Intuitive decision-making processes may lead to cognitive biases and fallacies, impacting the accuracy of estimations and judgments.	**2.Imagination and creativity:** AI has limited ability to think creatively or generate ideas beyond the models and information that have been taught.
3.Information Processing: Information processing in irrational or illogical way may lead to multiple biases like limited attention, overconfidence, confirmation bias, conservatism bias, and representativeness bias.	**3. Common Sense:** AI lacks inherent common sense, making it challenging to make decisions in situations where human intuition and common sense are vital.
4. Personality features: e.g. extroversion or introversion may influence decision-making and strict adherence to specific traits may lead to inflexibility and an unwillingness to adjust to changing circumstances.	**4. Emotional intelligence:** AIs absence of emotional intelligence makes interpreting and reacting to human's emotions challenging, which can be necessary in various decision-making contexts.
5. Genetic Variation: Some individual differences in investment decisions may be explained by genetics, and such factors may also influence risk-taking behaviou**r** and willingnes**s** to take risk.	**5. Moral and ethical judgement**: AI's incapability to make moral and ethical decisions. Making decisions exclusively with algorithms does not always align with social standards or ethical principles.
6.Emotional Variables: Emotions like anxiety and self-control can cause biased decision-making. Emotions may affect judgment and lead to poor decisions when emotions override logical considerations.	**6. Unforeseen situations**: AI may struggle to adjust to new or unforeseen circumstances that did not arise during training phase, which could result in suboptimal decisions.
7. Emotional Influences: Major life events may impact investment decisions and may lead to emotional responses that deviate from rational reasoning.	**7. Dependency on training data:** The representativeness and quality of training data are critical components for AI models. Biases in the data can lead to biased decision-making.
8. Behavioural biases: Irrational beliefs or behaviours may unconsciously influence the decision-making process, such as regret avoidance, framing effect, mental accounting, loss aversion, affect and feelings.	**8. Historical data**: Models trained on historical data may not accurately predict outcomes in rapidly changing environments or new situations because they may not capture evolving patterns
	9. Computational requirements: Deep learning-based AI models in particular can demand a lot of processing power, which makes them resource-intensive and may limit their availability.

Aside from weaknesses, both humans and AI have specific advantages in decision making. Table 8 summarizes the findings of this study, which indicated that both AI and human systems have multiple features that influence their distinct abilities under specific conditions.

Table 8. Weaknesses in decision-making processes between human and AI.

Human	AI
Strengths	
1.Context, nuance, and adaptability: Ability to adapt decision-making processes to a wide range of situations and contexts. Humans are capable of adjusting their strategies based on changes in the environment, new information, or unexpected events.	**1. Adaptability and real-time decision-making:** Ability to make and adapt decisions based on real-time data, adapt investment strategies quickly based on market data and react quickly to changes, volatility and new information or opportunities.
2. Complexity and multidimensionality: Humans may make complex decisions based on cognitive, emotional, and experience factors that enables the consideration of multiple perspectives, which is based on humans' natural abilities and nature.	**2. Data processing and analysis:** Efficiently process and analyse vast amounts of data from many sources, which enables AI to identify patterns, trends, and insights effectively via ML, sentiment analysis, and natural language processing.
3. Intuition and instincts: Capability of making rapid decisions based on prior knowledge and experiences or intuition and instincts which can be useful in situations where quick decisions are necessary.	**3. Model training and selection:** AI models are trained on historical data using a cost function. Continuous monitoring and evaluation of AI models supports responsible decision-making.
4. Psychological factors: Personality traits, psychological factors, emotions, and experiences play a crucial role in shaping decisions related to investments and predict investment perceptions.	**4. Deep Learning:** Applying predictive DL models to a range of factors such as economics, news, data, and governance, helping AI to assess upside potential, uncertainty, and pick the best performing stocks.
5. Emotional intelligence: With emotional intelligence humans are able to recognize, understand, and manage their emotions as well as the emotions of others, influencing decision outcomes.	**5. Ensemble methods and many models:** Various AI techniques enhance accuracy, including elastic networks, ANNs, SVMs, and tree-based models, as do ensemble methods, by combining many techniques.
6. Social, ethical, moral, and cultural considerations: The ability to consider the impact of decisions on others, as well as adherence to cultural norms and values, contributes to the complexity and depth of the decision-making process.	**6. Portfolio optimization and ML tools:** ML tools such as genetic algorithms, RL, and neural networks contribute to portfolio optimization, risk management, and optimal execution. ML methods are used to understand the cost of market impacts and improve the analysis of trade data.
7.Creativity and Innovation: The ability to think creatively, allowing humans to generate novel solutions to problems, which increases innovation and the ability to consider new possibilities in decision-making.	**7. Consistency:** Consistent application of preset rules and algorithms without being influenced by emotions, fatigue, or external factors, which is useful in a high level of precision and repeatability.
8. Long-Term Planning: A forward-thinking perspective allows for actions that take into account future consequences and promote personal and collective objectives.	8. **Efficiency:** Automating difficult processes reduces processing times and increases efficiency, and is important in processes like data analysis, optimization, and decision-making.
9. Communication Skills: The humans' ability to explain opinions, listen to others, and engage in successful communication, facilitating group decision-making processes.	**9. Pattern Recognition:** AI is highly effective at finding connections and patterns in data, which is useful for image recognition, NLP, and predictive modelling.
10. Self-awareness: Humans have a level of self-awareness that enables them to reflect on their own ideas, feelings, and motivations, and can lead to more conscious and focused decision-making.	**10. Improvement:** Machine learning, a subset of artificial intelligence, enables AI systems to learn from data and improve their performance over time.

The research examined decision-making differences and systematically classified data into groups to demonstrate the opposite methods between humans and artificial intelligence. The results underscored significant disparities in decision-making mechanisms between humans and artificial intelligence.

Table 7 summarized the weaknesses in decision-making processes between humans and AI, addressing the individual challenges of each group. Humans, for example, confronted cognitive biases, emotional influences, and individual variances, but AI suffered with lack of context understanding, creativity, and emotional intelligence. Table 8, on the other hand, outlined the strengths of both humans and AI in decision-making. Humans outperformed in adaptability, intuition, and psychological component consideration, including nuanced and contextual understanding, as well as having a complex but versatile decision-making process abilities. AI, on the other hand, exhibited capabilities in real-time decision-making, efficient data processing, model training, and predictive abilities. The comparison revealed that, while both groups had weaknesses, they also had distinct strengths that influenced their decision-making ability under specific circumstances.

