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THE USE OF ARTIFICIAL INTELLIGENCE IN FINANCE

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Tekoälyn merkitys yhteiskunnassa on noussut lähivuosina suuresti. Sen sovelluksia voidaan hyödyntää jo monella eri tieteenalalla, ja tekoälyn kehitystahti on ainoastaan kiihtynyt lähivuosina. Tässä tutkielmassa tulen käsittelemään tekoälyn sovellutuksia ja mahdollisia käyttökohteita rahoitusalalla. Motivaationa tutkimuksen tekemiseen aiheesta oli oma kiinnostus rahoitusalaa kohtaan sivuaineopintojen kautta, sekä yleinen kiinnostus tekoälyä ja sen mahdollisuuksia kohtaan. Tutkimus on toteutettu kirjallisuuskatsauksena, käyttäen lähteinä varsinaisessa tutkimusosiossa tieteellisiä artikkeleita. Varsinaiset artikkelit on haettu Jykdok ja Google Scholar -palveluja hyödyntäen. Myös tekoälyn määrityskappaleessa on käytetty tieteellisiä artikkeleita, mutta rahoitusmarkkinoista kertovissa kappaleissa on lähteinä käytetty rahoituksen oppikirjoja. Tutkimuksen lopputuloksena löydettiin lukuisia erilaisia tapoja ja tehtäviä, joilla rahoitusalalla hyödynnetään tai voitaisiin tulevaisuudessa hyödyntää tekoälyä. Näitä olivat esimerkiksi arvopaperikauppa, mielipidelouhinta, portfolion kasaus ja optimointi sekä riskien hallinta.

Asiasanat: tekoäly, tekoäly rahoituksessa, tekoälyn sovellukset rahoitusalalla, tekoäly osakekaupassa

ABSTRACT

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The importance of artificial intelligence in society has increased substansially in the coming years. Its applications can already be utilized in many different scientific fields, and the pace of AI development has only accelerated in the recent years. In this thesis, I will discuss the applications and potential uses of AI in the financial sector. The motivation for this research was my own interest in finance through my minor studies in finance, as well as a general interest in AI and its potential for different industries. The research has been carried out as a literature review, using scientific articles as sources in the actual research section. The actual articles have been retrieved using Jykdok and Google Scholar. Scientific articles have also been used in the section on the definition of artificial intelligence, but in the sections on financial markets, financial textbooks have been used as sources. The study resulted in several different ways and tasks that the financial sector is using or could use AI in the future. These included portfolio accumulation and optimization, risk management, securities trading , and sentiment analysis.

Keywords: AI, AI in finance, applications of AI in finance, AI in stock trading

CONTENTS

1 INTRODUCTION

Artificial Intelligence (AI) has been increasingly popular among many in various industries, including finance. AI-based systems and algorithms are being increasingly utilized by financial institutions for a wide range of applications. These applications range from fraud detection and risk management to trading, portfolio management and even customer service. In this thesis, I will also present findings that have potential benefits for the industry but are not yet in use. The research question for this thesis is:

- How AI can be used in the financial industry?

In the first chapter I will briefly explain the history of AI and its relevant subfields in the field of finance. These subfields include Deep Learning (DL), Machine Learning (ML) and Natural Language Processing (NLP).

In the second chapter I will explain the structure of financial markets and how they work. I will explain different types of financial instruments and different types of institutions that participate into financial markets.

The third chapter is about the usage of AI in financial markets. I will present different applications of AI in finance such as trading, risk management and financial statement analysis. I will present studies that show how AI could be used, as well as bring up some problems with the usage of AI.

The study was done as a literature review. The sources I used are mostly from academic journals as well as textbooks. In addition, sources include some news articles. The academic sources have been found via search from Jykdok, Google Scholar and Springer. News articles have been found via Google search, and searches inside news sites.

Overall, this thesis seeks to provide a comprehensive view of AI in finance and its impact on the financial sector. Through this research, I hope to better understand how AI is currently changing financial industry, as well as its possible future applications.

2 ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) has infiltrated into a vast majority of our lives, and there doesn't seem to be an end in sight. AI is ever-evolving technology, and its applications seem to be matched only with the variance of its definitions among scientists and engineers. AI has currently a market size of about \$100-\$200 billion, and is estimated to grow to 1.8 trillion dollar industry in 2030 (*Artificial Intelligence Market Size 2030*, 2023). Currently about 50% of companies utilize AI in their business functions, and 22% of companies attribute at least 5% of their Earnings Before Interest and Taxes (EBIT) to AI. (*Global AI Survey 2020 – Desktop*, 2020).

2.1 Definition of Artificial Intelligence

AI has been notoriously difficult concept to define since it requires the definition of both artificial and intelligence. Different approaches have been presented not only by experts in the field of computer science, but also in fields such as psychology, biology and philosophy (Abbass, 2021). Therefore, the definition is largely dependent on the audience. Abbass (2021) provides us with two alternative definitions, the first one being:

> Extract 1: "Artificial Intelligence is the automation of cognition."

