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Chapter 1: The financial frontier: Redefining traditional finance in the era of artificial intelligence

1.1. Introduction

In the past several decades, both financial structures and technologies of financial products have evolved dramatically. With the emergence of social networks and mobile Internet, the vast amount and complexity of financial data have grown exponentially. Market participants become incredibly heterogeneous; signals of emerging platforms spread globally too quickly and have a more dramatic impact on decisions. Unavoidably, the complexities and uncertainties of the environment have generated considerable challenges for financial decision making (Shaffer et al., 2020; Ajay Bandi et al., 2023; Bi & Bao, 2024).

As the core technology of the new technological revolution, artificial intelligence (AI) offers effective tools to redefine finance and has profoundly transformed financial systems. AI broadly refers to the simulation of human intelligence by computer. Additionally, AI technique works dynamically across different time scales to judge the independent value of historical events through the structure of event impact propagation networks and builds a causal governance/network model that aids the interpretation of AI techniques in finance. AI-enabled finance will bring new dividends to boost the global economy, improve risk control, regulate marketing, and protect investors. However, learning trustworthy AI in finance is challenging because of its unrealistic assumptions, implementation limitations, and financial decision realization limitations. Finance lags in AI governance with challenges in responsibility, accountability, fairness, and privacy. Concerns and new concerns in terms of ethical AI, AI in algorithmic trading/money laundering/fraud detection, and ‘AI fatigue’ become more severe.

The capital market service providers, otherwise known as the next generation financial technology, comprise a FAI/machine learning-based technology group. They consider developing new AI-based products as the essential requirement, focusing on the hidden knowledge potentially available from the data of clients/services and expertise, i.e. the information inside the big data. The data intelligence policy is to mine this information knowledge by means of matching the big data with the FAI 2.0 algorithms and comprehension models. In the investment banking industry, the AI/FAI agents are designed to develop self-learning and adaptive smart systems that change and learn without being explicitly programmed or described.

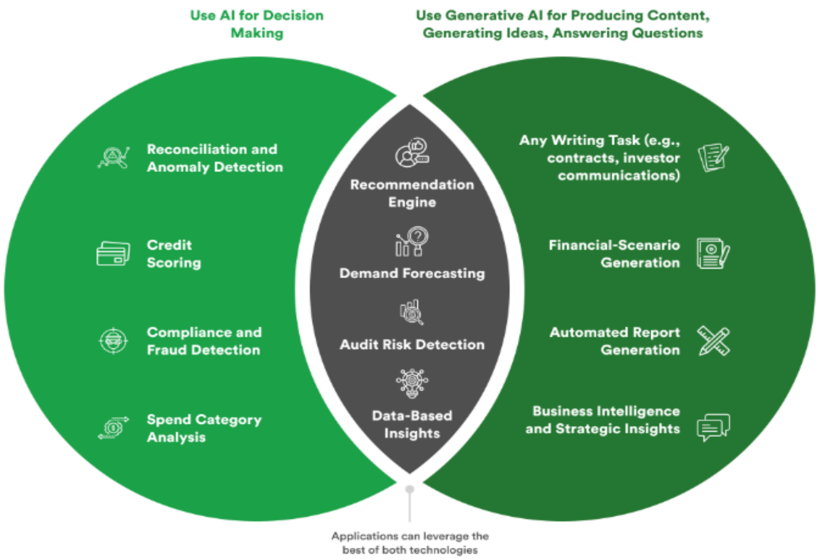

Fig 1.1: Frontier in Financial Services

1.1.1. Background and Significance

Human finance initially consisted of social exchanges of goods and services without the involvement of currency, a fiat. With time, gold became an accepted commodity, a currency against which paper-based bonds were issued, and then banks appeared. In such human-based finance, complex transaction systems performed business transactions and methods were created to price financial products. Relatively simple, mathematical pricing models were developed for derivatives based on complete market and risk-neutral martingale assumptions. These models were refined through a financial engineering revolution that systemized mathematical statistics-based financial systems and produced more accurate pricing with respect to data and information. Unfortunately, the traditional financial systems were unable to predict the unpredictable and the credit crisis led to a global financial disaster.

