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List of Acronyms

AA Advanced-Analytics

ACO Ant Colony Optimization

AI Artificial Intelligence

AML Anti-Money Laundering

API Application Programming Interface

BaH Buy&Hold

BFSI Banking, Financial Services and Insurance

CAGR Compound Annual Growth Rate

CCPA California Consumer Privacy Act

CFT Countering the Financing of Terrorism

CNNs Convolutional Neural Networks

DL Deep Learning

DLT Distributed Ledger Technology

DRL Deep Reinforcement Learning

ES Expert System

GDPR General Data Protection Regulation

HFT High-Frequency Trading

HKMA Hong Kong Monetary Authority

IoT Internet of Things

KYC Know Your Customer

LSTM Long Short-term Memory

ML Machine Learning

NER Named Entity Recognition SI Swarm Intelligence

NLP Natural Language Processing

OCR Optical Character Recognition

PO Portfolio Optimization

PSO Particle Swarm Optimization

RPA Robotics Process Automation

TDE Transaction Data Enrichment

TI-CNN Technical Indicators and Convolutional Neural Network

TOMS Trade Order Management

XAI Explainable Artificial Intelligence

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Abstract

The financial industry has been significantly transformed by the advent of Artificial Intelligence (AI), which has revolutionised the methods via which financial organisations develop and employ data-driven insights. The aforementioned developments have facilitated the emergence of fresh business model innovations, reconfigured competitive landscapes and labour forces, introduced new risk dynamics, and presented unprecedented difficulties for both organisations and policymakers. The utilisation of AI within the financial sector is anticipated to provide greater competitive benefits for financial institutions. This is primarily achieved through the optimisation of operational efficiency, cost reduction, and productivity enhancement. Additionally, AI implementation is likely to elevate the overall quality of services and goods provided to consumers. Nevertheless, although the implementation of AI in banks may result in long-term financial gains, it has some challenges to address. The implementation of these modifications is expected to result in enhanced financial welfare for a significant number of consumers. However, the consequences of these adjustments may be more challenging to categorize. This thesis examines the multifaceted impacts of AI on finance, from algorithmic trading, risk assessment, fraud detection to customer service automation. The research delves into the efficiencies introduced by AI-driven models, the optimization of asset management, and the personalized experiences offered to customers. Additionally, it identifies the challenges posed by the over-reliance on machine learning (ML) models, including ethical concerns, data biases, and potential systemic risk.

Keywords: AI, Finance, Innovation, FinTech.

Chapter1
Introduction

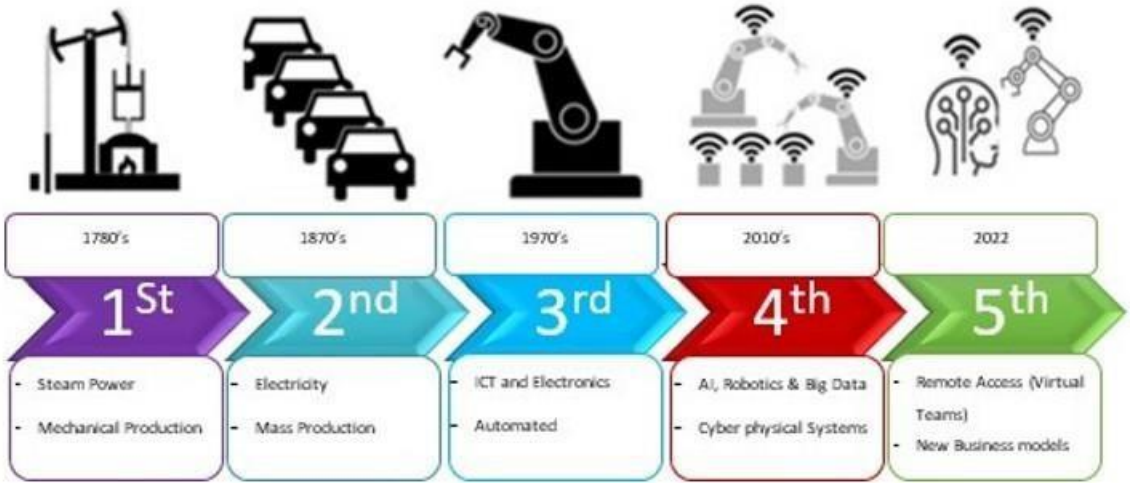
1.1. History and Evolution of AI

The First Industrial Revolution, which began in the 18th century and lasted until the mid-19th century, was characterized by a shift from hand-production methods to machines through the use of steam power and waterpower. The main sectors affected were the textile industry, the iron industry, and the introduction of the steam engine (Simon 2023).

The Second Industrial Revolution, alternatively referred to as the Technological Revolution, denotes a period of swift industrialization that transpired from the latter half of the 19th century to the first years of the 20th century. During this period, there were significant technological advancements, such as the extensive utilization of telegraph and railroad networks, as well as the establishment of gas and water supply systems, along with sewage systems. The introduction of electricity enabled more efficient factories and improved communication and transportation, leading to an economic boom (Robert Longley, 2021).

The Third Industrial Revolution, also known as the Digital Revolution, began in the mid-20th century with the development of digital systems, computer technology, and information networks. It marked a shift from mechanical and analog electronic technology to digital electronics. This revolution continued into the 21st century with the spread of digital technologies such as personal computers and the Internet (Simon 2023). (Hasan, S., 2020).

Figure 1.1: The steps of the industrial revolution



Source:(ElBatsh H.2020) https://hbatsh.medium.com/the-next-industrial-revolution-is-comin-742325c71409

The Fourth Industrial Revolution, sometimes referred to as Industry 4.0, is distinguished by technology advancements driven by the Internet, software consulting services, and software development. The ongoing revolution is effectively reshaping various industries by harnessing the capabilities of digital automation (Greenwood, A. 2023). In the finance sector, this revolution is expected to grow emerging economies by 6% by 2025 (Greenwood, A. 2023). The proliferation of digital technology poses a potential challenge to traditional banking within the ongoing fourth industrial revolution. The presence of Financial Technology (fintech) companies offering comparable or superior financial services poses a potential challenge to traditional banking institutions (Lauren, E. A. 2021).

The Fifth Industrial Revolution is projected to be driven by a strong collaboration between humans and machines (Greenwood, A. 2023). AI assumes a pivotal role in the ongoing transformation, with a special emphasis on its application within the finance industry (Greenwood, A. 2023). AI exerts a significant impact on the advancement of digital financial inclusion in various domains, such as risk identification, assessment, and mitigation. It effectively tackles the issue of information asymmetry by providing customer assistance and support via chatbots, as well as by enhancing fraud detection and cybersecurity measures. (Mhlanga, D. 2020). Financial inclusion encompasses the facilitation of reasonably priced and easily obtainable financial services to both

individuals and enterprises, particularly those who face limited access or exclusion from conventional banking institutions. Financial inclusion, as defined by the World Bank Group, pertains to the provision of financially advantageous and reasonably priced products and services that cater to the requirements of individuals and enterprises. These offerings encompass various aspects, including transactions, payments, savings, credit, and insurance, and are dispensed in a manner that is both responsible and sustainable (World Bank Group. 2022)

The Fifth Industrial Revolution, also known as Industry 5.0, is expected to have a substantial influence on the financial industry. This revolution is characterized by the integration of advanced technologies such as AI, ML, and robotics with human skills (Ball, C. 2022).

In the banking sector, Industry 5.0 is seen as the future of modern banking. It is based on strategies for successful entry into the field in a completely different way (Mehdiabadi et al. 2022). The use of new technologies in the banking industry with the entry of Industry 5.0 is expected to change current markets and business models (Mehdiabadi et al. 2022), (Nicoletti, B et al. 2021).

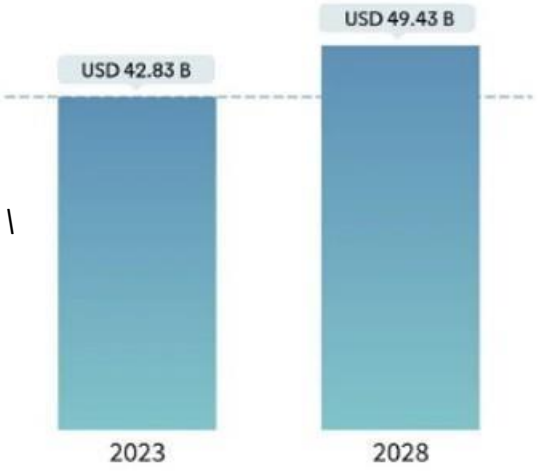
The financial industry has been greatly influenced by the Fourth Industrial Revolution, also referred to as Industry 4.0, due to the implementation of digitalization in financial services. AI and ML have significantly contributed to the automation of many processes, the enhancement of decision-making capabilities, and the improvement of user and customer experiences (Greenwood, A. 2023). The anticipated emergence of the Fifth Industrial Revolution is projected to bring about significant transformative effects within the financial sector (Mehdiabadi, A.et al. 2022). The current period is distinguished by the amalgamation of AI and human capabilities, resulting in the provision of financial services that are tailored to individual needs and exhibit enhanced effectiveness (Mehdiabadi, A.et al. 2022). The utilization of AI in the realm of finance is undergoing a significant transformation of business models and marketplaces pertaining to trade, credit, and finance based on blockchain technology (Mehdiabadi, A.et al. 2022).

1.2. The Global Growth of the AI in financial Industry

Nowadays, the use of AI is increasing dramatically. As of 2023, 35% of companies worldwide are using AI, and 42% are exploring it. A staggering 91.5% of leading businesses are investing in AI, and 44% of private sector companies plan to invest in AI systems by 2023(Castillo, L. 2023).

Within the financial services sector, a significant majority of firms, over 70%, have adopted ML techniques to forecast cash flow occurrences, refine credit scoring mechanisms, and identify instances of fraudulent activity (Castillo, L. 2023). In addition, it is anticipated that AI would make a substantial contribution of 21% to the gross domestic product (GDP) of the United States by the year 2030 (Haan, K. 2023). The estimated market size of AI in Fintech is projected to be USD 42.83 billion in 2023, with a forecasted increase to USD 49.43 billion by 2028 as depicted in Figure1.2. (Mordor Intelligence 2023).

Figure 1.2: AI in Fintech market size



Study Period	2018 – 2028
Market Size (2023)	USD 42.83
Billion Market Size (2028)	USD 49.43
CAGR (2023 - 2028) compound annual growth rate	2.91 %
Fastest Growing Market	Asia-Pacific
Largest Market	North America

Source: (Mordor Intelligence, 2023) https://www.mordorintelligence.com/industry-reports/ai-in-fintech- market.

Global AI in Finance: The utilization of AI systems and methodologies in the field of finance has experienced significant growth. This expansion has been facilitated by the ample availability of

data and the increased affordability of computing capacity (OECD 2021). Global spending on AI is expected to double during the period 2020-24, growing from USD50.1bn in 2020 to more than USD110bn in 2024 (OECD 2021). Furthermore, the AI market was valued at USD 428.00 billion in 2022 and is anticipated to expand from USD 515.31 billion in 2023 to USD 2,025.12 billion by 2030, demonstrating a compound annual growth rate (CAGR) of 21.6% (Fortune Business Insights. 2023). According to projections, the anticipated market size of AI in the financial technology sector on a global scale is estimated to attain USD 41.16 billion by the year 2030. This growth is projected to occur at a compound annual growth rate (CAGR) of 16.5% over the timeframe spanning from 2022 to 2030 (GlobeNewswire 2022).

AI in Europe: Several of Europe's prominent economies are at the forefront of AI exploration and implementation, with advancements that are above the worldwide average. The funding allocated to Start-ups in this highly sought-after technology exceeded 1.4 billion U.S. dollars as of late 2022 (Statista 2023).

1.3. The Future Role of Generative AI in the Finance Function

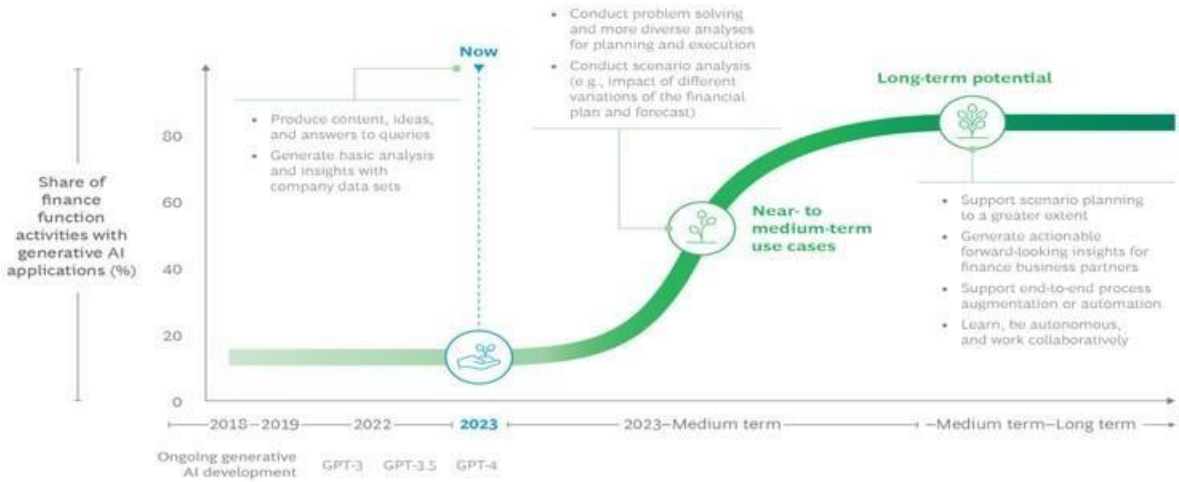
In the future, there will be a collaboration between generative AI "copilots" that is an AI assistant feature for Microsoft 365, and finance specialists, which will lead to the transformation of fundamental processes, the reinvention of business partnering, and the reduction of risks. The implementation of generative AI into financial operations presents some obstacles, such as concerns regarding precision, as well as issues related to data security and privacy. (Demyttenaere, M, et al 2023).

Similar to other technological advancements, the integration of generative AI into financial operations is expected to adhere to a typical S-curve trajectory. (Refer to Figure 1.3) At this time, finance teams are deliberating on the potential of technology to enhance established procedures through the generation of textual content and the facilitation of research activities. In the future, the incorporation of generative AI is expected to significantly impact fundamental operational procedures, revolutionize collaborative relationships within the corporate sector, and effectively

address potential dangers. Furthermore, in the future, there is the possibility that generative AI and traditional AI forecasting tools could work together to provide reports, elucidate discrepancies, and offer suggestions. This collaboration has the potential to enhance the finance function's capacity to generate prospective insights. The proposed enhancements will provide financial professionals with the ability to make better informed strategic decisions, resulting in enhanced operational efficiency and effectiveness (Demyttenaere, M, et al 2023).

An instance of the practical application of generative AI and combine with traditional way in the field of forecasting may be observed through the utilization of this technology by Panorama Consulting, a prominent organization. A generative AI tool has been developed, which has the capability to generate forecasts that beyond the limitations of traditional models. These reports encompass a variety of complex details regarding issues that have the potential to influence demand. The software retrieves data from traditional AI and diverse datasets and also incorporates real-time patterns (Panorama Consulting. 2023).

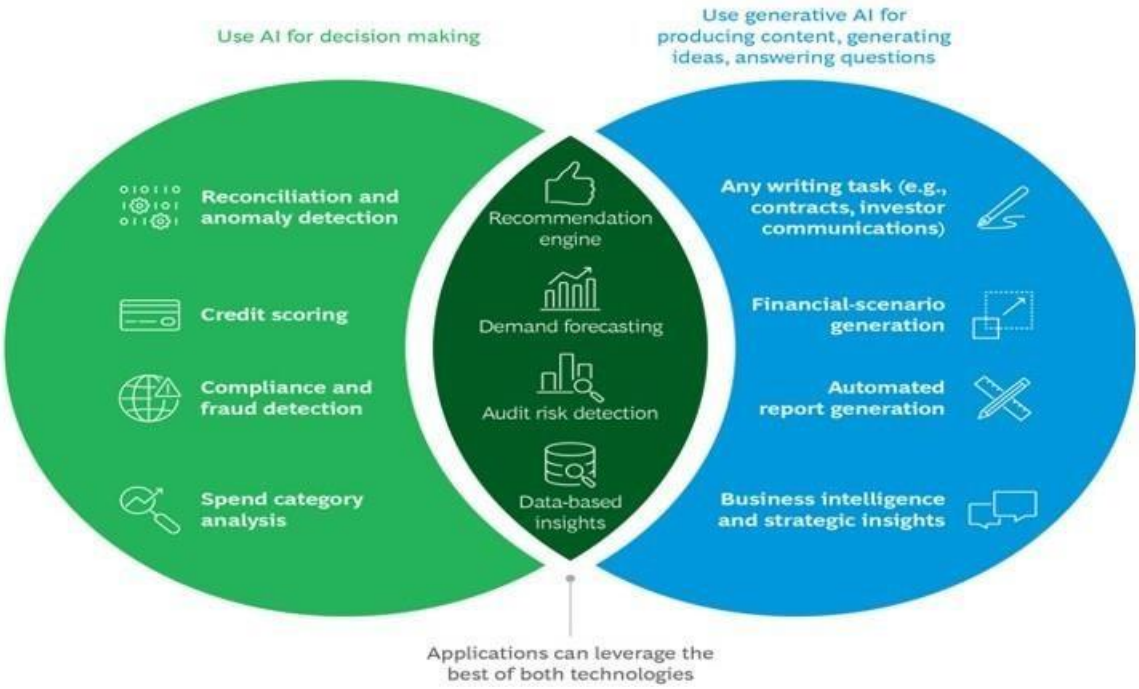
Figure 1.3: Generative AI adoption in finance will likely follow an S-Curve



Source: (Demyttenaere, M, et al 2023) https://www.bcg.com/publications/2023/generative-ai- in-finance- and-accounting.