7 Discussion and conclusions

7.1 Interpretation of the results

The main purpose of this thesis was to observe if artificial intelligence can outperform traditional human portfolio managers in terms of generating abnormal returns during volatile market conditions. To compare the performance of AI and human portfolio managers, an event study method was applied to determine abnormal returns. Daily historical data from Bloomberg was carefully collected and evaluated, producing a comprehensive dataset. The study's findings underwent statistical analysis to quantify and compare the abnormal returns generated by AI versus human-managed portfolios. Furthermore, the study delved into the elements that influence investment decisions made by humans and artificial intelligence. This comprehensive analysis through prior literature attempted to determine the underlying causes of performance differences. The study's multi-method strategy aimed to provide an in-depth evaluation of the relative efficacy of these two investing approaches.

Looking at performance evaluation in more detail, the study examined volatile market conditions by analysing the event windows corresponding to the beginning of the Ukrainian conflict and the collapse of the Silicon Valley Bank. The performance was analysed utilizing the daily statistics of average abnormal returns. In addition to daily statistics, this thesis explored cumulative and holding period statistics, focusing on cumulative average abnormal returns and buy-and-hold average abnormal returns. Furthermore, statistical analysis was employed to assess the significance of the results. In addition to the event window period, cumulative and holding period returns were analysed in eight distinct observation periods, including the event window's end date and the last banking days of the same and seven subsequent months.

In the first chapter of the thesis, the study established its two hypotheses. The null hypothesis assumed that utilizing artificial intelligence does not impact investment performance in volatile market conditions, while the alternative hypothesis asserted that the utilization of artificial intelligence does impact investment performance in volatile market conditions.

Statistically significant abnormal returns were observed for AI funds through cumulative and holding period returns during both the beginning period of the Ukrainian conflict and the collapse of the SVB. Empirical findings demonstrate the ability of artificial intelligence to generate abnormal returns during both events, with AI producing positive abnormal returns in the context of the Ukraine conflict and negative abnormal returns during the SVB collapse. Therefore, the study supports the alternative hypothesis, H1, suggesting that the incorporation of AI significantly impacts investment performance in volatile market conditions. This finding encourages a reconsideration of the assumption that all available information is already incorporated in asset prices, showing convincing evidence of market inefficiencies during periods of volatility. Consequently, the study rejects the null hypothesis, providing evidence that incorporation of AI does impact investment performance under volatile market conditions.

Furthermore, the aim of the first research question was to find out how AI performs in volatile market conditions and to evaluate the profitability of AI-powered funds compared to traditional human-managed funds during such periods. The results indicate that AI funds outperformed human-managed funds during the event window of Ukrainian conflict. In particular, AI funds' cumulative abnormal returns at the last day of the event window were 3.29 percent, whereas human-managed funds demonstrated corresponding cumulative returns of 0.70 percent. Moreover, the results indicate that holding the AI ETFs for the entire event window, 41 days, proven to be profitable, with holding period abnormal returns reaching 3.27 percent for the period. In contrast, holding the human-managed ETFs for the entire event window was not as profitable, since the holding period abnormal returns for the same period realized at 0.68 percent for human-managed funds, as the results indicate.

Conversely, the circumstances reversed during the event window of the SVB collapse, with human-managed funds outperforming AI funds. The results demonstrated that cumulative abnormal returns at the end of the event window were -2.41 percent for human-managed funds and -3.55 percent for AI funds. The holding period abnormal returns aligned the turnaround, as the results implied that holding AI funds for the entire event window was not profitable, with holding period abnormal returns reaching -3.49 percent for AI funds.

Conversely, holding the human-managed funds for the entire event window proved to be a better decision, although still negative, with -2.40 percent for human-managed funds, the findings imply.

Nevertheless, when examining returns over the long term, the results indicated that AI funds outperformed human-managed funds for both events. In the context of the Ukrainian conflict, for the latest observation period ending on September 30, 2022, AI funds cumulative abnormal returns were 13.01 percent, while human-managed funds achieved 5.79 percent. Similarly, the holding period abnormal returns for the same period were 12.52 percent for AI funds and 5.69 percent for human-managed funds. Furthermore, in relation to the SVB collapse, over the latest observation period ending on 31 October 2023, AI funds exhibited CAARs of 3.29 percent, while human-managed funds realized a return of -1.73 percent. Similarly, holding period abnormal returns for the same term were 3.01 percent for AI funds and -1.78 percent for human-managed funds. These findings suggest that AI funds demonstrate higher long-term returns, improving their potential for investors with longer investment horizons, despite being subject to greater short-term fluctuations and a more volatile nature, as the results suggest. Therefore, it can be concluded that AI funds outperformed human-managed funds, particularly in the long run. This finding on the higher performance of artificial intelligence funds was also consistent with previous studies by Chen et al. 2022, Grobys, 2022 and Ning, 2012.

In general, the results regarding the performance through abnormal returns were relevant. More comprehension was gained by examining not only the daily statistics of abnormal returns but also the cumulative and holding period statistics returns of abnormal returns. These findings advanced the research output to a more detailed level, emphasizing the importance of monitoring cumulative performance statistics and highlighting the impact of variances that may be overlooked when solely evaluating daily statistics.

The second research question aimed to identify the psychological factors and other elements influencing the investment decision-making process in artificial intelligence compared to humans. In summary, the findings indicated significant differences in the decision-making processes between humans and machines. The human decision-making process, defined by Kahneman's dual-process model theory (2011), was described through the impulsive tendencies of system 1, and the deliberate but vulnerable nature of system 2. The intricate relationship of biases, heuristics, and emotional variables demonstrated the complex nature of human decision-making, which included both advantages and limitations. According to the findings, AI encountered difficulties in contextual comprehension, creativity, and emotional intelligence. The dependency on training data and computational requirements further reinforced its limitations. Despite these weaknesses, both groups also demonstrated distinct advantages. Humans outperformed in terms of adaptability, emotional intelligence, and nuanced decision-making, while acquiring the ability to make complicated decisions based on cognitive, emotional, and experience elements, allowing humans to consider multiple perspectives. In contrast, artificial intelligence succeeded in data processing, pattern detection, and efficient decision execution through adaptability and real-time capabilities. The findings of the study revealed significant differences in the investment decision-making process, addressing a wide range of weaknesses and advantages in both human and artificial intelligence decision-making.

When assessing the validity and reliability of the study, it can be affirmed that the research's validity was reinforced by its meticulous selection of the appropriate research sample and research questions. The methods employed were adequate and addressed the phenomena to be studied, focusing on abnormal returns and the decision-making framework. The methodologies employed in the research were carefully chosen to extract relevant data and results, and the use of properly selected methods increased the study's reliability. Furthermore, the study's findings were not only statistically significant, but also confirmed existing theories such as the deficiencies of the efficient market hypothesis. The combination of rigorous methodology increased the overall validity and reliability of the research findings. The obtained results illustrated the use of robust and appropriate methods, which enhanced the reliability and validity of the overall research process.