While human trading institutions, hedge funds and investment banks have special financial intelligence on top of perfect technologies, such human cognitive computing-hardware networks still account for less than 10% of the total market capitalisation. It is a race between human-financial artificial intelligence (FAI)/computational finance systems and financial intelligence machines. Big data, technology, and liquidity are the core themes of the era of the financial big machine. The technological transformation and financial/big data intelligence industries via blockchain, as the AI 2.0 root architecture, are produced by technology-centered capital market service providers in response to any market stage. The AI 2.0 applications of the capital market include textual/clinical big data prediction, recommendation system, financial data bus and events extraction, arbitrage machine vision, multi-object tracking landmark/well prediction, streaming big data news/image/text/data prediction extraction, sentiment analysis/market reaction/effect and other financial intelligence.

1.2. The Evolution of Finance

FinTech has become a buzzword over the past few years, like many other terms, and people's perceptions of it broadly but vaguely range from brave new worlds, slow motions, wrappers of old finance, to gimmicks dreaming of easy cash. If retrospective dimensions are allowed, there are two extremes rooted in earlier eras. The first type is known because there were very few financial innovations and disruptions before the 1980s. More recently, the second finance revolution began with the advent of the Internet stocks in the late 1990s (as a burst, but its underlying technologies continued). A technological movement for real digital finance began with advancements like the establishment of Alipay, decentralized finance, and the launch of Bitcoin in 2009. Nonetheless, the current era of finance redefinition is not based on a single technology such as the internet or blockchain.

The most representative event marking the current frontiers of finance may be the complete chip deflation of the shorts on GameStop stocks on 26th January 2021. This event happened within 2 days and triggered a moonshot increase in GameStop stocks, taking them from 40 USD to 450 USD or even more. Two platforms played crucial roles: Reddit forum r/wallstreetbets, where anyone could freely share opinions about investment, discuss stocks/topics, and retweet ideas that could easily trigger momentum for short-clamping or pump-missing; therefore, this platform can be seen as an instant and efficient AI crowd-sourcing tool. In addition, Robinhood restricted the buy orders of the highest-boarded stocks and stopped trading at the peak, which can be understood as the first exercise and tool of machine-learning denormalization and black-shoe traffics.

This ecosystem constructed by these platforms and transferred from ivory towers to public retailers suddenly gave many a feeling of the gaming engine, where traders may become hunters, preys, or keep quiet and watch. Participants of the modern Behav-Fin and Game Theory have a limitless space for playing the game of million-dollar hands. Emotions like fear of missing or regret of holding, greed of shorting, and panic of selling overflowed, too. Money on the board became meaningless and was gradually replaced by recognition and meme labels. Like other complex adaptive systems, the discussed fin-tech should evolve with an ever-changing thought-structure-movement-growing economy and society.

1.2.1. Historical Overview

The integration of AI in finance has a development history going back to the latter half of the 20th century. After World War II, financial institutions embraced operations research for quantitative modelling and analysis to improve business operations. A widely-adopted off-the-shelf analytical system was the Swift Financial Schematic. SFS is a rule-based system that was popularly applied in banks for automating collateralized loan evaluation and approval. Hand-crafted sets of rules were built by business analysts and risk analysts based on their finance domain knowledge and experience, and then coded into the SFS programming language. This high level of automation addressed problems such as increasing loan processing throughput and meeting timely business demands. The SFS syntax was like rule-based programming languages due to its flexibility in handling any application and its rigorous syntax. However, such rule-based systems had trouble dealing with the growing complexities and availability of financial data entering banks.

Over the past two decades, as more financial data has become readily accessible, machine learning techniques, specifically supervised learning and deep learning, have been adopted by a broader range of financial institutions. Financial institutions need to gain insight into complex high-dimensional time-series data, including diverse forms of structured and unstructured financial data. Such high-dimensional data pose enormous challenges in information collection and representation, and understanding, which has transformed with new data collection and representation technologies. In contrast to the information collection and representation challenges, recent years have seen the emergence and boom of diverse forms of data presentation technologies. Words, numbers, images, sounds, graphs, videos, etc., can now be collected and represented using powerful technologies. For example, news articles are now daily available in different texts, images, and videos, and they have vastly changed stock price movements and the moods of retail investors.

