THE IMPACT OF ARTIFICIAL INTELLIGENCE IN THE FINANCE SECTOR AND ITS CHANCES

Thorsten Vocke[1], Doc. RNDr. Mikuláš Gangur[2]

[1] Dipl.-Betriebswirt Thorsten Vocke, University of West Bohemia, Plzeň, Faculty of Economics, Study Program: Economics and Management, thorsten.vocke@web.de, 0000-0001-7773-078X

[2] Doc. RNDr. Mikuláš Gangur, Ph.D., University of West Bohemia, Faculty of Economics, Department of Economics and Quantitative Methods, gangur@kem.zcu.cz, 0000-0002-7731-9146

Abstract: Since Artificial Intelligence has entered almost all parts of the industry, the finance sector is highly influenced by Big data and Artificial Intelligence. For the article, the following research question has been formulated: "What are the key success factors to implement AI for the finance industry?" The aim of this paper is to research the factors for success to implement AI in the finance industry, how the key success factors have developed so far and which limitations can be expected. Those companies that regularly invest in Artificial Intelligence will likely have competitive advantages compared to their contestants. One significant impact of Artificial Intelligence is the topic of cost reduction and also the optimization of processes. To maximize their profitability, banks rely on the optimization of their capital. Artificial Intelligence algorithms can be applied to handle large quantities of data to increase mathematical calculations´ efficiency, accuracy, and speed. Banks also use AI algorithms for back-testing to assess the overall risk models. Regarding credit scoring, historically, most financial institutions based their credit ratings on the lender's payment history. Increasingly, banks are looking towards additional data sources, including mobile phone activity and social media usage, to capture a more accurate creditworthiness assessment and improve loan profitability. Many developments might impact the future adoption of a broad range of AI and machine learning financial applications. This includes a growing number of data repositories, data quality, increasing processing power, but also new regulations and laws.

INTRODUCTION

Improved processor speeds, lower hardware costs, and access to computing power have increased the number of FinTech companies. The number of high-quality datasets for learning and prediction has also grown due to increased digitization. The financial sector is characterized by high competition. Artificial Intelligence is at a reasonably fast developing phase, with new use cases and algorithms uncovered in days rather than years. The availability of AI-powered systems lies in most cases on the existing data and infrastructure of the companies. A study (Financial Stability Board, 2017) figured out that the following key factors primarily drive the control of data science among financial institutions:

1. general advancement of technology
2. factors particular to the financial sector
3. potential for increased profitability
4. competition
5. regulatory compliance

The promises to develop machines capable of outperforming humans in several tasks in a few years and the actual performance reached have been described widely (McCorduck, 2004). Despite what can now be considered immoderate and optimistic promises for AI outcomes during the 1950s and 1960s, steady progress has continued over the last four decades in the main areas of AI (Cantu-Ortiz, 2014). For decision-making, AI has been one of the most significant applications in the past. The roles of AI have

been categorized in various ways. In general, AI systems can be implemented to assist the human being as a decision-maker or replace them (Edwards, Duan, & Robins, 2000). To be more precise, the early study by Bader, Edwards, Harris-Jones, and Hannaford (1988) described six knowledge-based systems characteristics: Assistant, critic, second opinion, expert consultant, tutor, and automaton. Edwards et al. (2000) analyzed expert systems for business decision-making levels and roles based on experiments carried out twenty years ago. The functions of AI (e.g. expert systems) are examined using the three organizational decision-making levels, e.g. strategic, tactical, and operational. Their research show that

- Expert systems in a replacement role are, e.g., effective at the operational and tactical decision levels but have limitations at the strategic level
- Expert systems in a support role can help users make better decisions at all three decision-making levels, but their effectiveness can only be fulfilled through their users.
- An expert system acting in a support role does not necessarily save a user's time, but an expert system in a replacement role does improve the efficiency of decision-making.
- The users of expert systems in a support role did not believe that they had learned from using the system.

The role of AI systems, like expert systems, decision making is also discussed based on the structure of decisions that is defined by Simon (1987) as structured, semi-structured and unstructured decisions. The results by Edwards et al. (2000) recommend that Artificial Intelligence might be used to supplant human decision makers for structured or semi-structured decisions. But it would be far better to be used at the strategic level in organizations as a decision support tool for dealing with unstructured decisions. In a meaningful evaluation on the feasible use of AI in organizations in 1985, Lee (1985 (p.8)) stated "Because mechanical inference relies on a stable, fixed semantics, the utility of an idealized, fully integrated, knowledge-based inference system will be limited to organizations in completely stable environments." and "integrated information systems will only be of use for those aspects of the organization's activities where semantic stability can be maintained. This conclusion corresponds to the empirical observations made by Gorry and Scott-Morton (1971)." This shows that with the restrictions of Artificial Intelligence technologies in the beginning, dealing with fast developing environments, Artificial Intelligence for organizational decision making was more effective working in long-lasting and known conditions.