To summarise the findings, the study implies that the choice of whether to use AI or human portfolio managers in investment decisions depends on the circumstances of the situation.

AI excels in data-driven, rule-based, and real-time situations, allowing for faster processing, pattern discovery, and consistent rule application. Human portfolio managers, on the other hand, excel at adaptability, nuanced and contextual decision-making, and considering multiple points of view, especially in situations that require creativity and the ability to make complicated context-based decisions. The findings demonstrated that neither method, AI nor human-driven, is mutually exclusive but serves different purposes. A hybrid approach, combining the strengths of both AI and human portfolio managers in investment decision-making, could provide a powerful solution for a wide range of investment situations.

7.2 Limitations and future research

It is important to note that the number of the samples in the form of funds for this thesis was rather limited, and the inclusion of additional samples could improve the implication of comparative analysis. Nonetheless, the results obtained were considered satisfactory within the constraints of the dataset employed in the study. A study with a larger sample size, on the other hand, may not facilitate the same in-depth examination of each fund's individual techniques, which was an important aspect of this study.

As a suggestion for further research, it is recommended to increase the number of samples, thereby achieving greater certainty in results through expanding and refining the research with a broader and more diverse sample. With a broader sample size and a higher number of observations in general, the study could gain increased significance. Furthermore, the observation period could have been extended, across multiple years, to derive more meaningful results for comparing AI and human performance over an extended period. Moreover, the research objective of this study could be enhanced by testing various AI techniques for making investment decisions, also on a practical level. However, implementing this proposal in reality is challenging, particularly because the average researcher may not have exclusive access to test AI techniques for investment purposes solely for their own research. Larger companies generally encrypt such technologies, establishing a barrier to external use, maintaining their competitive advantage.

7.3 Implications for policy and practice

This thesis provides answers to how AI-managed funds move and respond to the experiments caused by increased market volatility, offering valuable insights into their behaviour and performance during times of higher uncertainty. Also, the findings of this study contribute to comprehending the risks associated with AI or human decision-making in volatile markets, potentially advancing in the development of effective risk management practices. Additionally, financial institutions and investors may reassess and adjust their risk management strategies based on the identified strengths and weaknesses of both AI and humans.

Furthermore, the findings provide a quantitative assessment of the performance of AI algorithms versus human portfolio managers, particularly in an atmosphere of market volatility. This assessment holds significant value for various stakeholders, including investors, fund managers, and financial institutions, as it assists in determining the effectiveness of AI-driven investment strategies further. Additionally, exploring the psychological factors influencing investment decisions offers valuable insights into the impact of human emotions on portfolio management. Such understanding becomes beneficial in refining decision-making processes, supporting investors in identifying common behavioural biases.

Moreover, this study may influence the adoption of AI technologies in the financial industry by providing evidence of their effectiveness as long-term investment instruments. Financial companies may be more persuaded to invest in AI technologies or develop hybrid models that combine human expertise with AI capabilities based on the research outcomes. Furthermore, insights from this thesis enhance the understanding of the risks and possibilities of AI-driven investments for financial professionals. In conclusion, this study can provide important information that may influence perspectives on innovative investment practices and contribute to the continuing evolution of the financial industry.

7.4 Further considerations

Artificial Intelligence has the potential to significantly revolutionize the financial sector. Although AI offers several advantages, it also comes with challenges, underlining the need for a responsible approach to innovation while AI development continues. Despite the perceived advantage of AI's emotional objectivity, potential risks exist. Overreliance on proprietary AI models establishes challenges, with any deviation leading to performance failures and potential loss of fund value. The presence of inaccurate or biased data increases the chance of faulty decision-making, which is compounded by the complex structure of AI algorithms.

The application of artificial intelligence in finance raises concerns about market manipulation. Dynamic AI models may identify interdependencies on their own, encouraging machine collaboration without human intervention. The 2010 Flash Crash, a trillion-dollar event lasting 36 minutes, illustrates this risk, with major indices including the S&P 500 and Dow Jones experiencing rapid decreases and rebounding actions, driven by algorithmic trading. Regulatory proceedings followed, as evidenced in the case of Navinder Singh Sarao, a stock trader who faced 22 counts for using cheating algorithms before the Flash Crash (Hope et al., 2015). This episode underscores the significant role that high-frequency traders might play in market disruptions.

On the other hand, AI provides significant opportunities because to its objectivity, efficiency in routine tasks, and capacity to extract knowledge from unstructured data. AI-based techniques depend on data rather than conventional presumptions, allowing for rapid adaptation to changing market conditions. However, the complexity of these models makes training and comprehension difficult to humans.

Overall, AI holds significant potential in finance, particularly in risk management, efficiently handling vast datasets. It generates accurate predictions, aids in credit risk management, and refines lending decisions. AI's impact extends to advancing trade execution, with algorithmic, quantitative, and high-frequency trading offering real advantages. Market sentiment analysis benefits from AI's swift processing of extensive data, while personalised banking undergoes a revolution with AI-chatbots. In general, AI-based technologies have begun a revolution in the financial industry, pointing to a promising future for AI and finance integration.

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Appendices

Appendix 1. Event study calculations

Equations are explained in the methodology section.