Currently, generative AI techniques are predominantly employed for the purpose of processing and generating textual content as well as visual imagery. The capacity to produce precise numerical analyses necessary for finance is still undergoing development. The tools possess the capability to conduct preliminary analysis on restricted data sets; however, the dependability of the results must be enhanced prior to obviating the need for human interaction. On the other hand, conventional uses of AI in the domain of finance are capable of effectively analysing numerical data to facilitate tasks such as forecasting and risk assessment, along with other relevant applications. Certain use cases may be exclusive to either generative AI or classical AI techniques. (Demyttenaere, M, et al. 2023). However, there are instances where it is feasible to employ these technologies in conjunction with each other (Refer to Figure 1.4.).

Figure 1.4: Generative AI Traditional AI Have Both Separate and Combined Finance Applications



Source: (Demyttenaere, M, et al 2023). https://www.bcg.com/publications/2023/generative-ai-in-finance- and-accounting.

For more clarification in conjunction traditional AI and generative AI in Demand forecasting sector:

Demand forecasting plays a vital role in the realm of supply chain management, enabling organizations to anticipate and project forthcoming demand for their offerings. Through the utilization of AI, organizations have the ability to harness past data in order to discern recurring patterns and emerging trends. This capability empowers enterprises to enhance their predictive capabilities, hence enabling more precise forecasts pertaining to future demand. The integration of conventional AI methods with generative AI tools has the potential to significantly augment the precision of these prognostications and so influence in financial streams and revenue. (Amazon 2022).

An illustration of a corporation that has effectively integrated traditional AI and generative AI into its operations for demand forecasting is Amazon. Amazon employs a hybrid approach that encompasses conventional AI methodologies, including ML and DL, in along with generative AI tools like GPT-3, to predict the level of demand for its merchandise. Through the examination of user behavior and purchase history, Amazon possesses the capability to forecast the potential popularity of products and then adapt its inventory management strategies (Amazon 2022).

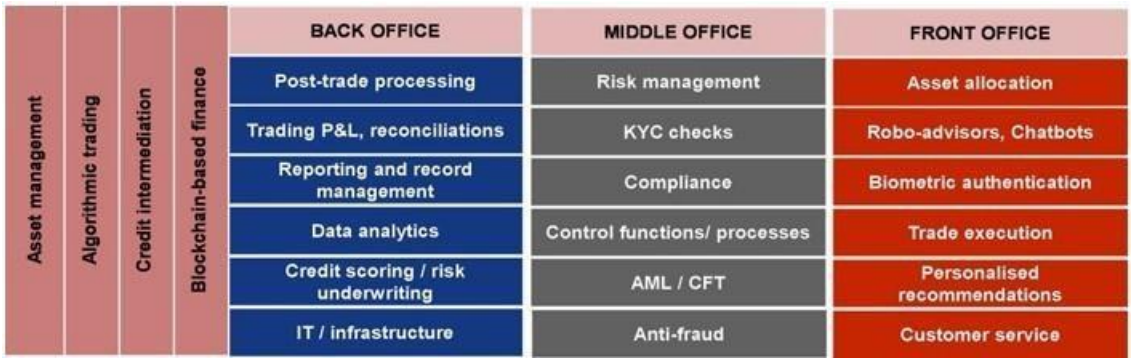
Another illustrative case is Walmart. Walmart employs AI and ML algorithms to evaluate sales data and make predictions regarding the future demand for its products. Through the utilization of ML techniques, Walmart has the capability to discern intricate patterns and emerging trends in customer behavior that may not be readily discernible to human analysts (Walmart2022).

In summary, the utilization of both traditional AI methods and generative AI tools can boost the efficacy of demand forecasting within the realm of supply chain management. Organizations such as Amazon and Walmart have effectively employed these strategies to enhance their predictive precision.

The use of generative AI in financial operations primarily centers around enhancing preexisting procedures by means of generating narratives and conducting isolated analyses on limited data sets (Demyttenaere, M, et al 2023).

Advancements in the financial system and financial markets have facilitated the availability of a substantial volume of data within the realm of finance (Riyazahmed, K. 2023). The expansion of stock markets and the increasing amount of trading contribute to the exponential increase of financial data on a global scale (Riyazahmed, K .2023). Algorithmic trading and blockchain-based finance represent two emerging advancements in the realm of finance, incorporating AI technologies (see Figure 1.5). Algorithmic trading refers to a systematic approach to executing trading orders by employing automated and pre-programmed instructions. These instructions take into account several factors, including price, timing, and volume (Chen, 2022).

Figure 1.5: Application of AI in Financial Market Activities



Source: (OECD, Business and Finance Outlook, 2021) https://www.oecd-ilibrary.org/sites/39b6299a- en/index.html?itemId=/content/component/39b6299a-en

Similarly, the utilisation of blockchain technology in the financial sector would effectively foster trust by means of smart contracts, which may be likened to tangible contracts that are executed in real-time through the use of blockchains (Schroer, 2022). Furthermore, the utilisation of AI-based blockchain technology in the field of finance encompasses significant applications such as streamlined payment processing, sophisticated trading mechanisms, and efficient digital identity management (Daley, 2022). In the following, we review this new trend in finance.

1.4. AI in Blockchain-based Financial Services

The utilisation of distributed ledger technology (DLT) [1] which is called Blockchain in the financial sector is on the rise due to its perceived advantages in terms of rapidity, effectiveness, and openness. These benefits are facilitated by the automation and removal of intermediaries (OECD, 2020). The financial services sector extensively employs DLTs in several crucial domains, including the issue of securities, post-trade activities like as clearing and settlement, payment systems, central bank digital currencies, and stablecoins backed by fiat currencies. Additionally, DLTs are also employed for the tokenization of assets on a broader scale. The combination of AI models, which have been subject to criticism due to their lack of transparency, and blockchain technologies, which are renowned for their transparency, may initially appear contradictory. (OECD. 2021). The industry promotes the confluence of AI and DLTs in blockchain-based finance as a means to enhance system performance. However, empirical evidence does not now support this claim. The utilisation of automation in DLT-based systems leads to enhanced efficiency. However, it is important to note that the current level of AI application in DLT-based projects seems to be insufficient to substantiate assertions of convergence between these two technologies. Currently, there is a noticeable trend in using particular AI applications within systems that are based on blockchain technology. These applications are employed, for instance, to facilitate the process of curating data [2]onto the blockchain. Additionally, DLT systems are being employed to support the functioning of AI models, such as data storage and sharing (OECD. 2021).

DLT solutions are employed to facilitate the data management component of AI methodologies. These solutions leverage the inherent properties of blockchain, such as immutability and trustlessness, to ensure secure and reliable data handling. Additionally, DLT enables the exchange of sensitive information on a zero-knowledge basis, ensuring compliance with confidentiality and privacy regulations (OECD. 2021).

[1] Blockchain and distributed ledger technologies (DLT) are terms used inter-changeably in this thesis.

[2] Data curation involves managing data throughout its lifecycle to ensure long-term accessibility, sharing, and preservation. Data curation is an iterative process that includes preserving, sharing, and discovering data. It also involves maintaining and managing metadata rather than the database itself (Knight. M. 2017).

The present focus of integrating AI applications into blockchain systems primarily revolves around use cases pertaining to risk management, fraud detection, and compliance processes. This includes the incorporation of automated restrictions within a network. AI has the potential to mitigate security vulnerabilities and enhance network protection, particularly in payment applications. By leveraging AI algorithms, abnormal behaviors can be identified and flagged, therefore reducing the risk of network compromise. However, it is important to note that while AI can significantly minimize security susceptibilities, it cannot completely eradicate them. In a similar vein, AI applications have the potential to enhance the onboarding procedures inside a network, such as utilizing biometrics for AI-based identification. Additionally, AI can play a role in strengthening anti-money laundering (AML) and countering the financing of terrorism (CFT) checks when providing any form of financial services based on DLT. AI programmes have the capability to generate analyses of wallet addresses[3]. These analyses can be utilised for the purpose of regulatory compliance or for conducting internal risk assessments of transaction participants (Ziqi Chen et al., 2020).

AI has the potential to enhance the performance of third-party off-chain nodes[4], sometimes referred to as 'Oracles, which are responsible for providing external data to the network. The utilisation of Oracles inside DLT networks entails the potential hazard of inaccurate or insufficient data inputs into the network due to the sub-par performance or malicious intent of third-party off-chain nodes (OECD, 2020). The transfer of data curation responsibilities from external nodes to autonomous AI systems enhances the integrity of information recording and dissemination, as these systems are less susceptible to manipulation. In a hypothetical situation, the utilisation of AI has the potential to enhance disintermediation by implementing AI inference directly on the blockchain, hence eliminating the need for Oracles. In theory, this approach has the capacity to function as a safeguard by evaluating the precision and dependability of the data provided by the

[3] A blockchain wallet address refers pertains to alphanumeric codes utilized for the purpose of transmitting or receiving cryptocurrency, hence establishing the precise position of a digital wallet within the blockchain network. Unique addresses are produced for individual users. The addresses consist of an amalgamation of alphanumeric characters and are readily comprehensible to the computer network (Uluçay,S 2023).

[4] Third-party off-chain nodes, commonly known as 'Oracles', assume the responsibility of supplying external data to blockchain networks. They are bridges and middleware that allow a blockchain to communicate with off-chain data (Khan, S.et al 2021)

Oracles, thereby reducing the possibility of manipulation of the Oracles. Nevertheless, the integration of AI into DLT networks does not intrinsically resolve the problem of "garbage in, garbage out." The aforementioned quandary, denoting the issue of acquiring imprecise or inadequate data inputs, poses a formidable obstacle that is similarly pervasive in AI-driven applications (OECD, 2021).

1.5. The Growing Impact OF AI in the Financial Sector

AI as a prominent representation of the contemporary and prospective landscape of the financial industry, exerts its influence in several domains, where the ubiquity of rapid and precise digital computation is becoming prevalent (Kuzior et al., 2022). Without digital technology and algorithms capable of processing and interpreting the huge amounts of data generated by the presence and daily operations of financial institutions and markets, modern financial activities would be impossible. The financial industry is one of the early adopters of AI, along with the high-tech and telecommunications industries, automotive manufacturing, and assembly (Taherdoost H et al. 2023).

The year 2023 has witnessed notable growth and transformation in the impact of AI in the financial industry. The significance of AI as a fundamental element for financial services firms is highlighted in the "State of AI in Financial Services" report (NVIDIA, 2023). In this report which conducted a survey among more than 500 financial services experts throughout the world, it has been observed that apps empowered by artificial AI have transitioned from being confined to the innovation lab to assuming a central role in the emerging AI-driven financial services industry. Below are several highlighted benefits that financial sector organizations anticipate will come from implementing AI (NVIDIA, 2023).

Client/customer acquisition: AI is being leveraged to augment the degree of customization, data protection, customer support, pricing, and other aspects involved in the development and provision of financial products (NVIDIA, 2023).

Optimization of business operations: A significant proportion of survey participants, namely over 30 percent, said that the implementation of AI has resulted in an annual revenue rise exceeding 10 percent. Additionally, more than a quarter of respondents indicated that AI has contributed to an annual expense reduction of over 10 percent (NVIDIA, 2023). Enhancement of Employee Empowerment: AI is providing financial services firms with the means to expedite revenue generation, optimize operational processes, and elevate consumer experiences (NVIDIA, 2023).

Transformation of Products and Service: The integration of AI-powered apps has enabled banks, insurers, asset managers, and fintech companies to enhance their service offerings, surpass competitors, enhance client lifetime value, and expand their market presence (NVIDIA, 2023). The aforementioned findings emphasize the extensive influence of AI inside the financial services industry and emphasize its potential for future expansion and metamorphosis (NVIDIA, 2023).

It is apparent that contemporary society has been defined by the presence of autonomous vehicles, virtual agents, intelligent residences, facial recognition technology, speech recognition systems, and other similar advancements. Presently, society and the economy are undergoing the initial stages of a novel industrial revolution, each with its own distinct characteristics. AI and ML are playing a prominent role in this transformative process, significantly impacting various aspects of society and the economy. As a result, a natural question that is equally relevant to our research is raised: How is AI changing the financial sector? (Jamie N, 2023)

To obtain a comprehensive comprehension of the influence of AI on the financial sector and to effectively address the important topics, this thesis will initially examine the current utilization of AI in the financial sector and identify the prominent AI applications that are revolutionizing and augmenting the financial industry.

1.5.1. AI in the financial sector today

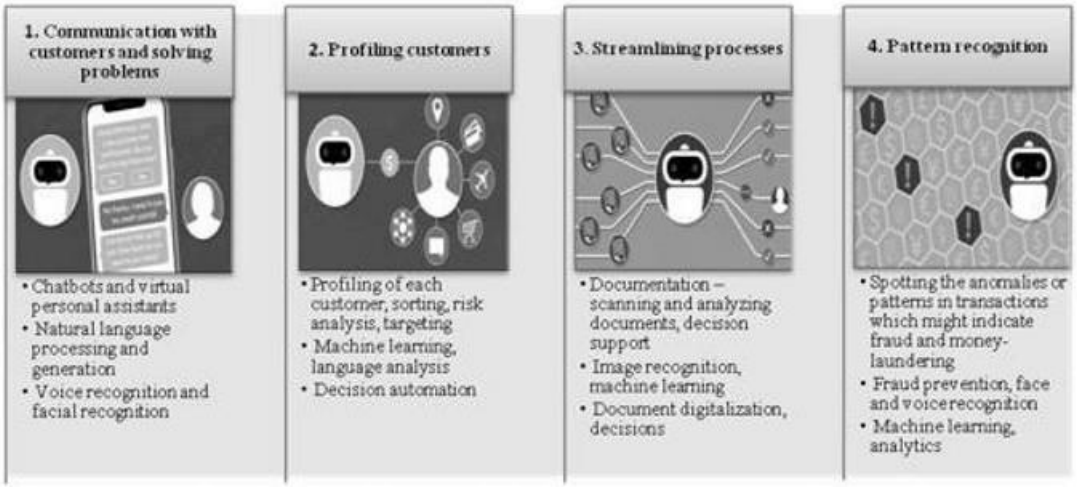
In the current era, the financial industry is experiencing a significant transformation driven by the extensive integration of AI in various operational aspects. Leading financial institutions, including Bank of America, UBS, Citibank, Morgan Stanley, HSBC, JPMorgan Chase, and Wells Fargo, have embraced AI technology to enhance the quality of client service they provide (Forbes, 2022).

The Bank of America has introduced a virtual assistant named Erica. This AI-powered assistant has surpassed 1 billion interactions with Bank of America clients since its launch in 2018(Bank of America, 2022b). Erica provides clients with insights to help them review their finances, alerts about eligibility for Preferred Rewards, and weekly snapshots of spending (Bank of America, 2022a). UBS has been using Amazon's digital assistant, Alexa, for customer service needs (Bank of America, 2022b). Citibank made a strategic investment in Feedzai, a data science firm that uses ML to combat fraud (Business Insider.2022). Morgan Stanley has been using AI to help spot money laundering, fraud, and terrorist funding (CoinTelegraph. 2023). In 2023, they announced a strategic initiative with OpenAI to create a bespoke solution for risk management (Manuel A. et al., 2023). HSBC is using AI to help spot money laundering, fraud, and terrorist funding (WF, 2022). JPMorgan Chase has implemented automated systems for trade executions (Bank of America. 2022c). They also offer FX Algos on their platform Execute to manage costs and efficiently access liquidity (EricH. 2022). In 2022, Wells Fargo announced the rollout of a new virtual assistant named Fargo, which leverages Google Clouds AI to provide a more personalized banking experience (Yahoo Finance, 2022).

The field of AI in the banking industry is progressing and evolving, offering the possibility of more advanced solutions that yield favorable returns on investment (ROI) in various business areas. The integration of AI solutions in the banking sector has become increasingly prevalent, with a majority of financial services firms reporting the implementation of such technology in key domains such as risk management (56%) and the generation of revenue through novel products and processes (52%), as indicated by research conducted by the Cambridge Centre for Alternative Finance and the World Economic Forum (Digalaki, E. 2022), (Fares, O.H et al. 2022).

According to the survey data, a significant majority of respondents (75%) from banks with assets over $100 billion have reported that they are presently in the process of implementing AI strategies. In contrast, a comparatively lower percentage (46%) of respondents from banks with assets below $100 billion have indicated the same (Digalaki, E. 2022), (Fares, O.H et al. 2022). Moreover, Figure 1.6 shows the data generated in specific areas where banks use AI.