He argues that while artificial intelligence is not merely automation as some claim it to be, but "automation of automation". This claim is also supported by an article titled "Artificial Intelligence Yesterday, Today and Tomorrow" (Jaakkola et al., 2019), where AI is defined as computer systems capable of presenting human-like intelligence while solving problems. The second definition by Abbass (2021) is:

> Extract 2: "Artificial Intelligence is social and cognitive phenomena that enable a machine to socially integrate with a society to perform competitive tasks requiring

> cognitive processes and communicate with other entities in society by exchanging messages with high information content and shorter representations."

This definition has less to do with computer science and technical side of AI, and more with the sociological impact and definition of AI, and supports his thesis that AI is not only phenomenon in computer science, but also in other fields as well. The definition problem also rises from a phenomenon known as "AI effect". This phenomenon has been seen happening as certain applications have reached mainstream usage, it is considered normal technological solution, rather than some higher-level engineering (Haenlein & Kaplan, 2019).

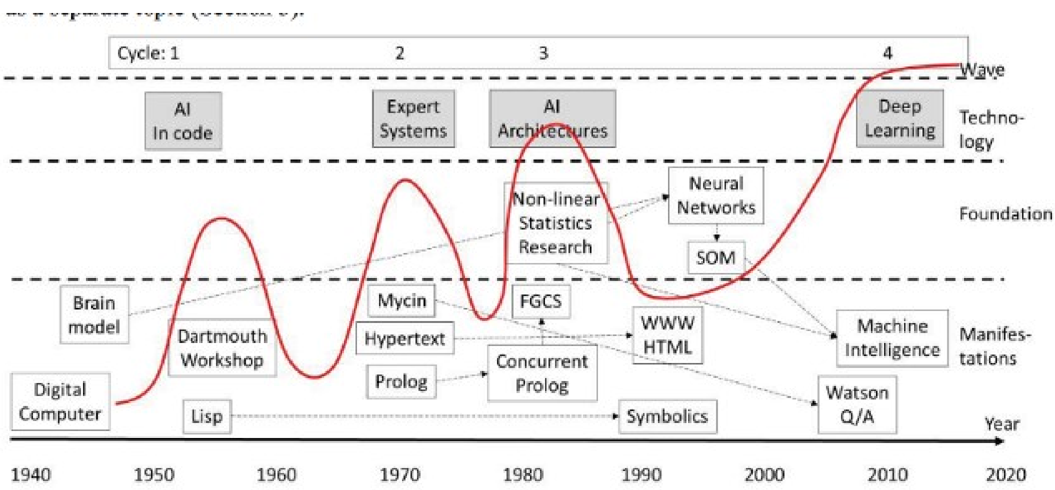
There has also been discussion on what should be described as intelligence and whether robotic intelligence is even close to human intelligence. Kaplan (2016) argues in his book "Artificial Intelligence: What Everyone needs to Know" that the measurement of intelligence is hard for humans, let alone machines, and therefore the traditional measurement of IQ score is quite inefficient. He gives an example of a simple calculator: if the measurement of intelligence would be to calculate numbers and formulas fast, a cheap calculator would beat any human by a long shot. But does this make the calculator an intelligent system? Most would say no. Prior to the invention of calculators, people who worked as calculators were considered intelligent. This would support Haenlain's and Kaplan's (2019) description of the AI effect. Kaplan (2016) also states that while machines and programs can perform tasks with a speed unmatched by its human counterparts and even tasks that humans are unable to perform, that itself does not make them intelligent.

For this thesis, we will be using John McCarthy's definition of AI as machines completing tasks, which could be described as intelligent if they were made by human actors and combining it with Kaplan's (2016) statement about machines being intelligent, if they can "make appropriate generalization in timely fashion based on limited data".

2.2 History of Artificial Intelligence

The era of modern-day AI is claimed to have started in 1955, when John McCarthy along with Marvin Minsky, Nathaniel Rochester and Claude Shannon proposed an artificial intelligence research project to Dartmouth College. The project got approved, and the workshop was held in the campus of Dartmouth College in summer of 1956. McCarthy was the original inventor of programming language LISP, which had the ability to make changes to its own code while it was being ran making it extremely useful in AI research and development. (McCarthy et al., 1955).Artificial Intelligence has had four major waves, as the interest in AI research and projects has had multiple cycles of massive interest, followed by steep decline as it has fallen out of the minds of people. The different waves can be seen from Picture 1 as well as the technologies that have been popular during that wave.

Picture 1 The history of AI and its development cycles



(Jaakkola et al., 2019)

The first wave started in 1956 with the Dartmouth College summer workshop and lasted until the early 1960s. For this era's algorithms it was typical that the algorithms had the knowledge to solve the problems they were given. In other terms, during this period algorithms had not yet developed the ability to learn on their own, but rather to merely follow the logic given by the programmer.