Rate of return %					Expected return (Market Model)				Abnormal return (AR)				Cumulative Abnormal return (CAR)				Buy-and-Hold Abnormal return (BHAR)				AAR			CAAR			BHAAR		
AIEQ	QRFT	DFAC	AVUS	SPX Index	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AI	Human	Difference	AI	Human	Difference	AI	Human	Difference
-0,0068	-0,0047	-0,0068	-0,0045	-0,0015	-0,003	-0,002	-0,002	-0,002	-0,004	-0,003	-0,005	-0,003	-0,004	-0,003	-0,005	-0,003	-0,0042	-0,0029	-0,0050	-0,0027	-0,35 %	-0,39 %	0,03 %	-0,35 %	-0,39 %	0,03 %	-0,35 %	-0,39 %	0,03 %
-0,0094	-0,0226	-0,0057	-0,0061	-0,0054	-0,007	-0,006	-0,006	-0,006	-0,003	-0,017	0,000	0,000	-0,007	-0,020	-0,005	-0,003	-0,0067	-0,0195	-0,0049	-0,0029	-0,96 %	-0,01 %	-0,95 %	-1,31 %	-0,39 %	-0,92 %	-1,31 %	-0,39 %	-0,92 %
0,0213	0,0385	0,0206	0,0186	0,0241	0,025	0,025	0,025	0,025	-0,004	0,013	-0,004	-0,007	-0,010	-0,006	-0,009	-0,010	-0,0104	-0,0063	-0,0090	-0,0095	0,49 %	-0,53 %	1,02 %	-0,83 %	-0,93 %	0,10 %	-0,84 %	-0,92 %	0,09 %
0,0354	0,0322	0,0177	0,0192	0,0187	0,019	0,019	0,019	0,020	0,016	0,013	-0,002	0,000	0,006	0,007	-0,010	-0,010	0,0056	0,0064	-0,0105	-0,0099	1,45 %	-0,09 %	1,54 %	0,62 %	-1,02 %	1,64 %	0,60 %	-1,02 %	1,62 %
0,0130	0,0075	0,0087	0,0101	0,0068	0,006	0,007	0,007	0,007	0,007	0,001	0,002	0,003	0,012	0,007	-0,009	-0,007	0,0122	0,0070	-0,0086	-0,0069	0,36 %	0,24 %	0,12 %	0,98 %	-0,78 %	1,76 %	0,96 %	-0,78 %	1,74 %
0,0013	0,0094	0,0058	0,0065	0,0094	0,009	0,010	0,010	0,010	-0,008	0,000	-0,004	-0,003	0,005	0,007	-0,012	-0,010	0,0043	0,0067	-0,0124	-0,0102	-0,40 %	-0,35 %	-0,05 %	0,57 %	-1,13 %	1,70 %	0,55 %	-1,13 %	1,68 %
-0,0230	-0,0214	-0,0192	-0,0214	-0,0247	-0,028	-0,026	-0,026	-0,026	0,005	0,005	0,007	0,005	0,009	0,012	-0,006	-0,005	0,0091	0,0116	-0,0059	-0,0053	0,48 %	0,57 %	-0,09 %	1,06 %	-0,56 %	1,62 %	1,04 %	-0,56 %	1,60 %
0,0024	0,0042	0,0029	0,0046	0,0051	0,005	0,005	0,005	0,005	-0,002	-0,001	-0,002	-0,001	0,007	0,011	-0,008	-0,006	0,0070	0,0107	-0,0081	-0,0060	-0,15 %	-0,14 %	-0,01 %	0,90 %	-0,70 %	1,61 %	0,88 %	-0,71 %	1,59 %
-0,0019	-0,0067	-0,0007	-0,0016	-0,0037	-0,005	-0,004	-0,004	-0,004	0,003	-0,003	0,003	0,003	0,010	0,008	-0,005	-0,003	0,0101	0,0081	-0,0049	-0,0035	0,03 %	0,29 %	-0,26 %	0,93 %	-0,41 %	1,34 %	0,91 %	-0,42 %	1,33 %
0,0131	0,0111	0,0120	0,0110	0,0084	0,008	0,009	0,008	0,009	0,005	0,002	0,004	0,002	0,015	0,011	-0,001	-0,001	0,0152	0,0106	-0,0014	-0,0012	0,38 %	0,29 %	0,08 %	1,31 %	-0,12 %	1,43 %	1,29 %	-0,13 %	1,41 %
0,0340	0,0136	0,0147	0,0147	0,0144	0,015	0,015	0,015	0,015	0,019	-0,001	0,000	0,000	0,035	0,010	-0,001	-0,001	0,0349	0,0092	-0,0014	-0,0015	0,91 %	-0,02 %	0,92 %	2,21 %	-0,14 %	2,35 %	2,21 %	-0,14 %	2,35 %
-0,0187	-0,0176	-0,0172	-0,0155	-0,0183	-0,021	-0,020	-0,019	-0,019	0,002	0,002	0,002	0,004	0,037	0,011	0,001	0,003	0,0371	0,0112	0,0005	0,0025	0,20 %	0,29 %	-0,09 %	2,41 %	0,16 %	2,26 %	2,41 %	0,15 %	2,26 %
-0,0328	-0,0188	-0,0153	-0,0159	-0,0192	-0,022	-0,020	-0,020	-0,020	-0,011	0,002	0,005	0,005	0,026	0,013	0,005	0,007	0,0257	0,0128	0,0052	0,0071	-0,47 %	0,46 %	-0,93 %	1,95 %	0,62 %	1,33 %	1,93 %	0,61 %	1,31 %
-0,0100	-0,0067	-0,0044	-0,0053	-0,0038	-0,005	-0,004	-0,004	-0,004	-0,005	-0,002	0,000	-0,001	0,021	0,011	0,005	0,006	0,0208	0,0104	0,0049	0,0060	-0,36 %	-0,07 %	-0,29 %	1,59 %	0,55 %	1,04 %	1,56 %	0,55 %	1,01 %
0,0266	0,0139	0,0187	0,0179	0,0156	0,016	0,016	0,016	0,016	0,011	-0,002	0,003	0,002	0,032	0,008	0,008	0,008	0,0317	0,0081	0,0076	0,0076	0,42 %	0,21 %	0,21 %	2,01 %	0,76 %	1,24 %	1,99 %	0,76 %	1,23 %
0,0030	-0,0008	0,0022	0,0016	0,0009	0,000	0,001	0,001	0,001	0,003	-0,001	0,001	0,001	0,035	0,007	0,009	0,008	0,0348	0,0066	0,0091	0,0084	0,08 %	0,11 %	-0,03 %	2,09 %	0,88 %	1,21 %	2,07 %	0,87 %	1,20 %
-0,0321	-0,0203	-0,0220	-0,0212	-0,0214	-0,024	-0,023	-0,022	-0,023	-0,008	0,003	0,000	0,002	0,027	0,009	0,009	0,010	0,0267	0,0092	0,0094	0,0100	-0,27 %	0,10 %	-0,36 %	1,82 %	0,97 %	0,85 %	1,79 %	0,97 %	0,82 %
-0,0070	-0,0215	-0,0048	-0,0067	-0,0072	-0,009	-0,008	-0,008	-0,008	0,002	-0,014	0,003	0,001	0,029	-0,004	0,012	0,011	0,0285	-0,0046	0,0123	0,0111	-0,59 %	0,20 %	-0,79 %	1,23 %	1,17 %	0,06 %	1,20 %	1,17 %	0,03 %
-0,0124	0,0027	-0,0127	-0,0124	-0,0102	-0,012	-0,011	-0,011	-0,011	0,000	0,014	-0,002	-0,001	0,028	0,010	0,010	0,010	0,0282	0,0091	0,0103	0,0096	0,67 %	-0,17 %	0,84 %	1,90 %	1,00 %	0,90 %	1,86 %	0,99 %	0,87 %
-0,0195	-0,0185	-0,0175	-0,0161	-0,0186	-0,021	-0,020	-0,019	-0,020	0,002	0,001	0,002	0,004	0,030	0,011	0,012	0,013	0,0298	0,0104	0,0122	0,0133	0,15 %	0,28 %	-0,13 %	2,05 %	1,28 %	0,77 %	2,01 %	1,28 %	0,74 %
0,0333	0,0214	0,0141	0,0125	0,0148	0,015	0,015	0,015	0,016	0,018	0,006	-0,001	-0,003	0,048	0,017	0,011	0,010	0,0487	0,0165	0,0111	0,0102	1,21 %	-0,21 %	1,42 %	3,26 %	1,07 %	2,19 %	3,26 %	1,07 %	2,19 %