Modern AI technologies, specifically ML and deep learning techniques, have become popular and readily usable tools for extracting insights from massive amounts of financial data. Such techniques have been widely applied in abnormal event detection, quantitative trading, risk analysis, sentiment analysis, and many other important businesses and areas. New AI application opportunities as well as associated technical challenges have arisen. It is becoming a promising research area due to the broad and rich aspects of financial business, data, and techniques. Many classic AI techniques have been and are being actively applied or transferred and improved for existing applications, while many state-of-the-art advancements in modern AI, especially in ML, data mining, and computer vision, are rapidly being adopted and tailored for finance-related businesses.

1.2.2. Key Milestones in Financial Development

Financial intelligence has emerged as a new field involving the use of advanced techniques from mathematics and computer science, including tactics from artificial intelligence (including machine learning), signal processing, statistics, etc., to extract useful information from financial data and thus provide intelligence services to investors and businesses in finance and related areas [1]. With the introduction of portfolio selection, optimal asset allocation becomes a long-lasting challenge in the field of finance, and optimal asset allocation guides investors to achieve favorable investment return gearing risks on various financial instruments including stocks, funds, bonds, etc. The architecture of financial intelligence is composed of information service layers, service layers, and information input/output layers. In the information service layers, platforms and models are established to provide extensive information services to customers. Such service layers can tackle many sub-challenges in finance and the related areas, including wealth management, risk management, credit scoring, financial consulting, financial security, and monitoring tools for the stock exchange, blockchain, and so forth.

The financial intelligence field is still in its infancy. Most of the existing works can only be recognized as either algorithm-centric or application-centric studies. In addition, the methods in most financial intelligence studies are so engineering-oriented that they cannot be applied directly to real scenarios without extensive modification. Since financial intelligence has the potential to become a 'financial brain', several possible major technical focuses and direction in the future are discussed. Thanks to the explosive growth of financial data (ranging from price, and volume-to-news, and sentiment), a machine learning-based intelligent quantitate trading system to automatically implement a long/short equity trading strategy is put forward. However, after many years of development, the trading strategy generated by such methods has not been marketable yet because of its unreasonable execution price. To fill the gap, an order price estimation method is utilized to perturb the execution price according to its price impact and market impacts (or fairness). Moreover, thanks to the Eureka effect, there is a sudden increase in trading volume when earnings reports of companies have a large impact on the stock. Thus, computer vision techniques are employed to monitor the entire Chinese stock market for stocks with abnormal price movement and change in trading volume ratios, and these stocks are regarded as suspected meteoric stocks to alert investigation departments.

1.3. Artificial Intelligence in Finance

Finance is the core engine of wealth creation and economic growth, and financial systems integrate a variety of business, legal, regulatory, credit, market, and investment activities in which huge amounts of funds and capital flows around the world. All these activities have their own complexity and dynamics. AI has penetrated into most of the activities in today's finance industry ranging from stock picking/execution and robo-advising services in personal finance, algorithmic trading and high-frequency trading in asset management, credit assessment and suspicious transactions detection in risk management, to insurance policy pricing and claim fraud identification in insurance. The essence of AI-driven solutions is to extract knowledge and insights from data generated by complex systems, so as to uncover deeper characteristics, rules, patterns, and dependencies of these systems to better understand, model, analyze, optimize, and manage events, processes, and mechanisms. However, recent rapid development of AI brings unprecedented challenges for traditional finance including the new types of data presented in an unprecedented scale/volume, variety, velocity, and veracity. Finance is an interdisciplinary field that draws from mathematics, statistics, economics, computer science, operation research, etc. For centuries, the financial theories and mathematics models proposed are mainly Euclidean models and theories. But recently, data have been projected into a non-Euclidean space. The Euclidean models still shed a lot of light on understanding the behaviors of economic agents, but they have limitations in capturing the highly volatile nonlinear coupling and interconnectedness among agents in the networks wherein agents interact with each other. To deepen understanding of this complex and dynamic financial world, a new class of mathematical and statistical models is required. For example, the complexities of network systems wherein agents with heterogeneous structures and interactions are embedded require network-based modeling.

