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Chapter 12: The road ahead: future trends, challenges, and opportunities in artificial intelligence-driven finance

12.1. Introduction

Artificial intelligence (AI) is reshaping the world in every aspect. Financial industry is leading in the AI frontier for competitiveness and profitability. New AI techniques, such as deep learning and graph learning, are rapidly emerging and impacting the finance sector. In addition to the new techniques, there are huge challenges and opportunities in research and practice. This paper delivers a comprehensive analysis and exploration of AI in finance. It introduces the financial domain diversity, distinctly astonishing informatics and challenging issues related to the broad AI avenue in finance at domain, knowledge, modeling, infrastructure, method, and algorithm levels, and summarize horizon issues of overarching topics and booming trends, which can be chartered as a fiscal cosmos and analyzed as a galaxy. AI in finance has been broadly explored, with many methods proposed. Nevertheless, the quest for opportunities and the need for solutions remain. Broader, newer, and smarter financial AI methods, applications, and businesses are needed as high-impact, precedent-setting and high-benefits approaches to resolve the largely unsolved problems or challenges in the aspect of technique, knowledge, analytics, and infrastructure (Boni, 2021; Syed & Syed, 2021; Bandi et al., 2023).

AI is not a new concept to finance. Employing mathematical models with the differences in interest exchange rates and security prices, arbitrage in options, futures, or bonds for profit has been widely used well before the advent of the term AI. Other than traditional Economics, Finance, and Political Science disciplines explored during the 20–30th centuries, plenty of finance/economics datasets have become open access. These intellectually leading datasets and unprecedented advances in information technology have accelerated vigorous interests in applying AI on wider, broader, generic, or bigger financial modeling, knowledge mining, and information prediction. The finance domain is a galactic world with tremendous astronomy (financial informatics), many celestial (financial) bodies (financial businesses), stars (operators/types of stocks), and even hundreds of thousands of satellites (customers/traders/entities). It is redefined, transformed, and appraised by deep distributed financial modeling through distributed diverse platforms or services involving multi-market/domain/channel/sector applications. Considerable analysis on cross-market financial data is still emerging with respect to the huge broadband and diversity of finance domain datasets (Gartner, 2023; Gupta et al., 2024; Banerjee et al., 2025).

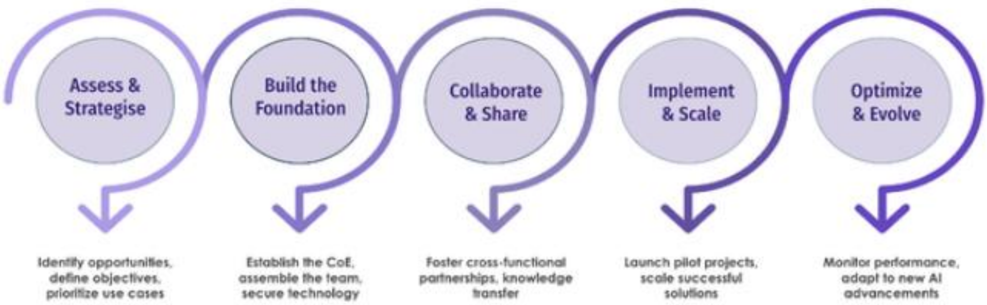

Fig 12.1: AI and data analytics-driven finance

12.1.1. Background and Significance

Fueled by the intensive big data wave and advanced information technologies, artificial intelligence (AI) enabled finance is ushering in a new era with revolutionary changes. Following decades of the complexity and turbulence increase in the financial environment, traditional financial systems, models, analytics, and regulations at every level have been under intensive challenges. Data-driven and AI-enabled financial modeling, analytics, and algorithms are becoming crucial in effectively addressing the challenges, empowering the changes, and exploring the future. AI-enabled financial modeling can support decision making in limitless styles and at unlimited levels, including more timely, accurate, easy, effective, and user-adaptive decision makings. Finance, jointly with its closely related disciplines of economics and business, is an important and indispensable branch of academic/scientific research, industry development, and even nation construction as the lifeblood of global prosperity.

Analysis and observations of the data, modeling, algorithms, and technology used in the five main AI fronts in finance research can help the economics and finance communities clarify the states and establish up-to-date fine-grained research agendas.