1. IMPACT OF MACHINE LEARNING ON THE FINANCE AND BANKING INDUSTRY
Machine learning could support companies in lowering costs by increasing productivity and making decisions based on information unclear to a human being. Intelligent algorithms might be able to highlight differences and fraudulent information in a matter of a short period. Outside of the technology sector, the financial services industry is one of the biggest investors in AI products and is realizing a very fast expansion (Citi, 2018). Hedge funds and HFT firms were, until recently, the leading operators of AI in finance. Still, the programs have now spread to other areas of the finance industry, including banks, regulators, Fintech, and insurance firms, to list a few of them. Within the financial services industry, AI programs include numerous options like algorithmic trading, portfolio composition and optimization, model validation, backtesting, robo-advising, virtual customer assistants, market impact analysis, regulatory compliance, and stress testing. In the following, we especially will highlight the key success factors for the finance industry:
- Cost reduction and process optimization
- Fraud detection and Credit Scoring
- Fully Automated Customer Service

2. COST REDUCTION AND PROCESS OPTIMIZATION
The finance industry uses machine learning to minimize operational costs and develop high profitability. This describes and includes both front- and back-office activities across multiple institutions.

2.1 COST REDUCTION IN INSURANCE

Insurance companies (Liimal, Harry, 2021) sort through numerous data sets to identify high-risk cases and lower the risk. Artificial Intelligence refers to functions such as underwriting and claims processing. One of the key technologies here is the application of Natural Language Processing (NLP) (Sadekov, Konstantin, 2020) that improves decision-making by analyzing large volumes of text and identifying key considerations affecting specific claims and actions. With the success of digital and IoT (Internet of Things), the contact points with the insured will get even more valuable. Other areas can be included in the insurance claim evaluation process. For instance, a continuing AI-powered dialogue managed by bracelets, sensors, etc., leads to an improved comprehensive understanding of the insured. By collecting and analyzing additional data, insurers might be able to analyze the habits of their policyholders and offer individualized services and products adapted quickly to the needs and expectations of their customers.

2.2 COST REDUCTION IN THE BANKING INDUSTRY

To maximize their profitability, finance companies, like banks, trust in the optimization of their capital. Artificial Intelligence algorithms might handle a huge amount of data to improve scientific evaluations' efficiency, correctness, and speed. Using machine learning, banks might find the optimal combination of the initial margin-minimizing trades at a time, which is set, based on the degree of initial margin reduction in the past under different combinations of those trades. Banks are also looking to apply AI algorithms to back-testing to manage the broad risk models. Using a range of financial metrics for back-testing might help to recognize unforeseeable changes in market behavior and other trends, leading to appropriate decision-making. A similar approach often refers to stress testing. Technological advancements (Kolesnikova, 2022) can also help financial companies by introducing a machine learning habit to minimize the trading influence on prices and liquidity, thereby assuming the market influence of specific trades (and the optimal timing for those trades). This might directly lead to the reduced impact of trading both into and out of significant market positions.

3. CREDIT SCORING

Credit scoring and insurance can be optimized because many financial decisions are based on wide-scale data analysis. Such data can help assess risks for selling and pricing insurance policies. Banks have long relied on credit score data to make private and corporate lending decisions. AI-powered credit scoring tools are created to fasten lending decisions while minimizing incremental risk. Quite a few finance companies built their credit ratings on the lender's payment history. Additionally, banks are looking towards additional data sources, including mobile phone activity and social media usage, to capture a more accurate creditworthiness assessment and improve loan profitability. Leveraging such technologies allows for faster and cheaper credit scoring and ultimately makes quality loan assessments accessible to many people. In the past years, many customer-oriented FinTech enterprises have been founded. Using an algorithmic procedure, some of these enterprises use data analysis to prepare credit scores for persons with low credit files, using alternative data sources to review loan applications rejected initially by banks.