Then, these interpreted data are mined and processed to find complex hidden patterns to provide knowledge and predictions. Based on the understanding and knowledge, AI can also make decisions and suggestions (as being instructed) and consequently perform actions. From the application perspective, AI tools are to automate and enhance processes and systems in a wide range of areas. In research, AI generally focuses on algorithms and mechanisms for intelligence in complex systems. It is now widely believed that AI will reshape future finance along with the fast developments of Internet-of-Things (IoT) and big data.

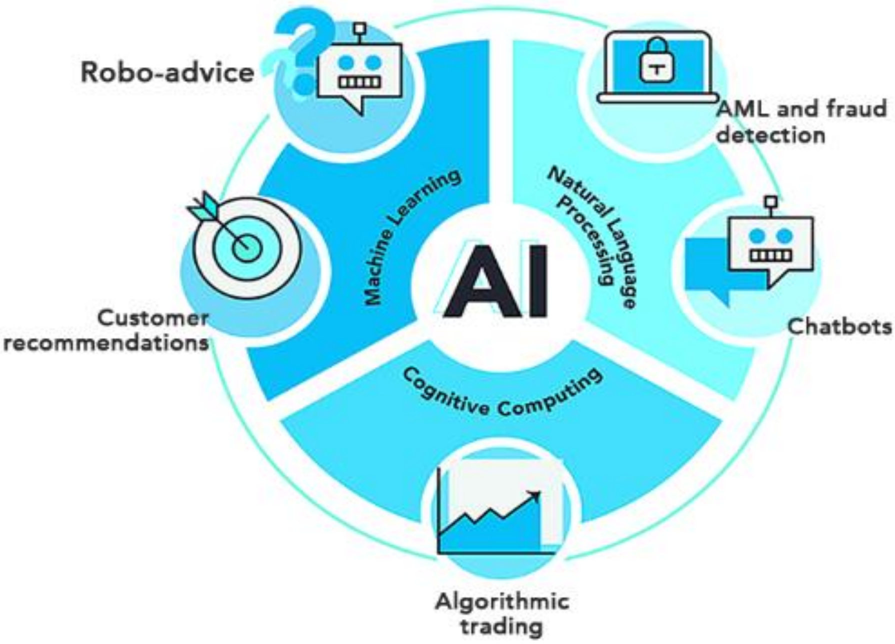

Fig 1.2: Artificial Intelligence in Financial Services

1.3.1. Overview of AI Technologies

Artificial Intelligence (AI) is the simulation of human intelligence processes by machines, mainly computer systems. According to the classification of AI technologies, there are three basic types of AI technologies: artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI). In the current market, most AI applications, including those in finance, employ narrow intelligence, which is focused on a specific task like driving, image recognition, or language translation. Some progress has been made in developing general intelligence, but its totality is so extensive that it is beyond the current capabilities of machines. Thus, the motivations for it are still tentative and unclear. AI has been extensively reviewed in the general literature. But the development and applications of AI tools in finance have only recently started to get attention.

Artificial Intelligence (AI) has been attracting attention from both academia and business for decades since AI prompts breakthroughs in automation and intelligence. It generally refers to the simulation of human intelligence processes by computers and other intelligent devices, including learning, reasoning, and self-correction. By mimicking human vision, hearing, text, and other physical senses, AI can understand and interpret input data.

1.3.2. Applications of AI in Financial Services

AI applications in Finance can be broadly classified into these categories: Automated Trading System, Fraud Detection & Prevention, Risk Management, Customer Service, Market Forecasting, Financial Advisory Services, Underwriting Credit, Tax Compliance, Prevention of Money Laundering, Budget Forecasting and Portfolio management.

1. Automated Trading System

With AI set in algorithms, it has become possible for traders to leverage automated trading systems to automate trading, analyze market trends and come up with predictions. Investment firms can automate the entire investment process, from investment opportunity recommendation to execution, using AI technologies. According to an estimate, 54% of institutional investors believe AI investment systems will have a significant impact on the investment process.

2. Fraud Detection & Prevention

With the extent of digitization and online transactions in finance, there have also been an ever-growing variety of fraudulent activities in finance. Detecting fraud is tremendously useful in the Finance Industry, especially in credit and debit card payments. AI has become an integral part of fraud detection systems. For financial institutions, fraud detection is a key part of their business and is always bound by heavy regulations. Payment processing networks process billions of transactions across the globe. They need to implement fraud detection systems before approving every transaction.