The second wave lasted from the late 1960s to the early 1970s and was coined the era of expert systems, first being created by a research group in Stanford University and then led by Edward Feigenbaum. An expert system has been defined to be computer application that reasons using knowledge to solve complex (dedicated) problems (Jaakkola et al., 2019). Expert systems were divided into three different groups based on their way of approaching problem solving. The rule-based system used a set of programmed rules and it included a set of different IF-THEN rules, knowledge and facts about the problem area and some kind of terminating component that decides on whether the decision was made or even could be found (Grosan & Abraham, 2011). The frame-based expert system was a bit more advanced version of the rule-based system, as it classified problems into a certain frame. Once the frame was selected, there were certain attributes which tie into the problem and instructions for program on how the frame should be utilized in decision-making process (*MITECS: Frame-Based Systems*, 1999). The last system in discussion was the hyper-text system, which basically consisted of multiple interconnected documents, which helped in the decision-making process. While Jaakkola et al. (2019) acknowledged that hyper-text-systems are not AI, they still decided to include them as they do play a big part in the industry, especially in the birth of the internet.

The third wave of AI began lasted through 1980s, and was centered around an idea that computer architectures should be developed for specific purposes, so they could be utilized more effectively in information processing. A Japanese project called "New (Fifth) Generation Computer System" (FGCS) aimed to build a large system that could be ran in parallel with multiple workstations connected to a central computer.

The fourth and latest wave in AI started in 2010s. Its research has been centered around the subject of machines learning from data to build their expertise. The development of neural networks and deep learning has offered the possibility to train the network with data. This is the opposite to the traditional way of coding the rules of decision process into the machine. Self-learning machines adapt into situations quickly and can manage to make decisions even when the situation is new to them. For example, Google's AlphaGo program has been able to beat the best player of Go in the world (Google AI Defeats Human Go Champion, 2017).

2.3 Machine Learning

Machine learning has gained enormous popularity in the recent years due to its ability to process large amounts of data, the ability to automate tasks and find patterns and insights from it (Alpaydin & Bach, 2014; Kurdi, 2016). Data-driven approach has become a norm in business, for example in online shopping. If data shows that people who buy shoes have a 70% probability of buying socks as well, the system can recommend socks to the shopper. This action is known as cross-selling.

The traditional way to build computer algorithms is for the programmer to know the rules by themselves, and merely write it to computer code. Machine learning flips this concept upside down, as the programmer just chooses a machine learning algorithm and gives it training data. The algorithms then write themselves, based on data. Machine analyzes said data, marks down which parameters are useful and constructs a model based on that data. There are multiple different types of learning paradigms. Most important ones for this research are supervised learning, unsupervised learning, reinforcement learning and artificial neural networks (ANN). Machine learning can solve multiple different types of problems. These include classification problems, anomaly detection problem and clustering problem.

The idea behind supervised learning is somewhat similar to human learning, although humans tend to learn from experience and machines through data (Alzubi et al., 2018). The basic idea is that the algorithm is shown a dataset, alongside with labels. This could be a set of pictures with different animals, each labeled with their specific species. Another example would be a set of simulations from the stock market, where the algorithm is supposed to buy or sell in that specific situation. This is used largely for classification problems. (Alzubi et al., 2018.) Unsupervised learning has quite the opposite idea about learning. In unsupervised learning the algorithm is only given the dataset, and it must find the patterns from it on its own. This is especially useful in clustering problems, where the machine finds hidden patterns and discriminants in the data. Discriminant in AI means a simple rule, which decides the classification of an object. An example of a discriminant could be that the algorithm deduces that the key difference between mammals and fish is that mammals live on land, whereas fish live in water. (Alzubi et al., 2018.) In reinforcement learning, the machine is not given direct answers, but rewards and punishments. The algorithm receives a point when it commits an action that the programmer wants and loses a point when it does something the programmer does not want. A good example of the usage of reinforcement learning is AlphaGo, AI software that beat the world champion in the game of Go, often considered too complex for machines to play (*AlphaGo*, n.d.; Alzubi et al., 2018). The last method of learning in consideration is artificial neural network (ANN). The idea of ANN is to build an algorithm that mimics the inner working of the human brain. ANN is composed of input layer, hidden layers and output layers. The inner workings of an ANN are based on lowering levels of abstraction, e.g. first layer recognizes that there is an object, next that the object is round, third that it is a football etc. (*AI vs. Machine Learning vs. Deep Learning vs. Neural Networks*, 2022; Anurag Bhardwaj et al., 2018). Neural networks are explored further in chapter 2.5 "Deep Learning", as they are at the core of deep learning.

Machine learning can be used to solve multiple different types of problems. Problems have different types of attributes, and different types of problems need different types of solutions. In classification problem, the task for machine learning algorithm is to classify into which class the object being analyzed belongs to. For example, if the algorithm is shown a picture of an animal, the task is to deduce whether it is a cat or an elephant. In anomaly detect problem, the task is to search and find the outlier from the dataset. This method is used largely in cybersecurity to weed out potential threats. (Cui et al., 2019.) In clustering problems, the algorithm is given a dataset on which it is supposed to find patterns and discriminants, which help it to group the objects by some certain attributes. This can be especially useful in advertising, where people can be grouped based on their purchasing activity, and then directly advertise to said group products that might be relevant for them (Alpaydin & Bach, 2014).