12.2. Overview of AI in Finance

Despite the rapid progress made in AI in Finance, many challenges and opportunities remain to be addressed and explored, including those existing within Finance and general areas of AI, as well as their intersections, which are the frontiers of FinTech and may require interdisciplinary collaborations to tackle. AI in Finance is by far not a niche research area and demand for financial modeling and learning continues to grow. Increasingly complicated and denser financial applications provide opportunities to explore AI-driven technical and Financial innovations, theories and methodologies, which are attracting interest from academia and various community groups. Many application areas also require new solutions and models to understand and regulate their complications and applications' effectiveness and safety.

Deep Distributed Financial Modeling. AI with data-driven general analytics and learning is increasingly important in Finance. Some typical examples are the newly emerged Internet finance, mobile payments, digitized asset management, etc. During the financial applications' lifetime, diverse indexing financial learning and modeling approaches, requirements, contexts, constraints, channels, and contents are co-evolving, which present a new and challenging modeling paradigm—i.e., deep distributed analytics and learning for crowd-sourcing/crowd-funding campaigns of finance. Such distributed and deep learning are to model the cross-sector, -domain, multi-channel, -contextual, and -constituent diversity and co-evolving information and knowledge in ad-hoc crowds for a Finance campaign along the crowd's action trail. The crowd-sourcing financial paradigms and models may also shed new light for better crowd-sourcing Finance systems and applications. Active explorations on these fronts in both Finance and Computer Science communities are desirable.

12.2.1. Research design

The present study employs a multifaceted comprehensive scientometric approach to explore the intellectual underpinnings of AI and ML in financial technologies (FinTechs) and financial services (FSs). This study examines the publication patterns of their related articles based on a rigorous methodological framework that provides graphical and numerical knowledge maps of AI-ML & FinTech, encompassing the spatio-temporal evolution of disciplines, countries, institutions, authors, and journals. Besides, the emerging non-formal clusters or keywords associations dynamically reflected the hot topics and the initial research streams in uncharted domains. Those prominent influences, novel insights, and burgeoning research frontiers holistically foster a more profound understanding of the knowledge structure in AI & ML finance research.

The results unveil a marked increase of publications from 2017-2022 [2]. Besides, there are increasingly multidisciplinary and international collaborations among these disciplines. A pronounced gradual rise in the frequency of citations concerning these emergent publications reflects their increasing research impacts. A rank of novelty and usefulness is presented on the thirty emerging non-disciplines with strong sub-disciplines keywords associations from the 2021-2022 novel keywords co-occurrence clusters. In-depth discussions of a transformation or a bibliometric review on AI-ML & FinTech in finance provide thoughtful insights for future studies in academia and practices.

Significant advances of AI/ML in financial time-series forecasting (TSF) emerged during the big-data era. Nowadays, AI/ML economic-financial models, focused on multi-market, domain, channel, and sector applications, transfer modelling across markets, be it domestic and global, stocks and commodities, become a prominent but under-studied area in FinFBs. With the increased interest in and expanding stock trading channels, there are more public institutions and initial public offering (IPO) firms of different sectors and countries. Parallel with newer types of data sources, AI-ML modelling of these big entities becomes more challenging yet rewarding in terms of financial returns.

12.3. Current Trends in AI-Driven Finance

Over the past decades, financial businesses have seen the overwhelming impact of technologies. Further, those in the finance industry have been aware of the threats posed by unfinished transactions or wrong decisions in financial businesses. Growing markets and companies means more transactions as well as larger risks as time goes on. Trading in financial markets has become a race among high-speed computers. Changes in business perception and models mean high demands and requests in service quality and efficiency. Various technologies like deep learning, machine learning, data science and algorithms have boosted financial businesses from different aspects, resulting in widely adopted systems like faster transaction engines, forecasting models, loan and credit analysis, customer segmentation, smart agents, as well as digital currencies and financial trading instruments.

AI in finance is an evolving area with increasing industrial applications and impact. Understanding the overview as well as opportunities and challenges of AI in finance is of interest to both researchers and practitioners in the finance and technology industries. Finance refers to broad areas including capital markets, trading, banking, insurance, investment, asset/wealth management, risk management, marketing, compliance and regulation, payment, auditing, and financial services.

Artificial Intelligence (AI) broadly refers to the emulation of human intelligence by computational machines. Those machines possessing intelligence not only ingest information but also learn from experience and adapt to new inputs and perform human-like tasks. AI techniques in general can be categorized as classic vs. modern. Classic AI techniques include rule-based systems, expert systems, decision trees, regression analysis, kernel methods, and clustering techniques, basically restricted to a particular problem domain. People have been using them to automate human intelligence outside of finance, and some classic AI techniques have been employed in trading, investment, risk management, and insurance. Modern AI techniques include machine learning, deep learning, data mining and analytic techniques, and natural language processing and analysis.