0,0202	0,0201	0,0239	0,0240	0,0221	0,023	0,023	0,023	0,023	-0,003	-0,003	0,001	0,001	0,046	0,014	0,012	0,011	0,0458	0,0134	0,0123	0,0110	-0,29 %	0,10 %	-0,38 %	2,97 %	1,17 %	1,80 %	2,96 %	1,17 %	1,80 %
0,0019	-0,0047	-0,0015	0,0001	-0,0024	-0,004	-0,003	-0,003	-0,003	0,006	-0,002	0,001	0,003	0,051	0,012	0,014	0,014	0,0517	0,0116	0,0136	0,0139	0,19 %	0,21 %	-0,02 %	3,16 %	1,38 %	1,79 %	3,16 %	1,38 %	1,79 %
-0,0241	-0,0074	-0,0190	-0,0188	-0,0156	-0,018	-0,017	-0,016	-0,017	-0,006	0,009	-0,003	-0,002	0,045	0,021	0,011	0,012	0,0452	0,0210	0,0109	0,0118	0,16 %	-0,24 %	0,40 %	3,32 %	1,13 %	2,19 %	3,31 %	1,13 %	2,18 %
0,0219	0,0191	0,0223	0,0233	0,0185	0,019	0,019	0,019	0,019	0,003	0,000	0,003	0,004	0,048	0,021	0,014	0,016	0,0482	0,0210	0,0143	0,0158	0,14 %	0,37 %	-0,23 %	3,46 %	1,50 %	1,96 %	3,46 %	1,50 %	1,95 %
-0,0134	-0,0097	-0,0052	-0,0054	-0,0053	-0,007	-0,006	-0,006	-0,006	-0,007	-0,004	0,000	0,000	0,041	0,017	0,015	0,016	0,0413	0,0170	0,0148	0,0161	-0,52 %	0,04 %	-0,56 %	2,94 %	1,54 %	1,39 %	2,91 %	1,54 %	1,37 %
-0,0167	-0,0064	-0,0115	-0,0104	-0,0080	-0,010	-0,009	-0,008	-0,009	-0,007	0,002	-0,003	-0,002	0,034	0,020	0,012	0,014	0,0339	0,0193	0,0116	0,0142	-0,24 %	-0,25 %	0,01 %	2,70 %	1,30 %	1,40 %	2,66 %	1,29 %	1,37 %
-0,0340	-0,0328	-0,0316	-0,0304	-0,0300	-0,033	-0,032	-0,031	-0,032	-0,001	-0,001	0,000	0,001	0,034	0,019	0,011	0,016	0,0334	0,0184	0,0113	0,0156	-0,07 %	0,05 %	-0,12 %	2,62 %	1,35 %	1,28 %	2,59 %	1,34 %	1,24 %
-0,0015	-0,0087	-0,0045	-0,0035	-0,0073	-0,009	-0,008	-0,008	-0,008	0,007	-0,001	0,003	0,004	0,041	0,018	0,015	0,020	0,0410	0,0176	0,0146	0,0201	0,33 %	0,38 %	-0,05 %	2,95 %	1,73 %	1,23 %	2,93 %	1,73 %	1,20 %
0,0215	0,0250	0,0251	0,0235	0,0254	0,026	0,027	0,026	0,027	-0,005	-0,002	-0,001	-0,003	0,036	0,017	0,014	0,017	0,0358	0,0160	0,0136	0,0169	-0,33 %	-0,20 %	-0,12 %	2,63 %	1,52 %	1,11 %	2,59 %	1,52 %	1,07 %
0,0001	-0,0051	-0,0023	-0,0005	-0,0043	-0,006	-0,005	-0,005	-0,005	0,006	0,000	0,002	0,004	0,042	0,016	0,016	0,021	0,0419	0,0157	0,0160	0,0211	0,28 %	0,33 %	-0,05 %	2,91 %	1,85 %	1,06 %	2,88 %	1,86 %	1,02 %
-0,0155	-0,0130	-0,0122	-0,0116	-0,0130	-0,015	-0,014	-0,014	-0,014	0,000	0,001	0,001	0,002	0,042	0,017	0,017	0,023	0,0415	0,0168	0,0175	0,0235	0,04 %	0,19 %	-0,15 %	2,94 %	2,04 %	0,90 %	2,92 %	2,05 %	0,87 %
-0,0087	-0,0071	-0,0062	-0,0087	-0,0074	-0,009	-0,008	-0,008	-0,008	0,000	0,001	0,002	-0,001	0,042	0,018	0,019	0,023	0,0419	0,0178	0,0192	0,0229	0,07 %	0,05 %	0,01 %	3,01 %	2,09 %	0,91 %	2,98 %	2,10 %	0,88 %
0,0209	0,0216	0,0184	0,0171	0,0212	0,022	0,022	0,022	0,022	-0,001	0,000	-0,003	-0,005	0,041	0,018	0,016	0,018	0,0409	0,0173	0,0158	0,0176	-0,07 %	-0,42 %	0,35 %	2,94 %	1,67 %	1,27 %	2,91 %	1,67 %	1,24 %
0,0325	0,0260	0,0240	0,0231	0,0221	0,023	0,023	0,023	0,023	0,010	0,003	0,001	0,000	0,051	0,021	0,017	0,017	0,0508	0,0203	0,0171	0,0174	0,62 %	0,06 %	0,57 %	3,56 %	1,73 %	1,84 %	3,56 %	1,73 %	1,83 %
0,0153	0,0125	0,0114	0,0128	0,0123	0,012	0,013	0,013	0,013	0,003	0,000	-0,001	0,000	0,054	0,021	0,016	0,017	0,0540	0,0201	0,0160	0,0175	0,14 %	-0,05 %	0,20 %	3,71 %	1,67 %	2,03 %	3,71 %	1,67 %	2,03 %
0,0149	0,0164	0,0098	0,0105	0,0116	0,012	0,012	0,012	0,012	0,003	0,004	-0,002	-0,002	0,057	0,025	0,014	0,016	0,0576	0,0247	0,0140	0,0159	0,39 %	-0,18 %	0,57 %	4,10 %	1,50 %	2,60 %	4,11 %	1,49 %	2,62 %
-0,0053	-0,0056	-0,0018	-0,0004	-0,0004	-0,001	-0,001	-0,001	-0,001	-0,004	-0,005	-0,001	0,000	0,053	0,020	0,013	0,016	0,0536	0,0196	0,0128	0,0161	-0,43 %	-0,05 %	-0,39 %	3,66 %	1,45 %	2,21 %	3,66 %	1,45 %	2,21 %
0,0112	0,0124	0,0069	0,0068	0,0112	0,011	0,012	0,011	0,012	0,000	0,001	-0,005	-0,005	0,053	0,021	0,008	0,011	0,0536	0,0204	0,0082	0,0111	0,04 %	-0,48 %	0,52 %	3,70 %	0,97 %	2,73 %	3,70 %	0,96 %	2,74 %
-0,0157	-0,0157	-0,0145	-0,0126	-0,0123	-0,014	-0,013	-0,013	-0,013	-0,001	-0,002	-0,002	0,001	0,052	0,018	0,007	0,012	0,0523	0,0179	0,0066	0,0117	-0,18 %	-0,05 %	-0,14 %	3,52 %	0,92 %	2,59 %	3,51 %	0,91 %	2,60 %
0,0122	0,0124	0,0124	0,0125	0,0142	0,014	0,015	0,015	0,015	-0,002	-0,002	-0,002	-0,002	0,050	0,016	0,005	0,009	0,0499	0,0155	0,0044	0,0093	-0,23 %	-0,23 %	0,00 %	3,29 %	0,70 %	2,59 %	3,27 %	0,68 %	2,59 %
0,0019	0,0004	0,0043	0,0064	0,0051	0,004	0,005	0,005	0,005	-0,003	-0,005	-0,001	0,001	0,047	0,011	0,004	0,011	0,0473	0,0108	0,0037	0,0106	-0,36 %	0,03 %	-0,39 %	2,93 %	0,73 %	2,20 %	2,90 %	0,71 %	2,19 %
0,0004	0,0075	0,0036	0,0013	0,0071	0,007	0,007	0,007	0,007	-0,006	0,000	-0,004	-0,006	0,041	0,012	0,000	0,005	0,0406	0,0110	0,0001	0,0045	-0,31 %	-0,48 %	0,18 %	2,62 %	0,24 %	2,38 %	2,58 %	0,23 %	2,35 %