2.4 Natural Language Processing

Kurdi (2016) states that natural language processing (NLP) is one of the most important fields in AI, as words and language are about transmitting and understanding ideas between people. The basic idea of NLP is to understand language and words, but the ultimate goal is the understanding of the meaning (also known as semantics) from the text (Nadkarni et al., 2011). NLP algorithms typically utilize a lexicon or list of words with predefined positive or negative meanings to determine sentiment analysis based on the number of words used that can be found in the lexicon. The objective is to capture the sentiment conveyed by a given text by identifying the words and phrases that carry an emotional weight, such as positivity or negativity.

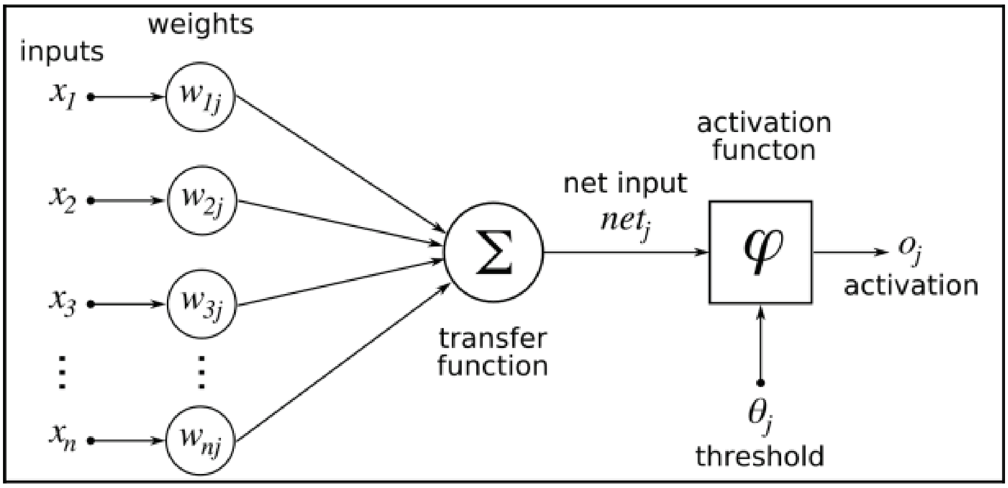
One of the primary challenges of NLP is the vast complexity of language and its inherent nuances. Words often have multiple meanings and can be used in various contexts, making it challenging to accurately decipher their intended meaning. Despite these challenges, advancements in NLP have allowed for more precise and nuanced language comprehension, with applications ranging from chatbots and virtual assistants to sentiment analysis and language translation.

2.5 Deep Learning

Deep learning is a branch of artificial intelligence, which intends to mimic the way the human brain works. It is often considered a subfield of machine learning, and sometimes considered to push machine learning towards general AI (Anurag Bhardwaj et al., 2018).

Deep Learning is a method that builds on the knowledge about the human brain. An example of deep learning could be the previously mentioned ANN's. It consists of an input layer, several hidden layers and output layers. The structure of the layers can be seen in Picture 2. The model receives inputs, which assigns random weights. Then it will calculate all the weight and inputs it into a transfer function, which it is then passed to the activation function. If the activation function's value exceeds the value of the threshold function, the activation is completed. This could mean that for example suspicious credit card usage is labeled as possible fraud.

Picture 2 Artificial Neural Network Layer



(Anurag Bhardwaj et al., 2018)

At its core, deep learning mimics the way the human brain works. It moves from low to high level recognition. Let's take an example: First, the network recognizes that there is an object. The second layer can recognize that the object is a ball, and the third layer that the ball is moving. The fourth layer deduces that the ball is about the height of 10 meters. The fifth recognizes that the speed is about 10 meters per second, and the seventh layer deduces that the ball should end up in place X based on the previous parameters. Deep learning works similarly to machine learning in a sense that when given examples to train (supervised learning) it will adjust the weights of the layers to optimize the neural net.

Deep learning has shown potential for technological advancements in various fields, and its applications in finance are vast. Deep learning's ability to both extract hidden patterns and learn from raw data are useful in finance, and studies shown further in this thesis demonstrate the abilities of deep learning for finance.

3 FINANCE

Financial markets are fundamentally just a way to move funds from those who have a surplus and wish to invest it, to those who have productive investment ideas and wish to get them funded (Mishkin, 2022). It has evolved from traditional banking system where banks loaned the deposited money to corporations and individuals who needed funding to a full blown system where everything is securitized and tradeable, and even the slightest edge over competition will result in hefty profits (Caprio, 2012).

3.1 Financial instruments

Financial markets facilitate the trading of various instruments, including stocks, bonds, currencies, and derivatives. Stocks represent partial ownership in a business and offer the investor potential profits through stock price appreciation or dividends in case the company pays out its profits to the investors. The combined valuation of NYSE and Nasdaq, the largest stock exchanges, was $38.9 trillion by the end of 2022 (Mishkin, 2022, p. 78; *NYSE and Nasdaq: Market Cap Comparison 2022 | Statista*, 2023).

Bonds are securities that pay investors based on the coupon rate. They allow companies to raise funds without losing ownership but instead increasing their debt. Bondholders have priority in case of bankruptcy. Although bonds are generally considered less risky than stocks, their value can fluctuate due to changes in interest rates. Higher interest rates lead to lower bond valuations, while lower rates result in appreciation. Bonds are issued by various entities to raise money for their activities, including governments, municipalities and corporations. (Mishkin, 2022, p. 79.).