Fig 12.2: Current Trends in AI-Driven Finance

12.3.1. Algorithmic Trading

Automated trading developed in conjunction with exchanges in the 1980s. At the same time, Japanese financial institutions began the work of developing the first computer programs capable of executing trades automatically. These systems were based on rules that would outline when a buy or sell order should be placed based on a range of price and trading volume data signals. Nonetheless, it is important to note that this first automated trading algorithm acted more like a signal generator, which suggested buy or sell orders to a human trader who would intervene to send the orders to market. This is called ‘semi-automated’ trading.

With the emergence of the first electronic exchanges, the introduction of protocols for transmitting trade orders and market data, and the high-speed communication systems, trading systems began to be developed. Such systems enabled market participants to place orders with low latency and automatically execute them at market prices. In the new century, the increasing computational power of computer processors, greater internet bandwidth for the transmission of market data, and a proliferation of market trading venues offered a huge opportunity for market participants to innovate new trading strategies. As a result, trading systems with the aforementioned capabilities have evolved to where they effectively replace human traders in order execution decisions based on real-time market feedback. This is called ‘fully automated’ trading systems, often referred to as trading algorithms.

Traditionally, algorithmic trading refers to any type of trade execution that uses a computer program to send orders to market. The directive on ‘algorithmic trading’ covers order execution algorithms which send orders exploring different markets. Such algorithms compare trading opportunities on different limit orders to perform price improvement. All of these rely on econometric models of the order book dynamics and are underpinned by high-speed, low-latency co-location services. Algorithmic trading is also referred to as trading strategies that embed a set of buy/sell signals into trading programs. Most such strategies rely on predictive models of univariate time series or multiple price and volume time series data. Such statistical machine-learning models often demonstrate substantial interpretability gaps and have relatively inferior real performance.

12.4. Technological Advancements

The technological advancements in AI-driven finance have been rapid and enabled by the digitization of finance. The data flow in finance has been reconstructed, and big data has become a basic requirement for AI technology applications in finance. Intensive computing power, together with advancements in machine learning, allowed previously inapplicable or infeasible algorithms to be realized. Most importantly, despite several negative events caused by AI applications, the benefits of AI solutions are hard to argue against. Instead of questioning the usability of AI, sceptics ask which AI solutions to adopt, and industry experts are therefore called on to popularize their adoption and implementation. With standardized components, platforms, protocols, and taxonomies, AI solutions are better designed to be easily utilized by various financial institutions. The education levels in finance and AI have greatly improved, opening plenty of investment opportunities and alternative career choices. These evolutions created many champions in the banking, insurance, and capital market areas who could convince CEOs or board members about the need for AI as partners. Thence, with the technological, social, and economic environments being favorable, a wide range of financial AI technology applications have flourished. The development of AI technology has led to major impacts on financial institutions through the implementation of unlimited applications. AI technology is able to create new business models, redefine existing supply chains, transform enterprise landscape, enhance management, upgrade operation modes, improve customer relationships, develop multi-agent systems, and strengthen strategic cooperation in the financial environment. With AI technology embedded in finance, conventional finance will be transformed in great depth and broad scope, resulting in more flammable phenomena. A regulatory framework will be re-imagined intentionally or inadvertently to control the implosive momentum come up with by the feedback loop of current developments. An urgently needed regulatory framework for AI finance has emerged. With AI technology, finance will come with great deep transformations. In this context of being unreliable, fast-evolving, and deeply disruptive current AI finance landscape, significant emerging future research directions are needed.

12.4.1. Machine Learning Techniques

Deep distributed (asynchronous and parallel) modeling of AI in finance (and other finance highly SMSA) domains is essentially modelling of distributed, asynchronous events with multiple channels and domains (as events) and multiple sectors (as domains). To maximize the economic capital of financial modeling, it is necessary to maximize usage of all available information and knowledge by suppose distributed, multi-domain/channel/sector analytics and learning at the lowest level and harmonization and synchronization between distributed, multi-domain/channel/sector learning for deep learning or deep modelling (and results) at the highest level. On its own, deep learning as a model/modeling technique could not learn any knowledge from its own.