3. Risk Management

AI for Risk Management is used in Finance to predict and analyze financial risks for individuals and institutions and create tailored solutions or financial products. For lenders or credit institutions, AI is widely used for credit and mortgage fraud detection and prevention, default prediction, credit rating, and risk management.

1.4. Impact of AI on Traditional Financial Models

The advent of AI in the finance industry signifies a transformative shift akin to the rise of the internet in the 1990s. AI encompasses a variety of computer algorithms capable of executing tasks that are typically assigned to humans, leading to automation. These algorithms differ from machine learning and traditional statistics, primarily due to their ability to both generate recommendations and make decisions, impacting real-world environments. AI's chief utility lies in its exceptional capacity to automate classification and prediction tasks, exploiting structures in massive unstructured datasets. The relatively small financial datasets have made it challenging to use AI effectively until recently.

The two primary objectives of a financial authority include microprudential regulation of individual firms and macroprudential regulation concerning financial stability. The perils of financial institution data at the daily operating level are more foreseeable than for systemic activities. AI is generally expected to be advantageous for microprudential regulation, which is concerned with day-to-day questions such as those surrounding risk management and fraud. However, macroprudential regulation is more challenging to conduct and less precise, leading to uncertainty regarding AI's capabilities, benefits, and the dangers that can emerge from its use.

AI is more useful when the processes it is applied to include a great deal of data, are mechanical, adhere to specified rules, and have clear loss functions. In the financial context, few applications fit the description. However, some also remain cautiously pessimistic about AI's potential to breach the foundation for fair and rational finance in an abstract, undiscovered manner. The AI tools appearing in the finance field include artificial neural networks (ANNs), who imitate the information processing ability of the human brain by linking the attributes and mapping input-output pairs in the training data.

1.4.1. Disruption of Banking Operations

Just as the telegraph and the telephone fundamentally altered how individuals communicated, the internet and mobile telephony altered how they transacted. They shattered the business models of many telecommunication firms that had monopolized the market by focusing consumers' attention through scarcity. The enormous disruption brought by technologically driven transactions, dubbed "disintermediation," was regarded by many as a once-in-a-decade shift that essentially drove many conventional players from the field.

Telecoms and banks were two of the industries that sought to capitalize on these considerable disruptions. The latter resisted the onslaught of "internet banking" and "fintechs" for nearly a decade through early deployments of eBanking or "fintechs."

Having witnessed years of heated competition, only for the majority of firms to fail at the finish, banking was at the forefront of this second wave of devolved disruption, now popularly referred to as “open banking,” a major restructuring in how banks and fintechs will work together to meet consumer needs. Open banking allows third parties to transform the banking landscape via an application programming interface, enabling fintechs to compete with banks.

The deployment of artificial intelligence raises questions about the valuable aspects of banking and finance that cannot be learned from data. As crucial competences shift from banks to third parties or even consumers, there have been calls for intensely regulating those operationalized new sources of competences outside of banks. AI will not necessarily create fundamentally new sources of financial sector activities outside of banks, but it will lead to a shift in the frontiers of distance-based competition and a redefinition of how to deliver products and services in a rapid-growth financial marketplace.

1.4.2. Changes in Investment Strategies

It is supposed that the emergence of AI technology will renew the landscape of asset management: wealth managers will be coached to adapt to technologies which are radically different from those they grew up with — cloud storage and computing, data analytics, true information access, understanding of which supersedes finance knowledge. Creating value in the industry of money management means educating new revenue drivers: Lifestyle management, active control of tax implications, choice of effect over face value, the model of access and exposure to financial opportunities. Wealth management firms will recognize that they need to shed bureaucracy, hierarchical structure and become nimbler, faster, ultimately challenging their traditional view of making available only ‘high return’, market beating opportunities. It will be acknowledged that understanding the needs and constraints of clients can be better enabled with AI technology and that establishing true client contact goes far beyond meetings. Clients will prefer firms willing to take full control over their needs and expects pro-active and ongoing wealth management across all asset classes.