Derivatives, such as options and futures, derive their value from underlying assets and are affected by their market movements. Their valuation is more complex than stocks or bonds. Derivative's value is not only determined by the value of an underlying asset, but also by the time until expiration and probability of the derivative increasing in value. Options provide buyers with the right to buy or sell shares at predetermined prices. They offer leverage and the potential for profit through price differences. One option contract gives investor a right to buy or sell 100 shares of underlying security. Options have components, such as implied volatility, that influence their price. Future's contracts oblige buyers to purchase assets at specified dates and prices. Settlement occurs daily through mark-to-market, where differences in value are transferred between buyer and seller accounts. (Hull, 2013, p. 7.)

3.2 Defining Financial Markets

There are multiple ways to define and divide financial markets. In this chapter, I will introduce four different ways. The first way is to divide it into money markets and capital markets. Money markets mean the trading of bonds, where the maturity is in under one year. Capital markets on the other hand consist of bonds where the maturity is over one year and equity markets, which mean stocks and their derivatives. (Mishkin, 2022, p. 75.)

The second way to define the markets is primary and secondary market. Primary market means the market where the security is first issued. This can be for example the act of issuing a bond or stock into the market. Secondary market means the aftermarket for securities issued before.

The third way to divide the markets is based on where the exchange happens. In exchange-based trading, there is one centralized exchange where all the trading happens. Most of the securities are traded in exchanges. Over The Counter (OTC) markets resemble an open marketplace, where all the sellers are willing to trade with anyone who comes to them and wants to buy the securities they offer. This way, the markets are a bit less transparent, and there is not much retail investors as they would need a broker to represent them. OTC markets deal mainly bonds.

The fourth and final way to divide the financial markets is to divide between continuous and call markets. Most markets represent a continuous market, where anytime the market is open traders can place orders for buying and selling securities. Every time a trade between a buyer and a seller is conducted, the price of the security becomes the last price to which the future traders will reflect. Call markets operate quite differently. In call markets, the securities are only traded in certain times set by the exchange, and during that time the price of the security is negotiated. After the price is set, all of the buy and sell orders are settled and the price is the negotiated one in every trade. (Antelo & Peon, 2012; Mishkin, 2022.)

3.3 The Parties in Financial Markets

Financial markets have multiple different players with different strategies and goals. Their activities differ not only by strategies, but also by trading strategies and activities as well as regulations. Mishkin (2022) divides the institutions in three different categories: depository institutions, contractual savings institutions, and investment intermediaries.

The depository institutions consist of different types of banks, loan associations and credit unions. All these institutions get their funding from deposits and invest said funds mostly into different types of loans, bonds, and credit products. The credit unions invest their deposits into their members' loans, whereas banks can also invest in mortgages and business loans, as well as in government securities.

The contractual savings institutions consist of insurance companies, pension, and retirement funds. They get their funding in a form of premium from different policies e.g., life insurance or retirement savings. The contractual savings institutions get small number of deposits for a long time and eventually they must make a big one-time payoff, so they invest in lower risk assets, such as government and municipal bonds, as well as corporate bonds and low-risk stocks.

The investment intermediaries, such as mutual funds and money market funds, get their funds from shares, bonds and partnerships. Their goal is to make money for their shareholders and investors, so they operate with higher risk tolerance and invest in riskier assets. Mutual funds invest in stocks and bonds and are on the lower risk level, as well as finance companies that invest in consumer and business funds. Money markets funds invest in money market assets, such as treasury bills and repurchase agreements. On the highest end of the risk spectrum are hedge funds. They can invest in risky stocks, as well as use different derivatives to speculate on financial markets. Hedge funds can also use leverage, which means that they borrow money to invest more in their positions. For example, if the fund has a leverage ratio of 1 and $1 million in assets, it can invest a total of $2 million into its positions. This can make substantial profits for investors, or investors may lose everything like in the case of Archegos Capital where the fund traded in extremely risky derivatives and lost $20 billion in merely two days. (Schatzker et al., 2021.)

While these parties represent most parties in financial markets if accounted by trading volume, there are also other parties involved. These include family offices that manage the money of a single high net worth family, as well as individual traders, known as retail traders. The retail traders have traditionally been underdogs in trading since they are very diversified group of people and therefore unable to move the markets, but this has been changing in the recent years. Since 2020 there have been multiple situations where the retail investors have gathered to invest and drive the market price of a certain stock and communicating about it via the Internet. Headlines about the stock prices of video game retailer GameStop and movie theatre chain AMC have been made, since flood of retail investor's money has moved the stock price hundreds of percents in merely days or weeks (Fitzgerald, 2021; Hayes, 2022.)

In conclusion, there are multiple different types of parties and entities in the financial markets, and while they do share some similarities there are many differences. Profit and risk increase simultaneously, and the entities have different goals for their investments as the hedge funds aim to make profit and risk the whole fund doing so, and the pension funds merely seek to have a stable and low-risk profit for their clients.