After the knowledge base is learnt from either manual knowledge engineering or machine knowledge discovery auto-analytics and learning, it needs to be distributed extensively to either domains/areas and channels or sectors/assets at the lowest level of modelling/analysis. Applications include but are not limited to distributed model construction, parameter estimation, model event federation, and QA. Asynchronous distributed analytics learning or deep learning may be realized based on firstly parallel weight estimation and/or transfer learning federated either at hidden layer levels or the output level.

However, one of the biggest issues of ground to air finance modeling lies in hard to apply more effective and efficient analytics ML or distanced learning techniques. There are also other issues such as how to measure and control the impact of excessive information on decision-making outputs, how to understand the decisions made by such advanced AI, how to regulate its usage by legal instruments, how to build a more humanized AI or machine-human teams for superior performance fairness and ethicality, and how to visualize the learnt embedded knowledge or models/output events and their decisions. Another critical philosophical issue is about the understanding and interpretation of knowledge with either deep learning or deep modelling or deep game play outputs and hence the model led decisions and actions.

12.5. Regulatory Landscape

AI technologies present both opportunities and challenges for regulators and supervisors. AI-based systems offer significant promise to financial institutions and can help meet consumer protection objectives, particularly through the better detection of misconduct, but AI-based systems also raise a number of traditional and new regulatory and supervisory concerns. These address issues of fairness, transparency, accountability, consumer protection, data protection and privacy, systematic risk and resilience, adversarial attacks, hiccups and model collapses, and the extent to which traditional regulatory tools still work when AI-based systems are employed. Regulators and supervisors will need to decide how to adapt their frameworks in response to the growing application of AI-based systems or how to deal with remaining constitutional issues. Key recommendations are made.

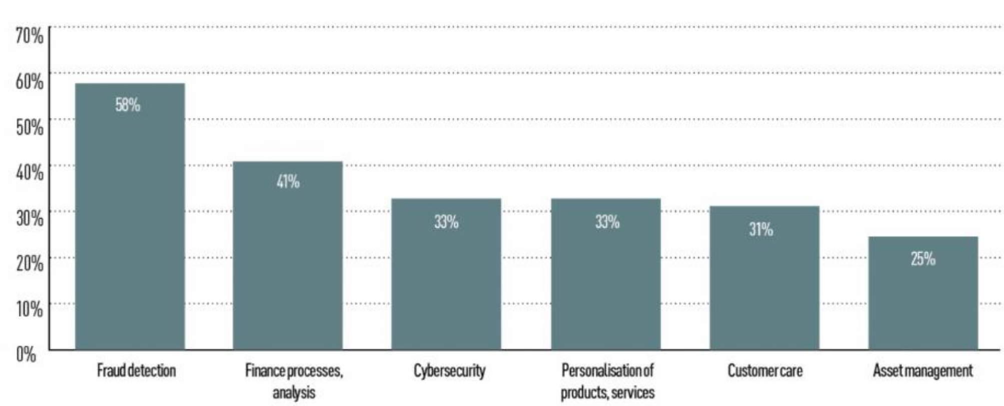

Fig : The future role of AI in finance

AI adoption could lead to large dividends for finance and the wider economy, but the growth of AI presents a complex policy and regulatory landscape. AI is proving to be a driver of productivity increase and can improve the quality of services provided in the finance sector and make risk management more efficient. Yet AI technologies also raise issues of bias, fairness, accountability, and transparency. This text explores the regulatory landscape which surrounds the use of AI technologies in finance, and also discusses avenues for possible regulatory reform. It analyses the potential benefits of AI in finance, the potential harms, and the challenges of AI regulation, especially with respect to data privacy and personal data protection. It considers the impact of AI regulation on innovation and the risks of regulatory arbitrage. It also offers policymakers a range of options for addressing the challenges posed by AI technologies.

Using AI technologies has great potential to improve financial services in various ways, including credit scoring, risk management and anti-money laundering systems using machine learning methods, robo-advisors offering investment advice using natural language processing methods, chatbots providing execution services, and automated claim processing. There is potential for AI to reduce costs, lower fees, quality-adjust adjustments, and offer previously unavailable services. There are risks that AI has the opposite effect. Biases may arise in training data, as even well-designed algorithms can produce outcomes that reinforce historical biases and systemic discrimination. Automation within a firm poses the risk of over-reliance on AI and systems failures, where AI-based decision-making differs from approved rules, recommendations, or policy. There are also new supervisory technology risks and firm-specific regulatory odds.