Rate of return %					Expected return (OLS Market Model)				Abnormal return (AR)				Cumulative Abnormal return (CAR)				Buy-and-Hold Abnormal return (BHAR)				AAR			CAAR			BHAAR		
AIEQ	QRFT	DFAC	AVUS	SPX Index	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AIEQ	QRTF	DFAC	AVUS	AI	Human	Difference	AI	Human	Difference	AI	Human	Difference
-0,0265	-0,0082	-0,0104	-0,0096	-0,0089	-0,011	-0,010	-0,009	-0,010	-0,016	0,001	-0,001	0,000	-0,016	0,001	-0,001	0,000	-0,0159	0,0014	-0,0010	-0,0001	-0,72 %	-0,05 %	-0,007	-0,72 %	-0,05 %	-0,007	-0,72 %	-0,05 %	-0,0067
-0,0121	0,0030	0,0042	0,0048	0,0022	0,001	0,002	0,002	0,002	-0,013	0,001	0,002	0,003	-0,029	0,002	0,001	0,003	-0,0291	0,0024	0,0012	0,0026	-0,62 %	0,24 %	-0,009	-1,35 %	0,19 %	-0,015	-1,33 %	0,19 %	-0,0152
0,0123	0,0112	0,0118	0,0109	0,0114	0,011	0,012	0,012	0,012	0,001	-0,001	0,000	-0,001	-0,028	0,002	0,001	0,002	-0,0281	0,0018	0,0014	0,0017	0,02 %	-0,03 %	0,001	-1,33 %	0,16 %	-0,015	-1,32 %	0,15 %	-0,0147
0,0164	0,0017	-0,0008	0,0005	-0,0003	-0,001	-0,001	0,000	0,000	0,018	0,002	0,000	0,001	-0,011	0,004	0,001	0,003	-0,0110	0,0040	0,0011	0,0027	0,99 %	0,04 %	0,010	-0,33 %	0,19 %	-0,005	-0,35 %	0,19 %	-0,0054
0,0063	0,0024	0,0042	0,0030	0,0028	0,002	0,003	0,003	0,003	0,004	0,000	0,001	0,000	-0,006	0,004	0,003	0,003	-0,0067	0,0038	0,0026	0,0029	0,21 %	0,09 %	0,001	-0,13 %	0,28 %	-0,004	-0,15 %	0,28 %	-0,0042
-0,0106	-0,0085	-0,0110	-0,0116	-0,0139	-0,016	-0,015	-0,015	-0,015	0,005	0,006	0,004	0,003	-0,001	0,010	0,006	0,006	-0,0013	0,0102	0,0062	0,0062	0,59 %	0,34 %	0,003	0,47 %	0,62 %	-0,002	0,45 %	0,62 %	-0,0017
-0,0067	-0,0050	-0,0027	-0,0041	-0,0028	-0,004	-0,003	-0,003	-0,003	-0,003	-0,002	0,000	-0,001	-0,004	0,008	0,007	0,005	-0,0039	0,0084	0,0065	0,0052	-0,22 %	-0,03 %	-0,002	0,24 %	0,59 %	-0,003	0,22 %	0,59 %	-0,0036
-0,0283	-0,0215	-0,0225	-0,0213	-0,0202	-0,023	-0,022	-0,021	-0,022	-0,005	0,000	-0,001	0,000	-0,009	0,009	0,005	0,006	-0,0092	0,0085	0,0052	0,0055	-0,26 %	-0,05 %	-0,002	-0,02 %	0,53 %	-0,006	-0,04 %	0,53 %	-0,0057
0,0079	-0,0028	0,0000	-0,0003	-0,0016	-0,003	-0,002	-0,002	-0,002	0,011	-0,001	0,002	0,002	0,002	0,008	0,007	0,007	0,0013	0,0076	0,0070	0,0071	0,49 %	0,17 %	0,003	0,47 %	0,70 %	-0,002	0,45 %	0,70 %	-0,0026
-0,0076	0,0057	0,0039	0,0043	0,0053	0,005	0,005	0,005	0,005	-0,012	0,000	-0,001	-0,001	-0,011	0,008	0,006	0,006	-0,0110	0,0079	0,0056	0,0060	-0,60 %	-0,12 %	-0,005	-0,13 %	0,58 %	-0,007	-0,15 %	0,58 %	-0,0073
-0,0214	-0,0086	-0,0071	-0,0080	-0,0106	-0,012	-0,011	-0,011	-0,011	-0,009	0,003	0,004	0,003	-0,019	0,011	0,010	0,009	-0,0198	0,0108	0,0097	0,0094	-0,30 %	0,37 %	-0,007	-0,43 %	0,95 %	-0,014	-0,45 %	0,95 %	-0,0141
0,0070	0,0025	0,0020	0,0037	0,0031	0,002	0,003	0,003	0,003	0,005	0,000	-0,001	0,001	-0,015	0,010	0,009	0,010	-0,0152	0,0104	0,0087	0,0100	0,21 %	-0,02 %	0,002	-0,22 %	0,93 %	-0,012	-0,24 %	0,93 %	-0,0118
0,0096	-0,0016	-0,0016	-0,0031	-0,0030	-0,004	-0,003	-0,003	-0,003	0,014	0,002	0,002	0,000	-0,001	0,012	0,010	0,010	-0,0015	0,0123	0,0104	0,0103	0,79 %	0,10 %	0,007	0,57 %	1,03 %	-0,005	0,54 %	1,04 %	-0,0050