The clientele of wealth management firms will be transformed: true institutional money will search a broadest spectrum of investment alternatives and wealth management firms which are able to absorb this additional responsibility of heavily structured money, to take decisions model agnostic and to employ the broadest range of tools will prevail. The arrival of Billions of nest eggs, cash acquisitions, Initial Coin/stock Offerings in crypto assets or hedge funds will lead providers of wealth management seeking firm of choice. The entry of AI technology will redefine asset management and distribution. Competition will refer to more sophisticated competition of data and faster, more accurate information. Traditional wealth management firms will come to the conclusion that more data is better, commoditized automation will push front-to-back office complexity better managed by AI technology. Whatever business case for using AI/ML, focus will be given to better explain, understanding and reporting of black box models to clients. Invasive fundamental analysis, heavy staff, prohibitive corporate memory will give in to AI driven automatic the natural language processing searching how to benefit from macro news. Consistently, the self-service model will embrace all factions of financial analysis and clients will query the investment house by free text searches on whatever issue. AI driven screening/Machine learning will interrogate databases of 'unconventional' data and combine qualitative with hard quant data in canvas-like mixtures of forms.

1.5. Risk Management in the Age of AI

AI Algorithms can help in risk management. Participation of AI in risk management can help risk factors identification, thus it also helps in risk management and avoiding losses because of risk factors. If an AI or ML model has continuously updated and the data used is accurate then intervention of AI in risk and ALM computations tend to beat the out of box results. AI-based models can provide an early flag to wide arrays of risk factors that are correlated to the occurrence of events which can become a large operational loss. AI risk helps in identifying the root cause or reason of non-conformity leading to fruitful identification of corrective and preventive actions [3]. In addition, operational risk management is often driven by strict guidelines on modeling which, given their timespan, soon become obsolete. This drives poor risk factors which either lose out on potentially advantageous seasoned variables or lag on historical events which would have otherwise been influential predictors. In this regard, usage of AI-based insight extraction tools can be extremely fruitful in wrangling repeat data such that materialized knowledge remains up to date and useful.

Operational risk assessment models generally elicit calibrated loss distributions from event data and extrapolated experienced risk factors. Given this well-understood mechanism behind operational loss events, intervention of AI can help treat data in batch mode with high observation, high-variate and deterministic predictive distributions. The AI-risks presented by these data preemptively flag correlating potential co-internal events surfacing with extreme inter-event temporal clustering behavior. Given fixed time-horizons, this flags a much wider array of potentially fruitful and hence alerting risk factors as otherwise would only be observed through on-site visits. This gives the manager an early signal and opportunity to manage pallbearers in a closed loop. This method is thus independent of speculative and hasty human judgment heuristics while still requiring a human intervention for validation; persistent false predictions are automatically available without management effort and may thus prompt review of current practice.

ML excels when there are large data sets whose underlying data-generating processes are complex and uncertain, and the aim is to extract a manageable set of patterns for the purpose of classification or prediction. Once trained on data supplied in a specific format, an ML algorithm will try to classify new, unseen inputs in the same format. AI is substantially different from ML. Older AI algorithms carry out fully automated inference; they receive something, create something, and yield something. More recent AI does not merely classify, but also generates outputs. Larger datasets and advances in computing power have given rise to a new generation of AI models, based on Artificial Neural Networks (ANNs). These patch together basic building blocks, inspired by human biology, into larger networks capable of automatic feature extraction and performance at levels previously believed impossible.