Figure 1.6: Use of AI in the financial sector



Source: (Zorica Goli 2019 adaptation according to Noonan 2018 and Georgiev 2018)

The specific domains in which banks employ AI, as depicted in Figure 1.6, can be explain as follows:

Communication with customers and solving problems: AI has been increasingly used to boost customer experience in the financial sector. For instance, chatbots and virtual personal assistants have become commonplace, providing daily AI-enabled interactions for over half of banking and insurance firm customers (Capgemini Research. 2020). These AI tools are powered by Natural Language Processing (NLP) and voice recognition technologies (Capgemini Research,2020).

Profiling customers: AI and ML techniques have been employed to gain a deeper understanding of customer behaviors, thereby enhancing client engagement (Dolgorukov, D.2022). This has allowed for more personalized product offerings and diversified services (Capgemini Research. 2020), (Cao, L. et al 2021).

profiling Customer is an emerging field in which AI is rapidly gaining traction. AI solutions assist financial institutions, such as banks and credit lenders, in making better informed underwriting choices. These solutions utilize a range of indicators to evaluate traditionally marginalized consumers more correctly inside the credit decision-making framework (Schroer, A. 2023).

An illustration of a corporation that employs AI in the realm of profiling customers and finance sector is Enova. Enova leverages AI and ML technologies into its lending platform to offer sophisticated financial analytics and credit evaluation capabilities. The company's objective is to cater to non-prime individuals and small businesses, offering assistance in addressing practical challenges such as emergency expenses and bank loans for small enterprises, while ensuring that neither the lender nor the beneficiary find themselves in an unsustainable predicament (Schroer, A. 2023).

Streamlining processes: AI has been instrumental in transforming business finance management by streamlining accounting processes and reliably completing predictable tasks related to data entry, bill pay, invoice processing, and more (Shinde, S. 2020). This has led to financial records being completed with the highest level of accuracy (Shinde, S. 2020). For a more complete explanation, I will explain it with an example:

ZA Bank, the pioneering virtual bank in Hong Kong, has effectively utilized AI to optimize their operating procedures and workflows, resulting in improved scalability. ZA Bank, within a span of two years, has witnessed a substantial expansion in its client base, surpassing 600,000 customers. Consequently, the bank has recognized the necessity for an enhanced treasury management system that can effectively handle its burgeoning treasury book, guarantee the accuracy and reliability of data, and meet regulatory obligations. (Bloomberg. 2023).

ZA Bank experienced challenges in handling its fixed income and foreign exchange transactions due to the substantial growth of its treasury portfolio. The manual process employed by the bank was proving to be cumbersome and was a potential obstacle to its future expansion. In order to address this challenge, ZA Bank pursued a solution that was characterized by enhanced efficiency, sophistication, and scalability (Bloomberg. 2023).

The implementation of Bloomberg Trade Order Management (TOMS) and its high-quality market data has enabled ZA Bank to enhance its operational control and make notable improvements in efficiency. TOMS is facilitating ZA Bank in addressing its existing investment requirements and preparing for sustained expansion and adaptability. The seamless integration of ZA Bank with Bloomberg Terminal Solutions for pre-trade analysis, research, and market-moving news significantly enhances the bank's decision-making process and front-to-back workflow. Significantly, the bank is now able to adequately fulfill the regulatory obligations set forth by the Hong Kong Monetary Authority (HKMA) (Bloomberg. 2023).

Pattern recognition: AI possesses the capability to evaluate and identify anomalies within patterns that would otherwise remain undetected by human observers (Insider Intelligence. 2023). This capability is particularly useful in detecting fraudulent activities, thereby enhancing the security of financial transactions (Insider Intelligence. 2023).

Pattern recognition plays a crucial role in the functioning of AI systems. ML is the capacity of computational systems to detect and analyze patterns inside datasets, then employing these patterns to generate decisions or predictions through the utilization of computer algorithms. This procedure entails the categorization of data using existing knowledge or statistical information derived from patterns and/or their representation (Boesch,G 2023).

Pattern recognition can be employed in diverse domains, encompassing textual data, visual imagery, and auditory recordings. Computer vision, which primarily concerns itself with the identification and interpretation of visual information, is somewhat narrower in scope when juxtaposed with the broader domain under consideration. The capacity to automate the identification of patterns and regularities within data holds numerous practical implications,

spanning from the development of facial recognition software to the detection of tumors (Boesch,G 2023).

In the realm of practical applications, AI has been employed in the domain of customer service with the aim of enhancing operational effectiveness and tailoring services to individual preferences. For example, the utilization of AI in virtual assistants and chatbots has significantly enhanced and simplified customer support services by offering immediate and round-the-clock responses to inquiries (Boesch,G 2023).

1.5.2. Personalized Banking

AI is increasingly being used to deliver personalized services in banking. AI-based methodologies have the potential to streamline customer interactions through the provision of tailored insights to customers, delegating less complex customer interactions to automated bots or voice assistants, and facilitating authentication procedures (Ernie S.2020). AI has the potential to enhance personalized banking experiences, hence encourage managers to establish a comprehensive banking ecosystem that effectively leverages AI to provide a smooth banking experience (Sheth, J. et al. 2022).

AI technologies have the potential to enhance automation and, when implemented with proper risk management measures, can frequently surpass human decision-making capabilities in terms of speed and accuracy (Suparna B. et al., 2023). The potential for value creation is significant across several industries, as AI has the capacity to unleash an estimated $1 trillion of additional value for banks on an annual basis (Suparna B. et al., 2023). AI technologies have the potential to enhance financial gains by facilitating more personalized services for both customers and employees. Additionally, they can contribute to cost reduction by improving automation, minimizing error rates, and optimizing resource allocation. Furthermore, AI technologies can enable the discovery of novel opportunities that were previously unknown or unexplored, owing to their enhanced capacity to analyze and generate valuable insights from extensive datasets (Suparna B. et al., 2023).

1.5.3. Credit Decisions

AI is increasingly being used to make bank loans fairer. Numerous financial organizations are increasingly adopting AI as a means to rectify historical instances of bias in lending practices and cultivate a more comprehensive economic environment (Townson, S. 2020). Banks are using AI to guide customer engagement and make credit decisions (Agarwal, A. et al. 2021).

AI has the potential to enhance the process of credit decision-making, hence increasing its accessibility and promoting fairness. The practice of manual credit underwriting is expected to become obsolete, which is a positive development for both borrowers and lenders (Gonçalves, A. 2023). The current shift towards digital channels presents banks with a favorable prospect to cater to a larger customer base, enhance their market presence, and augment their revenue while minimizing costs (Agarwal, A, et al. 2021). Significantly, financial institutions who actively seek this opportunity are able to gain access to larger and more comprehensive datasets, which are essential for powering advanced analytics (AA) and machine-learning (ML) decision engines (Agarwal, A, et al. 2021).

In order to effectively compete in the global and regional markets that are heavily impacted by digital ecosystems, banks must possess a comprehensive stack of AI and analytics capabilities. This stack should consist of four primary layers: reimagined engagement, AI-driven decision making, core technology and data infrastructure, and a cutting-edge operating model (Agarwal, A, et al. 2021).

1.5.4. Quantitative Trading

Deep Reinforcement Learning (DRL) agents have demonstrated promise in the domain of automated low-frequency quantitative stock trading. Nevertheless, a significant number of the research primarily focused on proof-of-concept concepts, conducting trials in settings that were not reflective of real-world trading scenarios and lacking real-time trading applications (Pricope,T. V.2021).

Quantitative trading has been profoundly influenced by AI since algorithms are employed to scrutinize extensive volumes of financial data and execute transactions predicated on discerned patterns and trends (TurinTech AI.2022).

Despite these advances, it is important to note that the use of AI in quantitative trading is still in its early stages. More research and real-world applications are needed to fully realize the potential of AI in this field (Gómez-Martnez et al. 2022).

1.5.5. Fraud Detection and Cybersecurity

Fraudulence permeates several domains of human activity, and the identification and mitigation of fraudulent behavior constitutes a significant area of scholarly inquiry that holds relevance for numerous societal stakeholders. The emergence of big data and AI has given rise to novel prospects in the realm of fraud detection, wherein sophisticated ML models are employed (Bao, Y, et al. 2021), (Bao,Y, et al. 2022). Its ability to analyze data at scale, adapt to new threats, and provide real-time detection makes it an invaluable tool for the fintech industry (Dalexander, G 2023).

In the financial sector, AI and ML are being used to detect credit card fraud, insurance fraud, and other types of financial fraud. These technologies can analyze transaction data in real-time, allowing them to identify suspicious activity quickly and accurately (Bao,Y, et al. 2021). This not only helps in preventing financial loss but also improves customer trust and satisfaction (Bao,Y, et al. 2021).

In terms of cybersecurity, AI is being used to detect and respond to cyberattacks. By analyzing network traffic, AI can identify unusual patterns that may indicate a cyberattack. Furthermore, AI can also predict potential vulnerabilities in a network and suggest preventive measures (Velasco, C. 2022). Pattern recognition plays an important part in contemporary AI systems. This approach is a variant of ML that employs data analysis techniques to identify and discern recurring and unusual patterns and regularities in incoming data. ML exhibits a notable proficiency in efficiently processing substantial volumes of data, enabling the identification of patterns as well as the detection of anomalies or outliers within this data. The primary concept underlying the recognition

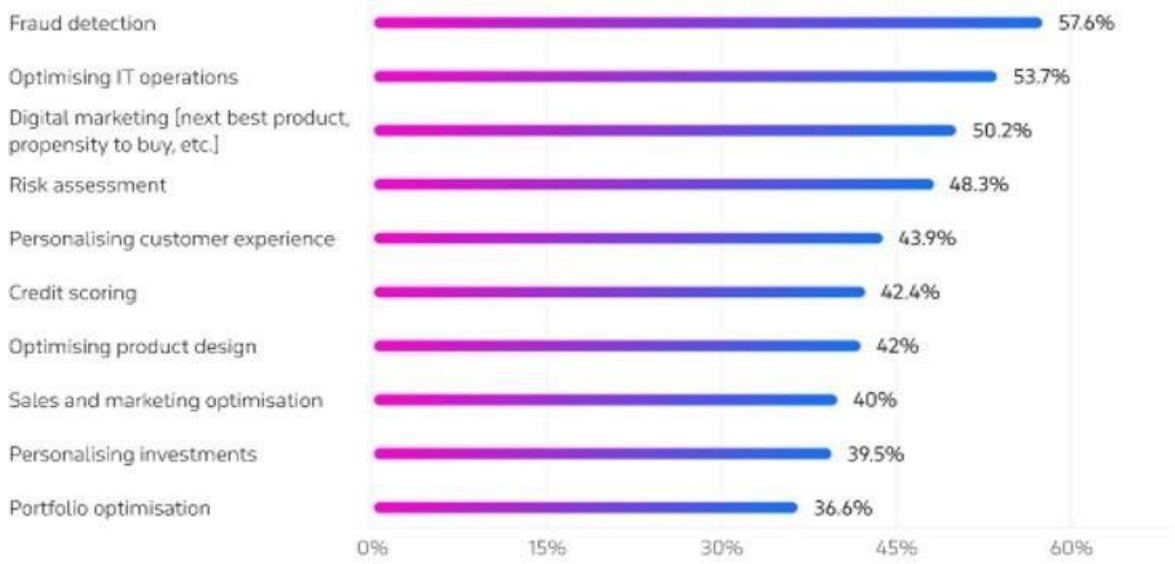
pattern in the field of AI involves the utilization of ML and cognitive technologies to facilitate the identification and classification of unstructured input into distinct categories (Boesch,G 2023)

Based on the findings of the Global Economic Crime and Fraud Survey 2022 conducted by PwC, it has been observed that within the past 24 months, approximately 46% of organizations have encountered instances of fraud, corruption, or other forms of economic crimes. The rapid proliferation of online banking and the digitization of payment systems have resulted in a substantial rise in transaction volumes. Consequently, financial institutions are faced with an urgent imperative to implement enhanced fraud prevention procedures (Shmat, D. 2022).

Rule-based systems are extensively employed in the domain of fraud detection. The researchers examine a range of atypical variables, including as timestamps, account numbers, IP addresses, transaction amounts, and locations, in order to detect instances of fraudulent conduct. These systems employ pre-established algorithms to identify instances of fraudulent activity, such as triggering an alarm when a transaction surpasses a specified threshold deemed as atypical (GRBOVIC, N 2023). It is not unexpected that perpetrators continually devise new strategies to exploit the vulnerabilities of rule-based systems utilised by the majority of institutions for fraud detection. However, via the utilisation of AI especially ML, financial institutions can effectively adjust to the ever-changing fraudulent techniques in near real-time. Sophisticated DL models, which are trained using extensive datasets commonly available to banks, enable organisations to uncover latent associations among diverse data sources and promptly detect anomalies (Shmat, D. 2022).

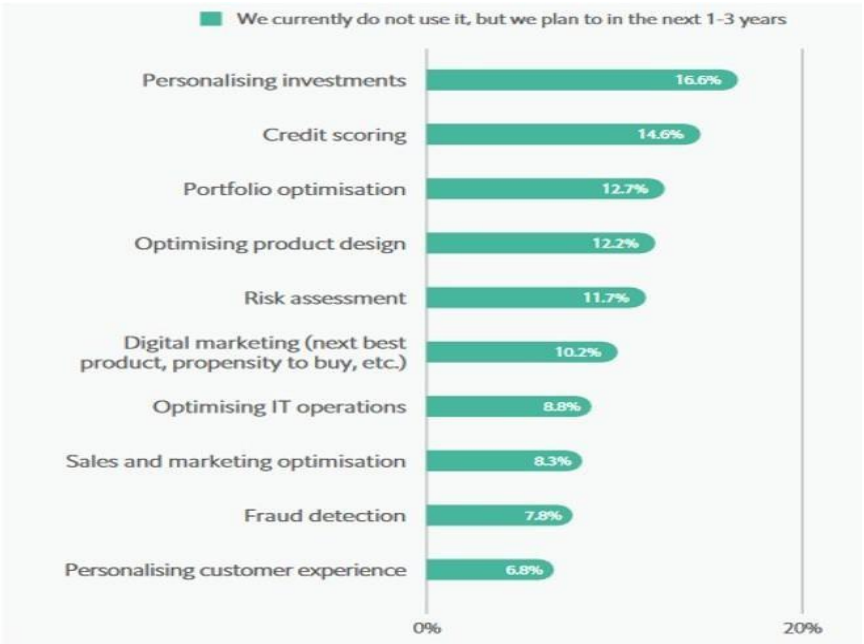
The two areas where banks employ AI most significantly are in fraud detection (58% heavily, 32% moderately, and 34% to some extent) and IT operations optimisation (54% heavily, 36% moderately) (Figure 1.7). The areas that are expected to have significant growth in the future encompassing the customization of investments, with about 17% of respondents indicating their intention to implement this practice within the next 1-3 years (Figure 1.8). Additionally, credit scoring is projected to be another area of growth, with approximately 15% of respondents planning to adopt this approach. Lastly, portfolio optimisation is anticipated to experience growth, with approximately 13% of respondents expressing their (Figure 1.8). (Kingsley, J. 2022).

Figure 1.7: AI for the following finance sector uses



Source:(Kingsley, J. 2022), (Shmat, D. 2022) https://impact.economist.com/perspectives/financial- services/banking-game- changer-ai-financial-services

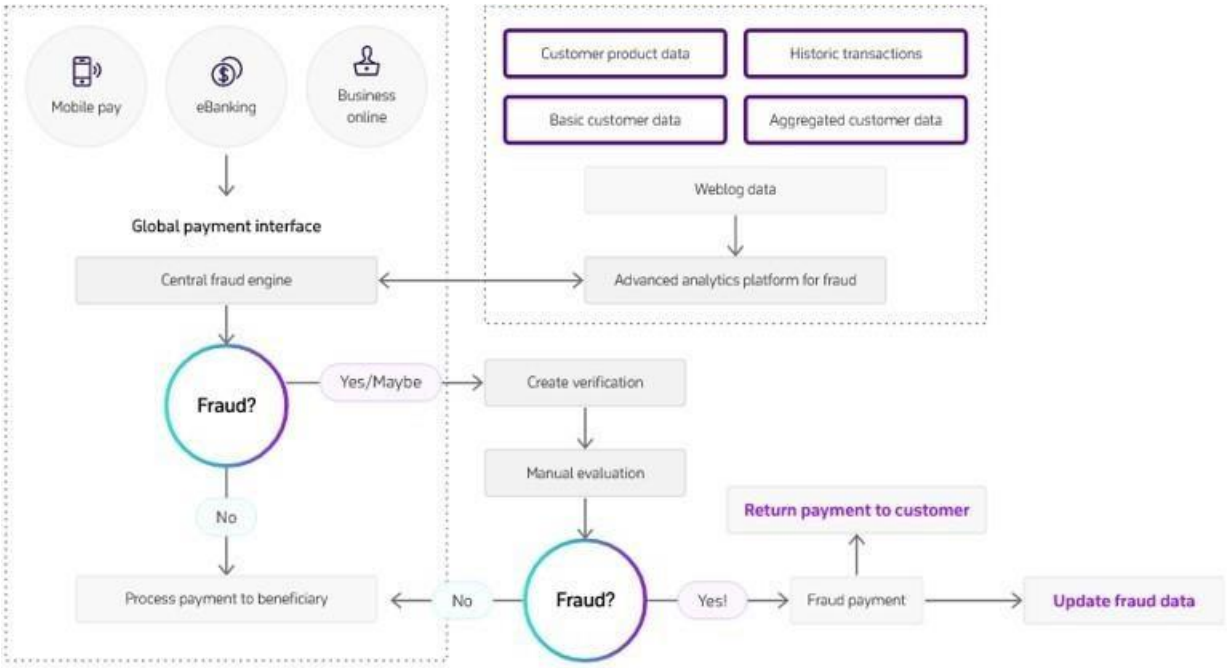
Figure 1.8: Plan to use of AI in the next three years



Source:(Kingsley, J. 2022) https://impact.economist.com/perspectives/financial- services/banking-game-changer-ai-financial-services

Danske Bank, a significant financial institution in Denmark, effectively implemented an ML-based system for detecting fraudulent activities within its operational framework. Danske Bank encountered a daily frequency of 1,200 instances of false positives and attained a fraud detection rate of 40% by employing a legacy rule-based system for the purpose of fraud detection. Danske Bank had a notable decrease in false positives by 60% and a commensurate increase in the identification of fraudulent activity by 50% following the effective integration of ML methodologies for the purpose of fraud detection (Abramovich, A. 2023). (Shmat, D. 2022).