-0,0173	-0,0020	-0,0008	-0,0001	-0,0047	-0,006	-0,005	-0,005	-0,005	-0,011	0,003	0,004	0,005	-0,012	0,016	0,015	0,015	-0,0126	0,0156	0,0148	0,0154	-0,39 %	0,47 %	-0,009	0,18 %	1,50 %	-0,013	0,15 %	1,51 %	-0,0136
0,0113	0,0062	0,0055	0,0062	0,0076	0,007	0,008	0,008	0,008	0,004	-0,001	-0,002	-0,002	-0,008	0,014	0,013	0,014	-0,0086	0,0141	0,0126	0,0137	0,13 %	-0,19 %	0,003	0,31 %	1,31 %	-0,010	0,28 %	1,32 %	-0,0104
0,0157	0,0124	0,0148	0,0145	0,0160	0,016	0,017	0,016	0,017	-0,001	-0,004	-0,002	-0,002	-0,008	0,010	0,011	0,011	-0,0092	0,0099	0,0110	0,0114	-0,24 %	-0,19 %	0,000	0,07 %	1,12 %	-0,010	0,03 %	1,12 %	-0,0109
-0,0137	-0,0017	-0,0039	-0,0043	0,0007	0,000	0,000	0,001	0,001	-0,013	-0,002	-0,004	-0,005	-0,022	0,008	0,007	0,007	-0,0225	0,0076	0,0066	0,0065	-0,78 %	-0,46 %	-0,003	-0,71 %	0,66 %	-0,014	-0,74 %	0,65 %	-0,0140
-0,0103	-0,0142	-0,0144	-0,0144	-0,0154	-0,018	-0,017	-0,016	-0,016	0,007	0,002	0,002	0,002	-0,015	0,010	0,008	0,009	-0,0153	0,0100	0,0083	0,0087	0,49 %	0,19 %	0,003	-0,22 %	0,85 %	-0,011	-0,26 %	0,85 %	-0,0111
-0,0046	0,0030	0,0016	0,0004	0,0014	0,001	0,001	0,001	0,001	-0,005	0,002	0,000	-0,001	-0,020	0,012	0,009	0,008	-0,0203	0,0118	0,0086	0,0077	-0,17 %	-0,03 %	-0,001	-0,39 %	0,82 %	-0,012	-0,43 %	0,82 %	-0,0124
-0,0283	-0,0151	-0,0218	-0,0219	-0,0186	-0,021	-0,020	-0,019	-0,020	-0,007	0,005	-0,002	-0,002	-0,027	0,017	0,006	0,006	-0,0273	0,0167	0,0062	0,0057	-0,12 %	-0,22 %	0,001	-0,51 %	0,60 %	-0,011	-0,53 %	0,60 %	-0,0113
-0,0283	-0,0175	-0,0178	-0,0190	-0,0146	-0,017	-0,016	-0,015	-0,016	-0,011	-0,002	-0,003	-0,003	-0,038	0,015	0,004	0,002	-0,0385	0,0147	0,0037	0,0023	-0,67 %	-0,30 %	-0,004	-1,18 %	0,30 %	-0,015	-1,19 %	0,30 %	-0,0148
-0,0018	-0,0005	-0,0107	-0,0127	-0,0015	-0,003	-0,002	-0,002	-0,002	0,001	0,001	-0,009	-0,011	-0,037	0,016	-0,005	-0,009	-0,0376	0,0161	-0,0053	-0,0087	0,11 %	-0,99 %	0,011	-1,07 %	-0,69 %	-0,004	-1,08 %	-0,70 %	-0,0038
0,0092	0,0137	0,0160	0,0165	0,0163	0,017	0,017	0,017	0,017	-0,008	-0,003	-0,001	-0,001	-0,045	0,013	-0,006	-0,009	-0,0448	0,0127	-0,0060	-0,0093	-0,54 %	-0,07 %	-0,005	-1,61 %	-0,76 %	-0,009	-1,61 %	-0,76 %	-0,0084
-0,0152	-0,0128	-0,0135	-0,0148	-0,0070	-0,009	-0,008	-0,007	-0,008	-0,007	-0,005	-0,006	-0,007	-0,051	0,008	-0,012	-0,016	-0,0511	0,0075	-0,0120	-0,0165	-0,59 %	-0,67 %	0,001	-2,19 %	-1,42 %	-0,008	-2,18 %	-1,42 %	-0,0076
0,0211	0,0188	0,0163	0,0170	0,0174	0,018	0,018	0,018	0,018	0,003	0,001	-0,001	-0,001	-0,048	0,008	-0,013	-0,018	-0,0480	0,0082	-0,0135	-0,0176	0,20 %	-0,13 %	0,003	-1,99 %	-1,56 %	-0,004	-1,99 %	-1,56 %	-0,0043
-0,0126	-0,0107	-0,0155	-0,0164	-0,0111	-0,013	-0,012	-0,012	-0,012	0,000	0,001	-0,004	-0,005	-0,048	0,010	-0,017	-0,022	-0,0476	0,0095	-0,0173	-0,0221	0,09 %	-0,42 %	0,005	-1,91 %	-1,98 %	0,001	-1,90 %	-1,97 %	0,0007
0,0042	0,0101	0,0110	0,0115	0,0089	0,009	0,009	0,009	0,009	-0,004	0,001	0,002	0,002	-0,052	0,011	-0,015	-0,020	-0,0518	0,0105	-0,0153	-0,0199	-0,17 %	0,22 %	-0,004	-2,08 %	-1,76 %	-0,003	-2,06 %	-1,76 %	-0,0030
0,0205	0,0112	0,0133	0,0168	0,0129	0,013	0,013	0,013	0,013	0,008	-0,002	0,000	0,003	-0,045	0,008	-0,015	-0,017	-0,0446	0,0083	-0,0151	-0,0166	0,27 %	0,18 %	0,001	-1,81 %	-1,58 %	-0,002	-1,81 %	-1,58 %	-0,0023