3.4 Evolution of Modern Banking and Financial Markets

The standard business for banking was the same for a long time. The bank got funding via deposits from households and corporations with the need to store capital. Most of that money was lend to households or corporations who needed capital. Bank's profit was the margin between the deposit and borrower interest rates. A small amount of deposits was held in liquid assets, such as government bonds, central bank deposits and plain cash (Caprio, 2012).

The Bretton-Woods system, proposed in 1944 as a modernized monetary system for the post-war global economy, established stable exchange rates with fixed rates for the US dollar and gold. It also created the International Monetary Fund (IMF) with the goal of international monetary cooperation, economic growth and trade expansion. However, the system came to an end in the early 1970s when it was dismantled by President Nixon to address the US financing crisis brought on by the Vietnam War. (Bordo, 2019; Caprio, 2012.)

The dismantling of the Bretton-Woods system led to significant changes in the banking industry. Banks were allowed to operate across international borders on a large scale, leading to a substantial increase in the volume of transactions. The development of information technology further facilitated international business deals, allowing them to be conducted from the banks' offices without leaving the country. This resulted in a more centralized banking industry, with larger banks gaining an even bigger market share.

In addition to the increased globalization, the role of banks also evolved from traditional banking to encompass securities trading, financial advising and facilitating large syndicate bonds. Banks became more like loan facilitators rather than just borrowers, as raising capital from financial markets became more prevalent for corporations. This shift was driven by the growing importance of the financial markets, with companies opting to issue bonds or stocks rather than borrow from the banks. Proprietary trading, or trading securities with the bank's own money, also became a significant source of profits for banks. (Caprio, 2012). Three major differences between traditional banking and modern banking were identified by Caprio (2012). First, banks became more dependent on wholesale funding, also known as money market funding, as the loan-to-deposit ratio increased. This meant that banks needed access to money markets to meet customer demands for withdrawals. Second, securitization, the process of packaging similar assets into baskets and selling them to third-party investors, became popular, particularly for mortgages. This allowed companies to raise debt or equity in efficient capital markets, shifting from the traditional model where companies had to borrow from banks to a more market-centered model where banks merely underwrote securities for companies. This resulted in the emergence of specialized organizations focused on pooling and offloading assets, such as Bear Stearns and Northern Rock.

The third difference in modern banking is the increased reliance on proprietary trading for profits. Trading activity, including over the counter (OTC) derivatives, became a significant source of income for banks, with derivatives posing higher risks compared to stocks and bonds. However, engaging in trading, issuing and market-making of derivatives also exposed banks to substantial risks, as seen during the 2007 financial crisis.

Overall, the transition from traditional banking to modern banking has brought significant changes to the financial markets and the nature of banking. Banks now operate on a global scale, engage in a wide range of financial activities beyond traditional banking and rely on proprietary trading for profits. These changes have reshaped the banking industry and its operations, reflecting the evolving landscape of the global economy and financial markets.

4 USE OF ARTIFICIAL INTELLIGENCE IN FINANCE

AI has various applications in the field of finance, as its abilities to recognize patterns and dependencies is extremely useful due to the mathematical and interdependent nature of finance. Via unsupervised learning AI can extract hidden patterns that humans are unable to see, make accurate decisions faster and thus outperform human in stock trading and read thousands of financial reports effortlessly. It also has applications in wealth management, banking and market research (Zhang & Kedmey, 2018). AI utilization has the potential to lower the costs in finance by up to 22% in 2030, according to OECD's report (OECD, 2021).

Although AI is useful in the field of finance, it does not come without risks of its own (Alpaydin & Bach, 2014; Alzubi et al., 2018). AI does not give exact and precise results, but rather an estimate based on historical data. AI is trained with historical data, so the possibility of bias and the inability to make creative solutions might bring some issues to users, since the models can read things wrong and make assumptions that are completely irrational from a human perspective. A good example of models failing is the 2010 flash crash, where the algorithms were briefly trading assets with massive price differences causing a massive turmoil in the markets. Algorithms were trading with assets as low as one penny and as high as $100,000. (Treanor, 2015.) A professional trader might have realized that there was something odd happening, but the algorithm only responded with what it knew.

There are also other applications of AI that might prove to be problematic in the long run. AI has been used to read financial statements, and sometimes it has understood the meaning of a certain word wrong, thus presenting the company's financial situation incorrectly. There is also a problem with the data. If the data is low-quality or biased, these qualities will translate into the AI model. This can result in an unfair treatment of individuals e.g., in loan applications where the model focuses on irrelevant attributes such as race, gender or age.

In the following subchapters, I will present how AI is used in the different subfields of finance. I will cover topics such as trading, risk management, portfolio management and stock price prediction.

4.1 AI in trading

AI has significant potential for trading, and the largest hedge funds and banks already utilize it, including the world's largest hedge fund Bridgewater Associates and Asian bank HSBC. Machine learning has proven itself to be a useful tool in multiple different fields, and the rise of alternative data has brought interesting possibilities to utilize AI. As alternative data is mostly unclassified, qualitative and unstructured, it could prove to be too much of a work for an analyst to go over everything. The number of variables exceeding numbers of observations also creates issues for traditional valuation models, since they are often based on a linear algebra and thus are overwhelmed. (Karachun et al., 2021; *Nine out of Ten Hedge Funds to Use AI in 2023, Says Survey*, 2023.)