Figure 1.9: Real-world examples of AI for fraud detection in Danske Bank



Source: (Ahramovich, A. 2023) https://www.itransition.com/machine-learning/fraud-detection

However, while AI provides significant advantages in fraud detection and cybersecurity, it also presents certain challenges. These include the need for large volumes of high-quality data for training AI models, the risk of bias in AI decisions, and the need for transparency and explainability in AI decision-making processes (Bao, Y, et al. 2021), (Bao,Y, et al. 2022).

Notwithstanding these hurdles, the utilization of AI in the realms of fraud detection and cybersecurity is anticipated to experience growth in the forthcoming years. This growth may be

attributed to the progress made in AI technology as well as the escalating digitization of financial services (Tahmasebi, M. n.d).

Cybersecurity Enhancement

The findings of a study conducted by IBM in 2022 indicate that the finance and insurance sectors have consistently experienced the highest frequency of cyber-attacks for a consecutive period of five years. Given the vast quantities of very sensitive data that banks possess, a significant hack has the potential to be catastrophic. Furthermore, it is no longer viable to depend solely on traditional security measures, as the arsenal of cybercriminals is rapidly developing and evolving at an unprecedented pace (Shmat, D. 2022).

Greenhill, a prominent international investment firm, employs a cutting-edge cybersecurity system called Falcon, which has been built by CrowdStrike, a reputable security business based in the United States. The technology utilises an exclusive cloud-based ML algorithm that consistently examines several events within Greenhill's system in order to detect potential risks. Greenhill's analysis indicates that the deployment of Falcon has led to a significant reduction of approximately 75% in false alerts, resulting in substantial yearly savings of approximately $300,000 (Shmat, D. 2022).

1.5.6. AI-Influenced Financial Sector Transformation

The financial sector has been significantly influenced by the integration of AI technologies. The adoption and modification of AI in this sector are driven by several factors, including technological advancements, industry infrastructure, data availability, and demand factors such as competition among enterprises, profitability necessities, and regulatory requirements (OECD. 2021)(Boukherouaa, E.et al 2021), (Yong, J. et al 2021), (Insider Intelligence. 2022).

The infrastructure of the financial industry has also evolved to accommodate AI technologies. For instance, cloud computing has liberated financial services players, enabling them to deploy AI techniques more efficiently (Fong, D. 2021).

Data availability is another critical factor. The abundance of available data and the increase in the affordability of computing capacity have substantially driven the adoption of AI systems and techniques in finance (OECD. 2021).

Demand factors have also influenced the integration of AI in the financial sector. There is intense competition among enterprises to adopt AI. The necessity for profitability is another demand factor. AI methodologies in finance can generate efficiencies by reducing friction costs and improving productivity levels. Consequently, these advancements contribute to increased profitability within financial institutions (OECD. 2021).

Regulatory requirements in the financial domain have also necessitated the adoption of AI. A number of financial authorities have initiated the development of frameworks that delineate their anticipated standards regarding the governance and utilization of AI by financial organizations (Yong et al. 2021).

As these trends continue to evolve, it will be interesting to observe how the financial sector navigates this dynamic landscape (Suparna B, et al 2023). However, the primary uses of AI that are revolutionizing the financial sector and have the capability to significantly enhance many operations within this industry are outlined below:

In-app Banking Experience: Today, most financial institutions offer mobile applications that allow customers to perform a variety of banking activities such as transactions, balance inquiries, statement generation, card replacement requests, and more. However, only a select few have integrated AI into their applications to enhance the user experience (Suparna B, et al 2023), (Fares, O.H.,2022).

AI chatbots, for instance, have emerged as a valuable tool for banks to provide personalized support to their customers (Suparna B, et al. 2023), (Fares, O.H.,2022). These chatbots assist clients by automating simple operations such as initiating the process of opening a new account, facilitating bill payments, executing fund transfers between accounts, and handling various application procedures (Suparna B, et al. 2023), (Fares, O.H. 2022).

However, the adoption of AI in finance is not without challenges. Issues such as data privacy and security, regulatory requirements, and the need for relevant skills and IT infrastructure pose significant hurdles (Rahman, M 2021).

Smart Loans: The application of AI in the financial sector has undergone a substantial transformation the lending market, particularly in the area of smart loans. AI has revolutionized the loan-underwriting process, disrupting traditional lending practices (Agarwal, A. et al 2021), (Fares, O et al., 2022), (Boukherouaa, E. et al., 2021).

Financial institutions traditionally offer loans to their clients through a credit-scoring framework (Agarwal, A. et al 2021). However, AI in finance can effectively identify intricate patterns within customer data by analyzing various factors, including company and personal finance, credit score, and revenue. This analytical process allows for the identification of borrowers who are more likely to default on their financial obligations (Agarwal, A. et al. 2021), (Fares, O et al., 2022).

A novel development in this area is the use of AI in credit scoring systems to gather wealth-related information from individuals cellphones, particularly those with limited access to traditional banking services (Agarwal, A. et al 2021; Fares, O et al, 2022). This data is used to assess their creditworthiness, providing these individuals with additional avenues to obtain credit from financial institutions (Agarwal, A. et al 2021; Fares, O et al, 2022).

AI's impact on the finance industry extends to making bank loans more fair (Agarwal, A. et al 2021). Numerous financial institutions are increasingly adopting AI as a means to rectify historical instances of discriminatory lending practices and cultivate a more inclusive economic environment. (Agarwal, A. et al 2021). The crux of the matter is in the development of AI-driven

systems that are specifically geared to promote greater justice, even at the expense of historical accuracy (Agarwal, A. et al 2021). This entails the training and evaluation of AI systems not solely based on historical loans or mortgages, but rather on the principles of equitable lending in a more equitable world (Agarwal, A. et al 2021).

As we move forward into an era increasingly dominated by AI and ML, it's clear that these developments are here to stay. The only question is how companies will use these tools to implement digital transformation and make it count (Townson, S. 2020).

Smart Sales Processes: Intelligent technologies, such as AI chatbots, have changed sales processes in the financial industry. These virtual salespersons overcome the limitations of human sales executives, such as restricted working hours and varying levels of industry knowledge (Sharan, V. 2020; Edelman, D. C, et al 2022), (Agarwal, A., et al 2021). AI chatbots provide continuous customer support, addressing inquiries at any time of the day, as long as the relevant information is accessible within their database (Sharan, V. 2020), (Edelman, D.C. et al. 2022). This is facilitated by a distinctive algorithm that enables seamless negotiation with customers without the need for human intervention (Sharan, V. 2020; Edelman, D. C. et al. 2022).

The impact of AI on smart sales processes extends beyond customer service. AI is transforming how consumers and companies manage their finances (Agarwal, A, et al 2021). The projected cost reductions for banks resulting from the use of AI applications are predicted to reach $447 billion by the year 2023 (Agarwal, A, et al 2021). Financial institutions are actively exploring creative approaches to integrate this technology into their range of services. The field of AI in sales comprises a wide range of applications, including the use of chatbot assistants, fraud detection systems, and work automation tools (Agarwal, A., et al 2021). The majority of banks, over 80%, possess a high level of awareness regarding the potential advantages that can be derived from the implementation of AI technologies (Agarwal, A., et al 2021). The adoption of AI by financial institutions is being expedited due to advancements in technology, growing acceptability among users, and evolving regulatory frameworks (Agarwal, A. et al. 2021). However, the integration of AI into smart sales processes is not without its challenges. The utilization of AI technology in the industry enables the identification of potential security threats and attacks in real-time. However,

it is important to acknowledge that the implementation of AI also introduces new vulnerabilities and threats (FINRA,2020). Moreover, there are concerns about job disruption and data privacy (Sharan, V. 2020). I will explain data privacy in chapter 3 in details.

Algorithmic trading (Automated Trading Systems): Algorithmic trading, also known as automated trading systems, involves the use of sophisticated AI systems to facilitate rapid decision-making in trade (Zhang, L.et al 2022; Bowne, A, et al 2020; Agarwal, A. 2021). Contemporary institutional investors and investment firms are increasingly relying on data scientists rather than market specialists (Zhang, L.et al. 2022). These data scientists use complex ML algorithms to identify potential trends in the market by analyzing past data patterns (Zhang, L.et al. 2022; Bowne, A, et al. 2020; Agarwal, A 2021).

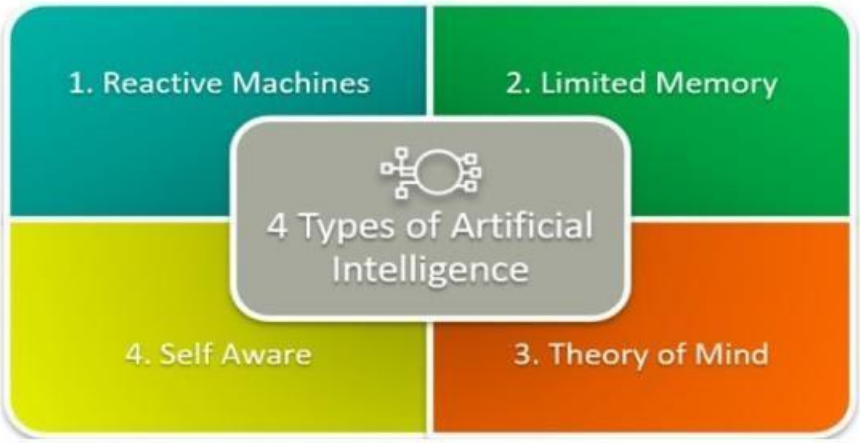
Algorithmic systems have the capacity to generate a substantial volume of trades, ranging from thousands to millions, within a single day (Tsamados, A, et al. 2021), (Dennehy, D, et al. 2023). These algorithms can be trained to detect triggers for abnormalities occurring in the market (Zhang, L.et al. 2022; Bowne, A., et al. 2020; Agarwal, A, 2021). Both institutional investors and individual investors can utilize AI in their decision-making processes related to the timing and selection of stocks for buying, selling, or holding (Zhang, L.et al. 2022; Bowne, A, et al. 2020; Agarwal, A 2021). We will explain this matter in detail in the following chapter.

Transaction Data Enrichment (TDE): The role of AI in TDE has become increasingly significant in the financial industry. TDE, powered by AI, has the capability to simplify complex transactional data, thereby enhancing comprehension and providing valuable insights (Colic, M,2021). This technology has been instrumental in aiding customers in various aspects such as budget management, credit assessment, monitoring spending patterns, and analyzing and forecasting future income and expenditure(Colic, M ,2021). Furthermore, AI enables speedy and accurate analysis based on predicted transactional categories(Singh, P 2021). Its self-learning capabilities allow constant analysis of billions of bank transactions (Singh, P 2021). The use of structural modeling techniques also gives the required flexibility (Singh, P 2021). Therefore, AI-powered TDE is not only improving the customer experience but also revolutionizing the financial industry by providing personalized insights and recommendations (Colic, M ,2021).

1.6. Types of AI

AI is a multifaceted technology with numerous subfields and applications. It can be broadly categorized into four distinct types: reactive machines, limited memory machines, theory of mind, and self-aware AI (Figure 1.10). These classifications provide a foundational understanding of AI, facilitating a more comprehensive exploration of its diverse domains (Johnson, J. 2020).

Figure 1.10: The four A.I. types



Source: (Johnson, J. 2020) https://www.bmc.com/blogs/artificial-intelligence-types/

Reactive Machines refer to AI systems characterized by their lack of memory and task-specific nature, wherein a given input consistently yields a predetermined output (Johnson, J. 2020). In the financial services sector, one of the applications of Reactive Machines is in the form of chatbots (Fintechnews 2020). These chatbots follow a rule-based model with programmed responses and cannot deviate from the structure (Rodrigue, E et al. 2023). The organization acquires consumer data, including records of purchases and search activities, which is subsequently utilized to provide personalized suggestions to the respective customers (Johnson, J. 2020). This particular form of AI operates in a reactive manner, allowing finance organizations to enhance their customer experience, decrease expenses, and expand their service offerings (Fintechnews 2020).

Limited Memory AI refers to machines that are capable of learning from historical data to make decisions (Akhtar, A. 2023). In the financial services sector, one of the applications of Limited Memory AI is in credit card fraud detection (Akhtar, A. 2023). These systems analyze past transaction data and user behavior to identify suspicious activities and block unauthorized transactions, thereby minimizing financial losses (Akhtar, A. 2023).

Another application is in the area of financial deepening and efficiency (Boukherouaa, E, et al. 2021). AI and ML systems have been rapidly adopted in the financial sector, with advances in ML responsible for most of the recent achievements (Boukherouaa, E, et al. 2021). These systems are fundamentally transforming client experiences, encompassing the realm of communication with financial service providers (for example, chatbots), investing (for example, robo-advisors), borrowing (for example, automated mortgage underwriting) and identity verification (for example, image recognition) (Boukherouaa, E, et al 2021).

Theory of Mind AI refers to machines that are capable of understanding and attributing mental states to others (Cuzzolin, F, et al. 2020). This type of AI is still in its early stages, but it has the potential to revolutionize many sectors, including financial services (Insider Intelligence 2023).

One potential application of the Theory of Mind AI in financial services could be in enhancing customer interactions. For instance, an AI system with Theory of Mind capabilities could potentially understand a customer's financial goals and intentions, even in ambiguous or new situations, and provide personalized financial advice or services accordingly (Frontiers 2023).

However, it’s important to note that these are potential applications and the use of Theory of Mind AI in financial services is still largely theoretical and subject to ongoing research (Cuzzolin, F, et al. 2020; Frontiers 2023).

Self-aware AI is a type of AI that has its own consciousness and is aware of its surroundings, its state, and can predict the feelings of others (Insider Intelligence 2023). This type of AI is still largely theoretical and not yet fully realized (Insider Intelligence 2023).

In the context of financial services, while there are no current examples of self-aware AI being used, the potential applications could be transformative. For instance, a self-aware AI system could potentially understand a customer's financial goals and intentions at a much deeper level, even in ambiguous or new situations, and provide highly personalized financial advice or services accordingly (Ivey, A. 2023; Schroer, A. 2023).

However, it's important to note that these are potential applications and the use of self-aware AI in financial services is still largely theoretical and subject to ongoing research (Ivey, A. 2023; Schroer, A. 202).

1.7 Overview of AI

Given the breadth of AI subfields, it is crucial to focus on specific technologies applicable within this industry (Yuxin Li et al., 2021). In the following, we will discuss their different types:

1.7.1. Machine Learning (ML)

ML is a branch of AI that enables systems to acquire knowledge and enhance their performance through the process of spontaneous learning, without the need for explicit programming (Wasserbacher, H, 2022; Sarker, I. H.,2021). The primary focus of ML revolves around the advancement of computer programs that possess the capability to retrieve data and subsequently utilize it in a manner that facilitates autonomous learning (Wasserbacher, H, 2022; Sarker, I. H.,2021).

Resistant.ai is a startup located in Prague that uses ML technology to safeguard AI systems against targeted manipulation, adversarial ML attacks, and advanced fraudulent activities. Riskified utilizes ML algorithms in order to offer payment insights that empower organizations to make informed decisions about whether to accept or decline transactions. Feedzai is a United States-based firm that leverages ML techniques to create risk management solutions aimed at mitigating instances of fraud and money laundering inside transactional activities (Datsyuk, Y. 2021).

There are three main types of ML: supervised learning, unsupervised learning, and reinforcement learning (Wasserbacher, H, 2022). (Sarker, I. H. ,2021).

Supervised Learning models are trained using labeled data. After sufficient training, the model should be able to predict an output value for any valid input object (Boukherouaa, E. B, et al. 2021).

Supervised learning methods have been used to detect money laundering transactions (Jullum, M, et al 2020) and to predict cash holdings (Özlem, et al. 2022). Investment banking organizations are at the forefront of adopting AI and ML technology in the Financial Services industry. They utilize ML techniques to refine algorithms and prediction models, with the aim of quantifying and mitigating risks (Columbus, L. 2020).

Unsupervised learning refers to a category of ML algorithms that are employed to derive insights from datasets containing input data without accompanying labeled answers. Cluster analysis is widely recognized as the predominant approach in unsupervised learning. This method is commonly employed in the field of exploratory data analysis, with the primary objective of uncovering latent patterns or identifying distinct groupings within a dataset (Huang, J, et al 2020).