4. USING AI IN CREDIT SCORING MODELS - ADVANTAGES/DISADVANTAGES

Advantages:
- AI allows an enormous amount of data to be broken down quite fast
- Possible cost-reduction of locating credit risks
- Increasing the number of persons with measurable creditworthiness

Disadvantages:
- Lack of transparency for customers
- Difficult to understand the relevant factors of algorithmic decisions
- New data sources can bring bias to credit decisions
- Gender or racial discrimination based on historical data analysis
- Lack of availability or untrustworthiness of third-party data

5. ALGORITHMIC TRADING AND RISK MANAGEMENT

A few companies use machine learning to develop trading and investment strategies. Big data and machine learning support large trading firms in enlarging their risk management techniques by combining risks from multiple parts of their businesses. Algorithms are being applied to spot different signals on changing prices and to make more profitable and quick trading decisions in portfolio management. An AI unit is usually part of a larger team to help the asset manager with portfolio construction. Using the foreseeable power of data can support funds to allocate new trends and potentially profitable trades beyond human understanding. For instance, the Hong Kong-based Aidiva (Nanalyze, 2016) is a fully autonomous hedge fund that drives all stock trades using Artificial Intelligence.

Fig. 1: The rise of algorithmic trading in recent years
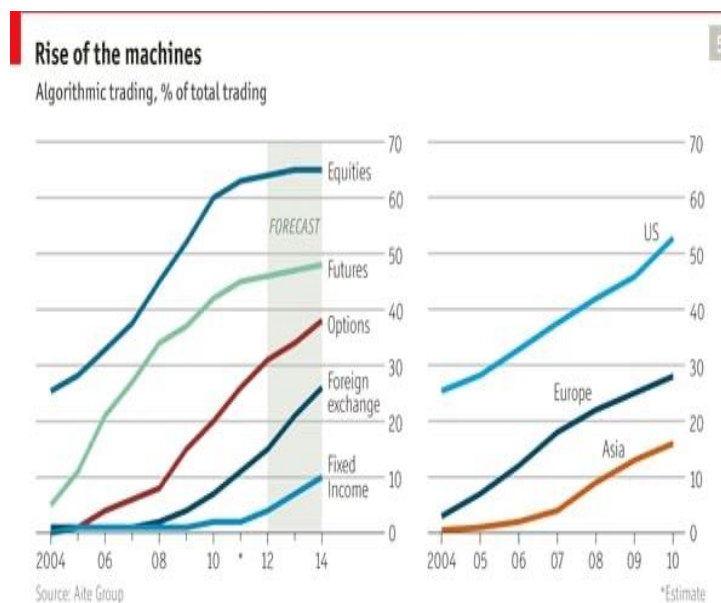
Source: Alite Group

A precise study (Financial Stability Board, 2017) shows that machine learning drives a smaller subset of quant funds' trades. Quant funds manage on the order of $1 trillion in assets, out of total assets under management invested in two-sided funds worldwide more than $40 trillion. A growing number of vendors also offer Big data services for financial market customers. Those players could scrape news and support customers to identify specific features (e.g., web pages viewed) that refer to the events their customers are interested in forecasting. In March 2018, Bloomberg (Burger, 2018) announced that the index of hedge funds using AI had decreased by 7.3 percent in the past month, compared to a 2.4 percent drop for the broader Hedge Fund Research index.

6. FRAUD DETECTION USING ARTIFICIAL INTELLIGENCE

Referring to an Intel report, the United Nations argues that less than 1% of the worldwide illegal financial flows are frozen or seized and that up to 5% of global GDP – $5 trillion annually – are money laundering transactions. AI has been shown to be quite exercisable in security and fraud detection use cases (Liimal, 2020). Machine learning algorithms can break down a huge amount of data in real-time and detect dangerous fraudulent transactions, stopping many fraudulent claims. Samir Hans mentioned, an advisory principal at Deloitte Transactions and Business Analytics LLP, „With cognitive analytics, fraud detection models can become more robust and accurate. If a cognitive system sorts out something that it determines as potential fraud and a human determines it's not fraud because of X, Y, and Z, the computer learns from those human insights. Next time it won't send a similar detection your way. The computer is getting smarter and smarter. (Hans, 2016, p. 2)"