12.5.1. Compliance Challenges

AI has gained popularity in an increasing number of verticals in services and industries, and various financial institutions have joined the trend by implementing machine learning and deep learning. Furthermore, the more recent rise of cloud computing has significantly lowered the cost of computing resources required for implementing AI-heavy models and their usage in real life. Meanwhile, opaque black-box algorithms such as non-linear machine learning and deep learning have been proposed as a competitor to the traditional models. Trained using a massive amount of input data and computing resources, the models can deliver promising results in many service areas. However, their inability to explain the model behavior and difficult-to-understand decisions has raised questions on accountability, trustworthiness, bias, and regulatory compliance.

2020 was a pivotal year in terms of regulatory oversight on AI in financial services. For instance, the Office of the Comptroller of the Currency has heavily scrutinized banks' adoption of AI. Compliance departments are under pressure to come up with a satisfactory plan for compliance and oversight on these models before the regulatory bodies require more stringent measures. Regardless of time-consuming data preparation, model training, and testing, financial institutions face further difficulties in model governance and auditability after deployment due to poor maintainability and the AI-induced complicated workflow. The challenge includes models changing over time, extensive flow, and labor-heavy processes. One crucial aspect and first step towards effective model auditability and compliance is transparency, which is highly related to simplicity and credibility. However, despite strong incentives for financial institutions to ward against black-box AI models, they are reluctant to abandon AI techniques to ensure model explainability.

12.6. Conclusion

The applications of AI in finance will increase rapidly over the next decade. Revolutionizing financial services, AI technology can increase organizational efficiency, provide personalized experiences to customers, and detect financial fraud and misconduct, etc. AI will also improve difficult data processing efficiency and enable more intelligent, automated decision-making and investment. Most obviously, it helps reduce the labor force, but in a good sense such as reducing human use of financial resources hence growth of economic financial well-being.

With the proliferation of data, the scarcity of human resources to build comprehensive knowledge of data grows larger. Highly customized, smart recommendation services will suddenly ubiquity in the finance sector, enabling all levels of customers to benefit from such financial services that will be tailored to fit personal needs. While both retail banking and investment banking will be transformed radically, the fixed income area will keep best amid the enormous evolving era due to its high stability and degree of automation, and the entire growth will be much less volatile than other areas. With the great success of AI, it is quite possible that some financial products, having been a black box to quantitative analysts and the public now will be automated and personalized, such as consumer credit, ICO types of financing and parametric insurance.

12.6.1. Future Trends

The birth of a new economic mode at the end of last century drives a radical change of economics and finance, and meanwhile a fundamental progress of graphical and statistical modeling of economics and finance. The economics and finance communities have been showing more interest in AI and FinTech (especially in finance or finance-driven smart FinTech). More and more forums on AI in finance are organized, focusing on smart payment, blockchain, as well as Internet finance, cloud finance (referred generally to financial and economic distributed platforms). AI-in-finance driven smart FinTech is regarded as a timeless evolution in financial history, but in a new perspective. The motivation and importance of AI in finance (smart FinTech) for real economics and finance rest on their historical data. In the mathematical framework of AI or smart FinTech modeling in economics and finance, two questions about the plausibility and need of designing deeper AI models arise. The first question relates to a practitioner's complaint that common Indices and trading strategies are simple and explainable, and there is no need for complicated smarter AI models. The question also refers to less innovative FinTech known in the economics and finance community, which acts as knowledge-transferring analysis rather than rediscovery modeling. Many prediction solutions contained in AI papers are rejected for deployment as focused in unexpected domains such as stock market analysis. Many AI or data-driven solutions only took a fraction of the computing time that original theoretical models occupied. On the one hand, innovations of deep computing and distributed graphics modeling in the machine learning community are enablers to transform grid-computed mathematical models into deep distributed finance-driven AI systems. On the other hand, many registration tracking files are required to ensure the intelligibility of employed AI techniques by regulators. An alternative explanation is Gemini of NASA, an astrodynamic computer program for spacecraft trajectory analysis which was built after several years' effort and fold-in time made exemplary by the Apollo 11 moon mission. Similar difficulties lie in the demand of absolutely complete descriptions or models of practical applications including Navier-stokes equations in aerodynamics. Continuous Data and Money then pose new challenges for AI-in-FinTech. Latest technology advancements demand beyond conventional continuous data analysis from both data modeling and computing perspectives. Crowd-computed platform leads radical computing power shift opportunities and challenges, especially in business intelligence and finance.

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