-0,0272	-0,0131	-0,0195	-0,0195	-0,0166	-0,019	-0,018	-0,017	-0,018	-0,008	0,005	-0,002	-0,002	-0,053	0,013	-0,017	-0,018	-0,0524	0,0130	-0,0172	-0,0183	-0,18 %	-0,19 %	0,000	-1,99 %	-1,77 %	-0,002	-1,97 %	-1,77 %	-0,0020
0,0063	0,0018	0,0000	-0,0047	0,0030	0,002	0,003	0,003	0,003	0,004	-0,001	-0,003	-0,008	-0,049	0,012	-0,020	-0,026	-0,0485	0,0119	-0,0200	-0,0258	0,15 %	-0,53 %	0,007	-1,83 %	-2,30 %	0,005	-1,83 %	-2,29 %	0,0046
-0,0017	0,0019	0,0045	0,0049	0,0056	0,005	0,006	0,006	0,006	-0,007	-0,004	-0,001	-0,001	-0,055	0,008	-0,021	-0,027	-0,0550	0,0081	-0,0211	-0,0267	-0,53 %	-0,10 %	-0,004	-2,36 %	-2,41 %	0,000	-2,35 %	-2,39 %	0,0005
-0,0119	0,0041	0,0061	0,0067	0,0016	0,001	0,001	0,002	0,002	-0,013	0,003	0,005	0,005	-0,068	0,011	-0,017	-0,022	-0,0670	0,0107	-0,0167	-0,0217	-0,50 %	0,49 %	-0,010	-2,87 %	-1,92 %	-0,009	-2,81 %	-1,92 %	-0,0090
-0,0091	-0,0022	0,0004	0,0004	-0,0016	-0,003	-0,002	-0,002	-0,002	-0,006	0,000	0,002	0,002	-0,074	0,010	-0,014	-0,019	-0,0729	0,0104	-0,0145	-0,0194	-0,33 %	0,23 %	-0,006	-3,20 %	-1,69 %	-0,015	-3,13 %	-1,70 %	-0,0143
0,0178	0,0148	0,0121	0,0132	0,0141	0,014	0,015	0,014	0,015	0,004	0,000	-0,002	-0,002	-0,071	0,011	-0,017	-0,021	-0,0697	0,0106	-0,0168	-0,0210	0,19 %	-0,20 %	0,004	-3,01 %	-1,89 %	-0,011	-2,95 %	-1,89 %	-0,0106
0,0028	0,0059	0,0044	0,0036	0,0057	0,005	0,006	0,006	0,006	-0,002	0,000	-0,001	-0,002	-0,073	0,011	-0,018	-0,023	-0,0718	0,0107	-0,0181	-0,0232	-0,11 %	-0,18 %	0,001	-3,12 %	-2,07 %	-0,011	-3,05 %	-2,07 %	-0,0099
0,0263	0,0133	0,0146	0,0149	0,0143	0,014	0,015	0,015	0,015	0,012	-0,002	0,000	0,000	-0,062	0,009	-0,018	-0,023	-0,0609	0,0091	-0,0181	-0,0233	0,51 %	0,00 %	0,005	-2,62 %	-2,07 %	-0,005	-2,59 %	-2,07 %	-0,0052
0,0063	0,0040	0,0043	0,0042	0,0037	0,003	0,004	0,004	0,004	0,003	0,000	0,001	0,001	-0,058	0,010	-0,017	-0,023	-0,0578	0,0095	-0,0175	-0,0228	0,19 %	0,06 %	0,001	-2,43 %	-2,01 %	-0,004	-2,41 %	-2,01 %	-0,0040
-0,0196	-0,0108	-0,0122	-0,0112	-0,0058	-0,007	-0,006	-0,006	-0,006	-0,012	-0,004	-0,006	-0,005	-0,070	0,005	-0,023	-0,028	-0,0694	0,0051	-0,0233	-0,0275	-0,84 %	-0,54 %	-0,003	-3,27 %	-2,56 %	-0,007	-3,22 %	-2,54 %	-0,0067
-0,0202	-0,0038	-0,0036	-0,0033	-0,0025	-0,004	-0,003	-0,003	-0,003	-0,016	-0,001	-0,001	0,000	-0,087	0,004	-0,024	-0,028	-0,0847	0,0042	-0,0241	-0,0279	-0,87 %	-0,06 %	-0,008	-4,13 %	-2,62 %	-0,015	-4,03 %	-2,60 %	-0,0142
0,0027	-0,0006	0,0016	0,0011	0,0036	0,003	0,004	0,004	0,004	0,000	-0,004	-0,002	-0,002	-0,087	0,000	-0,026	-0,031	-0,0849	0,0001	-0,0260	-0,0303	-0,21 %	-0,22 %	0,000	-4,35 %	-2,84 %	-0,015	-4,24 %	-2,82 %	-0,0142
0,0116	0,0052	0,0047	0,0055	0,0010	0,000	0,001	0,001	0,001	0,012	0,004	0,004	0,005	-0,076	0,005	-0,022	-0,026	-0,0743	0,0045	-0,0222	-0,0258	0,80 %	0,43 %	0,004	-3,55 %	-2,41 %	-0,011	-3,49 %	-2,40 %	-0,0109
0,0129	0,0035	0,0039	0,0042	0,0000	-0,001	0,000	0,000	0,000	0,014	0,004	0,004	0,004	-0,062	0,008	-0,018	-0,021	-0,0614	0,0083	-0,0181	-0,0215	0,009	0,004	0,005	-0,0266	-0,0198	-0,007	-0,0266	-0,0198	-0,0068
-0,0074	-0,0048	-0,0039	-0,0047	-0,0041	-0,006	-0,005	-0,004	-0,005	-0,002	0,000	0,001	0,000	-0,064	0,008	-0,018	-0,022	-0,0632	0,0081	-0,0176	-0,0216	-0,001	0,000	-0,001	-0,0277	-0,0196	-0,008	-0,0276	-0,0196	-0,0080