In 2022, the global market for unsupervised learning was estimated at $4.2 billion, with a projected growth to reach $86.1 billion by 2032 (Apoorv P, et al 2023). Corporations and organizations employ unsupervised learning techniques to extract insights from vast and intricate datasets (Apoorv P, et al 2023). The past decade has seen an immense proliferation of ML techniques within the field of finance (Rubtsov, A. 2021).

Deep Learning (DL), a subsection of ML, approaches employ neural networks consisting of multiple layers, therefore gaining the designation ’deep,’ to effectively represent and comprehend intricate patterns within datasets. These methodologies have demonstrated potential in forecasting stock prices and market fluctuations. DL has been applied in various ways in the finance industry. Here are two examples:

Insurance Underwriting: DL algorithms are utilized by insurance companies to train models based on past consumer data. The consumer data encompasses a range of information, such as health records, data collected from wearable devices, prospective health concerns, age, income, occupation, and loan repayment history. (E, W., Hu, R. & Peng, S. 2023).

Lending: DL algorithms leverage acquired patterns and outcomes from document processing in order to evaluate credit risks and loan applications. The dataset encompasses several socioeconomic variables, including income, occupation, age, current financial assets, current credit scores, over drafts, outstanding balance, foreclosures, and loan payments. Subsequently, a determination can be made regarding the client's eligibility for loan approval (Dilmegani, C. 2023).

Reinforcement Learning (RL) is a subfield within the domain of ML, wherein an autonomous agent acquires the ability to interact with an environment and improve its behavior through a process of action execution and subsequent observation of outcomes (Wasserbacher, H, 2022). In the context of reinforcement learning, an AI agent is presented with a scenario that resembles a game. The computer uses a method of problem-solving known as trial and error in order to generate a solution (Wasserbacher, H, 2022).

RL has the capability to effectively leverage extensive financial data while minimizing the reliance on model assumptions, hence enhancing decision-making in intricate financial settings (Hambly, B., et al.2023). DRL has been used for automated stock trading (Asodekar, E, et al. 2022).

1.7.2. Expert system

Expert system (ES) is a type of AI that is designed to mimic the decision- making capabilities of a human expert, particularly in the field of finance. These systems utilize a knowledge base, which is a collection of rules or decision trees, and an inference engine to solve complex financial problems that typically require human expertise (Shafiee, S. et al 2022). Recent studies have shown

that ES can be used to personalize financial decisions (Shafiee, S.et al 2022). They can educate consumers in achieving their financial goals, leading to improved financial literacy and individual financial decision-making (Shafiee, S. et al. 2022).

1.7.3. Natural Language Processing (NLP)

NLP is a subfield of AI that empowers computational systems to comprehend, decipher, and produce human language, hence promoting effortless communication between humans and machines (Mah, P. et al 2022).

In the financial services sector, NLP has numerous practical applications. For instance, chatbots can be used to enhance customer experience (Mah, P. et al 2022). NLP can also extract relevant information and manage large volumes of paperwork efficiently, benefiting both regulatory bodies and financial institutions (Mah, P. et al 2022), (Mayor, T. 2020). Various algorithms are commonly used in NLP (Mah, P. et al 2022).

Recent research has shown that financial analytics firms are turning to NLP to parse textual data hundreds of thousands of times faster and more accurately than humans can (Mayor, T. 2020). This is particularly useful in finance where timely decisions often rely on text-based data (Mayor, T. 2020). For example, earnings reports are released as text, and by the time this data is structured and entered into a database, hours may have passed. NLP can transcribe this information in minutes, providing analysts with a competitive advantage (Mayor, T. 2020).

1.7.4. Robotics Process Automation

Robotics Process Automation (RPA) is increasingly being adopted in the financial services sector to automate repetitive, rule-based tasks that are typically performed by humans (Nguyen, T. D, et al 2023). The main goal of this initiative is to reduce operating costs, enhance operational

efficiency, minimize human errors, and improve the overall customer experience (Nguyen, T. D, et al 2023).

Recent research findings indicate that RPA has been greatly affecting the banking sector by enhancing the efficiency of basic financial processes and enabling banks to customize services for consumers. Simultaneously, RPA has also contributed to the enhancement of safety and security measures within the business (Nguyen, T. D, et al 2023). Intelligent automation has facilitated a redefinition of operational processes within the banking sector. However, this advancement has also presented issues pertaining to safeguarding customer interests and maintaining the stability of the financial system (Nguyen, T. D, et al 2023).

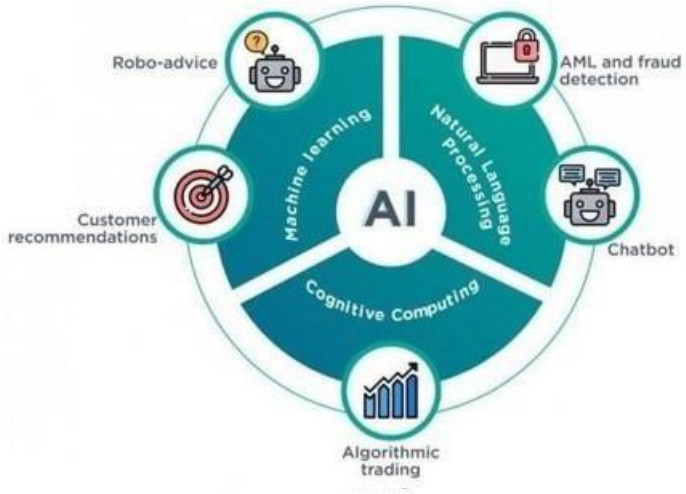
According to recent research, the market for RPA in the financial services sector experienced a revenue of $0.3 billion in the year 2020. It is anticipated that this the market would grow significantly and reach a value of $4.8 billion by the year 2030, exhibiting a Compound Annual Growth Rate (CAGR) of 30.9% from 2021 to 2030 (Gartner. 2022). The expansion observed in this context can be attributed to the increasing demand for business process automation, a factor that consistently propels the advancement of AI and software robots (Otero, A. R. 2020).

Chapter2

AI and Finance

In the domain of algorithmic trading and automated investment strategies, the incorporation of AI has significantly enhanced efficiency and productivity. Algorithmic trading utilizes AI's ability to learn from historical trading data, dynamically adapting trading strategies for improved returns (Powers, J. 2023). Moreover, automated investment platforms employ AI algorithms to construct diversified portfolios and optimize them for tax implications (GÜNEYSU, Y. 2023; OECD 2021).

Figure 2.1: AI applications for Financial Services



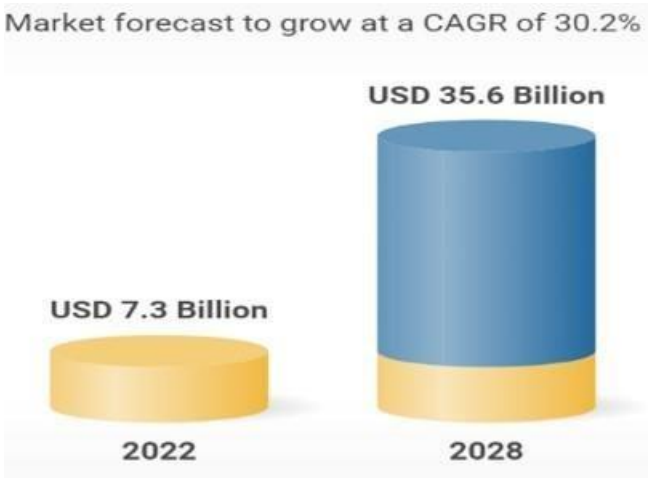
Source: https://jelvix.com/blog/ai-in-finance

With regard to the impact of AI on financial advising and asset management roles, robo-advisors have emerged as significant players, making financial advice more affordable and accessible (Tepper, T., & Curry, B. 2023; Bhatia, A et al. 2021). Simultaneously, asset management firms are using AI to enhance risk modeling and devise innovative investment strategies, transforming traditional roles in the sector (Joshi, N. 2021).

In terms of robo-advising, it has become increasingly widespread. In 2021, North America emerged as the largest market for the global robo-advisory market, with a market share of around 39.4% and $4.13 billion of the market revenue. The Asia-Pacific Robo Advisory Market is expected to grow at the fastest compound annual growth rate (CAGR) between 2021 and 2030. Furthermore, the global robo-advisory market size was valued at USD 4.13 billion in 2021 and is expected to grow at a CAGR of 29.7% from 2022 to 2030.

The predicted growth of the worldwide robo-advisory market size is expected to be substantial (Riya, V. et al. 2023). The global robo advisory market size was valued at USD 4.13 billion in 2021 and is expected to grow at a CAGR of 29.7% from 2022 to 2030 (GVR, 2023). Furthermore, in 2022, the market size was valued at USD 7.3 billion (Riya, V. et al., 2023). Looking forward, it is expected to reach USD 35.6 billion by 2028, exhibiting a compound annual growth rate (CAGR) of 28.4% during 2023-2028 (Figure 2.2)(Riya, V. et al. 2023). The expansion is propelled by the pervasive adoption of digital technology in the financial industry and a swift transition from conventional investment services to automated robo-advising investment services. (GVR, 2023).

Figure 2.2: Global robo advisory market



Source: (RM, 2023). https://www.researchandmarkets.com/reports/5578100

2.1. AI-Powered Portfolio

AI-powered portfolios operate by leveraging a fusion of AI methodologies, including ML, sentiment analysis, and predictive analytics, to scrutinize past market and stock information, generate investment concepts, construct portfolios, and execute trades (Powers, J. 2023). The investment industry has historically employed algorithms and quantitative trading programmes with the aim of enhancing profitability (Pound, J. 2023). However, the latest advancements in AI present novel opportunities. According to a preliminary study conducted by two scholars based in South Korea, it has been shown that ChatGPT exhibits superior performance as a portfolio manager in comparison to a random selection approach, such as tossing darts (Pound, J. 2023). According to the researchers, the preliminary findings indicate that ChatGPT has the potential to serve as a "co-pilot" for investors, rather than functioning as a "prophet" (Pound, J. 2023).
The researchers constructed a portfolio consisting of 20 large-cap companies representing various sectors of the US market. Additionally, they included five assets from each of the following categories: cryptocurrencies, commodities, currencies, and bonds (Pound, J. 2023). Subsequently, the researchers conducted 10,000 simulations whereby ChatGPT was tasked with selecting a diverse range of available assets in order to construct a portfolio. The results of the data's backtest demonstrated that the picks made by ChatGPT yielded a portfolio that exhibited greater diversification, with assets that were less correlated compared to a random selection approach (Pound, J. 2023).

The democratization of portfolio management can offer advantages to retail investors, especially those who may lack education or accurate information. Moreover, professional portfolio managers can enhance their productivity by prioritizing critical activities and leveraging the assistance of ChatGPT in the process of selecting a variety of assets for a certain portfolio (Pound, J. 2023).

AI trading technology operates by analyzing a vast amount of data points in real-time, thereby catching valuable information that conventional statistical models may overlook. The rapid evolution of this technology has led to its early adoption by financial institutions. AI trading constitutes approximately 60 to 73 percent of equities trading in the United States (Powers, J. 2023). There are several distinct classifications of AI trading, encompassing quantitative trading,

algorithmic trading, HFT, and automated trading. Quantitative trading employs quantitative modeling techniques to assess the price and volume of stocks and trades, hence discerning optimal investment prospects (Powers, J. 2023).

Here are some real-world examples of AI-powered portfolios with statistics and their comparison with traditional methods:

Traders' AI: The analysis of this AI trading model encompassed its decision- making processes and performance evaluation for the period spanning from 2019 to 2021. The model has the capability to assume both long and short positions and has the flexibility to switch between these positions at any given time throughout the day. During the three-year examination period, it exhibited superior performance compared to its benchmark, the S&P 500 (Figure 2.3). The model exhibited superior performance in terms of market-adjusted returns when it adopted a short position (Horstmeyer et al. 2022).

Figure 2.3: Traders AI Model vs. S&P 500 Monthly Equity Curve ($10k Investment)

Source: (Horstmeyer,D.etal.2022). https://blogs.cfainstitute.org/investor/2022/12/15/what-can-ai-do-for- investment- portfolios-a-case-study/

Finally, the AI model had superior performance during periods of high market volatility, outperforming the S&P 500 by an average daily margin of 0.19%. Conversely, its performance was comparatively weaker on low-volatility days (Figure 2.4).

Figure 2.4: AI models average return/ S&P 500s average return

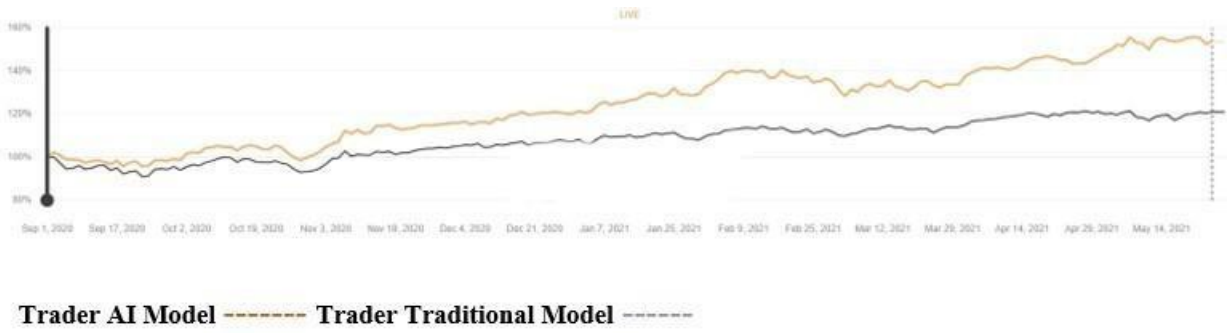
	AI Model's Average Return	S&P 500's Average Return
When Model Is Active	0.1517%	-0.0201%
When Model Sits Out	0%	0.8584%
When Model Is Long	0.1786%	0.6615%
When Model Is Short	0.1334%	-0.5215%
When Model Is Long and Short in a Day	0.1517%	-0.0201%
On High-Volatility Days	0.1313%	-0.0577%
On Low-Volatility Days	0.0916%	0.1915%
In Bull Markets (Annual)	17.0924%	46.6875%
In Bear Markets (Annual)	20.5598%	-23.0757%
In Bull Markets	0.0678%	0.1853%
In Bear Markets	0.0816%	-0.0916%

Source: (Horstmeyer, D et al. 2022) with updated and design author)

Wealthfront: The present system might be classified as a robo-advisor, which employs AI algorithms to effectively oversee and administer investment portfolios on behalf of its clientele (Ivey, A. 2023).

Boosted AI: The portfolio optimizer, which utilizes AI, has demonstrated notable superior performance when compared to traditional benchmarks. The portfolio subject to factor limitations has exhibited superior performance compared to IWB (iShares Russell 1000 ETF) by a margin of 29.33 percentage points from September 2020. Despite the absence of factor limits, their AI portfolio has outperformed its benchmark, albeit by a narrower margin of 2.23 percentage points (Figure 2.5)(Abe, F. 2021)

Figure 2.5: How Our AI Powered Portfolios



Source: (Abe, F. 2021)

2.2. AI in Algorithmic Trading and Automated Investments Strategies

Algorithmic trading, also known as quantitative trading, is a specialised domain within the subject of finance that involves the automated execution of trading choices. These judgments are derived from a predetermined set of mathematical rules that are generated by a machine (Théate and Ernst, 2021). The process of engaging in financial market trading is characterised by complexity and disorderliness due to the multitude of significant factors originating from both economic and psychological contexts. The field is additionally distinguished by the rapidity of information influxes that have a consequential impact on the profitability of trade within a few seconds. Researchers and practitioners have endeavored to utilise AI in order to assist individual investors in making trading decisions or autonomously executing the complete trading process (Cohen, G., 2022).

A conventional algorithmic trading system possesses the capability to effectively evaluate diverse datasets obtained from multiple sources. It generates buy and sell signals by employing ML or DL artificial neural networks. Additionally, it is proficient in executing a substantial volume of orders through HFT within a very short timeframe. Hence, numerous institutional traders are currently

engaged in the development of trading systems that enable them to execute a substantial volume of financial transactions within a condensed timeframe. HFT algorithms can also serve as a valuable tool for engaging in arbitrage trading, capitalising on the presence of disparate pricing for identical commodities. In order to implement these methods, HFT enterprises want access to real-time data without any delays. Consequently, they are willing to invest significant financial resources in order to obtain a rapid and uninterrupted data stream that can furnish them with trustworthy information ahead of their competitors (Cohen, G., 2022).

In recent times, there has been a growing recognition among researchers, institutional traders, and funders regarding the benefits associated with the use of AI in the development and implementation of trading systems. AI systems possess the capability to efficiently analyse vast quantities of data derived from diverse sources within a significantly reduced timeframe. Furthermore, the utilisation of fuzzy logic enables an imitation of human behaviour in trading processes, while mitigating the inherent biases associated with human decision-making (Cohen, G., 2022). DL algorithms can be utilised to analyse the relationship between the value of assets and market economic conditions, enabling the prediction of prices for stocks, exchange-traded funds (ETFs), currencies, and commodities (Cohen, G., 2022). This correlation may not be immediately apparent, but DL processes can effectively uncover and leverage it for predictive purposes. Algorithms provide the capability to not only generate precise predictions and execute live trading but also provide diverse back-testing outcomes that cater to the risk preferences of different investors (Cohen, G., 2022).