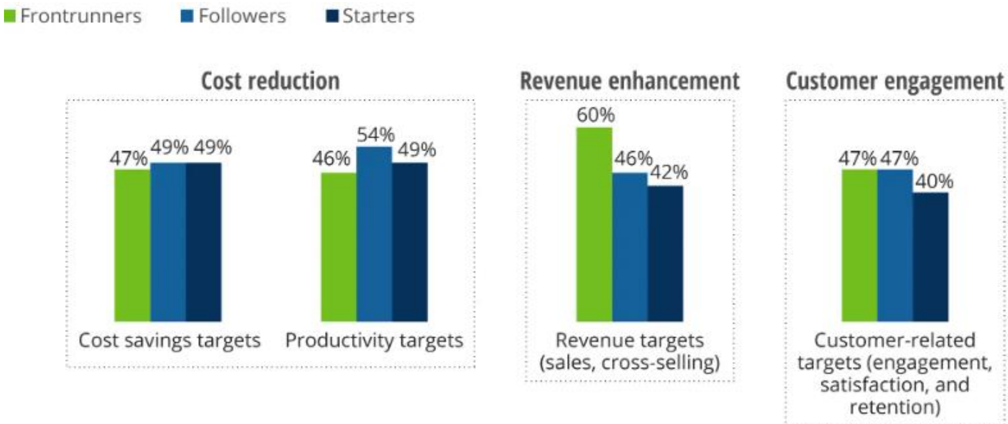

Fig : Artificial intelligence in financial services

1.5.1. AI-Driven Risk Assessment

AI in Finance: The Opportunities and Challenges Ahead The Financial Frontier Economic challenges arising from the banking crisis and rising interest rates will spark a wave of innovation aimed at cutting costs, improving transparency, and enhancing reporting. The dominant technology will be generative AI and automated machine-learning, allowing firms to create models faster, at lower costs, and with less oversight. This will transform the financial system, affecting jobs, industry structure, and market functioning. Generative AI will help bring models into production more easily and allow firms to develop algorithms that adapt better to datasets without the need for large in-house model development teams.

However, generative AI also poses challenges. Financial authorities will need to assess whether models used for financial stability are robust, including their real-time behavior and the consequences of limitations and edge cases. There is a possibility of malware being created for algorithmic trading. Moreover, there is uncertainty about one of generative AI's most desirable features: interpretability. Interpretation may be easier at the beginning of training, while advanced convergence may lead to more opaque models, and it may become impossible to assess whether model outputs are at all plausible. Currently, the understanding of non-linear financial models is poor, casting doubt on their robustness and suggesting that many poorly performing models may still give plausible results.

AI-Driven Risk Assessment The management of financial risks relies on a complex web of regulations that have evolved over decades. Central banks and financial authorities worldwide carry out this risk assessment in-house, drawing on a wide array of data, models, and expert opinions. Setting and interpreting these parameters is as much an art as a science. With the growing use of artificial intelligence (AI), some of this art may soon be automated, but it remains to be seen how safe the resulting output will be. AI consists of algorithms that allow computers to analyse large data sets, building on statistical methods developed in the early and mid-20th century. That said, there is a gulf between in-depth knowledge of statistics and, for example, the development of computer vision algorithms capable of identifying objects in unstructured images. Today’s AI is much more capable than traditional statistical methods, but it implies a loss of interpretability.

1.5.2. Regulatory Challenges and Compliance

AI has disrupted not just traditional industries, but also the complementary industries that exist to verify and regulate them. These have become new frontiers for AI firms and threaten traditional firms. This is especially pertinent in finance, a heavily regulated industry, where the interpretation of regulatory rules requires knowledge of what is being run, which is increasingly black-boxed. The introduction and use of different AI systems in finance, which could include applications in customer service, risk, loan pricing, or anti-money laundering, bring increased challenges of how to regulate these systems, given the stakes involved.

AI systems in finance could take on diverse forms, ranging from chatbots in customer service to ML/AI models in risk, loan pricing, or anti-money laundering. This creates a complicated landscape of regulatory oversight as each government agency has clear regimes. The multitude also includes other disruptions like competition to exchanges through dark pooling or smart routing, crypto exchanges, DeFi lending platforms, or robo-advisors. The avalanche of new systems would seem to require the capacity to understand how they work in order to interpret regulations or assess compliance, which ironically is limited by the AI trends just discussed.

Competence to regulate a new technology usually requires understanding it inside out. This is feasible for regulators of processing machines where the basic operations are limited: regulators would inspect machines before granting permissions; they could also seize machines for postoperative evaluations. The impenetrability of AI systems vastly complicates this. There is a procedural dilemma of regulatory competence. On the one hand, improper use of AI systems can lead to massive harm; denial of permissions or the ability to deploy a system could cost firms billions. On the other hand, civil compliance review and inspection mechanisms can be used to debug AI systems.