Besides that, Mastercard recently introduced its latest groundbreaking security platform, Decision Intelligence (Khodos, 2016). This system uses machine learning technology to create data-driven, real-time decisions defined to the account, considering alert and fall thresholds. The system can impede burglaries and fraudulent transaction demands by identifying different shopping spending behaviors. As e-commerce has become widespread, at the same time online fraud has also increased. Focussing on the FCA, UK banks spend 5 billion pounds annually to fight against financial delinquency (Arnold, 2018). Action Fraud mentions that between 2015 and 2016, there was a 66% rise in the number of reported cases of payments-related fraud (Walker, 2018) in the UK. US banks spend over $70 billion on compliance each year. Quite a few large banks have had massive penalties imposed upon them for failing to stop illegal financing, and as a result, many banks have turned to AI techniques to redefine and optimize their processes. "Benford's Law" is one of the simplest ways to detect fraud. It is created by analyzing the first digits in a given data set. A predictable distribution of first digits will exist in a group of existing data. Benford's Law has existed since the late 1800s. AI is useful here because ML algorithms can break down millions of data points to detect fraudulent transactions that would lead likely unrecognized by human beings. ML supports enhancing the precision of real-time approvals and minimizes the number of incorrect rejections simultaneously. Fraud detection includes more than a checklist of risk criteria. Using ML techniques, fraud detection systems can benefit, learn and calibrate in response to new feasible (or real) security threats. Using ML, banks' systems can identify unique actions or habits and flag them for analysis. Credit card fraud research is one of the most favorable programs of ML. Banks are provided with monitoring systems and workflow engines, which are trained on payment data of the past. Validation, backtesting, and algorithm training are based on large credit card transaction data datasets. Classification algorithms might identify events as "decection" versus "non decection," and the fraudulent transactions might then be stopped very quickly (van Liebergen, 2017).

7. CHATBOTS AND ROBO-ADVISORS

Robo-advisors have brought a data-driven and partially automated procedure to wealth management systems. AI-powered tools could help traders streamline the account opening process and support them in scaling their portfolios. This could include developing a financial plan, advising on planned home purchases, retirement, protection needs, and estate planning. Robo-advisors are low-cost alternatives to traditional advisors. In the long term, robo-advisor technologies might make financial counseling disposable to a larger number of people, resulting in more informed personal finance decisions. The unit cost of financial intermediation in the US has stayed at approximately 2% for 130 years (Philippon, 2015). The cost of financial transactions has dropped only marginally in Europe and the US after the 2008 financial crisis (Philippon, 2016; Bazot, 2013). As part of that later financial crisis response, robo-advisors and chatbots are emerging across the financial services sector, helping consumers select investments, banking services, and insurance policies. A "bot" is a software program created to automate certain functions using AI technology (Future Today Institute, 2017). A robo-advisor is an algorithm-based digital platform that offers automated investment management services or financial advice. The word "robo-advisor" was mainly unheard of roughly ten years ago, but it is now quite ordinary in the finance world. However, the term might confuse as it doesn't involve robots. Instead, robo-advisors are algorithms built to create a financial portfolio for the user's goals and risk tolerance. Robo-advisors and chatbots, supported by natural language processing (NLP) and ML algorithms, are meaningful and influential tools to offer users an individualized, conversational, and realistic experience in different domains. The appeal of chatbots and robo-advisors has gained significantly with consumers born around the year 2000, who do not need a physical advisor to feel convenient investing, and who are less able to estimate the fees paid to a human advisor. Banks are also using chatbots to redefine their self-service connections. The Bank of America has introduced its AI chatbot Erica, which can be used through voice or chat on the bank's mobile application. Erica's AI engine also creates analytics to support managing personal finance situations. JP Morgan has invested in COiN. This AI technology reviews different documents and extracts data in far less time than a human being. The COiN might review approximately 12,000 documents in a split second, whereas human beings would spend more than 360,000 hours of work on the same documents (Brummer and Yadav, 2019). Chatbots and conversational interfaces are rapidly expanding

venture investment and client service fields. Those chatbots have had to be created with strong natural language processing engines, considering finance-specific customer interactions. Natural language processing makes it more difficult for bank customers to figure out whether they communicate with an AI interface or a human being.

8. PERSONALISED OFFERS AND CUSTOMER RETENTION

Machine learning supports many customer solutions for improving the customer lifetime value and optimizing the sales of financial products. For instance, a reference engine capable of suggesting to new and existing customers the most convenient insurance package or recognizing new potential users fit for an upselling offer. Observing what makes some customer areas stay loyal and others find new financial service providers, banks, and other stakeholders can target the default areas with encouraging products and services.