Pattern recognition and breakout signaling are significant contributions of AI to the field of trading (Cohen, G., 2022). Within this domain of knowledge, the system is programmed to identify established patterns and make informed decisions regarding the optimal timing for initiating or concluding a trade. Candlestick patterns, boxes, and channel formations have been identified as valuable tools for forecasting the price trajectory of diverse financial assets (Cohen, G., 2022). Trading systems aim to enhance the accuracy of forecasting financial asset price movements, hence leading to improved trading outcomes. The advancements of these systems prompted them to actively pursue a wide range of pertinent inputs obtained from various channels, which can effectively contribute to the completion of their designated duty. A proficient trading system

incorporates diverse information that is analysed using a pre-established framework, which comprehends the significance of each piece of information and its role in the prediction process (Cohen, G., 2022).

The application of ML techniques in trading encompasses the utilization of algorithms capable of acquiring knowledge from data and then making informed decisions. The aforementioned methodologies have been specifically formulated to discern patterns and trends across extensive datasets, hence facilitating the ability to forecast future price fluctuations with a notable level of precision (Snow, D, 2020). J.P. Morgan is conducting trials on an advanced programming system that incorporates ML to autonomously detect profitable trading strategies from unprocessed data (ProjectPro, 2023). This represents a departure from previous algorithms that relied on complex rules. In a recent study centered on interest rate markets, a research team incorporated more than 1,250 raw input data points sourced from various channels (ProjectPro, 2023). These inputs encompassed daily relative prices of U.S. Treasuries, dates of Federal Reserve meetings, and overseas interest rates. After conducting a comprehensive evaluation of several ML techniques, it was determined that the "random forest" approach emerged as the most effective. This method involves the construction of a network of interconnected decision trees (ProjectPro, 2023).

RL is a notable AI technology employed in algorithmic trading (Hambly et al., 2023; Théate and Ernst, 2021). In this approach, an agent acquires the ability to make decisions by selecting behaviours that optimise a certain measure of overall reward. The agent acquires knowledge through the analysis of market feedback in order to optimise its behaviours. This technique is particularly well-suited for the dynamic and data-intensive nature of financial markets (Théate and Ernst, 2021). A recent study introduced a DRL approach to address the algorithmic trading problem, specifically focusing on establishing the optimal trading position at any given time in stock markets (Hambly et al., 2023). After undergoing a comprehensive performance evaluation, this novel trading method demonstrates encouraging outcomes, consistently outperforming the benchmark trading strategies on average. Furthermore, this algorithm exhibits numerous advantages in comparison to traditional methods, including notable adaptability and exceptional resilience to various transaction expenses. In addition, this data-driven method offers a significant

advantage by alleviating the intricate process of formulating explicit rules tailored to the specific financial markets under consideration (Hambly et al., 2023).

2.2.1. Deep Learning Applications for Predictive Analytics in Financial Markets

DL has garnered significant interest due to its capacity to extract and comprehend complex patterns from extensive datasets. This characteristic renders DL a promising tool for conducting predictive analytics within the realm of financial markets.

For instance, an empirical investigation was conducted to create a stock trading model through the integration of Technical Indicators and Convolutional Neural Network (TI-CNN). The utilised model incorporated a set of ten technical indicators that were derived from previous data and represented as feature vectors. The vectors underwent a transformation into a picture by the utilisation of the Gramian Angular Field technique and were subsequently utilised as an input for CNN. The stock data's closing price was classified into sell, buy, and hold points by a manual process that involved identifying the highest and lowest points within a sliding window. The model underwent testing using data from the NASDAQ and NYSE exchanges, resulting in a notable level of accuracy in its predictions and could achieve 77.75% accuracy in comparison with one dimensional CNN and CNN-LSTM models (Chandar, S. K, 2022). The group of chosen stocks encompassed Apple Inc, Bank of America Corporation, CTS Corporation, The Goldman Sachs Group Inc, Halliburton Company, Microsoft Corporation, Oil States International Inc, and Oracle Corporation. The historical stock data of the eight companies, covering the time frame from January 2009 to December 2018, has been obtained from Yahoo Finance (Chandar, S. K, 2022).

In another study, an examination was conducted on financial time series data, whereby it was transformed and represented as two-dimensional images. The objective was to forecast the entrance and exit points of the time series values by assigning "Buy," "Sell," and "Hold" labels to facilitate profitable trading decisions. The financial time series data utilised in this study consisted of the stock prices of the Dow Jones 30 index and exchange-traded funds (ETFs). The findings suggest that this unique strategy has strong performance relative to Buy&Hold (BaH) during

extended out-of-sample testing periods (Sezer and Ozbayoglu, 2018). The proposed approach exhibits an average annualized return of 13.01% and a success rate of 71.51% for transactions. In contrast, the average annualized return for BaH strategy is 4.63% (Sezer and Ozbayoglu, 2018).

2.2.2. Sentiment Analysis for Market

The advent of AI has brought about changes that are substantial in diverse domains, one of which is the realm of market research. Sentiment analysis, a topic within the realm of AI, has developed as a robust instrument for comprehending market trends and customer behavior (Taherdoost, H., & Madanchian, M. 2023; Chubb, J., et al.2022).

Sentiment analysis use AI techniques to discern and extract subjective information from various source materials. In addition to discerning the positive or negative implications of words, comprehending the tone of a speech extends beyond mere recognition (Taherdoost, H., & Madanchian, M. 2023). This feature enables enterprises to evaluate the level of interest in specific topics, analyze market circumstances, and examine rivals. (Taherdoost, H., & Madanchian, M. 2023).

In the realm of competitive market research, sentiment analysis is employed as a tool to discern and juxtapose significant market metrics (Chubb, J., et al.2022). This aids in differentiating the offerings of rival companies in terms of both services and products (Chubb, J., et al.2022). The utilization of sentiment analysis powered by AI can facilitate the acquisition of insights into the perceptions and opinions of rivals' customers pertaining to many dimensions of their enterprises (Taherdoost, H., & Madanchian, M. 2023).

AI is commonly seen as advantageous in the realm of information acquisition and other specific activities, yet it also poses certain difficulties. The integration of AI into the realm of research ought to serve as a facilitator rather than a substitute for human ingenuity (Chubb, J., et al.2022). The investigation pertaining to the prospective involvement of AI in the research process

necessitates the thorough examination and resolution of these aforementioned issues (Chubb, J., et al.2022).

Real-World Case Study

A bank, with its headquarters located in Johannesburg, South Africa, expressed apprehension regarding its market perception. Due to a high rate of client attrition resulting from intense competition, the bank sought to ensure customer retention and prevent their migration to other banking institutions. The sentiment analysis Application Programming Interface (API) developed by Repustate effectively utilized AI to extract data from a dataset consisting of 2 million messages. These texts were gathered from a social media campaign conducted over a period of three months and were associated with specific hashtags. Named entity recognition (NER) was employed to extract and interpret the underlying intention of a given comment. Subsequently, the obtained information was transformed into a sentiment visualization dashboard, facilitating comprehension (Repustate 2021). Please refer to the Figure 2.6 graphic provided below:

Figure 2.6: Sentiment analysis for banking in South Africa

Source: https://www.repustate.com/banking-sentiment-analysis-and-text-analytics/

The financial institution observed a notable trend in customer grievances, primarily concerning the lack of service provision at specific branch locations during the lunch hour. Based on the available information, the bank successfully resolved the customer's concerns. The bank implemented a strategy to ensure that its branches were adequately staffed with tellers during periods of high customer activity, therefore avoiding the presence of unattended teller stations during peak traffic hours, such as lunchtime and after-office hours. The implementation of these novel methods resulted in a decline in attrition rates and a concurrent rise in the acquisition of new clients by the bank (Repustate,2021).

2.2.3 Swarm Intelligence for Portfolio Management

A subset of AI called swarm intelligence (SI) draws its inspiration from the group behaviour of autonomous, decentralised systems like ant colonies, fish schools, and bird flocks (Thakkar and Chaudhari, 2021). In the context of the dynamic and unpredictable financial market, investors frequently employ portfolio optimisation (PO) as a proactive approach to asset management (Chen et al., 2022). The utilisation of SI algorithms has been extensively implemented in order to address PO difficulties, mostly due to their notable efficacy and capacity to achieve suitable solutions (Chen et al., 2022).

Ant Colony Optimisation (ACO) is a prominent algorithm employed in portfolio management (Thakkar and Chaudhari, 2021). ACO algorithm is a probabilistic technique that can be effectively employed to determine the most optimal path within a network. This characteristic renders it particularly applicable in the domain of portfolio optimisation (Thakkar and Chaudhari, 2021). The programme draws inspiration from the foraging behaviour exhibited by ants in their quest for sustenance. Ants leave behind pheromones as they navigate, providing a trail for other ants to follow and locate the source of food. Within the realm of portfolio management, it is crucial to note that each individual "ant" serves as a viable solution or portfolio option, and the term "pheromone" is used to denote the measure of quality or suitability of the portfolio (Thakkar and Chaudhari. 2021).

Particle Swarm Optimisation (PSO) is a frequently employed method in the field of portfolio management within the context of the SI framework. PSO draws inspiration from the collective behaviour observed in bird flocking or fish schooling (Shami et al., 2022). In the PSO algorithm, every individual particle symbolises a prospective solution or portfolio. Particles traverse the problem space by adhering to the trajectory of the most optimal particles. The motion of particles is governed by their individual optimal positions as well as the optimal positions of other particles. This phenomenon enables the collective behaviour of the swarm to gradually approach and ultimately identify the most optimal solutions (Shami et al., 2022).

Both ACO and PSO have been employed in practical applications (Thakkar and Chaudhari, 2021). A case study was undertaken on the Tehran Stock Exchange, wherein the ACO approach was employed for the purpose of portfolio optimization (Abolmaali and Roodposhti, 2018). This work has usually demonstrated the efficacy of employing ant foraging behaviour as a means of addressing optimisation difficulties.

2.2.4. Ensemble Learning Techniques for Improved Forecasting

Ensemble learning involves the combination of many learning algorithms in order to achieve enhanced predictive performance that surpasses the capabilities of each individual learning algorithm in isolation (Ganaie et al., 2022). The major objective of ensemble methods is to mitigate the issue of overfitting, enhance the resilience of models, and augment the accuracy of the prediction models. Overfitting is a suboptimal phenomenon in ML wherein the model exhibits a high degree of accuracy in predicting outcomes based on the training data, but fails to generalize well to novel data instances (Ying, X. 2019). The application of these strategies in the finance business has been extensively utilized to enhance the accuracy of forecasting (Ganaie et al., 2022).

Bagging, boosting, and stacking are three popular techniques of ensemble learning (Dong et al., 2020). Bagging is a technique that encompasses the creation of numerous subsets from the original dataset, followed by the training of a model on each subset, and ultimately combining the predictions obtained from these models (Dong et al., 2020). The boosting technique involves

iteratively applying a series of learners to successively update copies of the data. Following each prediction, the model assigns greater significance to the observations that were inaccurately anticipated, so compelling subsequent models to prioritize these more challenging instances (Dong et al., 2020). Stacking encompasses the process of training many distinct learners and subsequently amalgamating their predictions through the training of a meta-learner. The meta-learner then utilizes the predictions made by the individual learners to generate the final prediction (Dong et al., 2020). These models are mostly employed in stock market predictions, stock movements, financial data classification, and fraud detection (Nti et al., 2020; Li and Pan, 2022; Lahmiri et al., 2020; Zhang et al., 2022).

In addition, Deep ensemble learning models combine the advantages of DL models and ensemble learning techniques, leading to enhanced generalization performance of the ultimate model (Ganaie et al., 2022). These models are also commonly utilized in stock trading forecasting, and it has been demonstrated that the ensemble DL model significantly outperformed the most advanced existing prediction model (Li and Pan, 2022; Carta et al., 2021; Yang et al., 2020).

2.3. AI Impact on Financial Advising and Asset Management Roles

AI has been utilised by asset managers and the buy-side of the market for several years now. Its primary applications include portfolio allocation, risk management enhancement, and back-office operations optimisation. The application of AI methods holds promise in optimising operational workflows within investment management. This potential lies in the ability of AI to decrease back-office expenses, automate reconciliations, and expedite operations. Consequently, these efficiencies can lead to a reduction in friction, encompassing both direct and indirect transaction costs, while also improving overall performance by mitigating noise in decision-making processes, such as irrelevant features and information (Novick et al.,2019). AI models and ML algorithms enable the efficient monitoring of several risk characteristics on a daily basis and facilitates the simulation of portfolio performance across a wide range of market and economic scenarios (OECD,2021). The primary use of AI in asset management pertains to the development of strategies that impact decision-making regarding portfolio allocation. This utilisation heavily

depends on the utilisation of large datasets and ML models that have been trained on such datasets. The asset management industry and investment community have long relied on information as a basic component. Prior to the emergence of AI, many investment methods such as fundamental analysis, quantitative strategies, and sentiment analysis heavily relied on data as its foundation. The availability of copious quantities of unprocessed or disorganised data, combined with the predictive capabilities of ML models, offers a novel informational advantage to investors who employ AI to analyse these extensive datasets. This enables them to extract valuable insights that subsequently shape their strategies within brief timeframes (OECD,2021).

AI-driven hedge funds generated a cumulative return of 34 percent during the three-year period ending in May 2020 (Idzelis, C. 2020), exhibiting a notable growth in contrast to the 12 percent gain observed in the worldwide hedge fund business during June 2017 to May 2020. This demonstrates the potential and efficacy of AI approaches within the context of hedge funds (Idzelis, C. 2020).

A poll completed by Market Makers, a London-based market intelligence company, reveals that a significant majority of hedge fund traders, specifically nine out of ten, are anticipated to employ AI as a means to attain portfolio returns by the year 2023 (Hedgeweek, 2023). The utilisation of AI for the purpose of trading analysis has grown more prevalent inside prominent financial institutions such as Jane Street, Barclays, HSBC, Apollo, Bridgewater & Associates (Hedgeweek, 2023).

This aligns with the rapid expansion of generative AI technologies, as seen by the regular utilisation of gen AI in at least one business function by around one-third of organisations (Chui, M.et al. 2023; Haan, K., & Watts, R. 2023).

The top 50 traders, employing diverse methods especially AI, have consistently achieved net returns that surpass average benchmarks while assuming considerably lower levels of risk. Furthermore, their performance has remained largely unaffected by market fluctuations (Morgan, D. 2023). AI demonstrates a notable proficiency in pattern recognition, an area in which human capabilities are comparatively limited. There would be no necessity to allocate extensive time to

conducting research on the selection of currencies or stocks for trading purposes. AI has the potential to make decisions on behalf of individuals, so allowing them to allocate their time more efficiently. Additionally, it has the potential to mitigate inherent human biases in the realm of investment (Haan, K., & Watts, R. 2023).

The implementation of AI techniques in organisations necessitates significant investment, which may lead to a potential concentration of power among a limited number of large financial services firms. This concentration arises from the advantage that bigger and more influential players possess, enabling them to outperform their smaller competitors (Financial Times, 2020). The investment in AI technology includes not only the financial resources required, but also the talent and abilities of the workers involved in implementing these techniques. The utilisation of third-party providers helps mitigate the risk of concentration to some extent. (OECD, 2021). Importantly, the utilisation of identical AI algorithms or models by a considerable number of market participants may result in heightened uniformity within the market, hence fostering herding behaviour and creating one-sided markets. Consequently, this phenomenon may give rise to novel vulnerabilities within the market structure. Consequently, this phenomenon leads to heightened levels of volatility during periods of economic strain. This is further intensified by the simultaneous implementation of substantial transactions by numerous market participants, resulting in episodes of limited market liquidity and exerting an impact on the overall stability of the system during times of market distress.

2.3.1. AI for Risk Management

AI solutions, when employed for the purpose of risk management, enable traders to monitor their risk exposure and make necessary adjustments or exit positions based on predetermined objectives and environmental parameters, with limited or no human participation (OECD, 2021).

Credit risk management and market risk management are two areas that have witnessed notable advancements due to the progress made in the fields of AI and ML (Dwivedi et al., 2023). AI-based solutions have the potential to facilitate the analysis of the level of interconnectivity among

borrowers, hence enhancing the efficacy of risk management in lending portfolios (OECD, 2021). One example of a collaboration in the financial sector was ZestFinance, a firm established by a former Chief Information Officer of Google, which formed a partnership with Baidu in 2016. The objective of this collaboration was to enhance Baidu's lending decisions inside the Chinese market (Dwivedi et al., 2023). Baidu leveraged its extensive database of member information, including search and purchase habits, to inform its lending decisions. This method proves to be highly advantageous in economies such as China, where the percentage of individuals with credit profiles or credit ratings is less than 20% (Dwivedi et al., 2023).