1.6. Conclusion

The breakthroughs of artificial intelligence (AI) over the last decade have revolutionized and transformed everything from technology and space to healthcare and transportation, among many other fields. In financial markets, the development of digital financial assets, including cryptocurrencies and central bank digital currencies (CBDCs), has introduced a high level of uncertainty, representing a new set of problems in economics, accounting, auditing, regulation and risk management, among others. Such trends have motivated a rush for AI to overcome challenges brought by the smart technologies of the second financial revolution and the fourth industrial revolution that overlap and intertwine. AI in finance has gained increasing attention as it becomes a key driver of technology innovation and uplift across broader fields and industries worldwide. Financial AI shows a great potential to empower future intelligent and advanced finance through smartly automating traditionally labor-intensive and cumbersome finance processes that rely heavily on human intellect or experience. AI shares a critical and dominant responsibility for transforming traditional finance businesses across broader fields and industries, including banking, insurance, investment, risk, and consulting. These rapidly advancing frontier developments in AI are delineated, described, analysed, and discussed in the context of opportunities, challenges, and a suggested research roadmap towards a financially intelligent technosphere.

Financial technology and business have advanced remarkably over the past two decades. Big data technology has greatly changed how information is captured and managed. More recently, the boom in online and mobile films has transformed how customers, commerce, and markets connect and interact. These rapid advancements in technology have further aimed to elevate the potential transaction efficiency and integrity of financial technology. However, transaction and information asymmetry, opportunism, and capacity limits have once again become dominant subjects in the booming regimes. An era of smart technology has come along with the sixth information revolution in the face of the broad challenges of mainstream financial exploration and technology. The intelligence parallel to the financial technology revolution has the potential ability to address financial problems arising from rapid changes in traditional financial activities. It is a new concept that aims to achieve intelligent and smart financial technology similar to the industrial brain or smart-to-grain.

1.6.1. Future Trends

The world is at a pivotal juncture in 2023, where the existing traditional financial environment is moving into a new era fueled by AI and digital transformation. With the ability of AI to analyze massive data sets quickly and precisely, it is altering the basic components of finance, including transactions in the form of cryptocurrencies and security token offerings. As technology advances from basic automation tools to massive AI applications, companies are seizing opportunities to engage in the evolving world of AI. Meanwhile, their financial situation is in flux due to inflation or interest problems that erupt in the area of tech stocks, hedge funds, or crypto companies. Owing to these factors, the financial boundary has been increasingly redefined by AI. This paper analyzes the significant transformation brought by AI from perspectives of group moral hazard, mass customization and personalization, market microstructure, and tools of trade. It also discusses future research trends along with these developments.

With the rapid development of AI, human cognition, or more broadly, "intelligence," is being extensively augmented and embedded into systems to enhance human intelligence. The first aspect of AI debates should discuss the conceptual transformation, which is the blurred line between "fintech" and "AI Fintech." The difference between fintech and AI fintech is not technological but conceptual. Finance can be more precisely described in terms of information transmission or transformation instead of the economy. Actually, most economic transactions are simply payments that can be treated purely as information processing. AI can be applied to redefine finance more broadly, which is considered as "fin-data," as it emphasizes machine learning from data. Indeed, it can be considered as "fin-intelligence," which requires investments on data processing physical infrastructure and on-demand data governance, as well as extensive technology adoption from predictive analytics to computer vision. Regardless of the conceptual discussions, new boundaries are drawn as workloads, complexities, and jurisdictions of finance are transformed.

References

Bi, S., & Bao, W. (2024). Innovative Application of Artificial Intelligence Technology in Bank Credit Risk Management. arXiv. Retrieved from https://arxiv.org/abs/2404.18183arXiv

Zemankova, A. (2019). Artificial Intelligence in Fraud Detection. International Conference on Control, Artificial Intelligence, Robotics & Optimization.Wikipedia

Shaffer, K. J., Gaumer, C. J., & Bradley, K. P. (2020). Artificial Intelligence Products Reshape Accounting: Time to Re-Train. Development and Learning in Organizations.Wikipedia

Ajay Bandi, Pydi Venkata Satya Ramesh Adapa, Yudu Eswar Vinay Pratap Kumar Kuchi. (2023). The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges. Future Internet.Wikipedia

Bandi, A., Adapa, P. V. S. R., & Kuchi, Y. E. V. P. K. (2023). The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges. Future Internet.