9. REGULATORY COMPLIANCE IN THE FINANCIAL SECTOR

New rules have increased the need for efficient regulatory compliance, which has brought banks to select cost-effective means of fulfilling regulatory requirements. Regulatory technology (RegTech) focuses on making regulatory compliance more efficient. Asset management companies might use NLP to cope with new regulations. In the EU, investment managers have to fulfill specific requirements in the Markets in Financial Instruments Directive (MiFID II), the Undertakings for Collective Investments in Transferrable Securities (UCITS) Directive, and the Alternative Investment Fund Managers Directive (AIFMD). Companies can apply AI-powered data analysis to create integrated risk and reporting models to fulfill these rules. Machine learning might support trade repositories to solve data quality issues, increasing the value of trade repository data to the public and the authorities.

10. METHODOLOGY

Overview

For the proposed research it is intended to use the method of Qualitative Content Analysis to review the existing literature.

In Detail

After an intensive literature review in the field of the impact of Artificial Intelligence in the finance industry, the existing literature will be systematically analyzed to find answers to the proposed research question.

The qualitative part of the proposed research will substantiate and will complement the answers to the research question found in the literature. It will also contribute to further verification and possible generalization and transferability of the results.

This research intends to answer the following research question:

"What are the key success factors to implement AI for the finance industry?

To answer the proposed research question an extensive literature review was performed.

For this purpose, the following databases/library catalogues were used for literature searches:
- Google Scholar
- Google Search
- Research Gate
- Science Direct
- Scopus
- Springer Link
- Wiley Library

The following search terms were used as part of a targeted literature search:
- Artificial Intelligence+cost reduction
- Fintech+impact+Artificial Intelligence
- Trading+risk management
- Artificial Intelligence+enterprises
- Chatbots+robo-advisors
- Artificial Intelligence+personalised services

CONCLUSION AND OVERVIEW

Every single one of these fields of study is still in its initial phase, showing huge progress, and is still far away from full autonomy from human persons. We recommend that financial institutions take steps to introduce AI and machine learning to several processes in the company. In the long run, the organization will profit both in terms of better efficiency as well as a competitive advantage. A number of developments might influence the future adoption of a wide range of financial programs of AI and machine learning. This involves a larger number of data storages, increasing processing power and data quality, but also new rules and laws. AI will become more omnipresent in finance, and with that comes more challenges, including legal, ethical, economic, and social barriers. AI will also continue to bring new complexities to the global financial system. As continuously more and more data become available and the computing power increases, AI applications will become more complicated. The initial question is whether AI, ML, and DL are so different from previous advancements that they could upend the rules and laws of finance. (Kirk, 2018). A fascinating article edited by the Financial Times in 2018 asks this question. For instance, in 2017, roughly one-third of worldwide operating cash flows were reduced. But what will happen to a computer with AI that will become smarter soon? Artificial Intelligence combined with the Internet of Things (IoT) will make physical things more flexible and reactive, prolonging their useful lives. Along with Big data, AI is seen in the financial services sector as a method that can offer huge analytical power. But quite a few risks still need to be named. A lot of AI methods keep being untested in financial crisis scenarios. There have been quite a few examples in which the algorithms introduced by financial firms appeared to act in unexpected ways by their developers, leading to mistakes and errors and flash crashes. Lo (2016) calls for developing more robust technology capable of adapting to human mannerisms so that users can securely use those tools effectively and easily.

There are certain limitations which might have an impact on the success of Artificial Intelligence:
- The success of Artificial Intelligence and its implementation in the finance industry also depends on the costs. The process of data, e.g. mining, cleaning, structuring, storing, analyzing will cause a large financial effort also regarding the costs for energy and the specific hardware which is needed.
- The speed of the computers has significantly increased. But focussing on the tasks the computers should realize, we have to point out, that former computers would be able to do the same in comparison to today´s computers. Mainly the speed has changed: the computers are able to proceed the tasks a lot faster. The computer still depends on algorithms.
- There are limitations towards those non-algorithmic components. For example, it will be a challenge to create a computer program to analyze another computer program. Skills like creativity are also important factors for the success of Artificial Intelligence in the finance industry which still cannot be stimulated by a computer program.

Artificial Intelligence in the finance industry creates more opportunities for many individuals who are able to develop and optimise Artificial Intelligence technologies. However, Artificial Intelligence in the finance industry is in general terms about learning of structures and data. AI supports the finance industry and in the future it will try to hit the needs of the companies and the customers in an appropriate way.

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