Niang (2021) studied whether hedge funds using AI can outperform their human-based counterparts. In the thesis, the hedge funds using AI or ML were stated to be AI funds. The study followed the returns of 826 US-based hedge funds, of which 36 were AI funds. The study found that on average, AI funds had better cumulative returns over the experiment period of 14 years from 2006-2021, when compared to other human managed funds with different trading styles. According to OECD report, up to 19 % of hedge funds rely 80-100% on AI in their decision-making process.

There has also been research about the performance of AI-powered mutual funds compared to human-ran funds. Chen and Ren (2022) defined AI funds as funds that use machine learning to pick stocks and described their many benefits compared to humans. These included AI's ability to process vast amounts of data in a very small time compared to humans, lack of logical biases and rationalization that humans are prone to, and the ability to train the AI model to "think" like a fund manager since skilled fund managers are getting older and retiring. Chen and Ren also acknowledged that while AI is useful, it does have disadvantages such as that AI is not proving to be significantly better than humans, although the improvement is constant. This might also be caused by the training data since Chen and Ren stated that all machine learning models appear to have same triggers and use similar predictive signals. AI's constant optimization of portfolio also creates trading costs such as broker fees, and possible profits might melt away after accounting for fees and taxes. Their research showed that AI funds do have edge over the traditional fund managers, as AI funds outperformed human fund managers over a 26-month period with annual spread of returns about 5.8%. Of those 26 months, AI funds performed better in 22 months, and significantly worse in only one month of the period (Chen & Ren, 2022). While AI funds did outperform their human counterparts, they showed very little evidence of beating the comparison index. The outperformance of AI fund compared to market was only 0.08%.

AI can also be utilized in options trading, and the predicting abilities of certain algorithms can be utilized to predict option's prices. Many investors are interested in option trading, as it provides way to add a significant amount of leverage to the trade. Options trading can also be made easier with AI, as pricing of options is more complex when compared to stock prices. As stock prices can increase or decrease based the supply and demand, options can also increase and decrease in value based on the volatility of an underlying asset or the time until the expiration of a contract. Wu et al. (2022) studied how different types of machine learning algorithms could be utilized in trading options and could it improve the trading performance when incorporated with optimal risk management strategy. Machine learning is combined with money-management strategies to ensure an optimal risk-reward ratio. In their study Wu et al. found that using machine learning algorithms, the model could reach up to 69.9% accuracy when pricing call and put options. Combined with the optimized money management system, machine learning can be utilized to increase performance in trading.

In conclusion, using AI in trading can outperform humans as Karachun (2021) suspected, but while it did outperform its human counterparts the outperformance of total market was rather insignificant. Chen and Ren (2021) showed that while AI funds did outperform the market, the outperformance was merely 0.08%. In the hedge fund comparison, AI funds did outperform the market by 0.79%, thus being more valuable. This difference of market outperformance between mutual funds and hedge funds might be explainable to different rules of investing, as hedge funds can use whatever instruments they see fit, compared to mutual funds which are limited to trading in only corporate bonds and stocks (Mishkin, 2022). Hedge funds are also allowed to use leverage, and according to Niang (2021) average AI hedge funds used leverage 2.75 times their original fund size. Therefore added leverage can boost funds returns, although simultaneously raising the risk level as it increases losses as well. It also must be noted that while AI funds did outperform human-managed funds on both cases, the amount of AI powered funds relative to total market is still quite small, and the performance might be just short-term.

4.2 AI in risk management

AI and especially ML can also be applied to risk forecasting and management. Given the suitable training data, machine learning can be applied to continuously evaluate credit card activity and financial distress of companies (Aziz et al., 2022; Pandey, 2017). Credit card usage evaluation has had some issues about the availability of data, but the prediction about the customer's default is still possible to make an estimate of about 80%. In the case of financial distress evaluation, the models attempt to find the predicting discriminants that drive the default risk, ranging from macroeconomic reasons all the way to the firm-specific factors. (Pandey, 2017.) AI is utilized to decrease credit risk through processes such as Know Your Customer (KYC) and anomaly detection from transactions (OECD, 2021.)

In addition to detecting unusual credit card activity and financial distress, finance professionals also must detect possible fraud in companies' financial statements. In the U.S. alone, it was estimated that the cost of financial statement fraud was about $572 billion in 2011. The possibility of fraud increases the risk of issuing credit, thus making capital more expensive and markets less efficient (Perols, 2011). Machine learning's ability to detect anomalies can be utilized to spot fraud, and thus make the cost of funding cheaper for non-fraudulent companies.

AI is also used in accounting and auditing of companies. Its benefits in accounting include an increased efficiency, consistency, and a general structure for the audit. AI can also decrease the possibility of financial fraud since it does everything according to its training, it can reduce the costs of accounting and audit, as well as promote more data-driven approach to decision-making. (Hasan, 2021.) However, AI in accounting and audit might not be an efficient choice for all companies since the process of building and maintaining the AI system can be expensive. Laws about audit and accounting can change frequently, thus resulting in the system being updated to comply.