Six out of ten credit union executives surveyed at the NACUSO Network conference in 2021 indicated that the industry's underwriting technology is out- of-date, while eight out of ten felt that the use of AI and ML would improve risk rating. In contrast to traditional credit risk models such as FICO, ML models that are appropriately constructed possess the ability to evaluate borrowers' risk with significantly enhanced accuracy (Shmat, D. 2022). By leveraging ML engines, financial institutions have the ability to expand their customer base to include underserved populations and enhance loan approval processes, resulting in expedited decision-making while effectively managing risk (Shmat, D. 2022). The collaboration between 5Point Credit Union, an organisation operating in Texas and catering to a membership of 50,000 credit union members, and Zest AI, aimed at the development of a personalised credit score model utilising ML techniques. This partnership was established with the objective of enhancing the credit assessment process (Shmat, D. 2022). As a consequence of the implementation, 5Point now accrues an additional $1.5 million in annual earnings. The achievement of the project can primarily be ascribed to the comprehensive training of the model. In addition to historical consumer loan data, the model was supplemented with FCRA-compliant data obtained from telecom and utility firms, resulting in a notable improvement in the accuracy of the model's output (Shmat, D. 2022).

Simulation plays a crucial role in facilitating decision-making within the banking industry. The evaluation of a bank's capacity to endure specific economic shocks is not solely a regulatory obligation, but also a potent strategic tool. Although the conventional methodology for simulation has demonstrated a certain level of effectiveness, it is limited in its ability to consider minor yet potentially significant subtleties in data. In contrast, finely calibrated artificial intelligent and ML

models possess the capability to identify non-linear correlations and relations within the financial and industry data of banks (Shmat, D. 2022).

Barclays has established a strategic partnership with Simudyne, a British company renowned for its expertise in simulation platforms. Simudyne emerged as an early adopter in recognizing the advantages of real-time cloud computing in the realm of commercial applications within the banking sector. The company pioneered the development of an exclusive ML-driven technology, facilitating the expeditious generation of computer simulations. The utilization of cloud and ML technology enables the scalability of simulations as per demand, hence significantly reducing the costs associated with their production. In addition to evaluating market and credit risk, Barclays uses Simudyne's technology to forecast and simulate the phenomenon of 'default contagion', which refers to the propagation of financial distress from one bank to other interconnected institutions (Shmat, D. 2022).

In the realm of AI risk management, it is fundamental for every team to enhance their skills and capabilities (Baquero et al., 2020). This entails fostering a greater degree of overlap among skill sets across various tasks, surpassing the limitations imposed by traditional siloed approaches. An individual with a fundamental proficiency in risk management, compliance, and vendor risk is required to possess a sufficient level of analytical expertise in order to effectively collaborate with data scientists. Analytical risks must also be understood by data scientists so that they are cognizant of them as they carry out their duties (Baquero et al., 2020). In reality, analytics teams must manage model risk and comprehend how their models affect business outcomes while also adjusting to a talent influx from less conventional modeling backgrounds who might not be familiar with established model-management methods (Baquero et al., 2020).

2.3.2. AI in Personalized Financial Planning

ML algorithms possess the capability to comprehend an individual's financial practices, long-term objectives, and propensity for risk. These suggestions are customized to the specific financial circumstances and future objectives of each individual (Waliszewski and Warchlewska, 2020).

The capacity of AI to democratize financial advising stands as a prominent advantage in the realm of personalized financial planning. The inclusion of fixed and variable components in the cost structure of robo-advising is posited to have the potential to democratize the accessibility of financial services (Philippon T., 2020). This perspective is in accordance with the notion that financial planning platforms powered by AI have the potential to provide customized guidance at a reduced expense, therefore facilitating equal access to these services and yielding advantages for a broader demographic (Philippon T., 2020).

One potential use of ML in the realm of personal finance is the integration of budgeting tools into mobile banking applications. This integration has the potential to enhance customers' ability to make informed and advantageous financial choices. By analyzing the historical records of transactions, an ML algorithm has the capability to discern patterns in user spending behavior and provide recommendations for enhancing budget management. TransUnion bank has established a partnership with the ML-powered budgeting application Mint in order to offer its customers guidance on enhancing their credit scores. These tools have the ability to enhance customer loyalty and augment the worth of a customer across their lifetime (Shmat, D. 2022).

Recent research has indicated that a majority of wealth managers acknowledge the advantages associated with the implementation of AI. However, they encounter difficulties in expanding its utilization throughout the entire organization and optimizing its potential benefits. Wealth management is becoming increasingly client-centric through data and analytics (Refinitiv, 2020). McKinsey also highlighted that it is necessary for wealth managers to abandon ingrained attitudes and work methods, and instead adopt data-driven, individualized suggestions that are provided through a hybrid approach combining remote advice with personalized service (Katsuki, F. et al 2023). The impact of AI on the finance industry, particularly in personalized wealth management, is profound. It not only enhances the efficiency of wealth managers but also improves the client experience by providing tailored financial advice (Katsuki, F. et al., 2023).

Chapter 3

Challenges and opportunities

Both opportunities and challenges are provided by the financial sector's adoption of AI. AI-powered chatbots, for instance, may offer 24/7 customer support, and predictive analytics can spot fraudulent activity before it happens (Mashrur et al., 2020). Furthermore, the advent of AI-driven technology such as robo-advisors has facilitated the democratization of financial advice, hence enhancing affordability and accessibility for a wider spectrum of clients. AI has the capacity to offer individualized financial services, including customized insurance plans and personalized investing strategies (Allen et al., 2021).

However, the implementation of AI is not devoid of obstacles. One of the primary aspects to be examined in this context pertains to the ethical problems that emerge, encompassing data privacy, bias, and accountability. These issues will be further explored in subsequent sections. The subsequent task is addressing the technological challenge of guaranteeing the dependability and resilience of AI systems. The performance of AI models is significantly dependent on the quality of the data on which they are trained. In instances when the models encounter scenarios that were not included in their training data, they may exhibit poor results (Campbell et al., 2020). The third issue pertains to regulatory compliance, as the current regulatory frameworks may be insufficient in addressing the distinct threats presented by AI (Bedué and Fritzsche, 2022). Finally, a significant obstacle arises in the form of a talent deficit, wherein there is a scarcity of proficient individuals possessing the requisite expertise to comprehend and proficiently oversee AI technology within the realm of finance (Dwivedi et al., 2021).

3.1. Privacy Issues

The financial sector is responsible for managing a significant amount of confidential client data, encompassing financial transactions, credit ratings, and personal details. AI systems possess the capability to effectively process, analyze, and store data, enabling them to make well-informed decisions. However, this development gives rise to significant concerns over privacy (Safdar et al., 2020).

The significance of data privacy has garnered considerable attention in recent years, mostly driven by legislation modifications such as the General Data Protection Regulation (GDPR) (Das A. K., 2018) implemented by the European Union and comparable endeavors on a worldwide scale. The General Data Protection Regulation (GDPR) safeguards individuals' rights in situations where their personal data is being processed by both the private sector and a majority of the public sector. This technology enables individuals to exercise enhanced control over their personal data. Furthermore, this initiative serves to update and unify regulations, enabling firms to streamline bureaucratic processes and benefit from enhanced customer confidence (Das A. K., 2018). The aforementioned requirements impose stringent criteria for the acquisition, manipulation, and retention of individualized information. Adherence to these regulations is crucial, as financial institutions are bound by both legal and ethical obligations to comply with them (Anant et al., 2020).

Privacy concerns can act as a deterrent for individuals when it comes to the disclosure of personal data, impeding the progress of pioneering financial enterprises and ultimately restricting the advantages that financial innovation has the potential to offer to consumers (Doerr, Sebastian & Gambacorta,2023). Regulators are confronted with a dilemma in which they must strike a balance between ensuring effective privacy regulation to safeguard users' privacy and preserving the advantages derived from intermediaries' utilization of data. The 2020 California Consumer Privacy Act (CCPA) has effectively addressed the trade-off. The underlying principle of the CCPA is to empower customers with the ability to exercise control over their personal data, thereby mitigating their worries about privacy (Doerr, Sebastian & Gambacorta,2023). Consequently, this fosters a greater inclination among users to provide their personal information. In a difference-in-

differences framework, an examination of FinTechs and banks in counties located on both sides of the California border reveals that the implementation of the California Consumer Privacy Act (CCPA) leads to a 2-percentage point increase in the market share of FinTechs (Doerr, Sebastian & Gambacorta,2023).

The preservation of consumer data privacy and security holds significant importance due to many factors. Primarily, trust is of utmost importance. Customers have high expectations about the careful and secure handling of their sensitive financial information. Failure to adequately safeguard consumer data can result in depletion of trust, imposition of financial penalties, and infliction of reputational harm. Keeping regulations in compliance is also necessary to prevent serious legal consequences (Anant et al., 2020).

3.2. Bias Issues

AI systems possess the capacity to sustain and reinforce biases that are inherent in historical data. The issue of accidental discrimination against specific demographic groups is particularly pertinent in the context of lending and underwriting practices involving AI systems (Mehrabi et al., 2021). The utilization of ML techniques has the potential to amplify biases present in historical data. The inclusion of a multitude of input variables in the model is a common practice among users, mostly due to the ability of ML algorithms to automate the process of feature engineering. Moreover, prediction problems do not require the execution of time-consuming tasks such as screening for multi-collinearity and variable selection. Consequently, it is possible that biases within the data and the existence of surrogate variables for protected qualities may go undetected (Zhou et al., 2022).

One major area where AI bias is of concern is in lending. Traditional lending decisions are based on factors such as credit history, income, and employment status. However, AI-based systems can consider a broader range of variables, including some that may indirectly correlate with protected characteristics such as race or gender. This can lead to biased lending decisions, despite such discrimination being illegal under laws such as the U.S. Equal Credit Opportunity Act (Mehrotra

et al., 2020). Investment algorithms possess the capability to make choices by taking into account a multitude of elements, such as firm performance statistics, market trends, and even sentiment research derived from news or social media sources. The presence of biassed training data within any of these domains has the potential to result in biassed investment decisions, impacting the inclusivity of investment portfolios and potentially breaching the fiduciary responsibility of investment managers (Arrieta et al., 2020). The presence of bias within AI-driven risk assessment tools in the field of finance can result in the perpetuation of unfair treatment. In the event that an AI system undergoes training using biased data, it may generate predictions of elevated default risks for specific demographic cohorts. Consequently, this could result in the imposition of increased insurance premiums or interest rates upon individuals belonging to those groupings (Mhasawade et al., 2021).

Although it may be natural to try to "de-bias" AI models by removing particular factors or qualities, this strategy has turned out to be less successful than first thought. The existing body of research in this particular domain has shed light on the intricate nature of bias in AI systems. It has been shown that biases can manifest in AI systems, even when deliberate efforts are made to remove specific variables. These biases can arise from correlations with variables that may appear harmless at first glance. This issue arises due to the ability of AI systems to detect latent patterns in data that may not be immediately discernible to human observers. Consequently, biases become evident through indirect associations (Pessach and Shmueli, 2022).

In order to reduce bias concerns, it is imperative for financial institutions to adopt proactive steps. This encompasses the ongoing surveillance of AI systems to detect and address biased outcomes, as well as the implementation of data preparation techniques to alleviate past biases present in training data. Regulations should mandate the regular testing and auditing of AI systems for bias and set guidelines for transparent and explainable AI (EU Commission, 2021). Moreover, an enhanced level of public awareness can empower individuals to advocate for fairer AI systems and instigate transformative shifts through consumer decision-making and public dialogue (Minh et al., 2022). The implementation of algorithmic fairness measures can contribute to the promotion of non-discriminatory decision-making by AI systems (Mehrabi et al., 2021).

The potential ramifications of unmitigated bias in AI-powered financial decision-making can have significant implications. The adverse consequences of this phenomenon extend beyond the harm inflicted upon individuals and communities, encompassing legal ramifications and reputational impact for financial institutions. Hence, the imperative to reduce prejudice extends beyond ethical considerations, as it plays a crucial role in upholding equity and fostering confidence in AI-driven financial systems (Mehrabi et al., 2021).

3.3. Accountability

The issues of accountability and explainability in the context of financial services powered by AI are sophisticated. Several AI models have "black box" characteristics that frequently obfuscate their inner workings, making it challenging for developers and regulators to comprehend how these models arrive at their results (Weber et al., 2023). The establishment of clear lines of responsibility is of utmost importance as AI systems function autonomously, devoid of direct human engagement (Weber et al., 2023; Busuioc M., 2021). The establishment of tools that facilitate the monitoring of decisions made by AI systems is integral to the promotion of accountability. Furthermore, it is essential to establish frameworks and standards that delineate the respective duties of financial institutions, developers of AI, and regulatory bodies (Busuioc M., 2021).

The new discipline of Explainable Artificial Intelligence (XAI) endeavors to tackle these concerns (Weber et al., 2023). XAI refers to a collection of procedures and techniques that facilitate the comprehension and establishment of confidence among human users in relation to the outcomes and outputs generated by the ML algorithms (Héder, M. 2023). XAI serves as a solution to address the inherent opacity of ML algorithms, the "black box" phenomenon, when the rationale behind a single decision made by an AI system remains inexplicable even to its creators (Héder, M. 2023). XAI has the potential to assist banks and financial sectors in effectively addressing concerns related to transparency and trust, by offering enhanced insights into their AI governance practices. By incorporating the concept of explainability into the current AI governance frameworks and procedures, financial institutions may guarantee that their AI systems are both efficient and transparent, hence allowing for comprehension and responsibility (Surkov et al., 2022).

Although XAI presents a possible remedy for the AI systems' "black boxes," it is not without difficulties, particularly in the financial sector. One of the primary obstacles encountered in the development of XAI for the financial domain pertains to the considerable intricacy inherent in the algorithms employed (Weber et al.,2023). The current state of the technology is in its early stages, and there exist concerns regarding the trade-off between explainability and accuracy (Patel M., 2020). In essence, there exists a compromise between the interpretability of a model and its performance (Patel M., 2020). Furthermore, the broader implementation of XAI within the organization entails a complex and sequential procedure (Surkov et al., 2022). Implementing these changes requires modifications to the data sources, development of the model, interaction with diverse stakeholders, the establishment of governance systems, and collaboration with third-party vendors (Surkov et al., 2022). For numerous businesses, particularly those with restricted resources or low proficiency in AI, this undertaking can be perceived as challenging. Furthermore, there exist apprehensions regarding the potential impact of implementing XAI on the intellectual property (IP) of the organization. The increasing transparency and comprehensibility of AI models offer a potential threat of disclosing confidential information (Patel M., 2020; Weber et al.,2023).

3.4. Need for Education and Training for Employees to Adapt to New Technologies

The rapid evolution and integration of AI into the workplace necessitates a parallel evolution in employee skills and competencies. As AI alters the way work is performed, it becomes essential to equip the workforce with the necessary knowledge and abilities to adapt to these changes. This section explores the need for education and training to facilitate employee adaptation to AI technologies.

3.4.1. The Impact of AI on the Workforce

The influence of AI on the labor force within the financial sector is significant and encompasses various dimensions. To begin with, AI has the capability to revolutionize internal administrative functions by converting them into externalized services. In order to enhance their skills and prevent falling behind, institutions have the opportunity to utilize AI-enabled operations, hence compelling others to adopt and utilize these capabilities (Fares et al., 2022). This transition not only enhances the pace at which these skills advance but also transforms cost centers into profit centers (Fares et al., 2022).

Additionally, AI is emerging as a novel arena for the competition of client loyalty. As traditional approaches to differentiation diminish, the emergence of AI offers institutions the prospect of breaking free from a downward spiral of price-based competition. This is achieved by introducing novel strategies to effectively set themselves apart from competitors, hence enhancing their appeal to customers (Fares et al., 2022). The forthcoming customer experiences will revolve around AI, which effectively automates a significant portion of clients' financial activities and enhances their financial results (Fares et al., 2022).

Moreover, AI is facilitating the development of collaborative approaches to address common challenges. The utilization of shared datasets in collaborative solutions has the potential to significantly enhance the accuracy, timeliness, and performance of non-competitive tasks. This, in turn, can lead to mutual efficiencies in operations and contribute to the overall safety of the financial system (Fares et al., 2022; Boukherouaa et al., 2021). Nevertheless, the management of alliances with both current competitors and potential competitors will be of utmost importance, while it will be accompanied by significant strategic and operational risks (Fares et al., 2022).

Furthermore, AI is causing a division in market structures. The reduction in search and comparison costs for customers facilitated by AI technology will exert pressure on company structures, leading to the proliferation of market extremes. This phenomenon will result in enhanced returns for large-scale companies and the emergence of novel prospects for niche and agile innovators (Fares et al.,

2022; Boukherouaa et al., 2021). The transition at hand presents a range of difficulties and prospects for the labor force within the financial sector.

Finally, the process of talent transformation will pose the greatest obstacle to the successful integration of AI within institutions (Fares et al., 2022). Firms and areas that do not adequately manage the shift of talent alongside technology face a potential risk to their competitive positioning (Fares et al., 2022). Hence, it is important to ascertain a harmonized methodology toward talent acquisition in the current epoch of the AI-powered revolution within the banking sector (Fares et al., 2022).

3.4.2. The Need for Education and Training

The application of AI in financial services has given rise to novel positions and responsibilities within the industry. These positions necessitate a distinct combination of competencies, encompassing expertise in AI technology, comprehension of financial systems, and the capacity to analyze and implement AI results within a financial framework (Chaudhry and Kazim, 2021). Because of this, educational institutions, and training programs must modify their curricula to give pupils these abilities. One potential approach could be the implementation of multidisciplinary courses that integrate the fields of finance, computer science, and data analysis (Chaudhry and Kazim, 2021; Cao L., 2022).