4.3 AI in portfolio management and stock price prediction

AI also has the potential for portfolio optimization. Portfolio optimization aims to pick the optimal investments for portfolio, minimizing the risk of losses while maximizing the expected returns. Optimization consists of picking the most profitable assets to the portfolio, and then adjusting their weight accordingly to maximize the risk/return rate. (Almahdi & Yang, 2017.) In their study, Almahdi and Yang (2017) were able to produce an AI portfolio that outperformed traditional portfolio models over a two-year period while trading five different stock and bond indexes. Pinelis and Ruppert (2022) were also able to outperform the benchmark index by using machine learning to optimize the portfolio weights between a market index and a risk-free asset.

The nature of AI also enables it to recognize patterns, and this can be used to predict stock prices. Lam (2004) used neural network techniques to predict stock prices based on the financial data. De Oliveira et al. (2013) were able to predict Brasilian oil company's stock's price change direction with 93.62% accuracy combining both technical and fundamental variables that drive the stock price. Technical variables are variables that are related only to stock's price movement, including the trading volume and the ratio of the bought and sold stocks also known as Relative Strength Index (RSI). Fundamental variables are variables that impact underlying business, in this case the market price of crude oil and the amount of automobile sales. While they were not able to make a more accurate long-term prediction, this study does make a solid point on AI's abilities in stock price prediction. (de Oliveira et al., 2013.)

Another way to utilize AI in stock price prediction is sentiment analysis. Sentiment analysis is a process in which computer extracts opinions, categorizes them and extracts the meaning from text (Mishev, 2020). Sentiment analysis enables professional investors to extract the public's opinion about a certain economic situation through analysing different sources e.g., social media posts and news articles. Professional investors can use sentiment analysis to perform market research and trend spotting, as well as risk and reputation management.

In finance, the amount of data both alternative and traditional is large, and it is important to be able to extract the market sentiment from it. Sentiment analysis can be applied to stock prediction and has proven itself in the field. In a study about combining financial sentiment analysis to stock market price prediction in Hong Kong's stock market, AI was able to predict the stock's price movements with over 80% accuracy. (Li, 2020.) Thus, can be concluded that AI has abilities that can be exploited for finance, especially when combined with other tools.

In conclusion, AI has abilities to increase human performance in portfolio construction and stock picking. However, it must be noted that while AI has potential in stock picking, it is not without issues. The old saying "past performance is not indicative of future results" is still valuable, as AI models are based off the past financial data. The models cannot predict the future, but can rather give statistical odds based of past performance.

5 CONCLUSION AND RESULTS

In this thesis my aim was to find out how AI can be applied to the financial industry, since AI's applications have recently increased in popularity and AI has shown potential to disrupt entire industries e.g., customer service. The thesis began by defining artificial intelligence, some of its subfields that are more relevant to finance, presenting problems related to its definition and the history of AI. AI has been a difficult area to even define, as different scientific fields have had different definitions for intelligence. The definition of AI also changes due to technological advancements, after which the old technology seems less complicated and thus is no longer considered AI. The history of AI is quite long, beginning from 1950s. When examining the history of AI, the change in the definition can be seen. The history of AI starts from digital decision-trees that assist in the decision-making process and ends with neural networks and deep learning that mimic the human brain.

The AI chapter was followed by the description of the financial industry, its ways of operating and a brief history about the development of modern banks. I explained the difference between the old banking model, and how modern banking enables banks and financial institutions to conduct different types of business compared to the old model. These changes offer new opportunities to use AI to increase productivity, profit and security. I briefly explained the different types of securities and how they are traded in different types of markets. I also covered how the financial industry works, and how companies in the field make profit.

The final chapter was about how AI can and could be used in financial industry. I was able to answer the research question "How can AI be used in the financial industry?" by synthesizing the literature. By reviewing the source material, I was able to present multiple cases where AI has outperformed humans in tasks related to finance, e.g., trading and credit evaluation.

The literature review revealed that AI has a vast number of applications in the financial industry. It showed promising results in trading, as well as in credit evaluation and risk management. Different types of learning can be applied to solve different types of problems. However, one must remember when applying AI to a problem that AI is fully dependent on its training, so the quality of the training data is important. Biased or inadequate data will have impacts to AI, thus impacting the actions and accuracy of the model. The results from the study are gathered in Table 1.

Table 1 How is AI currently used in the financial industry?

How is AI currently used in the financial industry?	**What does it mean?**
Asset return prediction	Increased returns on investment portfolios and increased risk-adjusted returns. Increased optimization of portfolios.
Asset pricing	Increased precision on forecasting the financial markets, as well as individual asset prices. Increased efficiency of pricing derivatives.
Risk management	More efficient risk management. Increased ability to predict credit risk in e.g. mortgages and corporate loans.
Corporate governance and audit	Auditing companies becomes more effective. Corporate governance can be executed more broadly and abuse detection can happen sooner.

Further studies could cover areas like what are the costs of utilizing AI, and possibly new empirical studies covering certain tasks compared against humans over a longer period. These could include tasks that haven't yet been tested or testing established theories. The development of AI's applications is currently happening fast, old research about the performance of AI applications could be done again with new, more powerful models to see if they can perform better than previously.

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