The rapid advancement of AI technology requires individuals in the financial sector to actively participate in continuous education in order to remain up to date with the most recent advancements (Gadd et al., 2021). The facilitation of this objective could be achieved by implementing frequent training programs, workshops, and seminars that specifically concentrate on the most recent breakthroughs in AI and their practical applications within the realm of finance (Cao L., 2022). Additionally, there is a requirement for tailored training courses for various financial sector professions. For example, individuals working as financial analysts who utilize AI technologies for the purpose of risk assessment or investing strategies may necessitate specialized instruction in the utilization of particular AI models and algorithms. Similarly this, IT specialists

who create and manage these AI technologies might require training on the legal requirements and moral standards unique to the financial industry (Chaudhry and Kazim, 2021; Gadd et al., 2021).

Regulatory agencies assume a pivotal role in influencing the educational and training requirements within the financial sector. These organizations need to lay forward standards for the knowledge and abilities required of experts in this area as they create legislation for the use of AI in finance (Gadd et al., 2021). This measure will guarantee that educational and training programs are in accordance with legislative mandates and industry demands (Gadd et al., 2021).

3.5. Potential for Increased Efficiency and Cost Savings

A real case example of reducing costs is Datamatics, that is a company headquartered in India specializing in data management services using AI strategies, assisting a prominent financial institution in the United States with the categorization of more than 1.8 million unstructured mortgage papers. The organization was required to integrate the mortgage documents into a unified document management system to facilitate subsequent retrieval (Shmat, D. 2022). In order to efficiently index and categorize a vast collection of over 35 million mortgage papers into a comprehensive set of 275 categories, Datamatics developed a sophisticated workflow that incorporates Optical Character Recognition (OCR), Robotic Process Automation (RPA), NLP, and ML techniques. Consequently, the bank had a notable enhancement in classification accuracy, with an increase of 87%. Additionally, operational costs were cut by half, leading to substantial savings of over 150 man-hours on a monthly basis (Shmat, D. 2022). In the following sessions, we will explain in detail about this matter.

3.5.1. Automation and Efficiency

The utilization of AI-driven chatbots has the potential to facilitate communication between financial organizations and their clients. In addition, ML algorithms have the capability to facilitate algorithmic trading and can be utilized for risk management, fraud detection, and relationship management (Crenshaw S., 2021). Automation not only enhances the efficiency and effectiveness of several operations, but it also aids in the mitigation of human biases and the prevention of

failures resulting from sensitive or psychological factors (Crenshaw S., 2021). Moreover, the utilization of AI-powered automation has the potential to substantially decrease the amount of time and resources necessary for tasks such as data analysis, risk assessment, and customer support (Coombs et al., 2020). This, in turn, can lead to enhanced operational efficiency. Furthermore, the ability of AI to automate processes that are repetitive and based on predefined rules has resulted in the allocation of human resources toward activities that are more strategic in nature and provide greater value (Li and Xu, 2021).

Efficiency within the financial sector is more than mere cost reduction and expedited transaction processing; it also encompasses the effective management of risks. The utilization of ML algorithms for the purpose of real-time identification and evaluation of prospective hazards has been emphasized (Brealey et al., 2020). This use of ML algorithms helps reduce the occurrence of unforeseen financial downturns. In a particular instance, a research study employed an adaptive whale optimization algorithm in conjunction with a DL technique to develop a novel model for predicting financial distress (Elhoseny et al., 2022). The findings indicated that this method shown superiority when compared to alternative techniques, such as logistic regression and radial basis function network, as it achieved an average accuracy of 95.8% (Elhoseny et al., 2022). This creates a notable potential for the sector to prevent systemic crises while also assuring the effective deployment of capital (Brealey et al., 2020).

The process of conducting a bank audit and maintaining proper paperwork is widely recognized as both arduous and indispensable for every financial institution. Auditors dedicate significant amounts of time to regularly scrutinize documents in order to verify adherence to regulatory standards. AI and ML methodologies can be effectively employed to analyze extensive volumes of textual content and identify salient information, so enabling banks to significantly reduce their expenditure on billable hours (Shmat, D. 2022). For instance, Quon- tic, a small bank headquartered in New York, has implemented a novel ML-based task automation solution in addition to its existing legacy platform. During the period from October 2018 to November 2019, Quantic has observed significant growth in several metrics as it strives to enhance digital customer experience and address the issue of serving individuals who are unbanked or underbanked. There has been a significant surge of 210% in the overall count of banking clientele. There has been a

significant growth of 100% in the number of newly acquired customers in the personal banking sector. There was a substantial surge of 261% in retail deposits. There has been a notable 15% year-on-year increase in financing growth.

The initiative played a crucial role in enabling Quantic to maintain its agility and competitiveness within a market that is predominantly controlled by large industry players. Since the inception of the program, the bank has expanded its headquarters by an additional 20,000 square feet of office space, established a dedicated mortgage lending team, and is on the verge of inaugurating a novel New York office with the primary objective of catering to the Chinese American community (Shmat, D. 2022).

3.5.2. Cost Reduction Through AI

Financial institutions face an ongoing problem in finding the right equilibrium between innovation and cost reduction. They must navigate this delicate balance as they strive to lower expenses while simultaneously investing in new projects for application development (Rodriguez J., 2023). Throughout history, companies have traditionally depended on expensive external solutions in order to effectively discover potential areas for cost reduction. Nevertheless, the topography is undergoing swift transformations, as the advent of AI and ML has inaugurated a novel epoch of potentialities (Rodriguez J., 2023).

These advanced technologies offer cost-effective choices for identifying efficiencies in financial processes, whilst improving the quality of services provided (Rodriguez J., 2023). In the current dynamic business landscape, the utilization of AI and ML is emerging as a transformative factor for companies aiming to excel in a progressively competitive market (Rodriguez J., 2023). The utilization scenarios for these technologies are consistently broadening and enhancing, exerting a profound influence on the sector in manners that were previously inconceivable. For instance, the implementation of AI in automating middle-office processes has the potential to yield substantial cost savings for North American banks. It is projected that by the year 2025, these banks might achieve savings amounting to $70 billion (Insider Intelligence, 2023). Moreover, it has been expected that the collective potential cost savings for banks resulting from the implementation of

AI applications would reach $447 billion by the year 2023 (Insider Intelligence, 2023). Notably, the front and middle office sectors are projected to contribute $416 billion to this overall sum (Insider Intelligence, 2023). Furthermore, it is projected that the implementation of AI and augmented technologies would result in a substantial financial benefit for global financial services organizations, amounting to around $140 billion in productivity enhancements and expense reductions by the year 2025 (Cushing J., 2020).

3.5.3. Challenges and Considerations

The attainment of automation and efficiency through AI necessitates a workforce possessing expertise in the domains of data science, ML, and AI. As the financial sector increasingly adopts AI in its operations, it is imperative to strike a delicate equilibrium between optimizing productivity and preserving client trust and engagement (Cao L., 2022). Financial institutions must make sure that AI-driven operations are open to the public and focused on the needs of their customers in order to prevent automation from eroding the personal touch.

Although AI has the potential to decrease operational expenses in the long run, it is important to acknowledge the significant initial investments required for the development, implementation, and upkeep of AI systems. Financial institutions are required to spend substantial resources towards the development of AI infrastructure, effective data management systems, and comprehensive staff training (Maple et al., 2023). The precise expenditure is subject on regional disparities and specific configurations, but it often necessitates an annual investment exceeding $50 million in infrastructure (Appenzeller et al., 2023). In 2020, the average expenditure per employee for employee training by corporations was $1,111 (Malik P., 2023). There was a significant increase in the annual number of training hours per employee, rising from 35 hours in 2020 to 63.9 hours in 2021 (Statista Research Department, 2023). The cost for specialized AI training tailored for financial companies might commence at £600 (Mark Schlesinger, 2023).

3.6. Improved Customer Experiences and New Opportunities for Revenue Streams

The integration of AI in business operations presents unprecedented opportunities for enhancing customer experience and developing new revenue streams. This section explores how AI technologies can revolutionize businesses by creating personalized customer interactions and opening avenues for additional income.

3.6.1. AI and Enhanced Customer Experience

AI is set to have a pivotal role in shaping the trajectory of customer experience in the future. The proliferation of AI is becoming evident across all domains, exerting a transformative influence on the manner in which customers engage with brands. It is projected that AI technology will provide support for around 95% of customer contacts by the year 2025 (Edelman et al., 2022). AI facilitates the acquisition of customer insights for the purpose of improving personalization, encompassing many aspects such as chatbots and automation, within the context of brand operations (Edelman et al., 2022).

The conventional routes for customer service were facing challenges in meeting the demands of technologically inclined customers who wanted customized and immediate encounters. Regarding the employment of AI to enhance the customer experience, we can mention about the Global UK Bank. They used generative AI to develop the virtual customer care representative known as "Genie" (Bhattacharya G., 2023). The training of Genie involved extensive utilization of past customer data, transaction patterns, and frequently asked questions from a diverse range of sources. The Genie was enabled to partake in natural language dialogues, respond to inquiries, and provide personalized financial guidance. Prior to the installation of the system, the average duration of Talk Time per customer interaction was 8 minutes. However, following the setup, this duration decreased to 4 minutes per customer engagement (Bhattacharya G., 2023). Furthermore, prior to the deployment, it was observed that 15% of customer contacts necessitated either follow-up or several encounters in order to effectively address and resolve any issues (Bhattacharya G.,

2023). Nevertheless, subsequent to the deployment of this system, it has been seen that 5% of customer contacts necessitate further follow-up or numerous encounters in order to effectively address and resolve concerns. This represents a significant drop of 66.7% in comparison to the previous rate (Bhattacharya G., 2023).

AI has the potential to enhance the onboarding procedure for newly acquired consumers. The procedure frequently encompasses the verification of one's identification (commonly referred to as Know Your Customer or KYC checks), evaluation of product appropriateness, credit rating, and scrutiny for potential sanctions (Schuld et al., 2020). ML has the potential to facilitate the authentication of a customer's identity through the use of facial biometrics to compare government-issued identification documents with a corresponding image or video of the customer. Monzo, a challenger bank based in the United Kingdom, is frequently mentioned as an illustration of a financial institution that has effectively utilized AI to fulfill its Know Your Customer (KYC) and Anti-Money Laundering (AML) compliance obligations (Schuld et al., 2020). In addition, AI has the potential to deliver significant benefits to clients over the course of their interactions with a financial institution by offering valuable insights into their banking behaviors. ML-based real-time fraud management solutions can also assist banks in comprehending typical transaction patterns and identifying instances of fraudulent actions (Schuld et al., 2020).

3.6.2. AI-Driven Revenue Streams

The financial industry is experiencing a dramatic transformation in revenue streams as a result of the integration of cloud-based solutions, which is being facilitated by AI (Hussain M., 2023). Banks are progressively utilizing these solutions to effectively store, process, and analyze substantial volumes of data, hence enabling the extraction of valuable insights pertaining to customer behavior and market trends (Hussain M., 2023). The utilization of data-driven methodologies enables financial institutions to develop customized products and services, leading to an augmented level of customer contentment and ultimately fostering revenue expansion (Hussain M., 2023).

AI also generates substantial increases in income in domains such as Marketing and Sales, Strategy & Corporate Finance, and Supply Chain Management (Columbus L., 2020). The

utilization of AI in various domains facilitates enhanced operational efficiency, superior decision-making capabilities, and enhanced business performance (Columbus L., 2020). This phenomenon not only contributes to heightened levels of client involvement but also yields greater sales and revenue (Columbus L., 2020)

Chapter 4

Conclusion

Potential Future of These Industries with Growing Integration of AI The objective of this thesis has been to investigate the application of AI in the financial services sector and analyze its impact on contemporary society. Moreover, our research has encompassed an extensive examination of the diverse problems, opportunities, threats, and uses that AI presents to both our finance industry and the international economy.

The introduction of developing technologies has continually exerted a significant influence on several industries by improving existing industrial processes, services, consumer experiences, and other aspects. AI is presently making notable advancements across many sectors, such as manufacturing and retail (Haefner et al., 2023). Numerous industries, aside from the financial industry, face obstacles in the successful implementation of AI as a result of diverse constraints. The problems encompass a range of factors, such as the growing threat of cyber hazards, elevated customer expectations, stronger competitiveness, and more strict regulatory measures (Dahlin E., 2021; Hicks J., 2023). Nevertheless, AI presents distinctive approaches that have the potential to foster advancements and creativity in many areas, ultimately helping consumers and the financial industry as a whole (McKinsey & Company, 2023). AI offers the financial sector a new method for effectively dealing with occurrences of financial fraud, thereby promoting confidence, and developing a robust financial ecosystem (Drenik G., 2023a). The ongoing progress in AI is facilitating rapid and effective identification and capture of individuals involved in fraudulent activities. Additionally, the financial industry holds potential for future applications of AI in areas such as customer service and the marketing of financial products. In its capacity as a robo-advisor, AI has the capability to propose modification to investment portfolios (FM Contributors, 2023a). Moreover, there is a projection that the use of AI will potentially proliferate in the next years with regard to the selection of suitable life insurance policies (Ladva and Grasso, 2023). When it comes to personal finance, individuals are anticipated to proficiently handle their personal financial affairs by utilizing a financial "dashboard" that enables immediate access to all relevant financial data (FM Contributors, 2023b).

The adoption of AI in the financial industry is contingent upon several criteria. These considerations include the scale, location, and nature of the financial institution. Nevertheless, the extensive adoption of cutting-edge AI approaches in the worldwide financial industry is impeded by the significant costs linked to this technology (NVIDIA, 2023). Smaller financial institutions and organizations encounter a double problem. First, constrained financial resources may impose limitations on their capacity to invest in novel technologies, recruit proficient workers, and extend their business activities (Desai, M. A., 2023). Second, the limited availability of data can place these institutions at a comparative disadvantage in relation to larger organizations that possess greater resources and enjoy access to more extensive datasets. (Desai, M. A., 2023). The substantial quantity of everyday contacts between a prominent financial institution and its clientele yields a considerably more comprehensive dataset, which serves as the primary input for AI applications. On the other hand, a few financial institutions located in an emerging nation does not possess this advantageous characteristic, thereby constraining the prospective advantages for the deployment of AI. An exemplification of this phenomenon can be observed in the continuous pressure encountered by prominent financial institutions to simultaneously get new clientele and uphold the loyalty of their current consumer base. As a result, major financial institutions inherently place high importance on continuously improving their range of products and services, as well as using chatbot-driven automation to streamline customer support operations. In a similar vein, insurance companies are actively working to enhance their AI risk models, while hedge funds are seeking to optimize the alpha coefficient through the use of AI technology in conjunction with innovative data sources (McKinsey & Company, 2023). The implementation of data infrastructures that enable the effective use of AI continues to pose a significant issue for many financial institutions and organizations operating in developing countries. The aforementioned observation underscores the disparate implementation of AI across the international financial sector.

However, these advancements also carry potential risks to the financial sector, which could result in market destabilization within an extremely short timeframe (Kuzior et al., 2022). The establishment of comprehensive regulatory frameworks concerning data security and market integrity, along with the adoption of suitable regulations and policies to address algorithmic errors

while promoting innovation, plays a crucial role in facilitating the progress of AI sophistication (Kuzior et al, 2022).

The topic of AI and its implementation in the financial sector is currently a prominent subject of discussion. It is widely acknowledged that academic research on this matter often lags behind due to the time-consuming publication procedures. Consequently, the scarcity of scientific papers in this field has been compensated by alternative sources such as expert opinions and comments from the blogosphere, reputable publications like Financial Times and Forbes, insights from Microsoft, conference presentations, reports from various organisations and institutions, as well as literature available online from insiders, owners, and founders of AI companies in the financial sector. This implies that technology is not lagging behind, since it enables the rectification of various flaws and enhances user experiences, akin to the realms of finance and AI.

The potential outlook for AI-driven trading methods appears to be highly favorable. With the ongoing advancement of technology, it is anticipated that these methods will progressively evolve to be more refined and precise. Nevertheless, it is imperative to acknowledge that although AI has the potential to augment trading techniques, it does not ensure absolute success. The efficacy of these tactics remains contingent upon several factors, including market conditions and the integrity of the underlying data (Canals, J. et al., 2020).

It is anticipated that by the year 2030, individuals would increasingly rely on interconnected AI within intricate digital systems (Hunt W., 2020). AI possesses significant potential to either facilitate or impede numerous sectors. In the realm of technology, it is widely acknowledged that there are virtually no boundaries or limitations. Amidst the imminent transformations, it is imperative for both workers and consumers to possess the capacity to adjust, since we are on the brink of inhabiting a realm characterised by enhanced and more sophisticated technology. The advancement of AI is evident in the quick evolution of technologies. The phenomenon under consideration is characterised by a combination of exhilaration and apprehension, rendering it a compelling yet daunting aspect of financial markets and services. AI will have a transformative impact on the globe surpassing any other development in human history. The significance of the subject matter extends beyond the realm of electricity (Thomas, 2020). Presently, in the

foreseeable future, AI persists as the primary catalyst for burgeoning technologies, ushering in a paradigm shift in several facets of society, including daily routines, commercial enterprises, and market dynamics. In order to secure a position of success, individuals must adequately equip themselves to confront the forthcoming alterations and obstacles (Hunt, W., 2020).

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